test3

August 20, 2021

This document presents solutions to tasks 1 and 2.

We are tasked with completing a data quality assessment on the four datasets that were given by Sprocket Central and finding data insights. The four datasets are listed as followed:

- Transactions data in the past 3 months
- New Customer List
- Customer Demographic
- Customer Address

We will begin by importing the necessary libraries and loading the datasets.

[124]:
```
# Load libraries
import os
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from IPython.display import display
%matplotlib inline
```

[125]:
```
# Set working directory
os.chdir('/Users/saulchirinos/Documents/Data Science/Projects/Forage/KPMG/Data')
```

[126]:
```
# Load data
transactions = pd.read_excel('KPMG data.xlsx', sheet_name='Transactions',␣
 ↪header=1, usecols='A:M')
new_cust = pd.read_excel('KPMG data.xlsx', sheet_name='NewCustomerList',␣
 ↪header=1, usecols='A:W')
demographic = pd.read_excel('KPMG data.xlsx', sheet_name='CustomerDemographic',␣
 ↪header=1, usecols='A:M')
address = pd.read_excel('KPMG data.xlsx', sheet_name='CustomerAddress',␣
 ↪header=1, usecols='A:F')
```

Now that we have all four datasets loaded, we will go through the data quality assessment process for each one starting with transactions.

1 Data Quality Assessment

1.1 Transactions data

[127]:
```python
# Inspect transactions data
transactions.head()
```

[127]:
```
   transaction_id  product_id  customer_id transaction_date  online_order  \
0               1           2         2950       2017-02-25           0.0
1               2           3         3120       2017-05-21           1.0
2               3          37          402       2017-10-16           0.0
3               4          88         3135       2017-08-31           0.0
4               5          78          787       2017-10-01           1.0

  order_status           brand product_line product_class product_size  \
0     Approved           Solex     Standard        medium       medium
1     Approved   Trek Bicycles     Standard        medium        large
2     Approved      OHM Cycles     Standard           low       medium
3     Approved  Norco Bicycles     Standard        medium       medium
4     Approved  Giant Bicycles     Standard        medium        large

   list_price  standard_cost  product_first_sold_date
0       71.49          53.62                  41245.0
1     2091.47         388.92                  41701.0
2     1793.43         248.82                  36361.0
3     1198.46         381.10                  36145.0
4     1765.30         709.48                  42226.0
```

[128]:
```python
transactions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 13 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   transaction_id           20000 non-null  int64
 1   product_id               20000 non-null  int64
 2   customer_id              20000 non-null  int64
 3   transaction_date         20000 non-null  datetime64[ns]
 4   online_order             19640 non-null  float64
 5   order_status             20000 non-null  object
 6   brand                    19803 non-null  object
 7   product_line             19803 non-null  object
 8   product_class            19803 non-null  object
 9   product_size             19803 non-null  object
 10  list_price               20000 non-null  float64
 11  standard_cost            19803 non-null  float64
 12  product_first_sold_date  19803 non-null  float64
dtypes: datetime64[ns](1), float64(4), int64(3), object(5)
memory usage: 2.0+ MB
```

We can see that the columns `order_status`, `brand`, `product_line`, `product_class`, and `product_size` are of type `object`. This type of object is very storage intensive and makes our program slow. Therefore, we should convert these to either dummy variables or of type `category` for efficient storage. Additionally, the `product_first_sold_date` should be converted to datetime format.

[129]:
```python
# Convert object columns to category or dummy variables
LABELS_trans = ['order_status', 'brand', 'product_line',
                'product_class', 'product_size']

transactions[LABELS_trans] = transactions[LABELS_trans].apply(lambda x: x.
 ↪astype('category'))

# Convert product_first_sold_date to datetime format
transactions['product_first_sold_date'] = pd.
 ↪to_datetime(transactions['product_first_sold_date'],
                                                        unit='D',␣
 ↪origin='1900-01-01')

print(transactions.product_first_sold_date.head(), '\n'*3)
print(transactions.info())
```

```
0   2012-12-04
1   2014-03-05
2   1999-07-22
3   1998-12-18
4   2015-08-12
Name: product_first_sold_date, dtype: datetime64[ns]



<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 13 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   transaction_id           20000 non-null  int64
 1   product_id               20000 non-null  int64
 2   customer_id              20000 non-null  int64
 3   transaction_date         20000 non-null  datetime64[ns]
 4   online_order             19640 non-null  float64
 5   order_status             20000 non-null  category
 6   brand                    19803 non-null  category
 7   product_line             19803 non-null  category
 8   product_class            19803 non-null  category
 9   product_size             19803 non-null  category
 10  list_price               20000 non-null  float64
 11  standard_cost            19803 non-null  float64
```

```
 12  product_first_sold_date  19803 non-null  datetime64[ns]
dtypes: category(5), datetime64[ns](2), float64(3), int64(3)
memory usage: 1.3 MB
None
```

This looks better, however we can see that there are some missing values. Let's explore those further.

[130]:
```
# Check for missing values
transactions.isnull().sum()
```

[130]:
```
transaction_id               0
product_id                   0
customer_id                  0
transaction_date             0
online_order               360
order_status                 0
brand                      197
product_line               197
product_class              197
product_size               197
list_price                   0
standard_cost              197
product_first_sold_date    197
dtype: int64
```

There are a couple missing values in almost half of the columns but luckily there aren't that many. We could decide to filter them out completely or impute them. If we drop the rows corresopnding to missing values, the dataset will be minimally affected since we already have 20,000 samples of data.

[131]:
```
# Zoom in on missing values
transactions[transactions.online_order.isnull()].head()
```

[131]:
```
     transaction_id  product_id  customer_id transaction_date  online_order  \
97               98          49          333       2017-06-23           NaN
166             167          90         3177       2017-04-26           NaN
169             170           6          404       2017-10-16           NaN
250             251          63         1967       2017-04-11           NaN
300             301          78         2530       2017-03-24           NaN

    order_status           brand product_line product_class product_size  \
97      Approved   Trek Bicycles         Road        medium       medium
166     Approved  Norco Bicycles     Standard           low       medium
169     Approved      OHM Cycles     Standard          high       medium
250     Approved           Solex     Standard        medium       medium
300     Approved  Giant Bicycles     Standard        medium        large

     list_price  standard_cost product_first_sold_date
```

```
97      533.51         400.13              2003-07-23
166     363.01         290.41              2005-05-12
169     227.88         136.73              2003-08-07
250    1483.20          99.59              2015-05-23
300    1765.30         709.48              1997-01-27
```

[132]:
```python
transactions[transactions.brand.isnull()].head()
```

[132]:
```
     transaction_id  product_id  customer_id transaction_date  online_order  \
136             137           0          431       2017-09-23           0.0
159             160           0         3300       2017-08-27           0.0
366             367           0         1614       2017-03-10           0.0
406             407           0         2559       2017-06-14           1.0
676             677           0         2609       2017-07-02           0.0

    order_status brand product_line product_class product_size  list_price  \
136     Approved   NaN          NaN           NaN          NaN     1942.61
159     Approved   NaN          NaN           NaN          NaN     1656.86
366     Approved   NaN          NaN           NaN          NaN      850.89
406     Approved   NaN          NaN           NaN          NaN      710.59
676     Approved   NaN          NaN           NaN          NaN     1972.01

     standard_cost product_first_sold_date
136            NaN                     NaT
159            NaN                     NaT
366            NaN                     NaT
406            NaN                     NaT
676            NaN                     NaT
```

It seems that `brand`, `product_line`, `product_class`, `product_size`, `standard_cost`, and `product_first_sold_date` have the same rows of missing values. This may be to difficult or time consuming to track down all the missing values and impute them. Therefore, we will drop all rows corresopnding to null values.

[133]:
```python
# Drop missing values
transactions.dropna(inplace=True)

# Check there are no more missing values
transactions.isnull().any()
```

[133]:
```
transaction_id             False
product_id                 False
customer_id                False
transaction_date           False
online_order               False
order_status               False
brand                      False
product_line               False
```

```
product_class              False
product_size               False
list_price                 False
standard_cost              False
product_first_sold_date    False
dtype: bool
```

Let's also check for data entry errors.

[134]:
```
transactions.brand.unique()
```

[134]:
```
['Solex', 'Trek Bicycles', 'OHM Cycles', 'Norco Bicycles', 'Giant Bicycles',
'WeareA2B']
Categories (6, object): ['Solex', 'Trek Bicycles', 'OHM Cycles', 'Norco
Bicycles', 'Giant Bicycles', 'WeareA2B']
```

[135]:
```
transactions.product_line.unique()
```

[135]:
```
['Standard', 'Road', 'Mountain', 'Touring']
Categories (4, object): ['Standard', 'Road', 'Mountain', 'Touring']
```

[136]:
```
transactions.product_class.unique()
```

[136]:
```
['medium', 'low', 'high']
Categories (3, object): ['medium', 'low', 'high']
```

[137]:
```
transactions.product_size.unique()
```

[137]:
```
['medium', 'large', 'small']
Categories (3, object): ['medium', 'large', 'small']
```

[138]:
```
# Check for duplicate values
transactions.duplicated().any()
```

[138]:
```
False
```

There seems to be no data entry errors or duplicate values in this dataset. We will now explore the NewCustomerList dataset.

1.2 New Customer List data

[139]:
```
# Explore NewCustomerList dataset
new_cust.head()
```

[139]:
```
  first_name  last_name  gender  past_3_years_bike_related_purchases  \
0    Chickie    Brister    Male                                   86
1      Morly     Genery    Male                                   69
2    Ardelis  Forrester  Female                                   10
3     Lucine      Stutt  Female                                   64
```

```
4    Melinda     Hadlee  Female                                    34

         DOB                  job_title job_industry_category  \
0 1957-07-12            General Manager         Manufacturing
1 1970-03-22        Structural Engineer              Property
2 1974-08-28     Senior Cost Accountant    Financial Services
3 1979-01-28  Account Representative III         Manufacturing
4 1965-09-21          Financial Analyst    Financial Services

     wealth_segment deceased_indicator owns_car  …  state    country  \
0     Mass Customer                  N      Yes  …    QLD  Australia
1     Mass Customer                  N       No  …    NSW  Australia
2  Affluent Customer                 N       No  …    VIC  Australia
3  Affluent Customer                 N      Yes  …    QLD  Australia
4  Affluent Customer                 N       No  …    NSW  Australia

   property_valuation Unnamed: 16 Unnamed: 17  Unnamed: 18  Unnamed: 19  \
0                   6        0.93      1.1625     1.453125     1.235156
1                  11        0.45      0.4500     0.562500     0.478125
2                   5        0.65      0.6500     0.650000     0.650000
3                   1        0.68      0.8500     0.850000     0.850000
4                   9        0.69      0.6900     0.862500     0.862500

   Unnamed: 20  Rank     Value
0            1     1  1.718750
1            1     1  1.718750
2            1     1  1.718750
3            4     4  1.703125
4            4     4  1.703125

[5 rows x 23 columns]
```

[140]:
```
new_cust.columns
```

[140]:
```
Index(['first_name', 'last_name', 'gender',
       'past_3_years_bike_related_purchases', 'DOB', 'job_title',
       'job_industry_category', 'wealth_segment', 'deceased_indicator',
       'owns_car', 'tenure', 'address', 'postcode', 'state', 'country',
       'property_valuation', 'Unnamed: 16', 'Unnamed: 17', 'Unnamed: 18',
       'Unnamed: 19', 'Unnamed: 20', 'Rank', 'Value'],
      dtype='object')
```

[141]:
```
new_cust.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 23 columns):
 #   Column                               Non-Null Count  Dtype
```

```
---  ------                              --------------  -----
 0   first_name                          1000 non-null   object
 1   last_name                           971 non-null    object
 2   gender                              1000 non-null   object
 3   past_3_years_bike_related_purchases 1000 non-null   int64
 4   DOB                                 983 non-null    datetime64[ns]
 5   job_title                           894 non-null    object
 6   job_industry_category               835 non-null    object
 7   wealth_segment                      1000 non-null   object
 8   deceased_indicator                  1000 non-null   object
 9   owns_car                            1000 non-null   object
 10  tenure                              1000 non-null   int64
 11  address                             1000 non-null   object
 12  postcode                            1000 non-null   int64
 13  state                               1000 non-null   object
 14  country                             1000 non-null   object
 15  property_valuation                  1000 non-null   int64
 16  Unnamed: 16                         1000 non-null   float64
 17  Unnamed: 17                         1000 non-null   float64
 18  Unnamed: 18                         1000 non-null   float64
 19  Unnamed: 19                         1000 non-null   float64
 20  Unnamed: 20                         1000 non-null   int64
 21  Rank                                1000 non-null   int64
 22  Value                               1000 non-null   float64
dtypes: datetime64[ns](1), float64(5), int64(6), object(11)
memory usage: 179.8+ KB
```

[142]:
```
new_cust.describe()
```

[142]:
```
       past_3_years_bike_related_purchases       tenure     postcode  \
count                          1000.000000  1000.000000  1000.000000
mean                             49.836000    11.388000  3019.227000
std                              27.796686     5.037145   848.895767
min                               0.000000     0.000000  2000.000000
25%                              26.750000     7.000000  2209.000000
50%                              51.000000    11.000000  2800.000000
75%                              72.000000    15.000000  3845.500000
max                              99.000000    22.000000  4879.000000

       property_valuation  Unnamed: 16  Unnamed: 17  Unnamed: 18  Unnamed: 19  \
count         1000.000000  1000.000000  1000.000000  1000.000000  1000.000000
mean             7.397000     0.749970     0.841470     0.945218     0.873141
std              2.758804     0.208524     0.251219     0.294832     0.281528
min              1.000000     0.400000     0.400000     0.400000     0.340000
25%              6.000000     0.570000     0.630000     0.703125     0.659687
50%              8.000000     0.760000     0.825000     0.937500     0.858937
75%              9.000000     0.930000     1.026250     1.140625     1.073125
```

```
max              12.000000      1.100000      1.375000      1.718750      1.718750

       Unnamed: 20         Rank        Value
count  1000.000000  1000.000000  1000.000000
mean    498.819000   498.819000     0.881714
std     288.810997   288.810997     0.293525
min       1.000000     1.000000     0.340000
25%     250.000000   250.000000     0.649531
50%     500.000000   500.000000     0.860000
75%     750.250000   750.250000     1.075000
max    1000.000000  1000.000000     1.718750
```

Firstly, we should drop all unnamed columns since they exhibit any significance unless Sprocket Central can verify and give us the column names. Secondly, we should convert the columns with format `object` to either dummy variables or of type `category` wherever possible in order to improve system efficiency and storage.

