Project 3 - Walmart

May 20, 2022

0.1 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.

0.1.1 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).

0.1.2 Here the assumption is that 50 million customers are male and 50 million customers are female.

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

Black Friday is a term for the Friday after Thanksgiving in the United States. It traditionally marks the start of the Christmas shopping season in the United States.

[ ]:

```
```

[1]:

```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
from scipy import stats
```

[2]:
```
#Importing the dataset
df=pd.read_csv('Walmart.csv')
df.head()
```

[2]:
```
   User_ID Product_ID Gender   Age  Occupation City_Category  \
0  1000001  P00069042      F  0-17          10             A
1  1000001  P00248942      F  0-17          10             A
2  1000001  P00087842      F  0-17          10             A
3  1000001  P00085442      F  0-17          10             A
4  1000002  P00285442      M   55+          16             C

  Stay_In_Current_City_Years  Marital_Status  Product_Category  Purchase
0                          2               0                 3      8370
1                          2               0                 1     15200
2                          2               0                12      1422
3                          2               0                12      1057
4                         4+               0                 8      7969
```

[3]:
```
#No. of rows and columns of the dataset
df.shape
```

[3]:
```
(550068, 10)
```

[4]:
```
#No. of null values
df.isna().sum()/len(df)
#There are no null values in any of the columns.
```

[4]:
```
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
```

[5]:
```
#Information about the dataset
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
```

[6]:
```python
print(df['Product_Category'].nunique())
# There are 20 unique product categories.
print()
print(df['Product_Category'].unique().tolist())
print()
print(df['Product_Category'].value_counts())
```

```
20

[3, 1, 12, 8, 5, 4, 2, 6, 14, 11, 13, 15, 7, 16, 18, 10, 17, 9, 20, 19]

5     150933
1     140378
8     113925
11     24287
2      23864
6      20466
3      20213
4      11753
16      9828
15      6290
13      5549
10      5125
12      3947
7       3721
18      3125
20      2550
19      1603
14      1523
17       578
9        410
Name: Product_Category, dtype: int64
```

[7]:
```python
print(df['Product_ID'].nunique())
print()
# There are 3631 unique product IDs.
print(df['Product_ID'].value_counts()[:10]) #Top 10 product IDs
```

```
3631

P00265242    1880
P00025442    1615
P00110742    1612
P00112142    1562
P00057642    1470
P00184942    1440
P00046742    1438
P00058042    1422
P00059442    1406
P00145042    1406
Name: Product_ID, dtype: int64
```

[8]:
```python
print(df['Age'].nunique())
print()
# There are 7 unique age categories.
print(df['Age'].unique().tolist())
print()
print(df['Age'].value_counts())
```

```
7

['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25']

26-35    219587
36-45    110013
18-25     99660
46-50     45701
51-55     38501
55+       21504
0-17      15102
Name: Age, dtype: int64
```

[9]:
```python
print(df['Occupation'].nunique())
print()
# There are 20 unique Occupation years.
print(df['Occupation'].unique().tolist())
print()
print(df['Occupation'].value_counts())
```

```
21
```

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

4     72308
0     69638
7     59133
1     47426
17    40043
20    33562
12    31179
14    27309
2     26588
16    25371
6     20355
3     17650
10    12930
5     12177
15    12165
11    11586
19     8461
13     7728
18     6622
9      6291
8      1546
Name: Occupation, dtype: int64
```

[10]:
```python
print(df['City_Category'].nunique())
print()
# There are 3 unique City categories.
print(df['City_Category'].unique().tolist())
print()
print(df['City_Category'].value_counts())
```

```
3

['A', 'C', 'B']

B    231173
C    171175
A    147720
Name: City_Category, dtype: int64
```

[11]:
```python
print(df['Stay_In_Current_City_Years'].nunique())
print()
# There are 5 unique Current City Stay Years.
print(df['Stay_In_Current_City_Years'].unique().tolist())
print()
print(df['Stay_In_Current_City_Years'].value_counts())
```

```
5

['2', '4+', '3', '1', '0']

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

[12]:
```python
print(df['Gender'].nunique())
print()
# There are 2 unique Gender categories.
print(df['Gender'].unique().tolist())
print()
print(df['Gender'].value_counts())
```

```
2

['F', 'M']

M    414259
F    135809
Name: Gender, dtype: int64
```

[13]:
```python
print(df['Marital_Status'].nunique())
print()
# There are 2 unique Marital Status categories.
print(df['Marital_Status'].unique().tolist())
print()
print(df['Marital_Status'].value_counts())
```

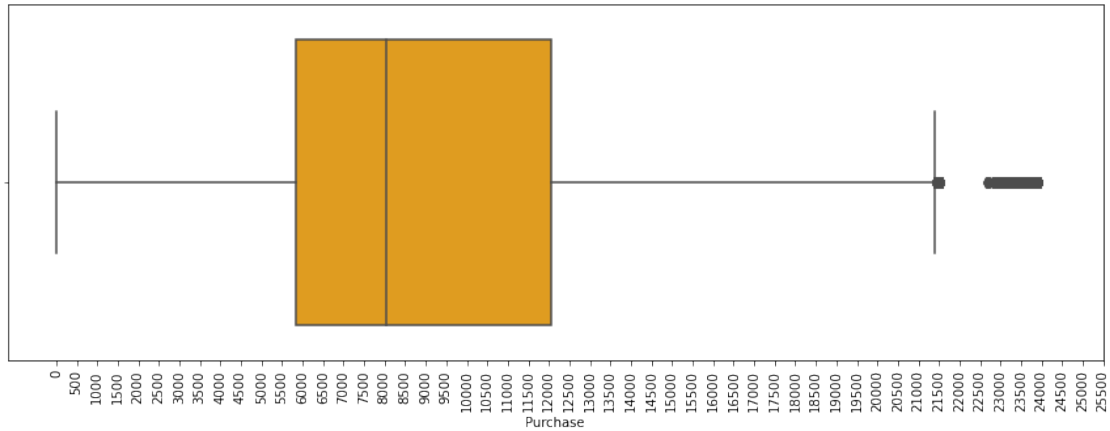
```
2

[0, 1]

0    324731
1    225337
Name: Marital_Status, dtype: int64
```

[14]:
```python
print(df['User_ID'].nunique())
# There are 5891 unique users.
```

```
5891
```

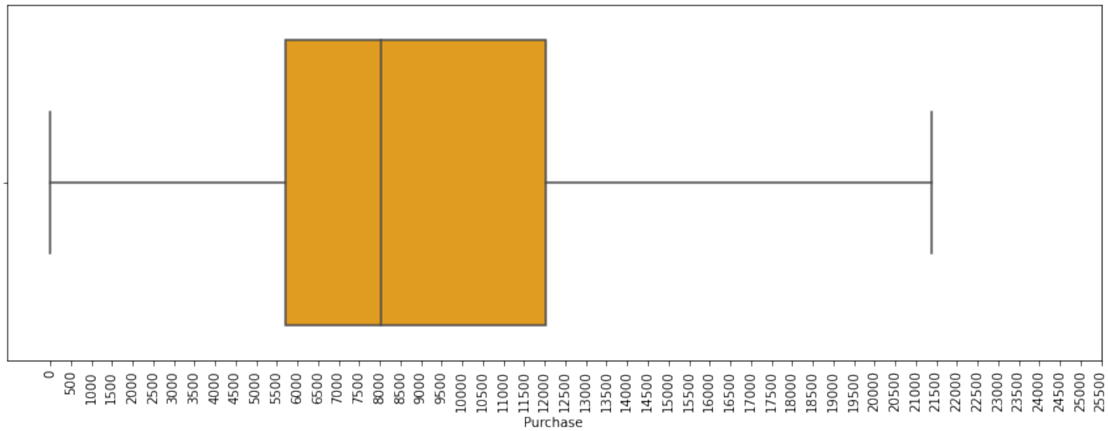
[ ]:
```python

```

[15]:
```
#Using Boxplot on Purchase
plt.figure(figsize=(15,5))
sns.boxplot(data=df,x='Purchase',color='orange')
plt.xticks(np.arange(0,26000,500),rotation=90)
plt.show()
#We see that there are few outliers after which are above 21500.
#The median is around 8000.
```



[16]:
```
#Removing the rows for which outliers are present in the Purchase column
q75,q25 = np.percentile(df['Purchase'],[75,25])
intr_qr = q75-q25
maximum = q75+(1.5*intr_qr)
minimum = q25-(1.5*intr_qr)
df.loc[df['Purchase'] < minimum,'Purchase'] = np.nan
df.loc[df['Purchase'] > maximum,'Purchase'] = np.nan
df.dropna(inplace=True)
```

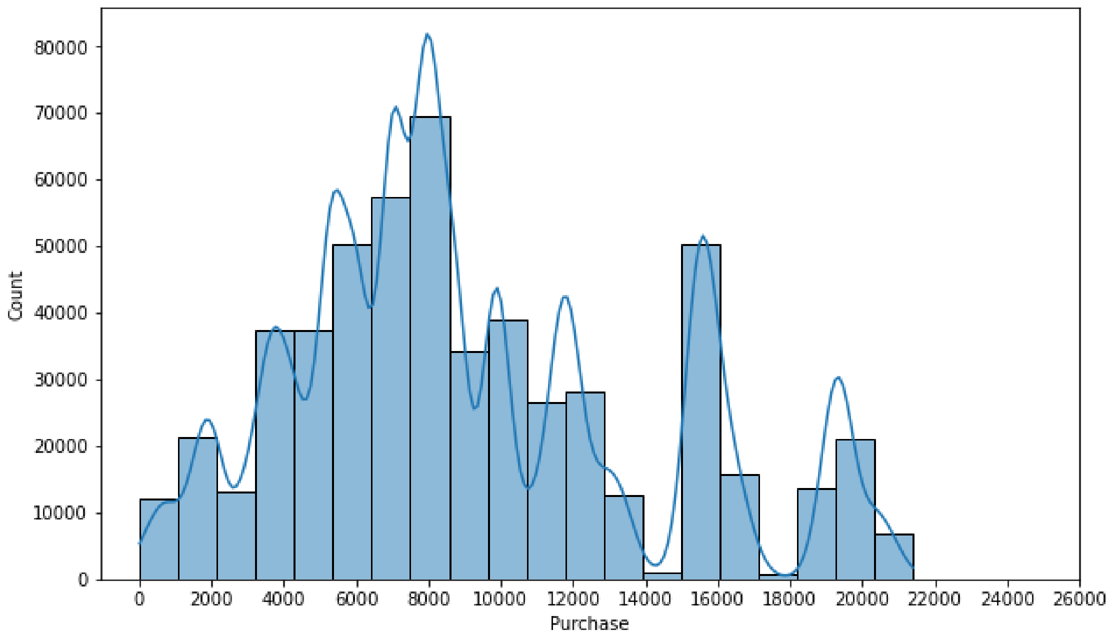
[17]:
```
#Using Boxplot on Purchase again. We see that the outliers have been removed.
plt.figure(figsize=(15,5))
sns.boxplot(data=df,x='Purchase',color='orange')
plt.xticks(np.arange(0,26000,500),rotation=90)
plt.show()
#We see that there are few outliers after which are above 21500.
#The median is around 8000.
```



[18]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 547391 entries, 0 to 550067
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   User_ID                     547391 non-null  int64
 1   Product_ID                  547391 non-null  object
 2   Gender                      547391 non-null  object
 3   Age                         547391 non-null  object
 4   Occupation                  547391 non-null  int64
 5   City_Category               547391 non-null  object
 6   Stay_In_Current_City_Years  547391 non-null  object
 7   Marital_Status              547391 non-null  int64
 8   Product_Category            547391 non-null  int64
 9   Purchase                    547391 non-null  float64
dtypes: float64(1), int64(4), object(5)
memory usage: 45.9+ MB
```

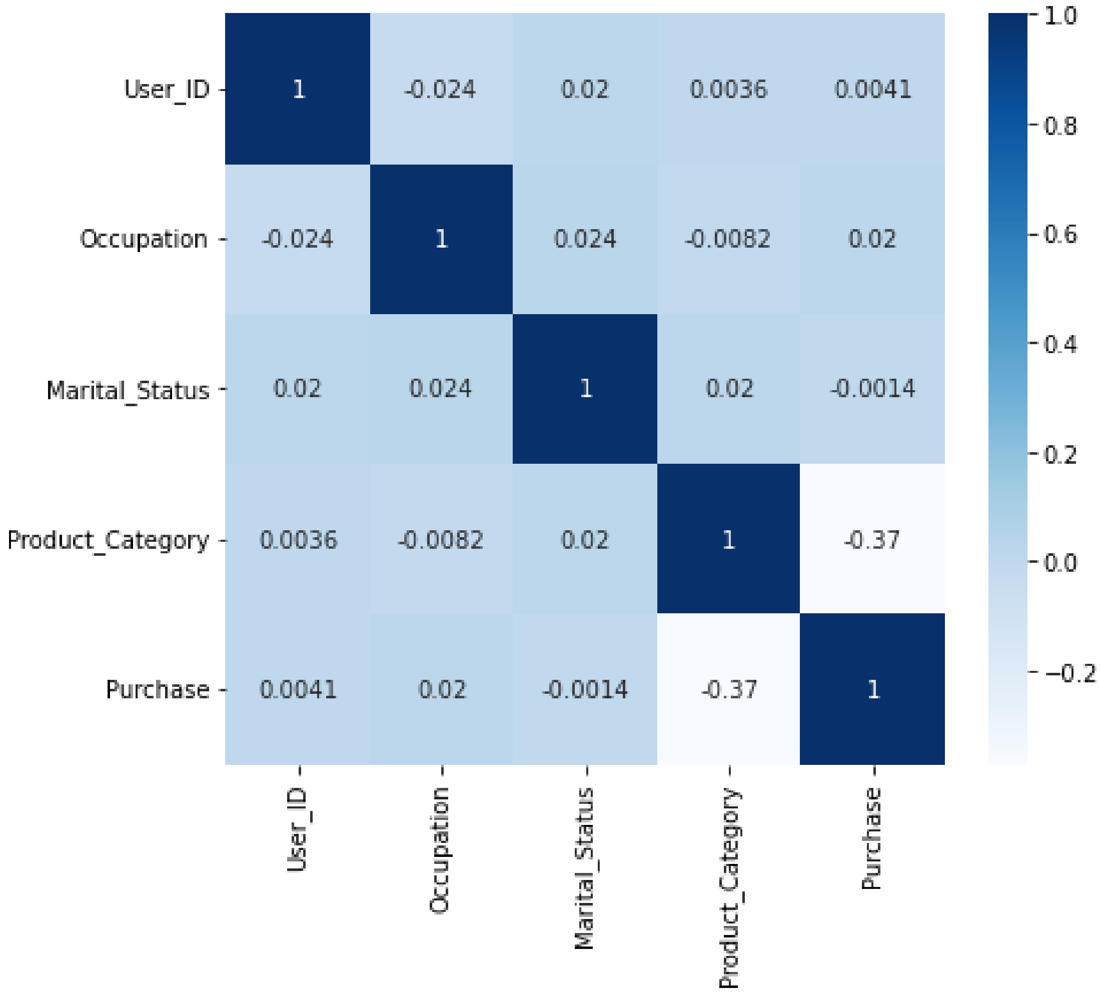
[19]:
```
#Distribution Of Purchase
plt.figure(figsize=(10,6))
sns.histplot(data=df,x='Purchase',bins=20,kde=True)
plt.xticks(np.arange(0,28000,2000))
plt.show()
#We see that the distribution is right skewed and most of the purchase prices␣
 ↪are in the range 4000-13000.
#There are also a few purchases between 15000-16000 and between 19000-21000.
#Since the distribution is right skewed, therefore the mean would be greater␣
 ↪than the median.
```



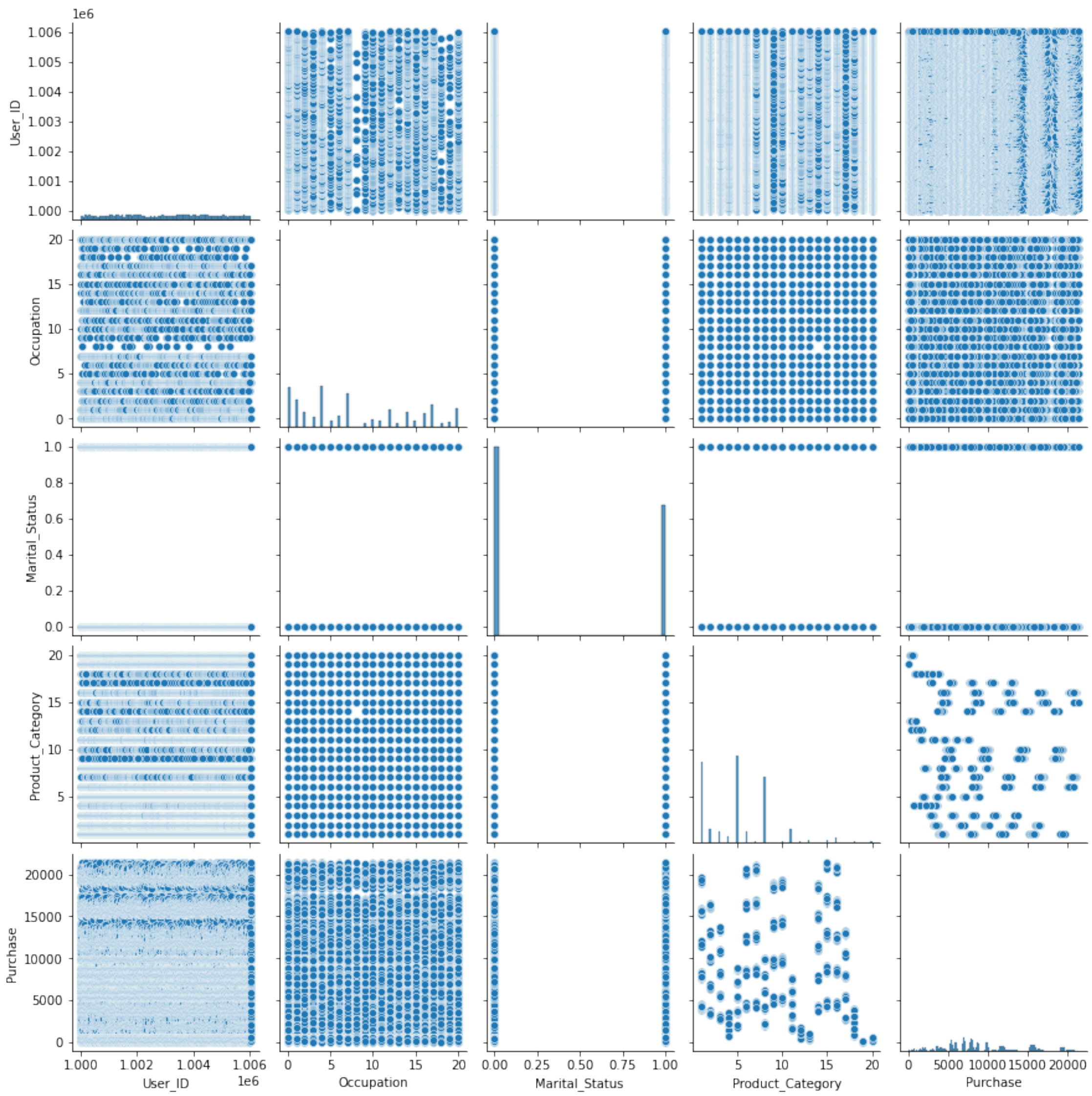
[20]:
```
df.describe()
# Here also we see that the mean Purchase price is greater than the median␣
↪Purchase price, since it is right skewed.
#The average purchase price is 9195.63 and the median purchase price is 8038.
```

[20]:
```
            User_ID     Occupation  Marital_Status  Product_Category  \
count  5.473910e+05  547391.000000   547391.000000     547391.000000
mean   1.003028e+06       8.074627        0.409486          5.378945
std    1.727357e+03       6.521586        0.491739          3.927383
min    1.000001e+06       0.000000        0.000000          1.000000
25%    1.001516e+06       2.000000        0.000000          1.000000
50%    1.003075e+06       7.000000        0.000000          5.000000
75%    1.004478e+06      14.000000        1.000000          8.000000
max    1.006040e+06      20.000000        1.000000         20.000000

            Purchase
count  547391.000000
mean     9195.627195
std      4938.872953
min        12.000000
25%      5721.000000
50%      8038.000000
75%     12019.000000
max     21399.000000
```

[21]:
```
plt.figure(figsize=(7,6))
sns.heatmap(df.corr(),cmap='Blues',annot=True)
plt.show()
#From the heatmap, we observe that there isn't a strong relationship between␣
↪any of the 2 columns.
#The strongest correlation we see is between Product_Category and Purchase.
```



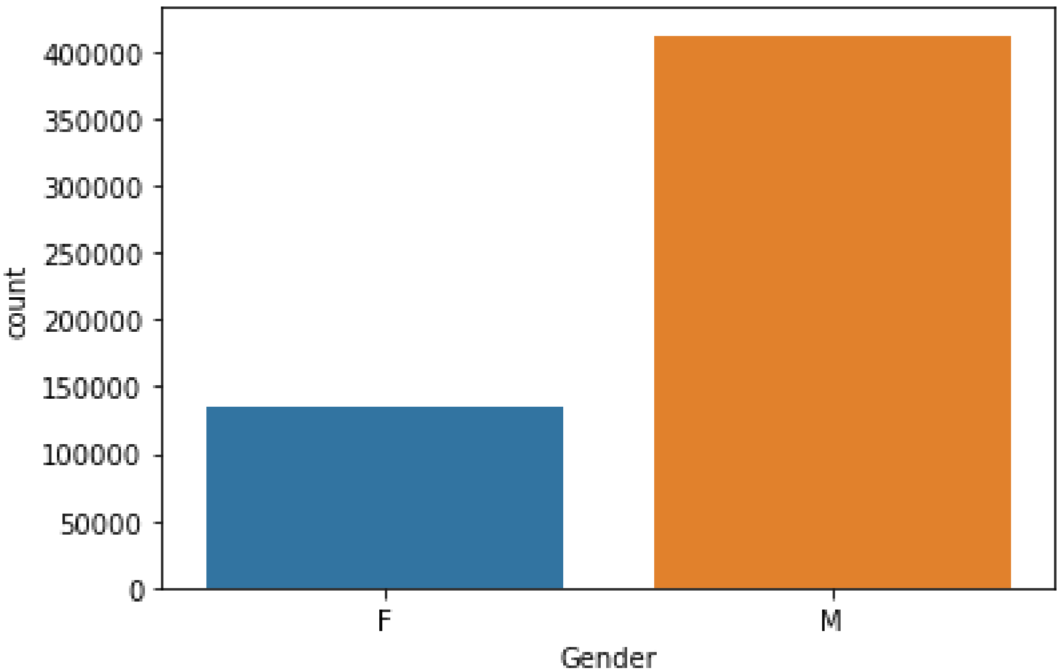
[22]:
```
sns.pairplot(df)
plt.show()
#From the pairplot, we get to see that we do not see a relationship between␣
↪product category and purchase.
#We therefore cannot rely on the correlation  coefficint value of -0.37.
```




