KPMG TASK 2

August 6, 2020

[1]:
```python
import pandas as pd
import datetime as DT
import numpy as np
import matplotlib.pyplot as plt
```

1 Customer Demographics

Upon loading the dataset, we see that the first row is just a notice. Hence, we skip it while reading it.

Then, we check its shape to see the number of rows and columns (features). Next, we check if there are duplicates for the customer id field. Luckily, there are none.

The default columns seems quite absurd and useless. It's best to drop it in the early stage.

[2]:
```python
df = pd.read_excel("KPMG_VI_New_raw_data_update_final.xlsx", sheet_name=3,␣
 ↪skiprows=1)

rows = df.shape[0]
cols = df.shape[1]
print("Number of Customer Id Entries: ", rows)
print("Number of Features: ", cols, "\n" )

print("Number of Duplicates", len(df['customer_id'])-len(df['customer_id'].
 ↪drop_duplicates()))

df = df.drop(['default'], axis=1)
df.head()
```

```
Number of Customer Id Entries:  4000
Number of Features:  13

Number of Duplicates 0
```

[2]:
```
   customer_id      first_name  last_name  gender  \
0            1         Laraine  Medendorp       F
1            2             Eli    Bockman    Male
```

```
2            3           Arlin     Dearle    Male
3            4          Talbot        NaN    Male
4            5  Sheila-kathryn     Calton  Female

   past_3_years_bike_related_purchases        DOB               job_title  \
0                                   93 1953-10-12     Executive Secretary
1                                   81 1980-12-16  Administrative Officer
2                                   61 1954-01-20      Recruiting Manager
3                                   33 1961-10-03                     NaN
4                                   56 1977-05-13           Senior Editor

  job_industry_category     wealth_segment deceased_indicator owns_car  tenure
0                Health      Mass Customer                  N      Yes    11.0
1    Financial Services      Mass Customer                  N      Yes    16.0
2              Property      Mass Customer                  N      Yes    15.0
3                    IT      Mass Customer                  N       No     7.0
4                   NaN  Affluent Customer                  N      Yes     8.0
```

1.1 Checking for Null Values

Now, we check the number of null values in all columns. We observe that there are around 125 N/A values for the last name. However, since last names might not have any impact on our business strategy, we can choose to ignore that column. However, DOB is a valuable asset for us. Hence, we drop the rows which have null values for the DOB.

Similarly, job titles could also be useful for us. Hence, we drop the rows which have null values for the job title as well.

[3]:
```python
print("Number of Initial Null Values: ")
print(df.isnull().sum(axis = 0),"\n")

df = df[df['DOB'].notnull()]
df = df[df['job_title'].notnull()]
```

```
Number of Initial Null Values:
customer_id                              0
first_name                               0
last_name                              125
gender                                   0
past_3_years_bike_related_purchases      0
DOB                                     87
job_title                              506
job_industry_category                  656
wealth_segment                           0
deceased_indicator                       0
owns_car                                 0
tenure                                  87
```

```
dtype: int64
```

1.2 Customer Ages

When preparing business and marketing strategies, targeting the right age bracket is quite essential. Hence, we need to know the exact ages of our customers. For this, we can add a new column for customer ages. We can calculate ages by subtracting the DOB from the current date.

[4]:
```python
now = pd.Timestamp('now')
df['age'] = (now - df['DOB']).astype('<m8[Y]')
df['age'] = df['age'].astype(np.int64)
df = df.reset_index(drop = True)
df.head()
```

[4]:
```
   customer_id      first_name  last_name  gender  \
0            1         Laraine  Medendorp       F
1            2             Eli    Bockman    Male
2            3           Arlin     Dearle    Male
3            5  Sheila-kathryn     Calton  Female
4            8             Rod      Inder    Male

   past_3_years_bike_related_purchases        DOB               job_title  \
0                                   93 1953-10-12     Executive Secretary
1                                   81 1980-12-16  Administrative Officer
2                                   61 1954-01-20      Recruiting Manager
3                                   56 1977-05-13           Senior Editor
4                                   31 1962-03-30         Media Manager I

  job_industry_category     wealth_segment deceased_indicator owns_car  \
0                Health      Mass Customer                  N      Yes
1    Financial Services      Mass Customer                  N      Yes
2              Property      Mass Customer                  N      Yes
3                   NaN  Affluent Customer                  N      Yes
4                   NaN      Mass Customer                  N       No

   tenure  age
0    11.0   66
1    16.0   39
2    15.0   66
3     8.0   43
4     7.0   58
```

1.3 Removing Contradiction in Genders

We notice that the values in the gender column are not consistent. By looking at the value counts, we observe that F and Female both represent the same thing. Similarly, M and Male represent the same thing. Additionally, terms U and Femal are also present in the dataset.

To fix this, we can replace Female/Femal with F and Male with M everywhere. Then, we can get rid of the row where gender is undefined (U). After this, the dataset seems to look good to go.