[143]:

```python
# Drop Unnamed columns
for i in range(16, 21):
    new_cust.drop(columns='Unnamed: ' + str(i), inplace=True)

# Convert dtype objects to categorical type
LABELS_new = ['gender', 'job_industry_category',
            'wealth_segment', 'owns_car']
new_cust[LABELS_new] = new_cust[LABELS_new].apply(lambda x: x.
 ↪astype('category'))

new_cust.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 18 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   first_name                           1000 non-null   object
 1   last_name                            971 non-null    object
 2   gender                               1000 non-null   category
 3   past_3_years_bike_related_purchases  1000 non-null   int64
 4   DOB                                  983 non-null    datetime64[ns]
 5   job_title                            894 non-null    object
 6   job_industry_category                835 non-null    category
 7   wealth_segment                       1000 non-null   category
 8   deceased_indicator                   1000 non-null   object
 9   owns_car                             1000 non-null   category
 10  tenure                               1000 non-null   int64
 11  address                              1000 non-null   object
 12  postcode                             1000 non-null   int64
 13  state                                1000 non-null   object
```

```
 14  country                              1000 non-null   object
 15  property_valuation                   1000 non-null   int64
 16  Rank                                 1000 non-null   int64
 17  Value                                1000 non-null   float64
dtypes: category(4), datetime64[ns](1), float64(1), int64(5), object(7)
memory usage: 114.1+ KB
```

We also see that there are some missing values. Let's explore these futher.

[144]:
```
# Explore missing values
new_cust.isnull().sum()
```

[144]:
```
first_name                              0
last_name                              29
gender                                  0
past_3_years_bike_related_purchases     0
DOB                                    17
job_title                             106
job_industry_category                 165
wealth_segment                          0
deceased_indicator                      0
owns_car                                0
tenure                                  0
address                                 0
postcode                                0
state                                   0
country                                 0
property_valuation                      0
Rank                                    0
Value                                   0
dtype: int64
```

[145]:
```
new_cust[new_cust.job_industry_category.isnull()].head()
```

[145]:
```
   first_name last_name  gender  past_3_years_bike_related_purchases  \
22       Otis     Ottey    Male                                   26
23   Tabbatha   Averill  Female                                    5
33      Mikel   McNess    Male                                   71
36     Farlie   Petford    Male                                   76
43    Corinna    Suggey  Female                                   52

          DOB                  job_title job_industry_category  \
22 1998-02-05           Quality Engineer                   NaN
23 1977-12-17  Quality Control Specialist                   NaN
33 1981-09-22                      Nurse                   NaN
36 1968-03-25         Recruiting Manager                   NaN
43 1966-09-18            Design Engineer                   NaN
```

```
       wealth_segment deceased_indicator owns_car  tenure  \
22      Mass Customer                  N       No       3
23  Affluent Customer                  N      Yes      13
33      Mass Customer                  N       No       9
36     High Net Worth                  N       No      13
43  Affluent Customer                  N       No       9

                  address  postcode state    country  property_valuation  Rank  \
22  1562 Merchant Street      4744   QLD  Australia                   4    23
23       663 8th Parkway      2257   NSW  Australia                   8    23
33      3 Pleasure Drive      4122   QLD  Australia                   9    32
36  2330 Butternut Trail      2017   NSW  Australia                  10    36
43         938 Ilene Road      2761   NSW  Australia                   8    44

       Value
22  1.500000
23  1.500000
33  1.453125
36  1.447656
43  1.421094
```

[146]:
```
new_cust[new_cust.last_name.isnull()].head()
```

[146]:
```
    first_name last_name  gender  past_3_years_bike_related_purchases  \
12        Olag       NaN    Male                                   60
58   Whittaker       NaN    Male                                   64
87    Kahaleel       NaN    Male                                    5
155       Bill       NaN  Female                                   74
202       Glyn       NaN    Male                                   47

            DOB                     job_title job_industry_category  \
12   1990-05-13       Human Resources Manager    Telecommunications
58   1966-07-29             Media Manager III                   NaN
87   1942-11-01       GIS Technical Architect                   NaN
155  1963-04-24  Human Resources Assistant II              Property
202  1945-02-13               General Manager         Manufacturing

        wealth_segment deceased_indicator owns_car  tenure  \
12       Mass Customer                  N       No       9
58       Mass Customer                  N      Yes       8
87      High Net Worth                  N       No      13
155      Mass Customer                  N      Yes      19
202  Affluent Customer                  N      Yes      21

                  address  postcode state    country  property_valuation  Rank  \
12     0484 North Avenue      2032   NSW  Australia                  11    13
58      683 Florence Way      3156   VIC  Australia                   5    57
```

```
87       12 Arapahoe Park      2035    NSW   Australia                         12     88
155   6704 Pine View Lane      2170    NSW   Australia                          9    155
202      67 Bluejay Plaza      2300    NSW   Australia                          9    202

        Value
12   1.609375
58   1.375000
87   1.314844
155  1.200000
202  1.140625
```

There are missing values in `last_name`, `DOB`, `job_title`, and `job_industry_category`. I am assuming the null values in `last_name` are simply customers without a last name. As for the other three columns, unless our client can provide us with these missing values we can drop all rows with null values except for nulls in `last_name`. We can do this because it will hardly affect our data given we already have 1,000 samples.

[147]:
```python
# Drop rows with missing values
new_cust.dropna(subset=['DOB', 'job_title', 'job_industry_category'],␣
↪inplace=True)
new_cust.isnull().any()
```

[147]:
```
first_name                              False
last_name                                True
gender                                  False
past_3_years_bike_related_purchases     False
DOB                                     False
job_title                               False
job_industry_category                   False
wealth_segment                          False
deceased_indicator                      False
owns_car                                False
tenure                                  False
address                                 False
postcode                                False
state                                   False
country                                 False
property_valuation                      False
Rank                                    False
Value                                   False
dtype: bool
```

Let's now check for consistency in our data.

[148]:
```python
new_cust.gender.unique()
```

[148]:
```
['Male', 'Female']
Categories (2, object): ['Male', 'Female']
```

[149]:
```
new_cust.job_title.value_counts()
```

[149]:
```
Cost Accountant             12
Associate Professor         12
Software Consultant         12
Environmental Tech          12
Junior Executive            11
                            ..
Developer II                 1
Staff Accountant I           1
Database Administrator I     1
Developer IV                 1
Database Administrator IV    1
Name: job_title, Length: 178, dtype: int64
```

[150]:
```
new_cust.job_industry_category.value_counts()
```

[150]:
```
Financial Services    187
Manufacturing         175
Health                138
Retail                 73
Property               51
Entertainment          34
IT                     30
Argiculture            24
Telecommunications     23
Name: job_industry_category, dtype: int64
```

[151]:
```
new_cust.wealth_segment.value_counts()
```

[151]:
```
Mass Customer        369
High Net Worth       184
Affluent Customer    182
Name: wealth_segment, dtype: int64
```

[152]:
```
new_cust.deceased_indicator.unique()
```

[152]:
```
array(['N'], dtype=object)
```

[153]:
```
new_cust.owns_car.value_counts()
```

[153]:
```
No     376
Yes    359
Name: owns_car, dtype: int64
```

[154]:
```
new_cust.state.unique()
```

[154]:
```
array(['QLD', 'NSW', 'VIC'], dtype=object)
```

[155]:
```
new_cust.country.unique()
```

[155]:
```
array(['Australia'], dtype=object)
```

[156]:
```
# Check for duplicates
new_cust.duplicated().any()
```

[156]:
```
False
```

Perhaps we can drop the `deceased_indicator` column, as well as the `country` column because they do not exhibit variation. Additionally, there are no duplicate values in this dataset.

[157]:
```
# Drop deceased_indicator and country columns
new_cust.drop(columns=['deceased_indicator', 'country'], inplace=True)
new_cust.head()
```

[157]:
```
  first_name last_name  gender  past_3_years_bike_related_purchases  \
0    Chickie   Brister    Male                                   86
1      Morly    Genery    Male                                   69
2    Ardelis Forrester  Female                                   10
3     Lucine     Stutt  Female                                   64
4    Melinda    Hadlee  Female                                   34

         DOB                  job_title job_industry_category  \
0 1957-07-12            General Manager         Manufacturing
1 1970-03-22        Structural Engineer              Property
2 1974-08-28     Senior Cost Accountant    Financial Services
3 1979-01-28  Account Representative III         Manufacturing
4 1965-09-21          Financial Analyst    Financial Services

      wealth_segment owns_car  tenure               address  postcode state  \
0      Mass Customer      Yes      14      45 Shopko Center      4500   QLD
1      Mass Customer       No      16     14 Mccormick Park      2113   NSW
2  Affluent Customer       No      10  5 Colorado Crossing      3505   VIC
3  Affluent Customer      Yes       5    207 Annamark Plaza      4814   QLD
4  Affluent Customer       No      19     115 Montana Place      2093   NSW

   property_valuation  Rank     Value
0                   6     1  1.718750
1                  11     1  1.718750
2                   5     1  1.718750
3                   1     4  1.703125
4                   9     4  1.703125
```

We can move forward into exploring the CustomerDemographic dataset.

1.3 Customer Demographic data

[158]:
```python
# Explore CustomerDemographic dataset
demographic.head()
```

[158]:
```
   customer_id first_name last_name  gender  \
0           34    Jephthah  Bachmann       U
1           66      Anselm     Gawne    Male
2         1888       Sibyl   Scholtz  Female
3         3435     Stevena   Allcock  Female
4         2858   Benedicto     Radki    Male

   past_3_years_bike_related_purchases        DOB           job_title  \
0                                   59 1843-12-21     Legal Assistant
1                                   46 2002-03-11   Account Executive
2                                   67 2002-01-26        Food Chemist
3                                   80 2002-01-15       Senior Editor
4                                    4 2002-01-09  Recruiting Manager

  job_industry_category     wealth_segment deceased_indicator  \
0                    IT  Affluent Customer                  N
1           Argiculture     High Net Worth                  N
2                Health      Mass Customer                  N
3                   NaN  Affluent Customer                  N
4                   NaN      Mass Customer                  N

           default owns_car  tenure
0              NaN       No    20.0
1    ï½ï½¨(Â´âï½â©       No     1.0
2              NaN      Yes     1.0
3  ÅâÂ´â°ËÃÂ¨ËÃâââ       No     1.0
4     testâ testâ«      Yes     1.0
```

[159]:
```python
demographic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4000 entries, 0 to 3999
Data columns (total 13 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   customer_id                          4000 non-null   int64
 1   first_name                           4000 non-null   object
 2   last_name                            3875 non-null   object
 3   gender                               4000 non-null   object
 4   past_3_years_bike_related_purchases  4000 non-null   int64
 5   DOB                                  3913 non-null   datetime64[ns]
 6   job_title                            3494 non-null   object
 7   job_industry_category                3344 non-null   object
```

```
 8   wealth_segment                         4000 non-null   object
 9   deceased_indicator                     4000 non-null   object
 10  default                                3698 non-null   object
 11  owns_car                               4000 non-null   object
 12  tenure                                 3913 non-null   float64
dtypes: datetime64[ns](1), float64(1), int64(2), object(9)
memory usage: 406.4+ KB
```

We should try to convert the `object` data types to `categorical` type as well as drop the `default` column. Additionally, we'll inspect `deceased_indicator` for variation.

[160]:
```
# Convert type object to type category
LABELS_demo = ['gender', 'job_industry_category',
            'wealth_segment', 'owns_car']
demographic[LABELS_demo] = demographic[LABELS_demo].apply(lambda x: x.
 ↪astype('category'))

# Drop default column
demographic.drop(columns='default', inplace=True)

demographic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4000 entries, 0 to 3999
Data columns (total 12 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   customer_id                            4000 non-null   int64
 1   first_name                             4000 non-null   object
 2   last_name                              3875 non-null   object
 3   gender                                 4000 non-null   category
 4   past_3_years_bike_related_purchases    4000 non-null   int64
 5   DOB                                    3913 non-null   datetime64[ns]
 6   job_title                              3494 non-null   object
 7   job_industry_category                  3344 non-null   category
 8   wealth_segment                         4000 non-null   category
 9   deceased_indicator                     4000 non-null   object
 10  owns_car                               4000 non-null   category
 11  tenure                                 3913 non-null   float64
dtypes: category(4), datetime64[ns](1), float64(1), int64(2), object(4)
memory usage: 266.6+ KB
```

[161]:
```
# Inspect deceased_indicator column
demographic.deceased_indicator.value_counts()
```

[161]:
```
N    3998
Y       2
Name: deceased_indicator, dtype: int64
```

There are two people in this dataset that are marked as deceased. Let's inspect further to see how we can deal with this.

[162]:
```
# Inspect deceased_indicator further
demographic[demographic.deceased_indicator == 'Y']
```

[162]:
```
      customer_id first_name    last_name  gender  \
2782          753       Josy  St. Quentin  Female
3538         3790     Kurtis       Morson    Male

      past_3_years_bike_related_purchases        DOB      job_title  \
2782                                   82 1970-03-07   Food Chemist
3538                                   91 1959-05-31  Senior Editor

     job_industry_category     wealth_segment deceased_indicator owns_car  \
2782                Health  Affluent Customer                  Y      Yes
3538                Retail      Mass Customer                  Y      Yes

      tenure
2782     6.0
3538     9.0
```

Since both these customers have passed away, they are no longer a part of our client's target customers.

[163]:
```
# Filter out deceased and drop deceased_indicator column
print(demographic.shape)
demographic = demographic[demographic.deceased_indicator == 'N']
demographic.drop(columns='deceased_indicator', inplace=True)

# Check data again
print(demographic.shape)
print(demographic.info())
```

```
(4000, 12)
(3998, 11)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3998 entries, 0 to 3999
Data columns (total 11 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   customer_id                          3998 non-null   int64
 1   first_name                           3998 non-null   object
 2   last_name                            3873 non-null   object
 3   gender                               3998 non-null   category
 4   past_3_years_bike_related_purchases  3998 non-null   int64
 5   DOB                                  3911 non-null   datetime64[ns]
 6   job_title                            3492 non-null   object
 7   job_industry_category                3342 non-null   category
```

```
 8   wealth_segment                       3998 non-null   category
 9   owns_car                             3998 non-null   category
 10  tenure                               3911 non-null   float64
dtypes: category(4), datetime64[ns](1), float64(1), int64(2), object(3)
memory usage: 266.3+ KB
None
```

Now lets check for data consistency and missing values in the data.