```
[ ]:
```

0.1.3 Question 1 - Purchase price of males and females?

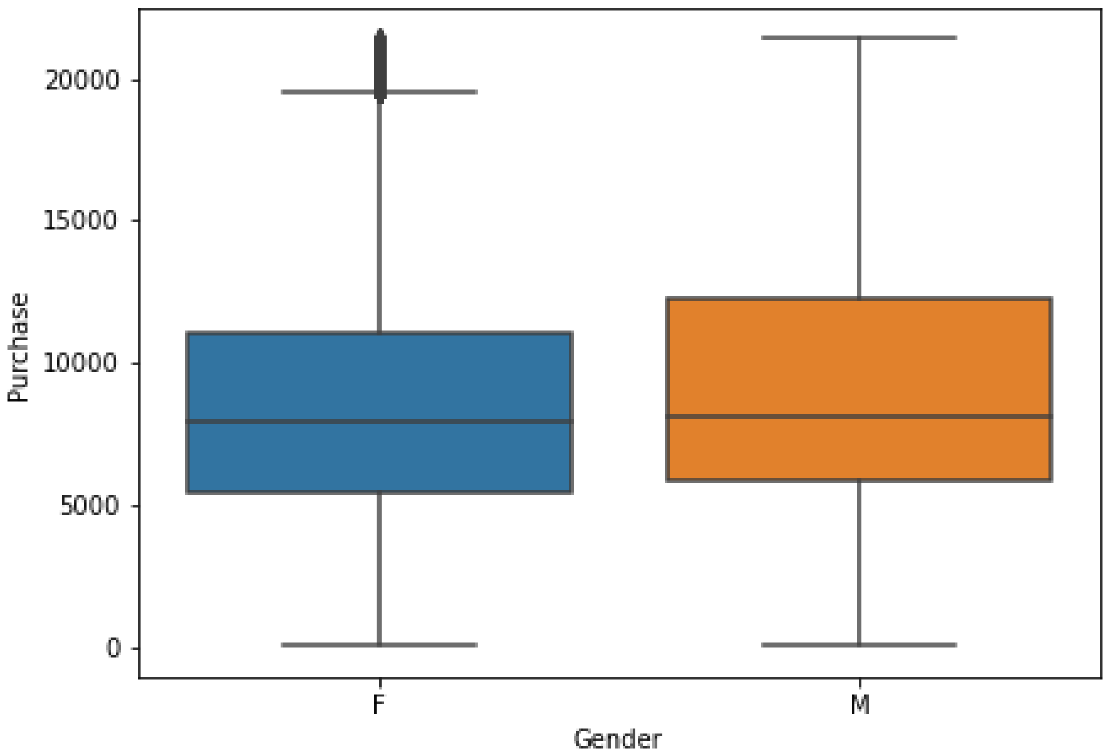
```
[23]: plt.figure()
      sns.countplot(data=df,x='Gender')
      plt.show()
```



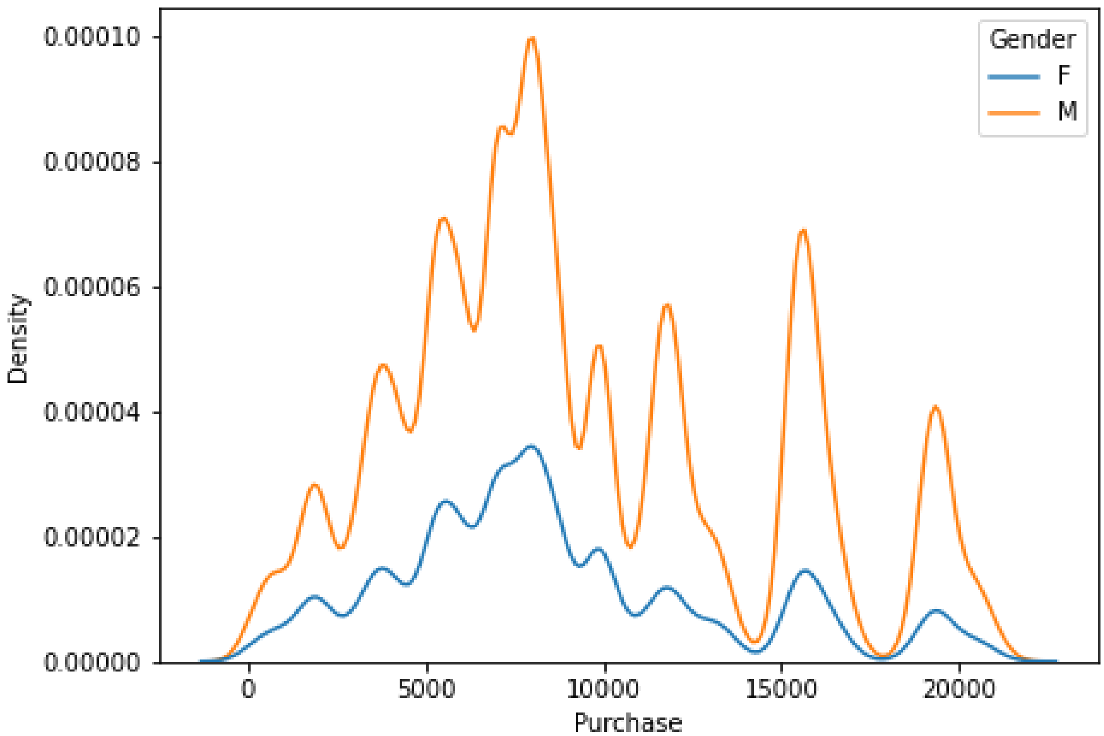
[24]:
```
print(df.groupby(by='Gender').count()['Purchase'])
```

```
Gender
F    135220
M    412171
Name: Purchase, dtype: int64
```

[25]:
```
plt.figure(figsize=(7,5))
sns.boxplot(data=df,x='Gender',y='Purchase')
plt.show()
```



[26]:
```
plt.figure(figsize=(7,5))
sns.kdeplot(data=df,hue='Gender',x='Purchase')
plt.show()
```



[27]:
```
print(df.groupby(by='Gender').mean()['Purchase'])
```

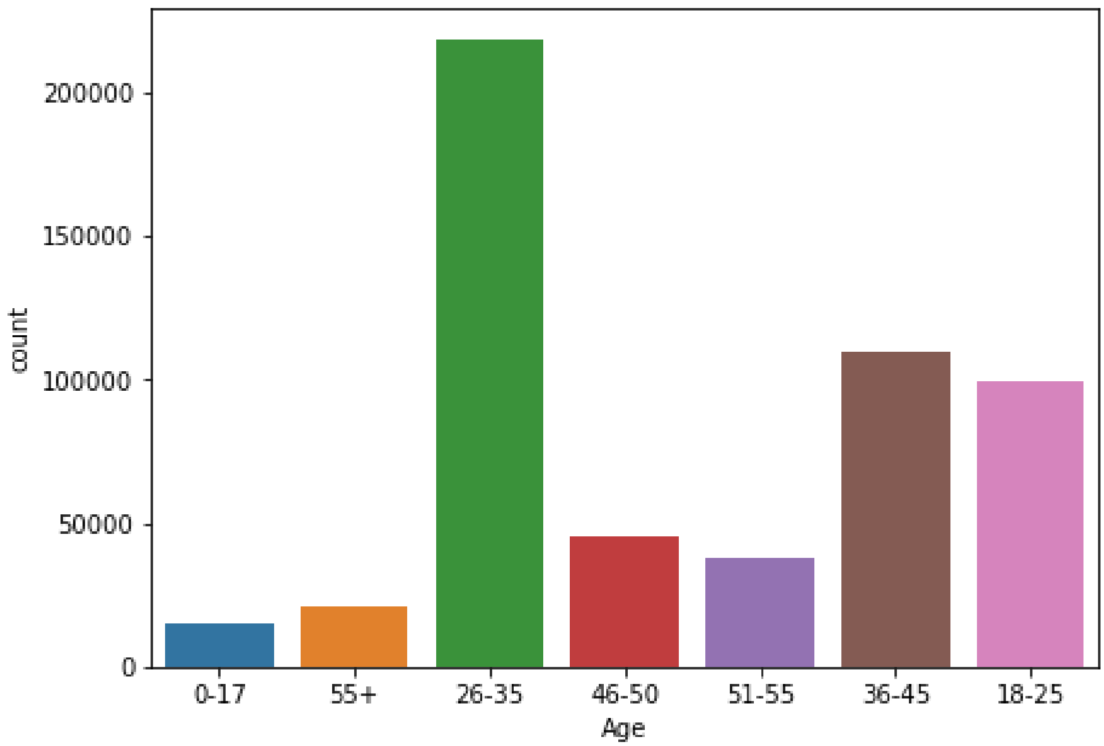
```
Gender
F    8671.049039
M    9367.724355
Name: Purchase, dtype: float64
```

Inference - We see that the average amount spent by males is more than females. In the dataset provided, the no of males making a purchase are 3 times of females making a purcahse.

[ ]:
```

```

0.1.4 Question 2 - Purchase price for each of the age categories?

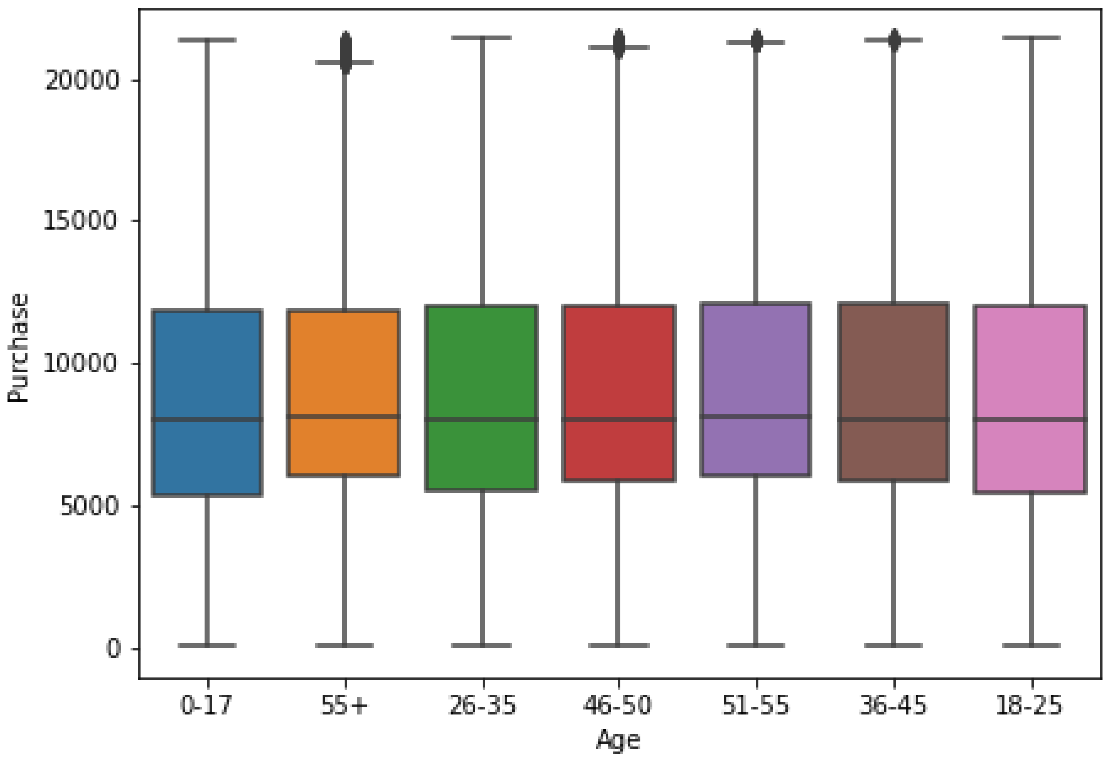
[28]:
```
plt.figure(figsize=(7,5))
sns.countplot(data=df,x='Age')
plt.show()
```



[29]:
```
print(df.groupby(by='Age').count()['Purchase'])
```

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

[30]:
```
plt.figure(figsize=(7,5))
sns.boxplot(data=df,x='Age',y='Purchase')
plt.show()
```



[31]:
```
print(df.groupby(by='Age').mean()['Purchase'].sort_values(ascending=False))
```

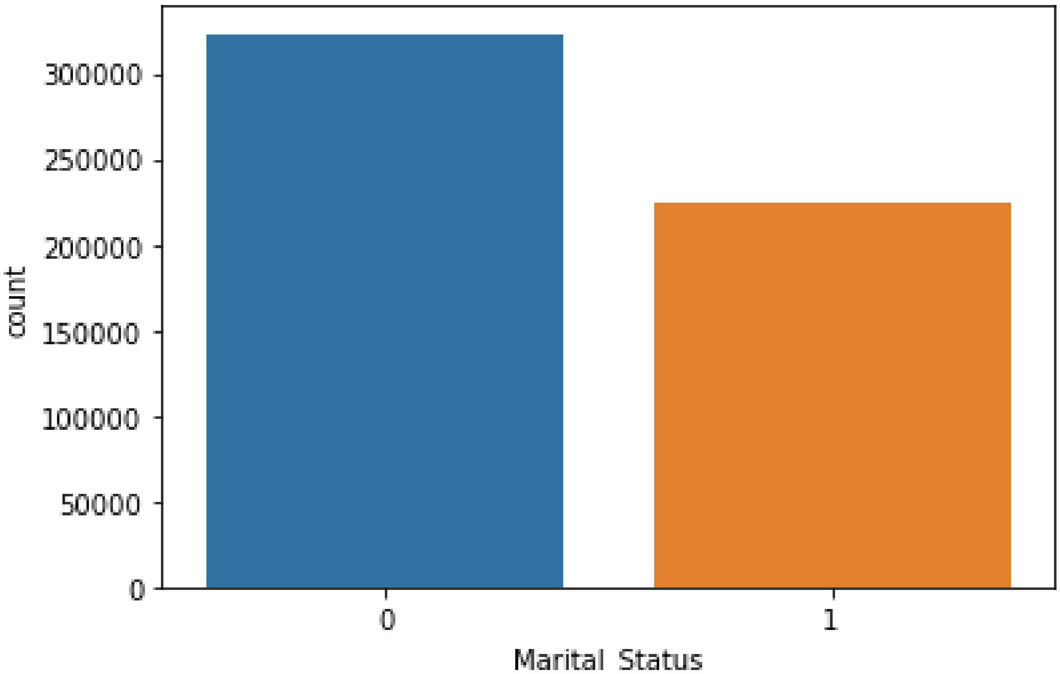
```
Age
51-55    9423.121704
36-45    9254.202214
55+      9216.650220
26-35    9193.469924
46-50    9128.985080
18-25    9124.031731
0-17     8867.447046
Name: Purchase, dtype: float64
```

Inference : We see that the average purchase price of all the age categories is almost same, with the age category 51-55 having the highest purchase price and the age group 0-17 having the lowest average purchase price. Most of the customers are in the age category 18-25, 36-45 and 26-35.

[ ]:

0.1.5 Question 3 - Purchase price for each of the marital status categories?

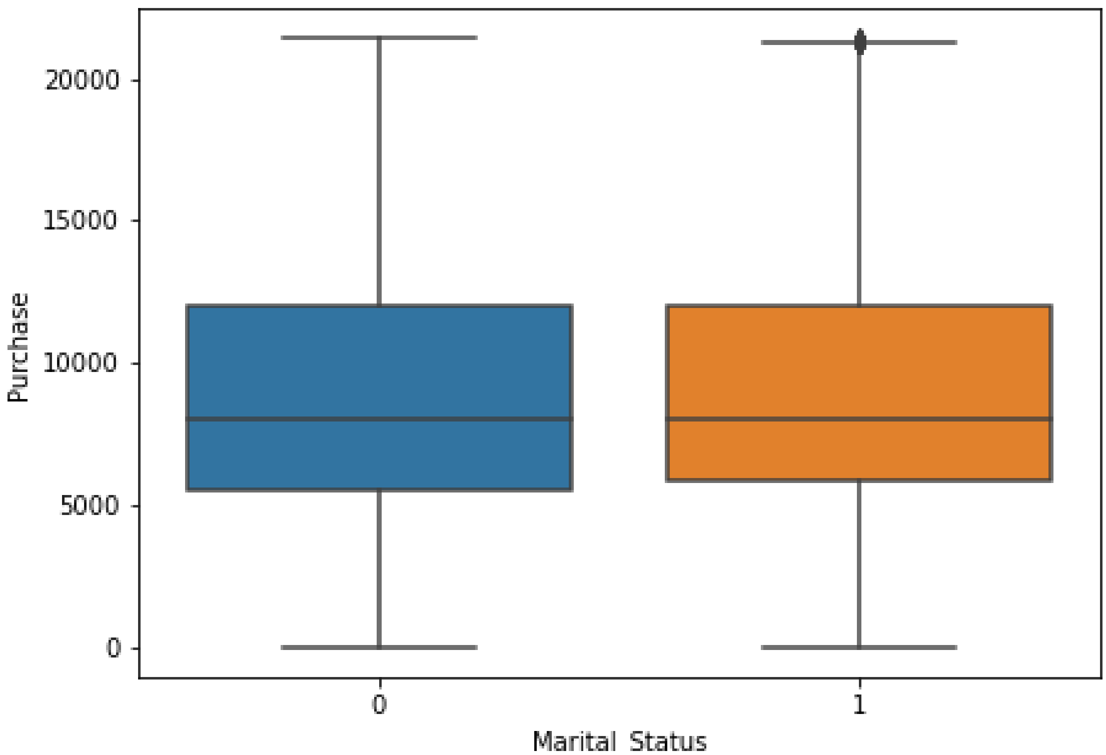
[32]:
```
plt.figure()
sns.countplot(data=df,x='Marital_Status')
plt.show()
```



[33]:
```
print(df.groupby(by='Marital_Status').count()['Purchase'])
```

```
Marital_Status
0    323242
1    224149
Name: Purchase, dtype: int64
```

[34]:
```
plt.figure(figsize=(7,5))
sns.boxplot(data=df,x='Marital_Status',y='Purchase')
plt.show()
```



[35]:
```
print(df.groupby(by='Marital_Status').mean()['Purchase'].
 ↪sort_values(ascending=False))
```

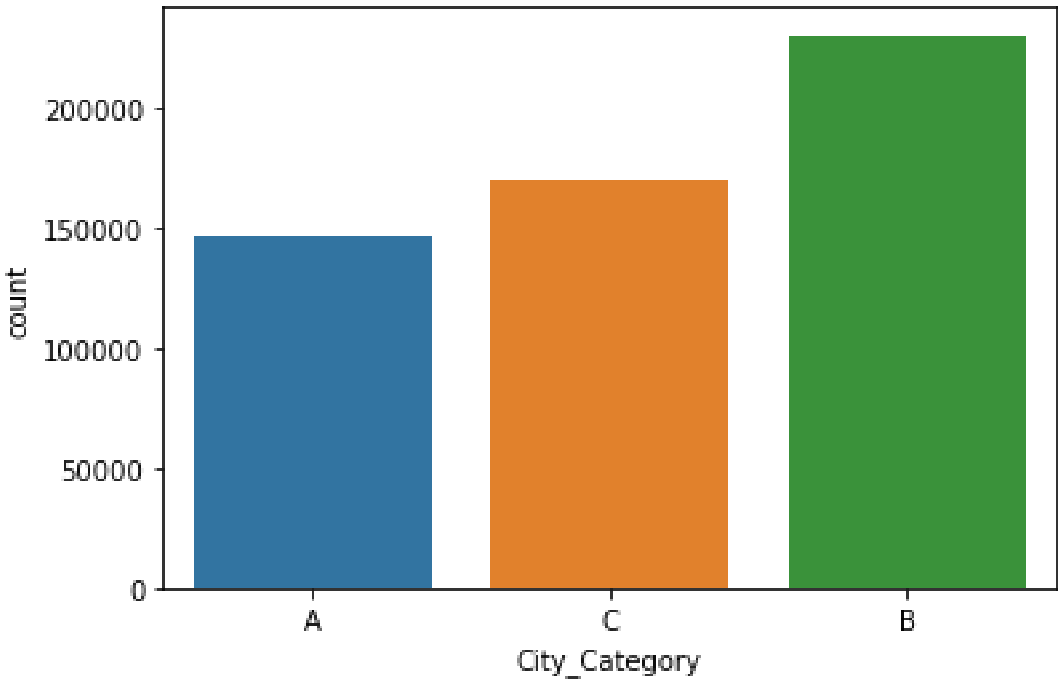
```
Marital_Status
0    9201.581849
1    9187.040076
Name: Purchase, dtype: float64
```

Inference - We see that the average purchase price of both the marital status categories is almost same. The number of unmarried people buying the products is almost 1.5x of that of who are married.

[ ]:
```

```

0.1.6 Question 4 - Average purchase price for each of the city categories ?

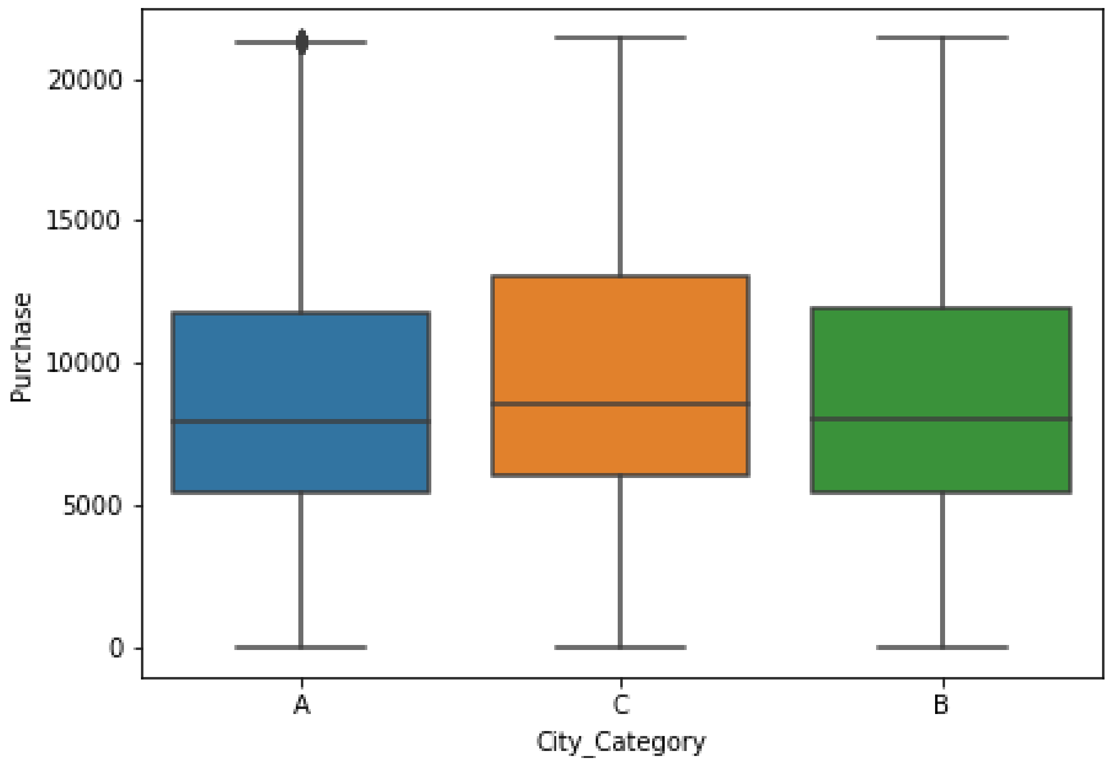
[36]:
```
plt.figure()
sns.countplot(data=df,x='City_Category')
plt.show()
```



[37]:
```
print(df.groupby(by='City_Category').count()['Purchase'])
```

```
City_Category
A    147036
B    230114
C    170241
Name: Purchase, dtype: int64
```

[38]:
```
plt.figure(figsize=(7,5))
sns.boxplot(data=df,x='City_Category',y='Purchase')
plt.show()
```



[39]:
```
print(df.groupby(by='City_Category').mean()['Purchase'].
 ↪sort_values(ascending=False))
```

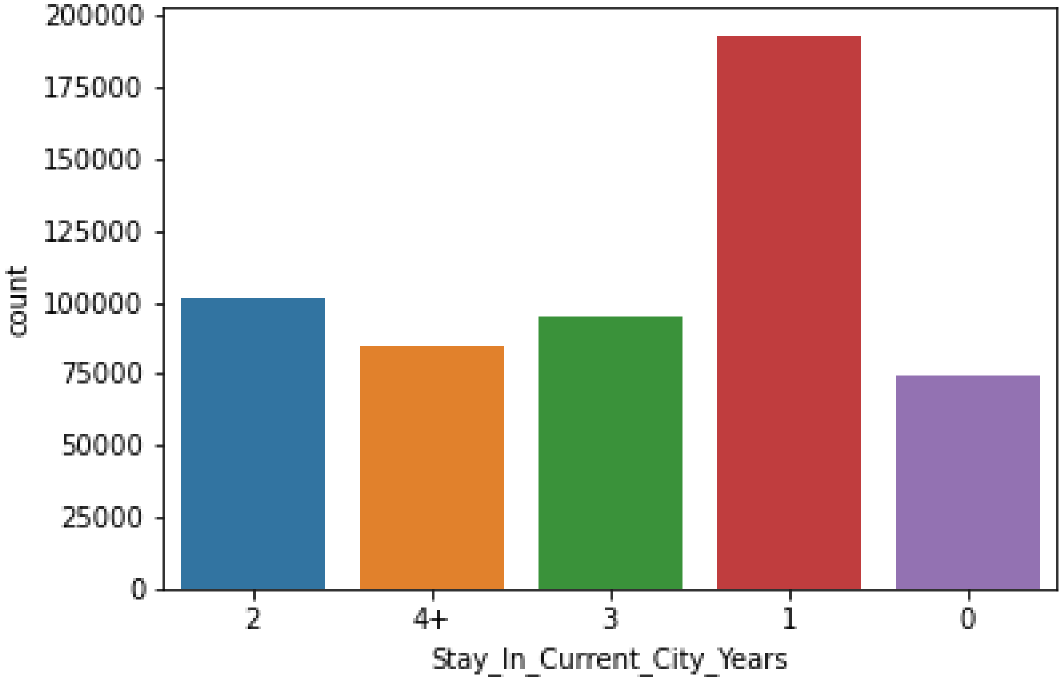
```
City_Category
C    9645.647300
B    9086.502707
A    8845.367393
Name: Purchase, dtype: float64
```

Inference - We observe that the average purchase price is highest in City C and least in city A. The number of people buying from City B is the highest and lowest for city A among all cities.

[ ]:
```

```

0.1.7 Question 5 - Purchase price for each of the stay_in_the_current_year categories ?

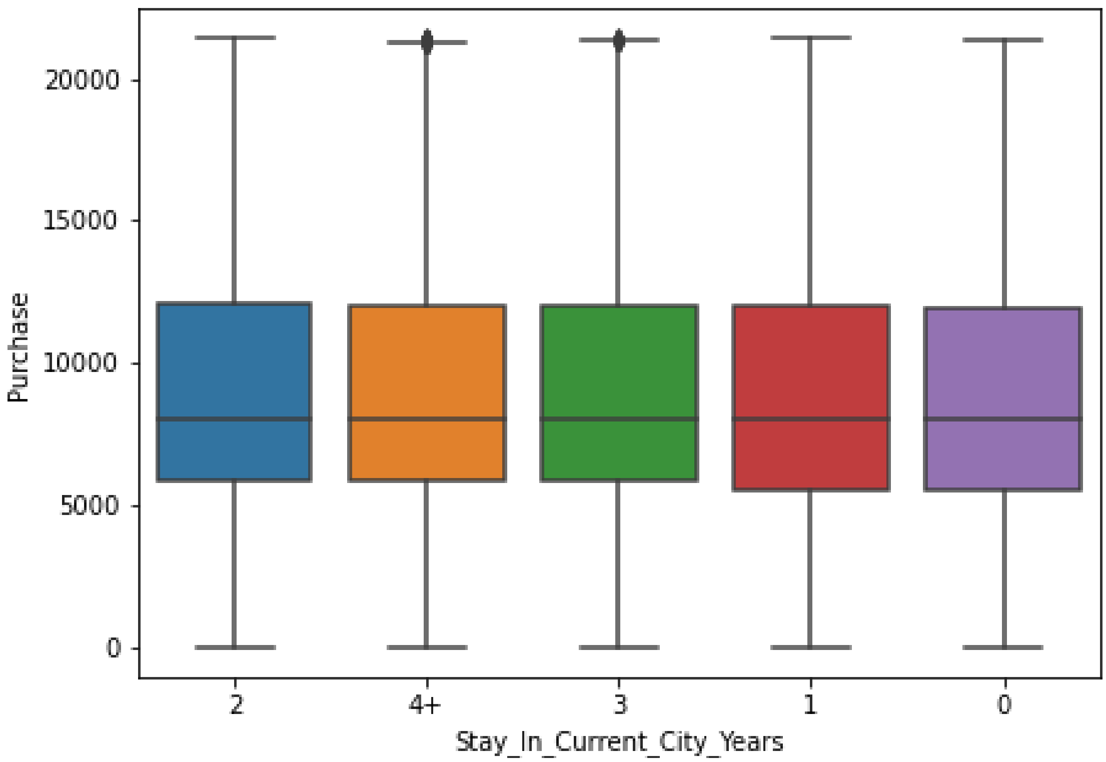
[40]:
```
plt.figure()
sns.countplot(data=df,x='Stay_In_Current_City_Years')
plt.show()
```



[41]:
```
print(df.groupby(by='Stay_In_Current_City_Years').count()['Purchase'].
    ↪sort_values(ascending=False))
```