[5]:
```python
print(df.gender.value_counts(),"\n")
df["gender"].replace({"Female": "F", "Male": "M", "Femal": "F"}, inplace=True)
```

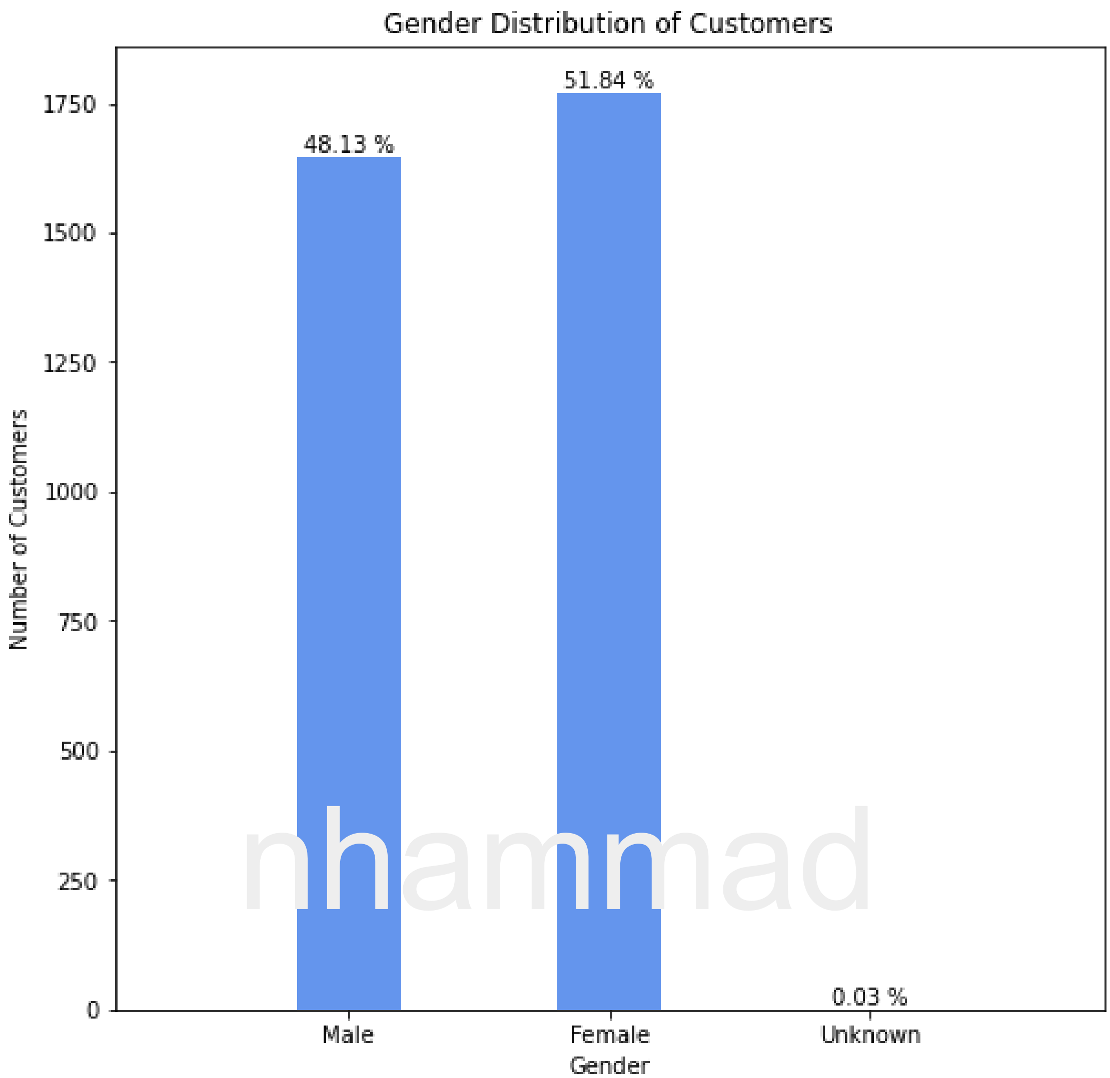
```
Female    1769
Male      1643
F            1
M            1
U            1
Femal        1
Name: gender, dtype: int64
```

