In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import norm
from scipy.stats import ttest_ind
import statsmodels.api as sm
import pylab as py
import scipy.stats as stats
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
data = pd.read_csv("walmart_data.csv")
data
```

Out[2]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
0	1000001	P00069042	F	0-17	10	A	2	0	3	8370
1	1000001	P00248942	F	0-17	10	A	2	0	1	15200
2	1000001	P00087842	F	0-17	10	A	2	0	12	1422
3	1000001	P00085442	F	0-17	10	A	2	0	12	1057
4	1000002	P00285442	M	55+	16	C	4+	0	8	7969
...	...	...	...	...	...	...	...	...	...	...
550063	1006033	P00372445	M	51-55	13	B	1	1	20	368
550064	1006035	P00375436	F	26-35	1	C	3	0	20	371
550065	1006036	P00375436	F	26-35	15	B	4+	1	20	137
550066	1006038	P00375436	F	55+	1	C	2	0	20	365
550067	1006039	P00371644	F	46-50	0	B	4+	1	20	490

550068 rows × 10 columns

In [3]:
```
data.info()
# User_ID, Occupation, Marital Status, Product_Category and Purchase are of integer data type.
# Product_ID, Gender, Age, City_Category and Stay_In_Current_City_Years are of object data type.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype 
---  ------                      --------------   ----- 
 0   User_ID                     550068 non-null  int64 
 1   Product_ID                  550068 non-null  object
 2   Gender                      550068 non-null  object
 3   Age                         550068 non-null  object
 4   Occupation                  550068 non-null  int64 
 5   City_Category               550068 non-null  object
 6   Stay_In_Current_City_Years  550068 non-null  object
 7   Marital_Status              550068 non-null  int64 
 8   Product_Category            550068 non-null  int64 
 9   Purchase                    550068 non-null  int64 
dtypes: int64(5), object(5)
memory usage: 42.0+ MB
```

In [4]:
```
# Converting the columns User_ID, Occupation, Marital Status, Product Category to object datatypes as they
# all are categorical variables.
data["User_ID"]= data["User_ID"].astype(str)
data["Occupation"]= data["Occupation"].astype(str)
data["Marital_Status"]= data["Marital_Status"].astype(str)
data["Product_Category"]= data["Product_Category"].astype(str)
```

In [5]:
```
data.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  object
 1   Product_ID                  550068 non-null  object
 2   Gender                      550068 non-null  object
 3   Age                         550068 non-null  object
 4   Occupation                  550068 non-null  object
 5   City_Category               550068 non-null  object
 6   Stay_In_Current_City_Years  550068 non-null  object
 7   Marital_Status              550068 non-null  object
 8   Product_Category            550068 non-null  object
 9   Purchase                    550068 non-null  int64
dtypes: int64(1), object(9)
memory usage: 42.0+ MB
```

In [6]:
```
data.shape
# There are 10 columns and 550068 records in the dataset.
```

Out[6]:
```
(550068, 10)
```

In [7]:
```
data.isna().sum(axis = 0)
# There are no missing values in the dataset.
```

Out[7]:
```
User_ID                       0
Product_ID                    0
Gender                        0
Age                           0
Occupation                    0
City_Category                 0
Stay_In_Current_City_Years    0
Marital_Status                0
Product_Category              0
Purchase                      0
dtype: int64
```

In [8]:
```
data[["User_ID", "Product_ID"]].drop_duplicates()
# The dataset consists of unique combinations of User_ID and Product_ID in each row. That is why the
# length of the above dataframe remains unchanged after removing duplicates.
```

Out[8]:

	User_ID	Product_ID
0	1000001	P00069042
1	1000001	P00248942
2	1000001	P00087842
3	1000001	P00085442
4	1000002	P00285442
...	...	...
550063	1006033	P00372445
550064	1006035	P00375436
550065	1006036	P00375436
550066	1006038	P00375436
550067	1006039	P00371644

550068 rows × 2 columns

In [9]:
```
data.describe()
# The minimum amount spent by a customer on a particular product id is 12
# The maximum amount spent by a customer on a particular product id is 23961
```

Out[9]:

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

In [10]:
```
data.describe(include = "object")
# There are 5891 distinct users. User_ID has purchased across a total of 1026 product_ids.
# There are 3631 distinct product_id's. Product id P00265242 has been purchased by 1880 users.
# There are 2 genders in the dataset.
# There are 7 age groups in the dataset.
# There are 21 Occupation categories in the dataset.
# There are 3 City categories in the dataset.
# Users in the dataset have 2 marital status.
# There are 20 distinct product categories in the dataset.
```

Out[10]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category
count	550068	550068	550068	550068	550068	550068	550068	550068	550068
unique	5891	3631	2	7	21	3	5	2	20
top	1001680	P00265242	M	26-35	4	B	1	0	5
freq	1026	1880	414259	219587	72308	231173	193821	324731	150933

In [11]:
```python
user_prof = data[["User_ID", "Gender", "Age", "Occupation", "City_Category", "Stay_In_Current_City_Years","Marital_Status"]].\
drop_duplicates().reset_index(drop = True)
user_prof
```

Out[11]:

	User_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status
0	1000001	F	0-17	10	A	2	0
1	1000002	M	55+	16	C	4+	0
2	1000003	M	26-35	15	A	3	0
3	1000004	M	46-50	7	B	2	1
4	1000005	M	26-35	20	A	1	1
...	...	...	...	...	...	...	...
5886	1004588	F	26-35	4	C	0	0
5887	1004871	M	18-25	12	C	2	0
5888	1004113	M	36-45	17	C	3	0
5889	1005391	M	26-35	7	A	0	0
5890	1001529	M	18-25	4	C	4+	1

5891 rows × 7 columns

In [12]:
```python
user_prof.describe()
# Of the 5891 users, 4225 are Males and rmaining are Females.
# Of the total users, 2053 are in the age group 26-35.
# 740 of the total users belong to catgory 4 of Occupation (maximum in a occupation category).
# 3139 of the total users live in City_Category C
# 2086 users have been staying in their current city for a year.
# 3417 of the users belong to the Marital_Status 0 (Unmarried)
```

Out[12]:

	User_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status
count	5891	5891	5891	5891	5891	5891	5891
unique	5891	2	7	21	3	5	2
top	1000001	M	26-35	4	C	1	0
freq	1	4225	2053	740	3139	2086	3417

In [13]:
```python
# Getting the count of users across categories in different attributes
for i in (user_prof.columns[1:]):
    print(user_prof[i].value_counts())
    print()
```

```
M    4225
F    1666
Name: Gender, dtype: int64

26-35    2053
36-45    1167
18-25    1069
46-50     531
51-55     481
55+       372
0-17      218
Name: Age, dtype: int64

4     740
0     688
7     669
1     517
17    491
12    376
14    294
20    273
2     256
16    235
6     228
10    192
3     170
15    140
13    140
11    128
5     111
9      88
19     71
18     67
8      17
Name: Occupation, dtype: int64

C    3139
B    1707
A    1045
Name: City_Category, dtype: int64

1     2086
2     1145
3      979
4+     909
0      772
Name: Stay_In_Current_City_Years, dtype: int64

0    3417
1    2474
Name: Marital_Status, dtype: int64
```

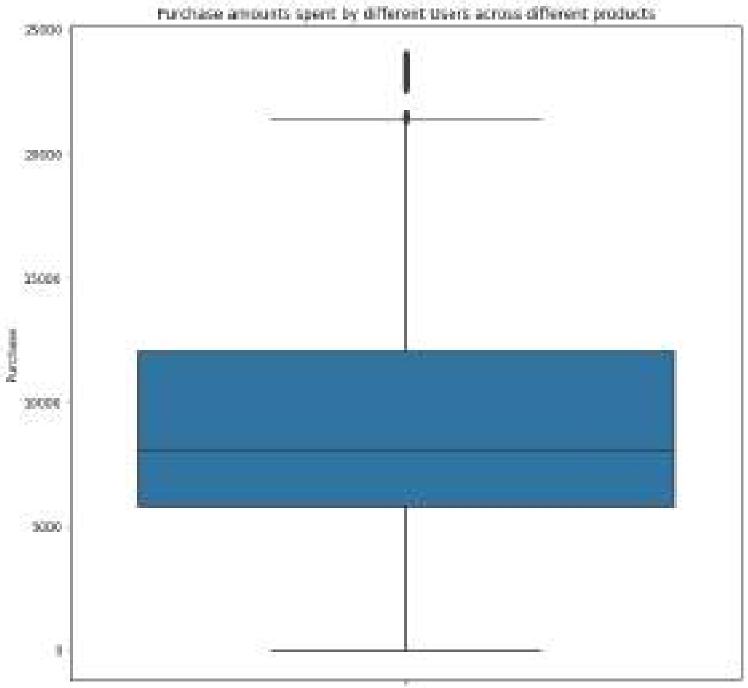
In [14]:
```python
# Identifying the outliers in purchase amount for User_Id and Product_ID ombinationd
pur25,pur75 = np.percentile(data["Purchase"],[25,75])
IQR = pur75-pur25
data.loc[(data["Purchase"] > (pur75 + IQR*1.5)) | (data["Purchase"] < (pur25-IQR*1.5)), ["User_ID", "Product_ID"]]
# Thus there are a total of 2677 outliers (in this case outliers represent that user has spent
# large amount on a particular product id)
```

Out[14]:

	User_ID	Product_ID
343	1000058	P00117642
375	1000062	P00119342
652	1000126	P00087042
736	1000139	P00159542
1041	1000175	P00052842
...	...	...
544488	1005815	P00116142
544704	1005847	P00085342
544743	1005852	P00202242
545663	1006002	P00116142
545787	1006018	P00052842

2677 rows × 2 columns

In [15]:
```
plt.figure(figsize = (10,10))
sns.boxplot(y = data["Purchase"])
plt.title("Purchase amounts spent by different Users across different products")
plt.show()
# All the outliers are above the upper whishker. Hence in this case outliers represent that user
# has spent large amount on a particular product id)
```



In [16]:
```
# Trying to underatsnd total no. of products across different product categories
prod_count_cat = data[["Product_Category", "Product_ID"]].drop_duplicates().groupby(["Product_Category"]).aggregate(product_count = ("Product_ID", "count")).reset_index()
prod_count_cat.sort_values("product_count", ascending = False)
# The maximum no. of unique products are present in Product Category 8 (1047 products available),
# followed by Categories 5,1,11, 2 with 967, 493, 254, 152 unique products in the given categories
# respectively.
```

Out[16]:

	Product_Category	product_count
18	8	1047
15	5	967
0	1	493
2	11	254
11	2	152
16	6	119
17	7	102
7	16	98
13	3	90
14	4	88
6	15	44
5	14	44
4	13	35
9	18	30
1	10	25
3	12	25
8	17	11
12	20	3
10	19	2
19	9	2

In [17]:
```
prod_count_cat["product_count"].sum() == len(data["Product_ID"].unique())
# Therefore a product id is not present in different Product Category groups
```

Out[17]:
```
True
```

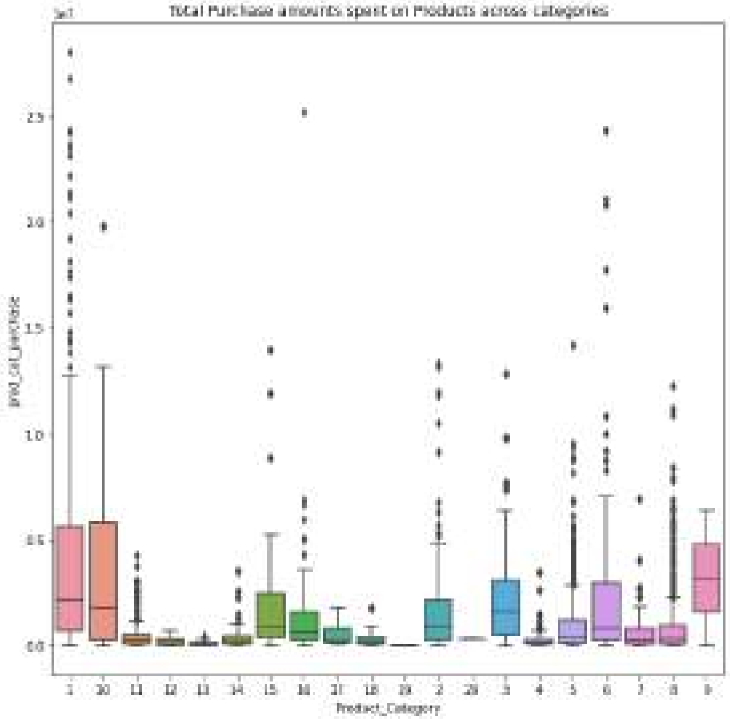
In [18]:

```
prod_cat_pur = data.groupby(["Product_Category"]).aggregate(prod_cat_purchase = ("Purchase", "sum")).\
sort_values("prod_cat_purchase", ascending = False).reset_index()
prod_cat_pur["%age purchase"] = prod_cat_pur["prod_cat_purchase"]*100/prod_cat_pur["prod_cat_purchase"].sum()
prod_cat_pur
# As can be seen from the following dataframe, product category 1 contributes to 37.48% of total purchases made from walmart,
# followed by categories 5 (18.48%), 8 (16.76%) and 6 (6.36%)
# Out of the 20 Product Categories, only 10 product categories (1,5,8,6,2,3,16,11,10,15,7) contribute more than 1 percent in
# total purchases.
```

Out[18]:

	Product_Category	prod_cat_purchase	%age purchase
0	1	1910013754	37.482024
1	5	941835229	18.482532
2	8	854318799	16.765114
3	6	324150302	6.361111
4	2	268516186	5.269350
5	3	204084713	4.004949
6	16	145120612	2.847840
7	11	113791115	2.233032
8	10	100837301	1.978827
9	15	92969042	1.824420
10	7	60896731	1.195035
11	4	27380488	0.537313
12	14	20014696	0.392767
13	18	9290201	0.182310
14	9	6370324	0.125011
15	17	5878699	0.115363
16	12	5331844	0.104632
17	13	4008601	0.078665
18	20	944727	0.018539
19	19	59378	0.001165

In [19]:
```
prod_cat_id_pur = data.groupby(["Product_Category", "Product_ID"]).aggregate(prod_cat_purchase = ("Purchase", "sum")).\
sort_values(["Product_Category", "prod_cat_purchase"], ascending = [True,False]).reset_index()
plt.figure(figsize = (10,10))
sns.boxplot(x = prod_cat_id_pur["Product_Category"], y = prod_cat_id_pur["prod_cat_purchase"])
plt.title("Total Purchase amounts spent on Products across categories")
plt.show()

# There are a number of products in product categories which are having purchases more than the other products in the group.
```



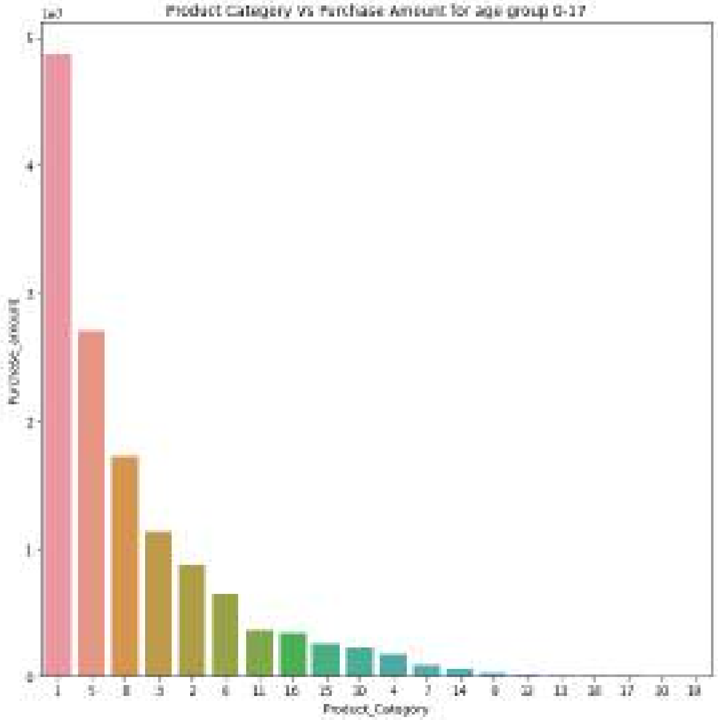
In [20]:
```python
# Finding the list of products in each product category which are selling more than other products in the same category.
# Such products can be considered as outliers in the above boxplot for Product Category Vs Product Catgory Purchase
# for each product category.
prod_category = []
prod_id = []
for i in prod_cat_id_pur["Product_Category"].unique():
    z = prod_cat_id_pur.loc[prod_cat_id_pur["Product_Category"] == i, ::]
    prod_category.append(i)
    per25, per75 = np.percentile(z["prod_cat_purchase"], [25,75])
    IQR = per75-per25
    prod_id.append(z.loc[(z["prod_cat_purchase"] > (per75 + 1.5*IQR)) | (z["prod_cat_purchase"] < (per25-1.5*IQR)),\
                         "Product_ID"].tolist())
oversell_prod_category = pd.DataFrame([prod_category, prod_id]).T.rename(columns = {0:"Product_Category",\
                                                                                    1: "Better performing products"})
oversell_prod_category["Better performing products count"] = pd.Series(map(lambda x: len(x),\
                       oversell_prod_category["Better performing products"]))
oversell_prod_category = pd.merge(oversell_prod_category,prod_count_cat, on = "Product_Category")
for i in oversell_prod_category["Product_Category"].unique():
    a = oversell_prod_category.loc[oversell_prod_category["Product_Category"] == i, "Better performing products count"].\
    values[0]
    b = oversell_prod_category.loc[oversell_prod_category["Product_Category"] == i, "product_count"].values[0]
    print(f"In product category {i}, {a} are performing very well out of {b} products in the category")
oversell_prod_category
```

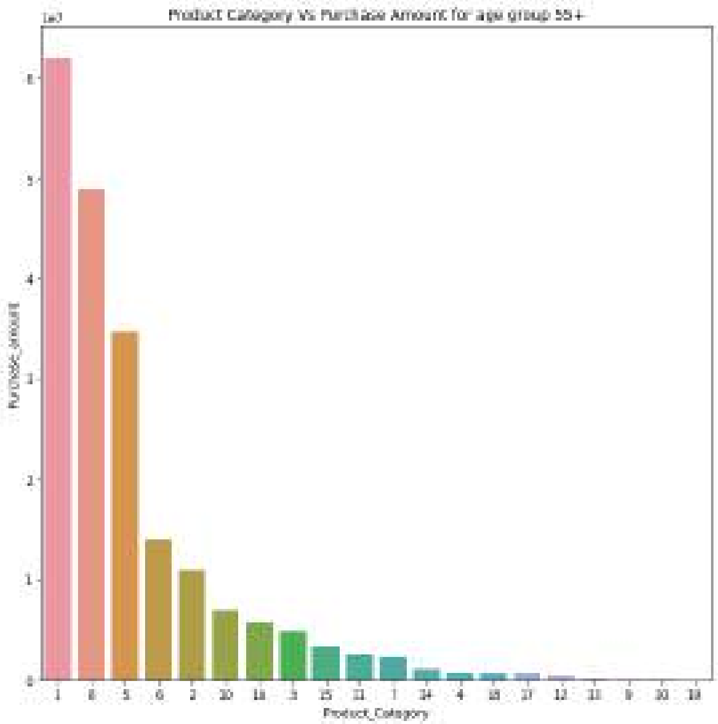
```
In product category 1, 26 are performing very well out of 493 products in the category
In product category 10, 1 are performing very well out of 25 products in the category
In product category 11, 25 are performing very well out of 254 products in the category
In product category 12, 0 are performing very well out of 25 products in the category
In product category 13, 4 are performing very well out of 35 products in the category
In product category 14, 5 are performing very well out of 44 products in the category
In product category 15, 3 are performing very well out of 44 products in the category
In product category 16, 8 are performing very well out of 98 products in the category
In product category 17, 0 are performing very well out of 11 products in the category
In product category 18, 1 are performing very well out of 30 products in the category
In product category 19, 0 are performing very well out of 2 products in the category
In product category 2, 13 are performing very well out of 152 products in the category
In product category 20, 0 are performing very well out of 3 products in the category
In product category 3, 6 are performing very well out of 90 products in the category
In product category 4, 8 are performing very well out of 88 products in the category
In product category 5, 87 are performing very well out of 967 products in the category
In product category 6, 10 are performing very well out of 119 products in the category
In product category 7, 7 are performing very well out of 102 products in the category
In product category 8, 99 are performing very well out of 1047 products in the category
In product category 9, 0 are performing very well out of 2 products in the category
```

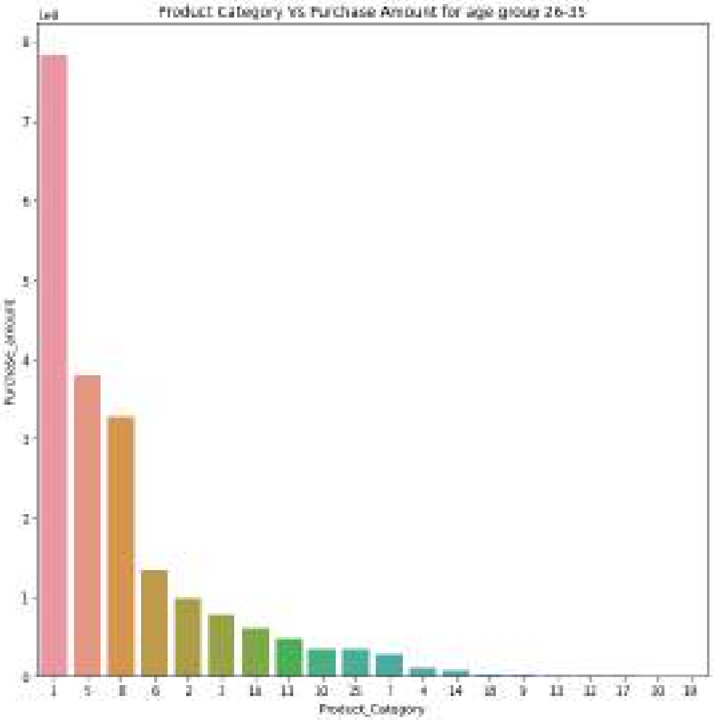
Out[20]:

	Product_Category	Better performing products	Better performing products count	product_count
0	1	[P00025442, P00110742, P00184942, P00112142, P...	26	493
1	10	[P00052842]	1	25
2	11	[P00113042, P00116742, P00250642, P00226342, P...	25	254
3	12	[]	0	25
4	13	[P00084442, P00084342, P00173042, P00149342]	4	35
5	14	[P00086842, P00165842, P00214842, P00087242, P...	5	44
6	15	[P00071442, P00111742, P00111042]	3	44
7	16	[P00255842, P00288642, P00115842, P00124642, P...	8	98
8	17	[]	0	11
9	18	[P00117542]	1	30
10	19	[]	0	2
11	2	[P00085942, P00116842, P00295942, P00277642, P...	13	152
12	20	[]	0	3
13	3	[P00000142, P00216342, P00289942, P00350942, P...	6	90
14	4	[P00102642, P00003442, P00053842, P0096442, P0...	8	88
15	5	[P00265242, P00117942, P00220442, P00278642, P...	87	967
16	6	[P00059442, P00028842, P00148642, P00005042, P...	10	119
17	7	[P00024042, P00015742, P00106642, P00110142, P...	7	102
18	8	[P00058042, P00051442, P00031042, P00110542, P...	99	1047
19	9	[]	0	2

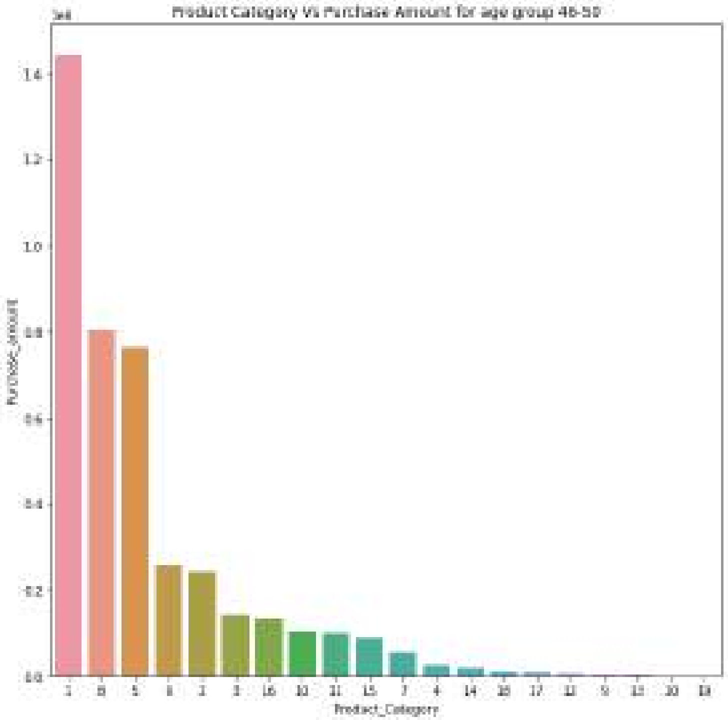
In [21]:
```
age_group = []
product_category_order = []

