Customer Segmentation of Sprocket Central Pty Ltd

Objective:

Sprocket Central Pty Ltd is an high-end bicycle and accessories company that is seeking to develop a new marketing strategy that targets their best customers. This project will involve 2 seperate datasets; the first with transactional data, and the later without transactional data (new customer list). Our analysis will involve the RFM and K-Means modelling to achieve the identification of who our client's best customers are. Let's begin by exploring their data, developing the model and concluding with dashboard of data visuals to support our discoveries.

I. MERGED DATASET ANALYSIS

Variable Description of Merged Dataset, with Transactions:

Our summary of data consists of the following attributes:

CustomerDemographic data:

- customer_id: unique customer id number
- first_name: customers' first name
- last_name: customers' last name
- gender: gender orientation - amended to 'Male', 'Female' or 'Other'
- past_3_years_bike_related_purchases: count of purchases made in 2017
- DOB: customers' date of birth
- job_title: title of job position
- job_industry_category: industry category of customers' jobs
- wealth_segment: customer's wealth status - 'Affluent', 'High Net Worth' and 'Mass Customer'
- deceased_indicator: indicates whether the customer has passed away - 'N' or 'Y'
- owns_car: indicates whether customer owns a car - 'Y' or 'N'
- tenure: the duration of years customer occupies their residence

CustomerAddress data:

- customer_id: unique customer id number
- postcode: customers' postal code
- state: customers' states of 'NSW', 'VIC', 'QLD'
- property_valuation: property valuation grade - numbers 1 to 12

Transactions data:

- product_id: unique id of product
- customer_id: unique customer id number

- transaction_date: date of transaction
- online_order: indicates whether order was purchased online - '0' Online or '1' Not Online
- order_status: indicates whether the order was a approved or cancelled
- brand: brand name of the product
- product_line: product catergory - 'Mountain', 'Road', 'Standard' and 'Touring'
- product_class: class level of the product = 'high', 'low', 'medium'
- product_size: size of the product - 'large', 'medium' and 'small'
- list_price: listed price of the product
- standard_cost: standard cost of transaction
- product_first_sold_date: date of product's first sale

1. Set Up

In [1]:
```
# import modules and uploading the worksheets into dataframes

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import datetime as dt
import warnings
warnings.filterwarnings('ignore')

# reading worksheets into different names for merging
# select row 1 to use as the header of columns

s1 = pd.read_excel('CustomerDemographic.xlsx', header=1)
s2 = pd.read_excel('CustomerAddress.xlsx', header=1)
s3 = pd.read_excel('Transactions.xlsx', header=1)
```

2. Merging Worksheets

Immediately excluding irrelevant columns from the original worksheets, such as 'default' from CustomerDemographic (due to nonsensical text), also 'address' and 'country' from CustomerAddress, as all customers are based in Australia.

In [2]:
```
# begin merge with s1 (CustomerDemogrpahic) and s2 (CustomerAddress) into s4
# only required columns from original data are included into dataframe s4 for analysis
# column 'customer_id' is the common column between all 3 worksheets to join data

s4 = s1[['customer_id', 'gender', 'past_3_years_bike_related_purchases', 'DOB', 'job_tit
         'wealth_segment','deceased_indicator', 'owns_car', 'tenure']].merge(s2[['custom
        'property_valuation']], on = 'customer_id', how='left')
```

In [3]:
```
# renaming long columns accurate names

s4 = s4.rename(columns={'past_3_years_bike_related_purchases': 'frequency_2017', 'job_in
```

In [4]:
```
# perform last merge to include s3 (Transactions worksheet)
# selecting only the required columns to include for analysis;
# 'transaction_id' and 'product_first_sold_date' will not be included into dataframe

s5 = s4.merge(s3[['product_id', 'customer_id', 'transaction_date', 'online_order', 'orde
                  'product_line', 'product_class', 'product_size', 'list_price', 'standa
              on='customer_id', how='left')
```