```
Stay_In_Current_City_Years
1      192845
2      101384
3       94804
4+      84322
0       74036
Name: Purchase, dtype: int64
```

[42]:
```
plt.figure(figsize=(7,5))
sns.boxplot(data=df,x='Stay_In_Current_City_Years',y='Purchase')
plt.show()
```



[43]:
```
print(df.groupby(by='Stay_In_Current_City_Years').mean()['Purchase'].
 ↪sort_values(ascending=False))
```

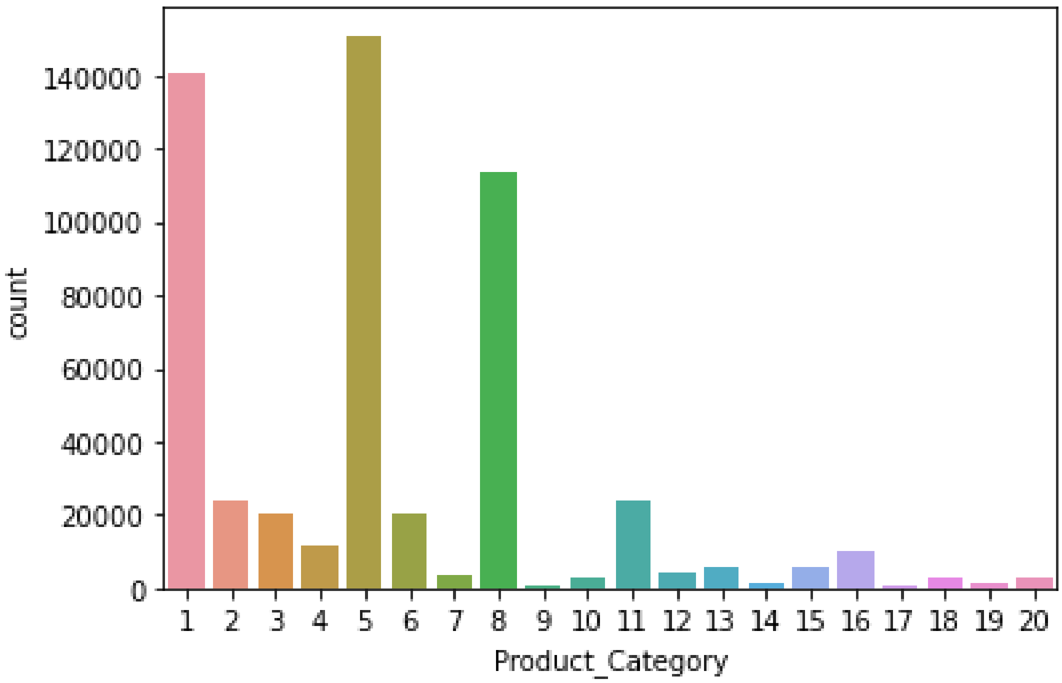
```
Stay_In_Current_City_Years
2     9258.292028
3     9215.953451
4+    9208.837895
1     9179.275916
0     9111.331555
Name: Purchase, dtype: float64
```

Inference - We observe that the average purchase price is higher for people whose current city staying years are greater than or equal to 2 years. The number of people who make the most purchases are those that have lived in the current city for 1 year.

[ ]:

0.1.8 Question 6 - Purchase price for each of the Product categories ?

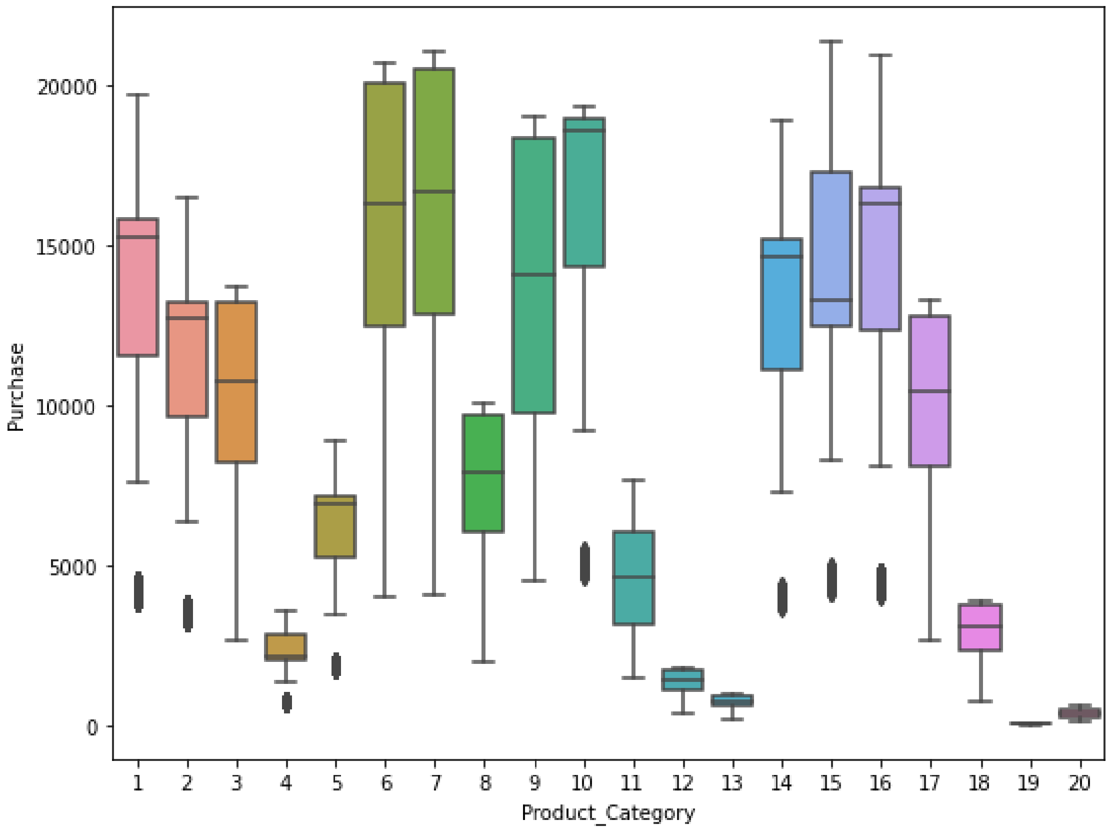
[44]:
```
plt.figure()
sns.countplot(data=df,x='Product_Category')
plt.show()
```



[45]:
```
print(df.groupby(by='Product_Category').count()['Purchase'].
 ↪sort_values(ascending=False))
```

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

[46]:
```
plt.figure(figsize=(9,7))
sns.boxplot(data=df,x='Product_Category',y='Purchase')
plt.show()
```



[47]:
```
print(df.groupby(by='Product_Category').mean()['Purchase'].
↪sort_values(ascending=False))
```

```
Product_Category
10    16626.385965
7     16365.689600
6     15838.478550
16    14766.037037
15    14412.504109
9     13852.325373
1     13606.218596
14    13141.625739
2     11251.935384
17    10170.759516
3     10096.705734
8      7498.958078
5      6240.088178
```

```
11      4685.268456
18      2972.864320
4       2329.659491
12      1350.859894
13       722.400613
20       370.481176
19        37.041797
Name: Purchase, dtype: float64
```

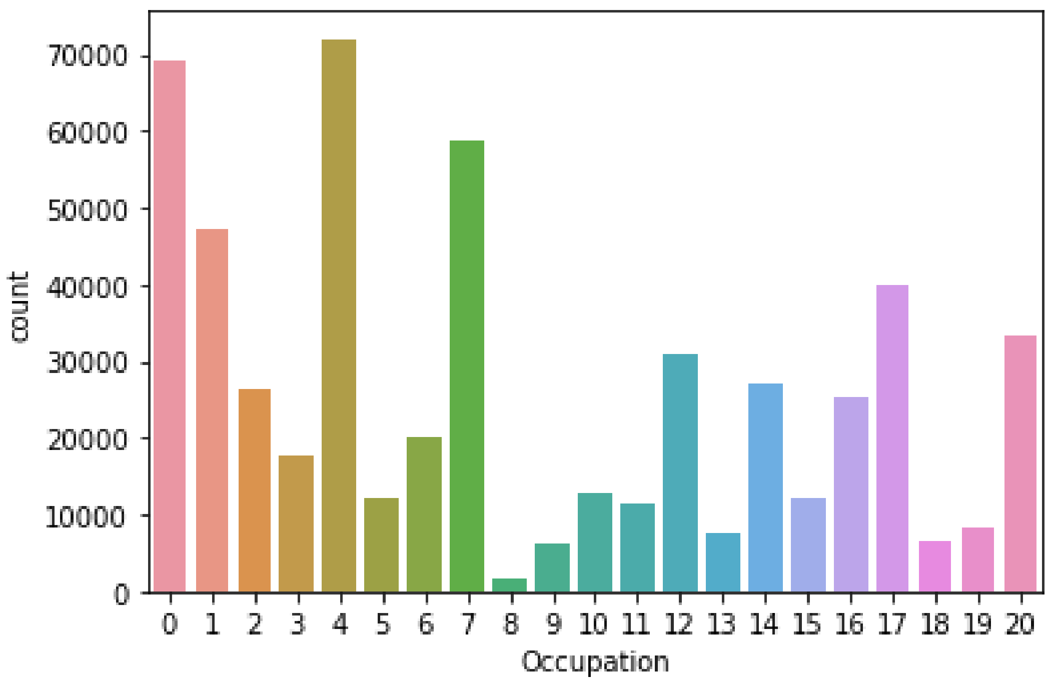
Inference - We see that the highest average purchase price is for product category 10, and the least average purchase price is for product category 19. The most sold product categories are 5,1 and 8.

[ ]:

0.1.9 Question 7 - Purchase price for each of the occupation categories ?

[48]:

```
plt.figure()
sns.countplot(data=df,x='Occupation')
plt.show()
```



[49]:

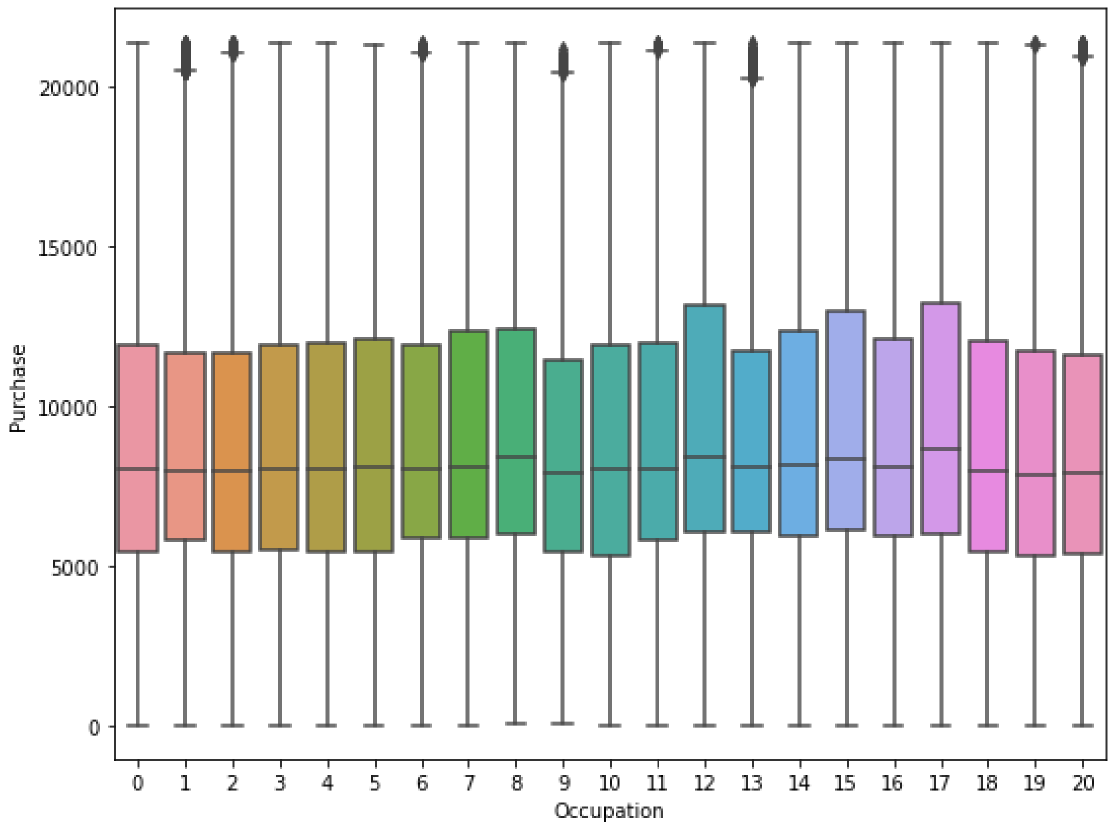
```
print(df.groupby(by='Occupation').count()['Purchase'].
 ↪sort_values(ascending=False))
```

```
Occupation
4     72040
```

```
0     69310
7     58875
1     47174
17    39855
20    33355
12    30995
14    27173
2     26435
16    25251
6     20261
3     17568
10    12888
5     12133
15    12086
11    11500
19     8412
13     7667
18     6595
9      6278
8      1540
Name: Purchase, dtype: int64
```

[50]:

```
plt.figure(figsize=(9,7))
sns.boxplot(data=df,x='Occupation',y='Purchase')
plt.show()
```



[51]:
```
print(df.groupby(by='Occupation').mean()['Purchase'].
    ↪sort_values(ascending=False))
```

```
Occupation
17    9758.679087
12    9717.192386
15    9691.443157
8     9479.513636
14    9431.785228
7     9365.188025
16    9328.979090
5     9283.268854
13    9194.099387
6     9191.133261
4     9161.759189
18    9113.718423
3     9112.929019
11    9108.370957
0     9057.506291
10    8912.886639
1     8876.457053
```

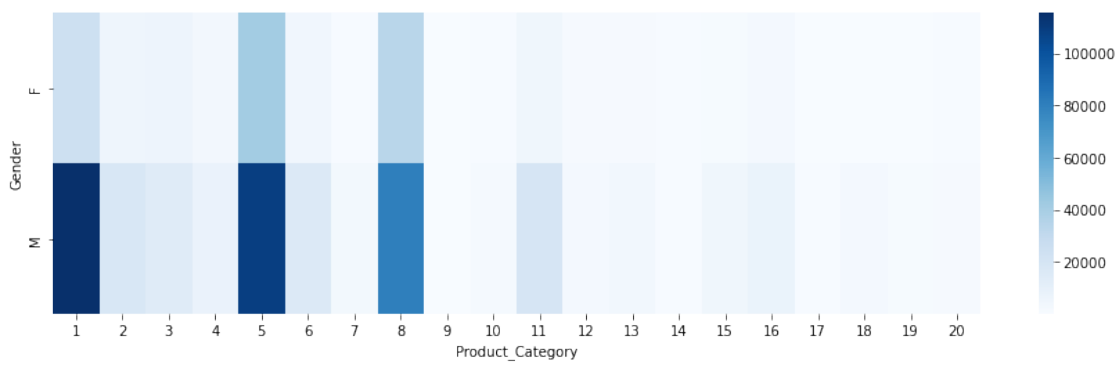
```
2     8869.590505
20    8746.967501
19    8627.760818
9     8607.359828
Name: Purchase, dtype: float64
```

Inference - We see that the highest average purchase price is for 17 years of occupation and lowest average purchase price is for 9 years of occupation. People having 4,0 and 7 years of occupation are the most frequent buyers.

[ ]:

0.1.10 Question 8 - What product categories are mostly bought by each of the gender?

[52]:
```
plt.figure(figsize=(15,4))
sns.heatmap(pd.
 ↪crosstab(index=df['Gender'],columns=df['Product_Category']),cmap='Blues')
plt.show()
```



[53]:
```
pd.crosstab(index=df['Gender'],columns=df['Product_Category'],normalize='index')
```

[53]:
```
Product_Category         1         2         3         4         5         6   \
Gender
F                 0.183634  0.041843  0.044417  0.026912  0.310317  0.033715
M                 0.280338  0.044171  0.034469  0.019686  0.264385  0.038593

Product_Category         7         8         9        10        11        12   \
Gender
F                 0.006974  0.248173  0.000414  0.004718  0.035047  0.011330
M                 0.006740  0.194985  0.000677  0.005367  0.047427  0.005859

Product_Category        13        14        15        16        17        18   \
Gender
F                 0.010812  0.004607  0.007358  0.017764  0.000459  0.002825
```

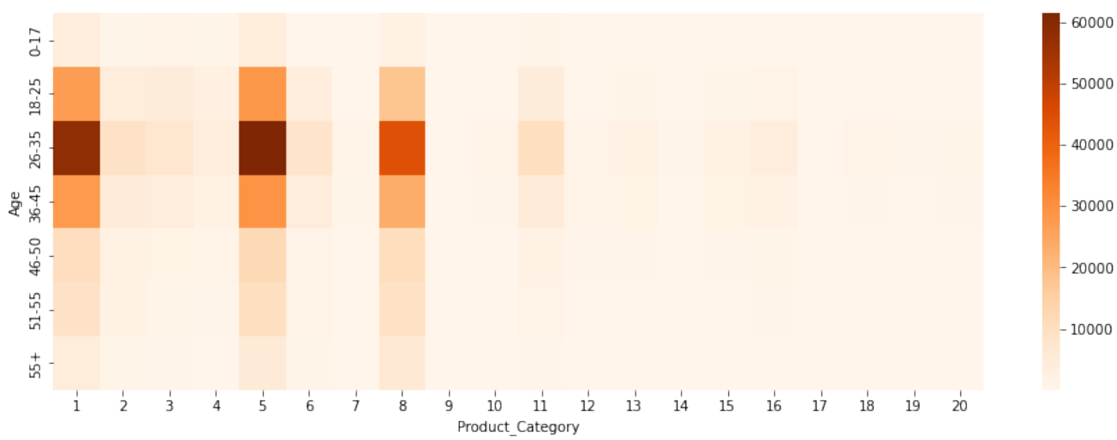
```
M                   0.009916  0.002184  0.012053  0.018017  0.001252  0.006655

Product_Category          19        20
Gender
F                   0.003335  0.005347
M                   0.002795  0.004433
```

Inference - We observe that irrespective of the gender, people mostly buy the products 1, 5 and 8.

[ ]:

0.1.11 Question 9 - What product categories are mostly bought by each of the age categories?

[54]:
```python
plt.figure(figsize=(15,5))
sns.heatmap(pd.
 ↪crosstab(index=df['Age'],columns=df['Product_Category']),cmap='Oranges')
plt.show()
```



[55]:
```python
pd.crosstab(index=df['Age'],columns=df['Product_Category'],normalize='index')
```

[55]:
```
Product_Category          1         2         3         4         5         6  \
Age
0-17                0.238491  0.053552  0.079830  0.050426  0.288052  0.026543
18-25               0.271428  0.044577  0.047416  0.024795  0.287132  0.037741
26-35               0.266390  0.040830  0.035041  0.019171  0.281134  0.038804
36-45               0.252703  0.044896  0.035226  0.021516  0.268506  0.035637
46-50               0.230492  0.046323  0.030280  0.021786  0.263435  0.035694
51-55               0.236941  0.046634  0.024194  0.017753  0.259040  0.037967
55+                 0.206876  0.042444  0.022840  0.014914  0.251712  0.040428
```

```
Product_Category         7         8         9        10        11        12  \
Age
0-17              0.003526  0.150213  0.000998  0.003725  0.049228  0.008316
18-25             0.004842  0.180311  0.000483  0.003584  0.046278  0.004419
26-35             0.007551  0.202395  0.000563  0.004582  0.045157  0.005012
36-45             0.007394  0.212926  0.000859  0.006416  0.045270  0.009085
46-50             0.007196  0.234497  0.000572  0.006668  0.046301  0.011443
51-55             0.006965  0.244560  0.000655  0.006415  0.038177  0.011338
55+               0.006285  0.291155  0.000188  0.008723  0.026311  0.015946

Product_Category        13        14        15        16        17        18  \
Age
0-17              0.007451  0.002594  0.009713  0.015234  0.000399  0.001796
18-25             0.007611  0.002315  0.009664  0.016087  0.000413  0.003413
26-35             0.009586  0.002579  0.010345  0.018833  0.000581  0.004765
36-45             0.011425  0.002852  0.012220  0.017869  0.001234  0.006416
46-50             0.012125  0.003279  0.012477  0.019343  0.002091  0.007724
51-55             0.012647  0.004032  0.012464  0.017596  0.002802  0.011076
55+               0.014117  0.003517  0.010083  0.017681  0.003142  0.011303

Product_Category        19        20
Age
0-17              0.003925  0.005987
18-25             0.002768  0.004721
26-35             0.002575  0.004107
36-45             0.002925  0.004625
46-50             0.003279  0.004995
51-55             0.003509  0.005237
55+               0.004831  0.007504
```

Inference - We observe that irrespective of the age category, people mostly buy the products 1, 5 and 8.

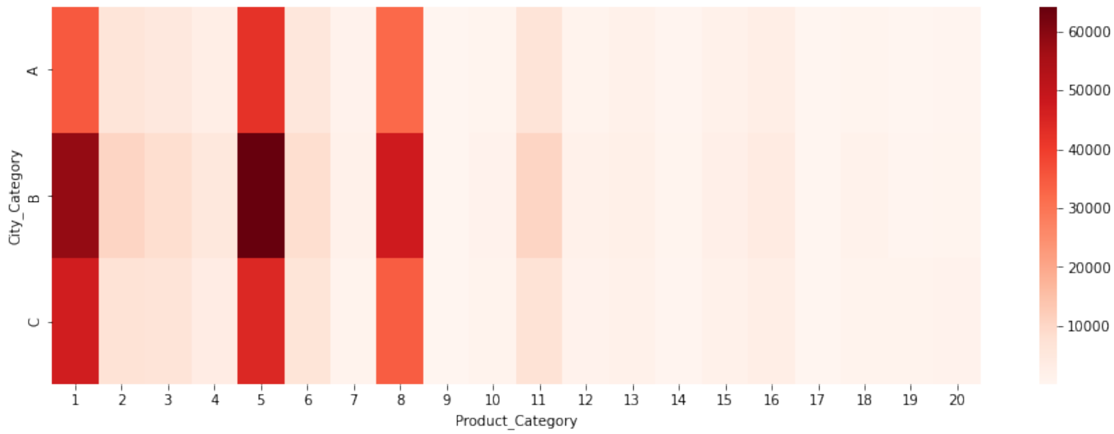
[ ]:

```

```

0.1.12 Question 10 - What product categories are mostly bought by each of the city categories?

[56]:

```
plt.figure(figsize=(15,5))
sns.heatmap(pd.
 ↪crosstab(index=df['City_Category'],columns=df['Product_Category']),cmap='Reds')
plt.show()
```



[57]:
```
pd.
↪crosstab(index=df['City_Category'],columns=df['Product_Category'],normalize='index')
```

[57]:

Product_Category City_Category	1	2	3	4	5	6
A	0.238588	0.041765	0.033618	0.020743	0.287079	0.037453
B	0.253148	0.045386	0.037316	0.022710	0.278723	0.037051
C	0.276338	0.042757	0.039256	0.020424	0.261888	0.037788

Product_Category City_Category	7	8	9	10	11	12
A	0.008338	0.218851	0.000667	0.005121	0.044894	0.007230
B	0.006949	0.206650	0.000626	0.005067	0.045564	0.007279
C	0.005263	0.200851	0.000546	0.005469	0.042299	0.007102

Product_Category City_Category	13	14	15	16	17	18
A	0.010977	0.003271	0.011052	0.019369	0.000823	0.005121
B	0.009869	0.002746	0.010890	0.017548	0.001160	0.006036
C	0.009774	0.002408	0.010761	0.017281	0.001116	0.005774

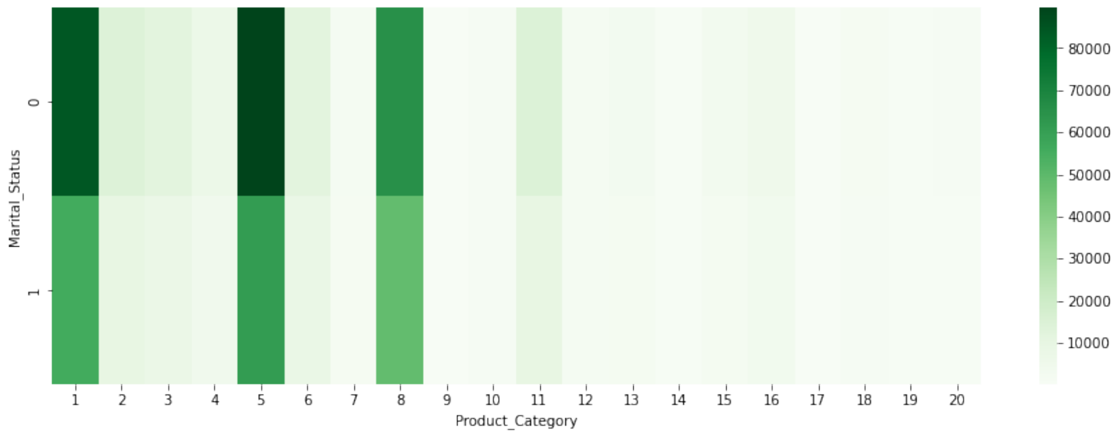
Product_Category City_Category	19	20
A	0.001857	0.003183
B	0.002008	0.003272
C	0.005099	0.007807

Inference - We observe that irrespective of the city category, people mostly buy the products 1, 5 and 8.

[ ]:
```

```

0.1.13 Question 11 - What product categories are mostly bought by each of the marital status categories?

[58]:
```
plt.figure(figsize=(15,5))
sns.heatmap(pd.
 ↪crosstab(index=df['Marital_Status'],columns=df['Product_Category']),cmap='Greens')
plt.show()
```



[59]:
```
pd.
 ↪crosstab(index=df['Marital_Status'],columns=df['Product_Category'],normalize='index')
```

[59]:
```
Product_Category         1         2         3         4         5         6  \
Marital_Status
0                 0.261027  0.043738  0.038235  0.022203  0.277365  0.037554
1                 0.249847  0.043391  0.035039  0.020415  0.273376  0.037149

Product_Category         7         8         9        10        11        12  \
Marital_Status
0                 0.006311  0.202359  0.000603  0.004724  0.045378  0.006292
1                 0.007499  0.216436  0.000625  0.005902  0.042913  0.008535

Product_Category        13        14        15        16        17        18  \
Marital_Status
0                 0.009782  0.002617  0.010633  0.017674  0.000922  0.005077
1                 0.010649  0.003020  0.011269  0.018358  0.001249  0.006621

Product_Category        19        20
Marital_Status
0                 0.002927  0.004579
1                 0.002931  0.004774
```

Inference - We observe that irrespective of the marital status, people mostly buy the products 1, 5 and 8.

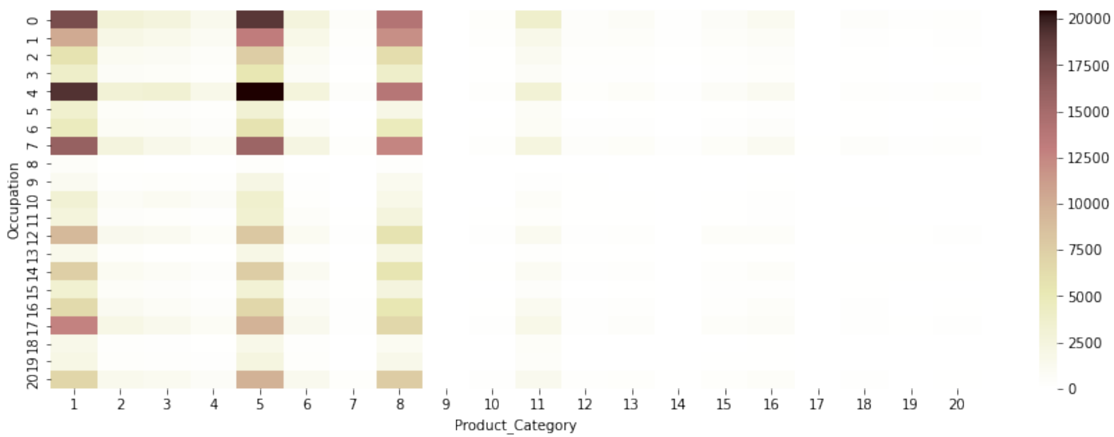
[ ]:

```

```

0.1.14 Question 12 - What product categories are mostly bought by each of the occupation categories?

[60]:

```
plt.figure(figsize=(15,5))
sns.heatmap(pd.
↪crosstab(index=df['Occupation'],columns=df['Product_Category']),cmap='pink_r')
plt.show()
```



[61]:

```
pd.
↪crosstab(index=df['Occupation'],columns=df['Product_Category'],normalize='index')
```

[61]:

Product_Category Occupation	1	2	3	4	5	6 \
0	0.254552	0.042865	0.038018	0.021368	0.273914	0.037051
1	0.218659	0.040743	0.033048	0.020626	0.279158	0.037457
2	0.217212	0.041990	0.036240	0.019368	0.287989	0.039304
3	0.224499	0.037910	0.034950	0.022655	0.300888	0.037056
4	0.267046	0.042185	0.045891	0.023640	0.283995	0.036882
5	0.300503	0.048545	0.036842	0.020770	0.270007	0.031237
6	0.227087	0.040521	0.037017	0.021963	0.280884	0.036277
7	0.272391	0.042650	0.027244	0.018667	0.265291	0.039117
8	0.332468	0.064286	0.043506	0.025325	0.240909	0.029221
9	0.180471	0.044600	0.057343	0.039822	0.343103	0.030742
10	0.253492	0.055866	0.082014	0.051831	0.281502	0.022346
11	0.230000	0.041391	0.029913	0.019043	0.294870	0.044435
12	0.298661	0.045878	0.038296	0.018487	0.259171	0.035393
13	0.201513	0.047215	0.019695	0.015912	0.257206	0.034303

```
14                0.276230  0.040629  0.028999  0.017407  0.281014  0.043462
15                0.279331  0.047907  0.036323  0.019030  0.263363  0.035744
16                0.257455  0.044751  0.030256  0.017623  0.269098  0.037385
17                0.320336  0.049454  0.037862  0.020374  0.244286  0.034826
18                0.265807  0.046247  0.024261  0.018954  0.264898  0.041698
19                0.246909  0.038635  0.031859  0.027104  0.281740  0.040181
20                0.206056  0.043832  0.037356  0.021166  0.294379  0.042332

Product_Category        7         8         9        10        11        12  \
Occupation
0                 0.008065  0.203246  0.000606  0.005107  0.054134  0.006420
1                 0.007928  0.254335  0.000339  0.006275  0.035634  0.009200
2                 0.008663  0.237034  0.000378  0.005599  0.043541  0.009192
3                 0.007798  0.218750  0.000740  0.007001  0.039447  0.010189
4                 0.006233  0.191977  0.000486  0.003526  0.044309  0.005164
5                 0.003050  0.158988  0.000495  0.004286  0.065194  0.006429
6                 0.007206  0.236168  0.000642  0.005182  0.042199  0.007946
7                 0.005554  0.214352  0.000594  0.005146  0.040968  0.007898
8                 0.003247  0.170779  0.000649  0.005195  0.040909  0.001948
9                 0.002389  0.208187  0.000159  0.003504  0.025645  0.013061
10                0.003259  0.141217  0.000776  0.002871  0.048805  0.008070
11                0.007304  0.224087  0.000783  0.007217  0.034087  0.009130
12                0.005936  0.184933  0.000903  0.006033  0.040878  0.005646
13                0.006391  0.290726  0.000130  0.009260  0.032738  0.014478
14                0.005741  0.202959  0.000699  0.004269  0.037059  0.006035
15                0.007033  0.206437  0.000993  0.004882  0.033262  0.005213
16                0.007762  0.211239  0.000792  0.004911  0.049265  0.007485
17                0.004316  0.170920  0.000979  0.005194  0.045114  0.005796
18                0.005155  0.169219  0.000303  0.006217  0.091281  0.004852
19                0.007370  0.196624  0.000594  0.004280  0.063956  0.006895
20                0.011363  0.231240  0.000540  0.006716  0.042153  0.007585

Product_Category       13        14        15        16        17        18  \
Occupation
0                 0.010388  0.002828  0.009797  0.017674  0.000909  0.006146
1                 0.011744  0.003582  0.010726  0.016619  0.001293  0.005045
2                 0.009344  0.003064  0.010895  0.016947  0.000530  0.005712
3                 0.012523  0.003871  0.009164  0.019467  0.000854  0.005749
4                 0.008204  0.002499  0.009883  0.016546  0.000639  0.003720
5                 0.007912  0.001896  0.011209  0.017555  0.000742  0.007830
6                 0.010118  0.003554  0.009328  0.020532  0.000888  0.004491
7                 0.010327  0.002718  0.010191  0.019839  0.001410  0.007830
8                 0.005195  0.000000  0.014935  0.010390  0.000649  0.004545
9                 0.009716  0.003664  0.005416  0.017999  0.000637  0.003664
10                0.007061  0.002250  0.010320  0.015518  0.000466  0.002017
11                0.010174  0.002609  0.009826  0.015739  0.001217  0.009217
12                0.009969  0.002323  0.015648  0.017551  0.000839  0.004291
```

```
13                0.014347  0.003522  0.010826  0.017738  0.002869  0.009000
14                0.010636  0.002024  0.009605  0.018953  0.000773  0.005594
15                0.010343  0.002234  0.013404  0.017127  0.001820  0.007364
16                0.010257  0.003129  0.011643  0.021029  0.001901  0.006970
17                0.011341  0.001907  0.013800  0.017940  0.001179  0.005796
18                0.010766  0.000910  0.009401  0.023199  0.001213  0.008036
19                0.008916  0.003447  0.012601  0.017237  0.000476  0.005825
20                0.010223  0.003628  0.011572  0.017509  0.001379  0.005396

Product_Category        19        20
Occupation
0                 0.002712  0.004199
1                 0.002947  0.004642
2                 0.002345  0.004653
3                 0.002789  0.003700
4                 0.002471  0.004706
5                 0.001978  0.004533
6                 0.003109  0.004886
7                 0.003261  0.004552
8                 0.003247  0.002597
9                 0.003504  0.006371
10                0.004268  0.006052
11                0.003391  0.005565
12                0.003839  0.005323
13                0.003782  0.008347
14                0.003349  0.004563
15                0.002979  0.005213
16                0.002535  0.004515
17                0.003638  0.004943
18                0.003791  0.003791
19                0.001545  0.003804
20                0.001949  0.003628
```

Inference - We observe that irrespective of the occupation years, people mostly buy the products 1, 5 and 8.

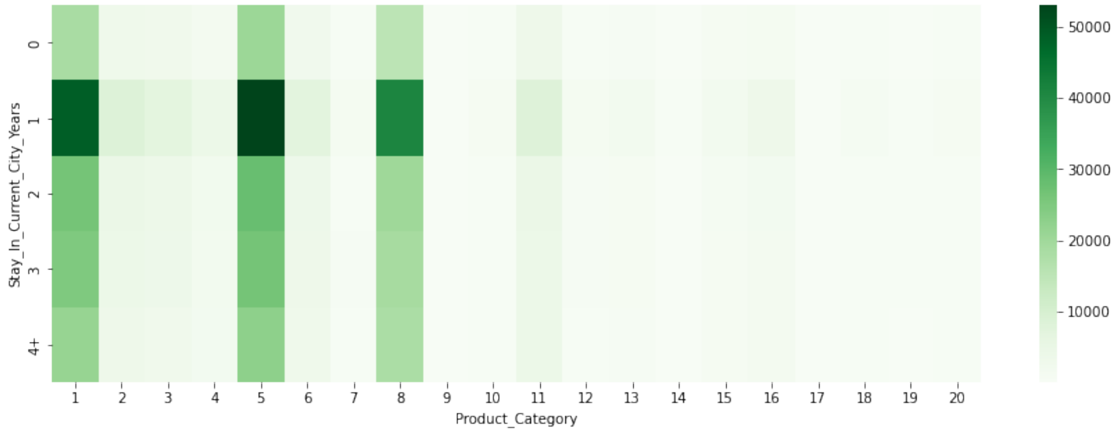
[ ]:

```

```

0.1.15 Question 13 - What product categories are mostly bought by each of the Current City Stay Years categories?

[62]:

```
plt.figure(figsize=(15,5))
sns.heatmap(pd.
 ↪crosstab(index=df['Stay_In_Current_City_Years'],columns=df['Product_Category']),cmap='Green
plt.show()
```



[63]:
```
pd.
↪crosstab(index=df['Stay_In_Current_City_Years'],columns=df['Product_Category'],normalize='i
```

[63]:

Product_Category / Stay_In_Current_City_Years	1	2	3	4	5
0	0.250621	0.043222	0.037671	0.021436	0.278243
1	0.253151	0.043449	0.036340	0.021255	0.275361
2	0.261511	0.045471	0.038586	0.021049	0.277223
3	0.263502	0.044618	0.037815	0.022172	0.278174
4+	0.255094	0.040855	0.034617	0.021714	0.269835

Product_Category / Stay_In_Current_City_Years	6	7	8	9	10
0	0.036969	0.007537	0.207210	0.000648	0.004822
1	0.037678	0.006694	0.213405	0.000565	0.005263
2	0.036820	0.005928	0.199617	0.000671	0.005346
3	0.036296	0.007278	0.201194	0.000686	0.005200
4+	0.039005	0.006890	0.214867	0.000534	0.005254

Product_Category / Stay_In_Current_City_Years	11	12	13	14	15
0	0.047072	0.007267	0.010468	0.002917	0.011832
1	0.042236	0.007301	0.010402	0.002982	0.010760
2	0.045431	0.007230	0.009656	0.002456	0.010722
3	0.042235	0.007162	0.009947	0.002489	0.010580
4+	0.047995	0.006985	0.010033	0.002929	0.010934

Product_Category / Stay_In_Current_City_Years	16	17	18	19	20
0	0.017829	0.001162	0.005754	0.002688	0.004633
1	0.018305	0.000871	0.006264	0.003148	0.004568
2	0.017794	0.001134	0.005188	0.002920	0.005247

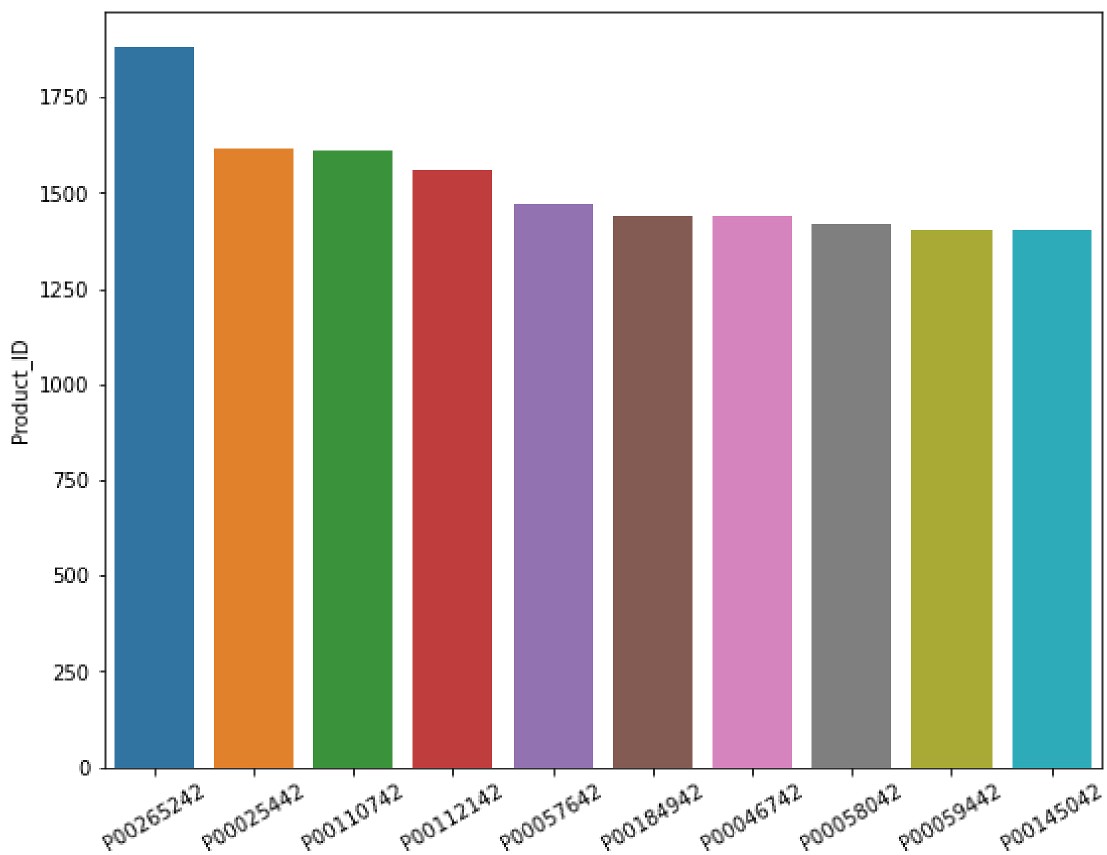
```
3                        0.017130  0.001213  0.005158  0.002679  0.004472
4+                       0.018382  0.001115  0.005645  0.002929  0.004388
```

Inference - We observe that irrespective of the current years stay, people mostly buy the products 1, 5 and 8.

[ ]:

0.1.16 Question 14 - Top 10 Product IDs and which product category they belong to?

[64]:
```python
plt.figure(figsize=(9,7))
sns.barplot(y=df['Product_ID'].value_counts()[:10],x=df['Product_ID'].
 ↪value_counts()[:10].index)
plt.xticks(rotation=30)
plt.show()
```



[65]:
```python
df.loc[df['Product_ID'].isin(df['Product_ID'].value_counts()[:10].
 ↪index),'Product_Category'].unique()
```

[65]: array([1, 5, 6, 8], dtype=int64)

Inference - The top 10 product IDs belong to the product categories 1,5,6 and 8.

[ ]:

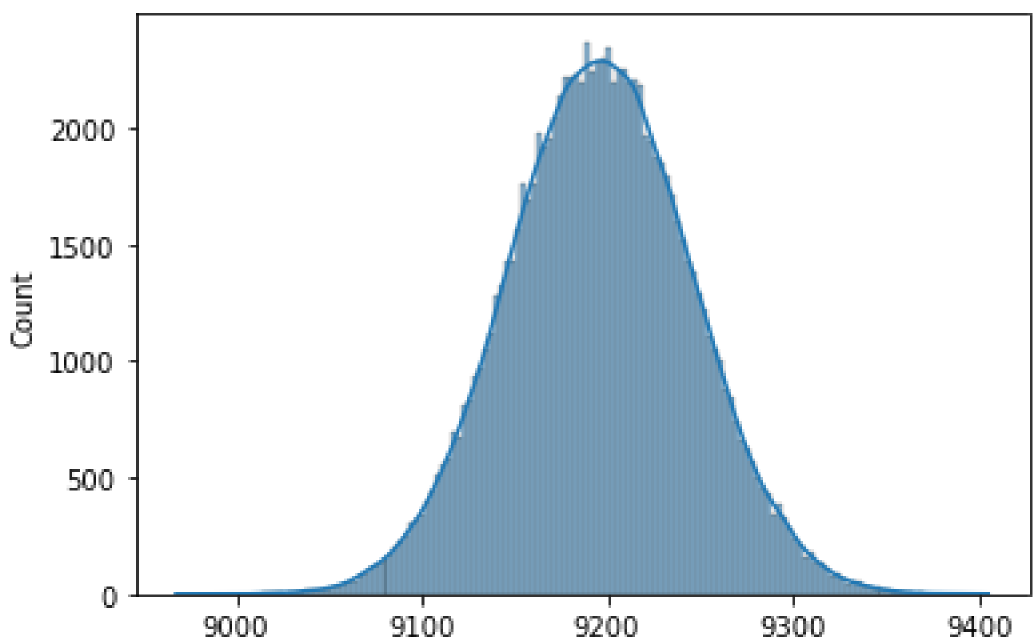
[ ]:

0.2 Confidence Interval Using The Central Limit Theorem For The Entire Population

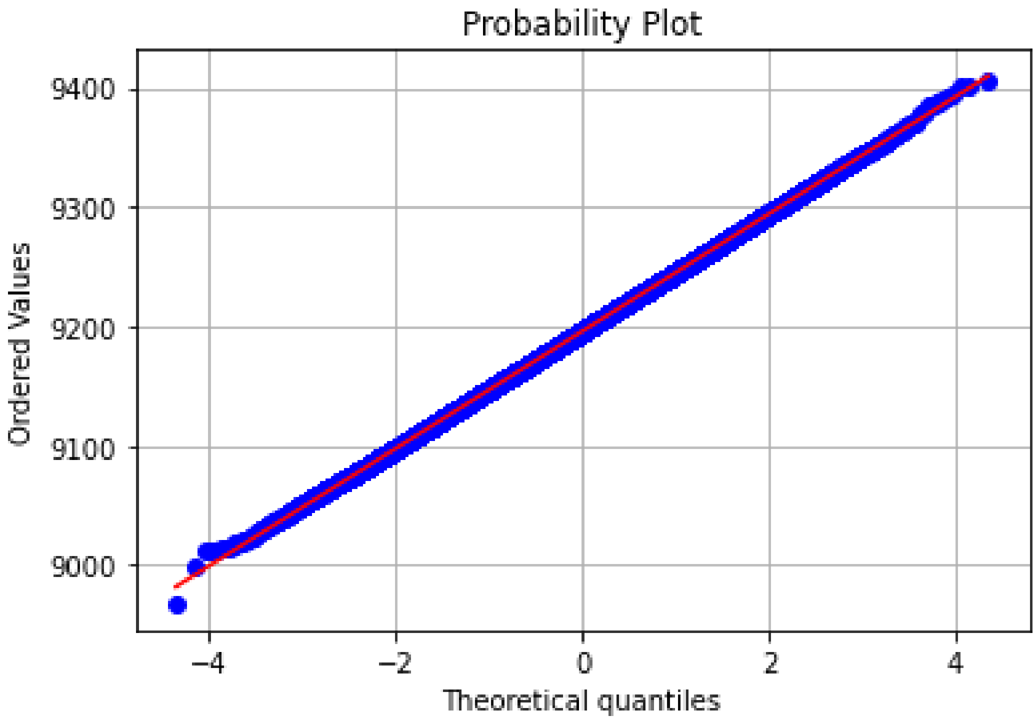
- Let's assume that the population mean and standard deviation are finite.
- Let us draw 1 lakh samples from the given dataset, with each sample having 10000 data points.

[66]:
```
data=df['Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[67]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm if it is␣
↪so.
#We can confirm using QQ Plot.
```



[68]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[69]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[70]:
```
#68% Confidence Interval :
print('Population Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Population Mean Purchase 68% Confidence Interval : 9146.522418690758 to
9245.009750147245
```

[71]:
```
#95% Confidence Interval :
print('Population Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

```
Population Mean Purchase 95% Confidence Interval : 9097.278752962513 to
9294.25341587549
```

[ ]:

```

```

0.3 Confidence Interval Using The Central Limit Theorem For Males

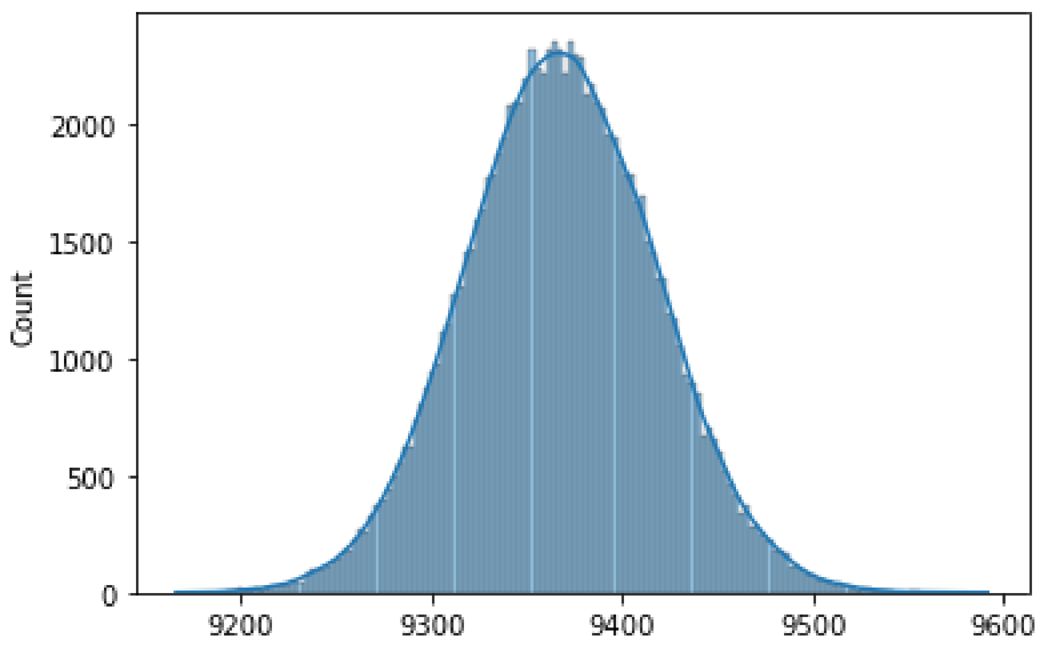
- Let's assume that the population mean and standard deviation are finite.
- Let us draw 1 lakh samples from the given dataset, with each sample having 10000 data points.

