```
In [1]:
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import norm
from scipy.stats import binom
import math
import seaborn as sns
```

In [2]:

data=pd.read_csv(r"C:/Users/shiva/OneDrive/Desktop/walmart_data.csv")

In [3]:

data

Out[3]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purch
0	1000001	P00069042	F	0- 17	10	А	2	0	3	8
1	1000001	P00248942	F	0- 17	10	А	2	0	1	15:
2	1000001	P00087842	F	0- 17	10	А	2	0	12	1.
3	1000001	P00085442	F	0- 17	10	А	2	0	12	1
4	1000002	P00285442	М	55+	16	С	4+	0	8	7:
550063	1006033	P00372445	М	51- 55	13	В	1	1	20	
550064	1006035	P00375436	F	26- 35	1	С	3	0	20	
550065	1006036	P00375436	F	26- 35	15	В	4+	1	20	
550066	1006038	P00375436	F	55+	1	С	2	0	20	
550067	1006039	P00371644	F	46- 50	0	В	4+	1	20	•

550068 rows × 10 columns

In [4]:

data.shape

Out[4]:

(550068, 10)

In [5]:

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067

Data columns (total 10 columns): # Column

```
Column
                               Non-Null Count
                                                Dtype
0
   User_ID
                               550068 non-null int64
1
    Product_ID
                               550068 non-null
                                                object
                               550068 non-null object
    Gender
2
3
                               550068 non-null object
    Age
4
    Occupation
                               550068 non-null
5
    City_Category
                               550068 non-null object
                               550068 non-null object
    Stay_In_Current_City_Years
6
7
    Marital_Status
                               550068 non-null
                                                int64
   Product_Category
                               550068 non-null int64
8
   Purchase
                               550068 non-null int64
```

dtypes: int64(5), object(5)
memory usage: 42.0+ MB

```
In [6]:

cols = ['Occupation', 'Marital_Status', 'Product_Category']
data[cols] = data[cols].astype('object')

In [7]:

data.head(20)
Out[7]:
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
0	1000001	P00069042	F	0- 17	10	А	2	0	3	8370
1	1000001	P00248942	F	0- 17	10	А	2	0	1	15200
2	1000001	P00087842	F	0- 17	10	А	2	0	12	1422
3	1000001	P00085442	F	0- 17	10	А	2	0	12	1057
4	1000002	P00285442	М	55+	16	С	4+	0	8	7969
5	1000003	P00193542	М	26- 35	15	А	3	0	1	15227
6	1000004	P00184942	М	46- 50	7	В	2	1	1	19215
7	1000004	P00346142	М	46- 50	7	В	2	1	1	15854
8	1000004	P0097242	М	46- 50	7	В	2	1	1	15686
9	1000005	P00274942	М	26- 35	20	А	1	1	8	7871
10	1000005	P00251242	М	26- 35	20	А	1	1	5	5254
11	1000005	P00014542	М	26- 35	20	А	1	1	8	3957
12	1000005	P00031342	М	26- 35	20	А	1	1	8	6073
13	1000005	P00145042	М	26- 35	20	А	1	1	1	15665
14	1000006	P00231342	F	51- 55	9	А	1	0	5	5378
15	1000006	P00190242	F	51- 55	9	А	1	0	4	2079
16	1000006	P0096642	F	51- 55	9	А	1	0	2	13055
17	1000006	P00058442	F	51- 55	9	А	1	0	5	8851
18	1000007	P00036842	М	36- 45	1	В	1	1	1	11788
19	1000008	P00249542	М	26- 35	12	С	4+	1	1	19614

Outlier Detection

```
In [8]:
```

data.describe()

Out[8]:

	User_ID	Purchase
count	5.500680e+05	550068.000000
mean	1.003029e+06	9263.968713
std	1.727592e+03	5023.065394
min	1.000001e+06	12.000000
25%	1.001516e+06	5823.000000
50%	1.003077e+06	8047.000000
75%	1.004478e+06	12054.000000
max	1.006040e+06	23961.000000

```
In [9]:
```

```
      data.isnull().sum()

      Out[9]:

      User_ID
      0

      Product_ID
      0

      Gender
      0

      Age
      0

      Occupation
      0

      City_Category
      0

      Stay_In_Current_City_Years
      0

      Marital_Status
      0

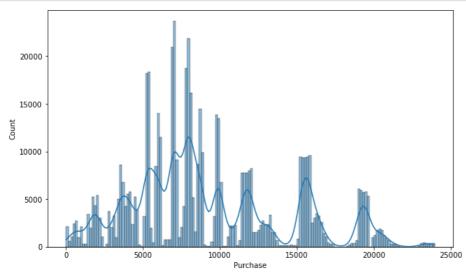
      Product_Category
      0

      Purchase
      0

      dtype: int64
```

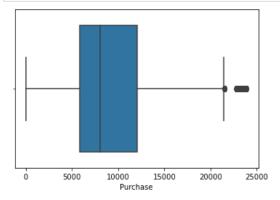
In [10]:

```
plt.figure(figsize=(10, 6))
sns.histplot(data=data, x='Purchase', kde=True)
plt.show()
```



In [11]:

```
sns.boxplot(data=data, x='Purchase', orient='h')
plt.show()
```



Observations

1. There are outliers in Purchase .

Univariate Analysis

```
In [12]:
data["Stay_In_Current_City_Years"].value_counts()
Out[12]:
1
      193821
2
      101838
       95285
3
4+
       84726
0
       74398
Name: Stay_In_Current_City_Years, dtype: int64
In [13]:
data["Product_Category"].value_counts()
Out[13]:
      150933
5
1
      140378
8
      113925
11
       24287
2
       23864
6
       20466
3
       20213
4
       11753
16
        9828
15
        6290
        5549
13
10
        5125
12
        3947
        3721
18
        3125
20
        2550
19
        1603
        1523
14
17
         578
         410
Name: Product_Category, dtype: int64
In [14]:
data["City_Category"].value_counts()
Out[14]:
     231173
В
     171175
     147720
Name: City_Category, dtype: int64
In [15]:
data.groupby("Gender")["User_ID"].nunique()
Out[15]:
Gender
     1666
     4225
Name: User_ID, dtype: int64
In [16]:
data["Age"].value_counts()
Out[16]:
26-35
         219587
36-45
         110013
          99660
18-25
46-50
          45701
51-55
          38501
55+
          21504
0-17
          15102
Name: Age, dtype: int64
In [17]:
data["Marital_Status"]=data["Marital_Status"].replace([0,1],["Single","Married"])
```

In [18]:

Out[18]:

data["Marital_Status"].value_counts()

Single 324731 Married 225337

Name: Marital_Status, dtype: int64

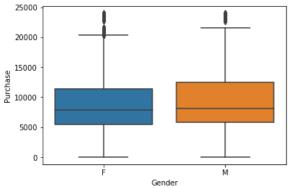
In [19]:

```
categorical_cols = ['Gender', 'Occupation','City_Category','Marital_Status','Product_Category']
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))
sns.countplot(data=data, x='Gender', ax=axs[0,0])
sns.countplot(data=data, x='Occupation', ax=axs[0,1])
sns.countplot(data=data, x='City_Category', ax=axs[1,0])
sns.countplot(data=data, x='Marital_Status', ax=axs[1,1])
plt.show()
plt.figure(figsize=(10, 8))
sns.countplot(data=data, x='Product_Category')
plt.show()
   400000
                                                                                 70000
    350000
                                                                                 60000
   300000
                                                                                 50000
   250000
   200000
                                                                                 30000
   150000
                                                                                 20000
   100000
                                                                                 10000
    50000
                                                                                                 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Occupation
                                                                                         0 1 2
                                        Gender
                                                                                 300000
   200000
                                                                                 250000
   150000
                                                                                 200000
                                                                                 150000
   100000
                                                                                100000
    50000
                                                                                 50000
                                     C
City_Category
                                                                                                     Single
                                                                                                                  Marital Status
    140000
    120000
    100000
     80000
     60000
     40000
     20000
                                                         10
                                                8
                                                              11
```

Bi-Variate Analysis

In [20]:

```
sns.boxplot(x="Gender",y="Purchase",data=data)
plt.show()
```

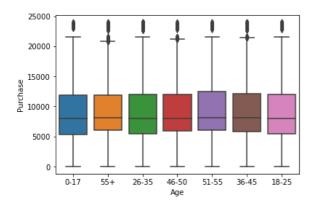


In [21]:

sns.boxplot(x="Age",y="Purchase",data=data)

Out[21]:

<AxesSubplot:xlabel='Age', ylabel='Purchase'>

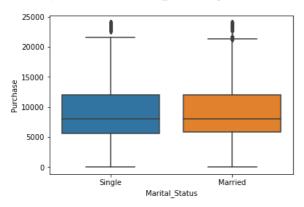


In [22]:

sns.boxplot(x="Marital_Status",y="Purchase",data=data)

Out[22]:

<AxesSubplot:xlabel='Marital_Status', ylabel='Purchase'>



5000