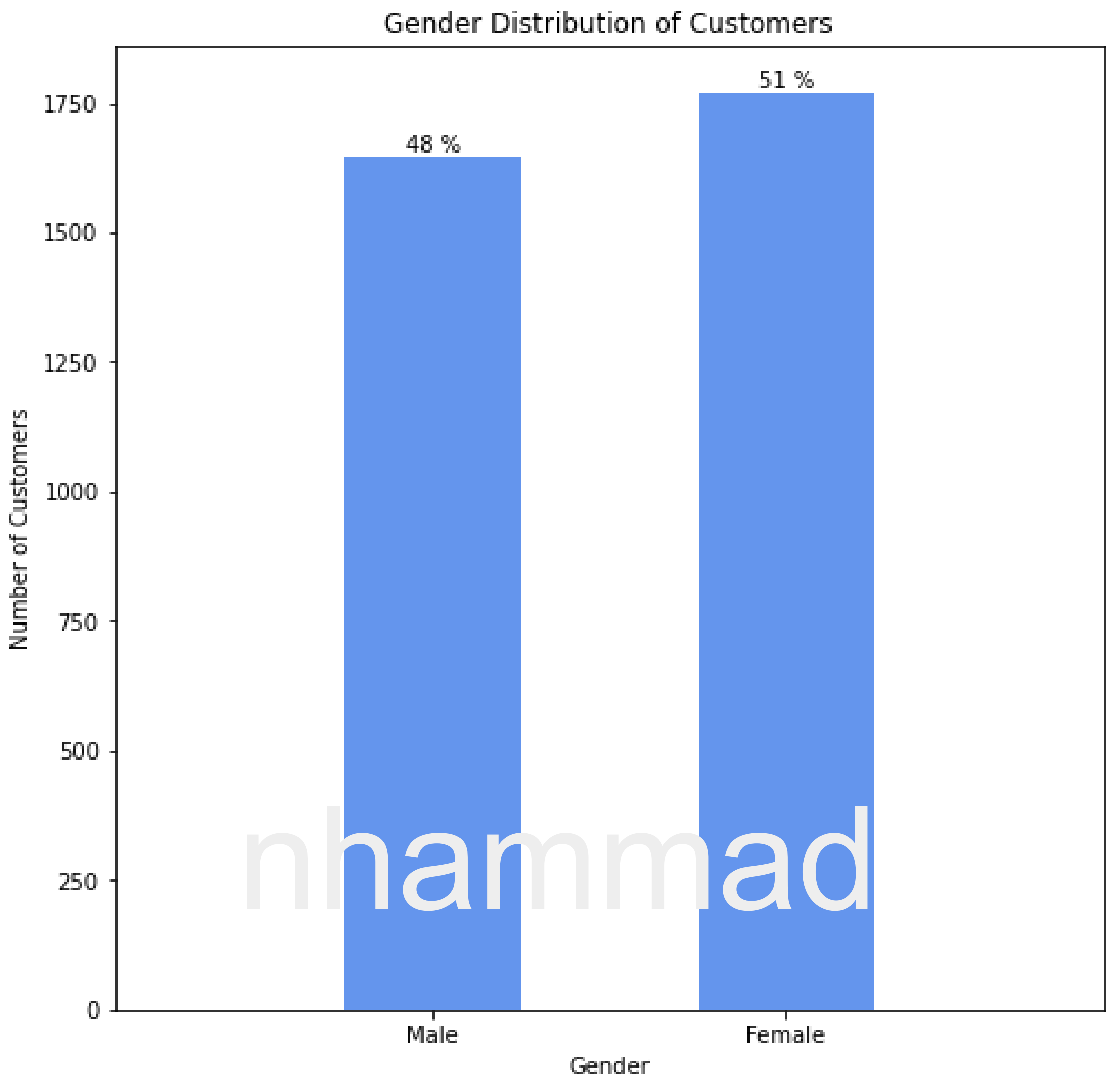
1.4 Visualizing Purchases Based on Gender

First we plot a bar chart of number of purchases according to different genders. Since the value for U is really small, we can drop that value and then visualize again.

[6]:
```python
total = df.gender.size
females = (df.gender == "F").sum()
males = (df.gender == "M").sum()
unknown = (df.gender == "U").sum()

gender = ['Male', 'Female', 'Unknown']
numbers = [males, females, unknown]

plt.figure(figsize=(8,8))
bars = plt.bar(gender, numbers, width=0.4, bottom=None, align='center', data=None, color='cornflowerblue')
plt.xlim(-0.9, len(gender) - 1 + 0.9)
for i in range(len(numbers)):
    percentage = ((numbers[i]/total)*100)
    percentage = str(round(percentage,2)) + " %"
    plt.annotate(percentage, xy=(gender[i], numbers[i] + 10), ha='center')
plt.xlabel('Gender')
plt.ylabel('Number of Customers')
plt.title('Gender Distribution of Customers')
plt.show()
```

```python
df = df[df['gender'] != "U"]

females = (df.gender == "F").sum()
males = (df.gender == "M").sum()

gender = ['Male', 'Female']
numbers = [males, females]

plt.figure(figsize=(8,8))
bars = plt.bar(gender, numbers, width=0.5, bottom=None, align='center', data=None, color='cornflowerblue')
plt.xlim(-0.9, len(gender) - 1 + 0.9)
for i in range(len(numbers)):
    percentage = ((numbers[i]/(total-1))*100)
    percentage = str(int(percentage)) + " %"
    plt.annotate(percentage, xy=(gender[i], numbers[i] + 10), ha='center')
plt.xlabel('Gender')
plt.ylabel('Number of Customers')
plt.title('Gender Distribution of Customers')
plt.show()
```


Gender Distribution of Customers
48.13 %
51.84 %
0.03 %
Number of Customers
0
250
500
750
1000
1250
1500
1750
Male
Female
Unknown
Gender