[164]:
```
# Check for consistency
demographic.gender.unique()
```

[164]:
```
['U', 'Male', 'Female', 'M', 'Femal', 'F']
Categories (6, object): ['U', 'Male', 'Female', 'M', 'Femal', 'F']
```

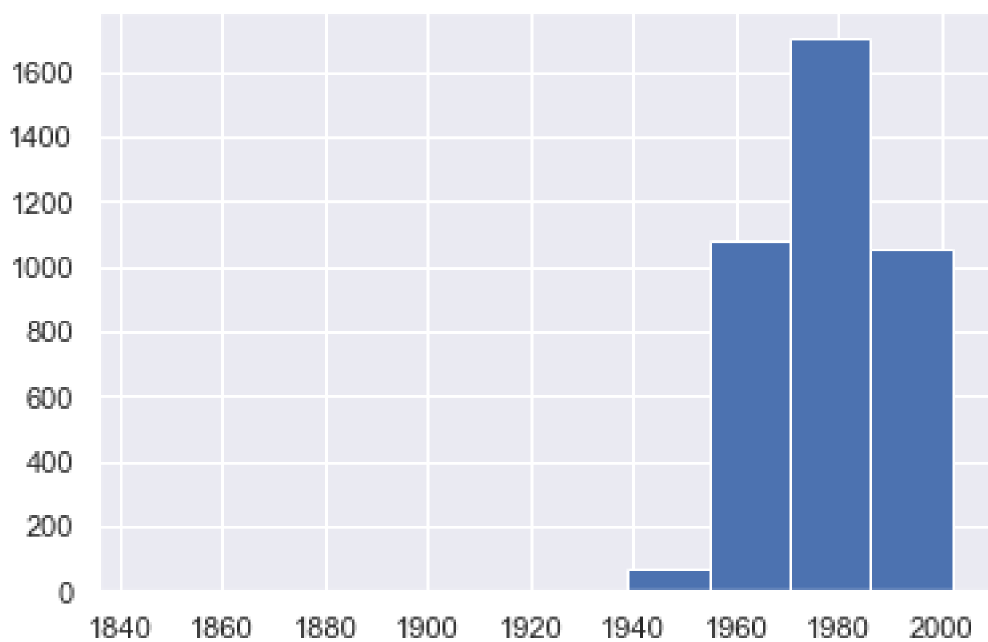
[165]:
```
demographic.wealth_segment.unique()
```

[165]:
```
['Affluent Customer', 'High Net Worth', 'Mass Customer']
Categories (3, object): ['Affluent Customer', 'High Net Worth', 'Mass Customer']
```

[166]:
```
demographic.owns_car.unique()
```

[166]:
```
['No', 'Yes']
Categories (2, object): ['No', 'Yes']
```

[167]:
```
demographic.DOB.hist()
plt.show()
```



[168]:
```
demographic.describe()
```

[168]:
```
       customer_id  past_3_years_bike_related_purchases      tenure
count  3998.000000                          3998.000000  3911.000000
mean   2000.364432                            48.871186    10.658655
std    1154.618313                            28.709682     5.661042
min       1.000000                             0.000000     1.000000
25%    1001.250000                            24.000000     6.000000
50%    2000.500000                            48.000000    11.000000
75%    2999.750000                            73.000000    15.000000
max    4000.000000                            99.000000    22.000000
```

[169]:
```
# Check for missing values
demographic.isnull().sum()
```

[169]:
```
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
owns_car                                 0
tenure                                  87
dtype: int64
```

There are inconsistent values in `gender` and `DOB`, as well as there are many missing values, especially in `job_title` and `job_industry_category`. Given how we do not have the ability to reach to Sprocket Central, the simplest thing for us to do is to drop the rows with missing values, except for the column for `last_name`. We will also correct the values in the `gender` column and explore the outlier in `DOB` in more detail.

[170]:
```
# Correct values in gender column
demographic['gender'].replace('M', 'Male', inplace=True)
demographic['gender'].replace(['F', 'Femal'], 'Female', inplace=True)
demographic['gender'].replace('U', 'Unisex', inplace=True)
print(demographic.gender.unique(), '\n')

# Drop missing values
demographic.dropna(subset=['DOB', 'job_title', 'job_industry_category',␣
↪'tenure'], inplace=True)
print(demographic.isnull().any())
```

```
['Unisex', 'Male', 'Female']
Categories (3, object): ['Unisex', 'Male', 'Female']
```

```
customer_id                             False
first_name                              False
last_name                                True
gender                                  False
past_3_years_bike_related_purchases     False
DOB                                     False
job_title                               False
job_industry_category                   False
wealth_segment                          False
owns_car                                False
tenure                                  False
dtype: bool
```

[171]:
```
# Inspect outlier in DOB column
demographic[demographic.DOB <= '1920-01-01']
```

[171]:
```
   customer_id first_name last_name  gender  \
0           34   Jephthah  Bachmann  Unisex

   past_3_years_bike_related_purchases        DOB        job_title  \
0                                   59 1843-12-21  Legal Assistant

  job_industry_category     wealth_segment owns_car  tenure
0                    IT  Affluent Customer       No    20.0
```

There is only one outlier who's DOB is in the 1800's. Let's fixed this by changing it to "1943-12-21".

[172]:
```
# Fix outlier
demographic.set_index('customer_id', inplace=True)
demographic.loc[34, 'DOB'] = pd.Timestamp('1943-12-21')
demographic.reset_index(inplace=True)

# Check
demographic[demographic.customer_id == 34]
```

[172]:
```
   customer_id first_name last_name  gender  \
0           34   Jephthah  Bachmann  Unisex

   past_3_years_bike_related_purchases        DOB        job_title  \
0                                   59 1943-12-21  Legal Assistant

  job_industry_category     wealth_segment owns_car  tenure
0                    IT  Affluent Customer       No    20.0
```

The CustomerDemographics data looks good, now let's review the last dataset, CustomerAddress.

1.4 Customer Address data

[173]:
```
# Explore CustomerAddress data
address.head()
```

[173]:
```
   customer_id              address  postcode            state    country  \
0            1   060 Morning Avenue      2016  New South Wales  Australia
1            2  6 Meadow Vale Court      2153  New South Wales  Australia
2            4   0 Holy Cross Court      4211              QLD  Australia
3            5  17979 Del Mar Point      2448  New South Wales  Australia
4            6     9 Oakridge Court      3216              VIC  Australia

   property_valuation
0                  10
1                  10
2                   9
3                   4
4                   9
```

[174]:
```
address.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3999 entries, 0 to 3998
Data columns (total 6 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   customer_id         3999 non-null   int64
 1   address             3999 non-null   object
 2   postcode            3999 non-null   int64
 3   state               3999 non-null   object
 4   country             3999 non-null   object
 5   property_valuation  3999 non-null   int64
dtypes: int64(3), object(3)
memory usage: 187.6+ KB
```

Looks like we don't have any missing values in this dataset! Let's explore the `state` and `country` columns further to make sure there are no data entry errors.

[175]:
```
# Inspect state and country columns
address.state.unique()
```

[175]:
```
array(['New South Wales', 'QLD', 'VIC', 'NSW', 'Victoria'], dtype=object)
```

[176]:
```
address.country.unique()
```

[176]:
```
array(['Australia'], dtype=object)
```

We can see that there are duplicates of "New South Wales" with "NSW" and "Victoria" with "VIC". Let's abbreviate these states and convert to `category` type. As for the `country` column, since we only have values for Australia we can drop this column entirely.

[177]:
```
# Match state names
address['state'] = address.state.str.replace('New South Wales', 'NSW')
address['state'] = address.state.str.replace('Victoria', 'VIC')

# Convert to category type
address['state'] = address.state.astype('category')
assert address.state.dtype == 'category'

# Drop country column
address.drop(columns='country', inplace=True)

# Check operations were done correctly
print(address.state.unique(), '\n')
print(address.info())
```

```
['NSW', 'QLD', 'VIC']
Categories (3, object): ['NSW', 'QLD', 'VIC']

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3999 entries, 0 to 3998
Data columns (total 5 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   customer_id         3999 non-null   int64
 1   address             3999 non-null   object
 2   postcode            3999 non-null   int64
 3   state               3999 non-null   category
 4   property_valuation  3999 non-null   int64
dtypes: category(1), int64(3), object(1)
memory usage: 129.1+ KB
None
```

Looks great so far. Now let's check for duplicates.

[178]:
```
address.duplicated().any()
```

[178]:
```
False
```

No duplicates! We are now finished with the data quality assessment process on all four datasets.

Now that all four datasets have been cleaned, let's merge the transactions data with the customer demographics data and the customer address data and see if we need to do some final clean-ups of the data. We can then begin the EDA process to find valuable insights.

[179]:
```
# Merge datasets
data = pd.merge(transactions, demographic, on='customer_id', how='left')
data = pd.merge(data, address, on='customer_id', how='left')

print(data.shape)
```

```python
print(data.columns)
```

```
(19445, 27)
Index(['transaction_id', 'product_id', 'customer_id', 'transaction_date',
       'online_order', 'order_status', 'brand', 'product_line',
       'product_class', 'product_size', 'list_price', 'standard_cost',
       'product_first_sold_date', 'first_name', 'last_name', 'gender',
       'past_3_years_bike_related_purchases', 'DOB', 'job_title',
       'job_industry_category', 'wealth_segment', 'owns_car', 'tenure',
       'address', 'postcode', 'state', 'property_valuation'],
      dtype='object')
```

Let's check for duplicates and null values.

[180]:
```python
# Check for duplicates
data.duplicated().any()
```

[180]:
```
False
```

[181]:
```python
# Check for missing values
data.isnull().sum()
```

[181]:
```
transaction_id                            0
product_id                                0
customer_id                               0
transaction_date                          0
online_order                              0
order_status                              0
brand                                     0
product_line                              0
product_class                             0
product_size                              0
list_price                                0
standard_cost                             0
product_first_sold_date                   0
first_name                             5379
last_name                              5805
gender                                 5379
past_3_years_bike_related_purchases    5379
DOB                                    5379
job_title                              5379
job_industry_category                  5379
wealth_segment                         5379
owns_car                               5379
tenure                                 5379
address                                  29
postcode                                 29
state                                    29
```

```
property_valuation                          29
dtype: int64
```

There are quite a few missing values, let's explore these further and see if we can impute them.

[182]:
```
data[data.first_name.isnull()][['customer_id', 'first_name', 'last_name',
                                'gender', 'DOB', 'job_title']].head()
```

[182]:
```
    customer_id first_name last_name gender DOB job_title
4           787        NaN       NaN    NaN NaT       NaN
10         1986        NaN       NaN    NaN NaT       NaN
16         2426        NaN       NaN    NaN NaT       NaN
24         2822        NaN       NaN    NaN NaT       NaN
25         2596        NaN       NaN    NaN NaT       NaN
```

[183]:
```
data[data.first_name.isnull()][['customer_id', 'first_name', 'last_name',
                                'gender', 'DOB', 'job_title']].tail()
```

[183]:
```
       customer_id first_name last_name gender DOB job_title
19433          714        NaN       NaN    NaN NaT       NaN
19436         1374        NaN       NaN    NaN NaT       NaN
19437            5        NaN       NaN    NaN NaT       NaN
19438         2618        NaN       NaN    NaN NaT       NaN
19443         2764        NaN       NaN    NaN NaT       NaN
```

[184]:
```
data.customer_id.value_counts()
```

[184]:
```
1068    14
2183    14
2476    14
637     13
3232    13
        ..
71       1
2532     1
1846     1
1632     1
2047     1
Name: customer_id, Length: 3492, dtype: int64
```

It seems that when we had merged all three datasets together, there were some customers who's activity was not tracked all the way through. Consequently, we are left with no other choice but to drop all missing values and move forward.