3. Data Wrangling

In [5]:
```
# inspect the head and tail of data

s5
```

Out[5]:

	customer_id	gender	frequency_2017	DOB	job_title	industry	wealth_segment	deceased_indic
0	1	F	93	1953-10-12	Executive Secretary	Health	Mass Customer	
1	1	F	93	1953-10-12	Executive Secretary	Health	Mass Customer	
2	1	F	93	1953-10-12	Executive Secretary	Health	Mass Customer	
3	1	F	93	1953-10-12	Executive Secretary	Health	Mass Customer	
4	1	F	93	1953-10-12	Executive Secretary	Health	Mass Customer	
...	...	...	...	...	...	...	...	
20499	3996	Female	8	1975-08-09	VP Product Management	Health	Mass Customer	
20500	3997	Female	87	2001-07-13	Statistician II	Manufacturing	High Net Worth	
20501	3998	U	60	NaT	Assistant Manager	IT	High Net Worth	
20502	3999	Male	11	1973-10-24	NaN	Manufacturing	Affluent Customer	
20503	4000	Male	76	1991-11-05	Software Engineer IV	NaN	Affluent Customer	

20504 rows × 23 columns

In [6]:
```
# view the summary of data

s5.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20504 entries, 0 to 20503
Data columns (total 23 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   customer_id          20504 non-null  int64
 1   gender               20504 non-null  object
 2   frequency_2017       20504 non-null  int64
 3   DOB                  20047 non-null  datetime64[ns]
 4   job_title            18027 non-null  object
 5   industry             17180 non-null  object
 6   wealth_segment       20504 non-null  object
 7   deceased_indicator   20504 non-null  object
 8   owns_car             20504 non-null  object
 9   tenure               20047 non-null  float64
 10  postcode             20475 non-null  float64
 11  state                20475 non-null  object
 12  property_valuation   20475 non-null  float64
 13  product_id           19997 non-null  float64
 14  transaction_date     19997 non-null  datetime64[ns]
```

```
 15  online_order         19637 non-null  float64
 16  order_status         19997 non-null  object
 17  brand                19800 non-null  object
 18  product_line         19800 non-null  object
 19  product_class        19800 non-null  object
 20  product_size         19800 non-null  object
 21  list_price           19997 non-null  float64
 22  standard_cost        19800 non-null  float64
dtypes: datetime64[ns](2), float64(7), int64(2), object(12)
memory usage: 3.8+ MB
```

- There are 20504 rows and 22 columns.
- Missing values in the following columns; DOB, job_title, industry, tenure, postcode, state, property_valuation, product_id, tansaction_date, online_order, order_status, brand, product_line, product_class, list_price and statndard_cost.
- Datatypes appear in correct format.

In [7]:
```
# check for any duplicate rows

s5.duplicated().any()
```

Out[7]:
```
False
```

In [8]:
```
# further drop irrelevant columns

s5.drop(['deceased_indicator'], axis=1, inplace=True)
```

Format Column Datatypes and Names

In [9]:
```
# correcting the 'gender' error values

s5.gender = s5.gender.replace(['U', 'F', 'Femal', 'M'], ['Other', 'Female', 'Female', 'M
```

In [10]:
```
# editing the year error of a DOB value

s5.DOB = s5.DOB.replace('1843-12-21', '1943-12-21')
```

In [11]:
```
# renaming 'state' values to align with existing abbreviated states

s5.state = s5.state.replace(['New South Wales', 'Victoria'], ['NSW', 'VIC'])
```

In [12]:
```
# remove $ sign from column for analysis

s5.standard_cost = s5.standard_cost.replace({r'\$':''}, regex=True)
```

Missing Data

In [13]:
```
# view % of missing values to determine the treatment method

round(s5.isnull().sum().sort_values(ascending = False)/len(s5)*100,2)
```

Out[13]:
```
industry            16.21
job_title           12.08
online_order         4.23
standard_cost        3.43
product_size         3.43
product_class        3.43
product_line         3.43
```

```
brand                  3.43
list_price             2.47
order_status           2.47
product_id             2.47
transaction_date       2.47
DOB                    2.23
tenure                 2.23
property_valuation     0.14
state                  0.14
postcode               0.14
gender                 0.00
owns_car               0.00
wealth_segment         0.00
frequency_2017         0.00
customer_id            0.00
dtype: float64
```

15 columns have missing data, with 'industry' having the most missing values.

If the missing values of a column doesn't exceed 5%, we can apply the imputation by mean, mode and median to fill missing values. In this instance, we assume the values are missing at random to correctly treat our missing values.