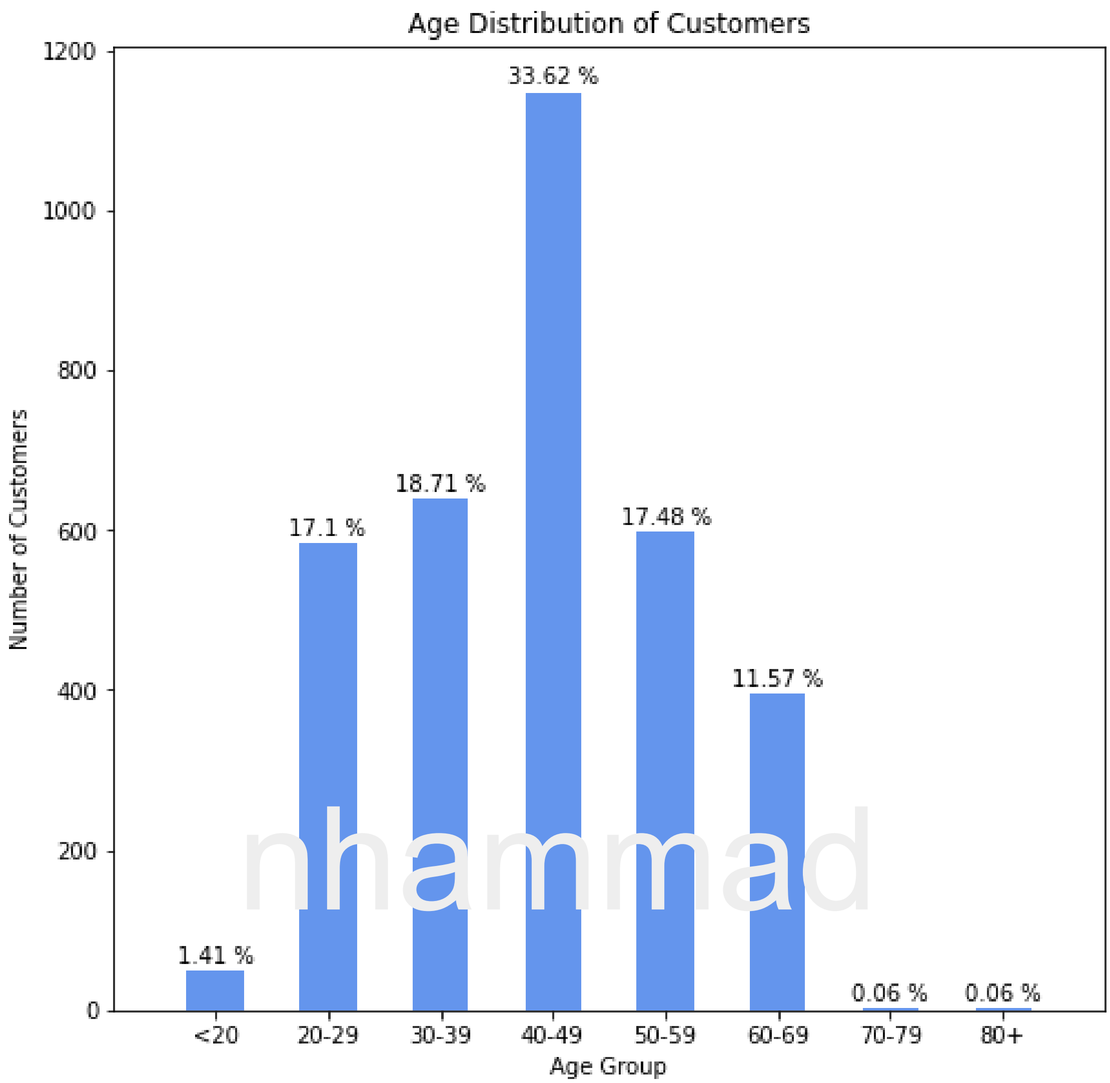
1.5 Visualizing Purchases Based on Age Groups

First we check the average age. Then, we plot a bar chart to see how the number of purchases are distributed amongst different age groups.

[7]:
```
print("Average Age" , int(df.age.mean()))

under20 = 0
_20To30 = 0
_30To40 = 0
_40To50 = 0
_50To60 = 0
_60To70 = 0
```

```
_70To80 = 0
above80 = 0

size = df.gender.size

for value in df['age']:
   if(value<20):
    under20+=1
   elif (value >=20 and value <30):
    _20To30 += 1
   elif (value >= 30 and value <40):
    _30To40 += 1
   elif (value >= 40 and value <50):
    _40To50 += 1
   elif (value >= 50 and value <60):
    _50To60 += 1
   elif (value >= 60 and value <70):
    _60To70 += 1
   elif (value >= 70 and value <80):
    _70To80 += 1
   else:
    above80 += 1


ageGroups = ['<20','20-29','30-39','40-49','50-59','60-69','70-79','80+']
numbers = [under20, _20To30, _30To40, _40To50, _50To60, _60To70, _70To80,␣
 ↪above80]

plt.figure(figsize=(8,8))
bars = plt.bar(ageGroups, numbers, width=0.5, bottom=None, align='center',␣
 ↪data=None, color='cornflowerblue')
plt.xlim(-0.9, len(ageGroups) - 1 + 0.9)
for i in range(len(numbers)):
    percentage = ((numbers[i]/(size))*100)
    percentage = str(round(percentage,2)) + " %"
    plt.annotate(percentage, xy=(ageGroups[i], numbers[i] + 10), ha='center')
plt.xlabel('Age Group')
plt.ylabel('Number of Customers')
plt.title('Age Distribution of Customers')
plt.show()
```

```
Average Age 42
```