[185]:
```
# Drop missing values
print(data.shape)
data.dropna(inplace=True)
print(data.shape)
```

```
(19445, 27)
(13628, 27)
```

2 Exploratory Data Analysis

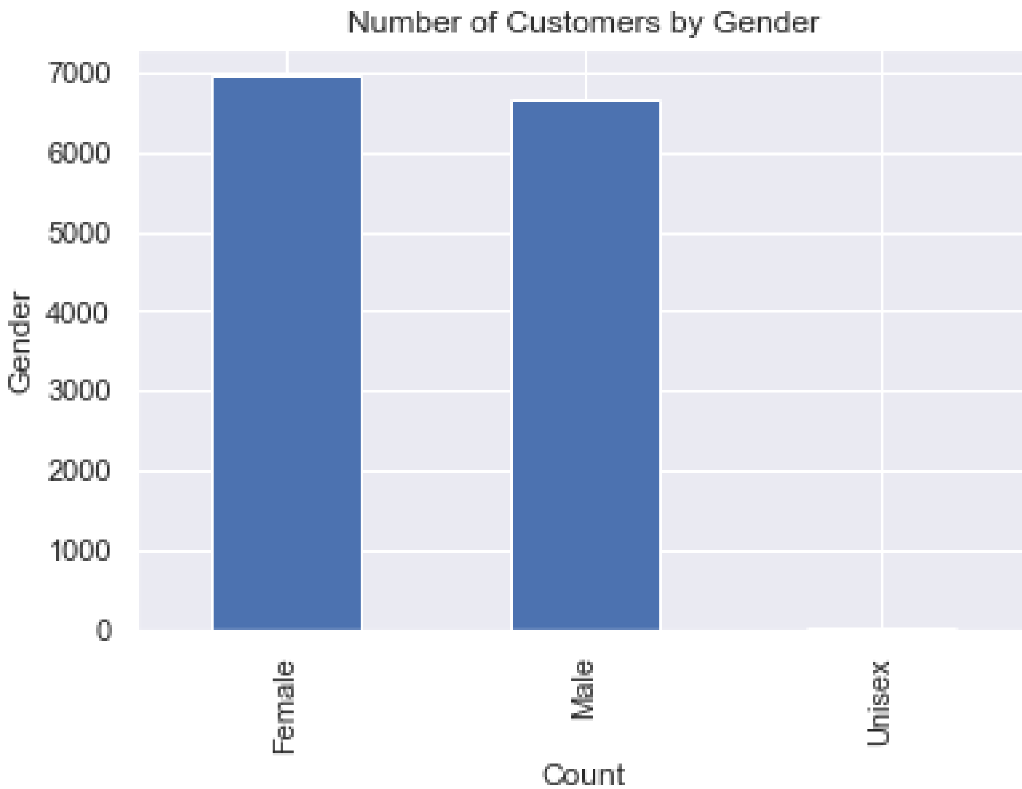
[186]:
```python
# Explore data
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 13628 entries, 0 to 19444
Data columns (total 27 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   transaction_id                       13628 non-null  int64
 1   product_id                           13628 non-null  int64
 2   customer_id                          13628 non-null  int64
 3   transaction_date                     13628 non-null  datetime64[ns]
 4   online_order                         13628 non-null  float64
 5   order_status                         13628 non-null  category
 6   brand                                13628 non-null  category
 7   product_line                         13628 non-null  category
 8   product_class                        13628 non-null  category
 9   product_size                         13628 non-null  category
 10  list_price                           13628 non-null  float64
 11  standard_cost                        13628 non-null  float64
 12  product_first_sold_date              13628 non-null  datetime64[ns]
 13  first_name                           13628 non-null  object
 14  last_name                            13628 non-null  object
 15  gender                               13628 non-null  category
 16  past_3_years_bike_related_purchases  13628 non-null  float64
 17  DOB                                  13628 non-null  datetime64[ns]
 18  job_title                            13628 non-null  object
 19  job_industry_category                13628 non-null  category
 20  wealth_segment                       13628 non-null  category
 21  owns_car                             13628 non-null  category
 22  tenure                               13628 non-null  float64
 23  address                              13628 non-null  object
 24  postcode                             13628 non-null  float64
 25  state                                13628 non-null  category
 26  property_valuation                   13628 non-null  float64
dtypes: category(10), datetime64[ns](3), float64(7), int64(3), object(4)
memory usage: 2.0+ MB
```

Now that we have our data in order, let's explore the customers and their activities.

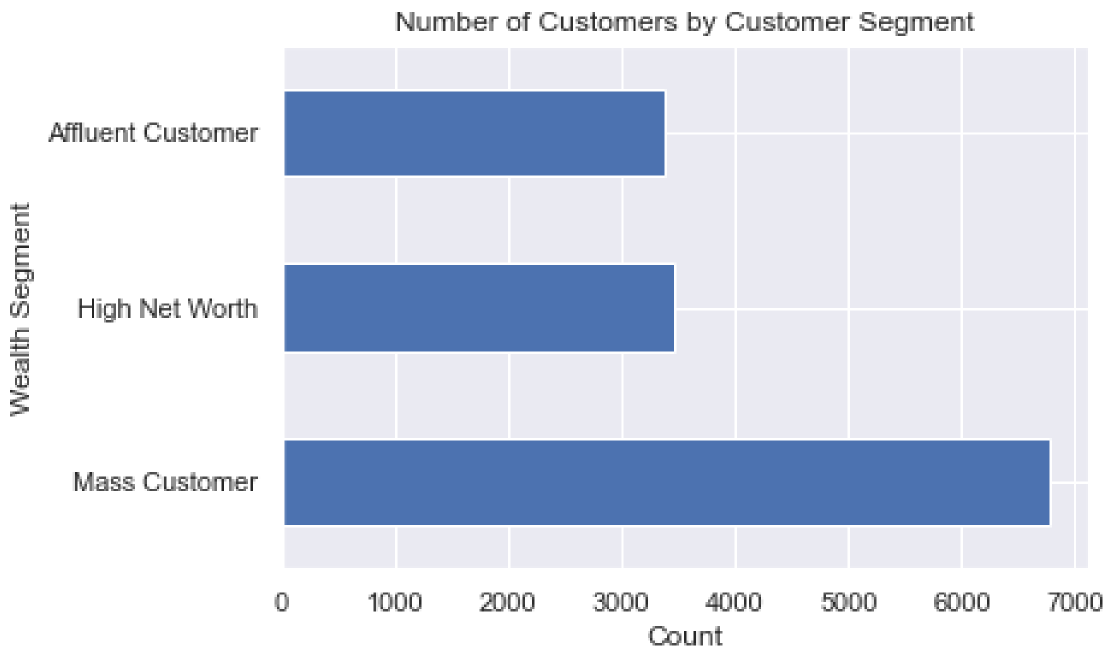
[187]:
```python
# Set graph style
sns.set()
```

```
# Plot gender count plot
data.gender.value_counts().plot(kind='bar')
plt.xlabel('Count')
plt.ylabel('Gender')
plt.title('Number of Customers by Gender')
plt.show()
```



[188]:

```
# Plot wealth segment count plot
data.wealth_segment.value_counts().plot(kind='barh')
plt.xlabel('Count')
plt.ylabel('Wealth Segment')
plt.title('Number of Customers by Customer Segment')
plt.show()
```



We can see that most of Sprocket Central's customers are split into males and females with a very small proportion being unisex. Furthermore, about 50% of customers are mass customers, the rest are split between affluent and high net worth. Before we analyze the product attributes, let's find which age group is responsible for the most transactions.

[189]:
```
# datetime library
import datetime as dt

# Function to get age
def dob_to_age(born):
    today = dt.date.today()
    return today.year - born.year - ((today.month, today.day) < (born.month,␣
 ↪born.day))
```

[190]:
```
# Get ages
data['age'] =  data.DOB.apply(lambda x: dob_to_age(x))

# Split customers into age groups
data['age_dec'] = (data.age // 10) * 10

data.age_dec.head()
```

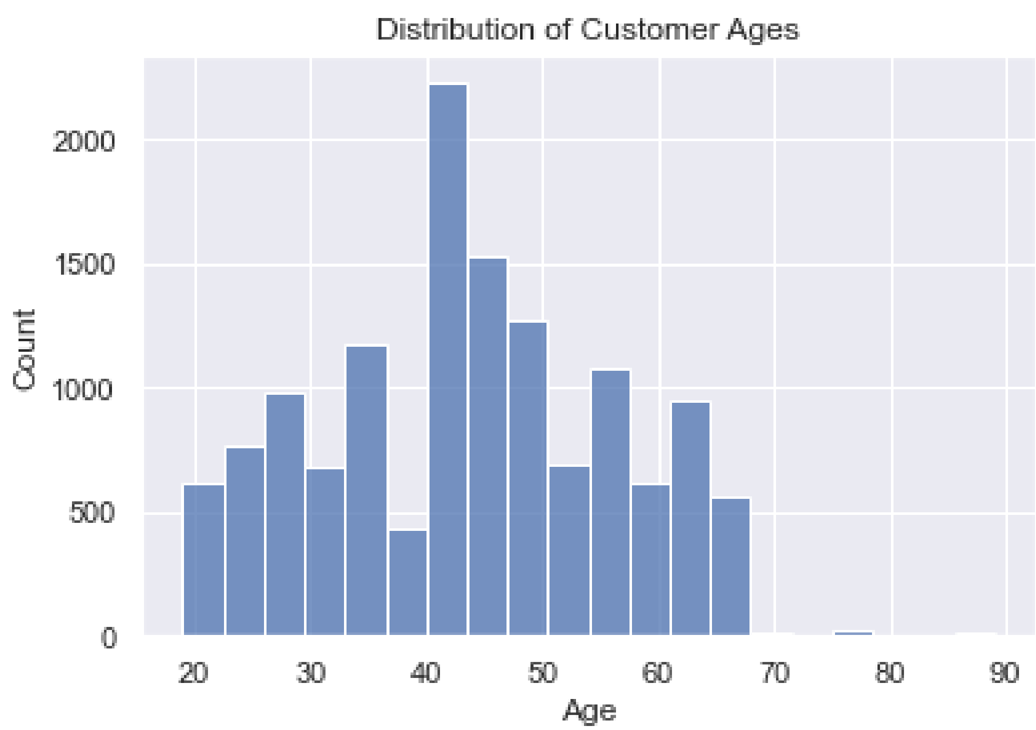
[190]:
```
0    60
1    40
2    40
3    50
```

```
5    60
Name: age_dec, dtype: int64
```

[191]:
```
data.age_dec.value_counts()
```

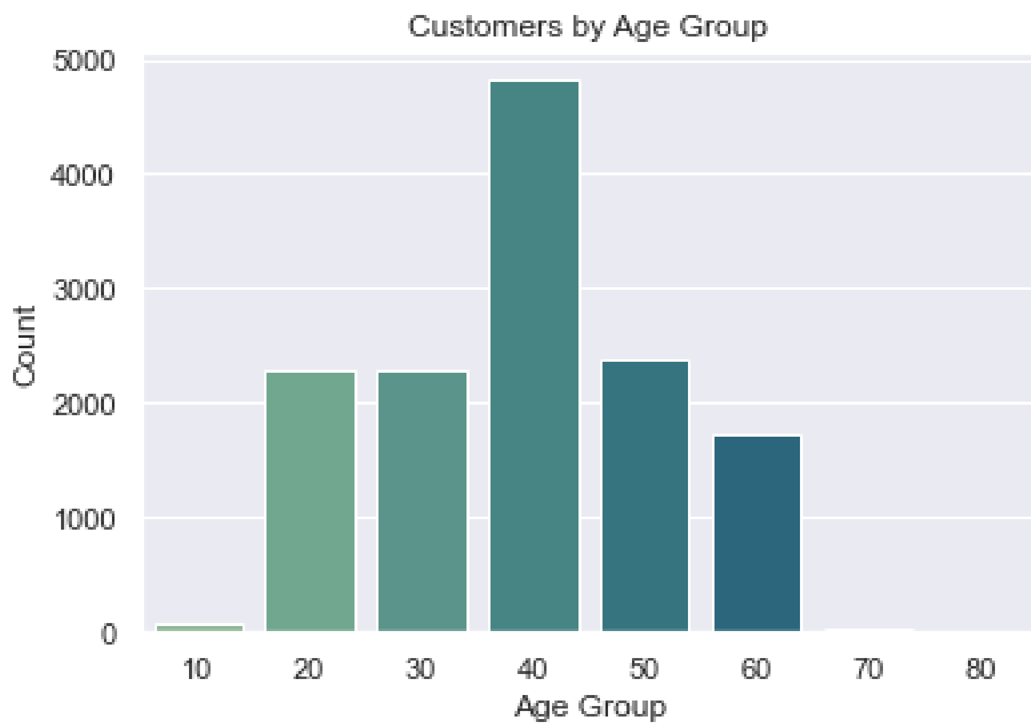
[191]:
```
40    4821
50    2391
30    2296
20    2287
60    1722
10      76
70      20
80      15
Name: age_dec, dtype: int64
```

[192]:
```
# Plot distribution of ages
sns.histplot(x='age', data=data, bins=20)
plt.title('Distribution of Customer Ages')
plt.xlabel('Age')
plt.show()
```



[193]:
```
# Plot age groups
sns.countplot(x='age_dec', data=data, palette='crest')
```

```python
plt.xlabel('Age Group')
plt.ylabel('Count')
plt.title('Customers by Age Group')
plt.show()
```



It looks like the majority of the customers are in their 40's. The rest are approximately evenely split, besides customers in their 60's and teens. Now let's explore customer activity by the product attributes.

[194]:
```python
data.brand.unique()
```

[194]:
```
['Solex', 'Trek Bicycles', 'OHM Cycles', 'Norco Bicycles', 'Giant Bicycles',
'WeareA2B']
Categories (6, object): ['Solex', 'Trek Bicycles', 'OHM Cycles', 'Norco
Bicycles', 'Giant Bicycles', 'WeareA2B']
```

There are 6 brands of bicycles these customers purchase, let's see which on is baught most frequently by gender, wealth segment, and whether or not they own a car.

[195]:
```python
# Color mapping
pal = {'Male': 'b', 'Female': 'pink', 'Unisex': 'green'}

# Plot chart of brands
g = sns.catplot(y='brand', hue='gender', palette=pal, row='owns_car',
```

```
                col='wealth_segment', data=data, kind='count')

g.set_axis_labels('Count', 'Brand')
g.set_titles('Owns Car: {row_name} | Wealth Segment: {col_name}')
g.legend.set_title('Gender')
plt.show()
```

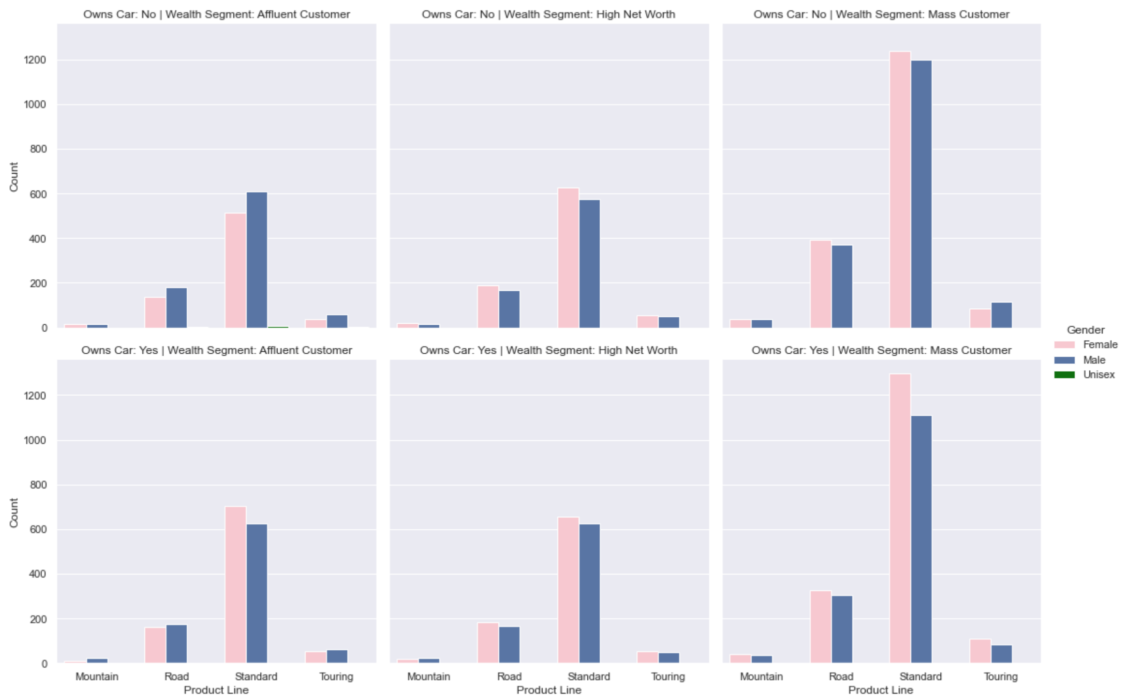
From the count plot shown above, we can see that the brand Solex has the most purchases for each wealth segment, not accounting for gender. If we account for gender, we find mostly females and males in the mass customer segment purchase the most products, Solex being the highest. Additionally, it seems as if owning a car does not play a huge role in purchases because transaction counts mostly stay consistent across the board. Another obvious note is that the unisex gender is extremely small relative to the female and male genders. Unisex can be found in the affluent customer segment reported without a car buying the brands Solex and WearaA2B. Let's explore the product line column with gender and wealth segment.