[72]:

```
data=df.loc[df['Gender']=='M','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

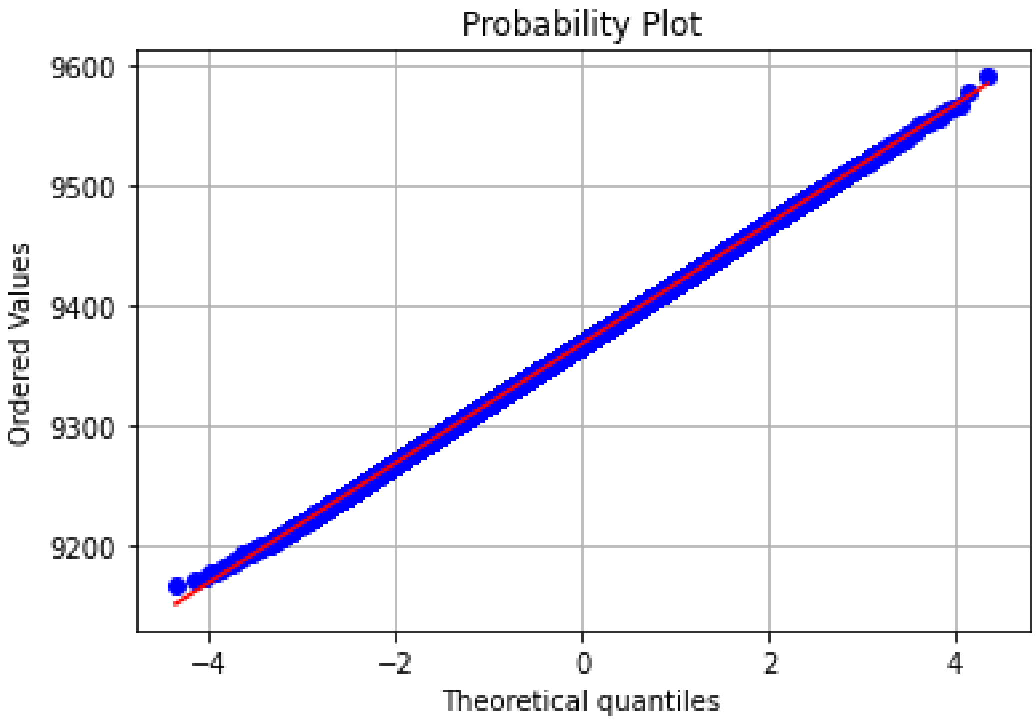
[73]:

```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[74]:

```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[75]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[76]:
```
#68% Confidence Interval :
print('Male Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Male Mean Purchase 68% Confidence Interval : 9317.892020424133 to
9417.956468955868
```

[77]:
```
#95% Confidence Interval :
print('Male Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

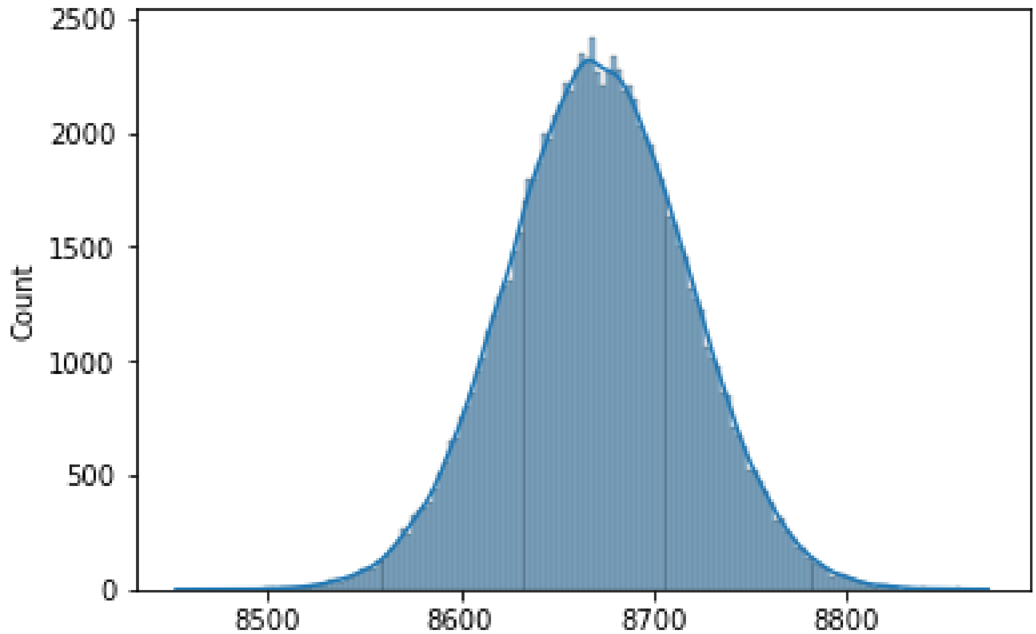
```
Male Mean Purchase 95% Confidence Interval : 9267.859796158267 to
9467.988693221734
```

[ ]:

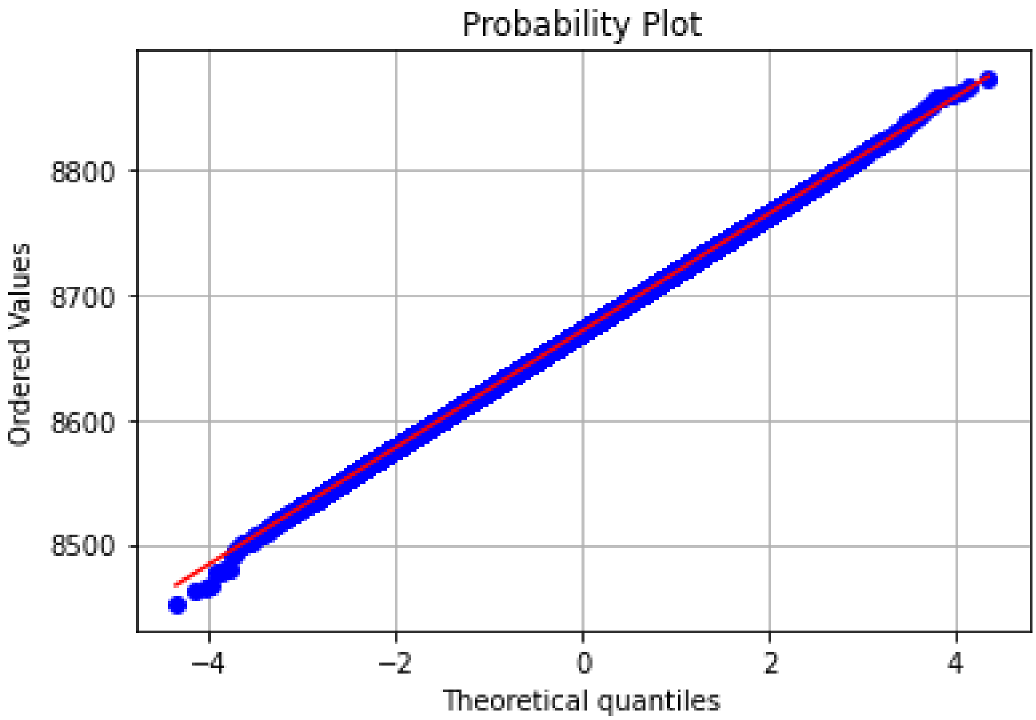
0.4 Confidence Interval Using The Central Limit Theorem For Females

[78]:
```
data=df.loc[df['Gender']=='F','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[79]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[80]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[81]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[82]:
```
#68% Confidence Interval :
print('Female Mean Purchase 68% Confidence Interval :
 ↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Female Mean Purchase 68% Confidence Interval : 8624.236932917702 to
8718.085025300297
```

[83]:
```
#95% Confidence Interval :
print('Female Mean Purchase 95% Confidence Interval :
 ↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

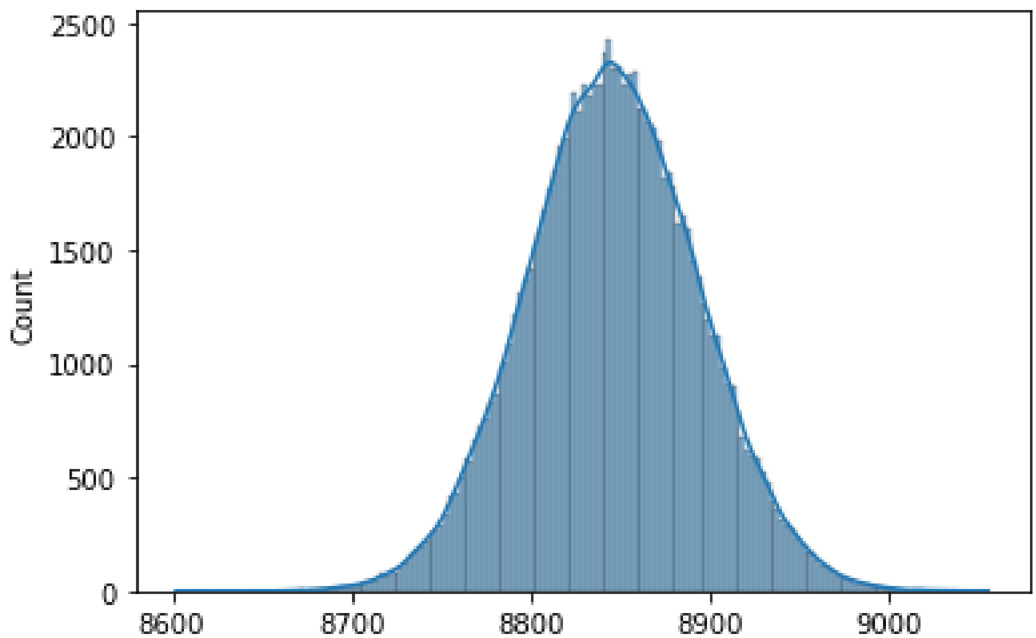
```
Female Mean Purchase 95% Confidence Interval : 8577.312886726402 to
8765.009071491597
```

[ ]:

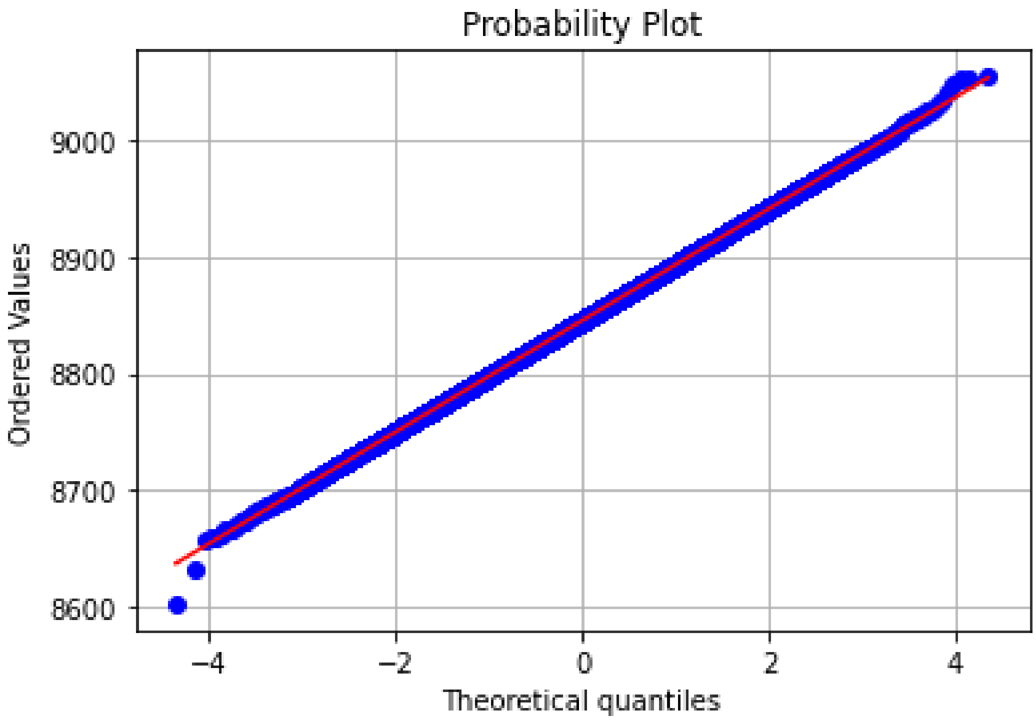
0.5 Confidence Interval Using The Central Limit Theorem For City A

[84]:
```
data=df.loc[df['City_Category']=='A','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[85]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[86]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[87]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[88]:
```
#68% Confidence Interval :
print('City A Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
City A Mean Purchase 68% Confidence Interval : 8797.471169466544 to
8893.498509299456
```

[89]:
```
#95% Confidence Interval :
print('City A Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

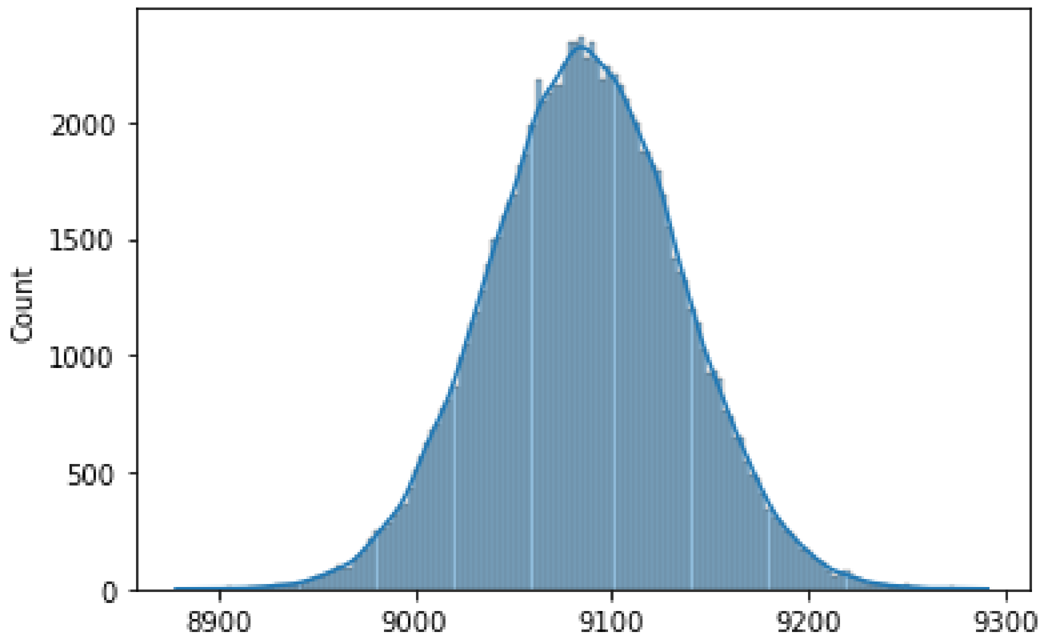
```
City A Mean Purchase 95% Confidence Interval : 8749.457499550088 to
8941.512179215912
```

[ ]:

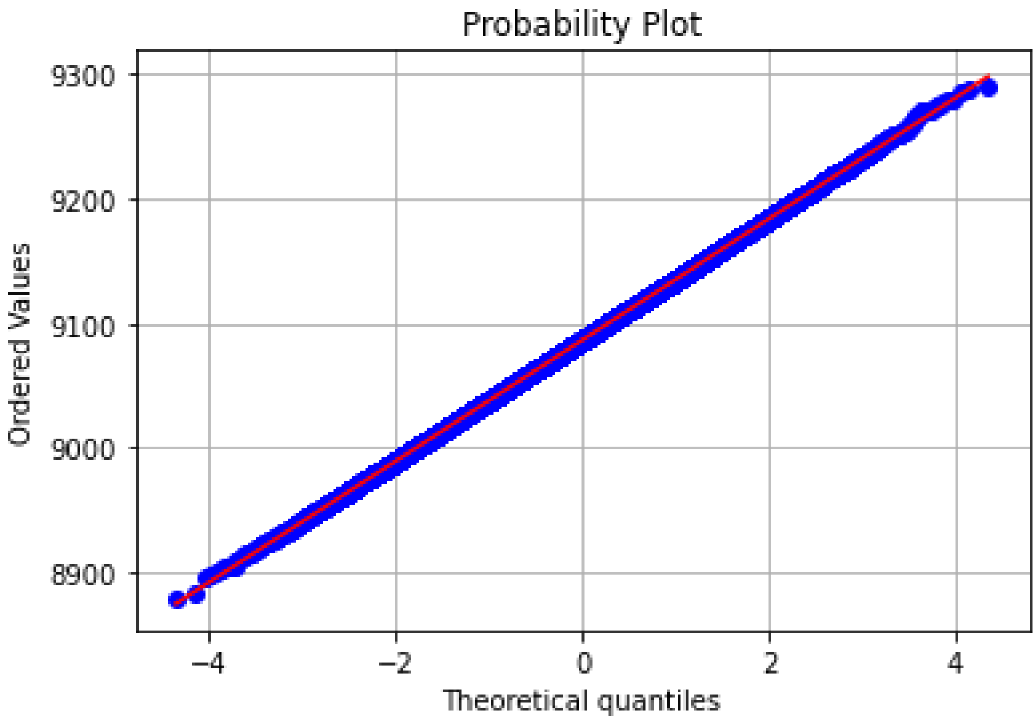
0.6 Confidence Interval Using The Central Limit Theorem For City B

[90]:
```
data=df.loc[df['City_Category']=='B','Purchase']
data
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[91]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[92]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[93]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[94]:
```
#68% Confidence Interval :
print('City B Mean Purchase 68% Confidence Interval :
 ↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
City B Mean Purchase 68% Confidence Interval : 9037.7509426006 to
9135.225770363399
```

[95]:
```
#95% Confidence Interval :
print('City B Mean Purchase 95% Confidence Interval :
 ↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

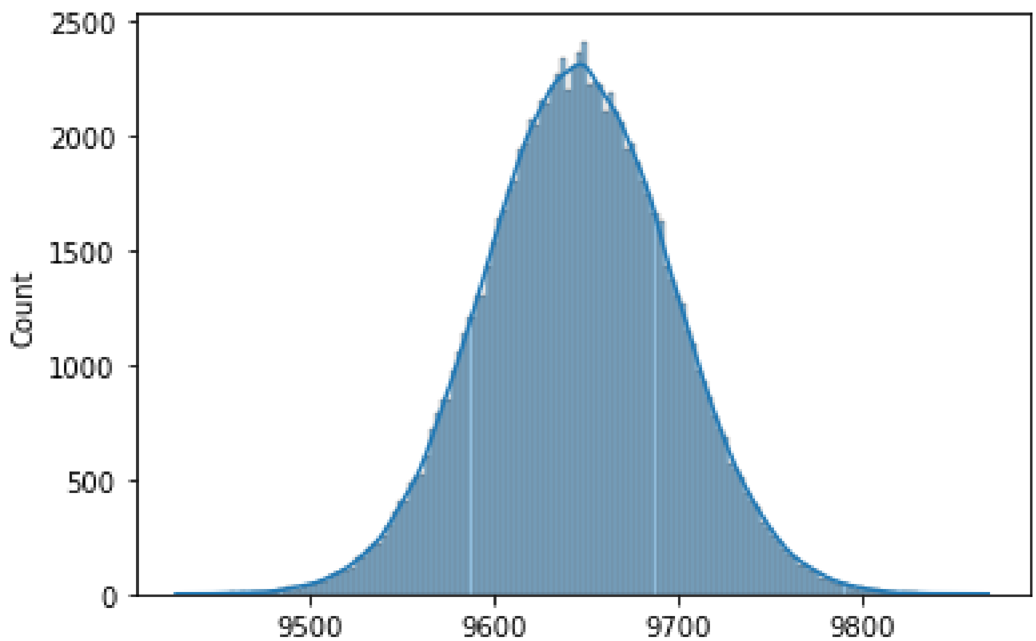
```
City B Mean Purchase 95% Confidence Interval : 8989.0135287192 to
9183.963184244798
```

[ ]:
```

```

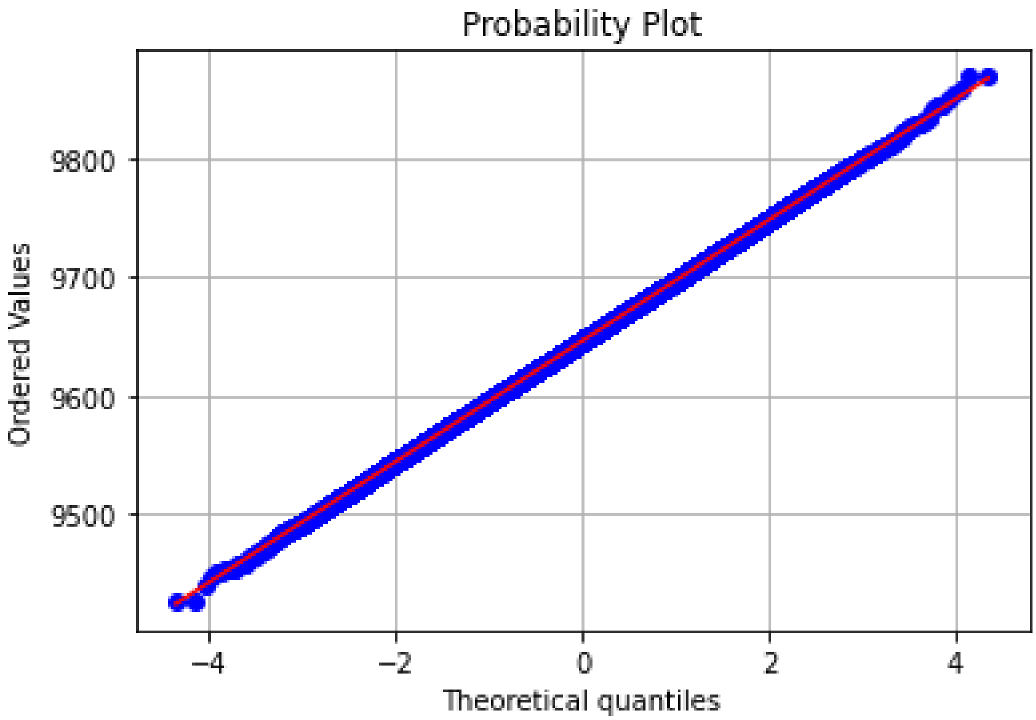
0.7 Confidence Interval Using The Central Limit Theorem For City C

[96]:
```
data=df.loc[df['City_Category']=='C','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[97]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[98]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[99]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[100]:
```
#68% Confidence Interval :
print('City C Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
City C Mean Purchase 68% Confidence Interval : 9594.768033726903 to
9696.675063373097
```

[101]:
```
#95% Confidence Interval :
print('City C Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

```
City C Mean Purchase 95% Confidence Interval : 9543.814518903804 to
9747.628578196196
```

[ ]:
```

```

[ ]:

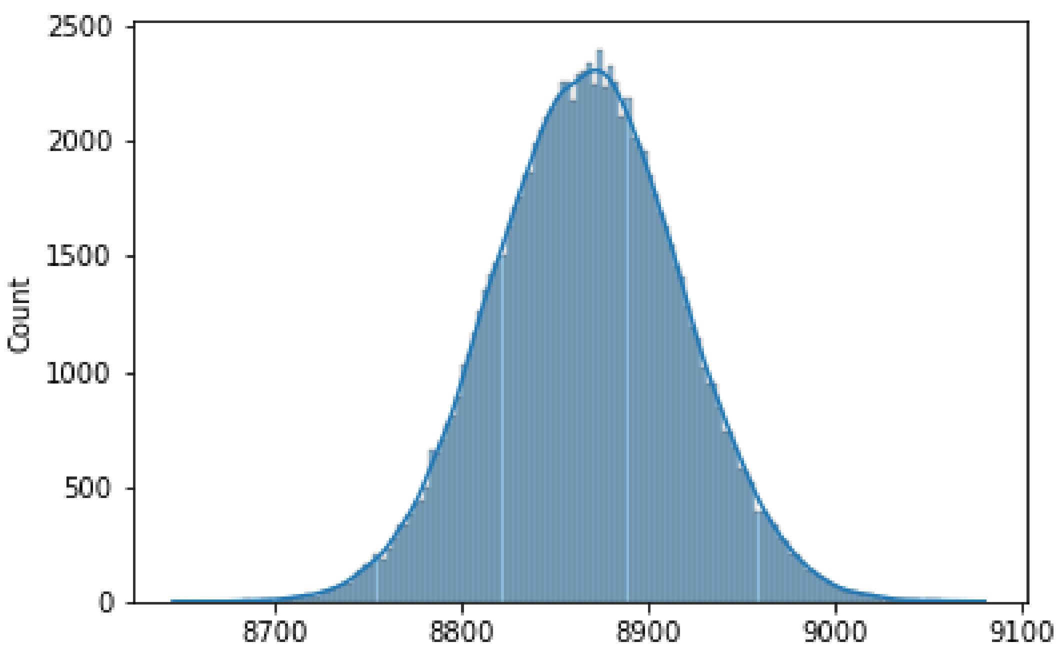
0.8 Confidence Interval Using The Central Limit Theorem For Age Group 0-17