```
In [23]:
sns.boxplot(x="Product_Category",y="Purchase",data=data)
<AxesSubplot:xlabel='Product_Category', ylabel='Purchase'>
   25000
   20000
   15000
10000
10000
```

Multivariate Analysis

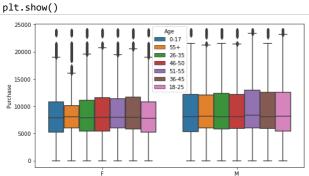
Product_Category

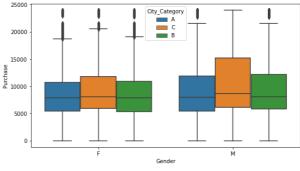
8

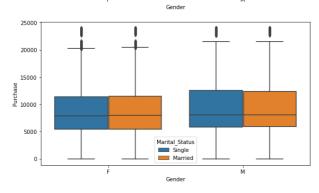
9 10 11 12 13 14 15 16 17 18 19 20

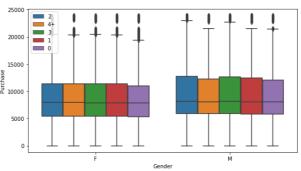
```
In [24]:
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(20, 6))
fig.subplots_adjust(top=1.5)
sns.boxplot(data=data, y="Purchase", x='Gender', hue='Age', ax=axs[0,0])
sns.boxplot(data=data, y='Purchase', x='Gender', hue='City_Category', ax=axs[0,1])
sns.boxplot(data=data, y='Purchase', x='Gender', hue='Marital_Status', ax=axs[1,0])
sns.boxplot(data=data, y='Purchase', x='Gender', hue='Stay_In_Current_City_Years', ax=axs[1,1])
```

axs[1,1].legend(loc='upper left')









In [25]:

s=300

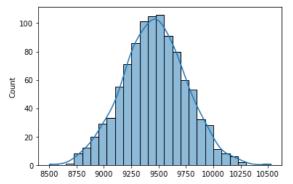
Gender vs Purchase

```
In [26]:
```

```
male_sample_mean=[data[data["Gender"]=="M"].sample(s)["Purchase"].mean() for i in range(iterations)]
```

```
In [27]:
```

```
sns.histplot(x=male_sample_mean,kde=True)
plt.show()
```



In [28]:

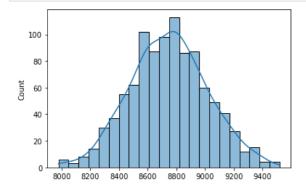
m_mean=np.mean(male_sample_mean)

In [29]:

```
female_sample_mean=[data[data["Gender"]=="F"].sample(s)["Purchase"].mean() for i in range(iterations)]
```

In [30]:

```
sns.histplot(x=female_sample_mean,kde=True)
plt.show()
```



In [31]:

f_mean=np.mean(female_sample_mean)

Confidence Interval

99% Confidence Interval

In [32]:

```
male_lower_interval_limit=m_mean-2.58*(np.std(male_sample_mean))
male_upper_interval_limit=m_mean+2.58*(np.std(female_sample_mean))
(male_lower_interval_limit,male_upper_interval_limit)
```

Out[32]:

(8717.631500467638, 10153.256346662705)

In [33]:

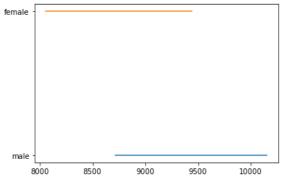
```
female_lower_interval_limit=f_mean-2.58*(np.std(female_sample_mean))
female_upper_interval_limit=f_mean+2.58*(np.std(female_sample_mean))
(female_lower_interval_limit,female_upper_interval_limit)
```

Out[33]:

(8054.327933337297, 9439.925173329371)

```
In [34]:
```

```
plt.plot((male_lower_interval_limit, male_upper_interval_limit), [0, 0])
plt.plot((female_lower_interval_limit, female_upper_interval_limit), [1, 1])
for i in range(2):
    plt.annotate([male_lower_interval_limit,male_upper_interval_limit],xy=[1,2])
plt.yticks(range(2), ["male", "female"])
plt.show()
```



95% Confidence Interval