[196]:
```
data.product_line.unique()
```

[196]:
```
['Standard', 'Road', 'Mountain', 'Touring']
Categories (4, object): ['Standard', 'Road', 'Mountain', 'Touring']
```

[197]:
```
# Plot
g = sns.catplot(x='product_line', hue='gender', palette=pal, row='owns_car',
                col='wealth_segment', data=data, kind='count')
```

```
g.set_axis_labels('Product Line', 'Count')
g.set_titles('Owns Car: {row_name} | Wealth Segment: {col_name}')
g.legend.set_title('Gender')
plt.show()
```



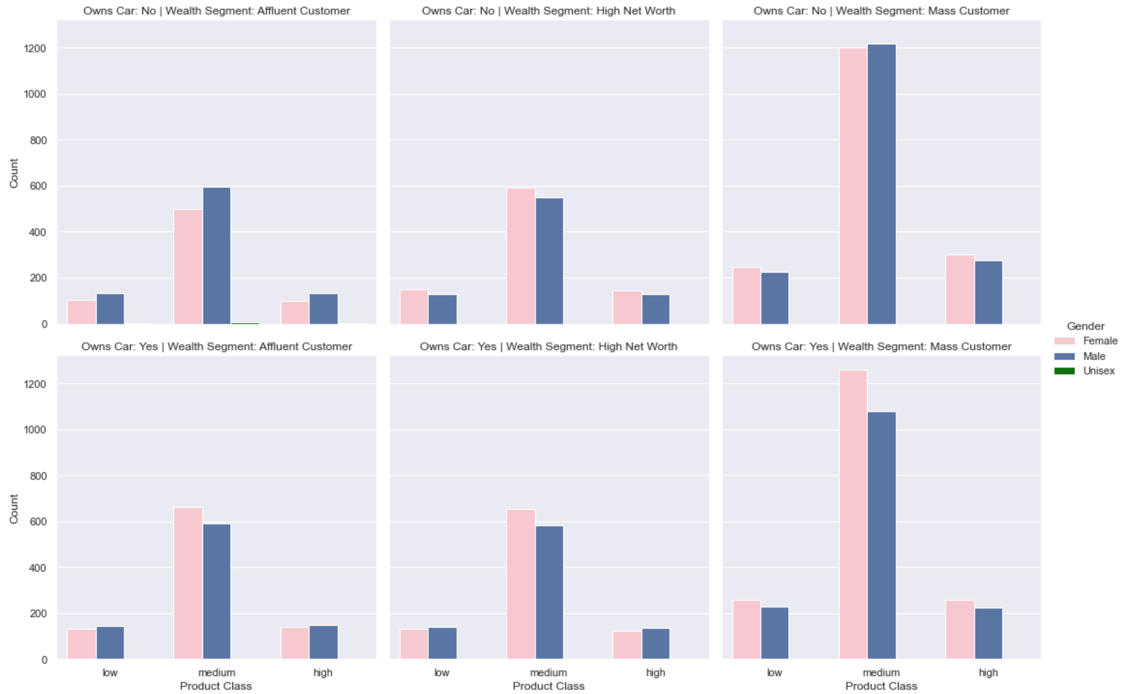
We can see from the chart generated that the mass customer segment is again the most segment to buy bicycles, specifically standards. Among the mass customer segement, females tend to purchase more then males regardless of whether or not they own a car when it comes to standard and even road bicycles. Let's do the same for the product class and product size columns.

[198]:
```
# Product class
data.product_class.unique()
```

[198]:
```
['medium', 'low', 'high']
Categories (3, object): ['medium', 'low', 'high']
```

[199]:
```
# Plot product class by gender and wealth segment
g = sns.catplot(x='product_class', hue='gender', palette=pal, row='owns_car',
                col='wealth_segment', order=['low', 'medium', 'high'],
                data=data, kind='count')

g.set_axis_labels('Product Class', 'Count')
g.set_titles('Owns Car: {row_name} | Wealth Segment: {col_name}')
g.legend.set_title('Gender')
plt.show()
```

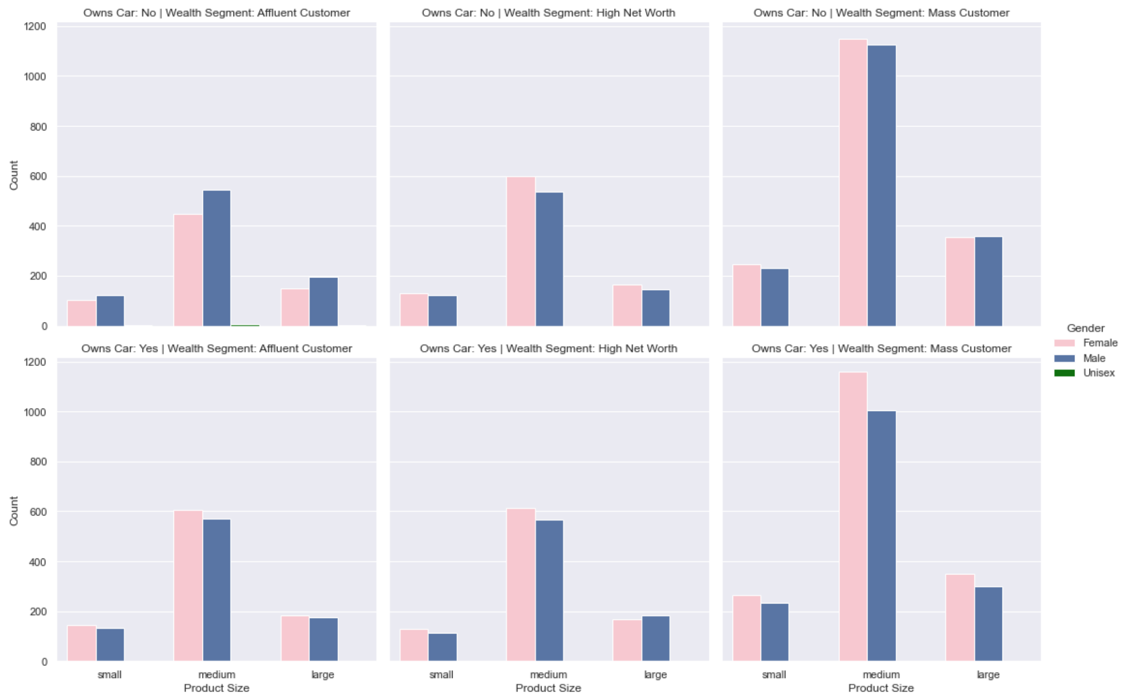


[200]:
```
# Product size
data.product_size.unique()
```

[200]:
```
['medium', 'large', 'small']
Categories (3, object): ['medium', 'large', 'small']
```

[201]:
```
# Plot product size by gender and wealth segment
g = sns.catplot(x='product_size', hue='gender', row='owns_car',␣
↪col='wealth_segment',
                palette=pal, order=['small', 'medium', 'large'], data=data,␣
↪kind='count')

g.set_axis_labels('Product Size', 'Count')
g.set_titles('Owns Car: {row_name} | Wealth Segment: {col_name}')
g.legend.set_title('Gender')
plt.show()
```



We can see that still the vast majority of customers come from the mass customer segment. Owning a car does not seem to affect the results in either chart, but we will have to explore that in further detail. Let's see the distribution in job industry.

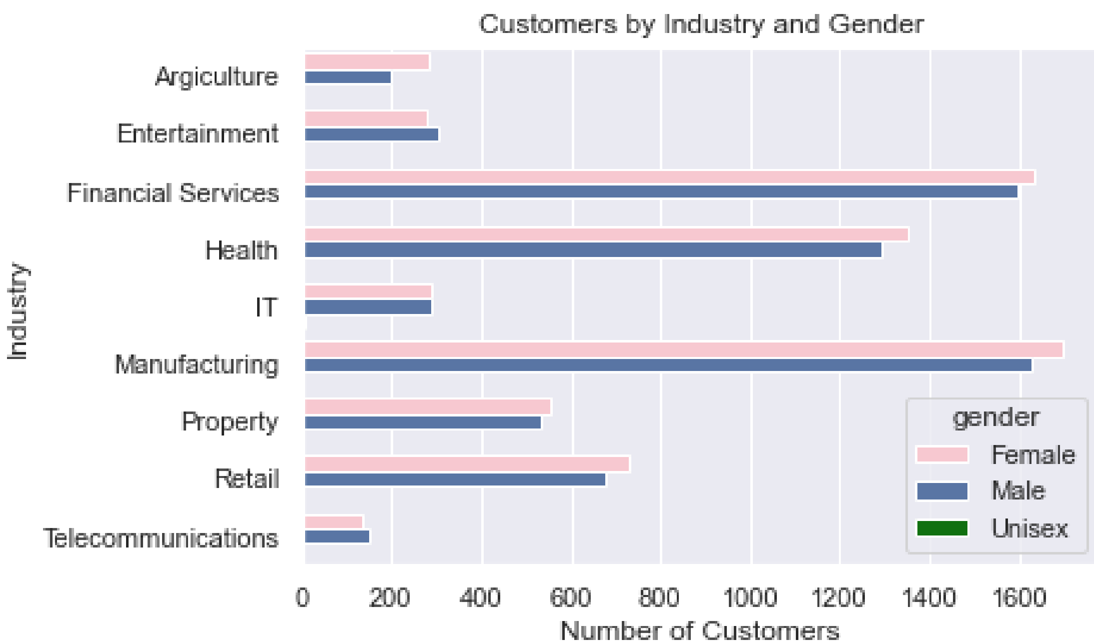
[202]:
```python
# Group by industry
job_cat = data.groupby('job_industry_category').agg(n_customers=('customer_id',␣
↪'count'))
job_cat.sort_values('n_customers', ascending=False)
```

[202]:

job_industry_category	n_customers
Manufacturing	3322
Financial Services	3228
Health	2645
Retail	1411
Property	1087
Entertainment	586
IT	582
Argiculture	482
Telecommunications	285

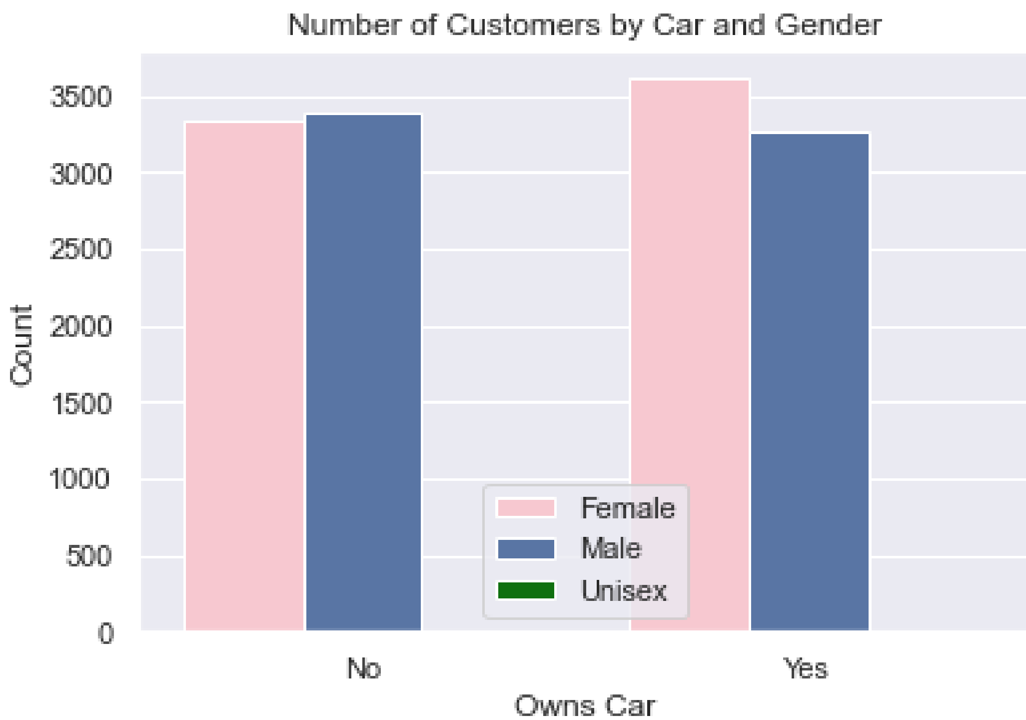
Looks like most customers are in manufacturing, financial services, and health industry. Let's plot a bar chart to get a better visual.