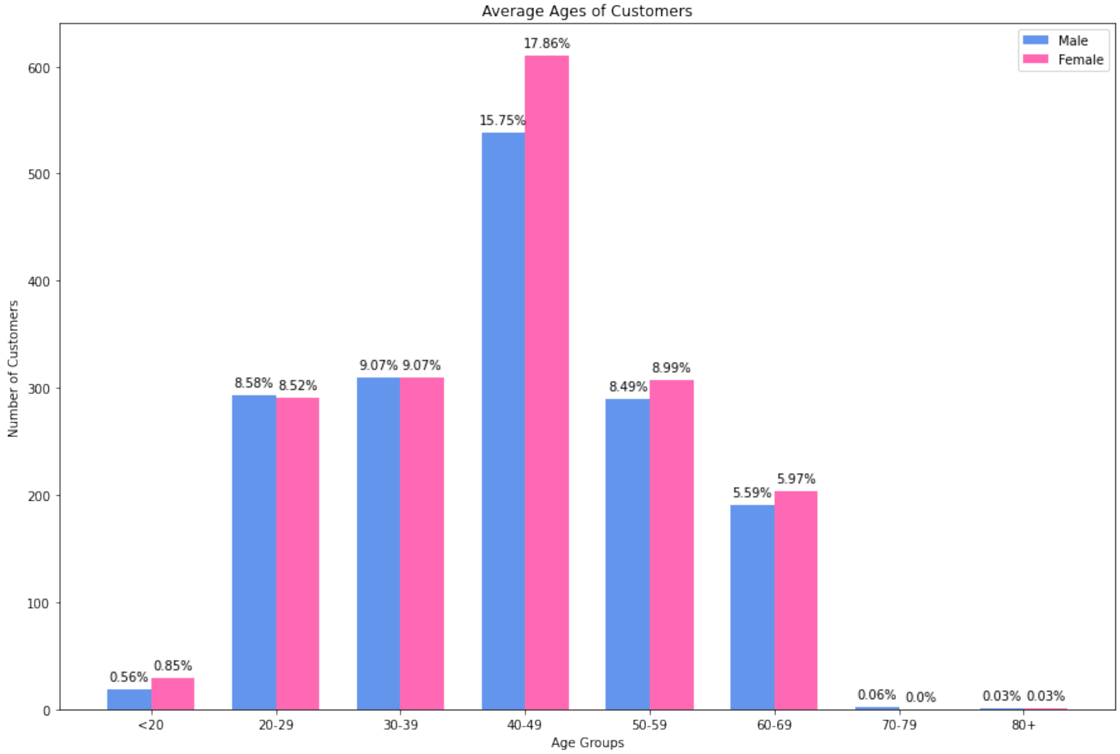


1.6 Visualizing Purchases Based on Gender & Age Groups

[8]:
```
femalesUnder20 = 0
females20To30 = 0
females30To40 = 0
females40To50 = 0
females50To60 = 0
females60To70 = 0
females70To80 = 0
femalesAbove80 = 0

femaleAgesData = df[df['gender']=="F"]
```

```
for value in femaleAgesData['age']:
   if(value<20):
    femalesUnder20+=1
   elif (value >=20 and value <30):
    females20To30 += 1
   elif (value >= 30 and value <40):
    females30To40 += 1
   elif (value >= 40 and value <50):
    females40To50 += 1
   elif (value >= 50 and value <60):
    females50To60 += 1
   elif (value >= 60 and value <70):
    females60To70 += 1
   elif (value >= 70 and value <80):
    females70To80 += 1
   else:
    femalesAbove80 += 1


malesUnder20 = 0
males20To30 = 0
males30To40 = 0
males40To50 = 0
males50To60 = 0
males60To70 = 0
males70To80 = 0
malesAbove80 = 0

maleAgesData = df[df['gender']=="M"]

for value in maleAgesData['age']:
   if(value<20):
    malesUnder20+=1
   elif (value >=20 and value <30):
    males20To30 += 1
   elif (value >= 30 and value <40):
    males30To40 += 1
   elif (value >= 40 and value <50):
    males40To50 += 1
   elif (value >= 50 and value <60):
    males50To60 += 1
   elif (value >= 60 and value <70):
    males60To70 += 1
   elif (value >= 70 and value <80):
    males70To80 += 1
   else:
```

```python
    malesAbove80 += 1

N = 8
labels = ['<20','20-29', '30-39','40-49','50-59','60-69','70-79','80+']
maleAges = (malesUnder20, males20To30, males30To40, males40To50, males50To60,␣
 ↪males60To70, males70To80,malesAbove80)
femaleAges = (femalesUnder20, females20To30,males30To40, females40To50,␣
 ↪females50To60, females60To70, females70To80,femalesAbove80)
ind = np.arange(N)
width = 0.35


figure, axes = plt.subplots()
figure.set_size_inches(15, 10, forward=True)
plt.bar(ind, maleAges , width, label='Male', color='cornflowerblue')
plt.bar(ind + width, femaleAges, width, label='Female', color='hotpink')

plt.xlabel('Age Groups')
plt.ylabel('Number of Customers')
plt.title('Average Ages of Customers')

plt.xticks(ind + width / 2,  ('<20','20-29',␣
 ↪'30-39','40-49','50-59','60-69','70-79','80+'))

for p in axes.patches:
    axes.annotate(f'{np.round((p.get_height()/total)*100, decimals=2)}%',
                xy=(p.get_x()+p.get_width()/2., p.get_height()),
                ha='center',
                va='center',
                xytext=(0, 10),
                textcoords='offset points')

plt.legend(loc='best')
plt.show()
```