[102]:
```
print(df['Age'].nunique())
# There are 7 unique age categories.
print(df['Age'].unique().tolist())
```

```
7
['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25']
```

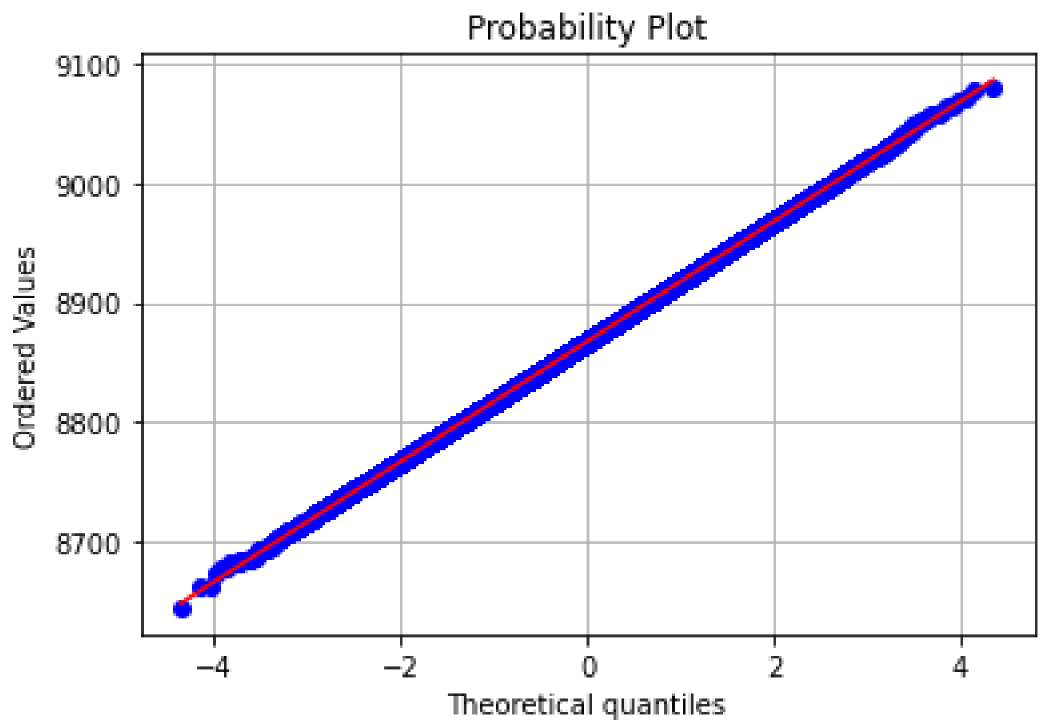
[103]:
```
data=df.loc[df['Age']=='0-17','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[104]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[105]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
```

```
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[106]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[107]:
```
#68% Confidence Interval :
print('Age Group 0-17 Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Age Group 0-17 Mean Purchase 68% Confidence Interval : 8817.16969308802 to
8917.755087865979
```

[108]:
```
#95% Confidence Interval :
print('Age Group 0-17 Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

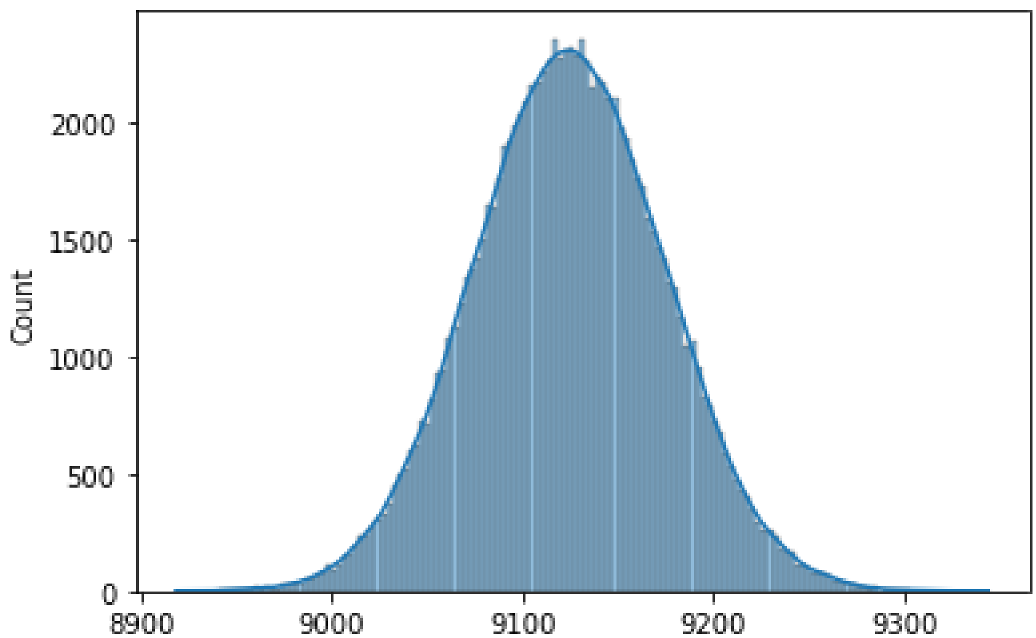
```
Age Group 0-17 Mean Purchase 95% Confidence Interval : 8766.876995699042 to
8968.047785254957
```

[ ]:

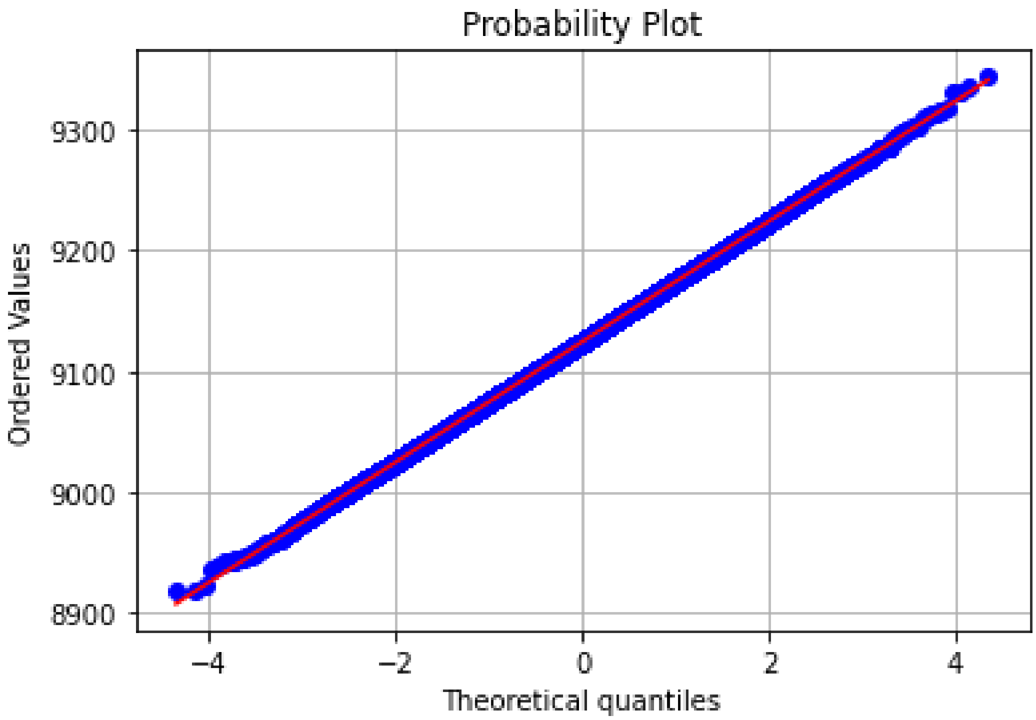
0.9 Confidence Interval Using The Central Limit Theorem For Age Group 18-25

[109]:
```
data=df.loc[df['Age']=='18-25','Purchase']
data
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[110]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[111]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[112]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[113]:
```
#68% Confidence Interval :
print('Age Group 18-25 Mean Purchase 68% Confidence Interval :
 ↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Age Group 18-25 Mean Purchase 68% Confidence Interval : 9074.407415798321 to
9174.163115891677
```

[114]:
```
#95% Confidence Interval :
print('Age Group 18-25 Mean Purchase 95% Confidence Interval :
 ↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

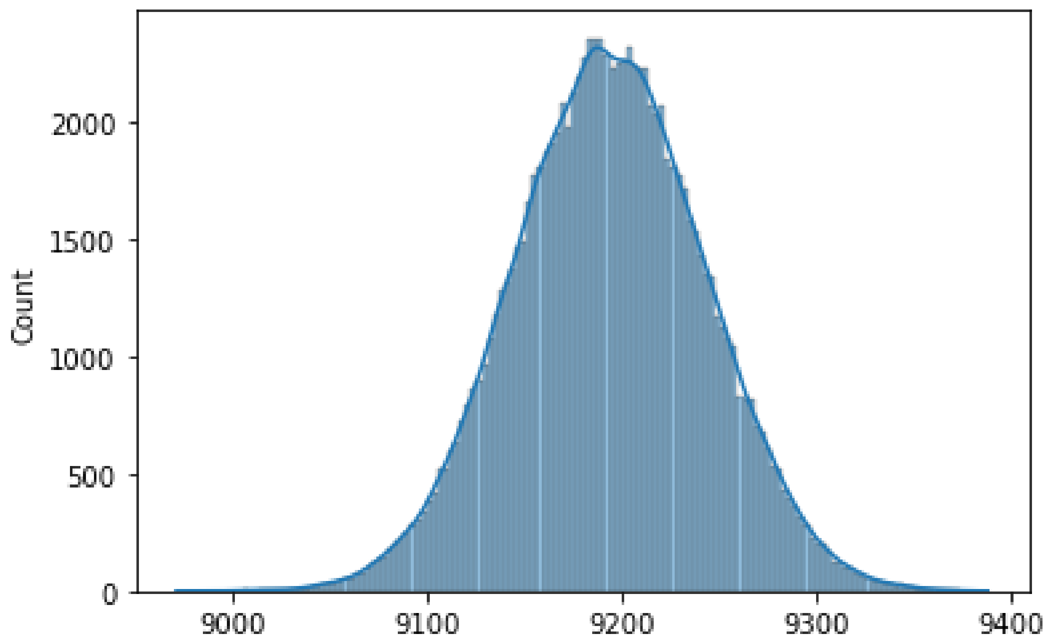
```
Age Group 18-25 Mean Purchase 95% Confidence Interval : 9024.529565751642 to
9224.040965938357
```

[ ]:
```

```

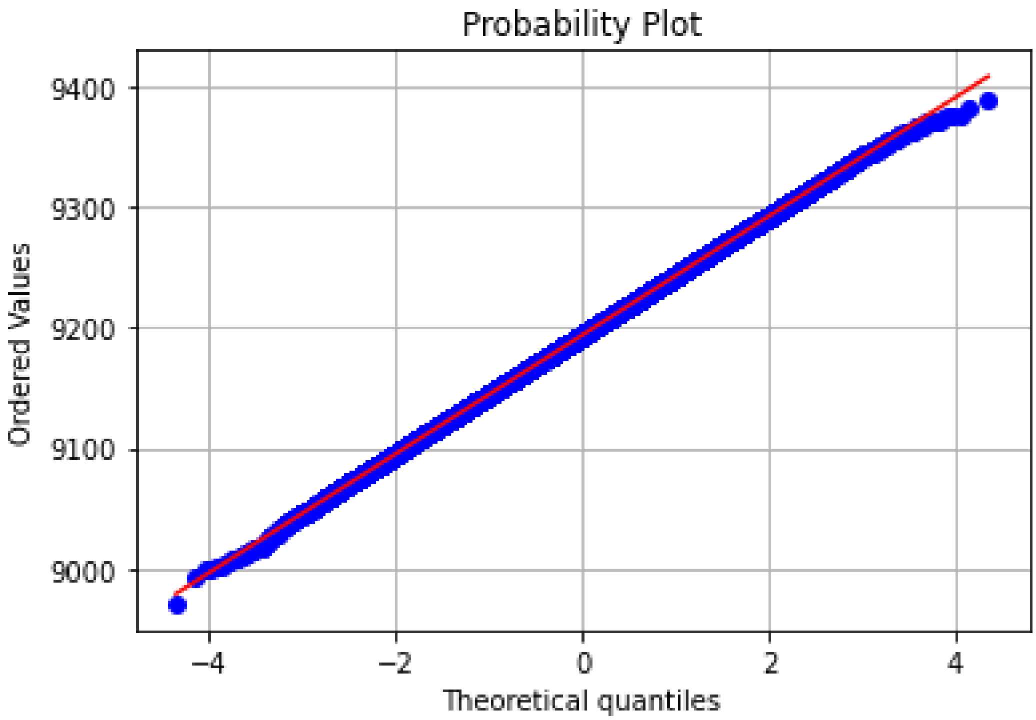
0.10 Confidence Interval Using The Central Limit Theorem For Age Group 26-35

[115]:
```
data=df.loc[df['Age']=='26-35','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[116]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[117]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[118]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[119]:
```
#68% Confidence Interval :
print('Age Group 26-35 Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Age Group 26-35 Mean Purchase 68% Confidence Interval : 9144.238069132618 to
9242.814961225387
```

[120]:
```
#95% Confidence Interval :
print('Age Group 26-35 Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

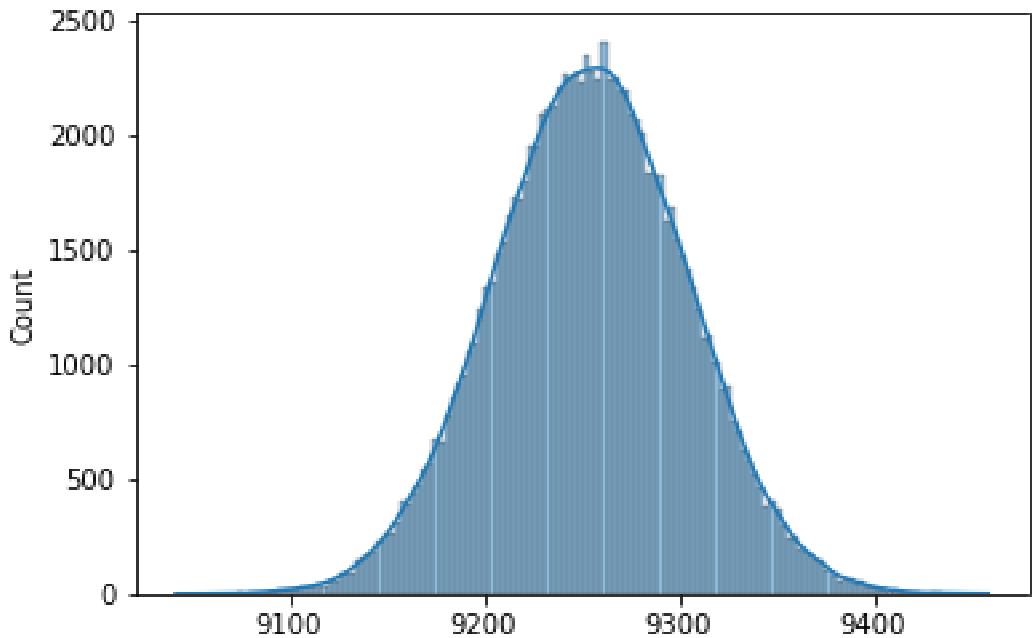
```
Age Group 26-35 Mean Purchase 95% Confidence Interval : 9094.949623086235 to
9292.10340727177
```

[ ]:
```

```

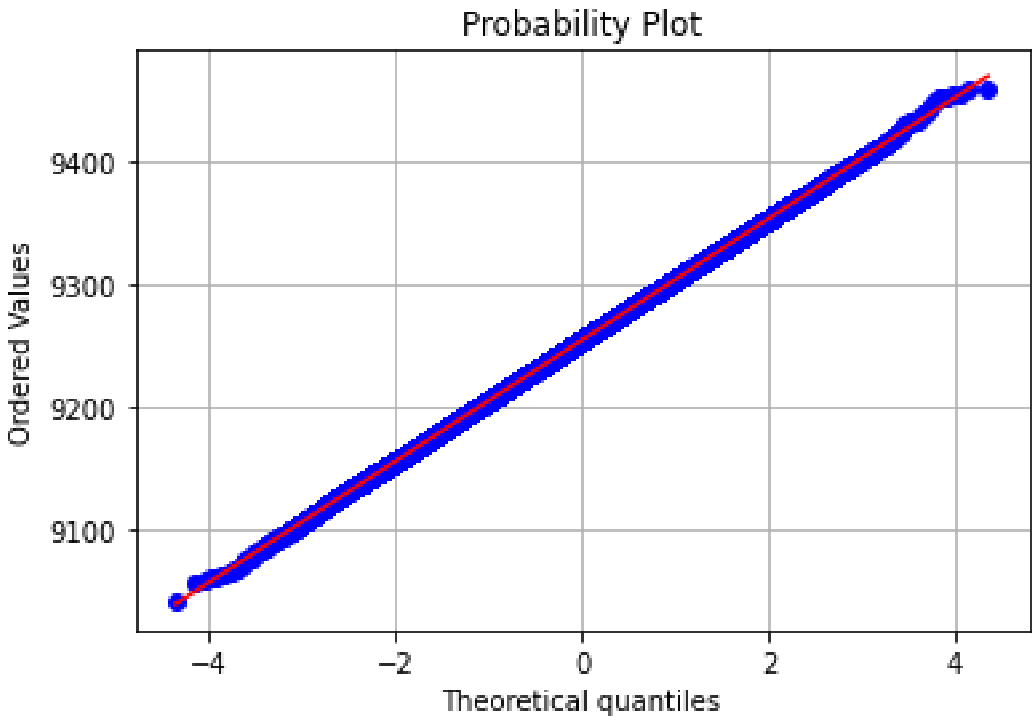
0.11 Confidence Interval Using The Central Limit Theorem For The Age Group 36-45

[121]:
```
data=df.loc[df['Age']=='36-45','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[122]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[123]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[124]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[125]:
```
#68% Confidence Interval :
print('Age Group 36-45 Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Age Group 36-45 Mean Purchase 68% Confidence Interval : 9204.905608025932 to
9303.751895302066
```

[126]:
```
#95% Confidence Interval :
print('Age Group 36-45 Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

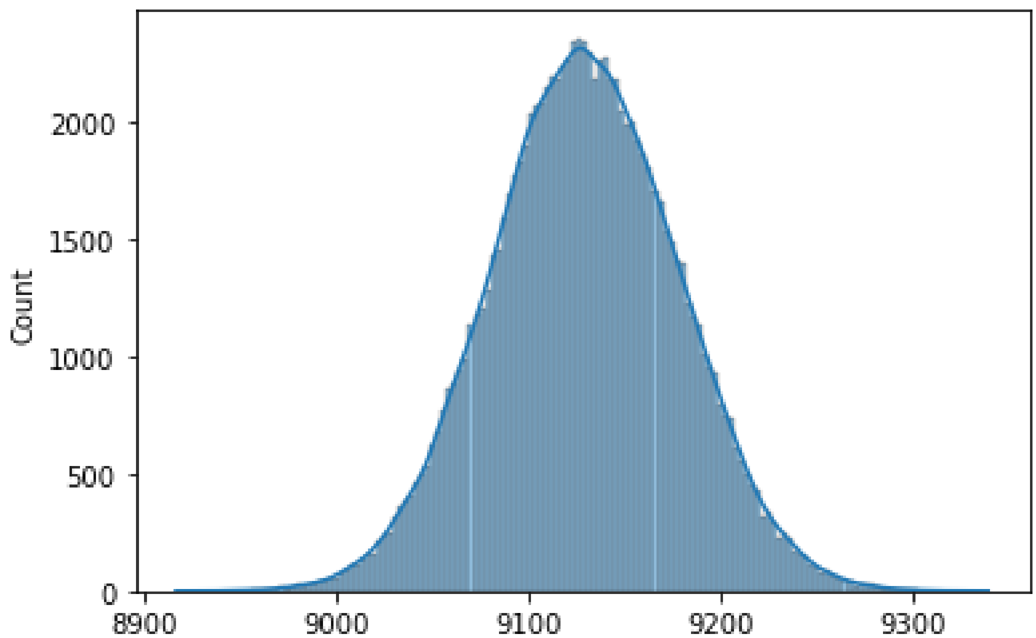
```
Age Group 36-45 Mean Purchase 95% Confidence Interval : 9155.482464387866 to
9353.175038940133
```

[ ]:
```
```

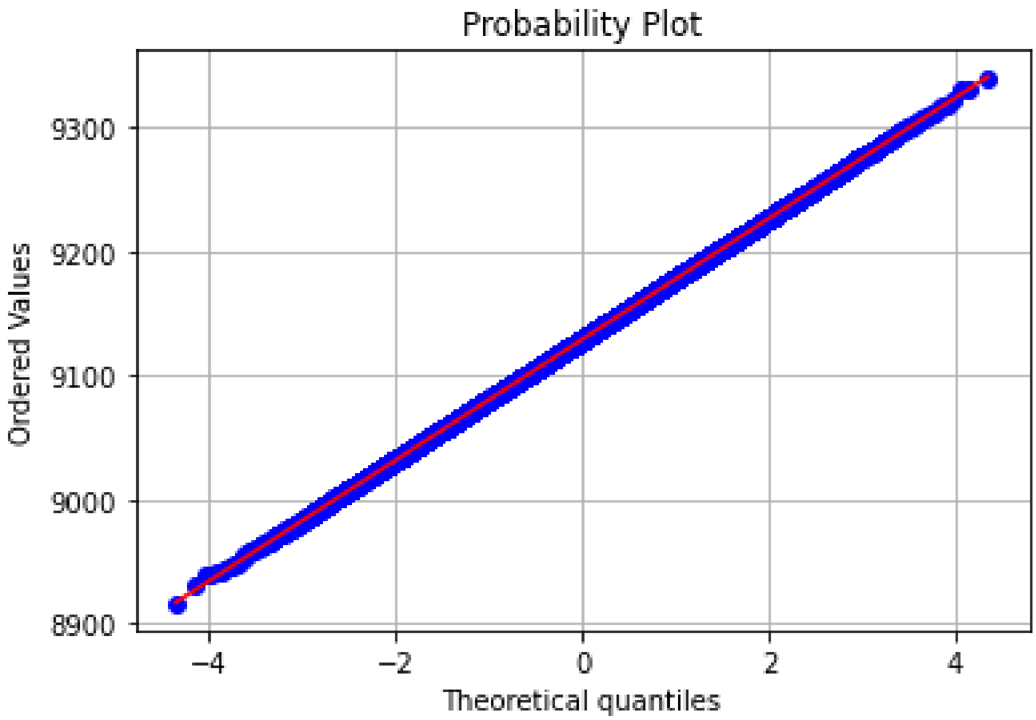
0.12 Confidence Interval Using The Central Limit Theorem For Age Group 46-50

[127]:
```
data=df.loc[df['Age']=='46-50','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[128]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[129]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[130]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[131]:
```
#68% Confidence Interval :
print('Age Group 46-50 Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Age Group 46-50 Mean Purchase 68% Confidence Interval : 9080.259436324037 to
9177.665785283962
```

[132]:
```
#95% Confidence Interval :
print('Age Group 46-50 Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

```
Age Group 46-50 Mean Purchase 95% Confidence Interval : 9031.556261844073 to
9226.368959763926
```

[ ]:
```

```

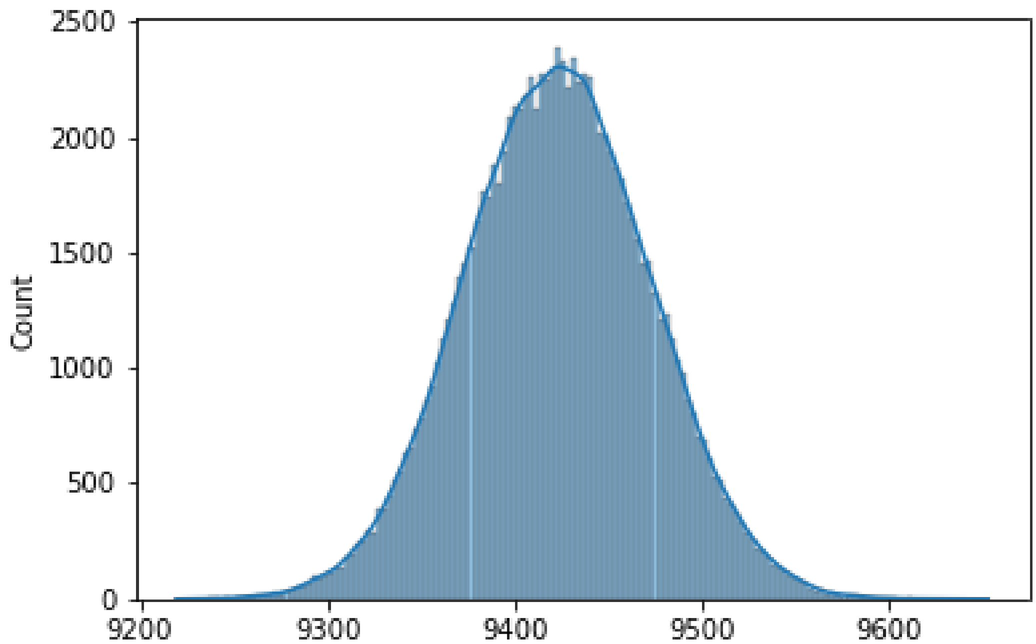
0.13 Confidence Interval Using The Central Limit Theorem For Age Group 51-55