for i in data["Age"].unique():
    z = data.loc[data["Age"] == i,::].groupby(["Age", "Product_Category"]).aggregate(Purchase_amount = ("Purchase", "sum"))\
    .reset_index().sort_values("Purchase_amount", ascending = False)
    plt.figure(figsize = (10,10))
    sns.barplot(x = z["Product_Category"] , y= z["Purchase_amount"])
    plt.title(f"Product Category Vs Purchase Amount for age group {i}")
    plt.show()
    age_group.append(i)
    product_category_order.append(z["Product_Category"].values)
```

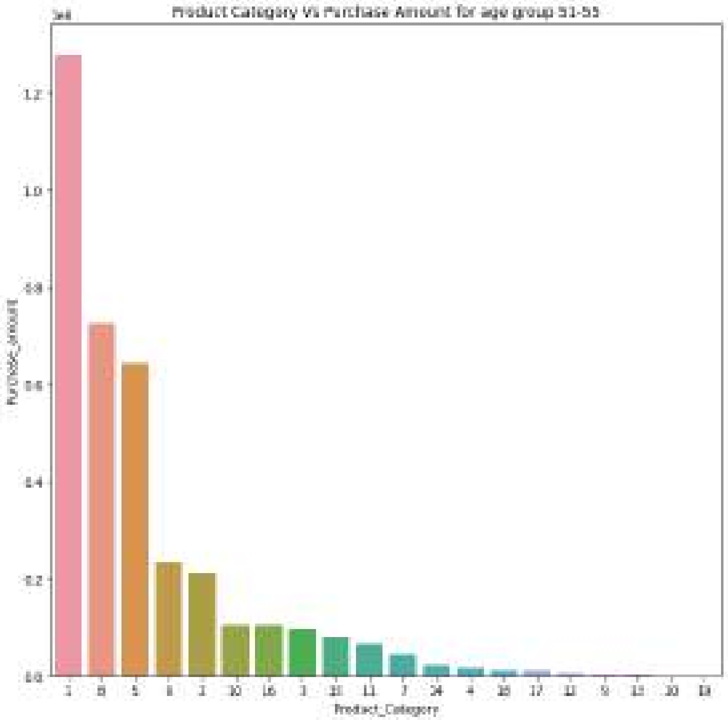


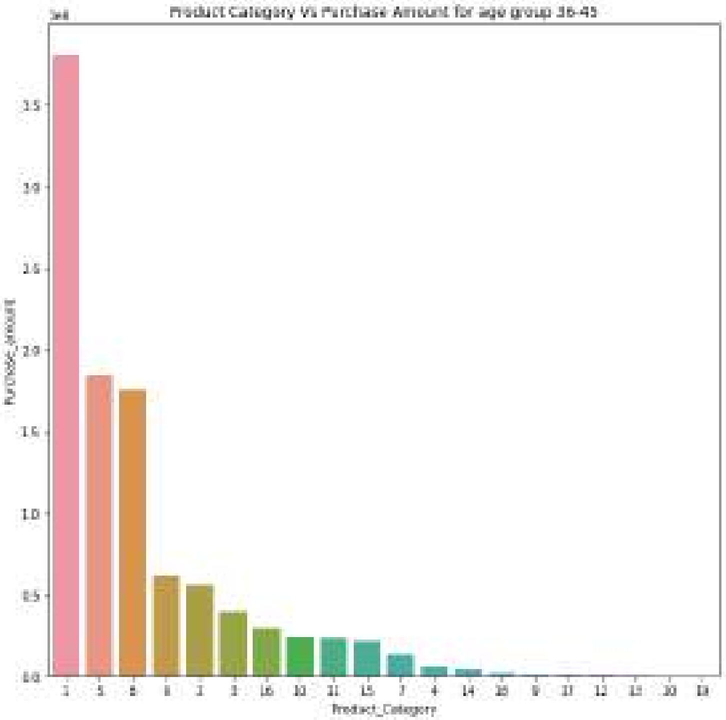

Product Category Vs Purchase Amount for age group 55+
Purchase_amount
Product_Category

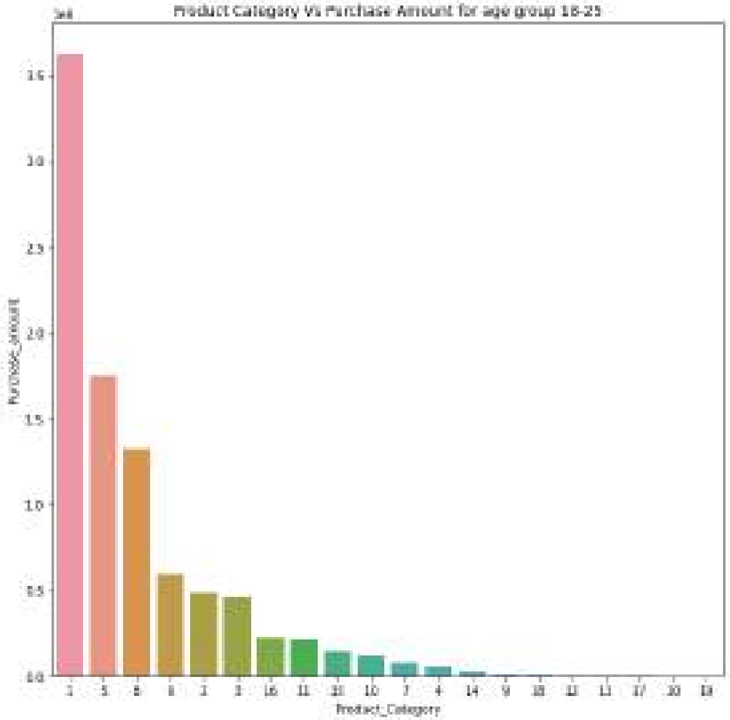


Product Category VS Purchase Amount for age group 26-35
1e8
Purchase_amount
Product_Category


Product Category Vs Purchase Amount for age group 46-50
1e8
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Purchase_Amount
1
8
5
6
2
3
16
10
11
15
7
4
14
18
17
12
9
13
20
19
Product_Category


Product Category Vs Purchase Amount for age group 51-55
1e8
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Purchase_amount
Product_Category


Product Category Vs Purchase Amount for age group 36-45
Purchase_amount
Product_Category



In [22]:
```python
pd.DataFrame([age_group, product_category_order]).T.rename(columns = {0: "Age_Group", 1 : "Product_Category_Order"})
# As can be seen in the above dataframe, product category 1,5,8 are the top 3 product categories for all age groups.
# Product Category 3 is the 4th best selling category in age group 0-17 whereas for the other age groups product category 6
# is the best selling Product Category.
# Product Category 2 is the 5th best selling product category in all age groups.
# Product Category 16 is the 7th best selling product category in all age groups except 0-17 where 11 is 7 best selling category.
# Thus based on the above observation, it can be concluded that best selling Product Categories are common across all age groups.
```

Out[22]:

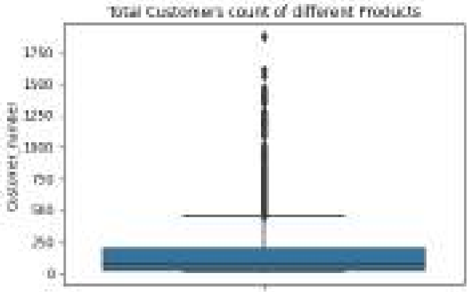
	Age_Group	Product_Category_Order
0	0-17	[1, 5, 8, 3, 2, 6, 11, 16, 15, 10, 4, 7, 14, 9...
1	55+	[1, 8, 5, 6, 2, 10, 16, 3, 15, 11, 7, 14, 4, 1...
2	26-35	[1, 5, 8, 6, 2, 3, 16, 11, 10, 15, 7, 4, 14, 1...
3	46-50	[1, 8, 5, 6, 2, 3, 16, 10, 11, 15, 7, 4, 14, 1...
4	51-55	[1, 8, 5, 6, 2, 10, 16, 3, 15, 11, 7, 14, 4, 1...
5	36-45	[1, 5, 8, 6, 2, 3, 16, 10, 11, 15, 7, 4, 14, 1...
6	18-25	[1, 5, 8, 6, 2, 3, 16, 11, 15, 10, 7, 4, 14, 9...

In [23]:
```python
# Identifying products which are in top 100 in order of decreasing purchase amount for all age groups
age_prod_pur = data.groupby(["Age", "Product_ID"]).aggregate(Purchase_amt = ("Purchase", "sum")).reset_index().sort_values(["Age",\
"Purchase_amt"], ascending = [False, False])
prod_id = []
for i in age_prod_pur["Age"].unique():
    prod_id.append(age_prod_pur.loc[age_prod_pur["Age"] == i,"Product_ID"][0:100].values)
A = set(prod_id[0])
for i in prod_id[1:]:
    A = A.intersection(set(i))
A, len(A)
# Out of the top 100 selling products in order of Decreasing Purchase amount, the following 38 products are common in all age
# groups
```

Out[23]:
```
({'P00005042',
  'P00010742',
  'P00025442',
  'P00028842',
  'P00031042',
  'P00044442',
  'P00046742',
  'P00051442',
  'P00052842',
  'P00057642',
  'P00059442',
  'P00071442',
  'P00073842',
  'P00080342',
  'P00085942',
  'P00105142',
  'P00110742',
  'P00110842',
  'P00110942',
  'P00111142',
  'P00112142',
  'P00112442',
  'P00112542',
  'P00114942',
  'P00117942',
  'P00120042',
  'P00128942',
  'P00145042',
  'P00148642',
  'P00184942',
  'P00220442',
  'P00237542',
  'P00242742',
  'P00255842',
  'P00265242',
  'P00277642',
  'P00295942',
  'P00334242'},
 38)
```

In [24]:
```
# Finding the products which are purchased by maximum customers.
prod_cust_cnt = data.groupby(["Product_ID"]).aggregate(Customer_number = ("User_ID", "count")).reset_index().\
sort_values("Customer_number", ascending = False)
sns.boxplot(y = prod_cust_cnt["Customer_number"])
plt.title("Total Customers count of different Products")
```

Out[24]:
```
Text(0.5, 1.0, 'Total Customers count of different Products')
```



In [25]:
```python
# Products which are purchased by maximum customer (product id's where customer count can be considered as an outlier)
per25, per75 = np.percentile(prod_cust_cnt["Customer_number"], [25,75])
prod_cust_cnt.loc[(prod_cust_cnt["Customer_number"] > (per75 + (per75-per25)*1.5)) | (prod_cust_cnt["Customer_number"] < \
(per25 - (per75-per25)*1.5)), "Product_ID"].values
# The top 5 products which have highest customer base are 'P00265242', 'P00025442', 'P00110742', 'P00112142', 'P00057642'.
```

Out[25]:
```
array(['P00265242', 'P00025442', 'P00110742', 'P00112142', 'P00057642',
       'P00184942', 'P00046742', 'P00058042', 'P00145042', 'P00059442',
       'P00237542', 'P00255842', 'P00117942', 'P00110942', 'P00010742',
       'P00220442', 'P00110842', 'P00117442', 'P00051442', 'P00102642',
       'P00278642', 'P00242742', 'P00034742', 'P00148642', 'P00080342',
       'P00031042', 'P00028842', 'P00251242', 'P00114942', 'P00270942',
       'P00000142', 'P00112542', 'P00044442', 'P00334242', 'P00111142',
       'P00277642', 'P00052842', 'P00116842', 'P00295942', 'P00005042',
       'P00003442', 'P00086442', 'P00258742', 'P00085942', 'P00110542',
       'P00216342', 'P00073842', 'P00128942', 'P00113242', 'P00112442',
       'P00105142', 'P0097242', 'P00147942', 'P00182142', 'P00106042',
       'P00120042', 'P00085242', 'P00371644', 'P00036842', 'P00121642',
       'P00289942', 'P00062842', 'P00003242', 'P00157542', 'P00372445',
       'P00259342', 'P00178942', 'P00156442', 'P00057742', 'P00370853',
       'P00240142', 'P00248142', 'P00375436', 'P00355142', 'P00323942',
       'P00161942', 'P00140742', 'P00199442', 'P00274942', 'P00271142',
       'P00370293', 'P00057942', 'P00324942', 'P00249542', 'P00210042',
       'P00021742', 'P00129642', 'P00250242', 'P00127642', 'P00113142',
       'P00318742', 'P00121342', 'P00317842', 'P00260042', 'P00037142',
       'P00129542', 'P00145442', 'P00003942', 'P00113642', 'P00070042',
       'P00084842', 'P00144642', 'P00221442', 'P00071442', 'P00350942',
       'P00002142', 'P00296042', 'P00338442', 'P00057542', 'P00100442',
       'P00174442', 'P00125942', 'P00100842', 'P00249642', 'P00115642',
       'P00178242', 'P00329542', 'P00114042', 'P00142142', 'P00220342',
       'P00245642', 'P00111742', 'P00243942', 'P00102342', 'P00034842',
       'P00113342', 'P00010842', 'P00014542', 'P00250642', 'P00113042',
       'P00293242', 'P00139942', 'P00277442', 'P00319042', 'P00183242',
       'P00111942', 'P00101842', 'P00150542', 'P00118742', 'P00126142',
       'P00116142', 'P00351142', 'P00035842', 'P00233542', 'P00213242',
       'P00192042', 'P00120342', 'P00212942', 'P00183342', 'P00057442',
       'P00086342', 'P00086042', 'P00154042', 'P00153742', 'P00173842',
       'P00119742', 'P00101942', 'P00193542', 'P00303242', 'P00294542',
       'P00127842', 'P00211142', 'P00116742', 'P00035542', 'P00127242',
       'P00158542', 'P00138542', 'P00226342', 'P00303042', 'P00129842',
       'P00070342', 'P00004742', 'P00313342', 'P00201442', 'P00058242',
       'P00303342', 'P00343042', 'P00346142', 'P00115142', 'P00030842',
       'P00177542', 'P00151742', 'P00034042', 'P00248942', 'P00182242',
       'P00321742', 'P00001142', 'P00090942', 'P00154642', 'P00147742',
       'P00103042', 'P00153842', 'P00190142', 'P00053842', 'P00268442',
       'P00129342', 'P00084442', 'P00216142', 'P00109542', 'P00286642',
       'P00255942', 'P00275842', 'P00351342', 'P00346242', 'P00241642',
       'P00032042', 'P00114442', 'P00058442', 'P00150342', 'P00085342',
       'P00117542', 'P00221542', 'P00130742', 'P00209842', 'P00052642',
       'P00207942', 'P00114342', 'P00002542', 'P00182742', 'P00285842',
       'P00187442', 'P00283942', 'P00173042', 'P00127442', 'P0096442',
       'P00289342', 'P00115942', 'P00127942', 'P00192542', 'P00250842',
       'P00022942', 'P00313542', 'P00046142', 'P00332242', 'P00365242',
       'P00122442', 'P00119142', 'P00074642', 'P00111842', 'P00100942',
       'P00159442', 'P00326742', 'P00254242', 'P00003642', 'P00000642',
       'P00227842', 'P00331942', 'P00112642', 'P00042742', 'P00142942',
       'P00001042', 'P00161442', 'P00111042', 'P00214442', 'P00205942',
       'P00028542', 'P00256642', 'P00006942', 'P00084342', 'P00169742',
       'P00159542', 'P00127742', 'P00118542', 'P00106742', 'P00282042',
       'P0097142', 'P00279542', 'P00105342', 'P00130642', 'P00270242',
       'P00157642', 'P00289242', 'P00331042', 'P00149342', 'P00295842',
       'P00115542', 'P00249742', 'P00274042', 'P00270842', 'P00144242',
       'P00177442', 'P00216042', 'P00251942', 'P00286742', 'P00345842',
       'P00244042', 'P00128242', 'P00173342', 'P00230942', 'P00190042',
       'P00356742', 'P00282642', 'P00188442', 'P00370242', 'P00223242',
       'P00192842', 'P00001742', 'P00299142', 'P00181842', 'P00109242',
       'P00182342'], dtype=object)
```

In [26]:
```python
df1 = data.groupby(["Product_Category", "Product_ID"]).aggregate(Purchase_amt = ("Purchase", "sum")).reset_index()
df2 = data[["Product_ID", "User_ID"]].drop_duplicates().groupby(["Product_ID"]).aggregate(Customer_count = ("User_ID", "count")).\
reset_index()
df3 = pd.merge(df1, df2, on = "Product_ID")
df3["% Purchase"] = round(df3["Purchase_amt"]/df3["Purchase_amt"].sum(),4)
df3.sort_values(["Product_Category", "Customer_count", "% Purchase"], ascending = [True, True, True], inplace = True)
df3
```

Out[26]:

	Product_Category	Product_ID	Purchase_amt	Customer_count	% Purchase
15	1	P00013542	15836	1	0.0000
32	1	P00027842	12128	1	0.0000
86	1	P00057842	4179	1	0.0000
90	1	P00060842	15737	1	0.0000
155	1	P00126742	15636	1	0.0000
...	...	...	...	...	...
2696	8	P00031042	10863768	1200	0.0021
2758	8	P00051442	11186280	1249	0.0022
2776	8	P00058042	12250634	1422	0.0024
3629	9	P00075042	18456	1	0.0000
3630	9	P00184242	6351868	409	0.0012

3631 rows × 5 columns

In [27]:
```python
df3["% Purchase"].describe()
```

Out[27]:
```
count    3631.000000
mean        0.000271
std         0.000522
min         0.000000
25%         0.000000
50%         0.000100
75%         0.000300
max         0.005500
Name: % Purchase, dtype: float64
```

In [28]:
```python
df3["Customer_count"].describe()
```

Out[28]:
```
count    3631.000000
mean      151.492151
std       212.852932
min         1.000000
25%        19.500000
50%        71.000000
75%       194.000000
max      1880.000000
Name: Customer_count, dtype: float64
```

In [29]:
```
# Products where high discount needs to br provided where there are low customer counts and also low purchase.
df3.loc[(df3["Customer_count"] < np.quantile(df3["Customer_count"],0.25)) & \
        (df3["% Purchase"] <= np.quantile(df3["% Purchase"],0.25))]
```

Out[29]:

	Product_Category	Product_ID	Purchase_amt	Customer_count	% Purchase
15	1	P00013542	15836	1	0.0
32	1	P00027842	12128	1	0.0
86	1	P00057842	4179	1	0.0
90	1	P00060842	15737	1	0.0
155	1	P00126742	15636	1	0.0
...	...	...	...	...	...
3193	8	P00215342	132298	19	0.0
3250	8	P00239342	127957	19	0.0
3458	8	P00310642	90395	19	0.0
3559	8	P00349542	144662	19	0.0
3629	9	P00075042	18456	1	0.0

898 rows × 5 columns

In [30]:
```
age_purchase_cont = data.groupby(["Age"]).aggregate(Purchase_amt = ("Purchase", "sum")).reset_index()
age_purchase_cont["%age contribution"] = round(age_purchase_cont["Purchase_amt"]*100/age_purchase_cont["Purchase_amt"].sum(),2)
age_purchase_cont
# As can be seen from the dataframe below:
# Maximum Purchase on Black Friday were made by users of Age group 26-35 (39.87%), followed by 36-45 (20.15%), 18-25 (17.93%)
```

Out[30]:

	Age	Purchase_amt	%age contribution
0	0-17	134913183	2.65
1	18-25	913848675	17.93
2	26-35	2031770578	39.87
3	36-45	1026569884	20.15
4	46-50	420843403	8.26
5	51-55	367099644	7.20
6	55+	200767375	3.94

In [31]:
```python
age_prodc_pur = data.groupby(["Age", "Product_Category"]).aggregate(Purchase_amt = ("Purchase", "sum")).reset_index().sort_values(["Age", \
"Purchase_amt"], ascending = [False, False])
age_prodc_pur["per_contribution"] = age_prodc_pur["Purchase_amt"]*100/age_prodc_pur["Purchase_amt"].sum()
age_prodc_pur.sort_values("per_contribution", ascending = False, inplace = True)
age_prodc_pur.reset_index(drop = True, inplace = True)
age_prodc_pur
# The maximum contribution to Purchase comes from age group 26-35, Product category 1 (15.38% of total purchase) followed by
# age group 36-45, Product Category 1 with 7.46% and Age group 26-35, product category 5 with 7.45%.
```

Out[31]:

	Age	Product_Category	Purchase_amt	per_contribution
0	26-35	1	783813459	15.381520
1	36-45	1	380631904	7.469503
2	26-35	5	379702493	7.451265
3	18-25	1	362607972	7.115803
4	26-35	8	327523339	6.427303
...	...	...	...	...
135	18-25	19	9913	0.000195
136	46-50	19	5521	0.000108
137	51-55	19	5080	0.000100
138	55+	19	4006	0.000079
139	0-17	19	2271	0.000045

140 rows × 4 columns

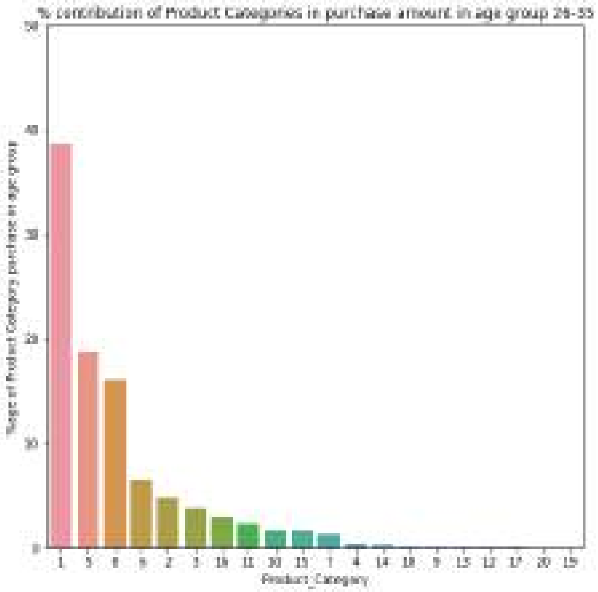
In [32]:
```python
prod_cate_pur_amt_dist_age = pd.merge(age_prodc_pur[["Age","Product_Category", "Purchase_amt"]],age_prodc_pur.groupby("Age")\
[["Purchase_amt"]].sum().reset_index(), on = "Age").rename(columns = {"Purchase_amt_x": "Purchase amt age and prod cat wise",\
"Purchase_amt_y": "Purchase amt age wise"})
prod_cate_pur_amt_dist_age["%age of Product Category purchase in age group"] = \
round(prod_cate_pur_amt_dist_age["Purchase amt age and prod cat wise"]*100/prod_cate_pur_amt_dist_age["Purchase amt age wise"],2)
prod_cate_pur_amt_dist_age.sort_values(["Age","%age of Product Category purchase in age group"], ascending = [False, False])
```

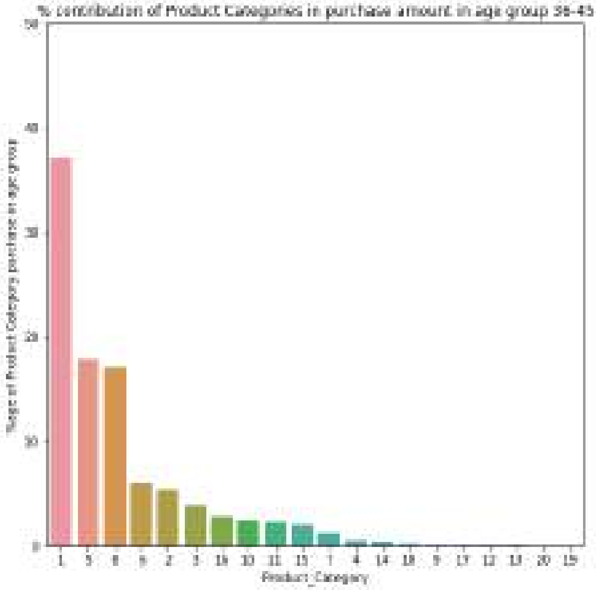
Out[32]:

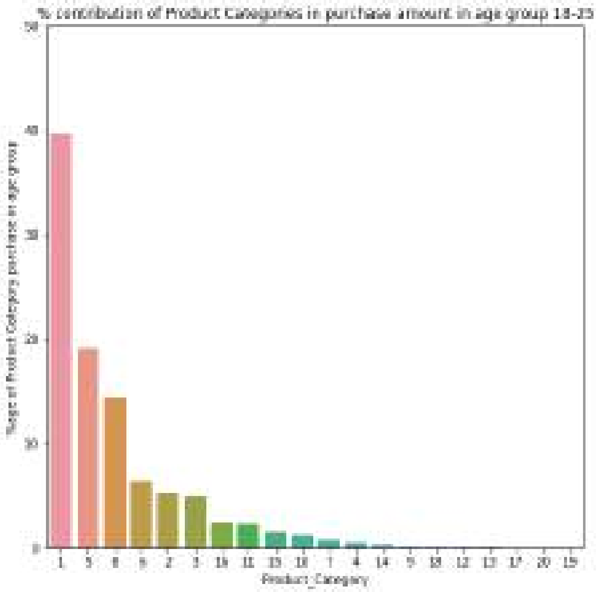
	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group
100	55+	1	62041252	200767375	30.90
101	55+	8	48995349	200767375	24.40
102	55+	5	34690406	200767375	17.28
103	55+	6	13980457	200767375	6.96
104	55+	2	11023487	200767375	5.49
...	...	...	...	...	...
135	0-17	13	82573	134913183	0.06
136	0-17	18	74703	134913183	0.06
137	0-17	17	60863	134913183	0.05
138	0-17	20	33121	134913183	0.02
139	0-17	19	2271	134913183	0.00

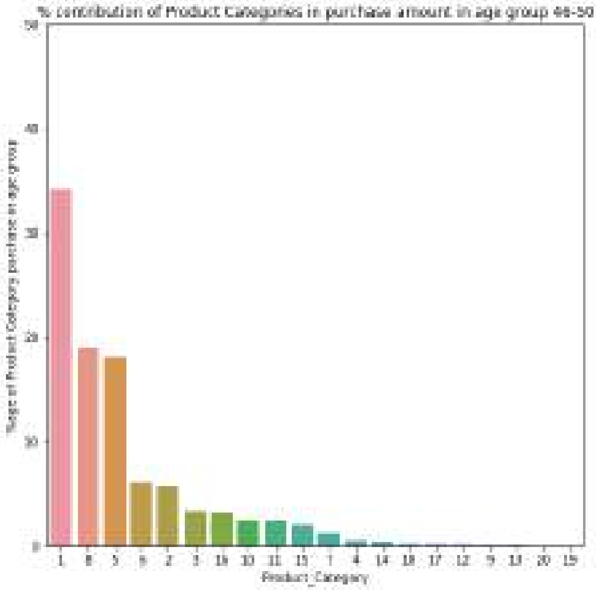
140 rows × 5 columns

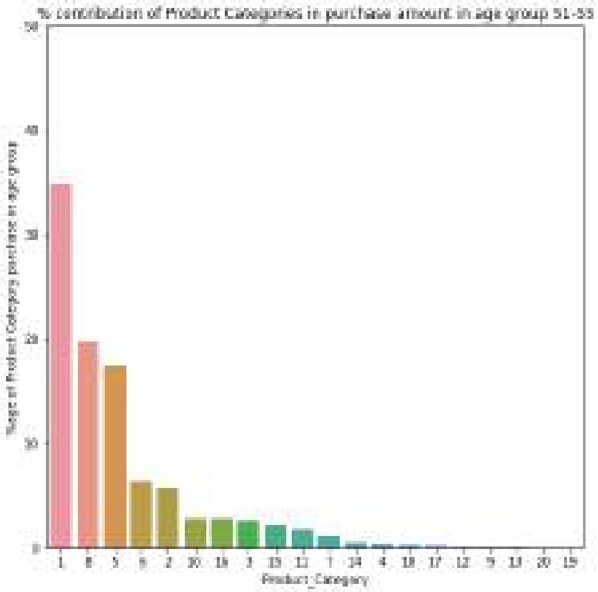
In [33]:
```
for i in prod_cate_pur_amt_dist_age["Age"].unique():
    plt.figure(figsize = (8,8))
    z = prod_cate_pur_amt_dist_age.loc[prod_cate_pur_amt_dist_age["Age"]==i, ::]
    ax = sns.barplot(x = z["Product_Category"], y = z["%age of Product Category purchase in age group"])
    plt.ylim(0,50)
    #plt.bar_label(ax.containers[0])
    plt.title(f"% contribution of Product Categories in purchase amount in age group {i}")
    plt.show()
# Observation:
```

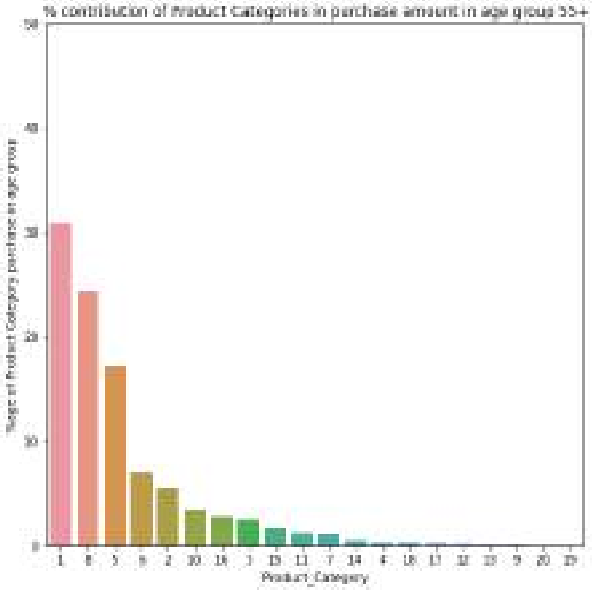


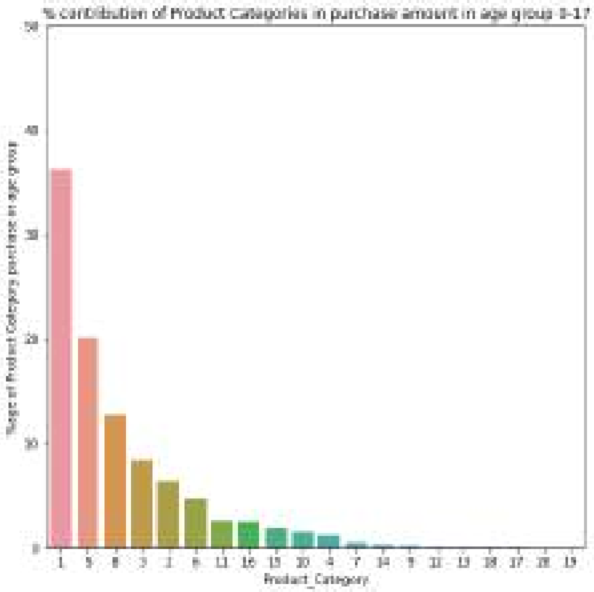

% contribution of Product Categories in purchase amount in age group 36-45
Product_Category


% contribution of Product Categories in purchase amount in age group 18-25
Product_Category


% contribution of Product Categories in purchase amount in age group 46-50
%age of Product Category purchase in age group
Product_Category


% contribution of Product Categories in purchase amount in age group 51-55
%age of Product Category purchase in age group
Product_Category


% contribution of Product Categories in purchase amount in age group 55+
Product_Category


% contribution of Product Categories in purchase amount in age group 0-17
Product_Category

In [34]:
```
# Average purchase made by a customer for a given age and Product Category
age_cat_cust_avg_pur = data.groupby(["Age", "Product_Category"]).aggregate(Purchase_amt = ("Purchase", "sum"), Customer_count = ("User_ID", "count"))\
.reset_index().sort_values(["Age"], ascending = True)
age_cat_cust_avg_pur["Avg Purchase by customer"] = round(age_cat_cust_avg_pur["Purchase_amt"]/age_cat_cust_avg_pur\
["Customer_count"],2)
age_cat_cust_avg_pur
```

Out[34]:

	Age	Product_Category	Purchase_amt	Customer_count	Avg Purchase by customer
0	0-17	1	48783247	3585	13607.60
19	0-17	9	246958	16	15434.88
18	0-17	8	17234789	2258	7632.77
17	0-17	7	821014	53	15490.83
16	0-17	6	6377154	399	15982.84
...	...	...	...	...	...
121	55+	10	6939900	350	19828.29
120	55+	1	62041252	4411	14065.12
138	55+	8	48995349	6208	7892.29
128	55+	17	710254	67	10600.81
139	55+	9	149011	8	18626.38

140 rows × 5 columns

In [35]:
```
age_cat_cust_avg_pur = pd.merge(age_cat_cust_avg_pur, pd.DataFrame(data.groupby("Age").aggregate(Customer_count_age = \
("User_ID", "count"))).reset_index(), on = "Age")
```

In [36]:
```
prod_cate_pur_amt_dist_age = pd.merge(prod_cate_pur_amt_dist_age, age_cat_cust_avg_pur[["Age", "Product_Category",\
"Customer_count","Customer_count_age", "Avg Purchase by customer"]],on = ["Age", "Product_Category"])
prod_cate_pur_amt_dist_age["%age customer in age_group"] = prod_cate_pur_amt_dist_age["Customer_count"]*100/\
prod_cate_pur_amt_dist_age["Customer_count_age"]
```

In [37]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '1'].sort_values(["Product_Category", "Age"])
# In age group 18-25, product category 1 contributes maximum of 39.68% of total purchase amount in the group.
# In age group 55+, product category 1 contributes minimum of 30.90% of total purchase amount in the group.
# The contribution of Product_Category 1 in different age groups is between 30.90 to 39.68%.
# The contribution of Product Category 1 in Purchase amount increase till age group 18-25 and then starts decreasing.
# The avergae purchase by customer in Product Category 1 varies between 13448 to 14125 across different age groups.
# It decreases by a 200 units from age group 0-17 till age 26-35, then increases with increase in age.
# Even though the Avergae Purchase mae by a customer increase from age 18-25 as age increases, the precentag of total amount
# spent by the group decreases. This implies there are other Product categories where purchase increases with increase in age.
# Out of 219587 people in the age group 26-35, 58249 purchased product category 1 products.
# The percentage of people who purchase in Product Category 1 increases till age group 18-25 and then decreases with increase
# in age. The Product Category 1 has maximum craze in age group 18-25, where 27 percent of users purchase a product from the
# categroy.
# If a company is targetting a discount campaign, they should target those products in Category 1 which have been
# purchased by customers belonging between age group 18-25, 26-35 and 36-45 as they are in the top 3 having highest customer
# count.
```