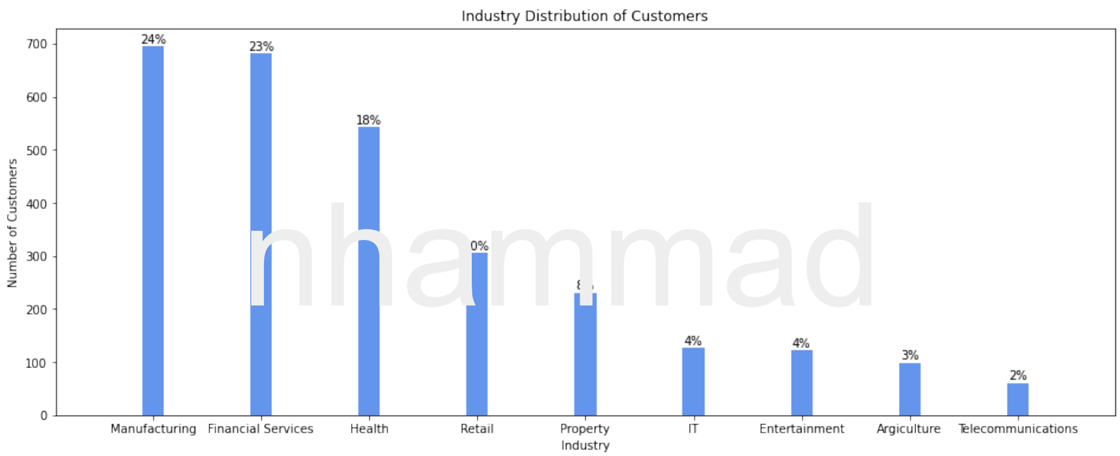


1.7 Visualizing Purchases Based on Industries

[9]:
```
print(df.job_industry_category.value_counts(),"\n")

total = df.job_industry_category.size
null_values = sum(pd.isnull(df['job_industry_category']))
total = total-null_values

industries = (df['job_industry_category'].sort_values()).value_counts().keys().tolist()
counts = (df['job_industry_category'].sort_values()).value_counts().tolist()

data = sorted(zip(industries, counts), key=lambda v: v[1], reverse=True)

plt.figure(figsize=(16, 6))
for (i, c) in data:
    bars = plt.bar(i, c, width=0.2, bottom=None, align='center', data=None, color='cornflowerblue')
    plt.annotate(f'{int((c/total)*100)}%\n', xy=(i, c), va='center', ha='center')
plt.xlim(-0.9, len(industries) - 1 + 0.9)
```

```
plt.xlabel('Industry')
plt.ylabel('Number of Customers')
plt.title('Industry Distribution of Customers')
plt.show()
```

```
Manufacturing          695
Financial Services     682
Health                 543
Retail                 305
Property               231
IT                     126
Entertainment          122
Argiculture             99
Telecommunications      61
Name: job_industry_category, dtype: int64
```

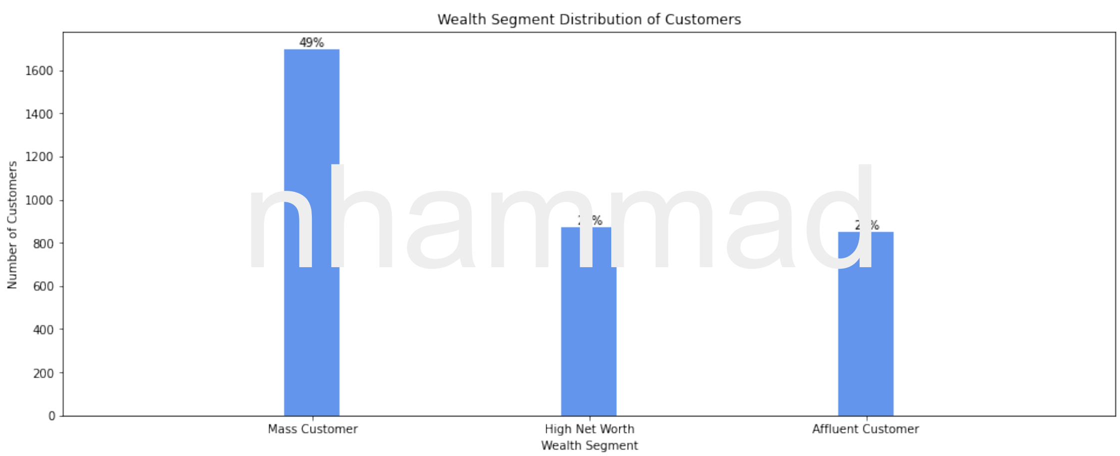


1.8 Visualizing Purchases Based on Wealth Segments

[10]:
```
print(df.wealth_segment.value_counts(),"\n")

total = df.wealth_segment.size
null_values = sum(pd.isnull(df['wealth_segment']))
total = total-null_values

segments = (df['wealth_segment'].sort_values()).value_counts().keys().tolist()
counts = (df['wealth_segment'].sort_values()).value_counts().tolist()

data = sorted(zip(segments, counts), key=lambda v: v[1], reverse=True)
```

```python
plt.figure(figsize=(16, 6))
for (i, c) in data:
    bars = plt.bar(i, c, width=0.2, bottom=None, align='center', data=None, color='cornflowerblue')
    plt.annotate(f'{int((c/total)*100)}%\n', xy=(i, c), va='center', ha='center')
plt.xlim(-0.9, len(segments) - 1 + 0.9)
plt.xlabel('Wealth Segment')
plt.ylabel('Number of Customers')
plt.title('Wealth Segment Distribution of Customers')
plt.show()
```

```
Mass Customer        1695
High Net Worth        871
Affluent Customer     849
Name: wealth_segment, dtype: int64
```