[133]:

```
data=df.loc[df['Age']=='51-55','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

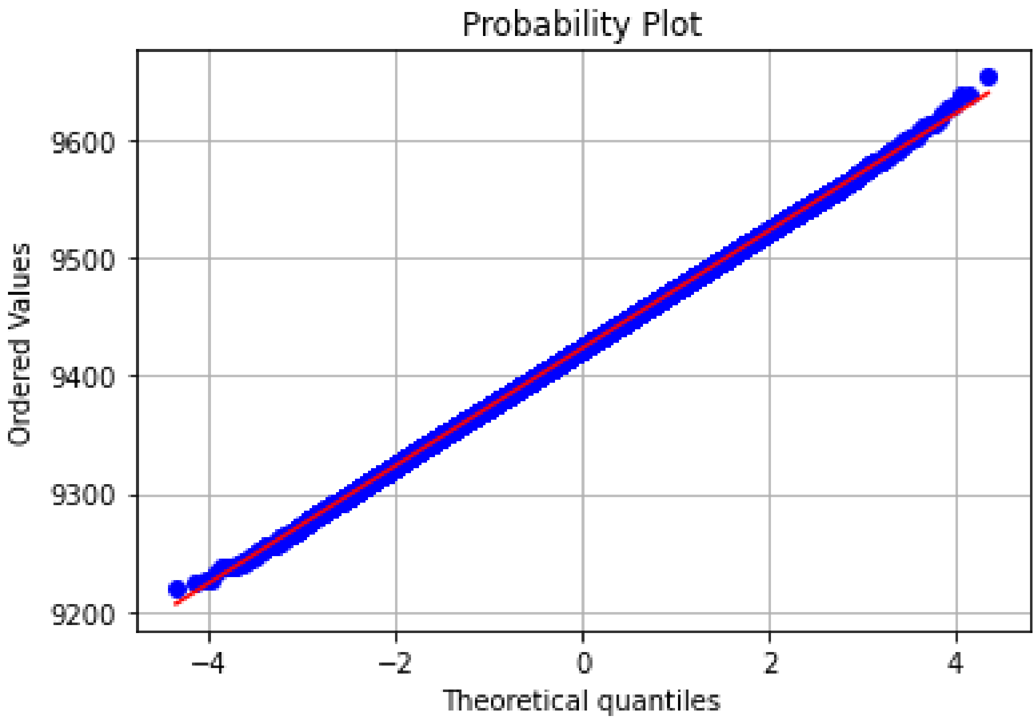
[134]:

```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[135]:

```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[136]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[137]:
```
#68% Confidence Interval :
print('Age Group 51-55 Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Age Group 51-55 Mean Purchase 68% Confidence Interval : 9373.080889980605 to
9472.571365837395
```

[138]:
```
#95% Confidence Interval :
print('Age Group 51-55 Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

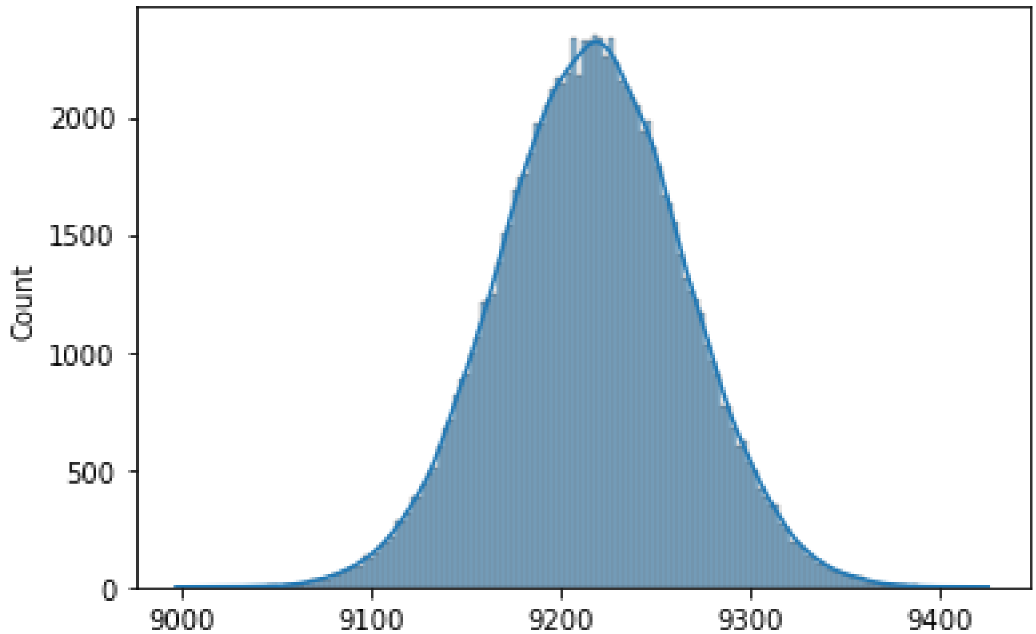
```
Age Group 51-55 Mean Purchase 95% Confidence Interval : 9323.33565205221 to
9522.31660376579
```

[ ]:
```
```

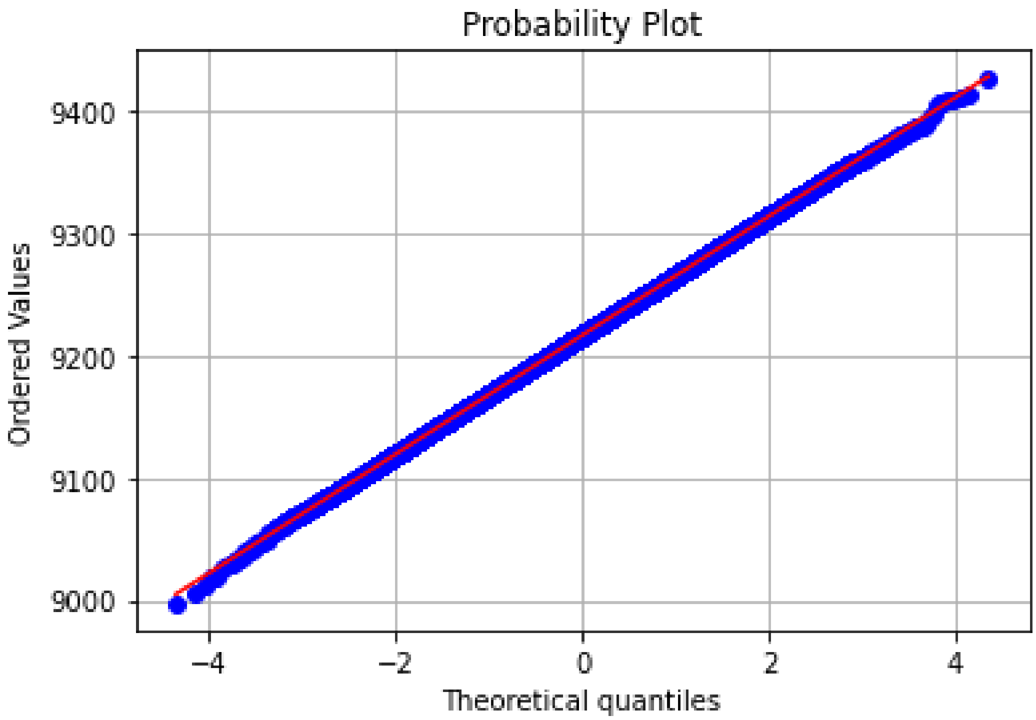
0.14 Confidence Interval Using The Central Limit Theorem For Age Group 55+

[139]:
```
data=df.loc[df['Age']=='55+','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[140]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[141]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[142]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[143]:
```
#68% Confidence Interval :
print('Age Group 55+ Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Age Group 55+ Mean Purchase 68% Confidence Interval : 9167.893286845856 to
9265.333105306143
```

[144]:
```
#95% Confidence Interval :
print('Age Group 55+ Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

```
Age Group 55+ Mean Purchase 95% Confidence Interval : 9119.173377615713 to
9314.053014536286
```

[ ]:

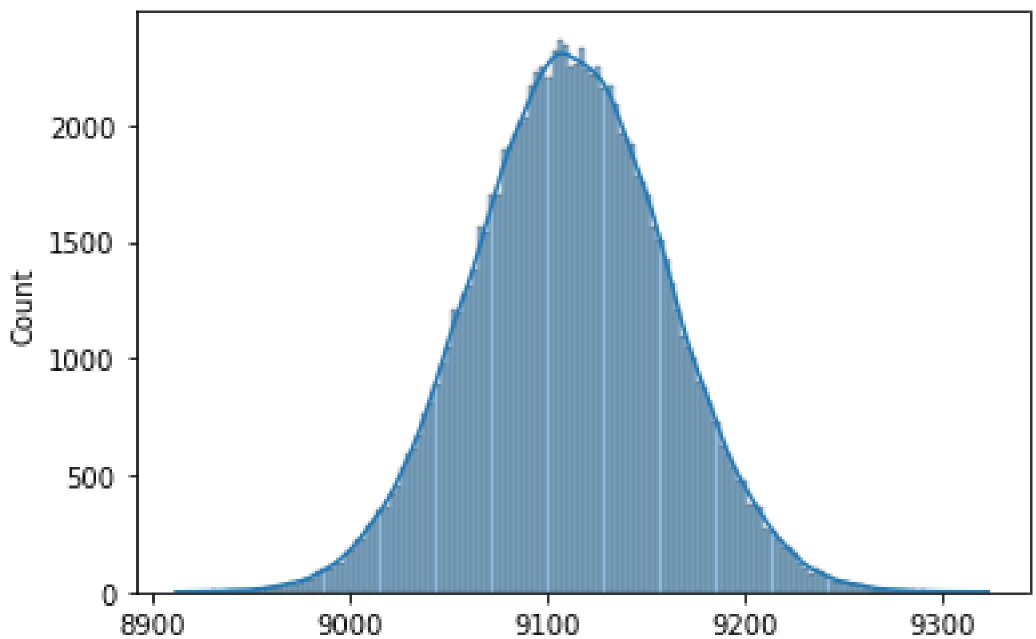
0.15 Confidence Interval Using The Central Limit Theorem For Stay In Current City 0 Year

[145]:
```
print(df['Stay_In_Current_City_Years'].nunique())
# There are 5 unique Stay In Cuurent City Years.
print(df['Stay_In_Current_City_Years'].unique().tolist())
```

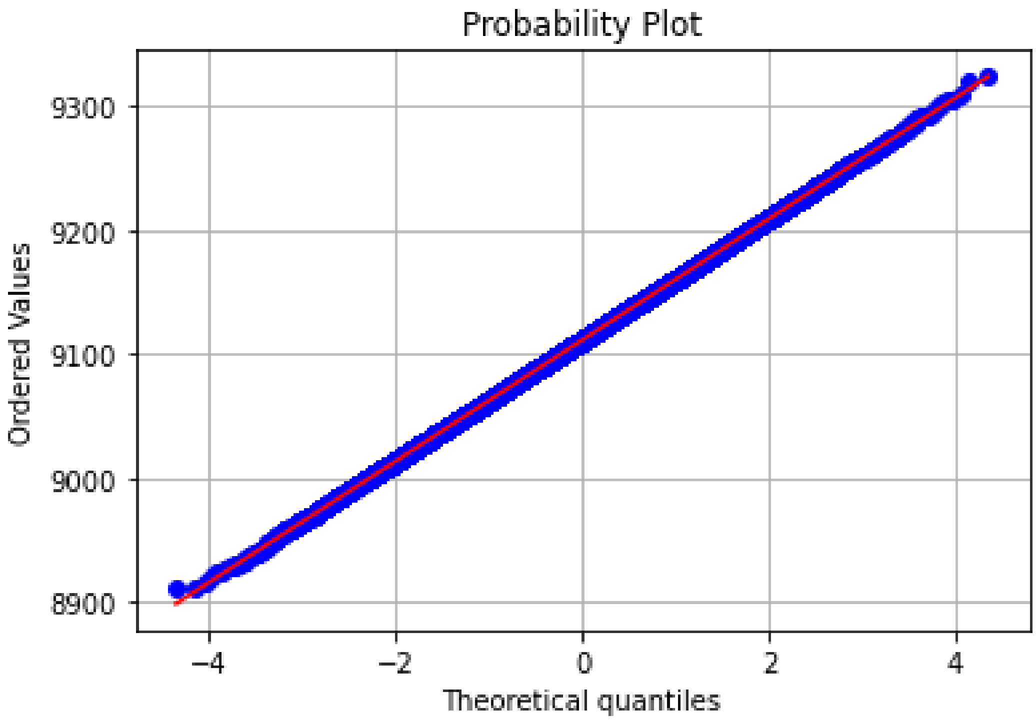
```
5
['2', '4+', '3', '1', '0']
```

[146]:
```
data=df.loc[df['Stay_In_Current_City_Years']=='0','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[147]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[148]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[149]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[150]:
```
#68% Confidence Interval :
print('Current City Stay 0 Year Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Current City Stay 0 Year Mean Purchase 68% Confidence Interval :
9062.30545395957 to 9160.26637463843
```

[151]:
```
#95% Confidence Interval :
print('Current City Stay 0 Year Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

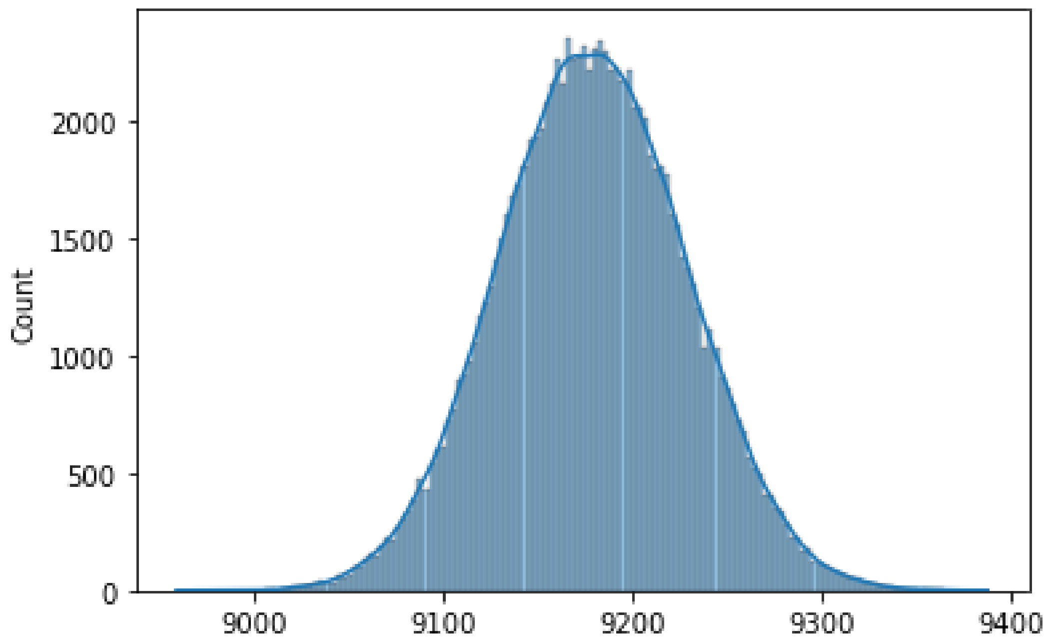
```
Current City Stay 0 Year Mean Purchase 95% Confidence Interval :
9013.324993620141 to 9209.24683497786
```

[ ]:
```

```

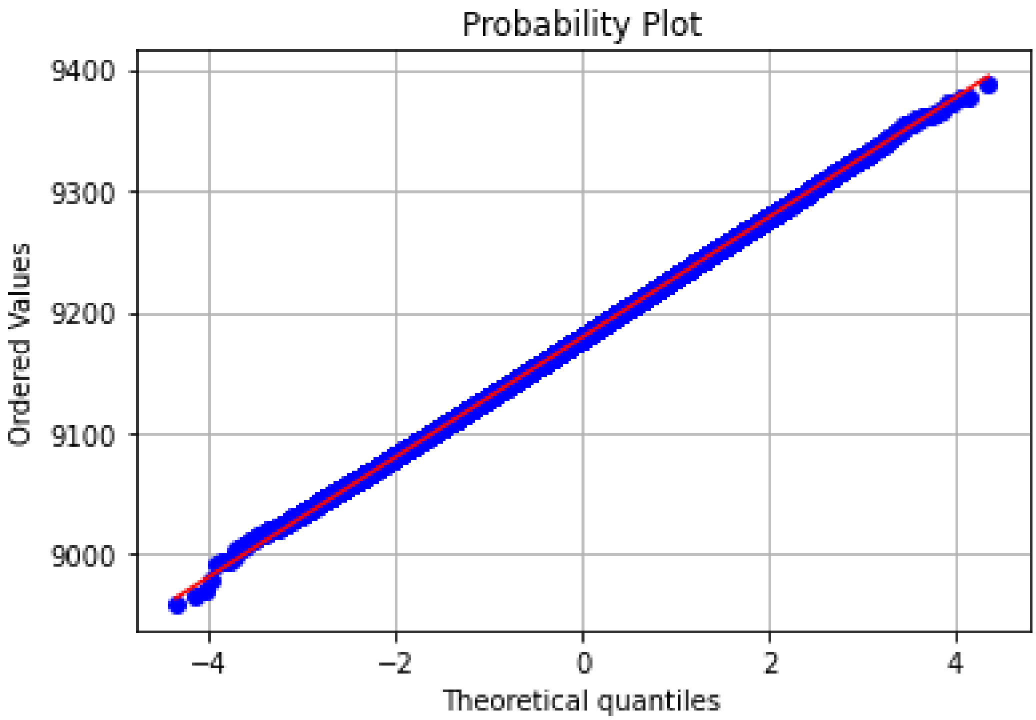
0.16 Confidence Interval Using The Central Limit Theorem For Stay In Current City 1 Year

[152]:
```
data=df.loc[df['Stay_In_Current_City_Years']=='1','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[153]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[154]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[155]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[156]:
```
#68% Confidence Interval :
print('Current City Stay 1 Year Mean Purchase 68% Confidence Interval :
 ↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Current City Stay 1 Year Mean Purchase 68% Confidence Interval :
9129.580985775216 to 9228.605304208782
```

[157]:
```
#95% Confidence Interval :
print('Current City Stay 1 Year Mean Purchase 95% Confidence Interval :
 ↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

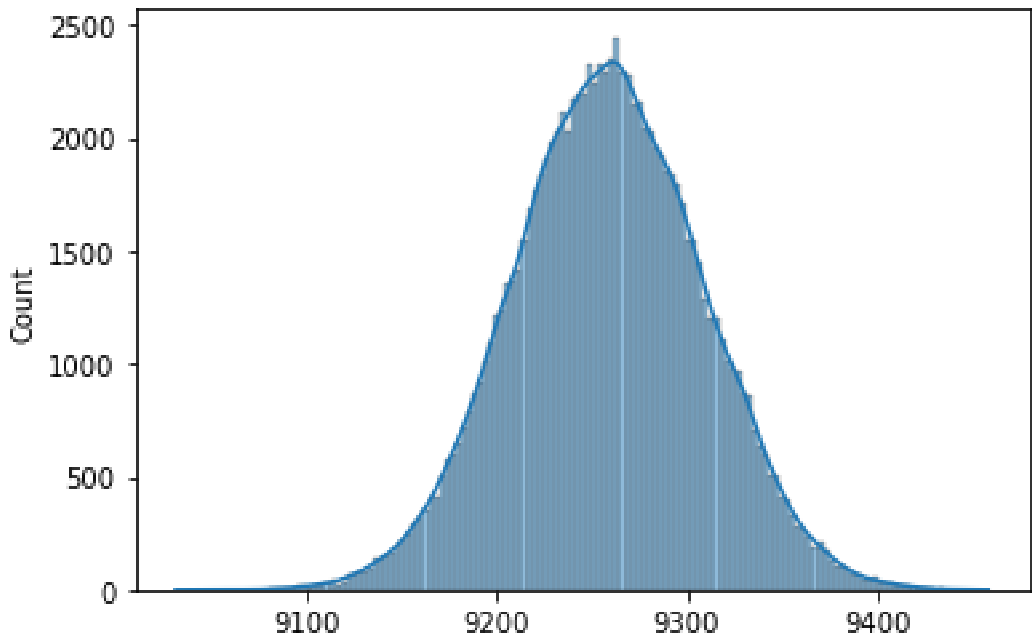
```
Current City Stay 1 Year Mean Purchase 95% Confidence Interval :
9080.068826558432 to 9278.117463425566
```

[ ]:
```

```

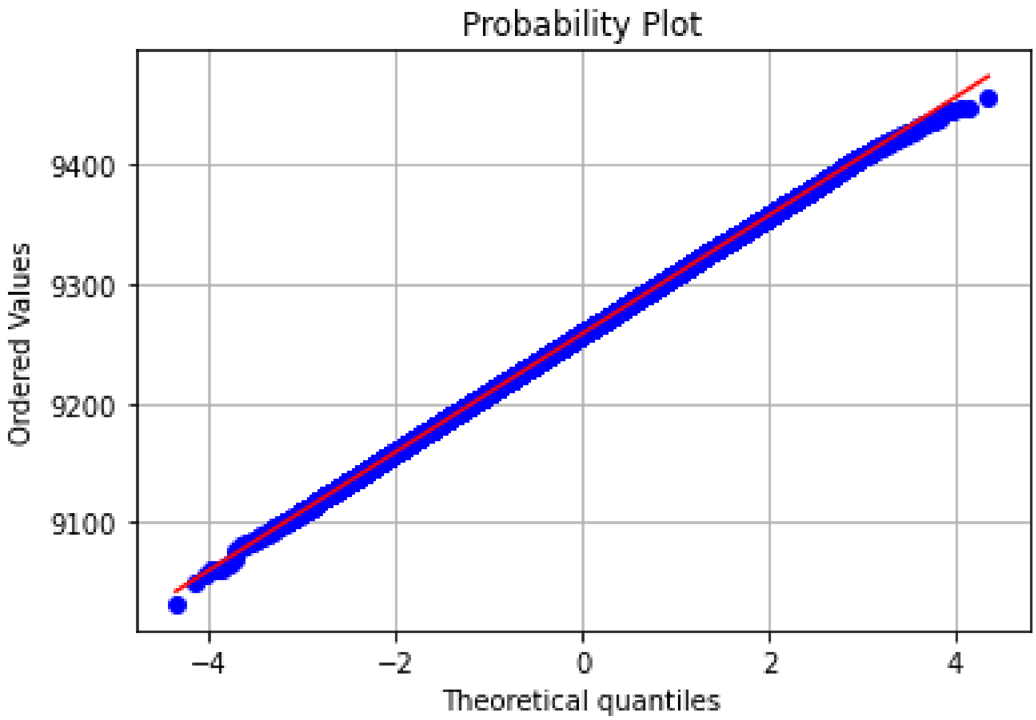
0.17 Confidence Interval Using The Central Limit Theorem For Stay In Current City 2 Years

[158]:
```
data=df.loc[df['Stay_In_Current_City_Years']=='2','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[159]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[160]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[161]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[162]:
```
#68% Confidence Interval :
print('Current City Stay 2 Years Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Current City Stay 2 Years Mean Purchase 68% Confidence Interval :
9208.49904511685 to 9307.956619385148
```

[163]:
```
#95% Confidence Interval :
print('Current City Stay 2 Years Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