```
In [35]:
```

```
male_lower_interval_limit=m_mean-1.96*(np.std(male_sample_mean))
```

In [36]:

```
male_upper_interval_limit=m_mean+1.96*(np.std(female_sample_mean))
```

In [37]:

```
E PURCHASE CONFIDENCE INTERVAL FOR POPULATION MEAN:- {:.2f} ,{:.2f} ".format(male_lower_interval_limit,male_upper_interval_limit
```

MALE PURCHASE CONFIDENCE INTERVAL FOR POPULATION MEAN: - 8896.14 ,9986.77

In [38]:

```
female_lower_interval_limit=f_mean-1.96*(np.std(female_sample_mean))
```

In [39]:

```
female_upper_interval_limit=f_mean+1.96*(np.std(female_sample_mean))
```

In [40]:

```
RCHASE CONFIDENCE INTERVAL FOR POPULATION MEAN:- {:.2f} ,{:.2f} ".format(female_lower_interval_limit,female_upper_interval_limit
```

FEMALE PURCHASE CONFIDENCE INTERVAL FOR POPULATION MEAN:- 8220.81 ,9273.44

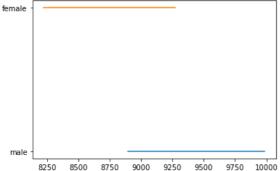
```
In [41]:

plt.plot((male_lower_interval_limit, male_upper_interval_limit), [0, 0])

plt.plot((female_lower_interval_limit, female_upper_interval_limit), [1, 1])

plt.yticks(range(2), ["male", "female"])

plt.show()
```



90% Confidence Interval

In [42]:

```
__interval_limit=m_mean-1.64*(np.std(male_sample_mean))
_interval_limit=m_mean+1.64*(np.std(female_sample_mean))

E PURCHASE CONFIDENCE INTERVAL FOR POPULATION MEAN:- {:.2f} ,{:.2f} ".format(male_lower_interval_limit,male_upper_interval_limit)

| |
```

MALE PURCHASE CONFIDENCE INTERVAL FOR POPULATION MEAN: - 8988.27 ,9900.84

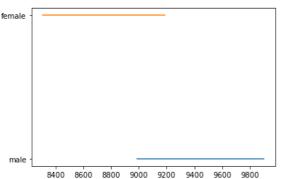
In [43]:

```
female_lower_interval_limit=f_mean-1.64*(np.std(female_sample_mean))
female_upper_interval_limit=f_mean+1.64*(np.std(female_sample_mean))
print("FEMALE PURCHASE CONFIDENCE INTERVAL FOR POPULATION MEAN:- {:.2f} ,{:.2f} ".format(female_lower_interval_limit,female_upper_interval_limit,female_upper_interval_limit
```

FEMALE PURCHASE CONFIDENCE INTERVAL FOR POPULATION MEAN: - 8306.74 ,9187.51

In [44]:

```
plt.plot((male_lower_interval_limit, male_upper_interval_limit), [0, 0])
plt.plot((female_lower_interval_limit, female_upper_interval_limit), [1, 1])
plt.yticks(range(2), ["male", "female"])
plt.show()
```



Marital_Status vs Purchase

```
In [45]:
```

data.groupby("Marital_Status")["Purchase"].describe()

Out[45]:

 Married
 225337.0
 9261.174574
 5016.897378
 12.0
 5843.0
 8051.0
 12042.0
 23961.0

 Single
 324731.0
 9265.907619
 5027.347859
 12.0
 5605.0
 8044.0
 12061.0
 23961.0

In [46]:

Married_sample_mean_dist=[data[data["Marital_Status"]=="Married"].sample(s)["Purchase"].mean() for i in range(iterations)]

In [47]

Single_sample_mean_dist=[data[data["Marital_Status"]=="Single"].sample(s)["Purchase"].mean() for i in range(iterations)]

In [48]:

Married_mean_of_sample_mean=np.mean(Married_sample_mean_dist)

In [49]:

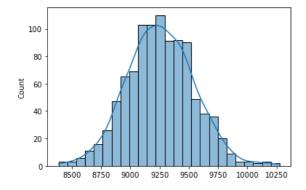
Single_mean_of_sample_mean=np.mean(Single_sample_mean_dist)

In [50]:

sns.histplot(x=Married_sample_mean_dist,kde=True)

Out[50]:

<AxesSubplot:ylabel='Count'>

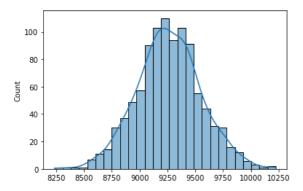


In [51]:

sns.histplot(x=Single_sample_mean_dist,kde=True)

Out[51]:

<AxesSubplot:ylabel='Count'>



Confidence Interval

99% Confidence Interval