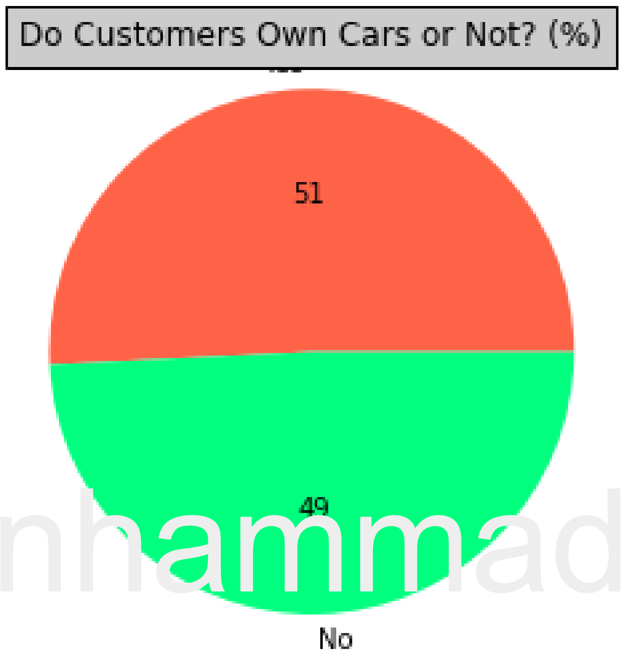


1.9 Visualizing Purchases Based on Whether the Customers Own A Car or Not

[11]:
```python
print(df.owns_car.value_counts(),"\n")

labels = (df['owns_car'].sort_values()).value_counts().keys().tolist()
counts = (df['owns_car'].sort_values()).value_counts().tolist()

figureObject, axesObject = plt.subplots()
axesObject.pie(counts, labels=labels, autopct='%1.0f', colors=['tomato','springgreen'])
axesObject.axis('equal')
```

```
plt.title("Do Customers Own Cars or Not? (%)", bbox={'facecolor':'0.8', 'pad':5})
plt.show()
```

```
Yes    1734
No     1681
Name: owns_car, dtype: int64
```



2 Customer Addresses

Now it's time to involve the second dataset.

2.1 Removing Contradiction in States

Upon seeing the head of our dataset, we observe something strange. Some state names are written full while others are abbreviations. To investigate further, we can check the value counts. After checking the value counts, we realize that there's a contradition in state names. For instance, New South Wales and NSW is the same but are written separately. Same is the case with Victoria and VIC. Hence, we make the necessary replacements.

[12]:

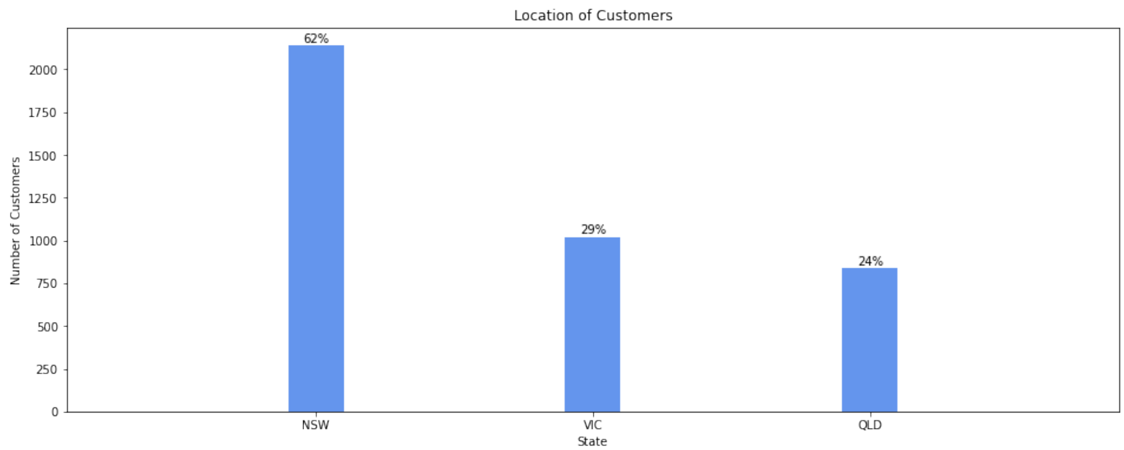
```
```

```
customerAddressDF = pd.read_excel("KPMG_VI_New_raw_data_update_final.xlsx",␣
 ↪sheet_name=4, skiprows=1)
print(customerAddressDF.state.value_counts(),"\n")
customerAddressDF["state"].replace({"New South Wales": "NSW", "Victoria":␣
 ↪"VIC"}, inplace=True)
```

```
NSW                2054
VIC                 939
QLD                 838
New South Wales      86
Victoria             82
Name: state, dtype: int64
```