Out[37]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
120	0-17	1	48783247	134913183	36.16	3585	15102	13607.60	23.738578
40	18-25	1	362607972	913848675	39.68	26962	99660	13448.85	27.053984
0	26-35	1	783813459	2031770578	38.58	58249	219587	13456.26	26.526616
20	36-45	1	380631904	1026569884	37.08	27648	110013	13767.07	25.131575
60	46-50	1	144311800	420843403	34.29	10474	45701	13778.10	22.918536
80	51-55	1	127824120	367099644	34.82	9049	38501	14125.77	23.503286
100	55+	1	62041252	200767375	30.90	4411	21504	14065.12	20.512463

In [38]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '2'].sort_values(["Product_Category", "Age"])
# In age group 0-17, product category 2 contributes maximum of 6.48% of total purchase amount in the group.
# In age group 26-35, product category 2 contributes minimum of 4.87% of total purchase amount in the group.
# The contribution of Product_Category 2 in different age groups is between 4.5 to 6.5%.
# The average purchase made by a customer in Product Category 2 also increases with age and is between 10851 and 12180.
# The maximum perentage in any age group that a person buys a product is 5.33% for 0-17 age group.
# The percentage of users in a age group who purchases some product from Category 2 lies between 4.06 to 5.33% of the customers
# in that group.
# If a company is targetting a discount campaign, they should target those products in Category 1 which have been
# purchased by customers belonging between age group 18-25, 26-35 and 36-45 as they are in the top 3 having highest customer
# count.
```

Out[38]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
124	0-17	2	8735846	134913183	6.48	805	15102	10851.98	5.330420
44	18-25	2	48560733	913848675	5.31	4428	99660	10966.74	4.443107
4	26-35	2	98957188	2031770578	4.87	8928	219587	11083.91	4.065814
24	36-45	2	55878648	1026569884	5.44	4912	110013	11375.95	4.464927
64	46-50	2	24163446	420843403	5.74	2105	45701	11479.07	4.606026
84	51-55	2	21196838	367099644	5.77	1781	38501	11901.65	4.625854
104	55+	2	11023487	200767375	5.49	905	21504	12180.65	4.208519

In [39]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '3'].sort_values(["Product_Category", "Age"])
# In age group 0-17, product category 3 contributes maximum of 8.39% of total purchase amount in the group.
# In age group 55+, product category 3 contributes minimum of 2.47% of total purchase amount in the group.
# The contribution of Product_Category 3 in different age groups is between 2.47 to 8.39%.
# Another intereseting observation is as the age group inceases towards older age, the contribution of Product Category 3 in
# total purchase amount decreases.
# The average purchase made in Product Category 3 also increases with increase in age and lies between 9431 and 10340.
# 7.94% of customers in Age group 0-17 purchase Product Category 3, where as only 2.26% in age group 55+ purchase in Product
# Category 3.
# Even though 4.72% or less purchase Product Category 3 products in age group 18-25, 26-35 and 36-45, the number of purchasers
# is very high and is 4710, 7662 and 3854 respectively. Also, the average purchase amount by a consumer is also comparable to
# other groups. Hence, if Walmart is trying to launch discount campaigns, it can do it in these age groups to attract more
# customers as compared to other groups.
```

Out[39]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
123	0-17	3	11317806	134913183	8.39	1200	15102	9431.50	7.945967
45	18-25	3	46495837	913848675	5.09	4710	99660	9871.73	4.726069
5	26-35	3	77805963	2031770578	3.83	7662	219587	10154.79	3.489278
25	36-45	3	39851494	1026569884	3.88	3854	110013	10340.29	3.503222
65	46-50	3	14120037	420843403	3.36	1376	45701	10261.65	3.010875
87	51-55	3	9542540	367099644	2.60	924	38501	10327.42	2.399938
107	55+	3	4951036	200767375	2.47	487	21504	10166.40	2.264695

In [40]:
```python
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '4'].sort_values(["Product_Category", "Age"])
# In age group 0-17, product category 3 contributes maximum of 1.26% of total purchase amount in the group.
# In age group 55+, product category 3 contributes minimum of 0.38% of total purchase amount in the group.
# The %age contribution of Product Category 4 in purchase amount of different age groups except 0-17 lie between 0.38 to 0.6%.
# The average purchase made by a customer also varies between 2194 and 2445 in product category 4 and increases with increase in
# age.
# While 5.02% of customers in age group 0-17 purchase a product from Product Category 4, only 1.48% of customers in age group 55+
# purchase a product from same category.
# The company can launch a discount campaign on products mostly bought in the age group 18-25, 26-35 and 36-45 because of large
# no. of customers in this product category. The average purchase amount in this category for these age groups is comparable to
# other groups.
```

Out[40]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
130	0-17	4	1701452	134913183	1.26	758	15102	2244.66	5.019203
51	18-25	4	5404706	913848675	0.59	2463	99660	2194.36	2.471403
11	26-35	4	9810046	2031770578	0.48	4192	219587	2340.18	1.909038
31	36-45	4	5650797	1026569884	0.55	2354	110013	2400.51	2.139747
71	46-50	4	2395813	420843403	0.57	990	45701	2420.01	2.166255
92	51-55	4	1658375	367099644	0.45	678	38501	2445.98	1.760993
112	55+	4	759299	200767375	0.38	318	21504	2387.73	1.478795

In [41]:
```python
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '5'].sort_values(["Product_Category", "Age"])
# In age group 0-17, product category 5 contributes maximum of 20.06% of total purchase amount in the group.
# In age group 55+, product category 5 contributes minimum of 17.28% of total purchase amount in the group.
# Across all age groups, Product Category 5 contributes between 17.28% to 20.06%.
# The average purchase by a customer in category 5 decrease till 18-25 and then increases with increase in age.
# For customers in age 55+, there is a dip in average price.
# 28.67% of users in group 0-17, 24.95% in group 55+, purchase a product from category 5.
# The company can launch a discount campaign on products mostly bought in the age group 18-25, 26-35 and 36-45 because of large
# no. of customers in this product category. The average purchase amount in this category for these age groups is comparable to
# other groups.
```

Out[41]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
121	0-17	5	27059712	134913183	20.06	4330	15102	6249.36	28.671699
41	18-25	5	175198782	913848675	19.17	28522	99660	6142.58	28.619306
1	26-35	5	379702493	2031770578	18.69	61473	219587	6176.74	27.994827
21	36-45	5	184577971	1026569884	17.98	29377	110013	6283.08	26.703208
62	46-50	5	76279651	420843403	18.13	11971	45701	6372.04	26.194175
82	51-55	5	64326214	367099644	17.52	9893	38501	6502.19	25.695436
102	55+	5	34690406	200767375	17.28	5367	21504	6463.65	24.958147

In [42]:
```python
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '6'].sort_values(["Product_Category", "Age"])
# In age group 0-17, product category 6 contributes minimum of 4.73% of total purchase amount in the group.
# In age group 55+, product category 6 contributes minimum of 6.47% of total purchase amount in the group.
# Across all age groups, Product Category 6 contributes between 4.73% to 6.96%.
# 4.01% of users in age group 55+ and 2.64% of users in 0-17 group purchase a product from category 6.
# The company can launch a discount campaign on products mostly bought in the age group 18-25, 26-35 and 36-45 because of large
# no. of customers in this product category. The average purchase amount in this category for these age groups is comparable to
# other groups.
```

Out[42]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
125	0-17	6	6377154	134913183	4.73	399	15102	15982.84	2.642034
43	18-25	6	59116571	913848675	6.47	3749	99660	15768.62	3.761790
3	26-35	6	133712687	2031770578	6.58	8485	219587	15758.71	3.864072
23	36-45	6	61617298	1026569884	6.00	3899	110013	15803.36	3.544127
63	46-50	6	25816828	420843403	6.13	1622	45701	15916.66	3.549156
83	51-55	6	23529307	367099644	6.41	1450	38501	16227.11	3.766136
103	55+	6	13980457	200767375	6.96	862	21504	16218.63	4.008557

In [43]:
```python
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '7'].sort_values(["Product_Category", "Age"])
# In age group 26-35, product category 7 contributes maximum of 1.33% of total purchase amount in the group.
# In age group 0-17, product category 7 contributes minimum of 0.61% of total purchase amount in the group.
# Across all age groups, Product Category 7 contributes between 0.61% to 1.13%.
# The percentage contribution of Product Category 7 increases till age group 36-45 and then decreases again as the age increases.
# 0.75% of users in age group 26-35 and 0.35% of users in 0-17 group purchase a product from category 7.
# The company can launch a discount campaign on products mostly bought in the age group 18-25, 26-35, 36-45 and 46-50 because of large
# no. of customers in this product category. The average purchase amount in this category for these age groups is comparable to
# other groups.
```

Out[43]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
131	0-17	7	821014	134913183	0.61	53	15102	15490.83	0.350947
50	18-25	7	7726231	913848675	0.85	481	99660	16062.85	0.482641
10	26-35	7	26979330	2031770578	1.33	1651	219587	16341.21	0.751866
30	36-45	7	13308854	1026569884	1.30	809	110013	16450.99	0.735368
70	46-50	7	5434726	420843403	1.29	327	45701	16619.96	0.715520
90	51-55	7	4356259	367099644	1.19	266	38501	16376.91	0.690891
110	55+	7	2270317	200767375	1.13	134	21504	16942.66	0.623140

In [44]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '8'].sort_values(["Product_Category", "Age"])
# In age group 55+, product category 8 contributes maximum of 24.40% of total purchase amount in the group.
# In age group 0-17, product category 8 contributes minimum of 12.77% of total purchase amount in the group.
# Across all age groups, Product Category 8 contributes between 12.77% to 24.40%.
# The percentage contribution of Product Category 8 increases as the age increases.
# As the age increases above 55, the Product Category contributes 24.4% (almost 25%) of the total purchase amount.
# 28.8% of customers in age group 55+ and 14.95% of customers in age group 0-17 purchased product from category 8.
# The average purchase made by a customer in the product category is minimum 7387.64 in 18-25 and maximum 7892.29 age group 55+.
# The company can launch a discount campaign on products mostly bought in the age group 18-25, 26-35, 36-45 and 46-50 because of large
# no. of customers in this product category.
# If there are some products which are specifically purchased by Age group 55+, then special discounts can be given on those products
# to encourage more purchase among that group.
```

Out[44]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
122	0-17	8	17234789	134913183	12.77	2258	15102	7632.77	14.951662
42	18-25	8	132320061	913848675	14.48	17911	99660	7387.64	17.972105
2	26-35	8	327523339	2031770578	16.12	44256	219587	7400.65	20.154199
22	36-45	8	175386080	1026569884	17.08	23296	110013	7528.59	21.175679
61	46-50	8	80267806	420843403	19.07	10656	45701	7532.64	23.316776
81	51-55	8	72591375	367099644	19.77	9340	38501	7772.10	24.259110
101	55+	8	48995349	200767375	24.40	6208	21504	7892.29	28.869048

In [45]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '9'].sort_values(["Product_Category", "Age"])
# In age group 0-17, product category 9 contributes maximum of 0.18% of total purchase amount in the group.
# In age group 55+, product category 9 contributes minimum of 0.07% of total purchase amount in the group.
# Across all age groups, Product Category 9 contributes between 0.18% to 0.07%.
# 0.11% of customers in age group 0-17 whereas 0.03% of users in age group 55+ purchase in product category 9.
# The average purchase made by a customer in the product category is minimum 14576 in 51-55 and maximum 18626.38 age group 55+.
# The company can launch a discount campaign on products mostly bought in the age group 18-25, 26-35, 36-45 because of large
# no. of customers in this product category.
```

Out[45]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
133	0-17	9	246958	134913183	0.18	16	15102	15434.88	0.105946
53	18-25	9	1079042	913848675	0.12	63	99660	17127.65	0.063215
14	26-35	9	2413758	2031770578	0.12	154	219587	15673.75	0.070132
34	36-45	9	1571771	1026569884	0.15	107	110013	14689.45	0.097261
76	46-50	9	487060	420843403	0.12	33	45701	14759.39	0.072208
96	51-55	9	422724	367099644	0.12	29	38501	14576.69	0.075323
117	55+	9	149011	200767375	0.07	8	21504	18626.38	0.037202

In [46]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '10'].sort_values(["Product_Category", "Age"])
# In age group 55+, product category 10 contributes maximum of 3.46% of total purchase amount in the group.
# In age group 18-25, product category 10 contributes minimum of 1.27% of total purchase amount in the group.
# Across all age groups, Product Category 10 contributes between 1.27% to 3.46%.
# As the age increases, Product Category 10 contribution decreases  till 18-25 and then increases in purchase amount across age
# groups.
```

Out[46]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
129	0-17	10	2224273	134913183	1.65	111	15102	20038.50	0.735002
49	18-25	10	11572908	913848675	1.27	603	99660	19192.22	0.605057
8	26-35	10	34954106	2031770578	1.72	1787	219587	19560.22	0.813800
27	36-45	10	24270193	1026569884	2.36	1235	110013	19651.98	1.122595
67	46-50	10	10220463	420843403	2.43	520	45701	19654.74	1.137831
85	51-55	10	10655458	367099644	2.90	519	38501	20530.75	1.348017
105	55+	10	6939900	200767375	3.46	350	21504	19828.29	1.627604

In [47]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '11'].sort_values(["Product_Category", "Age"])
# In age group 0-17, product category 11 contributes maximum of 2.64% of total purchase amount in the group.
# In age group 55+, product category 11 contributes minimum of 1.30% of total purchase amount in the group.
# Across all age groups, Product Category 11 contributes between 1.30% to 2.64%.
# As the age increases, Product Category 11 contribution decreases generally.
```

Out[47]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
126	0-17	11	3558043	134913183	2.64	740	15102	4808.17	4.900013
47	18-25	11	21132943	913848675	2.31	4597	99660	4597.12	4.612683
7	26-35	11	46181222	2031770578	2.27	9874	219587	4677.05	4.496623
28	36-45	11	23589872	1026569884	2.30	4953	110013	4762.74	4.502195
68	46-50	11	9977768	420843403	2.37	2104	45701	4742.29	4.603838
89	51-55	11	6748072	367099644	1.84	1458	38501	4628.31	3.786915
109	55+	11	2603195	200767375	1.30	561	21504	4640.28	2.608817

In [48]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '12'].sort_values(["Product_Category", "Age"])
# In age group 0-17, product category 12 contributes maximum of 0.13% of total purchase amount in the group.
# In age group 55+, product category 12 contributes minimum of 0.24% of total purchase amount in the group.
# Across all age groups, Product Category 12 contributes between 0.13% to 0.24%.
# As the age increases, Product Category 12 contribution decreases till 18-25 and then increases with increase in age.
```

Out[48]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
134	0-17	12	177964	134913183	0.13	125	15102	1423.71	0.827705
55	18-25	12	558864	913848675	0.06	439	99660	1273.04	0.440498
16	26-35	12	1449185	2031770578	0.07	1096	219587	1322.25	0.499119
36	36-45	12	1342165	1026569884	0.13	994	110013	1350.27	0.903530
75	46-50	12	719394	420843403	0.17	520	45701	1383.45	1.137831
95	51-55	12	597719	367099644	0.16	433	38501	1380.41	1.124646
115	55+	12	486553	200767375	0.24	340	21504	1431.04	1.581101

In [49]:
```python
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '13'].sort_values(["Product_Category", "Age"])
# In age group 0-17, product category 13 contributes maximum of 0.06% of total purchase amount in the group.
# In age group 55+, product category 13 contributes minimum of 0.11% of total purchase amount in the group.
# Across all age groups, Product Category 13 contributes between 0.06% to 0.11%.
# As the age increases, Product Category 13 contribution increases.
```

Out[49]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
135	0-17	13	82573	134913183	0.06	112	15102	737.26	0.741624
56	18-25	13	530639	913848675	0.06	756	99660	701.90	0.758579
15	26-35	13	1502297	2031770578	0.07	2096	219587	716.74	0.954519
37	36-45	13	899774	1026569884	0.09	1250	110013	719.82	1.136229
77	46-50	13	402618	420843403	0.10	551	45701	730.70	1.205663
97	51-55	13	368453	367099644	0.10	483	38501	762.84	1.254513
116	55+	13	222247	200767375	0.11	301	21504	738.36	1.399740

In [50]:
```python
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '14'].sort_values(["Product_Category", "Age"])
# In age group 18-25, product category 14 contributes minimum of 0.32% of total purchase amount in the group.
# In age group 51-55, product category 14 contributes maximum of 0.59% of total purchase amount in the group.
# Across all age groups, Product Category 14 contributes between 0.32% to 0.59%.
# As the age increases, Product Category 14 contribution decreases till 18-25 and increases till 51-55. It again drops in the
# age 55+
```

Out[50]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
132	0-17	14	512227	134913183	0.38	39	15102	13134.03	0.258244
52	18-25	14	2922039	913848675	0.32	230	99660	12704.52	0.230785
12	26-35	14	7208556	2031770578	0.35	564	219587	12781.13	0.256846
32	36-45	14	4219327	1026569884	0.41	312	110013	13523.48	0.283603
72	46-50	14	1954454	420843403	0.46	149	45701	13117.14	0.326032
91	51-55	14	2180826	367099644	0.59	154	38501	14161.21	0.399990
111	55+	14	1017267	200767375	0.51	75	21504	13563.56	0.348772

In [51]:
```python
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '15'].sort_values(["Product_Category", "Age"])
# In age group 18-25, product category 15 contributes minimum of 1.61% of total purchase amount in the group.
# In age group 51-55, product category 15 contributes maximum of 2.22% of total purchase amount in the group.
# Across all age groups, Product Category 15 contributes between 1.61% to 2.22%.
# As the age increases, Product Category 15 contribution decreases till 18-25 and increases till 51-55. It again drops in the
# age 55+
```

Out[51]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
128	0-17	15	2557534	134913183	1.90	160	15102	15984.59	1.059462
48	18-25	15	14702838	913848675	1.61	1024	99660	14358.24	1.027493
9	26-35	15	34455543	2031770578	1.70	2372	219587	14525.95	1.080210
29	36-45	15	20878773	1026569884	2.03	1395	110013	14966.86	1.268032
69	46-50	15	8855368	420843403	2.10	602	45701	14709.91	1.317258
88	51-55	15	8138987	367099644	2.22	508	38501	16021.63	1.319446
108	55+	15	3379999	200767375	1.68	229	21504	14759.82	1.064918

In [52]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '16'].sort_values(["Product_Category", "Age"])
# In age group 46.-50, product category 16 contributes maximum of 3.17% of total purchase amount in the group.
# In age group 18-25, product category 16 contributes maximum of 2.45% of total purchase amount in the group.
# Across all age groups, Product Category 16 contributes between 2.45% to 3.17%.
```

Out[52]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
127	0-17	16	3351633	134913183	2.48	229	15102	14635.95	1.516355
46	18-25	16	22361393	913848675	2.45	1598	99660	13993.36	1.603452
6	26-35	16	60527425	2031770578	2.98	4118	219587	14698.26	1.875339
26	36-45	16	29263813	1026569884	2.85	1955	110013	14968.70	1.777063
66	46-50	16	13348682	420843403	3.17	879	45701	15186.21	1.923371
86	51-55	16	10503288	367099644	2.86	672	38501	15629.89	1.745409
106	55+	16	5764378	200767375	2.87	377	21504	15290.13	1.753162

In [53]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '17'].sort_values(["Product_Category", "Age"])
# In age group 18-25, product category 17 contributes minimum of 0.04% of total purchase amount in the group.
# In age group 55+, product category 17 contributes maximum of 0.35% of total purchase amount in the group.
# Across all age groups, Product Category 17 contributes between 0.04% to 0.35%.
# As the age increases, Product Category 17 contribution decreases till 18-25 and increases with increase in age.
```

Out[53]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
137	0-17	17	60863	134913183	0.05	6	15102	10143.83	0.039730
57	18-25	17	388536	913848675	0.04	41	99660	9476.49	0.041140
17	26-35	17	1248285	2031770578	0.06	127	219587	9829.02	0.057836
35	36-45	17	1365016	1026569884	0.13	135	110013	10111.23	0.122713
74	46-50	17	978178	420843403	0.23	95	45701	10296.61	0.207873
94	51-55	17	1127567	367099644	0.31	107	38501	10538.01	0.277915
114	55+	17	710254	200767375	0.35	67	21504	10600.81	0.311570

In [54]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '18'].sort_values(["Product_Category", "Age"])
# In age group 0-17, product category 18 contributes minimum of 0.06% of total purchase amount in the group.
# In age group 55+, product category 18 contributes maximum of 0.36% of total purchase amount in the group.
# Across all age groups, Product Category 18 contributes between 0.06% to 0.36%.
# As the age increases, Product Category 18 contribution increases.
```

Out[54]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
136	0-17	18	74703	134913183	0.06	27	15102	2766.78	0.178784
54	18-25	18	986425	913848675	0.11	339	99660	2909.81	0.340157
13	26-35	18	3166855	2031770578	0.16	1042	219587	3039.21	0.474527
33	36-45	18	2070049	1026569884	0.20	702	110013	2948.79	0.638106
73	46-50	18	1016581	420843403	0.24	351	45701	2896.24	0.768036
93	51-55	18	1254082	367099644	0.34	423	38501	2964.73	1.098673
113	55+	18	721506	200767375	0.36	241	21504	2993.80	1.120722