In [14]:
```
# 'brand', 'product_line', 'product_class', 'product_size', and 'standard_cost' have cor

missing_values343 = s5[['brand', 'product_line', 'product_class', 'product_size', 'stand
missing_values343.tail()
```

Out[14]:

	brand	product_line	product_class	product_size	standard_cost
20499	True	True	True	True	True
20500	True	True	True	True	True
20501	True	True	True	True	True
20502	True	True	True	True	True
20503	True	True	True	True	True

In the following ffill treatment of missing values, we assume that missing data are MCAR (Missing Completely At Random), occuring randomly without any pattern, hence based on the the correspsonding missing value rows of the above columns, we can use ffill method to get values that are accurately related to each other. This reduces bias as compared to mean, median or mode methods.

In [15]:
```
# impute the missing values with ffill method

s5.brand.fillna(method='ffill', inplace=True)
s5.product_line.fillna(method='ffill', inplace=True)
s5.product_class.fillna(method='ffill', inplace=True)
s5.product_size.fillna(method='ffill', inplace=True)
s5.standard_cost.fillna(method='ffill', inplace=True)
```

In [16]:
```
# use ffill method to impute missing values from 'transaction_date' and 'job_title'

s5.transaction_date.fillna(method='ffill', inplace=True)
s5.job_title.fillna(method='ffill', inplace=True)
```

In [17]:
```
# % of 'order_status' values

s5.order_status.value_counts()/len(s5)*100
```

Out[17]:
```
Approved     96.654311
Cancelled     0.873000
Name: order_status, dtype: float64
```

In [18]:
```
# calculate 96% of all null values in 'order_status' to replace with 'Approved'

round(0.96*(s5.order_status.isnull().sum()),0)
```

Out[18]:
```
487.0
```

In [19]:
```
# replacing null values with 'Approved' with 487 rows limit, to follow 96% of missing va

s5.order_status.replace([np.nan], 'Approved', limit=487, inplace=True)
```

In [20]:
```
# remove all 'Cancelled' values as we require only 'Approved' transactions for analysis

s5 = s5.drop(s5[(s5['order_status'] == 'Cancelled')].index)
s5.reset_index(drop=True, inplace=True)
```

In [21]:
```
# removing remaining null values from 'order_status' to maintain accuracy of data

s5.dropna(subset=['order_status'], axis=0, inplace=True)

# reset the dataframe after dropping rows

s5.reset_index(drop=True, inplace=True)
```

In [22]:
```
# replace selected columns' missing values with mean and mode

s5.fillna(value={'DOB':s5['DOB'].mode()[0], 'list_price':s5['list_price'].mean(), 'produ
        'online_order':s5['online_order'].mode()[0], 'property_valuation':s5['property_v
```

In [23]:
```
# convert 'DOB' as 'age' column

from datetime import date

def calculate_age(born):
    today = date.today()
    return today.year - born.year - ((today.month, today.day) < (born.month, born.day))
```

In [24]:
```
s5.DOB = s5.DOB.apply(calculate_age).astype('int')
s5.DOB
```

Out[24]:
```
0        69
1        69
2        69
3        69
4        69
         ..
20320    47
20321    21
20322    45
20323    49
20324    31
Name: DOB, Length: 20325, dtype: int32
```

In [25]:
```
# rename the 'DOB' as 'age' column

s5.rename(columns={'DOB': 'age'}, inplace=True)
```

In [26]:
```
# identify the most common 'postcode'

s5.postcode.value_counts().idxmax()
```

Out[26]: 2153.0

In [27]:
```
# replacing missing 'postcode' values with most frequent column value '2153'

s5.postcode.fillna('2153', inplace=True)
```

In [28]:
```
# assigning 'NSW' value for 'state' missing values to correspond with postcode 2153

s5.state.fillna('NSW', inplace=True)
```

In [29]:
```
#  replacing 'indsutry' null values to 'n/a'

s5.industry.replace([np.nan], 'n/a', inplace=True)
```

By using the Arbitrary Imputation we filled the {nan} values in this column with {n/a} thus, making an additional value for the variable 'industry'.