2.2 Visualizing Purchases Based on States

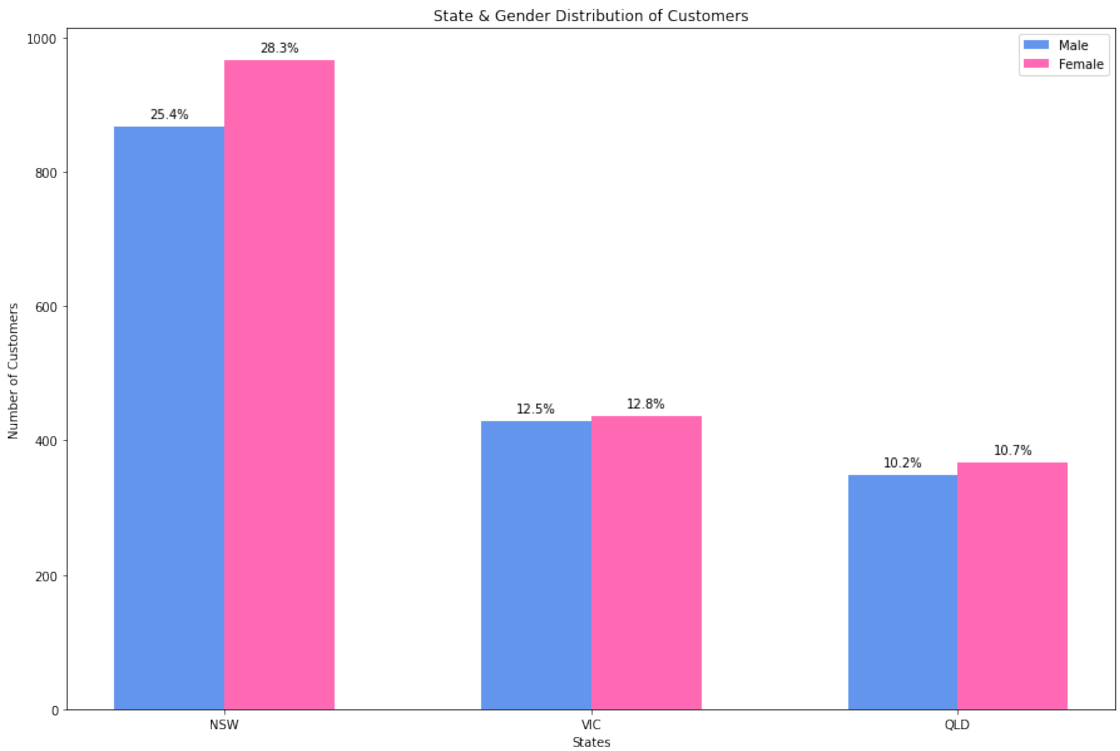
[13]:
```
states = (customerAddressDF['state'].sort_values()).value_counts().keys().
 ↪tolist()
counts = (customerAddressDF['state'].sort_values()).value_counts().tolist()

data = sorted(zip(states, counts), key=lambda v: v[1], reverse=True)

plt.figure(figsize=(16, 6))
for (i, c) in data:
    bars = plt.bar(i, c, width=0.2, bottom=None, align='center', data=None,␣
 ↪color='cornflowerblue')
    plt.annotate(f'{int((c/total)*100)}%\n', xy=(i, c), va='center',␣
 ↪ha='center')
plt.xlim(-0.9, len(states) - 1 + 0.9)
plt.xlabel('State')
plt.ylabel('Number of Customers')
plt.title('Location of Customers')
plt.show()
```



2.3 Visualizing Purchases Based on States & Gender

[14]:
```
customerAddressDF = pd.merge(customerAddressDF, df, on='customer_id',␣
 ↪how='inner')

maleNSW = 0
maleVIC = 0
maleQLD = 0

femaleNSW = 0
femaleVIC = 0
femaleQLD = 0

NSWData = customerAddressDF[customerAddressDF['state']=="NSW"]
VICData = customerAddressDF[customerAddressDF['state']=="VIC"]
QLDData = customerAddressDF[customerAddressDF['state']=="QLD"]


for value in NSWData['gender']:
    if(value=="F"):
     femaleNSW+=1
    else:
     maleNSW += 1

for value in VICData['gender']:
    if(value=="F"):
     femaleVIC+=1
    else:
     maleVIC += 1
```

```
for value in QLDData['gender']:
   if(value=="F"):
    femaleQLD+=1
   else:
    maleQLD += 1


N = 3
labels = ['NSW','VIC', 'QLD']
male = (maleNSW, maleVIC, maleQLD)
female = (femaleNSW, femaleVIC, femaleQLD)
ind = np.arange(N)
width = 0.30

figure, axes = plt.subplots()
figure.set_size_inches(15, 10, forward=True)
plt.bar(ind, male , width, label='Male', color='cornflowerblue')
plt.bar(ind + width, female, width, label='Female', color='hotpink')

plt.xlabel('States')
plt.ylabel('Number of Customers')
plt.title('State & Gender Distribution of Customers')

plt.xticks(ind + width / 2, ('NSW', 'VIC', 'QLD'))

for p in axes.patches:
    axes.annotate(f'{np.round((p.get_height()/total)*100, decimals=1)}%',
                xy=(p.get_x()+p.get_width()/2., p.get_height()),
                ha='center',
                va='center',
                xytext=(0, 10),
                textcoords='offset points')

plt.legend(loc='best')
plt.show()
```


State & Gender Distribution of Customers
Male
Female
Number of Customers
States
NSW
VIC
QLD
25.4%
28.3%
12.5%
12.8%
10.2%
10.7%
0
200
400
600
800
1000