In [55]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '19'].sort_values(["Product_Category", "Age"])
# Across all age groups, product category 19 contributes very little in Purchase amount for that group.
```

Out[55]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
139	0-17	19	2271	134913183	0.0	59	15102	38.49	0.390677
59	18-25	19	9913	913848675	0.0	275	99660	36.05	0.275938
19	26-35	19	20739	2031770578	0.0	563	219587	36.84	0.256390
39	36-45	19	11848	1026569884	0.0	320	110013	37.02	0.290875
79	46-50	19	5521	420843403	0.0	149	45701	37.05	0.326032
99	51-55	19	5080	367099644	0.0	134	38501	37.91	0.348043
119	55+	19	4006	200767375	0.0	103	21504	38.89	0.478981

In [56]:
```
prod_cate_pur_amt_dist_age[prod_cate_pur_amt_dist_age["Product_Category"] == '20'].sort_values(["Product_Category", "Age"])
# Across all age groups, product category contributes between 0.02 to 0.03% of the total purchase amount for that group|.
```

Out[56]:

	Age	Product_Category	Purchase amt age and prod cat wise	Purchase amt age wise	%age of Product Category purchase in age group	Customer_count	Customer_count_age	Avg Purchase by customer	%age customer in age_group
138	0-17	20	33121	134913183	0.02	90	15102	368.01	0.595948
58	18-25	20	172242	913848675	0.02	469	99660	367.25	0.470600
18	26-35	20	338102	2031770578	0.02	898	219587	376.51	0.408950
38	36-45	20	184237	1026569884	0.02	506	110013	364.10	0.459946
78	46-50	20	87209	420843403	0.02	227	45701	384.18	0.496707
98	51-55	20	72360	367099644	0.02	200	38501	361.80	0.519467
118	55+	20	57456	200767375	0.03	160	21504	359.10	0.744048

In [57]:
```
# Finding products in decreasing order of purchase amount in different age group, avg amount spent by a customer in a particular
# age group on a product.
prod_age_avg = data.groupby(["Product_ID", "Age"]).aggregate(Customer_count = ("User_ID", "count"), Purchase_amt = \
                                                              ("Purchase", "sum")).reset_index()
prod_age_avg["Avg Purchase"] = round(prod_age_avg["Purchase_amt"]/prod_age_avg["Customer_count"],2)
prod_age_avg = prod_age_avg.sort_values("Product_ID")
prod_age_avg = pd.merge(prod_age_avg, data[["Product_ID", "Product_Category"]].drop_duplicates(), on = "Product_ID")
prod_age_avg = prod_age_avg.sort_values(["Age", "Customer_count", "Avg Purchase"], ascending = [False, False, False]).\
reset_index(drop = True)
prod_age_avg
```

Out[57]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
0	P00265242	55+	104	744723	7160.80	5
1	P00080342	55+	80	1361428	17017.85	1
2	P00051442	55+	79	731911	9264.70	8
3	P00184942	55+	72	1257419	17464.15	1
4	P00025442	55+	72	1166560	16202.22	1
...	...	...	...	...	...	...
20870	P00066742	0-17	1	741	741.00	13
20871	P00175342	0-17	1	704	704.00	12
20872	P00331242	0-17	1	386	386.00	12
20873	P00041442	0-17	1	383	383.00	13
20874	P00025142	0-17	1	375	375.00	13

20875 rows × 6 columns

In [58]:
```
prod_age_avg[(prod_age_avg["Age"] == '55+')]
# In age group 55+, customers purchased 2584 different products.
```

Out[58]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
0	P00265242	55+	104	744723	7160.80	5
1	P00080342	55+	80	1361428	17017.85	1
2	P00051442	55+	79	731911	9264.70	8
3	P00184942	55+	72	1257419	17464.15	1
4	P00025442	55+	72	1166560	16202.22	1
...	...	...	...	...	...	...
2579	P00316942	55+	1	1413	1413.00	4
2580	P00034642	55+	1	1387	1387.00	4
2581	P00273842	55+	1	589	589.00	13
2582	P00135542	55+	1	581	581.00	13
2583	P00114242	55+	1	567	567.00	13

2584 rows × 6 columns

In [59]:
```
prod_age_avg[(prod_age_avg["Age"] == '55+')].describe()
# The 25 percentile for customer count is 2 and 75 percentile is 11.
# The upper whishker is at (11+1.5*9), at 24.5
```

Out[59]:

	Customer_count	Purchase_amt	Avg Purchase
count	2584.000000	2.584000e+03	2584.000000
mean	8.321981	7.769635e+04	8376.997101
std	10.397968	1.269411e+05	4164.963409
min	1.000000	5.670000e+02	38.550000
25%	2.000000	1.193175e+04	5873.622500
50%	4.000000	3.159250e+04	7649.860000
75%	11.000000	9.071325e+04	10882.502500
max	104.000000	1.361428e+06	21313.780000

In [60]:
```
prod_age_avg[(prod_age_avg["Age"] == '55+') & (prod_age_avg["Customer_count"] >= 25)]
# there are 186 products that have more than 25 customers in the age group 55+
```

Out[60]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
0	P00265242	55+	104	744723	7160.80	5
1	P00080342	55+	80	1361428	17017.85	1
2	P00051442	55+	79	731911	9264.70	8
3	P00184942	55+	72	1257419	17464.15	1
4	P00025442	55+	72	1166560	16202.22	1
...	...	...	...	...	...	...
181	P00129642	55+	25	165422	6616.88	5
182	P00246342	55+	25	156533	6261.32	11
183	P00221542	55+	25	151524	6060.96	5
184	P0096442	55+	25	66869	2674.76	4
185	P00176842	55+	25	39969	1598.76	12

186 rows × 6 columns

In [61]:
```
prod_age_avg[(prod_age_avg["Age"] == '0-17')]
# There are 2323 products that have been purchased by customers in the age group 0-17
```

Out[61]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
18552	P00255842	0-17	65	1112854	17120.83	16
18553	P00145042	0-17	64	950906	14857.91	1
18554	P00112142	0-17	58	931216	16055.45	1
18555	P00242742	0-17	56	787132	14055.93	1
18556	P00034742	0-17	56	404552	7224.14	5
...	...	...	...	...	...	...
20870	P00066742	0-17	1	741	741.00	13
20871	P00175342	0-17	1	704	704.00	12
20872	P00331242	0-17	1	386	386.00	12
20873	P00041442	0-17	1	383	383.00	13
20874	P00025142	0-17	1	375	375.00	13

2323 rows × 6 columns

In [62]:
```
prod_age_avg[(prod_age_avg["Age"] == '0-17')]["Customer_count"].describe()
# 75% of the products have been purchased by 8 or less customers. 25% of the products have been purchased by 1 customers
```

Out[62]:
```
count    2323.000000
mean        6.501076
std         7.862589
min         1.000000
25%         1.000000
50%         4.000000
75%         8.000000
max        65.000000
Name: Customer_count, dtype: float64
```

In [63]:
```
prod_age_avg[(prod_age_avg["Age"] == '0-17') & (prod_age_avg["Customer_count"] >= 19)]
# These are the products that have more than 50 customers in the age group 0-17
```

Out[63]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
18552	P00255842	0-17	65	1112854	17120.83	16
18553	P00145042	0-17	64	950906	14857.91	1
18554	P00112142	0-17	58	931216	16055.45	1
18555	P00242742	0-17	56	787132	14055.93	1
18556	P00034742	0-17	56	404552	7224.14	5
...	...	...	...	...	...	...
18723	P00247042	0-17	19	128501	6763.21	5
18724	P00295842	0-17	19	126431	6654.26	5
18725	P00256642	0-17	19	115176	6061.89	5
18726	P00139542	0-17	19	104364	5492.84	5
18727	P00251542	0-17	19	70223	3695.95	11

176 rows × 6 columns

In [64]:
```python
prod_age_avg[(prod_age_avg["Age"] == '18-25')]
# There are 3220 products that have been purchased by customers in the age group 18-25
```

Out[64]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
15332	P00265242	18-25	389	3052248	7846.40	5
15333	P00112142	18-25	338	5517457	16323.84	1
15334	P00110742	18-25	329	5629619	17111.30	1
15335	P00237542	18-25	298	5080428	17048.42	1
15336	P00046742	18-25	295	4271270	14478.88	1
...	...	...	...	...	...	...
18547	P00309042	18-25	1	726	726.00	12
18548	P00200742	18-25	1	570	570.00	13
18549	P00091742	18-25	1	405	405.00	13
18550	P00063242	18-25	1	389	389.00	13
18551	P00336342	18-25	1	362	362.00	12

3220 rows × 6 columns

In [65]:
```python
prod_age_avg[(prod_age_avg["Age"] == '18-25')]["Customer_count"].describe()
# 25% of the products have been purchased by 4 or less customers in the age group. 75% of the products have been purchased by
# 38 or less customers
```

Out[65]:
```
count    3220.000000
mean       30.950311
std        44.327855
min         1.000000
25%         4.000000
50%        13.000000
75%        38.000000
max       389.000000
Name: Customer_count, dtype: float64
```

In [66]:
```python
prod_age_avg[(prod_age_avg["Age"] == '18-25')& (prod_age_avg["Customer_count"] >= 89)]
# There are 302 products which are purchased by 50 or more customers of age group 18-25.
```

Out[66]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
15332	P00265242	18-25	389	3052248	7846.40	5
15333	P00112142	18-25	338	5517457	16323.84	1
15334	P00110742	18-25	329	5629619	17111.30	1
15335	P00237542	18-25	298	5080428	17048.42	1
15336	P00046742	18-25	295	4271270	14478.88	1
...	...	...	...	...	...	...
15629	P00254242	18-25	90	553871	6154.12	5
15630	P00178842	18-25	89	1119103	12574.19	2
15631	P00191442	18-25	89	999141	11226.30	1
15632	P00003642	18-25	89	704301	7913.49	8
15633	P00100942	18-25	89	651087	7315.58	5

302 rows × 6 columns

In [67]:
```
prod_age_avg[(prod_age_avg["Age"] == '26-35')]
# There are 3427 products that have been purchased by customers in the age group 26-35
```

Out[67]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
11905	P00265242	26-35	746	5664434	7593.08	5
11906	P00110742	26-35	634	10721082	16910.22	1
11907	P00025442	26-35	608	10808285	17776.78	1
11908	P00112142	26-35	606	9383355	15484.08	1
11909	P00057642	26-35	597	9345266	15653.71	1
...	...	...	...	...	...	...
15327	P00264842	26-35	1	1738	1738.00	11
15328	P00309742	26-35	1	1729	1729.00	5
15329	P00181142	26-35	1	1678	1678.00	11
15330	P00284542	26-35	1	1611	1611.00	11
15331	P00293442	26-35	1	777	777.00	13

3427 rows × 6 columns

In [68]:
```
prod_age_avg[(prod_age_avg["Age"] == '26-35')]["Customer_count"].describe()
# 25% of the products have been purchased by 9 or less customers in the age group. 75% of the products have been purchased by
# 83 or less customers
```

Out[68]:
```
count    3427.000000
mean       64.075576
std        87.963688
min         1.000000
25%         9.000000
50%        30.000000
75%        83.000000
max       746.000000
Name: Customer_count, dtype: float64
```

In [69]:
```
prod_age_avg[(prod_age_avg["Age"] == '26-35')& (prod_age_avg["Customer_count"] >= 194)]
# There are 291 products which are purchased by 100 or more customers of age group 26-35.
```

Out[69]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
11905	P00265242	26-35	746	5664434	7593.08	5
11906	P00110742	26-35	634	10721082	16910.22	1
11907	P00025442	26-35	608	10808285	17776.78	1
11908	P00112142	26-35	606	9383355	15484.08	1
11909	P00057642	26-35	597	9345266	15653.71	1
...	...	...	...	...	...	...
12191	P00128242	26-35	196	1257274	6414.66	5
12192	P00144242	26-35	196	1160359	5920.20	5
12193	P00106742	26-35	195	2368316	12145.21	3
12194	P00086042	26-35	195	1490765	7644.95	8
12195	P00270242	26-35	194	1536908	7922.21	8

291 rows × 6 columns

In [70]:
```python
prod_age_avg[(prod_age_avg["Age"] == '36-45')]
# There are 3328 products which are purchased by customers of age group 36-45.
```

Out[70]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
8577	P00025442	36-45	356	6035067	16952.44	1
8578	P00265242	36-45	322	2328270	7230.65	5
8579	P00110742	36-45	321	5166746	16095.78	1
8580	P00112142	36-45	301	4503958	14963.32	1
8581	P00057642	36-45	298	4761583	15978.47	1
...	...	...	...	...	...	...
11900	P00024442	36-45	1	817	817.00	4
11901	P00145342	36-45	1	813	813.00	4
11902	P00164742	36-45	1	801	801.00	4
11903	P00203742	36-45	1	219	219.00	13
11904	P00293442	36-45	1	192	192.00	13

3328 rows × 6 columns

In [71]:
```python
prod_age_avg[(prod_age_avg["Age"] == '36-45')]["Customer_count"].describe()
# 25% of the products have been purchased by 5 or less customers in the age group. 75% of the products have been purchased by
# 43 or less customers
```

Out[71]:
```
count    3328.000000
mean       33.056791
std        44.030628
min         1.000000
25%         5.000000
50%        16.000000
75%        43.250000
max       356.000000
Name: Customer_count, dtype: float64
```

In [72]:
```python
prod_age_avg[(prod_age_avg["Age"] == '36-45')& (prod_age_avg["Customer_count"] >= 100)]
# There are 269 products which are purchased by 100 or more customers of age group 36-45.
```

Out[72]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
8577	P00025442	36-45	356	6035067	16952.44	1
8578	P00265242	36-45	322	2328270	7230.65	5
8579	P00110742	36-45	321	5166746	16095.78	1
8580	P00112142	36-45	301	4503958	14963.32	1
8581	P00057642	36-45	298	4761583	15978.47	1
...	...	...	...	...	...	...
8841	P00233442	36-45	100	1289362	12893.62	1
8842	P00346342	36-45	100	1266641	12666.41	1
8843	P00122442	36-45	100	1198937	11989.37	1
8844	P00294542	36-45	100	732299	7322.99	8
8845	P00090842	36-45	100	545461	5454.61	11

269 rows × 6 columns

In [73]:
```
prod_age_avg[(prod_age_avg["Age"] == '46-50')]
# There are 3106 products which are purchased by customers of age group 46-50.
```

Out[73]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
5471	P00265242	46-50	138	1007796	7302.87	5
5472	P00046742	46-50	130	2002745	15405.73	1
5473	P00025442	46-50	123	2117120	17212.36	1
5474	P00051442	46-50	122	1106415	9068.98	8
5475	P00184942	46-50	119	2036445	17112.98	1
...	...	...	...	...	...	...
8572	P00185242	46-50	1	1434	1434.00	4
8573	P00132342	46-50	1	759	759.00	4
8574	P00357742	46-50	1	695	695.00	4
8575	P00207842	46-50	1	398	398.00	13
8576	P00069842	46-50	1	378	378.00	13

3106 rows × 6 columns

In [74]:
```
prod_age_avg[(prod_age_avg["Age"] == '46-50')]["Customer_count"].describe()
# 25% of the products have been purchased by 3 or less customers in the age group. 75% of the products have been purchased by
# 19 or less customers
```

Out[74]:
```
count    3106.000000
mean       14.713780
std        18.381242
min         1.000000
25%         3.000000
50%         8.000000
75%        19.000000
max       138.000000
Name: Customer_count, dtype: float64
```

In [75]:
```
prod_age_avg[(prod_age_avg["Age"] == '46-50')& (prod_age_avg["Customer_count"] >= 43)]
# There are 247 products which are purchased by 100 or more customers of age group 46-50.
```

Out[75]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
5471	P00265242	46-50	138	1007796	7302.87	5
5472	P00046742	46-50	130	2002745	15405.73	1
5473	P00025442	46-50	123	2117120	17212.36	1
5474	P00051442	46-50	122	1106415	9068.98	8
5475	P00184942	46-50	119	2036445	17112.98	1
...	...	...	...	...	...	...
5713	P00313442	46-50	43	286512	6663.07	5
5714	P00211142	46-50	43	285116	6630.60	5
5715	P00057442	46-50	43	279406	6497.81	5
5716	P00123742	46-50	43	258419	6009.74	11
5717	P00226242	46-50	43	225285	5239.19	11

247 rows × 6 columns

In [76]:
```python
prod_age_avg[(prod_age_avg["Age"] == '51-55')]
# There are 2887 products which are purchased by customers in the age group 51-55.
```

Out[76]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
2584	P00265242	51-55	140	1038339	7416.71	5
2585	P00025442	51-55	118	2056805	17430.55	1
2586	P00110742	51-55	117	1812670	15492.91	1
2587	P00059442	51-55	115	2041913	17755.77	6
2588	P00010742	51-55	110	1738741	15806.74	1
...	...	...	...	...	...	...
5466	P00090342	51-55	1	1074	1074.00	12
5467	P00207842	51-55	1	770	770.00	13
5468	P00357742	51-55	1	763	763.00	4
5469	P00101642	51-55	1	699	699.00	12
5470	P00114242	51-55	1	217	217.00	13

2887 rows × 6 columns

In [77]:
```python
prod_age_avg[(prod_age_avg["Age"] == '51-55')]["Customer_count"].describe()
# 25% of the products have been purchased by 2 or less customers in the age group. 75% of the products have been purchased by
# 18 or less customers
```

Out[77]:
```
count    2887.000000
mean       13.335989
std        16.774193
min         1.000000
25%         2.000000
50%         7.000000
75%        18.000000
max       140.000000
Name: Customer_count, dtype: float64
```

In [78]:
```python
prod_age_avg[(prod_age_avg["Age"] == '51-55')& (prod_age_avg["Customer_count"] >= 42)]
# There are 205 products which are purchased by 42 or more customers of age group 51-55.
```

Out[78]:

	Product_ID	Age	Customer_count	Purchase_amt	Avg Purchase	Product_Category
2584	P00265242	51-55	140	1038339	7416.71	5
2585	P00025442	51-55	118	2056805	17430.55	1
2586	P00110742	51-55	117	1812670	15492.91	1
2587	P00059442	51-55	115	2041913	17755.77	6
2588	P00010742	51-55	110	1738741	15806.74	1
...	...	...	...	...	...	...
2784	P00075542	51-55	42	343281	8173.36	8
2785	P00025942	51-55	42	340722	8112.43	8
2786	P00265742	51-55	42	314933	7498.40	5
2787	P00209842	51-55	42	297447	7082.07	5
2788	P00205442	51-55	42	285159	6789.50	5

205 rows × 6 columns

In [79]:
```
# Products which have customer base across all the age groups
prod_id = []
min_prod_id = []
max_prod_id = []
for i in prod_age_avg["Product_ID"].unique():
    z = prod_age_avg[(prod_age_avg["Product_ID"] == i)]
    if len(z) == 7:
        prod_id.append(i)
        min_prod_id.append(prod_age_avg[prod_age_avg["Product_ID"] == i]["Customer_count"].min())
        max_prod_id.append(prod_age_avg[prod_age_avg["Product_ID"] == i]["Customer_count"].max())
```

In [80]:
```
prod_id_all_age = pd.DataFrame([prod_id, min_prod_id, max_prod_id]).T.rename(columns = {0:"Product_id", 1: "Minimum count", 2: "Maximum count"}).\
sort_values(["Minimum count", "Maximum count"], ascending = [False, False]).reset_index(drop = True)
# There are 1840 products which have been purchased by customers across all age groups.
prod_id_all_age
```

Out[80]:

	Product_id	Minimum count	Maximum count
0	P00034742	55	464
1	P00025442	52	608
2	P00112142	48	606
3	P00110742	47	634
4	P00145042	47	525
...	...	...	...
1835	P00122342	1	4
1836	P00260942	1	4
1837	P00190642	1	4
1838	P00138142	1	4
1839	P00330042	1	3

1840 rows × 3 columns

In [81]:
```python
prod_id_all_age[prod_id_all_age["Minimum count"] >= 30]
# There are 30 products where atleast 30 customers purchased across all age groups.
```

Out[81]:

	Product_id	Minimum count	Maximum count
0	P00034742	55	464
1	P00025442	52	608
2	P00112142	48	606
3	P00110742	47	634
4	P00145042	47	525
5	P00184942	43	578
6	P00102642	43	476
7	P00265242	41	746
8	P00085942	41	350
9	P00255842	39	550
10	P00110942	39	530
11	P00278642	39	517
12	P00117442	39	500
13	P00003442	39	358
14	P00110842	37	541
15	P00117942	37	533
16	P00157542	37	319
17	P00046742	36	551
18	P00220442	36	478
19	P00242742	35	474
20	P00370853	35	286
21	P00295942	34	364
22	P00371644	34	328
23	P00057642	33	597
24	P00372445	33	277
25	P00216342	32	387
26	P00059442	31	545
27	P00251242	31	474
28	P00334242	31	459
29	P00350942	30	273

In [82]:
```python
# Finding products which are available only for 4 or less age groups
prod_id = []
age_groups = []
for i in prod_age_avg["Product_ID"].unique():
    z = prod_age_avg[(prod_age_avg["Product_ID"] == i)]
    if len(z) <= 4:
        prod_id.append(i)
        age_groups.append(sorted(prod_age_avg[(prod_age_avg["Product_ID"] == i)]["Age"].values.tolist()))
```

In [83]:
```python
pd.DataFrame([prod_id, age_groups]).T.rename(columns = {0:"Product_ID", 1:"Age Groups"})
# There are 699 products which are purchased by customers across 4 or less age age groups
```

Out[83]:

	Product_ID	Age Groups
0	P00108242	[26-35, 36-45, 51-55, 55+]
1	P00086542	[51-55, 55+]
2	P00269842	[26-35, 51-55, 55+]
3	P00139442	[26-35, 46-50, 51-55, 55+]
4	P00209242	[26-35, 36-45, 46-50, 55+]
...	...	...
694	P00104042	[18-25]
695	P00309042	[18-25]
696	P00091742	[18-25]
697	P00030242	[0-17]
698	P00081642	[0-17]

699 rows × 2 columns

In [84]:
```python
data1 = pd.merge(data.groupby(["User_ID"]).aggregate(Purchase= ("Purchase", "sum"), ).reset_index(),data[["User_ID", \
                 "Age", "Marital_Status"]].drop_duplicates().reset_index(drop = True))
data1
```

Out[84]:

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

5891 rows × 4 columns

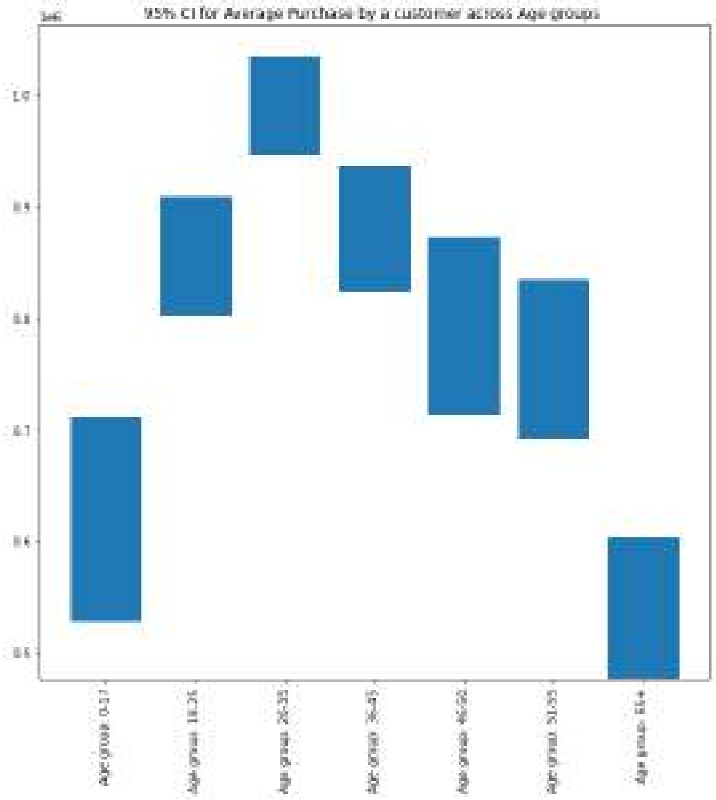
In [85]:

```
group = []
group_purchase_mean = []
group_std = []
size = []
group_se= []
lower_limit_95 = []
upper_limit_95 = []
for i in data1["Age"].unique():
    group.append(f"Age group: {i}")
    z = data1[data1["Age"] == i]
    group_purchase_mean.append(z["Purchase"].astype(int).mean())
    group_std.append(z["Purchase"].astype(int).std())
    size.append(len(z))
    group_se.append(z["Purchase"].std()/len(z)**0.5)
    lower_limit_95.append(z["Purchase"].astype(int).mean() + norm.ppf(0.025)*z["Purchase"].astype(int).std()/len(z)**0.5)
    upper_limit_95.append(z["Purchase"].astype(int).mean() + norm.ppf(0.975)*z["Purchase"].astype(int).std()/len(z)**0.5)
for i in data1["Marital_Status"].unique():
    group.append(f"Marital Status: {i}")
    z = data1[data1["Marital_Status"] == i]
    group_purchase_mean.append(z["Purchase"].astype(int).mean())
    group_std.append(z["Purchase"].astype(int).std())
    size.append(len(z))
    group_se.append(z["Purchase"].std()/len(z)**0.5)
    lower_limit_95.append(z["Purchase"].astype(int).mean() + norm.ppf(0.025)*z["Purchase"].astype(int).std()/len(z)**0.5)
    upper_limit_95.append(z["Purchase"].astype(int).mean() + norm.ppf(0.975)*z["Purchase"].astype(int).std()/len(z)**0.5)
for i in data1["Age"].unique():
    for j in data1["Marital_Status"].unique():
        z = data1[(data1["Age"] == i) & (data1["Marital_Status"] == j)]
        if len(z)>0:
            group.append(f"Age group: {i}, Marital Status = {j}")
            group_purchase_mean.append(z["Purchase"].astype(int).mean())
            group_std.append(z["Purchase"].astype(int).std())
            size.append(len(z))
            group_se.append(z["Purchase"].std()/len(z)**0.5)
            lower_limit_95.append(z["Purchase"].astype(int).mean() + norm.ppf(0.025)*z["Purchase"].astype(int).std()/len(z)**0.5)
            upper_limit_95.append(z["Purchase"].astype(int).mean() + norm.ppf(0.975)*z["Purchase"].astype(int).std()/len(z)**0.5)
data_ci = pd.DataFrame([group, group_purchase_mean,group_std, size, group_se,lower_limit_95,upper_limit_95]).T
data_ci.columns = ["Group", "Group Mean", "Group Standard Deviation", "Group Size", "Group SE", "Lower Limit 95", "Upper Limit 95"]
data_ci
```

Out[85]:

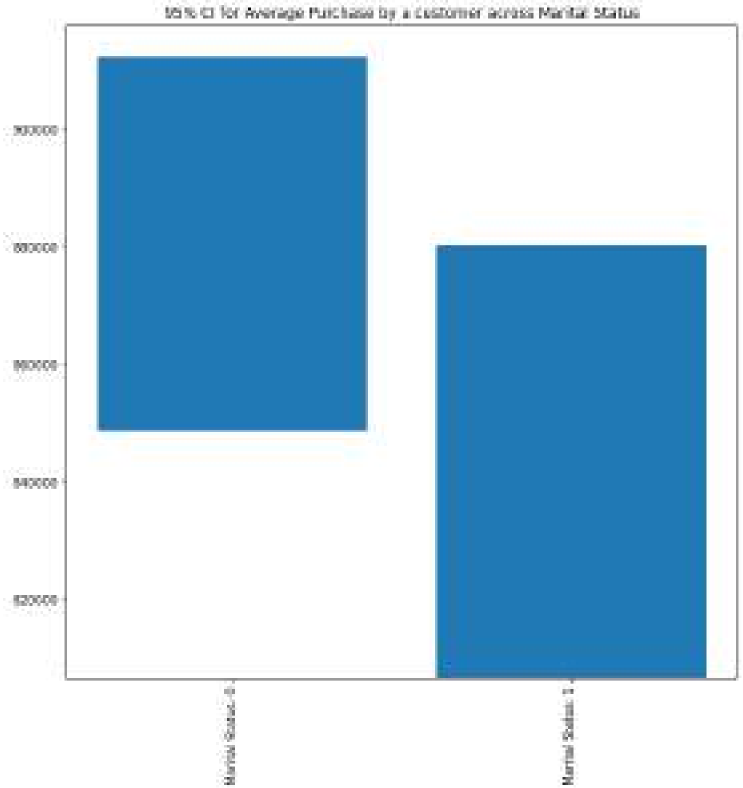
	Group	Group Mean	Group Standard Deviation	Group Size	Group SE	Lower Limit 95	Upper Limit 95
0	Age group: 0-17	618867.811927	687056.597887	218	46533.344496	527664.132634	710071.491219
1	Age group: 55+	539697.244624	617478.874761	372	32014.788282	476949.412618	602445.076629
2	Age group: 26-35	989659.317097	1031610.123801	2053	22767.80278	945035.243642	1034283.390552
3	Age group: 46-50	792548.781544	929298.877414	531	40328.136275	713507.086881	871590.476208
4	Age group: 51-55	763200.923077	792322.243484	481	36126.784643	692393.726299	834008.119855
5	Age group: 36-45	879665.710368	981580.387732	1167	28733.626649	823348.836991	935982.583746
6	Age group: 18-25	854863.119738	887957.252076	1069	27158.339056	801633.753309	908092.486168
7	Marital Status: 0	880575.781972	949436.249555	3417	16242.142622	848741.767402	912409.796543
8	Marital Status: 1	843526.796686	935352.115825	2474	18805.08433	806669.508672	880384.0847
9	Age group: 0-17, Marital Status = 0	618867.811927	687056.597887	218	46533.344496	527664.132634	710071.491219
10	Age group: 55+, Marital Status = 0	565428.917293	588520.217352	133	51031.174773	465409.652649	665448.181938
11	Age group: 55+, Marital Status = 1	525377.945607	633779.096942	239	40995.761783	445027.728993	605728.162221
12	Age group: 26-35, Marital Status = 0	991422.911576	1022996.537549	1244	29004.405861	934575.320695	1048270.502456
13	Age group: 26-35, Marital Status = 1	986947.436341	1045346.682122	809	36752.432137	914913.993008	1058980.879675
14	Age group: 46-50, Marital Status = 0	728579.230769	871472.768797	156	69773.662779	591825.364652	865333.096886
15	Age group: 46-50, Marital Status = 1	819160.114667	952178.92909	375	49170.308466	722788.080964	915532.148369
16	Age group: 51-55, Marital Status = 0	763179.367647	782912.258165	136	67134.172283	631598.80784	894759.927454
17	Age group: 51-55, Marital Status = 1	763209.42029	797130.229548	345	42916.048917	679095.510053	847323.330526
18	Age group: 36-45, Marital Status = 0	885263.489362	996544.34317	705	37532.031292	811702.059762	958824.918961
19	Age group: 36-45, Marital Status = 1	871123.645022	959304.727357	462	44630.895088	783648.698051	958598.591993
20	Age group: 18-25, Marital Status = 0	877479.517576	909608.004057	825	31668.485837	815410.42589	939548.609261
21	Age group: 18-25, Marital Status = 1	778393.741803	807547.876433	244	51697.955247	677067.611444	879719.872163

In [86]:
```python
plt.figure(figsize = (10,10))
plt.bar(data_ci[0:7].sort_values("Group") ["Group"], data_ci[0:7].sort_values("Group")["Upper Limit 95"]-data_ci[0:7].\
        sort_values("Group")["Lower Limit 95"],bottom = data_ci[0:7].sort_values("Group")["Lower Limit 95"])
plt.xticks(rotation = 90)
plt.title("95% CI for Average Purchase by a customer across Age groups ")
plt.show()
# As can be seen, the maximum overlap at 95 5 ci in Purchase amount in successive age groups is for age groups is 46-50 and
# 51-55
# The Purchase amount can be assumed to increase till age group 26-35 and decreases. Since there is overlap between 36-45,
# 46-50 and 51-55, we cannot conclude with certainity that these age groups have different Purchases but it decreases as
# compared to Age group 26-35. Age group 55+ has lower Purchase as compared to age groups 46-50 and 51-55.
```

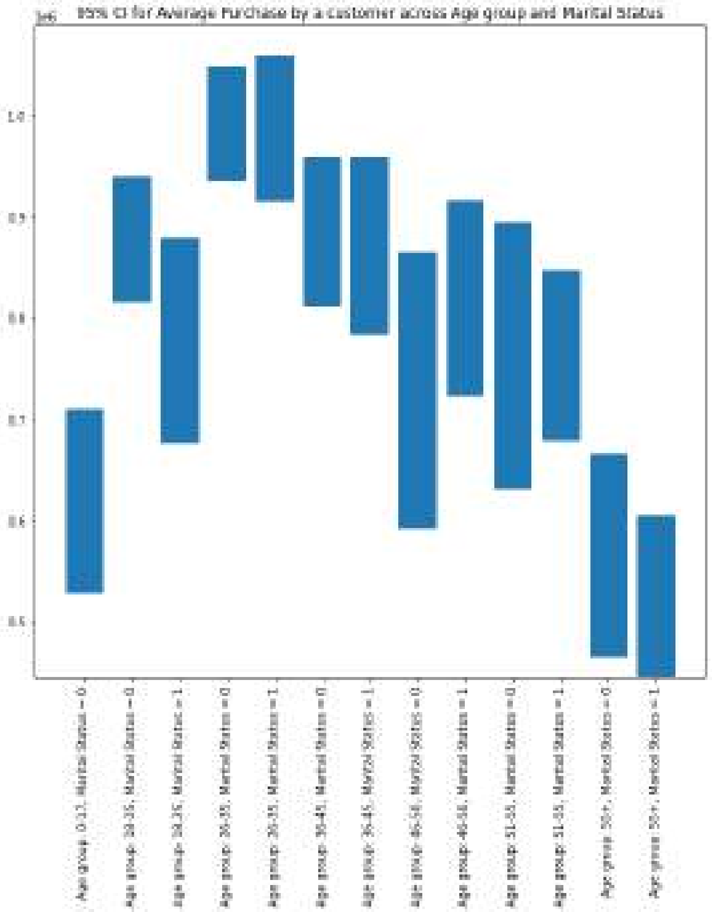


In [87]:

```python
plt.figure(figsize = (10,10))
plt.bar(data_ci[7:9].sort_values("Group") ["Group"], data_ci[7:9].sort_values("Group")["Upper Limit 95"]-data_ci[7:9].\
        sort_values("Group")["Lower Limit 95"],bottom = data_ci[7:9].sort_values("Group")["Lower Limit 95"])
plt.xticks(rotation = 90)
plt.title("95% CI for Average Purchase by a customer across Marital Status")
plt.show()
# As can be seen, there is overlap in the 95% CI interval for Purchase amount for Marital Status 0 and 1. Hence, we cannot
# conclude for sure about difference in Purchasing for the two groups/
```



In [88]:
```
plt.figure(figsize = (10,10))
plt.bar(data_ci[9:].sort_values("Group") ["Group"], data_ci[9:].sort_values("Group")["Upper Limit 95"]-data_ci[9:].\
        sort_values("Group")["Lower Limit 95"],bottom = data_ci[9:].sort_values("Group")["Lower Limit 95"])
plt.xticks(rotation = 90)
plt.title("95% CI for Average Purchase by a customer across Age group and Marital Status")
plt.show()
# As can be seen from the graphs below, there is overlap in 95% CI for people of Martial Status 0 and 1 in different age groups.
```



In [89]:
```
df1 = data.groupby(["Gender", "Product_Category"]).aggregate(Purchase_amt = ("Purchase", "sum")).reset_index().sort_values("Product_Category" )
df2 = data[["Gender","Product_Category", "Product_ID"]].drop_duplicates().groupby(["Gender","Product_Category"]).aggregate\
(Product_count = ("Product_ID", "count")).reset_index()
df3 = data[["Gender", "Product_Category", "User_ID"]].drop_duplicates().groupby(["Gender", "Product_Category"]).aggregate\
(Customer_count = ("User_ID", "count")).reset_index()
gen_prod_cat = pd.merge((pd.merge(df1, df2,on = ["Gender", "Product_Category"])),df3,on = ["Gender", "Product_Category"]).\
sort_values("Product_Category")
gen_prod_cat["Avg_Purchase"] = round(gen_prod_cat["Purchase_amt"]/gen_prod_cat["Customer_count"],2)
M,F = data[["User_ID","Gender"]].drop_duplicates()["Gender"].value_counts()
def per_customer(x):
    global M,F
    if x["Gender"] == "M":
        return round(x["Customer_count"]*100/M,2)
    else:
        return round(x["Customer_count"]*100/F,2)
gen_prod_cat["% of customer in respective gender"] = gen_prod_cat.apply( per_customer, axis = 1)
gen_prod_cat.sort_values(["Product_Category", "Gender"], inplace = True)
gen_prod_cat
```

Out[89]:

	Gender	Product_Category	Purchase_amt	Product_count	Customer_count	Avg_Purchase	% of customer in respective gender
0	F	1	337631145	470	1593	211946.73	95.62
1	M	1	1572382609	490	4174	376708.82	98.79
2	F	10	22882193	23	513	44604.66	30.79
3	M	10	77955108	24	1815	42950.47	42.96
4	F	11	22161326	232	867	25560.93	52.04
5	M	11	91629789	254	2716	33737.04	64.28
6	F	12	2179897	25	555	3927.74	33.31
7	M	12	3151947	24	1012	3114.57	23.95
8	F	13	1072884	33	586	1830.86	35.17
9	M	13	2935717	35	1686	1741.23	39.91
11	F	14	8564607	37	378	22657.69	22.69
10	M	14	11450089	42	593	19308.75	14.04
13	F	15	15371312	42	501	30681.26	30.07
12	M	15	77597730	44	1939	40019.46	45.89
15	F	16	35264942	92	816	43216.84	48.98
14	M	16	109855670	97	2314	47474.36	54.77
17	F	17	610477	9	60	10174.62	3.60
16	M	17	5268222	11	366	14394.05	8.66
18	F	18	1088168	27	207	5256.85	12.42
19	M	18	8202033	30	1077	7615.63	25.49
21	F	19	16992	2	451	37.68	27.07
20	M	19	42386	2	1152	36.79	27.27
22	F	2	64543617	141	1146	56320.78	68.79
23	M	2	203972569	151	3150	64753.20	74.56
25	F	20	268641	3	723	371.56	43.40
24	M	20	676086	3	1827	370.05	43.24
27	F	3	61637516	90	1093	56392.97	65.61
26	M	3	142447197	90	2745	51893.33	64.97
28	F	4	8933206	87	966	9247.63	57.98
29	M	4	18447282	87	2395	7702.41	56.69
31	F	5	264658078	909	1638	161573.92	98.32
30	M	5	677177151	957	4113	164643.12	97.35
33	F	6	71104116	113	1090	65233.13	65.43
32	M	6	253046186	119	2995	84489.54	70.89
35	F	7	15460347	81	351	44046.57	21.07
34	M	7	45436384	99	1110	40933.68	26.27
37	F	8	251682476	950	1614	155937.10	96.88
36	M	8	602636323	1027	4045	148983.02	95.74
38	F	9	1100702	1	70	15724.31	4.20
39	M	9	5269622	2	340	15498.89	8.05

In [90]:

```python
# Observations from the above table for the given data:
# We can say that a particular gender prefers a paricular product category if the difference in average purchase between Male
# and Female Genders is greater than 1000 and the percentage difference in customers in the genders is different by more than
# 5% for a paarticular category.
for i in gen_prod_cat["Product_Category"].unique():
    x = gen_prod_cat.loc[gen_prod_cat["Product_Category"] == i, ::].reset_index(drop = True)
    if (abs(x.loc[0,"% of customer in respective gender"] - x.loc[1,"% of customer in respective gender"]) >= 5) & \
    (abs(x.loc[0,"Avg_Purchase"] - x.loc[1,"Avg_Purchase"]) >= 1000):
        print(f"Product Category {i} has gender preference")
        print(f"The Average Purchase by Female is {x.iloc[0,5]} in product category {i}")
        print(f"The Average Purchase by Male is {x.iloc[1,5]} in product category {i}")
        print(f"{ x.iloc[0,6]}% of Females have purchased from Product Category {i}")
        print(f"{ x.iloc[1,6]}% of Males have purchased from Product Category {i}", end = '\n')
        print()
```

```
Product Category 10 has gender preference
The Average Purchase by Female is 44604.66 in product category 10
The Average Purchase by Male is 42950.47 in product category 10
30.79% of Females have purchased from Product Category 10
42.96% of Males have purchased from Product Category 10

Product Category 11 has gender preference
The Average Purchase by Female is 25560.93 in product category 11
The Average Purchase by Male is 33737.04 in product category 11
52.04% of Females have purchased from Product Category 11
64.28% of Males have purchased from Product Category 11

Product Category 14 has gender preference
The Average Purchase by Female is 22657.69 in product category 14
The Average Purchase by Male is 19308.75 in product category 14
22.69% of Females have purchased from Product Category 14
14.04% of Males have purchased from Product Category 14

Product Category 15 has gender preference
The Average Purchase by Female is 30681.26 in product category 15
The Average Purchase by Male is 40019.46 in product category 15
30.07% of Females have purchased from Product Category 15
45.89% of Males have purchased from Product Category 15

Product Category 16 has gender preference
The Average Purchase by Female is 43216.84 in product category 16
The Average Purchase by Male is 47474.36 in product category 16
48.98% of Females have purchased from Product Category 16
54.77% of Males have purchased from Product Category 16

Product Category 17 has gender preference
The Average Purchase by Female is 10174.62 in product category 17
The Average Purchase by Male is 14394.05 in product category 17
3.6% of Females have purchased from Product Category 17
8.66% of Males have purchased from Product Category 17

Product Category 18 has gender preference
The Average Purchase by Female is 5256.85 in product category 18
The Average Purchase by Male is 7615.63 in product category 18
12.42% of Females have purchased from Product Category 18
25.49% of Males have purchased from Product Category 18

Product Category 2 has gender preference
The Average Purchase by Female is 56320.78 in product category 2
The Average Purchase by Male is 64753.2 in product category 2
68.79% of Females have purchased from Product Category 2
74.56% of Males have purchased from Product Category 2

Product Category 6 has gender preference
The Average Purchase by Female is 65233.13 in product category 6
The Average Purchase by Male is 84489.54 in product category 6
65.43% of Females have purchased from Product Category 6
70.89% of Males have purchased from Product Category 6

Product Category 7 has gender preference
The Average Purchase by Female is 44046.57 in product category 7
The Average Purchase by Male is 40933.68 in product category 7
21.07% of Females have purchased from Product Category 7
26.27% of Males have purchased from Product Category 7
```

In [91]:
```
# Using 2 sample t-test to understand if there is significant difference in the Purchase made by genders in different Product
# Category
prod_cat= []
null_hyp = []
alt_hyp = []
t_score = []
p_val = []
for i in data["Product_Category"].unique():
    prod_cat.append(i)
    x = data[(data["Product_Category"] == i) & (data["Gender"] == 'M')]["Purchase"]
    y = data[(data["Product_Category"] == i) & (data["Gender"] == 'F')]["Purchase"]
    null_hyp.append("Average purchase by male is equal to average purchase by female for product category {i}")
    alt_hyp.append("Average purchase by male is not equal to average purchase by female for product category {i}")
    t_stat, p_value = ttest_ind(x,y,alternative = 'two-sided')
    t_score.append(t_stat)
    p_val.append(p_value)
ttest_gen_pur = pd.DataFrame([prod_cat, null_hyp, alt_hyp, t_score, p_val]).T.rename(columns = {0: "Product_Category", 1: "Null Hypothesis",\
                                                                2: "Alternate Hypothesis", 3: "T_Statistic",4: "P_value"})
ttest_gen_pur[ttest_gen_pur["P_value"] < 0.05]
# Below listed are the product categories where Average amount spent by Male and Female customer groups are different using
# 95% CI.
```

Out[91]:

	Product_Category	Null Hypothesis	Alternate Hypothesis	T_Statistic	P_value
0	3	Average purchase by male is equal to average p...	Average purchase by male is not equal to avera...	-5.434779	0.0
2	12	Average purchase by male is equal to average p...	Average purchase by male is not equal to avera...	-10.070974	0.0
4	5	Average purchase by male is equal to average p...	Average purchase by male is not equal to avera...	-8.481791	0.0
5	4	Average purchase by male is equal to average p...	Average purchase by male is not equal to avera...	-11.245711	0.0
6	2	Average purchase by male is equal to average p...	Average purchase by male is not equal to avera...	-3.752929	0.000175
7	6	Average purchase by male is equal to average p...	Average purchase by male is not equal to avera...	4.623822	0.000004
8	14	Average purchase by male is equal to average p...	Average purchase by male is not equal to avera...	-4.869503	0.000001
10	13	Average purchase by male is equal to average p...	Average purchase by male is not equal to avera...	-2.780882	0.005439
14	18	Average purchase by male is equal to average p...	Average purchase by male is not equal to avera...	3.572031	0.00036

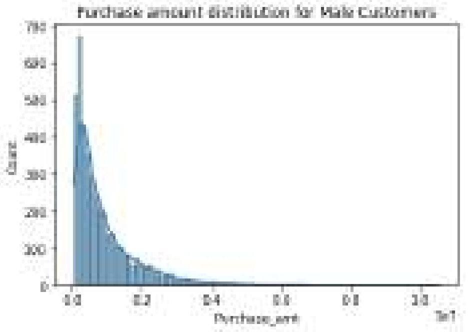
In [92]:
```
gen_data_pur = data.groupby(["User_ID","Gender"]).aggregate(Purchase_amt = ("Purchase", "sum")).reset_index()
gen_data_pur
```

Out[92]:

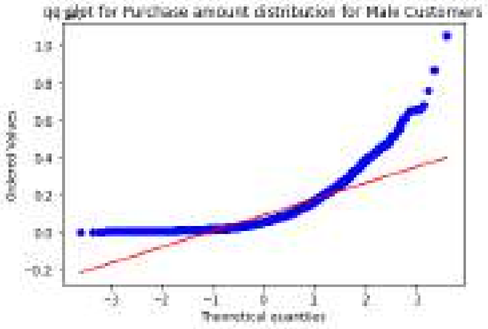
	User_ID	Gender	Purchase_amt
0	1000001	F	334093
1	1000002	M	810472
2	1000003	M	341635
3	1000004	M	206468
4	1000005	M	821001
...	...	...	...
5886	1006036	F	4116058
5887	1006037	F	1119538
5888	1006038	F	90034
5889	1006039	F	590319
5890	1006040	M	1653299

5891 rows × 3 columns

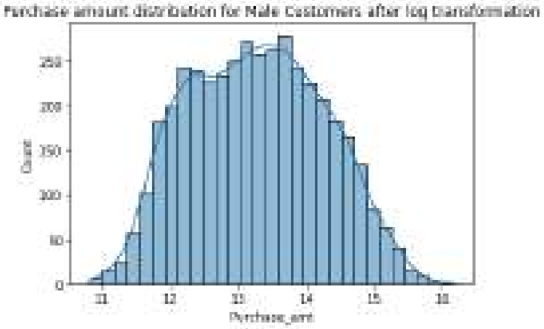
In [93]:
```
sns.histplot(gen_data_pur.loc[gen_data_pur["Gender"] == "M", "Purchase_amt"], kde = "True")
plt.title("Purchase amount distribution for Male Customers")
plt.show()
# The distribution of Purchase amount for Males appears to be right skewed as seen in the histplot below
```



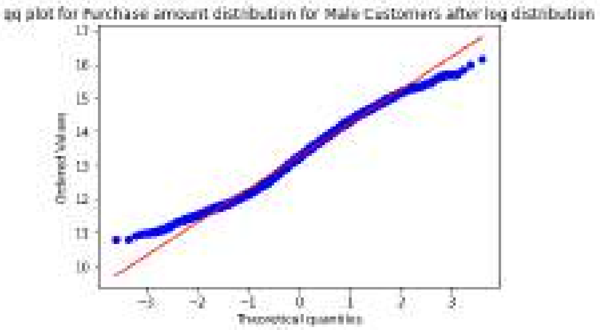
In [94]:
```
stats.probplot(gen_data_pur.loc[gen_data_pur["Gender"] == "M", "Purchase_amt"], dist="norm", plot=py)
plt.title("qq plot for Purchase amount distribution for Male Customers")
py.show()
# As seen from the image below, we can see that the distribution of Purchase amount for Males do not follow Normal Distribution.
# As the data is right skewed, we can apply log normal distribution to convert it to a normal distribution.
```



In [95]:
```
sns.histplot(gen_data_pur.loc[gen_data_pur["Gender"] == "M", "Purchase_amt"].apply(np.log), kde = "True")
plt.title("Purchase amount distribution for Male Customers after log transformation")
plt.show()
# after applying log transformation, the Purchase distribution appears to be normally distributed.
```



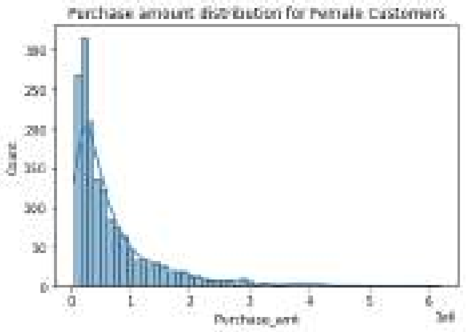
In [96]:
```
stats.probplot(gen_data_pur.loc[gen_data_pur["Gender"] == "M", "Purchase_amt"].apply(np.log), dist="norm", plot=py)
plt.title("qq plot for Purchase amount distribution for Male Customers after log distribution")
py.show()
# As can be seen from qq plot below, after log normal transformation, the distribution of Purchase for Males are closer to Normal
# Distribution. Hence, we can use log transformation and create the 95% interval for average Total Purchase by a male customer.
```



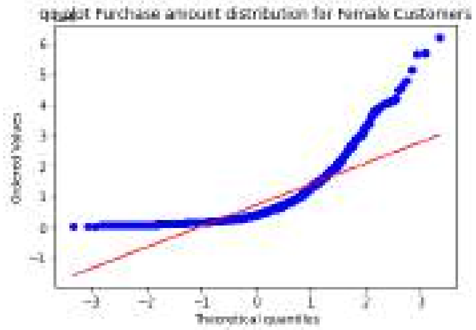
In [97]:
```
# Getting upper and lower limit of Purchase for 95% CI for Male Customers.
male_pur_mean = gen_data_pur.loc[gen_data_pur["Gender"] == "M", "Purchase_amt"].apply(np.log).mean()
male_pur_std = gen_data_pur.loc[gen_data_pur["Gender"] == "M", "Purchase_amt"].apply(np.log).std()/\
len(gen_data_pur.loc[gen_data_pur["Gender"] == "M", "Purchase_amt"])**0.5
lower_limit_male_purchase, upper_limit_male_purchase = np.exp(norm.ppf([0.025,0.975],loc = male_pur_mean,scale = male_pur_std))\
.round(2)
lower_limit_male_purchase,round(np.exp(male_pur_mean),2), upper_limit_male_purchase
```

Out[97]:
```
(558844.35, 575777.41, 593223.54)
```

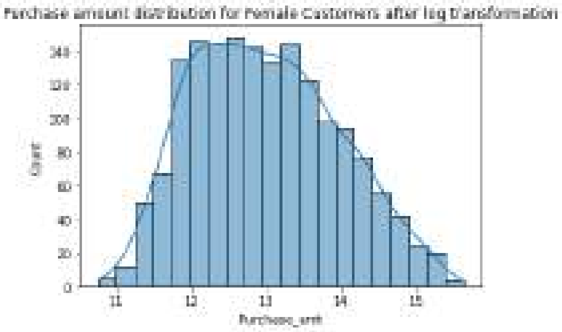
In [98]:
```
sns.histplot(gen_data_pur.loc[gen_data_pur["Gender"] == "F", "Purchase_amt"], kde = True)
plt.title("Purchase amount distribution for Female Customers")
plt.show()
# The Purchase amount distribution for Female Category also appears to be right skewed. Hence we need to transform this to Normal
# data before calculating the 95% CI for Purchase amount for Female Category.
```



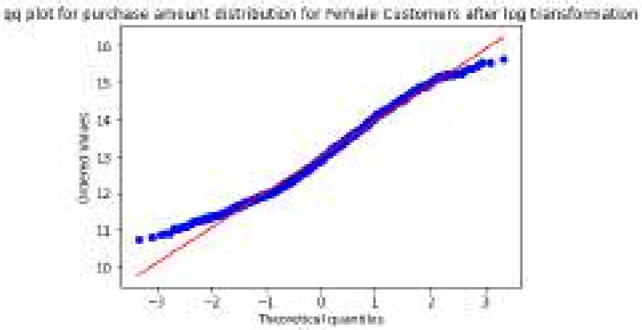
In [99]:
```
stats.probplot(gen_data_pur.loc[gen_data_pur["Gender"] == "F", "Purchase_amt"], dist="norm", plot=py)
plt.title("qq plot Purchase amount distribution for Female Customers")
py.show()
# As seen from the image below, we can see that the distribution of Purchase amount for Females do not follow Normal Distribution.
# As the data is right skewed, we can apply log normal distribution to convert it to a normal distribution.
```



In [100]:
```
sns.histplot(gen_data_pur.loc[gen_data_pur["Gender"] == "F", "Purchase_amt"].apply(np.log), kde = "True")
plt.title("Purchase amount distribution for Female Customers after log transformation")
plt.show()
# after applying log transformation, the Purchase distribution appears to be normally distributed for Female Distribution
```



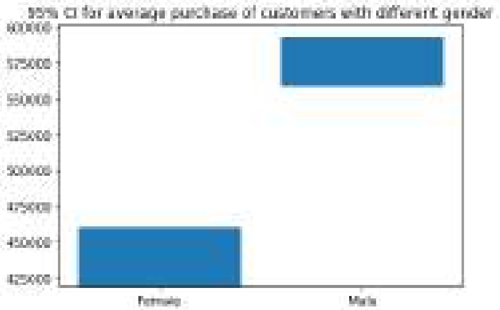
In [101]:
```python
stats.probplot(gen_data_pur.loc[gen_data_pur["Gender"] == "F", "Purchase_amt"].apply(np.log), dist="norm", plot=py)
plt.title("qq plot for purchase amount distribution for Female Customers after log transformation")
py.show()
# As can be seen from qq plot below, after log normal transformation, the distribution of Purchase for Females are closer to
# Normal Distribution. Hence, we can use log transformation and create the 95% interval for average Total Purchase by a customer.
```



In [102]:
```python
# Getting upper and lower limit of Purchase for 95% CI for Female Customers.
female_pur_mean = gen_data_pur.loc[gen_data_pur["Gender"] == "F", "Purchase_amt"].apply(np.log).mean()
female_pur_std = gen_data_pur.loc[gen_data_pur["Gender"] == "F", "Purchase_amt"].apply(np.log).std()/\
(len(gen_data_pur.loc[gen_data_pur["Gender"] == "F", "Purchase_amt"]))**0.5
lower_limit_female_purchase, upper_limit_female_purchase = np.exp(norm.ppf([0.025,0.975],loc = female_pur_mean,scale = \
                                female_pur_std)).round(2)
lower_limit_female_purchase,round(np.exp(female_pur_mean),2), upper_limit_female_purchase
```

Out[102]:
```
(419037.82, 439015.9, 459946.45)
```

In [103]:
```python
plt.bar(x = ["Female","Male"], bottom = [lower_limit_female_purchase, lower_limit_male_purchase], height = \
[upper_limit_female_purchase - lower_limit_female_purchase, upper_limit_male_purchase - lower_limit_male_purchase])
plt.title("95% CI for average purchase of customers with different gender")
plt.show()
# As can be seen, the average purchase made by a male customer is greater than that made by female customer.
```



In [104]:
```python
# st.t.interval(alpha=0.95, df=len(data)-1, loc=np.mean(data), scale=st.sem(data))
x = gen_data_pur.loc[gen_data_pur["Gender"] == "F", "Purchase_amt"].apply(np.log)
y = gen_data_pur.loc[gen_data_pur["Gender"] == "M", "Purchase_amt"].apply(np.log)
np.exp(stats.t.interval(alpha = 0.95, df = len(x)-1, loc = np.mean(x), scale = stats.sem(x)))
```

Out[104]:
```
array([419023.62536337, 459962.03567058])
```

In [105]:

```
np.exp(stats.t.interval(alpha = 0.95, df = len(y)-1, loc = np.mean(y), scale = stats.sem(y)))
# As can be seen, the Average Purchase amount is greater for Male than that of female.
```

Out[105]:

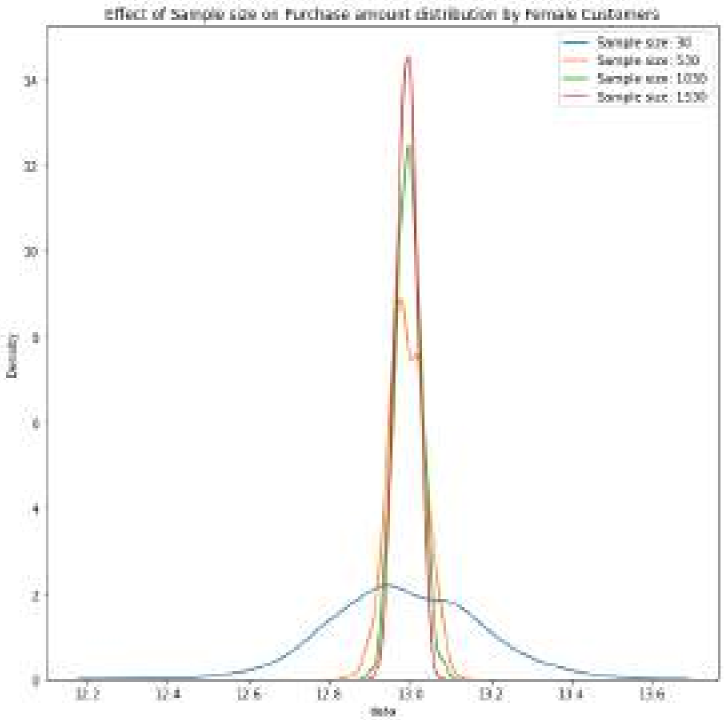
```
array([558839.56776615, 593228.61485073])
```

In [106]:

```
# Using Bootstrapping method to create CI for Avg Purchase for Purchases by Female Customers.
samp_size = []
samp_mean = []
for i in range(30,len(gen_data_pur.loc[gen_data_pur["Gender"] == "F", "Purchase_amt"].apply(np.log)),500):
    for j in range(500):
        samp_size.append(i)
        z = np.random.randint(low = 0, high = len(gen_data_pur.loc[gen_data_pur["Gender"] == "F", "Purchase_amt"])-1,size = i)
        z1 = gen_data_pur.loc[gen_data_pur["Gender"] == "F", "Purchase_amt"].apply(np.log).reset_index(drop = True)[z]
        samp_mean.append(z1.mean())
df = pd.DataFrame([samp_size, samp_mean]).T.rename(columns = {0:"samp_size", 1: "data"})
```

In [107]:

```
plt.figure(figsize = (10,10))
for i in df["samp_size"].unique():
    sns.distplot(df.loc[df["samp_size"]==i,"data"], hist = False, label = f"Sample size: {int(i)}")
plt.legend()
plt.title("Effect of Sample size on Purchase amount distribution by Female Customers")
plt.show()
# Effect of increasing the sample size:
# As the sample size increases, the peak of the distribution increases and the spread decreases. Hence, the width of 95% CI
# should decrease with increase in Sample size
```



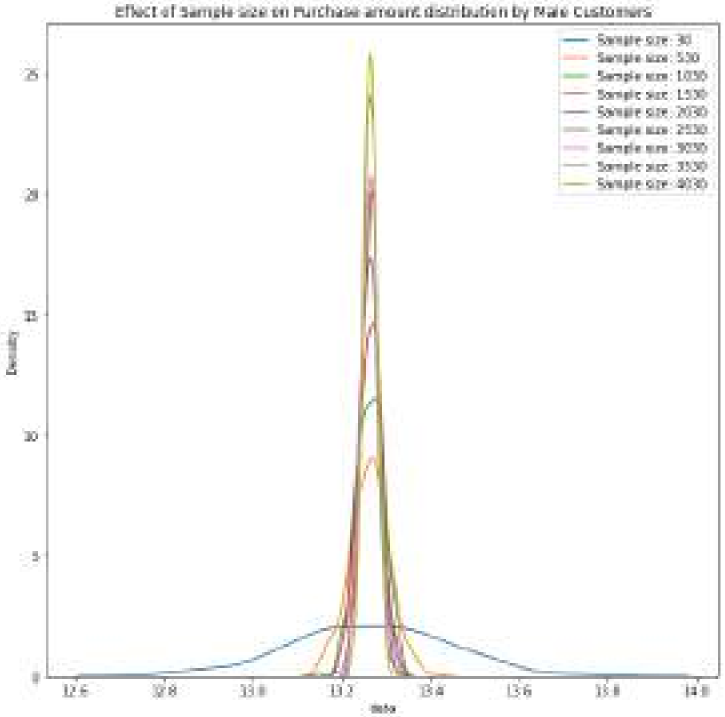
In [108]:
```
N = []
lower_ci = []
upper_ci = []
gend = []
for i in df["samp_size"].unique():
    N.append(i)
    df3 = df.loc[df["samp_size"] == i, "data"]
    low_lim, up_lim = np.exp(stats.t.interval(alpha = 0.95, df = len(df3)-1, loc = np.mean(df3), scale = np.std(df3)))
    lower_ci.append(low_lim)
    upper_ci.append(up_lim)
    gend.append("F")
gend_ci_avg_pur = pd.DataFrame(list(zip(N,gend, lower_ci,upper_ci)), columns =\
                               ["N", "Gender", "Lower_limit_CI", "Upper_Limit_CI"])
gend_ci_avg_pur
```

Out[108]:

	N	Gender	Lower_limit_CI	Upper_Limit_CI
0	30.0	F	307489.534070	620019.391542
1	530.0	F	403104.038287	476974.842550
2	1030.0	F	413762.812804	467514.467875
3	1530.0	F	417250.814370	460939.990478

In [109]:
```
# Using Bootstrapping method to create CI for Avg Purchase for Purchases by Male Customers.
samp_size = []
samp_mean = []
for i in range(30,len(gen_data_pur.loc[gen_data_pur["Gender"] == "M", "Purchase_amt"].apply(np.log)),500):
    for j in range(500):
        samp_size.append(i)
        z = np.random.randint(low = 0, high = len(gen_data_pur.loc[gen_data_pur["Gender"] == "M", "Purchase_amt"])-1,size = i)
        z1 = gen_data_pur.loc[gen_data_pur["Gender"] == "M", "Purchase_amt"].apply(np.log).reset_index(drop = True)[z]
        samp_mean.append(z1.mean())
df = pd.DataFrame([samp_size, samp_mean]).T.rename(columns = {0:"samp_size", 1: "data"})
```

In [110]:
```
plt.figure(figsize = (10,10))
for i in df["samp_size"].unique():
    sns.distplot(df.loc[df["samp_size"]==i,"data"], hist = False, label = f"Sample size: {int(i)}")
plt.legend()
plt.title("Effect of Sample size on Purchase amount distribution by Male Customers")
plt.show()
# Effect of increasing the sample size:
# As the sample size increases, the peak of the distribution increases and the spread decreases. Hence, the width of 95% CI
# should decrease with increase in Sample size
```



In [111]:
```
N = []
lower_ci = []
upper_ci = []
gend = []
for i in df["samp_size"].unique():
    N.append(i)
    df3 = df.loc[df["samp_size"] == i, "data"]
    low_lim, up_lim = np.exp(stats.t.interval(alpha = 0.95, df = len(df3)-1, loc = np.mean(df3), scale = np.std(df3)))
    lower_ci.append(low_lim)
    upper_ci.append(up_lim)
    gend.append("M")
gend_ci_avg_pur = gend_ci_avg_pur.append(pd.DataFrame(list(zip(N,gend, lower_ci,upper_ci)), columns =\
                               ["N", "Gender", "Lower_limit_CI", "Upper_Limit_CI"])).reset_index(drop = True)
```

In [112]:
```
gend_ci_avg_pur
# The below 95% CI has been created using t distribution.
# As the sample size increases, the lower limit CI increases and the upper limit CI decreases. Hence, width of CI decreases.
```

Out[112]:

	N	Gender	Lower_limit_CI	Upper_Limit_CI
0	30.0	F	307489.534070	620019.391542
1	530.0	F	403104.038287	476974.842550
2	1030.0	F	413762.812804	467514.467875
3	1530.0	F	417250.814370	460939.990478
4	30.0	M	405757.563351	815730.183046
5	530.0	M	526879.331397	627400.205552
6	1030.0	M	542108.035457	611563.514464
7	1530.0	M	546264.969172	605490.271253
8	2030.0	M	550661.802260	601650.223756
9	2530.0	M	555100.470329	599234.364222
10	3030.0	M	554573.671311	597006.834016
11	3530.0	M	558001.942354	593844.586157
12	4030.0	M	558522.731813	593600.342454

Analyzing the Purchases made by customers having different Marital Status

In [113]:
```
mar_data_pur = data.groupby(["User_ID", "Marital_Status"]).aggregate(Purchase_amt = ("Purchase", "sum")).reset_index()
mar_data_pur
```

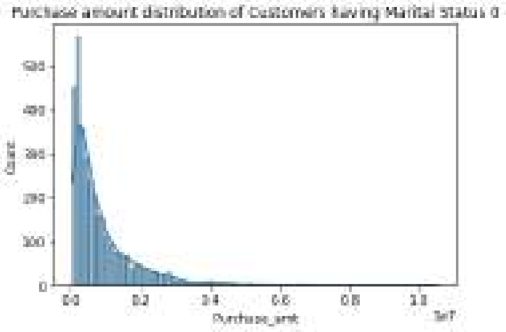
Out[113]:

	User_ID	Marital_Status	Purchase_amt
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

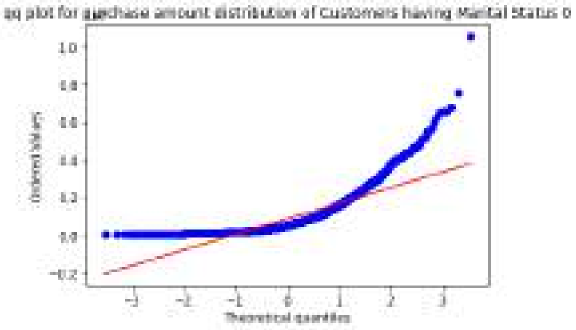
5891 rows × 3 columns

In [114]:
```
mar_pur_0 = mar_data_pur.loc[mar_data_pur["Marital_Status"] == '0', ::].reset_index(drop = True)
mar_pur_1 = mar_data_pur.loc[mar_data_pur["Marital_Status"] == '1', ::].reset_index(drop = True)
```

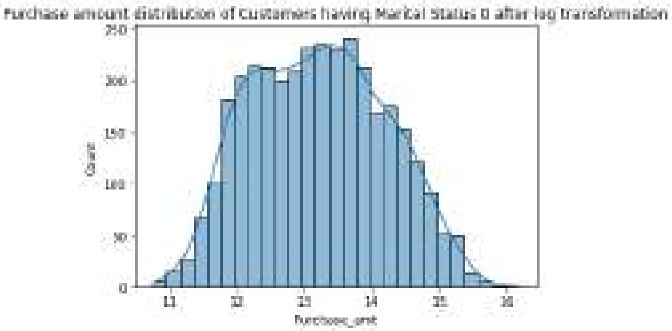
In [115]:
```
sns.histplot(mar_pur_0["Purchase_amt"], kde = True)
plt.title("Purchase amount distribution of Customers having Marital Status 0")
plt.show()
# As can be seen from the plot below, the Purchase amount distribution for customers with Marital Status 0 is right skewed.
```



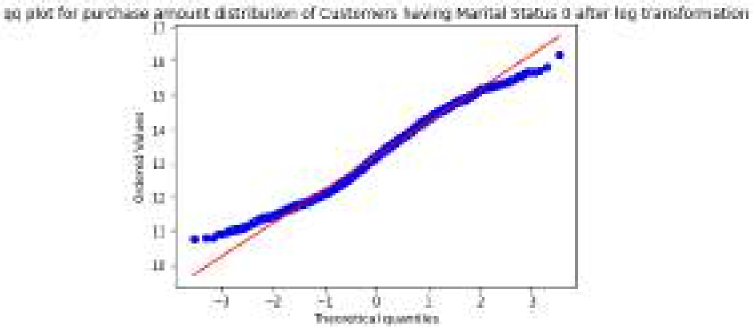
In [116]:
```
stats.probplot(mar_pur_0["Purchase_amt"], dist="norm", plot=py)
plt.title("qq plot for purchase amount distribution of Customers having Marital Status 0")
py.show()
# As can be seen from below qq-plot, the distribution of Purchase made by customers with Marital Status 0 is not Normal.
# Hence, we need to transform the data to Normal before calculating 95% CI for the group.
```



In [117]:
```
sns.histplot(mar_pur_0["Purchase_amt"].apply(np.log), kde = True)
plt.title("Purchase amount distribution of Customers having Marital Status 0 after log transformation")
plt.show()
# As can be seen from the plot below, the Purchase amount distribution for customers with Marital Status 0 becomes approximately
# Normal after applying Log transformation.
```



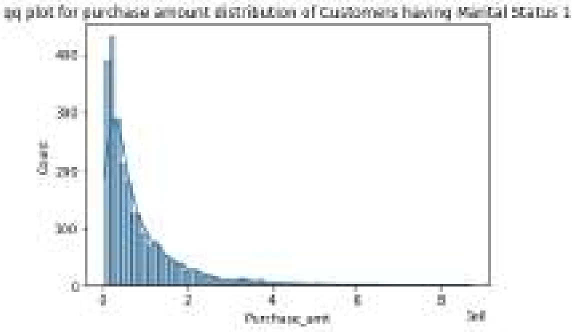
In [118]:
```
stats.probplot(mar_pur_0["Purchase_amt"].apply(np.log), dist="norm", plot=py)
plt.title("qq plot for purchase amount distribution of Customers having Marital Status 0 after log transformation")
py.show()
# After applying log transformation, the Purchase distribution for Customers with Marital Status 0 approximately becomes normal
# after log transformation.
```



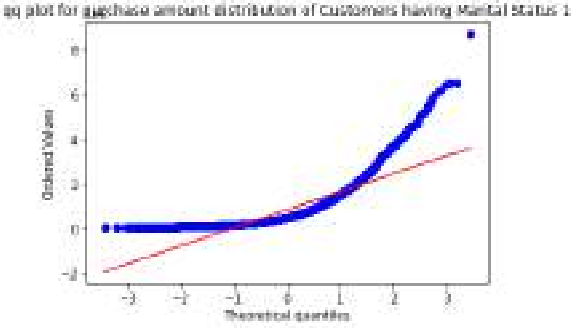
In [119]:
```
# Getting upper and lower limit of average Purchase for 95% CI for Customers with Marital status 0.
mar0_pur_mean = mar_pur_0["Purchase_amt"].apply(np.log).mean()
mar0_pur_std = mar_pur_0["Purchase_amt"].apply(np.log).std()/len(mar_pur_0["Purchase_amt"])**0.5
lower_limit_mar0_purchase, upper_limit_mar0_purchase = np.exp(norm.ppf([0.025,0.975],loc = mar0_pur_mean,scale = mar0_pur_std))\
.round(2)
lower_limit_mar0_purchase,round(np.exp(mar0_pur_mean),2), upper_limit_mar0_purchase
```

Out[119]: (525697.2, 543544.13, 561996.94)

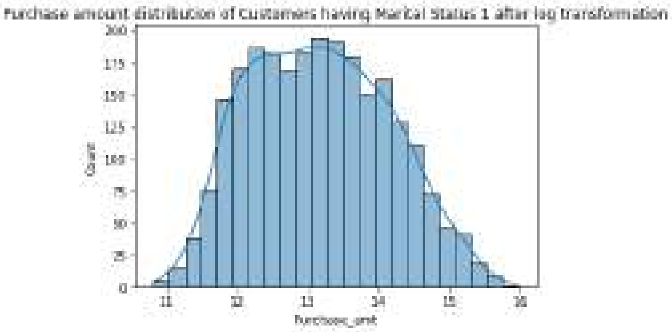
In [120]:
```python
sns.histplot(mar_pur_1["Purchase_amt"], kde = True)
plt.title("qq plot for purchase amount distribution of Customers having Marital Status 1")
plt.show()
# As can be seen from the plot below, the Purchase amount distribution for customers with Marital Status 1 is right skewed.
```



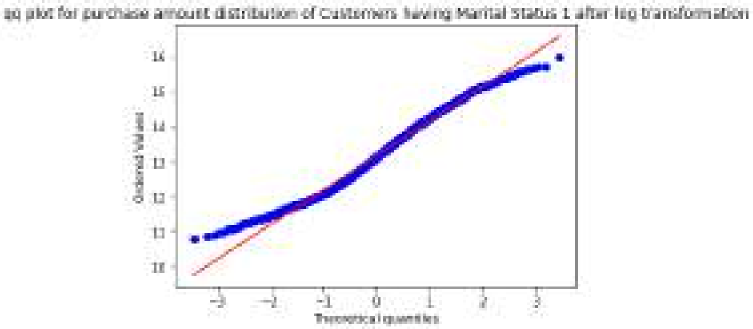
In [121]:
```python
stats.probplot(mar_pur_1["Purchase_amt"], dist="norm", plot=py)
plt.title("qq plot for purchase amount distribution of Customers having Marital Status 1")
py.show()
# As can be seen from below qq-plot, the distribution of Purchase made by customers with Marital Status 1 is not Normal.
# Hence, we need to transform the data to Normal before calculating 95% CI for the group.
```



In [122]:
```
sns.histplot(mar_pur_1["Purchase_amt"].apply(np.log), kde = True)
plt.title("Purchase amount distribution of Customers having Marital Status 1 after log transformation")
plt.show()
# As can be seen from the plot below, the Purchase amount distribution for customers with Marital Status 1 becomes approximately
# Normal after applying Log transformation.
```



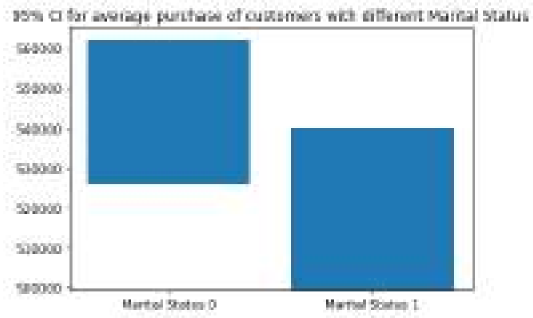
In [123]:
```
stats.probplot(mar_pur_1["Purchase_amt"].apply(np.log), dist="norm", plot=py)
plt.title("qq plot for purchase amount distribution of Customers having Marital Status 1 after log transformation")
py.show()
# After applying log transformation, the Purchase distribution for Customers with Marital Status 1 approximately becomes normal
# after log transformation.
```



In [124]:
```
# Getting upper and lower limit of Purchase for 95% CI for Customers with Marital status 1.
mar1_pur_mean = mar_pur_1["Purchase_amt"].apply(np.log).mean()
mar1_pur_std = mar_pur_1["Purchase_amt"].apply(np.log).std()/len(mar_pur_1["Purchase_amt"])**0.5
lower_limit_mar1_purchase, upper_limit_mar1_purchase = np.exp(norm.ppf([0.025,0.975],loc = mar1_pur_mean,scale = mar1_pur_std))\
.round(2)
lower_limit_mar1_purchase,round(np.exp(mar1_pur_mean),2), upper_limit_mar1_purchase
```

Out[124]:
```
(499607.08, 519399.38, 539975.76)
```

In [125]:
```
plt.bar(x = ["Marital Status 0","Marital Status 1"], bottom = [lower_limit_mar0_purchase, lower_limit_mar1_purchase], \
        height = [upper_limit_mar0_purchase - lower_limit_mar0_purchase, upper_limit_mar1_purchase - \
                  lower_limit_mar1_purchase])
plt.title("95% CI for average purchase of customers with different Marital Status")
plt.show()
# As can be seen, 95% CI for the average purchase made by a customer with Marital Status 0 overlaps with average purchase made by
# customer with Marital Status 1.
```



In [126]:
```
np.exp(stats.t.interval(alpha = 0.95, df = len(mar_pur_0)-1, loc = np.mean(mar_pur_0["Purchase_amt"].apply(np.log)), scale = \
                        stats.sem(mar_pur_0["Purchase_amt"].apply(np.log))))
```

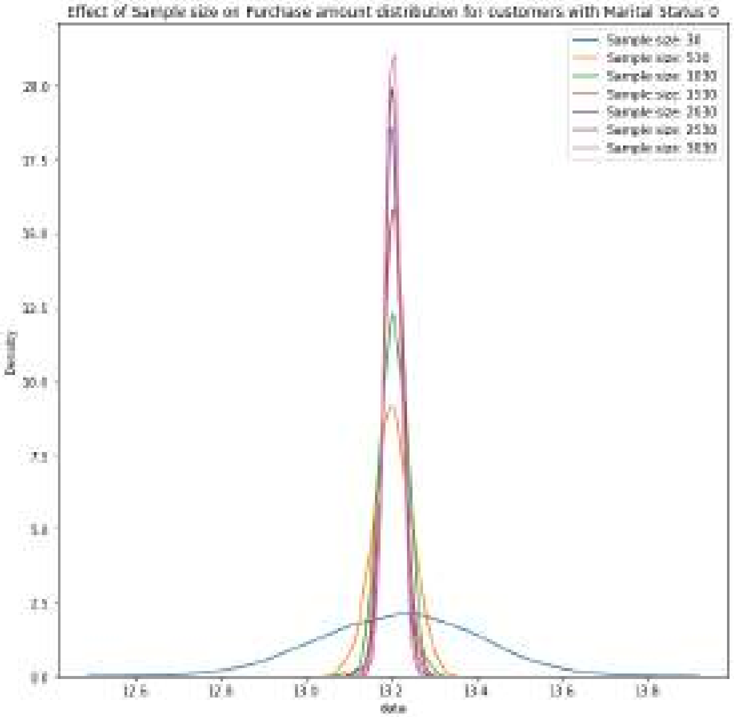
Out[126]:
```
array([525690.97570531, 562003.59317476])
```

In [127]:
```
np.exp(stats.t.interval(alpha = 0.95, df = len(mar_pur_0)-1, loc = np.mean(mar_pur_1["Purchase_amt"].apply(np.log)), scale = \
                        stats.sem(mar_pur_1["Purchase_amt"].apply(np.log))))
# As can be seen, even 95% CI for average purchase created using T distribution overlaps for customers with Marital Status 0 and
# 1.
```

Out[127]:
```
array([499600.20125979, 539983.1981923 ])
```

In [128]:
```
# Using Bootstrapping method to create CI for Avg Purchase for Purchases by Customers with Marital Status 0.
samp_size = []
samp_mean = []
for i in range(30,len(mar_pur_0["Purchase_amt"].apply(np.log)),500):
    for j in range(500):
        samp_size.append(i)
        z = np.random.randint(low = 0, high = len(mar_pur_0["Purchase_amt"]),size = i)
        z1 = mar_pur_0["Purchase_amt"].apply(np.log).reset_index(drop = True)[z]
        samp_mean.append(z1.mean())
df = pd.DataFrame([samp_size, samp_mean]).T.rename(columns = {0:"samp_size", 1: "data"})
```

In [129]:
```
plt.figure(figsize = (10,10))
for i in df["samp_size"].unique():
    sns.distplot(df.loc[df["samp_size"]==i,"data"], hist = False, label = f"Sample size: {int(i)}")
plt.legend()
plt.title("Effect of Sample size on Purchase amount distribution for customers with Marital Status 0")
plt.show()
# Effect of increasing the sample size:
# As the sample size increases, the peak of the distribution increases and the spread decreases. Hence, the width of 95% CI
# should decrease with increase in Sample size
```



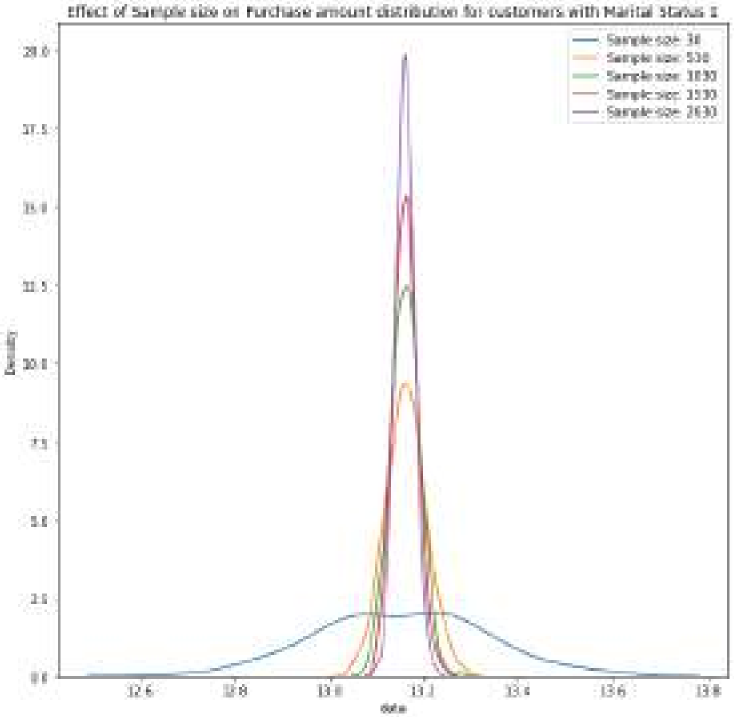
In [130]:
```
N = []
lower_ci = []
upper_ci = []
mar = []
for i in df["samp_size"].unique():
    N.append(i)
    df3 = df.loc[df["samp_size"] == i, "data"]
    low_lim, up_lim = np.exp(stats.t.interval(alpha = 0.95, df = len(df3)-1, loc = np.mean(df3), scale = np.std(df3)))
    lower_ci.append(low_lim)
    upper_ci.append(up_lim)
    mar.append("0")
mar_ci_avg_pur = pd.DataFrame(list(zip(N,mar, lower_ci,upper_ci)), columns =\
                              ["N", "Marital Status", "Lower_limit_CI", "Upper_Limit_CI"]).reset_index(drop = True)
mar_ci_avg_pur
```

Out[130]:

	N	Marital Status	Lower_limit_CI	Upper_Limit_CI
0	30.0	0	386554.689738	786434.133840
1	530.0	0	498622.605024	591301.167801
2	1030.0	0	512540.919827	578976.096676
3	1530.0	0	518342.564282	571798.043250
4	2030.0	0	520859.111149	568496.646556
5	2530.0	0	523008.149178	565709.325030
6	3030.0	0	524284.801732	562867.188502

In [131]:
```
# Using Bootstrapping method to create CI for Avg Purchase for Purchases by Customers with Marital Status 1.
samp_size = []
samp_mean = []
for i in range(30,len(mar_pur_1["Purchase_amt"].apply(np.log)),500):
    for j in range(500):
        samp_size.append(i)
        z = np.random.randint(low = 0, high = len(mar_pur_1["Purchase_amt"]),size = i)
        z1 = mar_pur_1["Purchase_amt"].apply(np.log).reset_index(drop = True)[z]
        samp_mean.append(z1.mean())
df = pd.DataFrame([samp_size, samp_mean]).T.rename(columns = {0:"samp_size", 1: "data"})
```

In [132]:
```
plt.figure(figsize = (10,10))
for i in df["samp_size"].unique():
    sns.distplot(df.loc[df["samp_size"]==i,"data"], hist = False, label = f"Sample size: {int(i)}")
plt.legend()
plt.title("Effect of Sample size on Purchase amount distribution for customers with Marital Status 1")
plt.show()
# Effect of increasing the sample size:
# As the sample size increases, the peak of the distribution increases and the spread decreases. Hence, the width of 95% CI
# should decrease with increase in Sample size
```



In [133]:
```
N = []
lower_ci = []
upper_ci = []
mar = []
for i in df["samp_size"].unique():
    N.append(i)
    df3 = df.loc[df["samp_size"] == i, "data"]
    low_lim, up_lim = np.exp(stats.t.interval(alpha = 0.95, df = len(df3)-1, loc = np.mean(df3), scale = np.std(df3)))
    lower_ci.append(low_lim)
    upper_ci.append(up_lim)
    mar.append("1")
mar_ci_avg_pur = mar_ci_avg_pur.append(pd.DataFrame(list(zip(N,mar, lower_ci,upper_ci)), columns =\
                                ["N", "Marital Status", "Lower_limit_CI", "Upper_Limit_CI"])).reset_index(drop = True)
```

In [134]:
```python
mar_ci_avg_pur
# The below 95% CI has been created using t distribution.
# As the sample size increases, the lower limit CI increases and the upper limit CI decreases. Hence, width of CI decreases.
# The 95% CI for average purchas made by customers with different Marital Status are overlapping.
```

Out[134]:

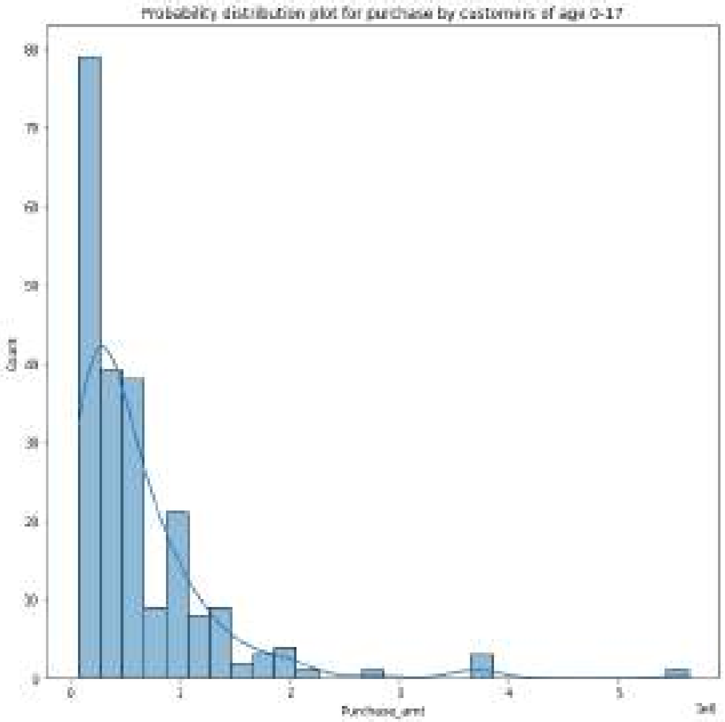
	N	Marital Status	Lower_limit_CI	Upper_Limit_CI
0	30.0	0	386554.689738	786434.133840
1	530.0	0	498622.605024	591301.167801
2	1030.0	0	512540.919827	578976.096676
3	1530.0	0	518342.564282	571798.043250
4	2030.0	0	520859.111149	568496.646556
5	2530.0	0	523008.149178	565709.325030
6	3030.0	0	524284.801732	562867.188502
7	30.0	1	364593.612308	729690.631658
8	530.0	1	478494.567330	565422.870982
9	1030.0	1	489321.894292	551861.782060
10	1530.0	1	494501.987059	545922.388599
11	2030.0	1	499205.597880	540179.984003

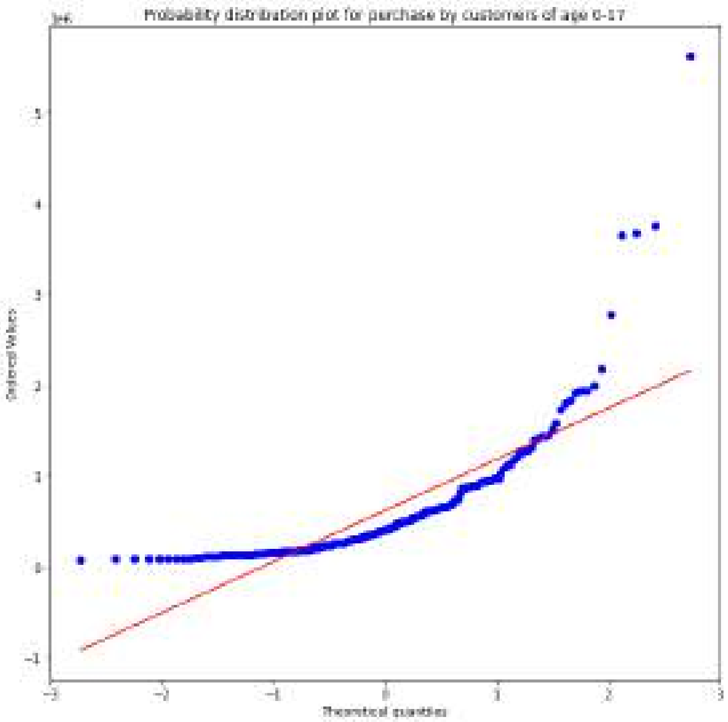
Analyzing the Purchases made by Customers from different age groups.

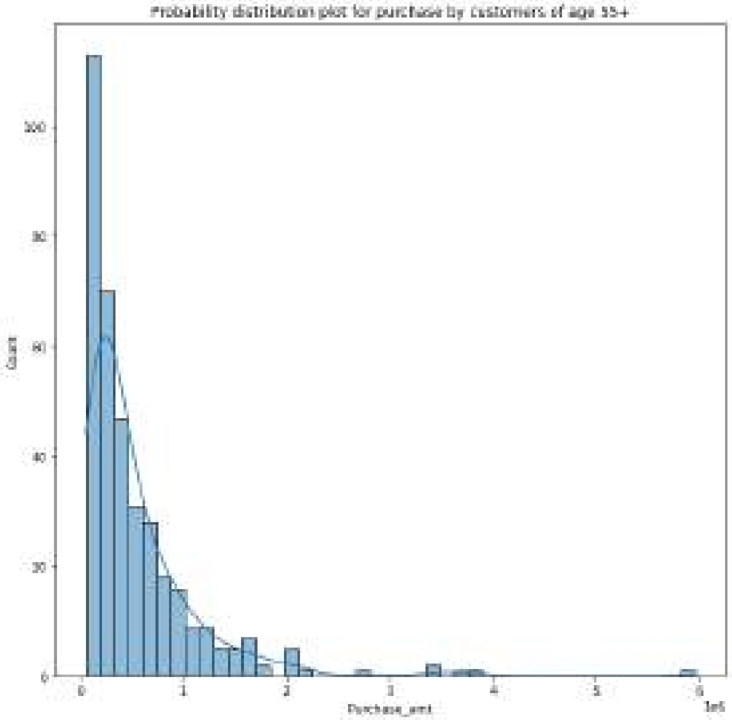
In [135]:
```python
age_data_pur = data.groupby(["User_ID", "Age"]).aggregate(Purchase_amt = ("Purchase", "sum")).reset_index()
age_data_pur["Age"].unique()
```

Out[135]:
```
array(['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25'],
      dtype=object)
```

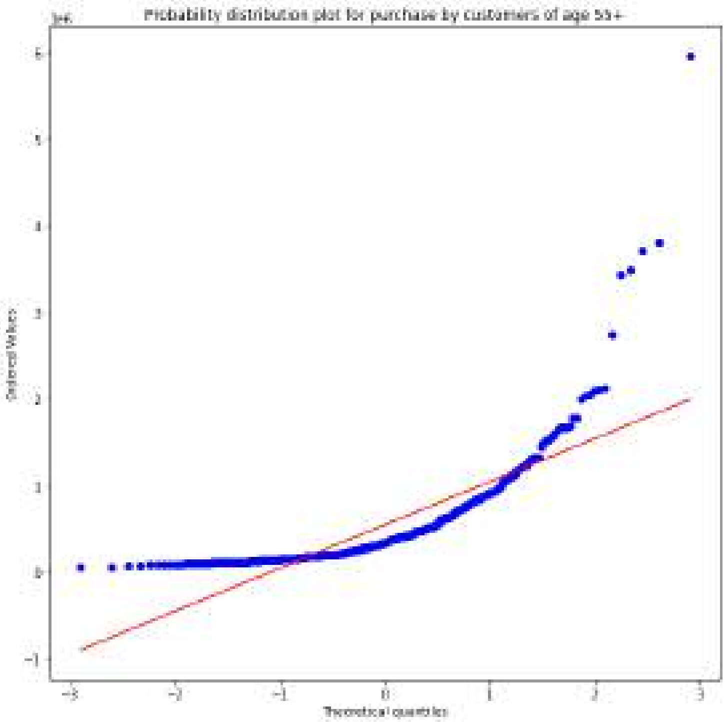
In [136]:
```
for i in age_data_pur["Age"].unique():
    plt.figure(figsize = (10,10))
    sns.histplot(age_data_pur.loc[age_data_pur["Age"] == i, "Purchase_amt"], kde = True)
    plt.title(f"Probability distribution plot for purchase by customers of age {i}")
    plt.show()
    plt.figure(figsize = (10,10))
    stats.probplot(age_data_pur.loc[age_data_pur["Age"] == i, "Purchase_amt"], dist="norm", plot=py)
    plt.title(f"Probability distribution plot for purchase by customers of age {i}")
    py.show()
# As csn be seen fromthe below plots, the Purchase amount distribution for all age groups are right skewed. Hence, they need to
# be transformed to Normal distribution before creating the Confidence interval for them.
```



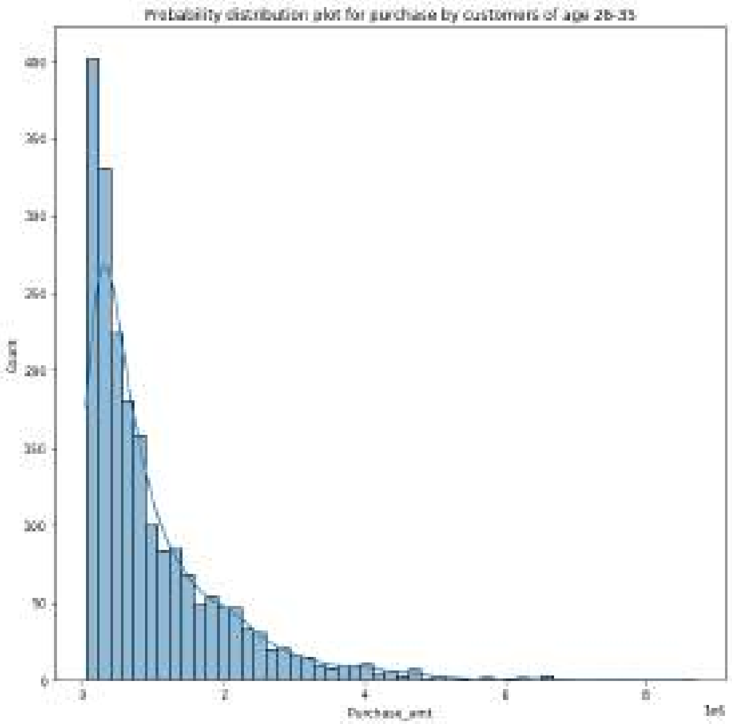

Probability distribution plot for purchase by customers of age 0-17
Ordered Values
Theoretical quantiles

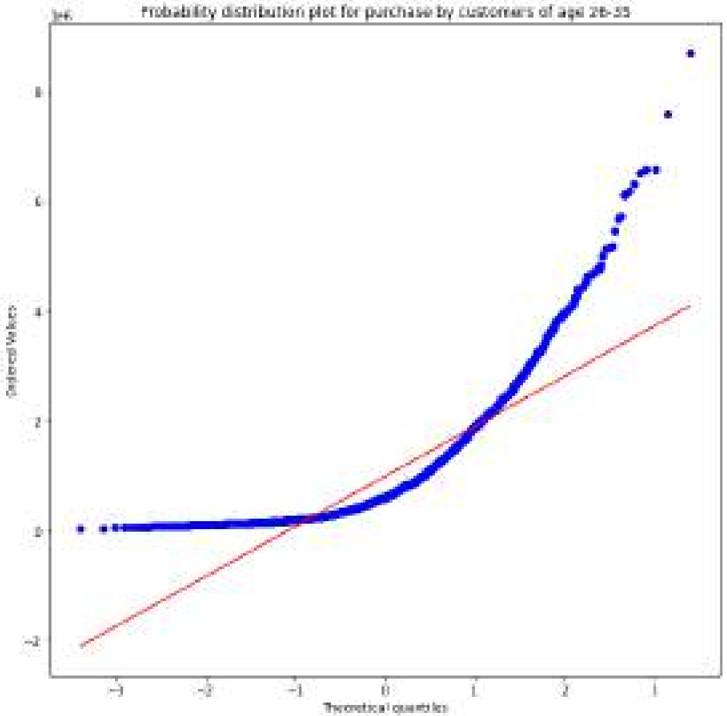


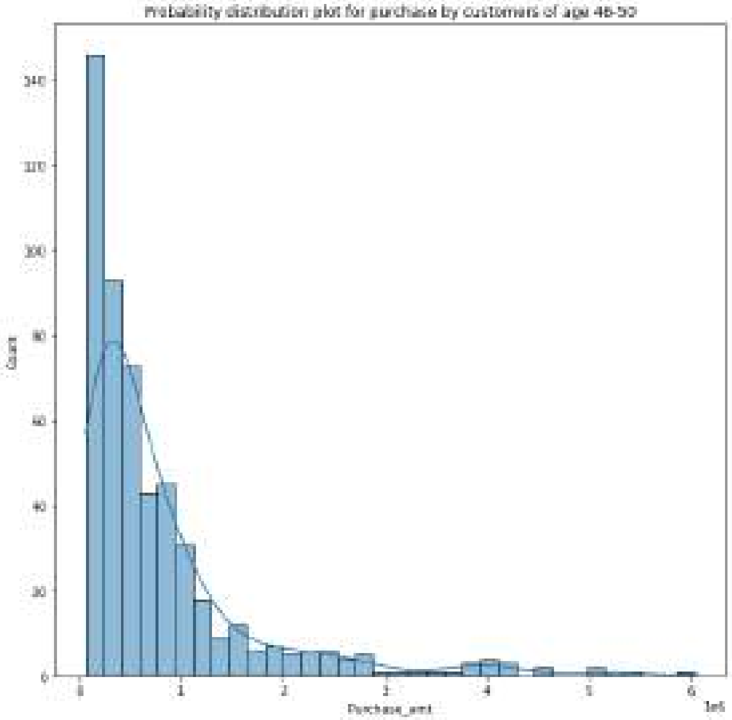
Probability distribution plot for purchase by customers of age 55+
Count
Purchase_amt
1e6



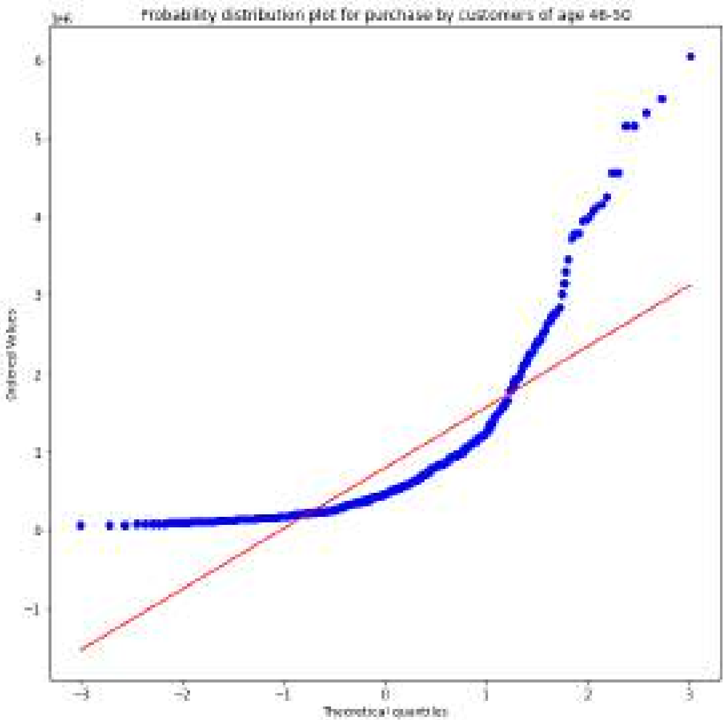
Probability distribution plot for purchase by customers of age 55+
1e6
Ordered Values
Theoretical quantiles


Probability distribution plot for purchase by customers of age 26-35
Count
Purchase_amt
1e6

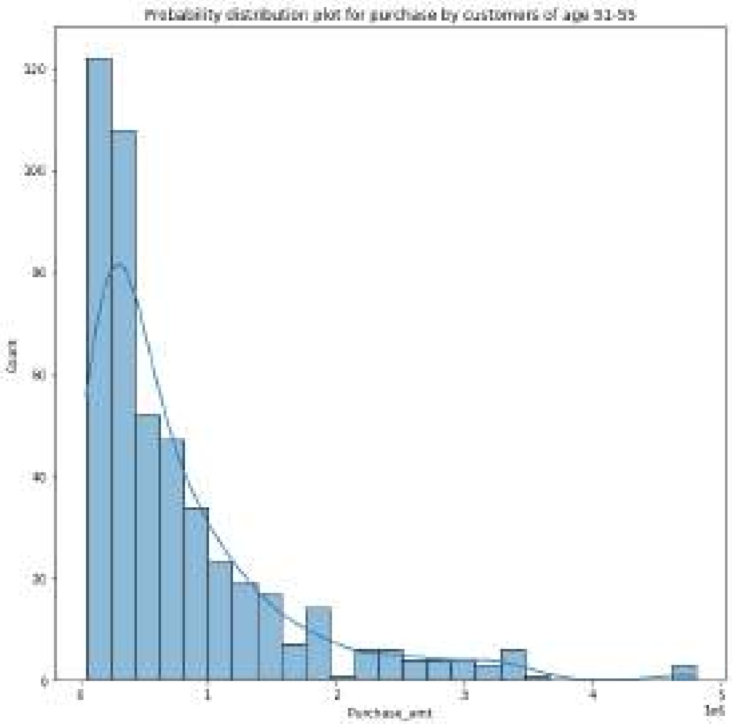

Probability distribution plot for purchase by customers of age 26-35
1e6
Ordered Values
Theoretical quantiles

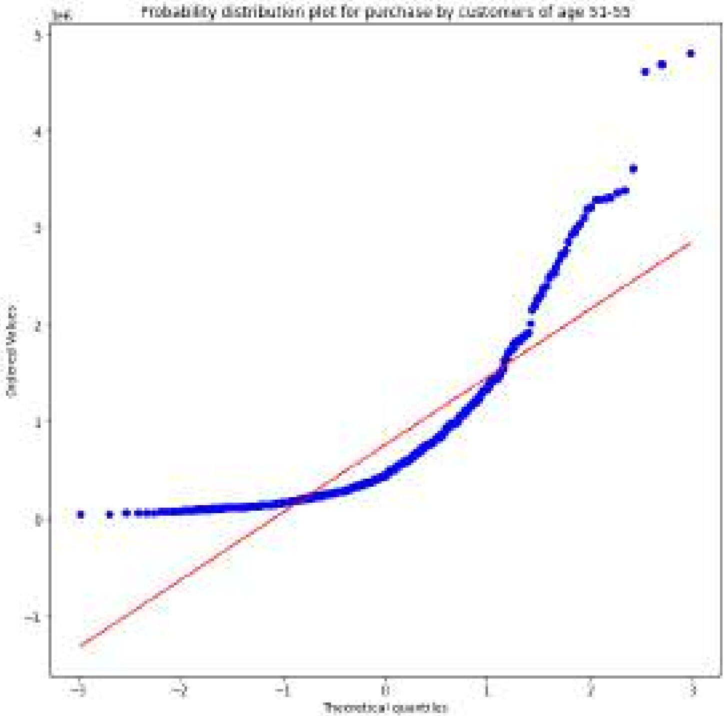


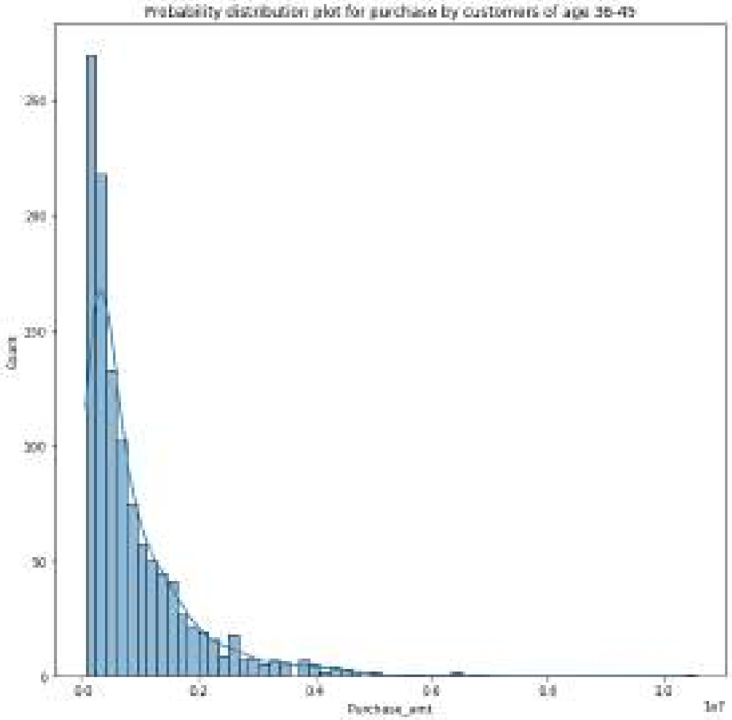
Probability distribution plot for purchase by customers of age 46-50
Count
Purchase_amt
1e6

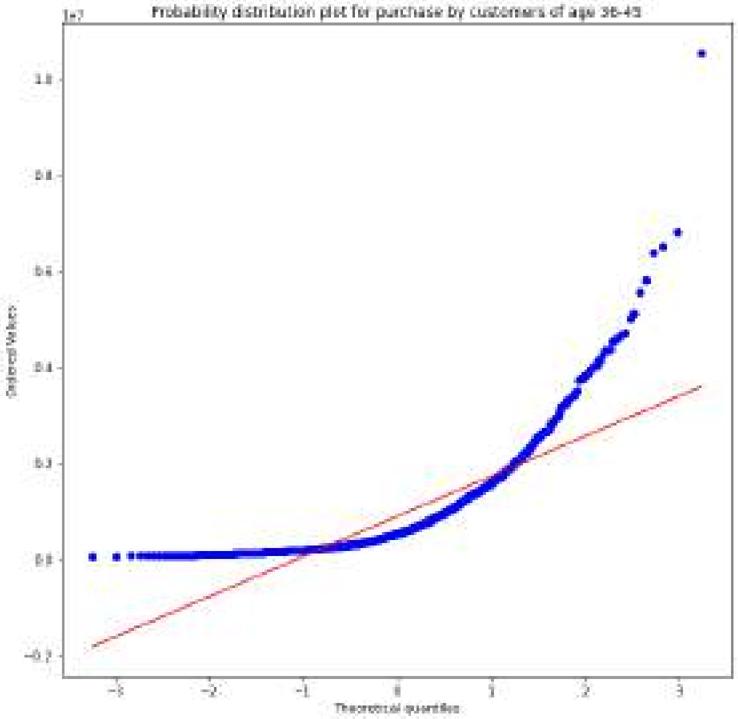


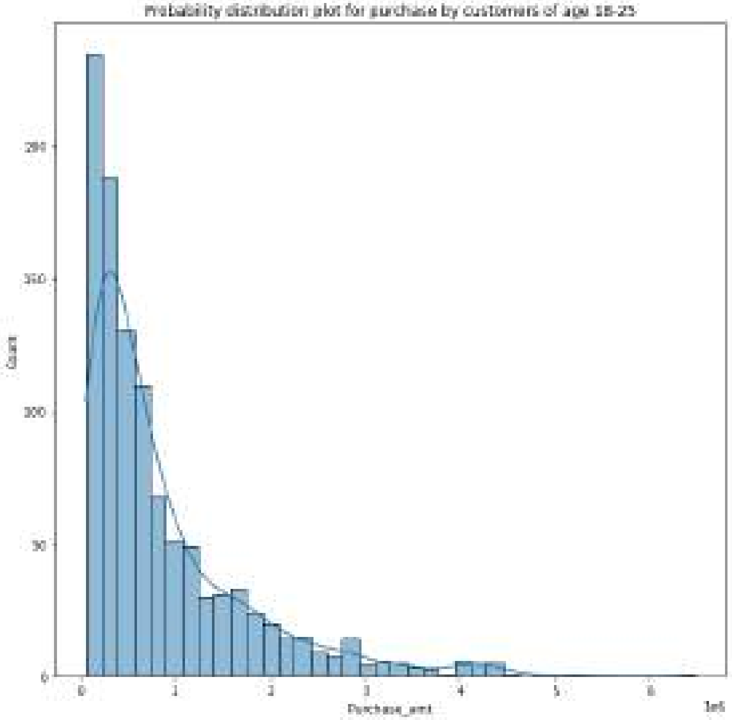
Probability distribution plot for purchase by customers of age 46-50
1e6
Ordered Values
Theoretical quantiles


Probability distribution plot for purchase by customers of age 51-55
Count
Purchase_amt
1e6
0
20
40
60
80
100
120
0
1
2
3
4
5

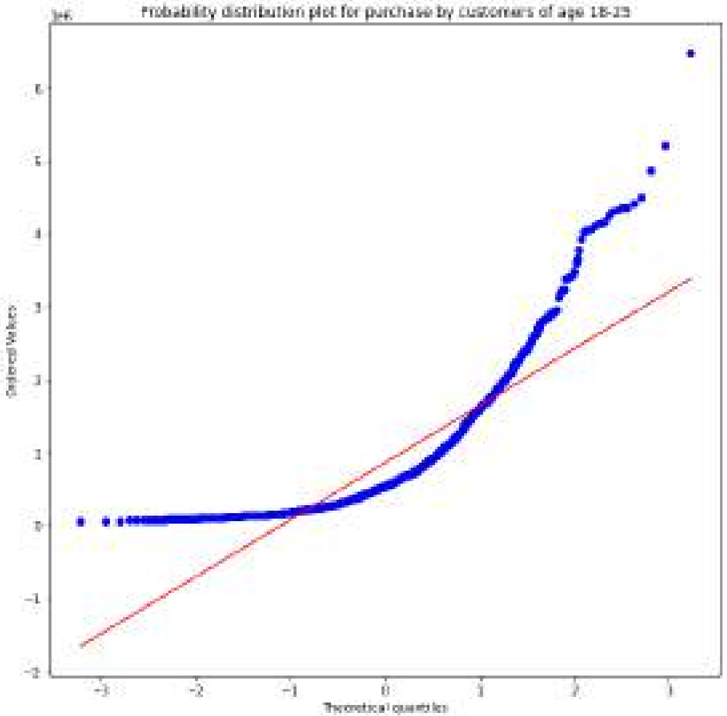

Probability distribution plot for purchase by customers of age 51-55
1e6
Ordered Values
Theoretical quantiles


Probability distribution plot for purchase by customers of age 36-45
Count
Purchase_amt
0.0
0.2
0.4
0.6
0.8
1.0
1e7
0
50
100
150
200
250


Probability distribution plot for purchase by customers of age 36-45
Ordered Values
Theoretical quantiles

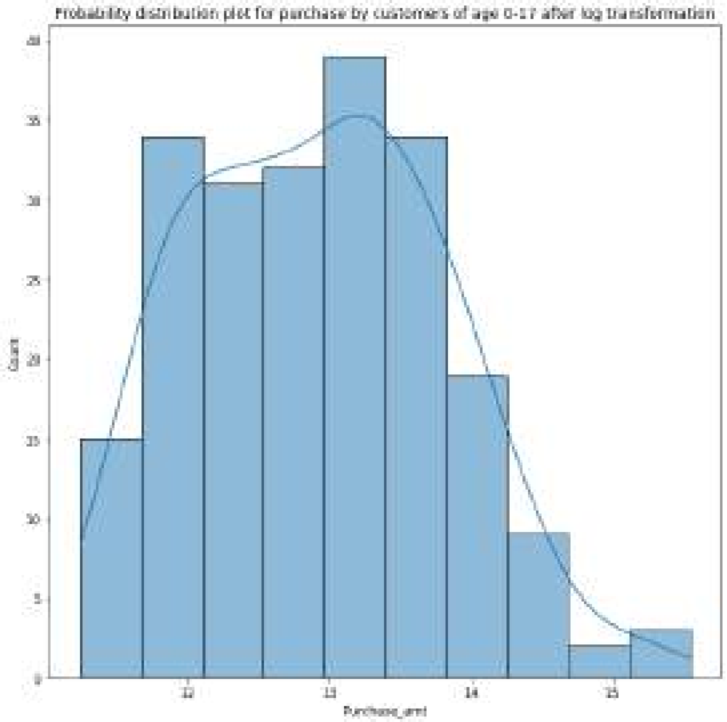


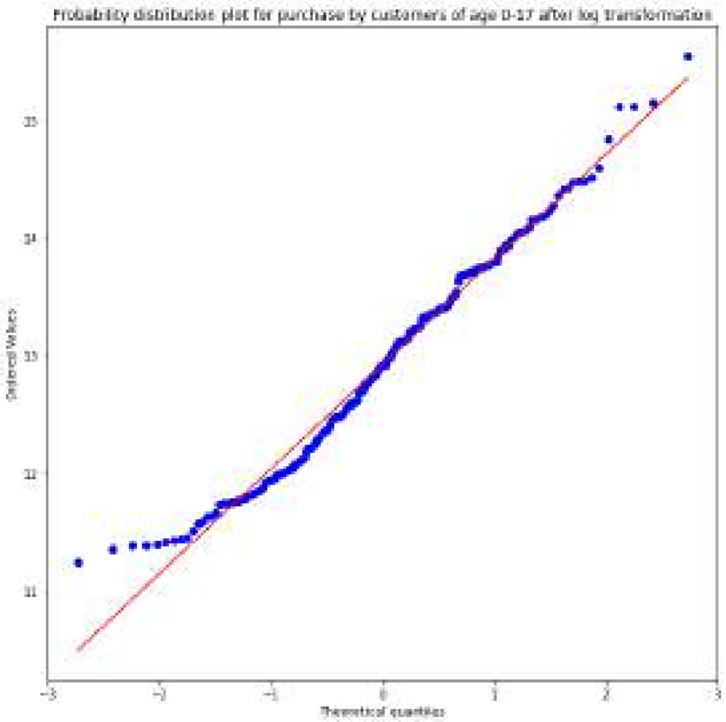
Probability distribution plot for purchase by customers of age 18-25
Count
Purchase_amt
0
1
2
3
4
5
6
1e6

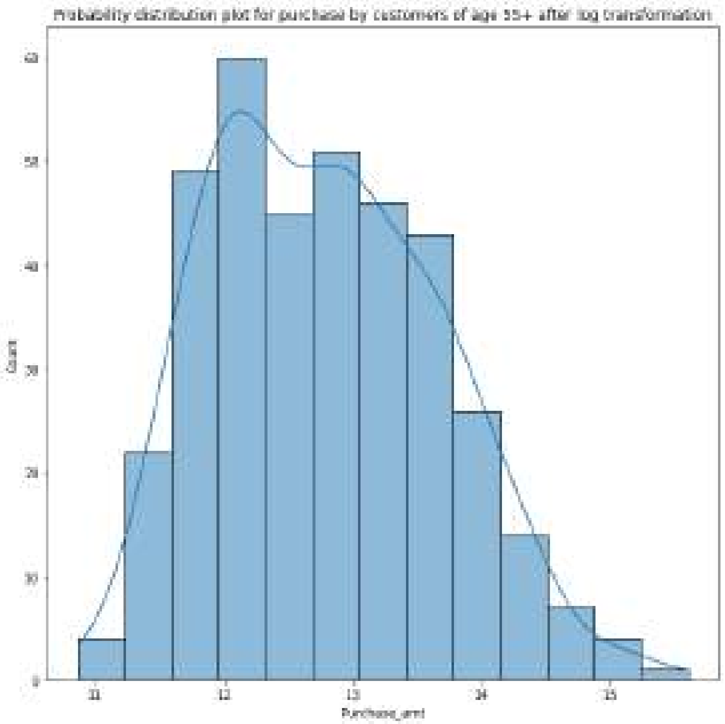


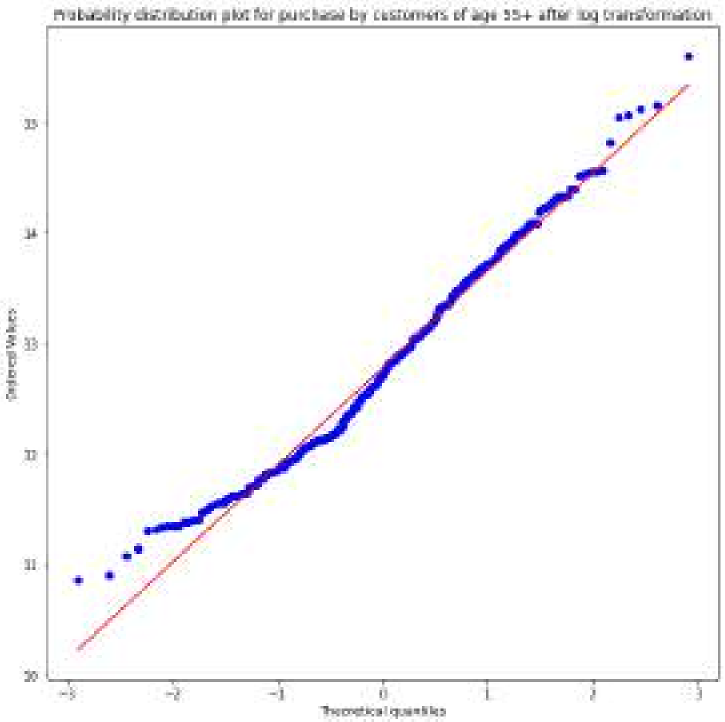
Probability distribution plot for purchase by customers of age 18-25
1e6
Ordered Values
Theoretical quantiles

In [137]:
```
for i in age_data_pur["Age"].unique():
    plt.figure(figsize = (10,10))
    sns.histplot(age_data_pur.loc[age_data_pur["Age"] == i, "Purchase_amt"].apply(np.log), kde = True)
    plt.title(f"Probability distribution plot for purchase by customers of age {i} after log transformation")
    plt.show()
    plt.figure(figsize = (10,10))
    stats.probplot(age_data_pur.loc[age_data_pur["Age"] == i, "Purchase_amt"].apply(np.log), dist="norm", plot=py)
    plt.title(f"Probability distribution plot for purchase by customers of age {i} after log transformation")
    py.show()
# As csn be seen fromthe below plots, the Purchase amount distribution for all age groups become approximately normal distributed
# after applying the log transformation.
```

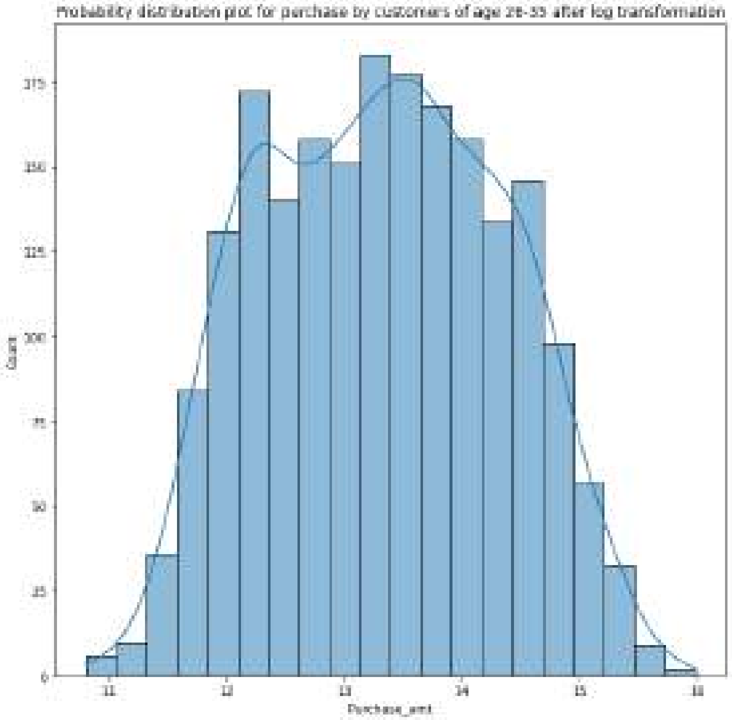



Probability distribution plot for purchase by customers of age 0-17 after log transformation
Ordered Values
Theoretical quantiles
11
12
13
14
15
−3
−2
−1
0
1
2
3

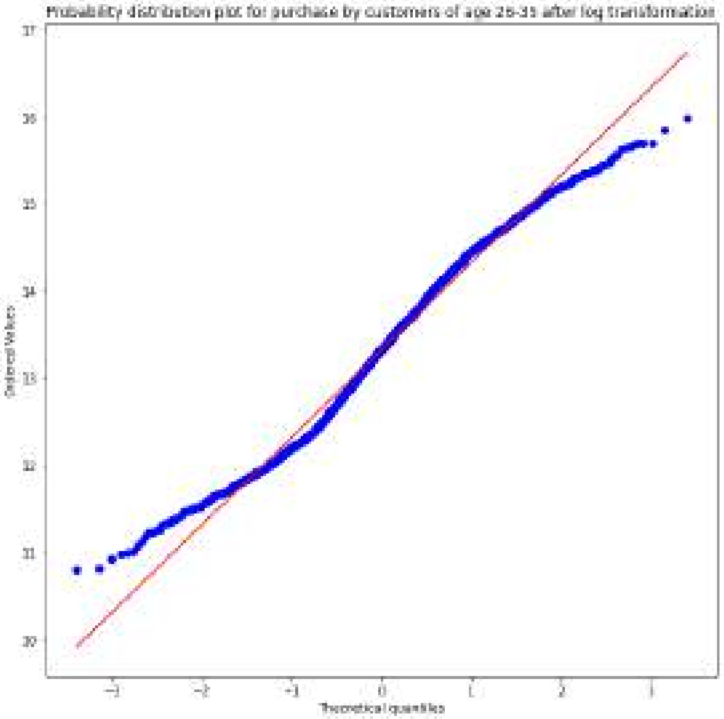

Probability distribution plot for purchase by customers of age 55+ after log transformation
Count
Purchase_amt

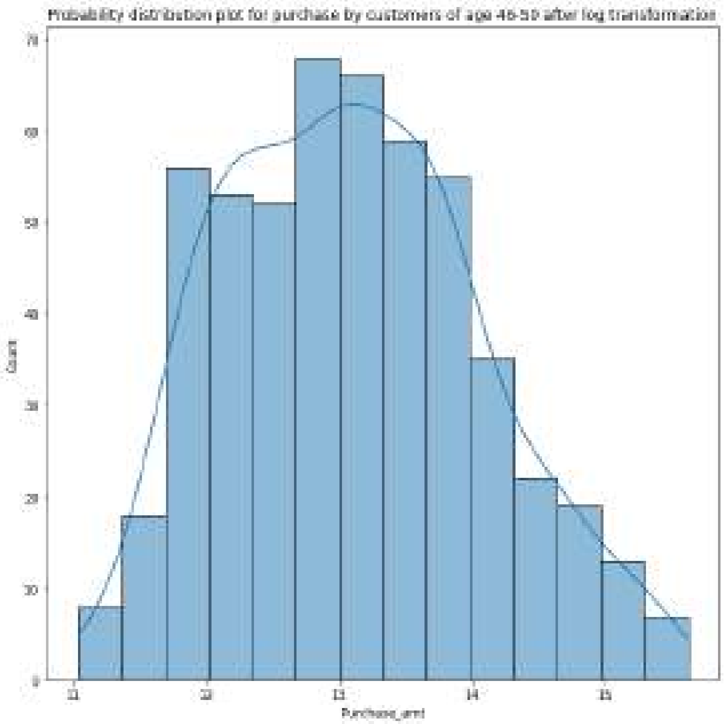


Probability distribution plot for purchase by customers of age 55+ after log transformation
Ordered Values
Theoretical quantiles

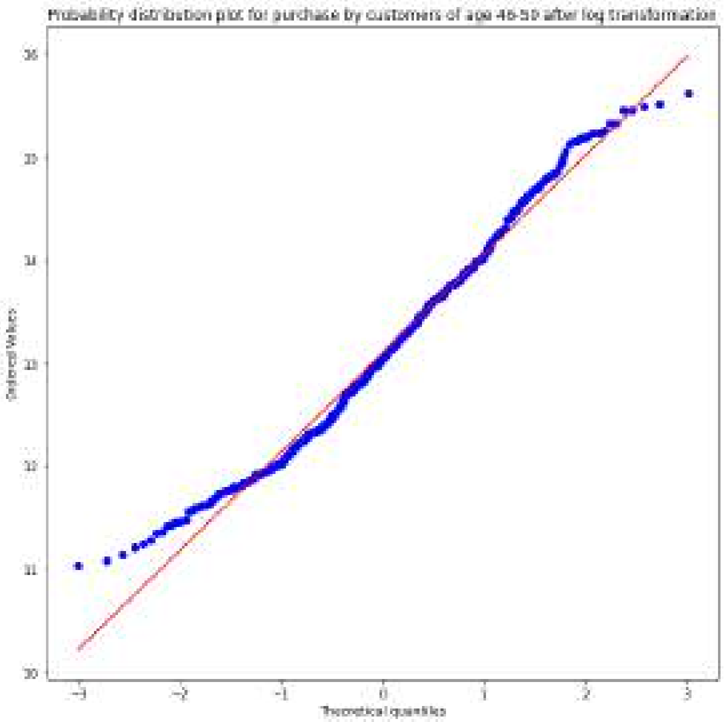


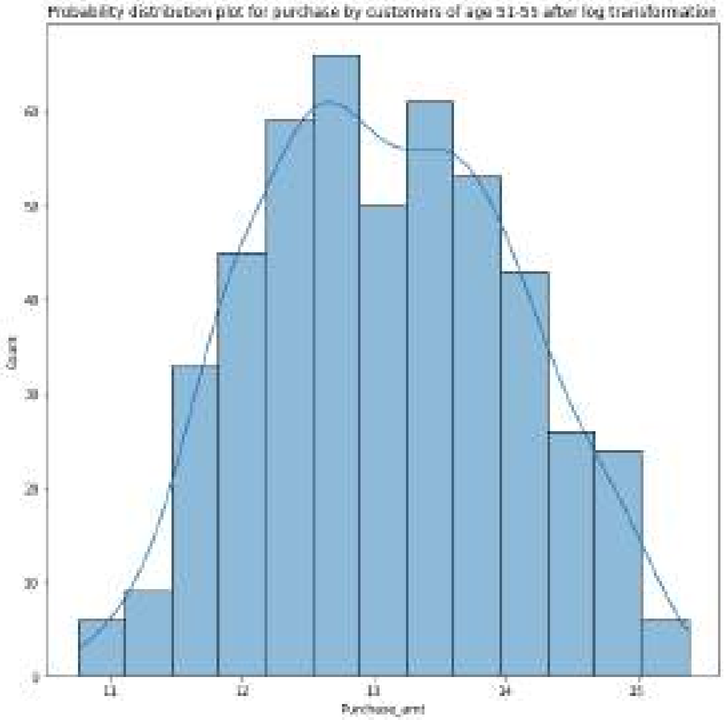
Probability distribution plot for purchase by customers of age 26-35 after log transformation
Count
Purchase_amt
0
25
50
75
100
125
150
175
11
12
13
14
15
16

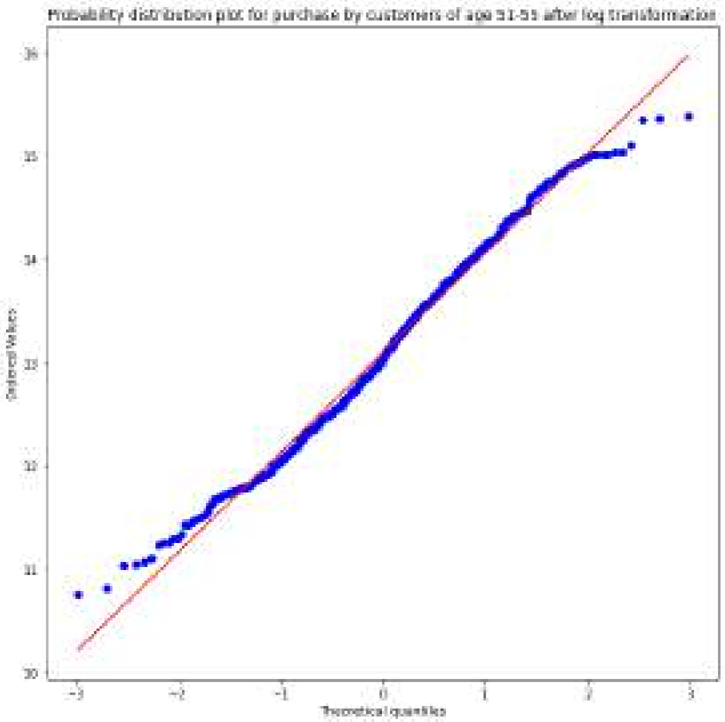

Probability distribution plot for purchase by customers of age 26-35 after log transformation
Ordered Values
Theoretical quantiles



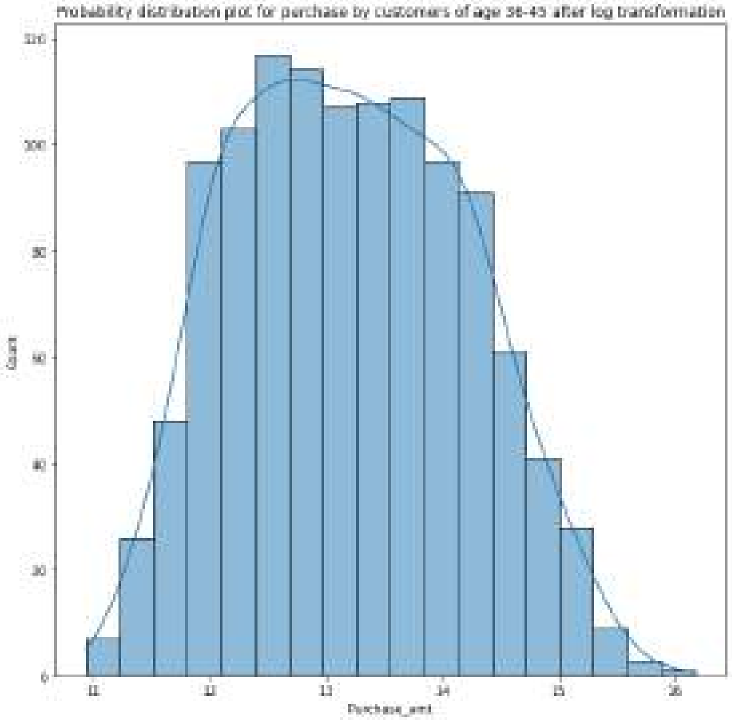
Probability distribution plot for purchase by customers of age 46-50 after log transformation
Count
Purchase_amt

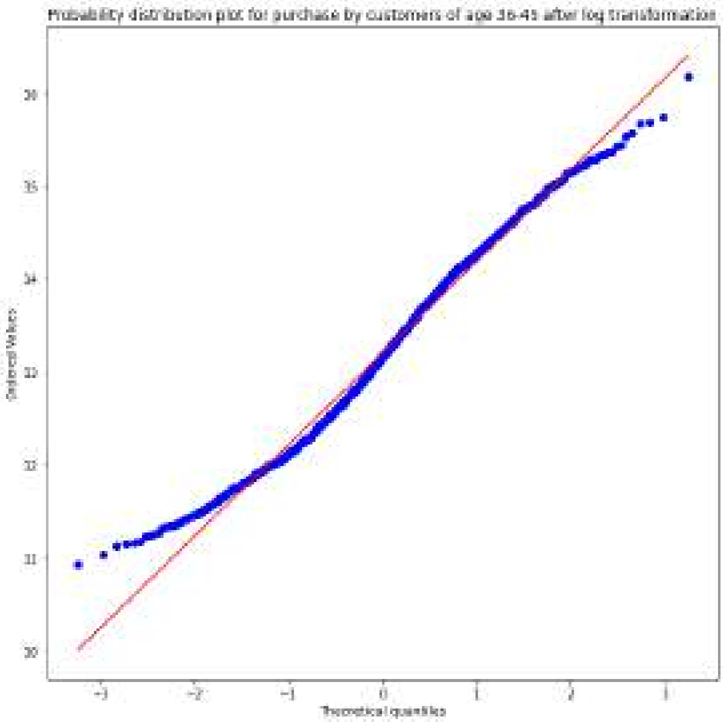

Probability distribution plot for purchase by customers of age 46-50 after log transformation
Ordered Values
Theoretical quantiles
−3
−2
−1
0
1
2
3

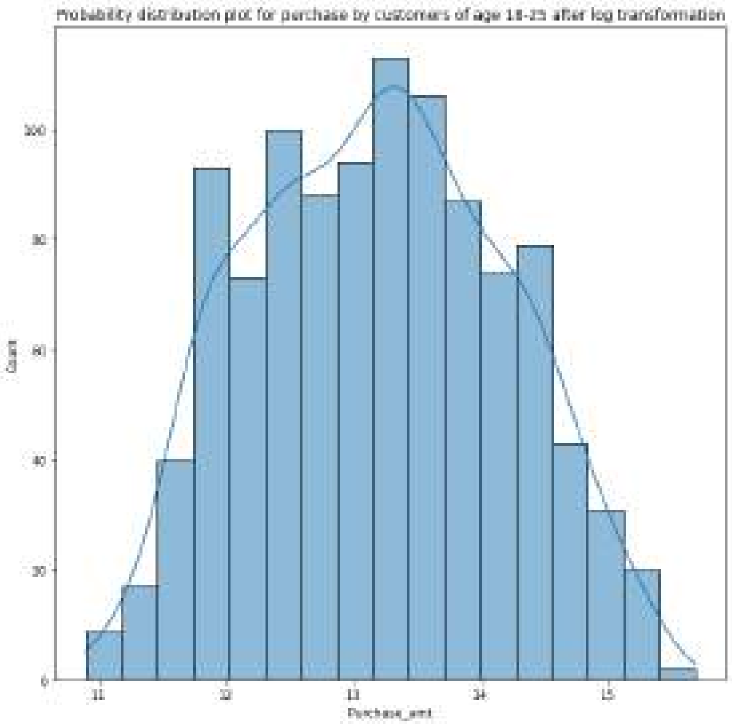

Probability distribution plot for purchase by customers of age 51-55 after log transformation
Count
Purchase_amt
0
10
20
30
40
50
60
11
12
13
14
15

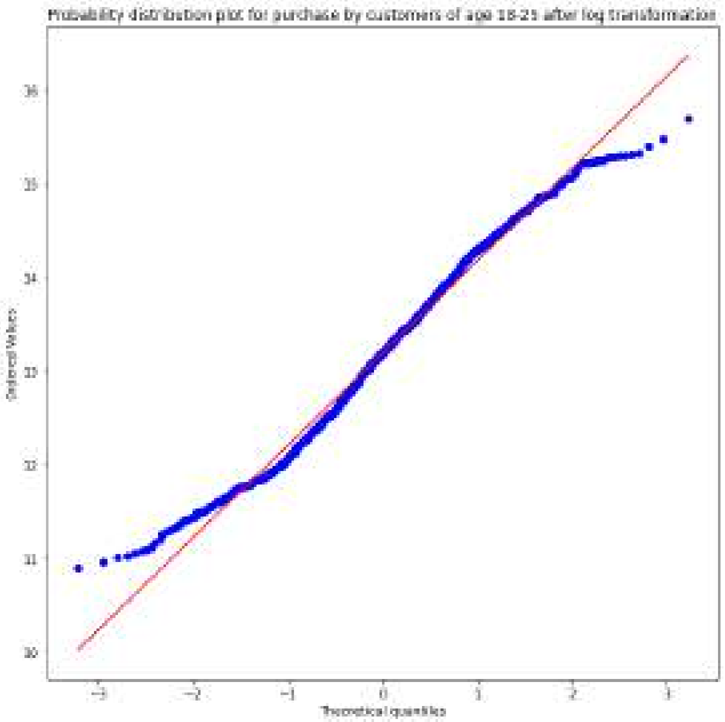


Probability distribution plot for purchase by customers of age 51-55 after log transformation
Ordered Values
Theoretical quantiles


Probability distribution plot for purchase by customers of age 36-45 after log transformation
Count
Purchase_amt
0
20
40
60
80
100
120
11
12
13
14
15
16


Probability distribution plot for purchase by customers of age 36-45 after log transformation
Ordered Values
Theoretical quantiles


Probability distribution plot for purchase by customers of age 18-25 after log transformation
Count
Purchase_amt



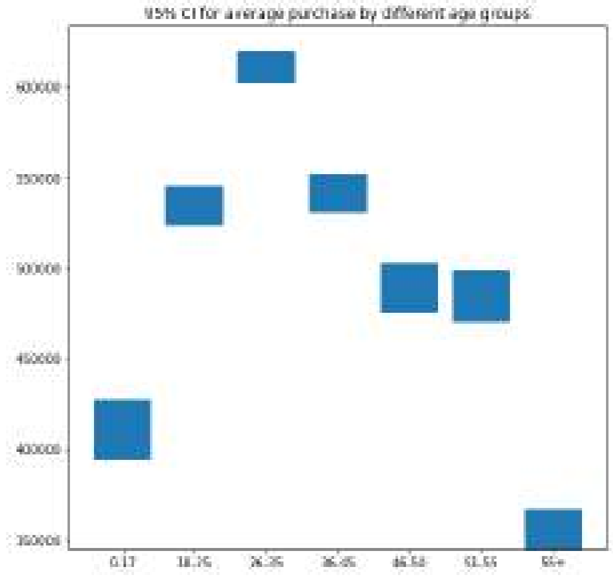
In [138]:
```
# Getting the upper and lower limit of CI for the average purchase of all age groups.
age = []
upper_ci = []
lower_ci = []
N = []
for i in age_data_pur["Age"].unique():
    z = age_data_pur.loc[age_data_pur["Age"] == i, "Purchase_amt"].apply(np.log)
    age.append(i)
    N.append(len(z))
    std = z.std()/(len(z)**0.5)
    mean = z.mean()
    lower_ci_, upper_ci_ = stats.norm.interval(alpha = 0.5, loc = mean, scale = std)
    lower_ci.append(np.exp(lower_ci_))
    upper_ci.append(np.exp(upper_ci_))
age_pur_ci = pd.DataFrame(list(zip(age,N, lower_ci, upper_ci )), columns = ["Age","N", "lower_ci", "upper_ci" ])
age_pur_ci.sort_values("Age", inplace = True)
age_pur_ci
# Note: The below mentioned CI was calculated using Z statistics.
```

Out[138]:

	Age	N	lower_ci	upper_ci
0	0-17	218	394254.439989	427653.779712
6	18-25	1069	523892.687277	545699.445692
2	26-35	2053	601812.073114	620157.153610
5	36-45	1167	530917.492898	552087.675811
3	46-50	531	475350.309378	502856.893423
4	51-55	481	470383.281937	499143.055639
1	55+	372	345131.700595	367119.581492

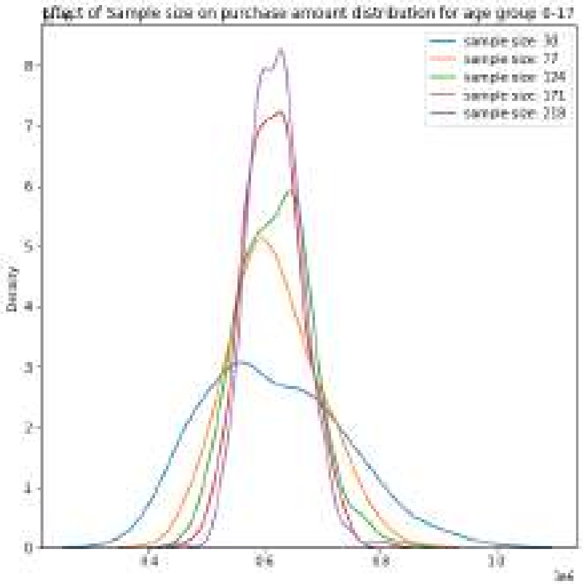
In [139]:

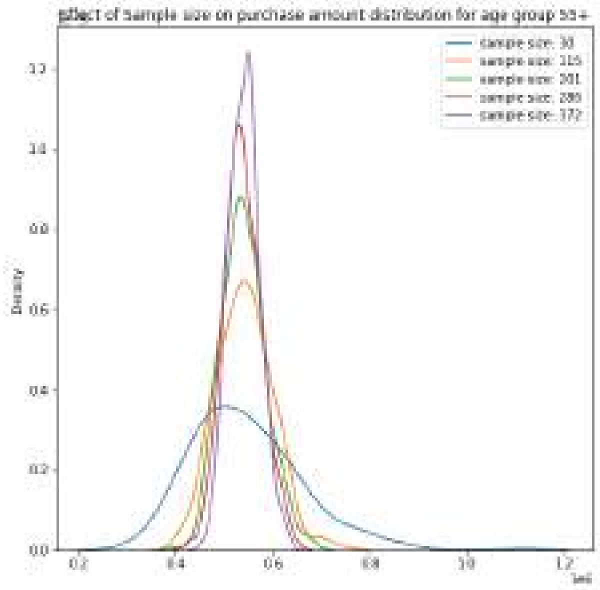
```python
plt.figure(figsize =(8,8))
plt.bar(x = age_pur_ci["Age"], bottom = age_pur_ci["lower_ci"], height = age_pur_ci["upper_ci"]-age_pur_ci["lower_ci"])
plt.title("95% CI for average purchase by different age groups")
plt.show()
# Observation: As the age increases from 0-17 till 26-35, the average purchase made by customers increase. There is no overlap in
# the CI intervals for these groups.
# As age increase beyond 36, the average purchase made by a customer decreases.
# The 95% CI for age groups 46-50 and 51-55 overlap. Hence there is no conclusive data to interpret the difference between the
# average purchase between these age groups.
# Age group 26-35 has highest average Purchase whereas age group 55+ has lowest average purchase.
```

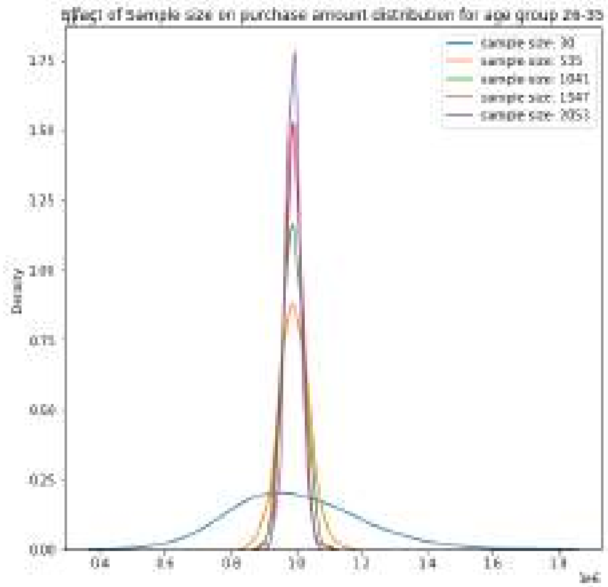


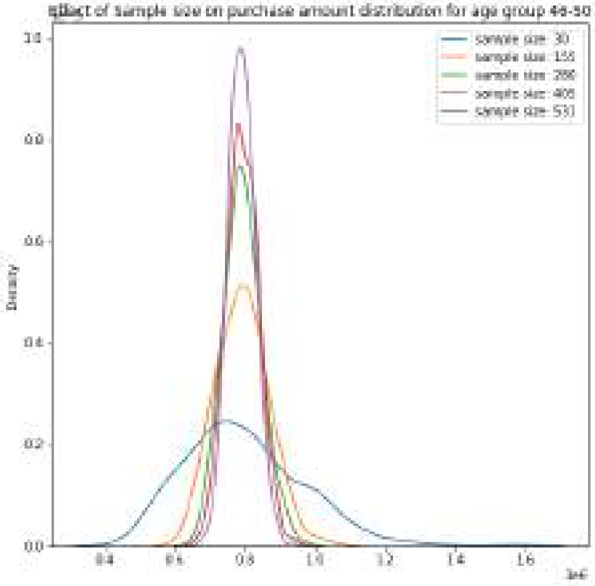
In [140]:

```python
# Understanding the effect of increasing sample size on the CI for different age groups.
import warnings
warnings.filterwarnings('ignore')
for i in age_data_pur["Age"].unique():
    z = age_data_pur.loc[age_data_pur["Age"] == i, "Purchase_amt"].reset_index(drop = True)
    plt.figure(figsize = (8,8))
    for k in np.linspace(30,len(z),5):
        data = []
        for l in range(500):
            x = np.random.randint(low = 0, high = len(z), size = int(k//1))
            data.append(z[x].mean())
        sns.distplot(data, hist = False, label = f"sample size: {int(k//1)}")
    plt.title(f"Effect of Sample size on purchase amount distribution for age group {i}")
    plt.legend()
    plt.show()
# As can be seen from the below graphs, as the sample size increases, the distribution has a sharper peak and a thinner tail.
# Thus width of 95% CI decreases as sample size increases and can be validated from the dataframe in the below cell in Jupyter
# Notebook
```

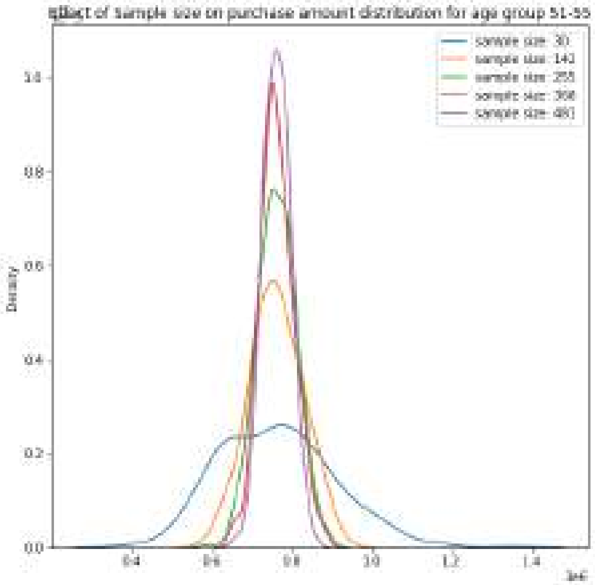



Effect of Sample size on purchase amount distribution for age group 55+
sample size: 30
sample size: 115
sample size: 201
sample size: 286
sample size: 372
Density
1e6

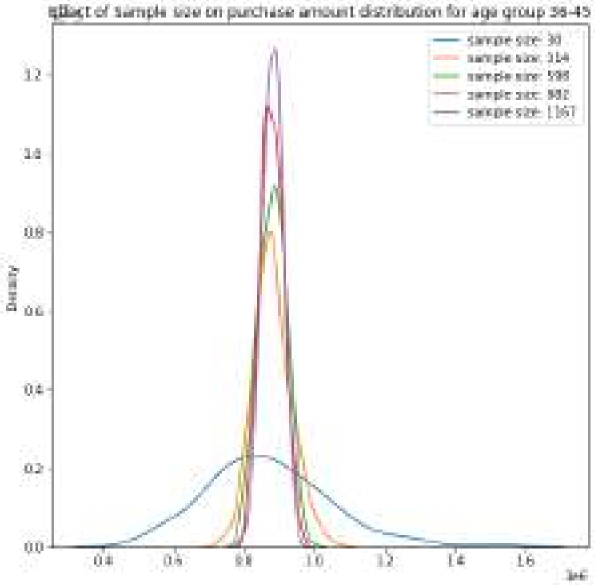

Effect of Sample size on purchase amount distribution for age group 26-35
sample size: 30
sample size: 535
sample size: 1041
sample size: 1547
sample size: 2053
Density
1e6

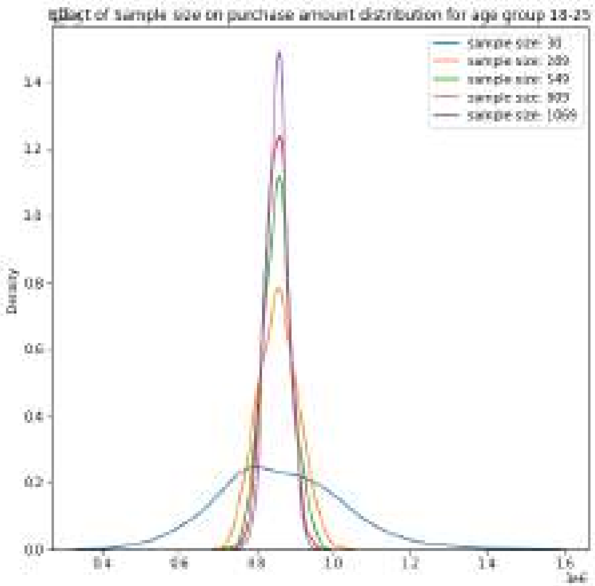


Effect of sample size on purchase amount distribution for age group 46-50
sample size: 30
sample size: 155
sample size: 280
sample size: 405
sample size: 531
Density
1e6



Effect of sample size on purchase amount distribution for age group 51-55
sample size: 30
sample size: 143
sample size: 255
sample size: 368
sample size: 481
Density
1e6


Effect of sample size on purchase amount distribution for age group 36-45
sample size: 30
sample size: 314
sample size: 598
sample size: 882
sample size: 1167
Density
1e6


Effect of sample size on purchase amount distribution for age group 18-25
sample size: 30
sample size: 289
sample size: 549
sample size: 809
sample size: 1069
Density
1e6

In [141]:

```
# Constructing 95% CI using T test for different age groups and sample sizes
age = []
N = []
lower_ci = []
upper_ci = []
for i in age_data_pur["Age"].unique():
    z = age_data_pur.loc[age_data_pur["Age"] == i, "Purchase_amt"].apply(np.log).reset_index(drop = True)
    for j in np.linspace(30,len(z)-1,3):
        data = []
        for k in range(100):
            x = np.random.randint(low = 0, high = len(z)-1, size = int(j))
            data.append(z[x].mean())
        lower_ci_, upper_ci_ = stats.t.interval(alpha = 0.05, df = len(z)-1, loc = np.array(data).mean(),scale = \
                                                np.array(data).std())
        age.append(i)
        N.append(int(j))
        lower_ci.append(np.exp(lower_ci_))
        upper_ci.append(np.exp(upper_ci_))
pd.DataFrame(list(zip(age,N,lower_ci, upper_ci)), columns = ["Age", "N (sample size)", "Lower_limit_CI", "Upper_Limit_CI"])
```

Out[141]:

	Age	N (sample size)	Lower_limit_CI	Upper_Limit_CI
0	0-17	30	395085.881735	402493.980699
1	0-17	123	405842.342727	410011.842968
2	0-17	217	410250.415536	413657.122308
3	55+	30	344972.619215	352507.888953
4	55+	200	355191.503401	357718.103090
5	55+	371	357442.691322	359325.462537
6	26-35	30	609428.070524	622735.941944
7	26-35	1041	610639.224191	612899.398630
8	26-35	2052	609055.566109	610745.865614
9	46-50	30	472345.102078	482362.216734
10	46-50	280	485519.472423	488917.096484
11	46-50	530	487249.164828	489722.885105
12	51-55	30	495360.380093	506578.034922
13	51-55	255	481883.989485	485248.192687
14	51-55	480	484451.596054	486758.429634
15	36-45	30	520928.275047	533635.103242
16	36-45	598	540014.076583	542964.576632
17	36-45	1166	540033.056600	541990.107610
18	18-25	30	528522.980615	540433.607664
19	18-25	549	533893.557486	536567.263500
20	18-25	1068	534490.706796	536568.144495

In [142]:
```
# Observation:
# As seen from the graphs above, there is no overlap between 95% CI for average purchases made by Male and Female
# customers. 95% CI for purchases made by Male is higher than purchase made by Female.
# As male customers are expected to spend more then Female customers, from a product category where both Male and
# Female customers purchases, Walmart can show higher priced products to Males as compared to Females.

# The 95% CI for average purchase made by customers with different Marital Status overlap. Hence, there is no
# sufficient data available to conclude any difference between average purchases made by these groups with 95%
# confidence. Since there is overlap in 95% CI, walmarts should not use Marital Status to predict amount spent by
# a customer. However, further profiling needs to be done to understand the impact of Marital Status on different
# Product Categories.

# There is no overlap between any two successive age groups except age group 46-50 and 51-55.
# The 95% CI for average purchase by an age group is maximum for group 26-35 and minimum for group 55+.
# The 95% CI for average purchase increases till age 26-35 and then starts decreasing.
# All age groups purchase from different Product Categories. If there are products which can be used across all age
# groups, Walmart can suggests higher priced products to Age group 26-35 and lower priced roducts to 55+ age groups.
# As the average purchase made by age groups 46-50 and 51-55 are almost similar, Walmart can show similar priced
# products to them.
# If new products are added to a Product category and is high priced as compared to other products in the category,
# It should be more recommended to age groups 26-35, 18-25 and 36-45.
# If the new product is medium priced, it can recommended to 18-25, 36-45, 46-50 and 51-55.
# If it is low priced, it can be recommended to 0-17, 46-50 and 51-55 and 55+.
```

In [143]:

```
# Recommndations:
# Product Category 8, 5 and 1 have maximum 1047, 967 and 493 products and conprise 16.76, 18.48 and 37.48% of the total
# purchases. These account for total 74.5% of total purchases for Walmart.

# Walmart must ensure adequate stocks of the most selling products in these 3 categories. They
# can benchmark the % increase in Sales for these 3 product categories over the upcoming Black Fridays
# to ensure the revenue of Walmart does not fall. If the revenue falls below the benchmarked value,
# they can offer discount on most selling products in these categories to attract more customers.
# For this they can target the products which are performing well in these categories.
# There are total 26 products in Category 1, 87 products in Category 5 and 99 products in category 8, which are selling
# very well # compared to other products in the same catgeory. For top products having highest customer base, refer
# cell 25. For top products having highest purchase amount refer cell 23.

# In order to get rid off the extra stocks of the products that do not have higher customer count
# and purchase amount, Walmart can offer them at large discounted prices to avoid any loss.
# These include products which are having low customer count and low purchase amount. Such list
# of products are in the dataframe in Jupyter cell 26. There are a total of 898 products where
# % Purchase is less than 25 percentile and Customer count is also less than 25 percentile.
# Walmart must try to offer excessive discoun on such products to avoid high losses on these
# products and avoid high stocks of these products in Stores on Black Friday.

# Refer Jupyter lines 37 through 56 for understanding the purchase behaviour of customers in different age groups.
# While 36.16% of total purchase come from Product Category 1 in age group 0-17, only 23.73%
# of total customers in the age group have purchased a product.
# While average purchase made by a customer in Product Category 1 and age group 55+ is 14065,
# only 20.5% of Customers have purchased a product from this Product Category which is lower as compared to other
# age groups. Hence, Walmart can provide targetted discount on Products in category 1 for
# age groups 55+. Customers in age group 0-17 purchase more from Product Categories 3 and 4.
# Hence if Walmart wishes to attract more customers from these age groups, it can offer products at
# higher discounts in these categories for these age groups.
# 28% of customers in age group 55+ purchase from Category 8 and have highest average purchase
# by a customer in any age group for this category. If Walmart wants to attract more customers in
# these age groups, they can offer products in these age group at a discounted category.

# The dataframe in Jupyter Line 80 confirms that there are a total of 1840 products which have
# been purchased across all age groups. For Product P00034742, across a particular age group,
# maximum 464 customers have purchased it while a minimum of 55 customers in another age group have purchased
# it.

# The dataframe constructed in line 83, consists of Product ID which have been purchases across
# 4 or less age groups.If Walmart wants to target Customers across all age groups, it should target those
# product id's which are available across all age groups and have have significant customer base.
# Refer dataframe 81 for products which have atleast 30 customers across all age groups.

# In the analysis, we have also tried to figure out product categories which are biased to a particular gender.
# Refer line 90 in the Jupyter Notebook.
# We can say that a particular gender prefers a paricular product category if the difference in average purchase
# between Male and Female Genders is greater than 1000 and the percentage difference in customers in the genders
# is different by more than 5% for a particular category. As per this assumption, we have found categories 10, 11,
# 14, 15, 16, 17, 18, 2, 6 and 7 to be preferred by a particular gender.

# By using T-test we have found that average Purchase amount made by different genders in Product Categories 3,12,5,4,2,
# 6,14,13 and 18 is having p values less than 0.05. Refer line 91 in the Jupyter Notebook for this analysis.
```