[203]:
```
sns.countplot(y='job_industry_category', hue='gender', palette=pal, data=data)
plt.xlabel('Number of Customers')
plt.ylabel('Industry')
plt.title('Customers by Industry and Gender')
plt.show()
```



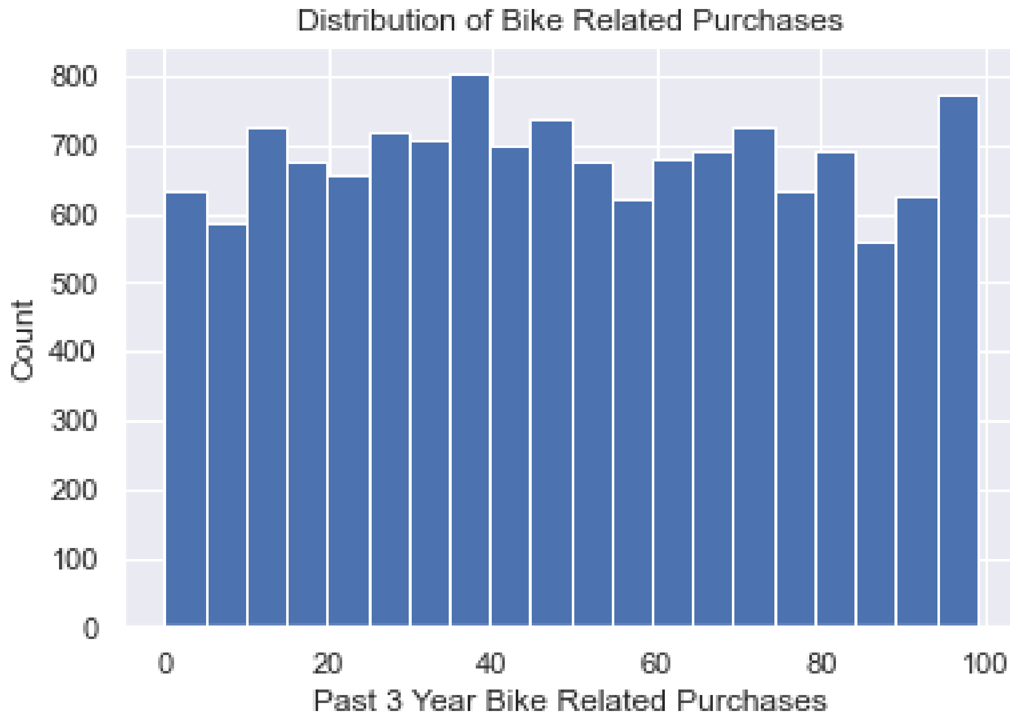
Looks great! Now coming back to customers owning a car, do most of these customers own a car? Let's plot a visual by gender to find out.

[204]:
```
# Plot graph
sns.countplot(x='owns_car', hue='gender', palette=pal, data=data)
plt.xlabel('Owns Car')
plt.ylabel('Count')
plt.title('Number of Customers by Car and Gender')
plt.legend(loc=8)
plt.show()
```



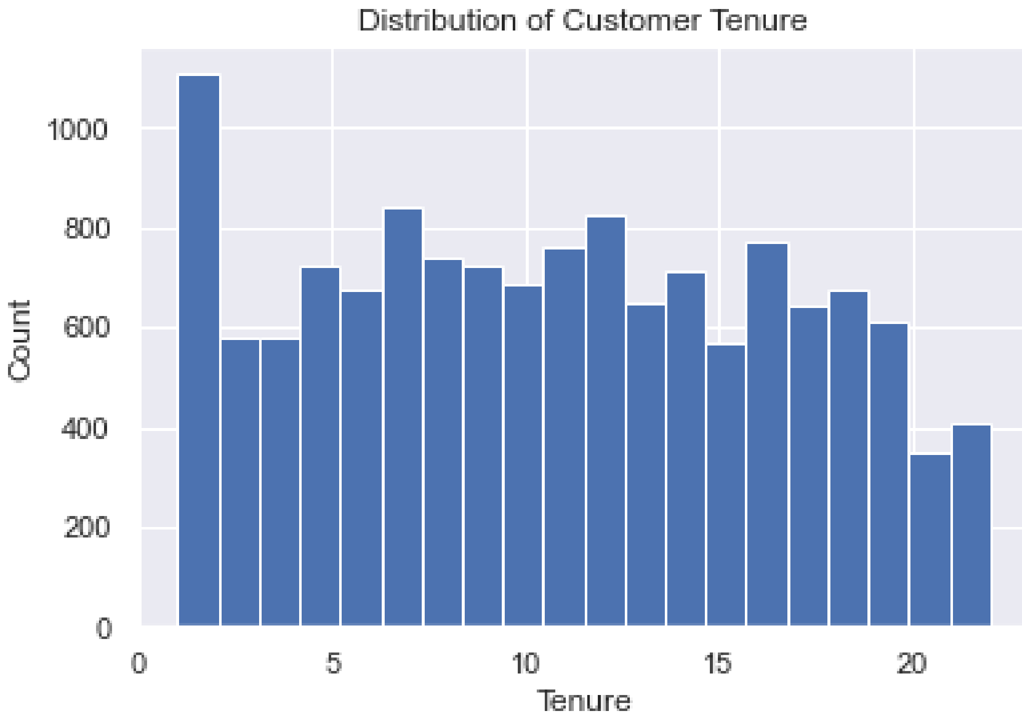
We can see that the distribution of customers who own a car and those who do not are approximately even. Let's now see the distribution of customers who have made a bike purchase in the past three years. Intuitevely, customers that have made frequent bike purchases will tend to be the target market.

[205]:
```
data.past_3_years_bike_related_purchases.hist(bins=20)
plt.xlabel('Past 3 Year Bike Related Purchases')
plt.ylabel('Count')
plt.title('Distribution of Bike Related Purchases')
plt.show()
```



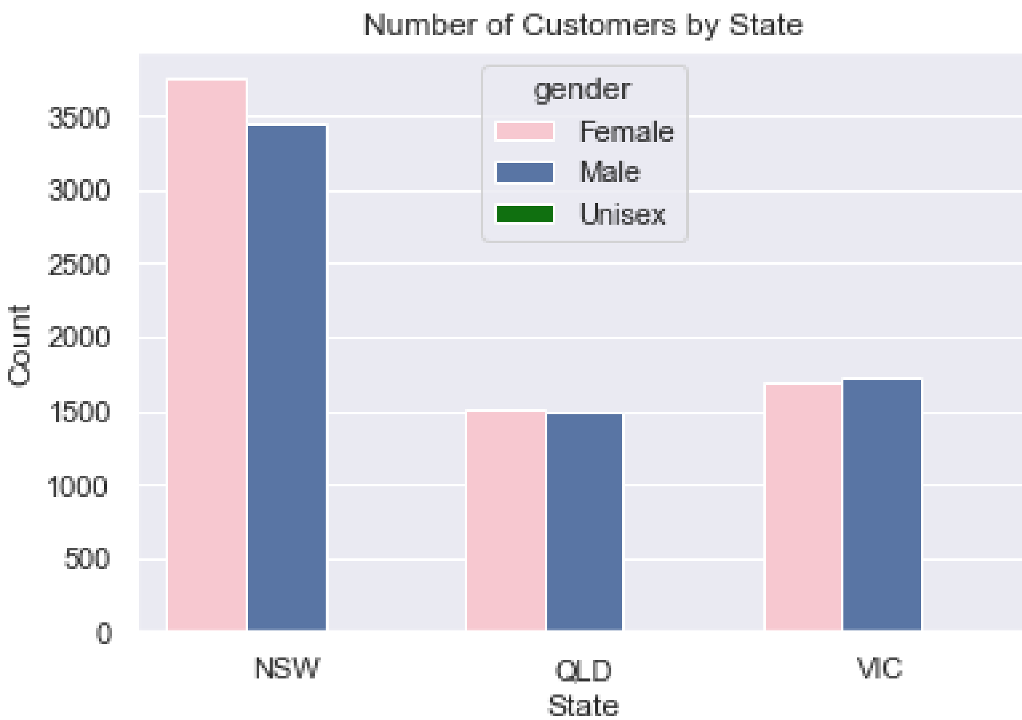
It looks pretty even all throughout the board! Let's have a look at the distribution of experience (tenure).

[206]:
```
data.tenure.hist(bins=20)
plt.xlabel('Tenure')
plt.ylabel('Count')
plt.title('Distribution of Customer Tenure')
plt.show()
```



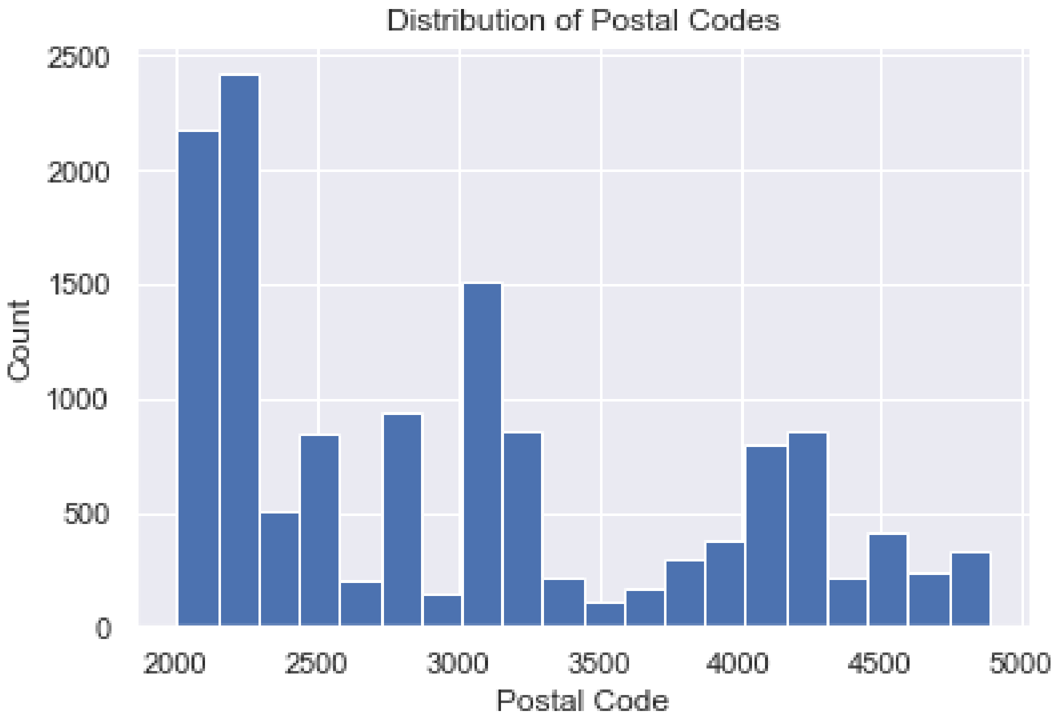
Almost the same as past related purchases, except there are a few more customers with less than 3 years of experience it seems like. Can we find any valuable insights by customer demographics?

[207]:
```
sns.countplot(x='state', hue='gender', palette=pal, data=data)
plt.xlabel('State')
plt.ylabel('Count')
plt.title('Number of Customers by State')
plt.show()
```



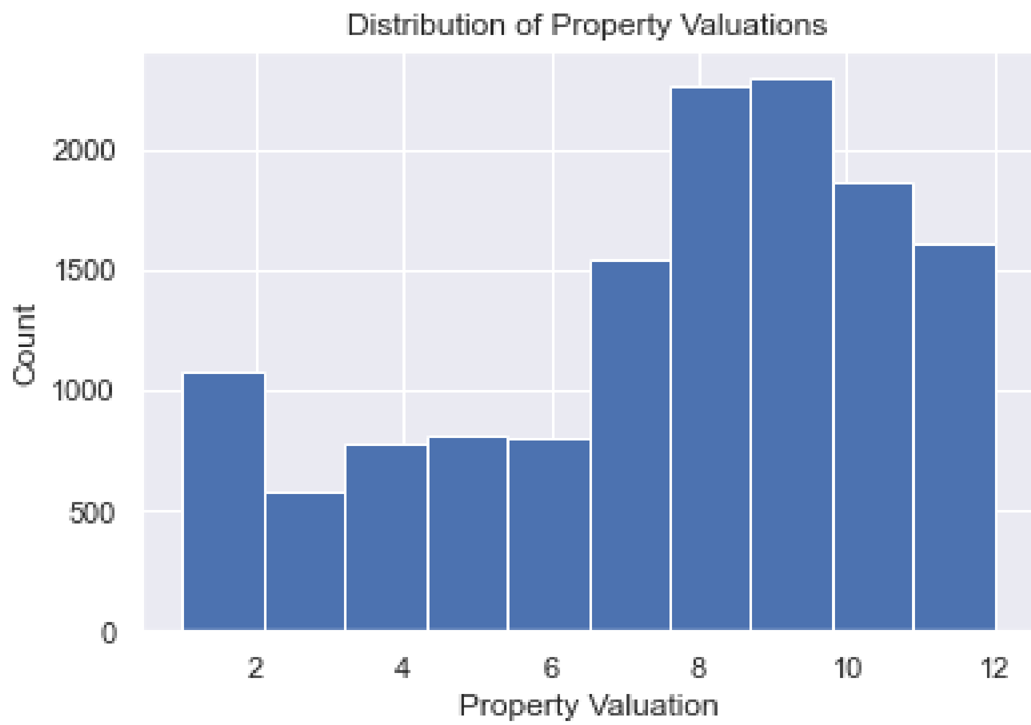
Looka like most customers, both male and female, are located in New South Wales! Perhaps postal codes can help us identify a more specific location.

[208]:
```
data.postcode.hist(bins=20)
plt.xlabel('Postal Code')
plt.ylabel('Count')
plt.title('Distribution of Postal Codes')
plt.show()
```



Seems as if mosts customers have a postal code around 2000-2250, as well as 3000-3100 approximately.

[209]:
```
data.property_valuation.hist()
plt.xlabel('Property Valuation')
plt.ylabel('Count')
plt.title('Distribution of Property Valuations')
plt.show()
```



[210]:
```
new_cust.head() # just for table reference
```

[210]:

```
  first_name  last_name  gender  past_3_years_bike_related_purchases  \
0    Chickie    Brister    Male                                   86
1      Morly     Genery    Male                                   69
2    Ardelis  Forrester  Female                                   10
3     Lucine      Stutt  Female                                   64
4    Melinda     Hadlee  Female                                   34

         DOB                   job_title job_industry_category  \
0 1957-07-12             General Manager         Manufacturing
1 1970-03-22          Structural Engineer              Property
2 1974-08-28      Senior Cost Accountant    Financial Services
3 1979-01-28  Account Representative III         Manufacturing
4 1965-09-21           Financial Analyst    Financial Services

      wealth_segment owns_car  tenure               address  postcode state  \
0      Mass Customer      Yes      14      45 Shopko Center      4500   QLD
1      Mass Customer       No      16     14 Mccormick Park      2113   NSW
2  Affluent Customer       No      10  5 Colorado Crossing      3505   VIC
3  Affluent Customer      Yes       5   207 Annamark Plaza      4814   QLD
4  Affluent Customer       No      19    115 Montana Place      2093   NSW
```

```
   property_valuation  Rank     Value
0                   6     1  1.718750
1                  11     1  1.718750
2                   5     1  1.718750
3                   1     4  1.703125
4                   9     4  1.703125
```

3 Model Development

We will be analyzing customer segements based on their recency, frequency, and monetary value. This analysis is called RFM analysis, and it helps us determine which cluster segements are most valueable to Sprocket Central.