In [30]:
```
# final check that missing values have been addressed

s5.isnull().sum()
```

Out[30]:
```
customer_id           0
gender                0
frequency_2017        0
age                   0
job_title             0
industry              0
wealth_segment        0
owns_car              0
tenure                0
postcode              0
state                 0
property_valuation    0
product_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
dtype: int64
```

4. Exploratory Data Analysis

In [31]:
```
# further drop irrelevant columns

s5 = s5.drop(columns=['postcode', 'job_title', 'order_status', 'owns_car', 'product_line
                      'product_size', 'brand'])
```

In [32]:
```
# create 'total_price' column to measure customers' total spending

total_price = s5['standard_cost'] + s5['list_price']
s5 = pd.concat([s5, total_price], axis=1)
```

In [33]:
```
# new data shape

s5.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20325 entries, 0 to 20324
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   customer_id         20325 non-null  int64
 1   gender              20325 non-null  object
 2   frequency_2017      20325 non-null  int64
 3   age                 20325 non-null  int32
 4   industry            20325 non-null  object
 5   wealth_segment      20325 non-null  object
 6   tenure              20325 non-null  float64
 7   state               20325 non-null  object
 8   property_valuation  20325 non-null  float64
 9   transaction_date    20325 non-null  datetime64[ns]
 10  online_order        20325 non-null  float64
 11  list_price          20325 non-null  float64
 12  standard_cost       20325 non-null  float64
 13  0                   20325 non-null  float64
dtypes: datetime64[ns](1), float64(6), int32(1), int64(2), object(4)
memory usage: 2.1+ MB
```

In [34]:

```
# amending the label error of 'total_price' appearing as '0'

s5.set_axis(['customer_id', 'gender', 'frequency_2017', 'age', 'industry', 'wealth_segme
             'state', 'property_valuation', 'transaction_date', 'online_order', 'list_pr
```

- Demographic Segmentation: 'gender', 'age', 'job_title', 'industry', 'wealth_segment'
- Geographic Segmentation: 'postcode', 'state'
- Behavioral Segmentation: 'purchases_3yrs', 'transaction_date', 'online_order', 'list_price'

5. Uniqueness Summary

In [35]:

```
s5.nunique()
```

Out[35]:

```
customer_id           3999
gender                   3
frequency_2017         100
age                     54
industry                10
wealth_segment           3
tenure                  22
state                    3
property_valuation      12
transaction_date       364
online_order             2
list_price             296
standard_cost          100
total_price            303
dtype: int64
```

- This dataframe contains 3999 in total of different customers
- 3 types of gender orientations
- There are 100 measureable frequency values
- 55 different ages
- 10 industries
- 'wealth_segment' is divided into 3 groups
- 'tenure' is measured by 22 lengths

- There are 3 states included
- 12 types of property valuation
- 'transaction_dates' cover 364 days
- 'online_order' will indicate either '0' yes or '1' no
- There are 296 different list prices
- 100 standard cost values
- 303 different total price values

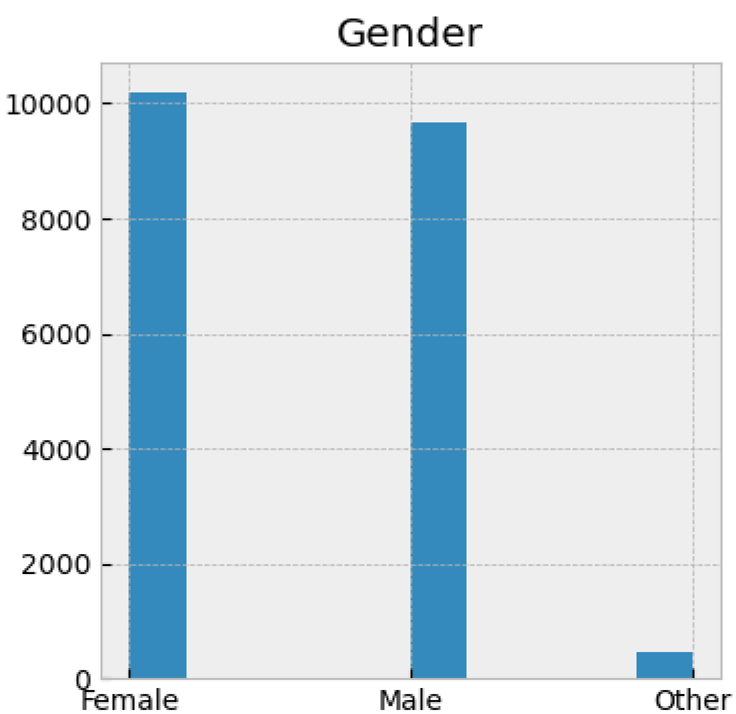
In [36]:
```
# saving the new dataframe into an excel file

#s5.to_excel('SprocketCleaned.xlsx')
```