```
In [52]:
```

```
lower_interval_limit_Single=Single_mean_of_sample_mean-2.58*(np.std(Single_sample_mean_dist))
upper_interval_limit_Single=Single_mean_of_sample_mean+2.58*(np.std(Single_sample_mean_dist))
(lower_interval_limit_Single,upper_interval_limit_Single)

Out[52]:
(8521.121021197492, 10005.498118802507)
```

In [53]:

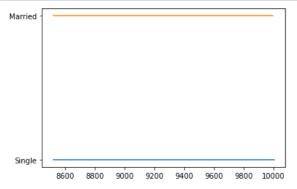
```
lower_interval_limit_Married=Married_mean_of_sample_mean-2.58*(np.std(Married_sample_mean_dist))
upper_interval_limit_Married=Married_mean_of_sample_mean+2.58*(np.std(Married_sample_mean_dist))
(lower_interval_limit_Married,upper_interval_limit_Married)
```

Out[53]:

(8522.718295658055, 9993.636511008615)

In [54]:

```
plt.plot((lower_interval_limit_Single, upper_interval_limit_Single), [0, 0])
plt.plot((lower_interval_limit_Married, upper_interval_limit_Married), [1, 1])
plt.yticks(range(2), ["Single", "Married"])
plt.show()
```



95% Confidence Interval

In [55]:

```
lower_interval_limit_Single=Single_mean_of_sample_mean-1.96*(np.std(Single_sample_mean_dist))
upper_interval_limit_Single=Single_mean_of_sample_mean+1.96*(np.std(Single_sample_mean_dist))
(lower_interval_limit_Single,upper_interval_limit_Single)
```

Out[55]:

(8699.47640889422, 9827.14273110578)

In [56]:

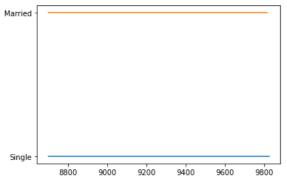
```
lower_interval_limit_Married=Married_mean_of_sample_mean-1.96*(np.std(Married_sample_mean_dist))
upper_interval_limit_Married=Married_mean_of_sample_mean+1.96*(np.std(Married_sample_mean_dist))
(lower_interval_limit_Married,upper_interval_limit_Married)
```

Out[56]:

(8699.456530835834, 9816.898275830836)

```
In [57]:
```

```
plt.plot((lower_interval_limit_Single, upper_interval_limit_Single), [0, 0])
plt.plot((lower_interval_limit_Married, upper_interval_limit_Married), [1, 1])
plt.yticks(range(2), ["Single", "Married"])
plt.show()
```



90% Confidence Interval

In [58]:

```
lower_interval_limit_Single=Single_mean_of_sample_mean-1.645*(np.std(Single_sample_mean_dist))
upper_interval_limit_Single=Single_mean_of_sample_mean+1.645*(np.std(Single_sample_mean_dist))
(lower_interval_limit_Single,upper_interval_limit_Single)
```

Out[58]:

(8790.092452643363, 9736.526687356636)

In [59]:

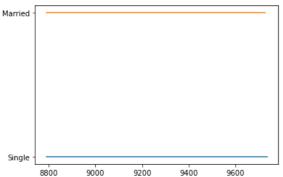
```
lower_interval_limit_Married=Married_mean_of_sample_mean-1.645*(np.std(Married_sample_mean_dist))
upper_interval_limit_Married=Married_mean_of_sample_mean+1.645*(np.std(Married_sample_mean_dist))
(lower_interval_limit_Married,upper_interval_limit_Married)
```

Out[59]:

 $(8789.250956772934,\ 9727.103849893736)$

In [60]:

```
plt.plot((lower_interval_limit_Single, upper_interval_limit_Single), [0, 0])
plt.plot((lower_interval_limit_Married, upper_interval_limit_Married), [1, 1])
plt.yticks(range(2), ["Single", "Married"])
plt.show()
```



Age vs Purchase

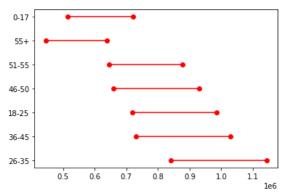
```
In [61]:
amt_df = data.groupby(['User_ID', 'Age'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
Out[61]:
      User_ID
              Age Purchase
   0 1000001
                      334093
               0-17
   1 1000002
               55+
                      810472
   2 1000003 26-35
                      341635
   3 1000004 46-50
                      206468
   4 1000005 26-35
                      821001
5886 1006036 26-35
                     4116058
 5887 1006037 46-50
                     1119538
     1006038
               55+
                       90034
 5888
 5889 1006039 46-50
                      590319
 5890 1006040 26-35
                     1653299
5891 rows × 3 columns
In [62]:
data1=data.groupby(["User_ID", "Age"])[["Purchase"]].mean()
In [63]:
amt_df["Age"].value_counts()
Out[63]:
26-35
         2053
36-45
         1167
18-25
         1069
46-50
          531
51-55
          481
55+
          372
          218
Name: Age, dtype: int64
```

Confidence Interval

99% Confidence Interval

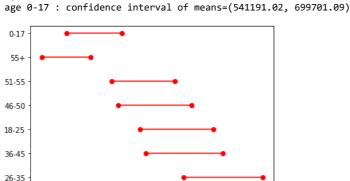
```
In [64]:
w=['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']
lower_list=[]
upper_list=[]
for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:
    sample mean distribution=[]
    for i in range(iterations):
        new_df = amt_df[amt_df['Age']==val]
        sample_mean = new_df.sample(s,replace=True)['Purchase'].mean()
        sample_mean_distribution.append(sample_mean)
    a=np.mean(sample_mean_distribution)
    lower_limit=a-2.58*np.std(sample_mean_distribution)
    upper_limit=a+2.58*np.std(sample_mean_distribution)
    print(" age {} : confidence interval of means=({:.2f}, {:.2f})".format(val, lower_limit, upper_limit))
    lower_list.append(lower_limit)
    upper_list.append(upper_limit)
data_dict = {}
data_dict['category'] = ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']
data_dict['lower'] = lower_list
data_dict['upper'] = upper_list
dataset = pd.DataFrame(data_dict)
for lower,upper,y in zip(dataset['lower'],dataset['upper'],range(len(dataset))):
    plt.plot((lower,upper),(y,y),'ro-')
plt.yticks(range(len(dataset)),list(dataset['category']))
plt.show()
```

```
age 26-35 : confidence interval of means=(840029.35, 1143479.05) age 36-45 : confidence interval of means=(729653.77, 1029517.28) age 18-25 : confidence interval of means=(718875.67, 985099.35) age 46-50 : confidence interval of means=(658266.43, 929862.40) age 51-55 : confidence interval of means=(645965.65, 877616.70) age 55+ : confidence interval of means=(444247.27, 637934.60) age 0-17 : confidence interval of means=(514793.50, 720126.01)
```



95% Confidence Interval

```
In [65]:
w=['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']
lower_list=[]
upper_list=[]
for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:
    sample mean distribution=[]
    for i in range(iterations):
        new_df = amt_df[amt_df['Age']==val]
        sample_mean = new_df.sample(s,replace=True)['Purchase'].mean()
        sample_mean_distribution.append(sample_mean)
    a=np.mean(sample_mean_distribution)
    lower_limit=a-1.96*np.std(sample_mean_distribution)
    upper_limit=a+1.96*np.std(sample_mean_distribution)
    print(" age {} : confidence interval of means=({:.2f}, {:.2f})".format(val, lower_limit, upper_limit))
    lower_list.append(lower_limit)
    upper_list.append(upper_limit)
data_dict = {}
data_dict['category'] = ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']
data_dict['lower'] = lower_list
data_dict['upper'] = upper_list
dataset = pd.DataFrame(data_dict)
for lower,upper,y in zip(dataset['lower'],dataset['upper'],range(len(dataset))):
    plt.plot((lower,upper),(y,y),'ro-')
plt.yticks(range(len(dataset)),list(dataset['category']))
plt.show()
 age 26-35 : confidence interval of means=(876435.96, 1104823.87)
 age 36-45 : confidence interval of means=(767865.68, 989408.77)
 age 18-25 : confidence interval of means=(750902.95, 961924.01)
 age 46-50 : confidence interval of means=(689713.91, 900322.91)
 age 51-55 : confidence interval of means=(670381.51, 851293.15)
 age 55+ : confidence interval of means=(468466.40, 609064.67)
```



90% Confidence Interval

0.6

0.7

0.9

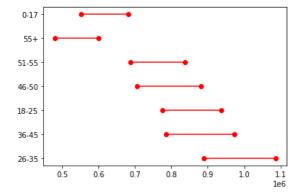
1.0

1.1 1e6

0.5