[211]:
```
data.head()
```

[211]:
```
   transaction_id  product_id  customer_id transaction_date  online_order  \
0               1           2         2950       2017-02-25           0.0
1               2           3         3120       2017-05-21           1.0
2               3          37          402       2017-10-16           0.0
3               4          88         3135       2017-08-31           0.0
5               6          25         2339       2017-03-08           1.0

  order_status           brand product_line product_class product_size  …  \
0     Approved           Solex     Standard        medium       medium  …
1     Approved   Trek Bicycles     Standard        medium        large  …
2     Approved      OHM Cycles     Standard           low       medium  …
3     Approved  Norco Bicycles     Standard        medium       medium  …
5     Approved  Giant Bicycles         Road        medium       medium  …

   job_industry_category     wealth_segment owns_car tenure  \
0     Financial Services      Mass Customer      Yes   10.0
1                 Health      Mass Customer      Yes   10.0
2                 Retail   Affluent Customer       No   22.0
3     Financial Services      Mass Customer       No   16.0
5               Property   Affluent Customer      Yes   16.0

               address postcode  state property_valuation age age_dec
0     984 Hoepker Court   3064.0    VIC                6.0  66      60
1       4 Shopko Circle   2196.0    NSW                5.0  42      40
2     586 Miller Parkway   2835.0    NSW                1.0  44      40
3    1617 Harper Parkway   2096.0    NSW               10.0  59      50
5  7174 Thackeray Point   2153.0    NSW               10.0  62      60

[5 rows x 29 columns]
```

[212]:
```
# Create new dataframe to store RFM results
rfm = pd.DataFrame(data.customer_id.unique(), columns=['customer_id'])
```

```
rfm.head()
```

[212]:

```
   customer_id
0         2950
1         3120
2          402
3         3135
4         2339
```

3.1 Recency

[213]:

```
# Obtain the most recent purchase date for each customer and create a dataframe␣
↪with it
recent_purchase = data.groupby('customer_id').transaction_date.max().
↪reset_index()
recent_purchase.columns = ['customer_id', 'recent_purchase_date']
recent_purchase
```

[213]:

```
      customer_id recent_purchase_date
0               1           2017-12-23
1               2           2017-08-24
2               9           2017-10-13
3              12           2017-10-24
4              13           2017-12-03
…             …                   …
2441         3493           2017-09-28
2442         3494           2017-12-26
2443         3495           2017-12-17
2444         3496           2017-04-18
2445         3497           2017-11-08

[2446 rows x 2 columns]
```

[214]:

```
# Calculate recency
recent_purchase['recency'] = (recent_purchase.recent_purchase_date.max() -
                              recent_purchase.recent_purchase_date).dt.days
recent_purchase.head()
```

[214]:

```
   customer_id recent_purchase_date  recency
0            1           2017-12-23        7
1            2           2017-08-24      128
2            9           2017-10-13       78
3           12           2017-10-24       67
4           13           2017-12-03       27
```

[215]:

```
rfm = pd.merge(rfm, recent_purchase[['customer_id', 'recency']],␣
↪on='customer_id')
```

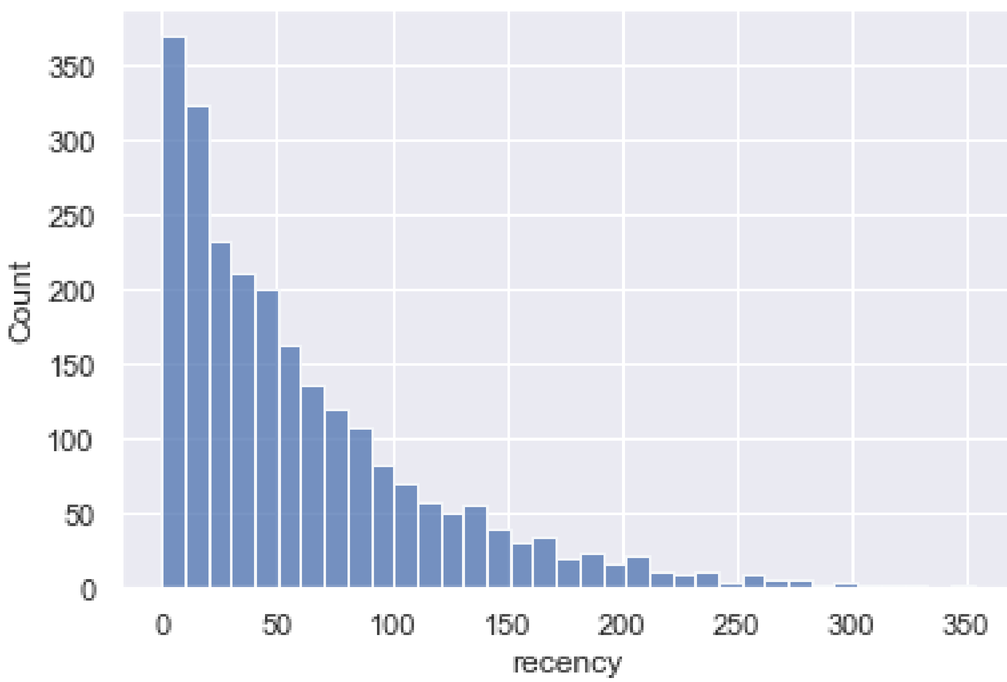
[216]:
```
display(rfm.head())
display(rfm.recency.describe())
```

```
   customer_id  recency
0         2950       75
1         3120       20
2          402       56
3         3135      121
4         2339       11
```

```
count    2446.000000
mean       62.432543
std        59.659272
min         0.000000
25%        18.000000
50%        44.500000
75%        87.000000
max       353.000000
Name: recency, dtype: float64
```

We can see that the average recency is 62 and the median is 45. Let's plot a histof

[217]:
```
sns.histplot(x='recency', data=rfm)
plt.show()
```

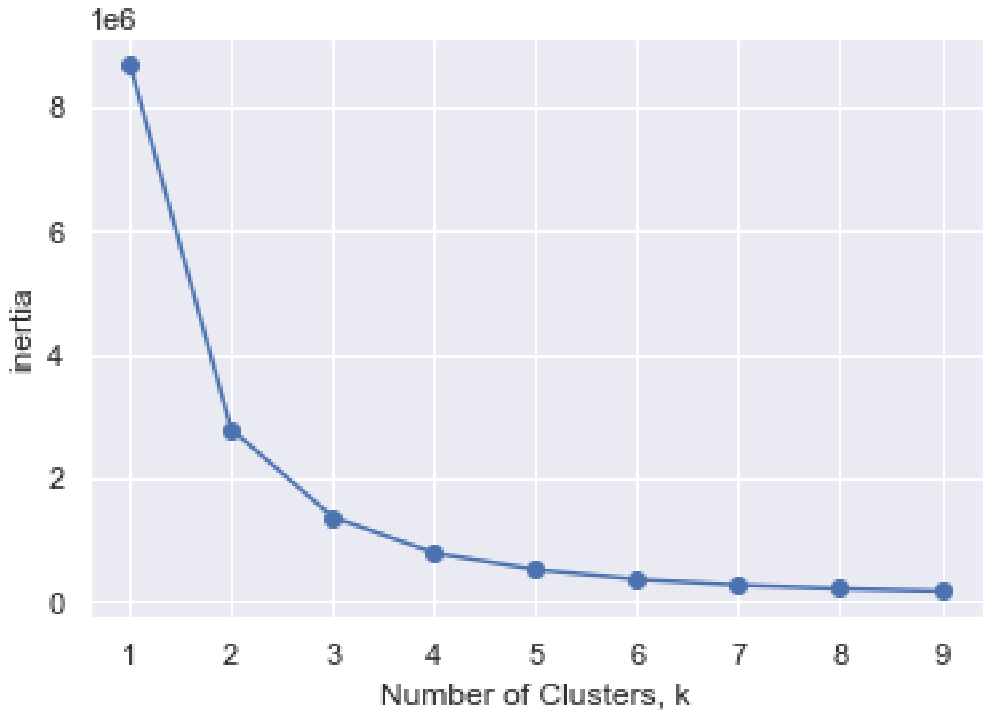


[218]:
```
# Find optimal number of clusters
from sklearn.cluster import KMeans
inertias = []

for k in range(1, 10):
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(rfm[['recency']])
    inertias.append(kmeans.inertia_)

def plot_elbow(values):
    """Line plot of the number of clusters and its inertia value"""
    plt.plot(range(1, 10), values, '-o')
    plt.xlabel('Number of Clusters, k')
    plt.ylabel('inertia')
    plt.show()

plot_elbow(inertias)
```



From the cluster graph above, we can see that the optimal number of clusters is 4.

[219]:
```
# Apply clustering
kmeans = KMeans(n_clusters=4)
kmeans.fit(rfm[['recency']])
rfm['recency_cluster'] = kmeans.predict(rfm[['recency']])
```

```
def order_cluster(cluster_field_name, target_field_name, df, ascending):
    new_cluster_field_name = 'new_' + cluster_field_name
    df_new = df.groupby(cluster_field_name)[target_field_name].mean().
 ↪reset_index()
    df_new = df_new.sort_values(by=target_field_name, ascending=ascending).
 ↪reset_index(drop=True)
    df_new['index'] = df_new.index
    df_final = pd.merge(df, df_new[[cluster_field_name,'index']],␣
 ↪on=cluster_field_name)
    df_final = df_final.drop([cluster_field_name], axis=1)
    df_final = df_final.rename(columns={"index":cluster_field_name})
    return df_final

rfm = order_cluster('recency_cluster', 'recency', rfm, True)
```

[220]:
```
rfm.head()
```

[220]:

	customer_id	recency	recency_cluster
0	2950	75	1
1	402	56	1
2	2459	53	1
3	2783	73	1
4	1243	70	1

[221]:
```
rfm.groupby('recency_cluster').recency.describe()
```

[221]:

recency_cluster	count	mean	std	min	25%	50%	75%	max
0	1177.0	18.515718	12.223749	0.0	8.0	17.0	28.0	42.0
1	770.0	66.633766	16.295337	43.0	52.0	64.0	80.0	99.0
2	363.0	133.093664	22.301476	100.0	113.0	131.0	149.0	181.0
3	136.0	230.117647	40.565824	182.0	198.0	218.0	256.0	353.0

3.2 Frequency

[222]:
```
# Obtain order counts for each customer and create a dataframe with it
frequency = data.groupby('customer_id').transaction_date.count().reset_index()
frequency.columns = ['customer_id', 'frequency']
frequency.head()
```

[222]:

	customer_id	frequency
0	1	11
1	2	3
2	9	6
3	12	7
4	13	7

[223]:
```
# Add frequency to rfm dataframe
rfm = pd.merge(rfm, frequency, on='customer_id')
rfm.head()
```

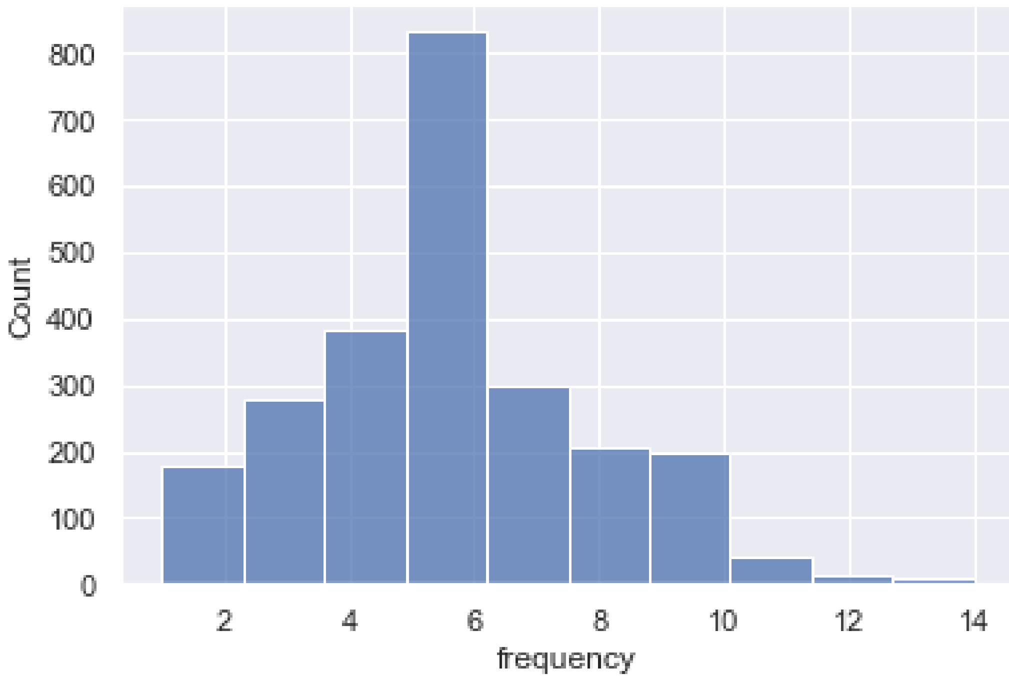
[223]:

	customer_id	recency	recency_cluster	frequency
0	2950	75	1	3
1	402	56	1	6
2	2459	53	1	11
3	2783	73	1	11
4	1243	70	1	10

[224]:
```
rfm.frequency.describe()
```

[224]:
```
count    2446.000000
mean        5.571545
std         2.273433
min         1.000000
25%         4.000000
50%         5.000000
75%         7.000000
max        14.000000
Name: frequency, dtype: float64
```

[225]:
```
sns.histplot(x='frequency', data=rfm, bins=10)
plt.show()
```



[226]:
```
# Find optimal number of clusters
inertias = []

for k in range(1, 10):
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(rfm[['frequency']])
    inertias.append(kmeans.inertia_)

plot_elbow(inertias)
```

We see again that judging from the graph, the optimal number of clusters is 4.