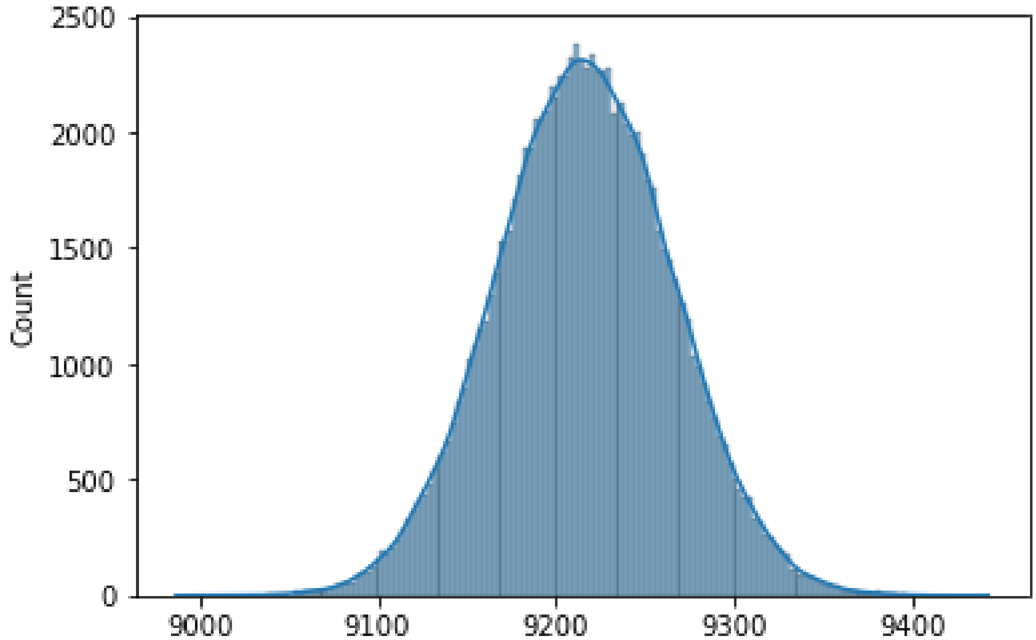
```
Current City Stay 2 Years Mean Purchase 95% Confidence Interval :
9158.770257982702 to 9357.685406519297
```

[ ]:

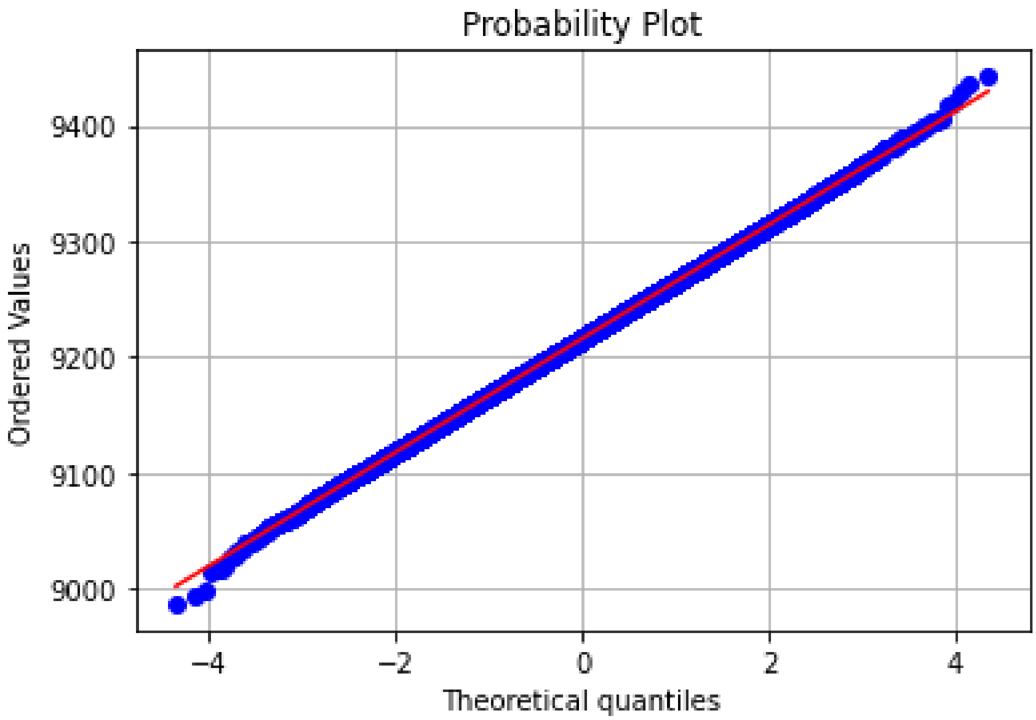
0.18 Confidence Interval Using The Central Limit Theorem For Stay In Current City 3 Years

[164]:
```
data=df.loc[df['Stay_In_Current_City_Years']=='3','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[165]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[166]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[167]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[168]:
```
#68% Confidence Interval :
print('Current City Stay 3 Years Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Current City Stay 3 Years Mean Purchase 68% Confidence Interval :
9166.689156775368 to 9265.08956621463
```

[169]:
```
#95% Confidence Interval :
print('Current City Stay 3 Years Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

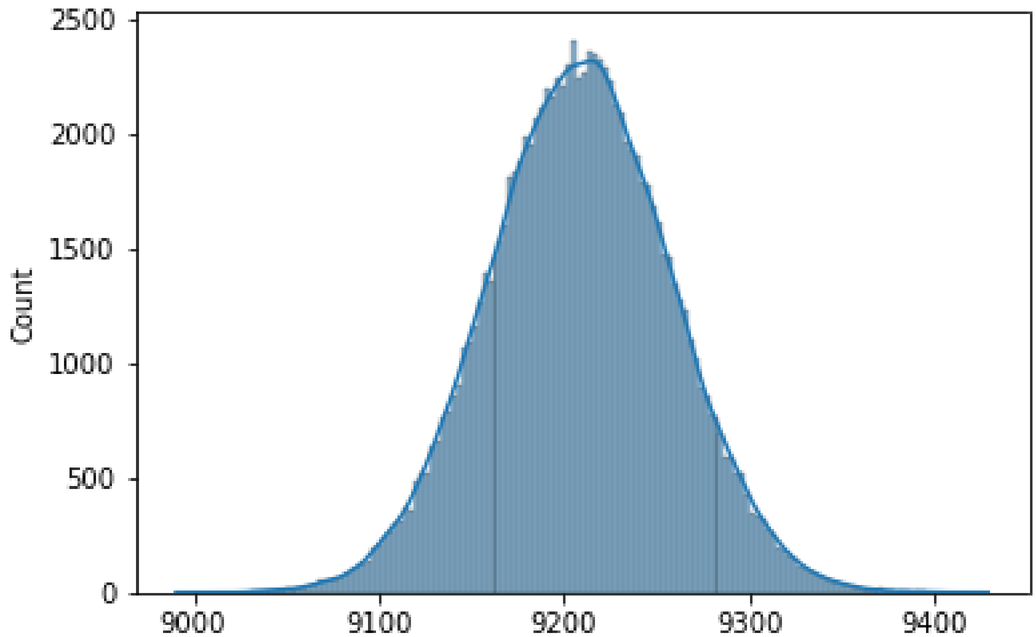
```
Current City Stay 3 Years Mean Purchase 95% Confidence Interval :
9117.488952055739 to 9314.28977093426
```

[ ]:
```

```

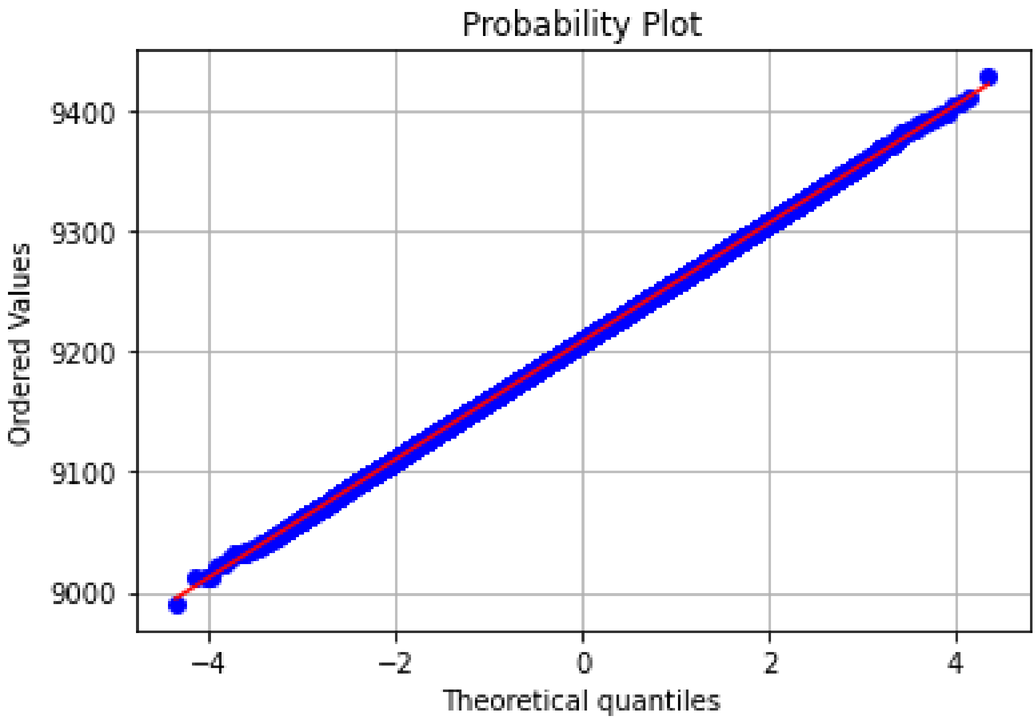
0.19 Confidence Interval Using The Central Limit Theorem For Stay In Current City 4+ Years

[170]:
```
data=df.loc[df['Stay_In_Current_City_Years']=='4+','Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[171]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[172]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[173]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[174]:
```
#68% Confidence Interval :
print('Current City Stay 4+ Years Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Current City Stay 4+ Years Mean Purchase 68% Confidence Interval :
9159.369842172933 to 9257.65787423307
```

[175]:
```
#95% Confidence Interval :
print('Current City Stay 4+ Years Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

```
Current City Stay 4+ Years Mean Purchase 95% Confidence Interval :
9110.225826142865 to 9306.801890263137
```

[ ]:
```

```

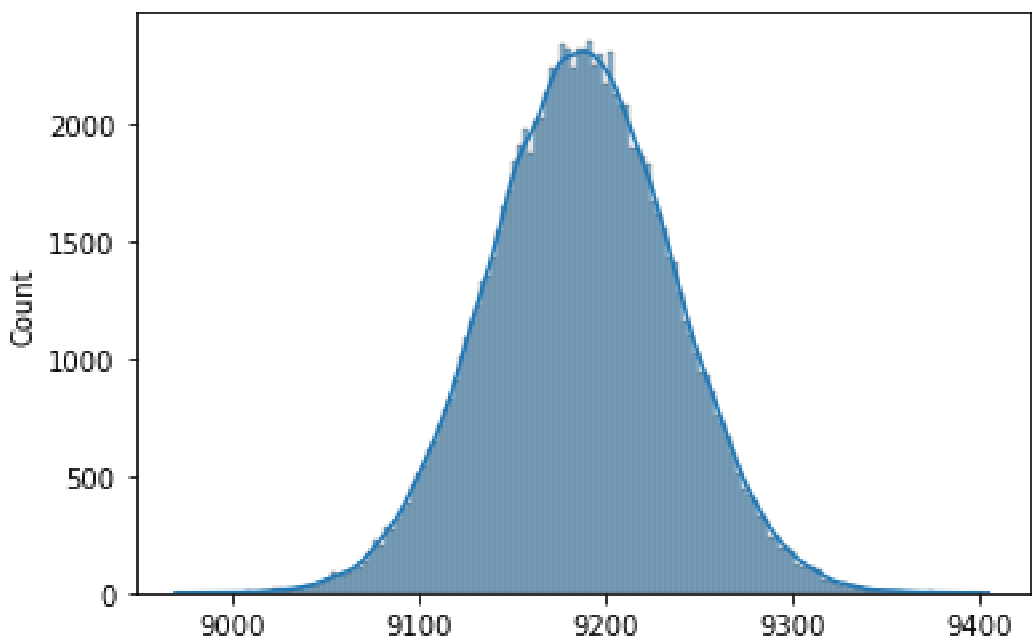
0.20 Confidence Interval Using The Central Limit Theorem For Married People

[176]:
```
print(df['Marital_Status'].nunique())
# There are 2 unique Marital Status categories.
print(df['Marital_Status'].unique().tolist())
```

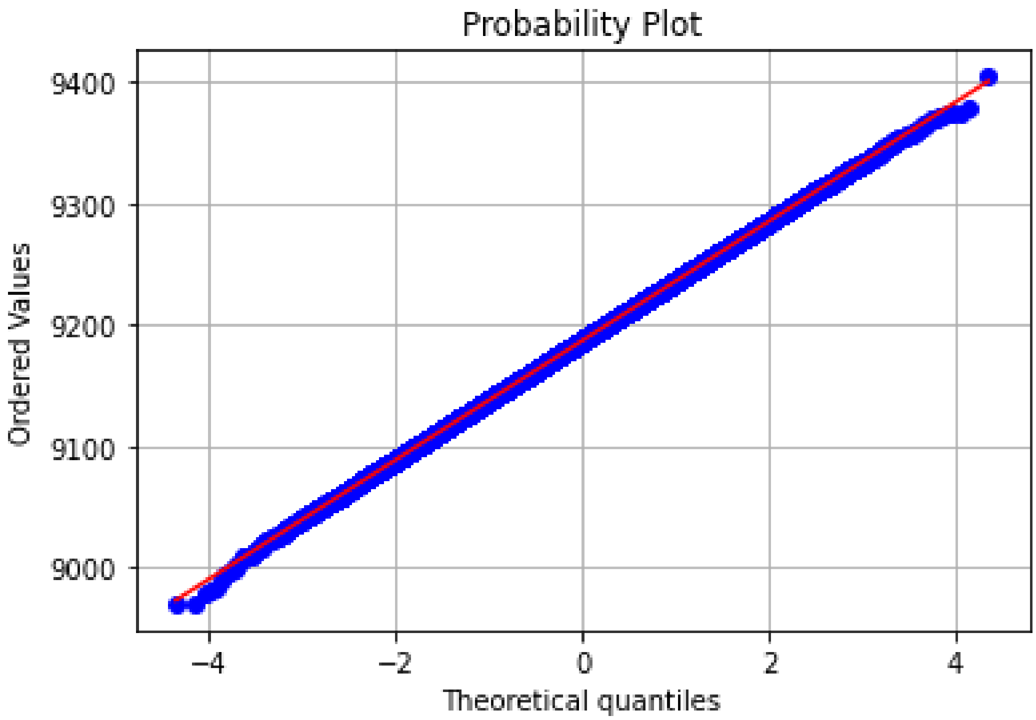
```
2
[0, 1]
```

[177]:
```
data=df.loc[df['Marital_Status']==1,'Purchase']
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(data, size=10000)))
```

[178]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[179]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[180]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[181]:
```
#68% Confidence Interval :
print('Married Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Married Mean Purchase 68% Confidence Interval : 9137.843988230801 to
9236.235351369203
```

[182]:
```
#95% Confidence Interval :
print('Married Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

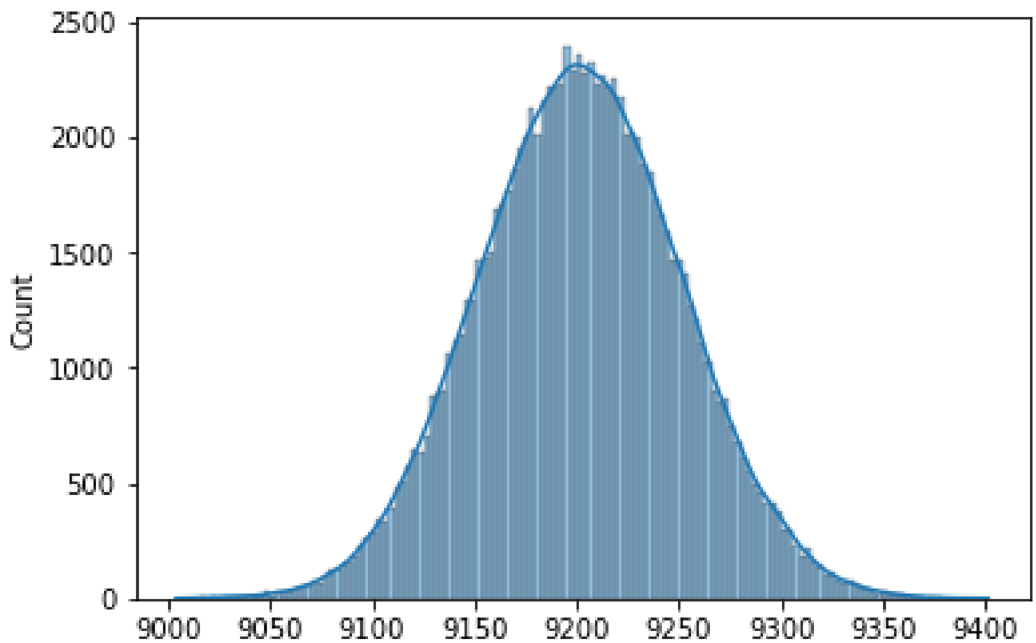
```
Married Mean Purchase 95% Confidence Interval : 9088.6483066616 to
9285.431032938404
```

[ ]:
```

```

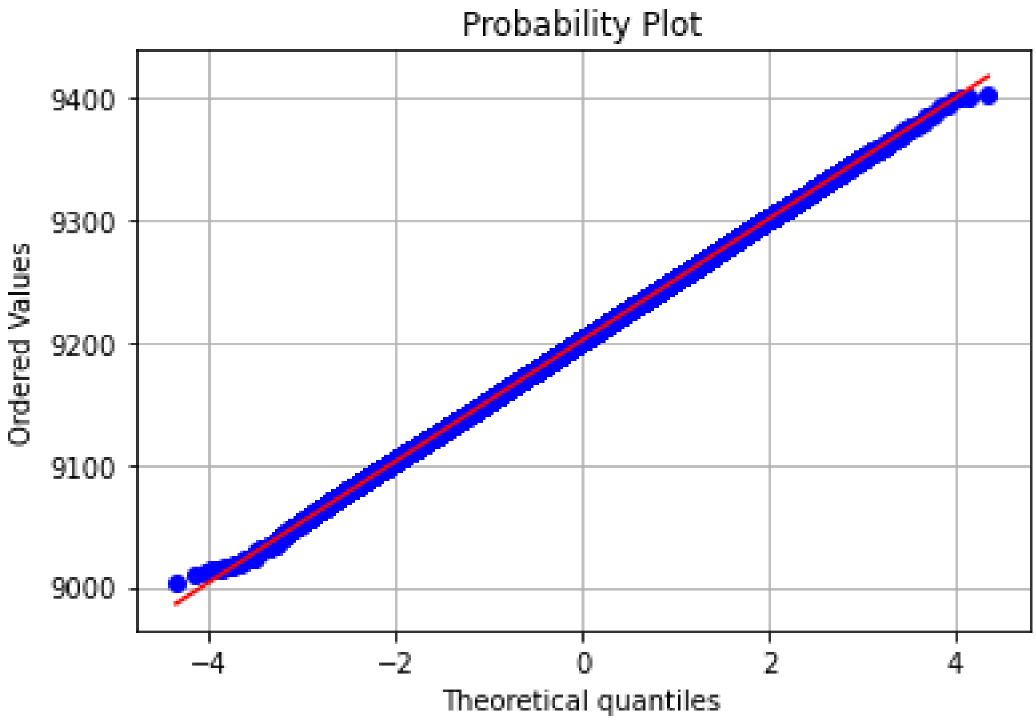
0.21 Confidence Interval Using The Central Limit Theorem For Unmarried People

[183]:
```
Unmarried_data=df.loc[df['Marital_Status']==0,'Purchase']
Unmarried_data
sampling_distribution=[]
for i in range(100000):
    sampling_distribution.append(np.mean(np.random.choice(Unmarried_data,␣
 ↪size=10000)))
```

[184]:
```
#Plotting the sampling distribution
sns.histplot(data=sampling_distribution,kde=True)
plt.show()
#It looks like this is a normal distribution. But we need to confirm it is so.
#We can confirm using QQ Plot.
```



[185]:
```
#QQ Plot
fig, ax1 = plt.subplots()
plt.grid()
prob = stats.probplot(sampling_distribution, dist=stats.norm, plot=ax1)
```



From the above QQ PLot, we can confirm that the sampling distribution follows a normal distribution, since almost all the points are lying on the 45 degree line.

[186]:
```
mean_sampling_distribution = np.mean(sampling_distribution)
std_sampling_distribution=np.std(sampling_distribution)
```

[187]:
```
#68% Confidence Interval :
print('Unmarried Mean Purchase 68% Confidence Interval :
↪',mean_sampling_distribution-std_sampling_distribution,
      'to',mean_sampling_distribution+std_sampling_distribution)
```

```
Unmarried Mean Purchase 68% Confidence Interval : 9152.00225431859 to
9251.066608847408
```

[188]:
```
#95% Confidence Interval :
print('Unmarried Mean Purchase 95% Confidence Interval :
↪',mean_sampling_distribution-2*std_sampling_distribution,
      'to',mean_sampling_distribution+2*std_sampling_distribution)
```

```
Unmarried Mean Purchase 95% Confidence Interval : 9102.47007705418 to
9300.598786111817
```

[ ]:
```
```

1 Recommendations

1)

From the analysis done in this notebook, we observe that not only the most sold product categories are 5,1 and 8, but also irrespective of the gender, age category, city category, marital status, occupation years and current city stay years, people mostly buy the product categories 1, 5 and 8. Therefore Walmart should always try to keep abundant stock of these 3 product categories at all times.

2)

The top 10 product IDs belong to the product categories 1,5,6 and 8, which indicate that these product IDs are the favourites from their product categories. Therefore Walmart should always try to keep abundant stock of these product IDs from their categories at all times.

3) The Male Mean Purchase 95% Confidence Interval is from 9267.859796158267 to 9467.988693221734 and the Female Mean Purchase 95% Confidence Interval is from 8577.312886726402 to 8765.009071491597. #### We see that the 95% confidence interval for the average amount spent by males is greater than females, and there is a clear distinction between the two. Therefore, we can expect that men will buy more on average than women. Also, the no of males making a purchase are 3 times of females making a purchase and the average spend by males is more than females, therefore Walmart should try to keep abundant stock of products which men usually buy and prefer.

4)

- Age Group 0-17 Mean Purchase 95% Confidence Interval : 8766.876995699042 to 8968.047785254957
- Age Group 18-25 Mean Purchase 95% Confidence Interval : 9024.529565751642 to 9224.040965938357
- Age Group 26-35 Mean Purchase 95% Confidence Interval : 9094.949623086235 to 9292.10340727177
- Age Group 36-45 Mean Purchase 95% Confidence Interval : 9155.482464387866 to 9353.175038940133
- Age Group 46-50 Mean Purchase 95% Confidence Interval : 9031.556261844073 to 9226.368959763926
- Age Group 51-55 Mean Purchase 95% Confidence Interval : 9323.33565205221 to 9522.31660376579
- Age Group 55+ Mean Purchase 95% Confidence Interval : 9119.173377615713 to 9314.053014536286 #### We see that the 95% confidence interval for mean purchase price for the age categories 51-55 are greater than all other categories, and the age category 0-17 has the lowest 95% mean purchase price confidence interval. We can therefore assume that people who are 51-55 years old have their mean purchase price on the higher side and their confidence interval can be easily distinguished from the other age categories. People who are 0-17 years old have the lowest average purchase price, and their confidence interval can also be easily distinguished from the other age categories. Since most of the customers are in the

age category 18-25, 36-45 and 26-35, therefore Walmart should try to keep abundant stock of products which they usually buy and prefer.

5)

- Married Mean Purchase 95% Confidence Interval : 9088.6483066616 to 9285.431032938404
- Unmarried Mean Purchase 95% Confidence Interval : 9102.47007705418 to 9300.598786111817 #### We see that the 95% confidence intervals for the mean purchase price for both married and unmarried are kind of similar, so we cannot find a distinction between their mean purchase prices. However, since the the number of unmarried people buying the products is almost 1.5x of that of who are married, therfore Walmart should try to keep abundant stock of products which unmarried people usually buy and prefer.

6)

- Current City Stay 0 Year Mean Purchase 95% Confidence Interval : 9013.324993620141 to 9209.24683497786
- Current City Stay 1 Year Mean Purchase 95% Confidence Interval : 9080.068826558432 to 9278.117463425566
- Current City Stay 2 Years Mean Purchase 95% Confidence Interval : 9158.770257982702 to 9357.685406519297
- Current City Stay 3 Years Mean Purchase 95% Confidence Interval : 9117.488952055739 to 9314.28977093426
- Current City Stay 4+ Years Mean Purchase 95% Confidence Interval : 9110.225826142865 to 9306.801890263137 #### We observe that the 95% confidence intervals of average purchase price for different current city staying years are overlapping and therefore we cannot conclude that there is a distinction among all the categories. However, the number of people who make the most purchases are those that have lived in the current city for 1 year, and thus Walmart can keep this factor in account and stock its inverntory accordingly.

7)

- City A Mean Purchase 95% Confidence Interval : 8749.457499550088 to 8941.512179215912
- City B Mean Purchase 95% Confidence Interval : 8989.0135287192 to 9183.963184244798
- City C Mean Purchase 95% Confidence Interval : 9543.814518903804 to 9747.628578196196 #### We observe that the 95% confidence interval for the mean purchase price for city C is greater than city B which is in turn greater than city A. There is a clear distinction between their average purchase prices, therefore we can conclude that city C on average makes higher purchases than city B which in turn is higher than city A. Also, we observe that the number of people buying from City B is the highest, followed by C and A. Therfore Walmart should try to keep abundant stock of products firstly in city B, then C and then A.

8)

We see that the highest average purchase price is for 17 years of occupation, which might be because people having more occupation years might be earning more. Therfore, Walmart can expect that people having higher occupation years might have higher purchase price on average. Also, people having 0,4 and 7 years of occupation

are the most frequent buyers. Therefore Walmart should try to keep abundant stock of products which these people usually buy and prefer.

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