```
In [66]:
w=['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']
lower_list=[]
upper_list=[]
for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:
    sample mean distribution=[]
    for i in range(iterations):
        new_df = amt_df[amt_df['Age']==val]
        sample_mean = new_df.sample(s,replace=True)['Purchase'].mean()
        sample_mean_distribution.append(sample_mean)
    a=np.mean(sample_mean_distribution)
    lower_limit=a-1.645*np.std(sample_mean_distribution)
    upper_limit=a+1.645*np.std(sample_mean_distribution)
    print(" age {} : confidence interval of means=({:.2f}, {:.2f})".format(val, lower_limit, upper_limit))
    lower list.append(lower limit)
    upper_list.append(upper_limit)
data_dict = {}
data_dict['category'] = ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']
data_dict['lower'] = lower_list
data_dict['upper'] = upper_list
dataset = pd.DataFrame(data_dict)
for lower,upper,y in zip(dataset['lower'],dataset['upper'],range(len(dataset))):
    plt.plot((lower,upper),(y,y),'ro-')
plt.yticks(range(len(dataset)),list(dataset['category']))
plt.show()
```

```
age 26-35 : confidence interval of means=(889620.36, 1086352.31) age 36-45 : confidence interval of means=(785344.94, 973230.97) age 18-25 : confidence interval of means=(774807.07, 937327.28) age 46-50 : confidence interval of means=(705538.00, 880699.74) age 51-55 : confidence interval of means=(687659.60, 837664.20) age 55+ : confidence interval of means=(479256.51, 599222.16) age 0-17 : confidence interval of means=(551601.37, 681757.33)
```



Insights

#Gender Related

- 1. Male customers spend more than female customers and we can see :-
 - for 99% interval :- MALE = (8660.93, 10150.21),Female = (8033.46, 9463.13)
 - for 95% interval :- MALE = (8847.04 ,9978.44),Female = (8205.25 ,9291.36)
 - for 90% interval :- MALE = (8943.10 ,9889.78),Female = (8293.91 ,9202.70)
 - the difference is not very significant

#Age Related

- 1. There is no significant difference in purchasing patterns among differnt age groups
- 2. Male customers in all age groups tend to spend mpre then their female counterparts.
- 3. It is clearly visible that age groups in the 18-50 spend more on average .

#Marital_Status Related

- 1. There is no significant difference among Married and Single Customers , as seen the confidence intervals completely overlap:-
 - for 99% interval:- Single (8515.41, 10000.98), Married (8501.39, 10015.50)

- for 95% interval:- Single (8693.91, 9822.48), Married (8683.32, 9833.57)
- for 90% interval:- Single (8784.60, 9731.79), Married (8775.75, 9741.14)

#Product_Category_Related

1. Products 1,5,8,11 are the products highly in demand and generate major revenue for the company

#City_Related

- 1. More Customers are in city B as compared to other two cities .
- 2. Customers in City C tend to spend more as compared to other cities.

Recommendations

- 1. As Products 1,5,8,11 genrate more revenue for the company, more discounts , schemes, offers should be made .
- 2. Other products should also be made attarctive by quantity discounts, buy get one offers .
- 3. As we have more customers in B City, and as male customers are more in number over there, we should target the males with the products and schemes to drive sales over there.
- 4. High or more Price products should be launched and made accessible in City C .
- 5. Age groups in the the category 18-50 are promising fot the company
- 6. The company should launch new products specifically for the age group 26-35, as they are the more aggressive spenders.
- 7. The Single customers > Married Customers so we need to bring them in the loop and icrease their contribution to sales .
- 8. Customers with Occupation as [0,1,4,7,17] need to be targeted products:- tailormade or necessary or more suitable to their professions.