[227]:
```
# Apply clustering
kmeans = KMeans(n_clusters=4)
kmeans.fit(rfm[['frequency']])
rfm['frequency_cluster'] = kmeans.predict(rfm[['frequency']])

rfm = order_cluster('frequency_cluster', 'frequency', rfm, False)

rfm.head()
```

[227]:

	customer_id	recency	recency_cluster	frequency	frequency_cluster
0	2950	75	1	3	3
1	1031	46	1	3	3
2	1612	67	1	2	3
3	455	67	1	3	3
4	678	94	1	3	3

[228]:
```
rfm.groupby('frequency_cluster').frequency.describe()
```

[228]:

	count	mean	std	min	25%	50%	75%	max
frequency_cluster								
0	263.0	9.863118	1.120714	9.0	9.0	9.0	10.5	14.0
1	924.0	6.774892	0.790777	6.0	6.0	7.0	7.0	8.0
2	800.0	4.521250	0.499861	4.0	4.0	5.0	5.0	5.0

```
3                    459.0  2.520697  0.651758  1.0  2.0  3.0   3.0   3.0
```

3.3 Monetary

[229]:
```
# Compute profit for each customer
data['profit'] = data.list_price - data.standard_cost
data[['list_price', 'standard_cost', 'profit']].head()
```

[229]:

	list_price	standard_cost	profit
0	71.49	53.62	17.87
1	2091.47	388.92	1702.55
2	1793.43	248.82	1544.61
3	1198.46	381.10	817.36
5	1538.99	829.65	709.34

[230]:
```
monetary = data.groupby('customer_id').profit.sum().reset_index()
monetary.head()
```

[230]:

	customer_id	profit
0	1	3018.09
1	2	2226.26
2	9	2353.11
3	12	3540.03
4	13	4337.38

[231]:
```
# Add monetary to rfm dataframe
rfm = pd.merge(rfm, monetary, on='customer_id')
rfm.columns = ['customer_id', 'recency', 'recency_cluster',
               'frequency', 'frequency_cluster', 'monetary']
rfm.head()
```

[231]:

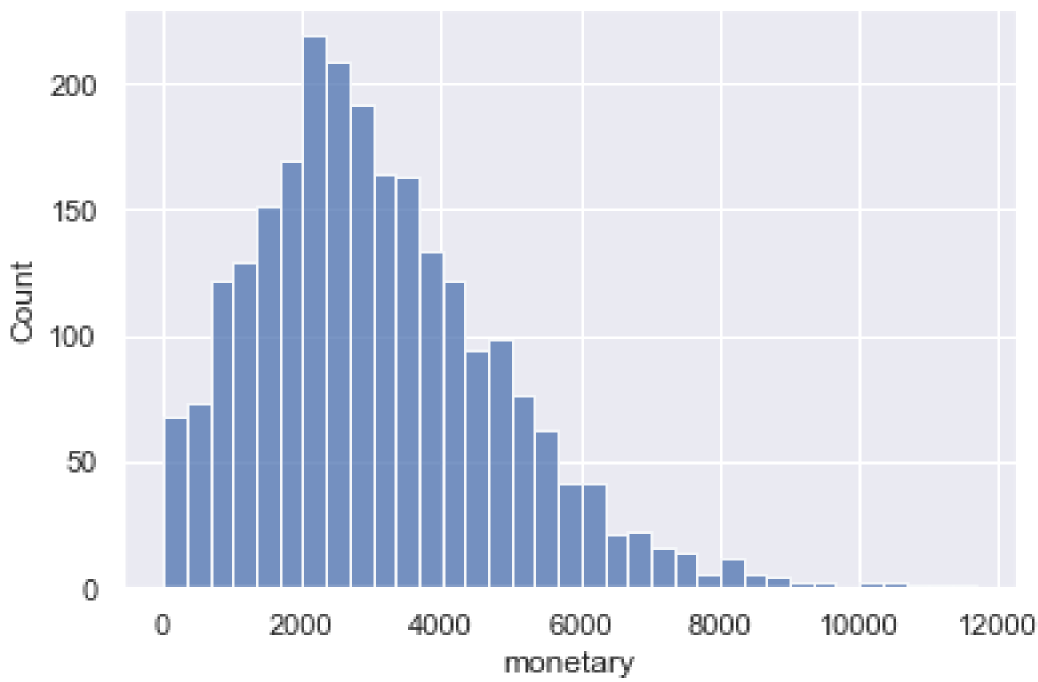
	customer_id	recency	recency_cluster	frequency	frequency_cluster	\
0	2950	75	1	3	3	
1	1031	46	1	3	3	
2	1612	67	1	2	3	
3	455	67	1	3	3	
4	678	94	1	3	3	

	monetary
0	645.99
1	1463.88
2	2932.82
3	1600.90
4	1606.99

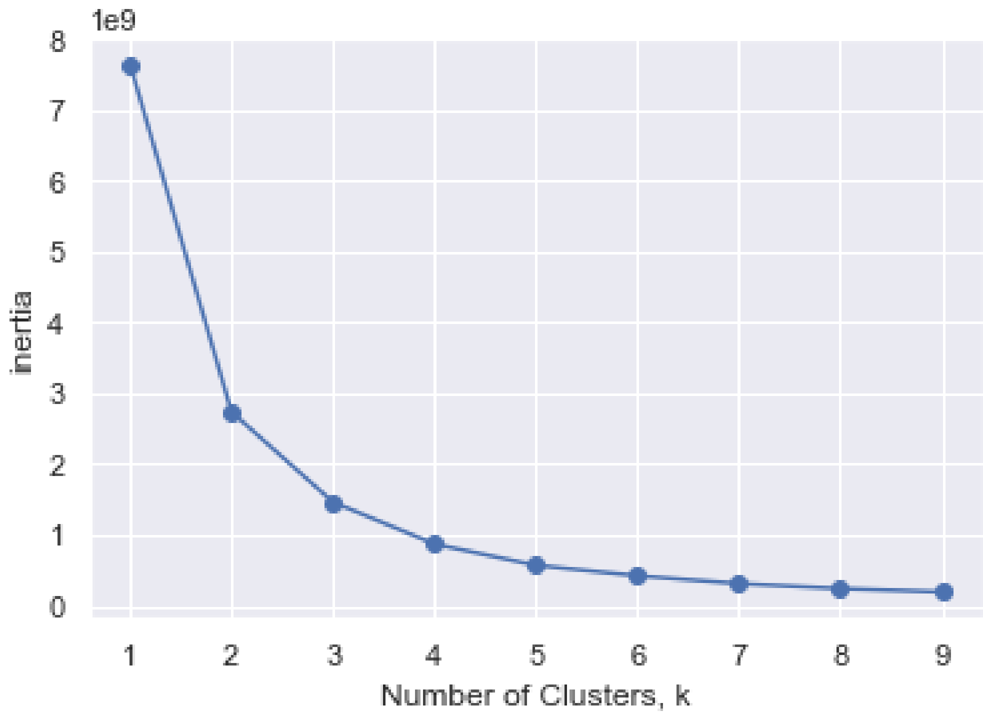
[232]:
```
rfm.monetary.describe()
```

[232]:
```
count      2446.000000
mean       3075.535699
std        1768.178040
min          15.080000
25%        1796.072500
50%        2795.780000
75%        4095.417500
max       11668.950000
Name: monetary, dtype: float64
```

[233]:
```
# Plot distribution
sns.histplot(x='monetary', data=rfm)
plt.show()
```



[234]:
```
# Find optimal number of clusters
inertias = []
for k in range(1, 10):
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(rfm[['monetary']])
    inertias.append(kmeans.inertia_)
plot_elbow(inertias)
```



Again, we see consistent results telling us that the optimal number of clusters is 4.

[235]:
```
# Apply clustering
kmeans = KMeans(n_clusters=4)
kmeans.fit(rfm[['monetary']])
rfm['monetary_cluster'] = kmeans.predict(rfm[['monetary']])

rfm = order_cluster('monetary_cluster', 'monetary', rfm, False)

rfm.head()
```

[235]:
```
   customer_id  recency  recency_cluster  frequency  frequency_cluster  \
0         2950       75                1          3                  3
1         1031       46                1          3                  3
2          455       67                1          3                  3
3          678       94                1          3                  3
4         3466       68                1          3                  3

   monetary  monetary_cluster
0    645.99                 3
1   1463.88                 3
2   1600.90                 3
3   1606.99                 3
4    272.79                 3
```

[236]:
```
rfm.groupby('monetary_cluster').monetary.describe()
```

[236]:
```
                   count         mean          std      min        25%  \
monetary_cluster
0                  186.0  6992.742688  1156.265127  5779.65  6148.6225
1                  603.0  4548.871973   579.186509  3666.94  4047.0650
2                  953.0  2778.437492   479.187884  1980.71  2355.7600
3                  704.0  1180.808878   535.781620    15.08   787.7450

                      50%        75%       max
monetary_cluster
0                 6649.37  7495.5775  11668.95
1                 4515.25  5005.7500   5763.13
2                 2739.50  3186.6300   3660.95
3                 1255.53  1645.4700   1970.78
```

3.4 Overall Score

[237]:
```
rfm['overall_score'] = rfm.recency_cluster + rfm.frequency_cluster + rfm.
 ↪monetary_cluster
rfm.groupby('overall_score')[['recency', 'frequency', 'monetary']].mean()
```

[237]:
```
                  recency  frequency     monetary
overall_score
0               16.885057  10.241379  7086.173333
1               21.813433   8.910448  5782.874104
2               27.778947   7.617544  4615.263930
3               38.302817   6.612676  3708.149977
4               46.501075   5.595699  2937.133054
5               61.450425   4.801700  2337.346317
6               73.163077   3.756923  1801.308062
7              113.384181   3.265537  1444.233220
8              154.560345   2.586207  1186.460086
9              243.500000   2.038462   856.437308
```

The scoring above tells us that the target customers are scored with a 3 or below and the worst customers are scored with a 7 or higher.

- 0 - 3: High Value
- 4 - 6: Mid Value
- 7+: Low Value

[238]:
```
rfm['segment'] = 'High Value'
rfm.loc[rfm.overall_score > 3, 'segment'] = 'Mid Value'
rfm.loc[rfm.overall_score > 6, 'segment'] = 'Low Value'
```

[239]:
```
rfm.shape
```

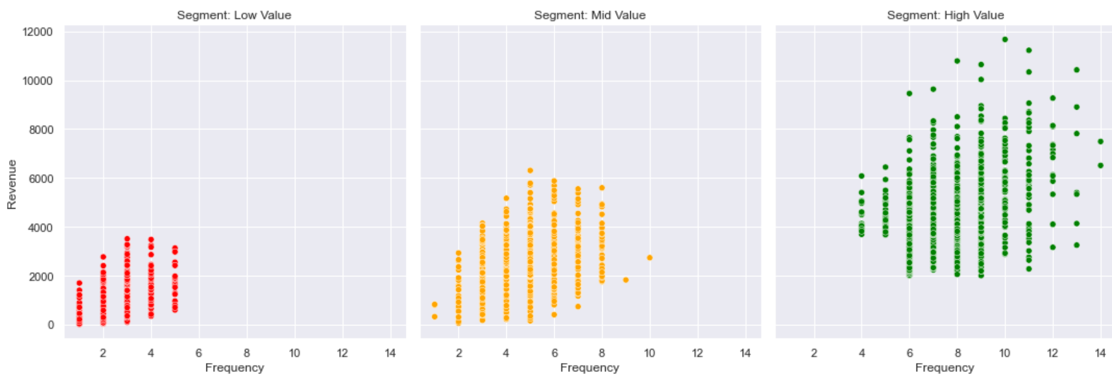
[239]: (2446, 9)

[240]:
```
g = sns.relplot(x='recency', y='monetary', hue='segment',
                palette=['red', 'orange', 'green'], col='segment',
                data=rfm)

g.set_axis_labels('Recency', 'Revenue')
g.set_titles('Segment: {col_name}')
g.legend.remove()
plt.show()
```

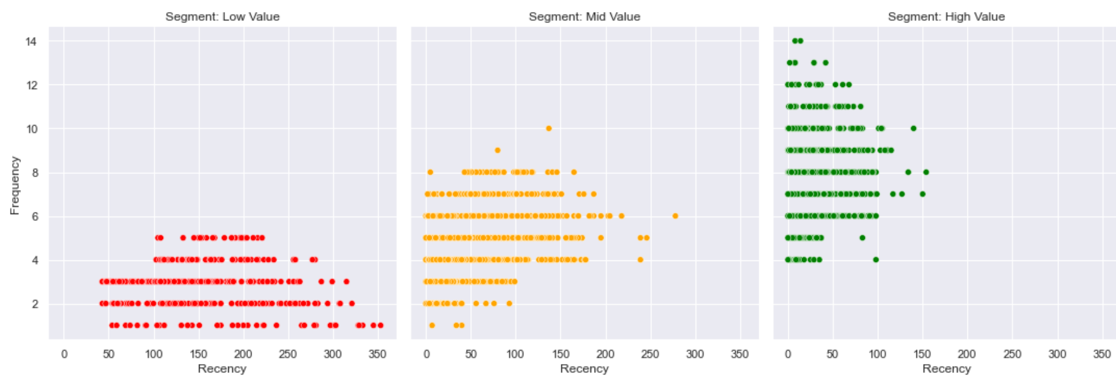
[241]:
```
g = sns.relplot(x='frequency', y='monetary', hue='segment',
                palette=['red', 'orange', 'green'], col='segment',
                data=rfm)

g.set_axis_labels('Frequency', 'Revenue')
g.set_titles('Segment: {col_name}')
g.legend.remove()
plt.show()
```



[242]:
```
g = sns.relplot(x='recency', y='frequency', hue='segment',
                palette=['red', 'orange', 'green'], col='segment',
                data=rfm)

g.set_axis_labels('Recency', 'Frequency')
g.set_titles('Segment: {col_name}')
g.legend.remove()
plt.show()
```



That concludes our RFM analysis! We have found which customers give significant value to Sprocket Central by finding how recent they have made a purchase, how frequent they purchase, and how much they spend.

[244]:
```
# Save datasets to csv
# writer = pd.ExcelWriter('KPMG_task2.xlsx')

# data.to_excel(writer, sheet_name='Data', index=False)
# rfm.to_excel(writer, sheet_name='RFM', index=False)

# writer.save()
```