In [37]:
```
df = s5.copy()
```

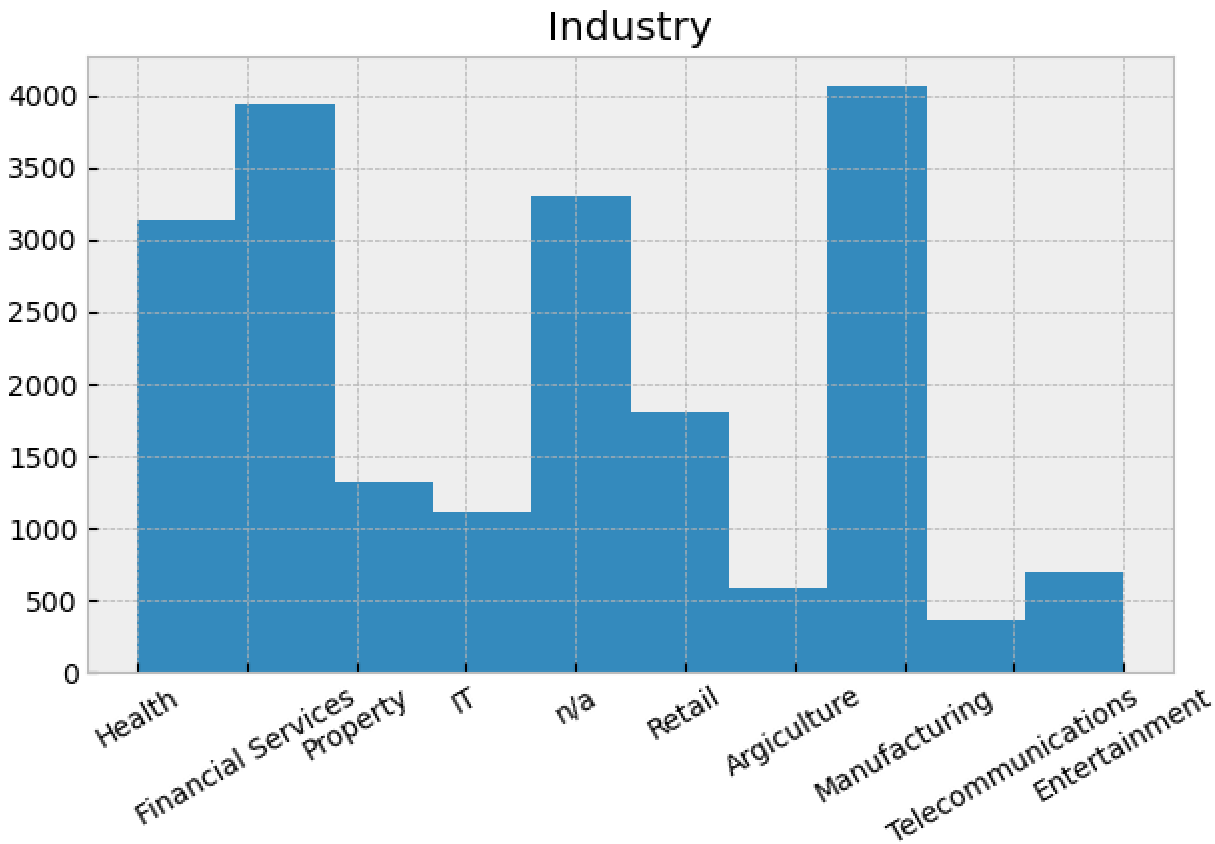
Univariate Analysis

Explore each attribute count to understand our data better

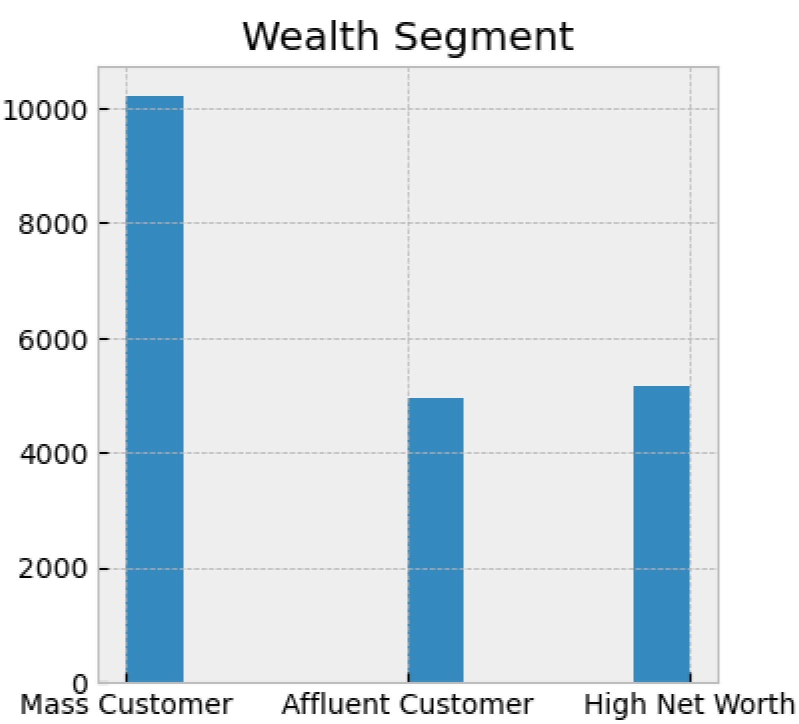
In [38]:
```
plt.style.use('bmh')
plt.figure(figsize=(4, 4))
plt.hist(df['gender'])
plt.title('Gender')
plt.show()
```



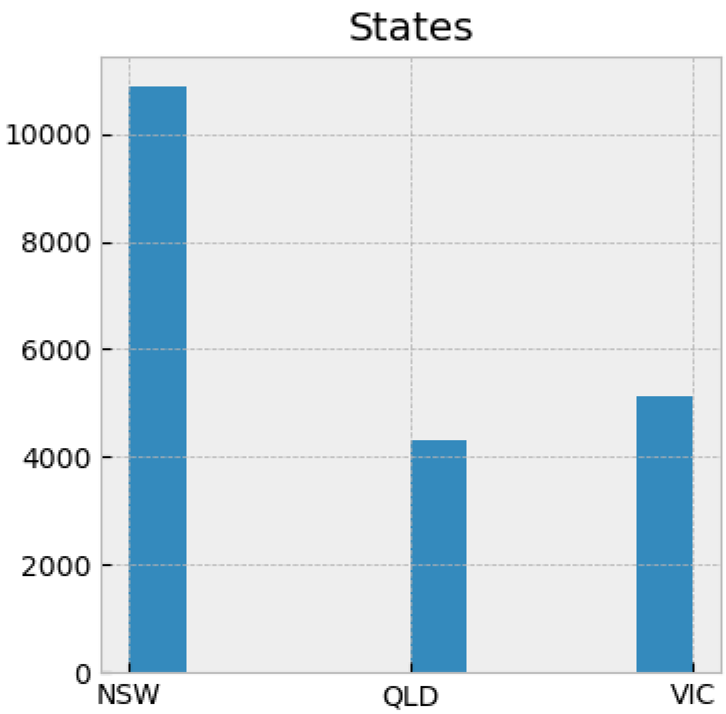
In [39]:
```
plt.style.use('bmh')
plt.figure(figsize=(7, 4))
plt.hist(df['industry'])
plt.xticks(rotation=30)
plt.title('Industry')
plt.show()
```



In [40]:
```
plt.style.use('bmh')
plt.figure(figsize=(4, 4))
plt.hist(df['wealth_segment'])
plt.title('Wealth Segment')
plt.show()
```



In [41]:
```
plt.style.use('bmh')
plt.figure(figsize=(4, 4))
plt.hist(df['state'])
plt.title('States')
plt.show()
```



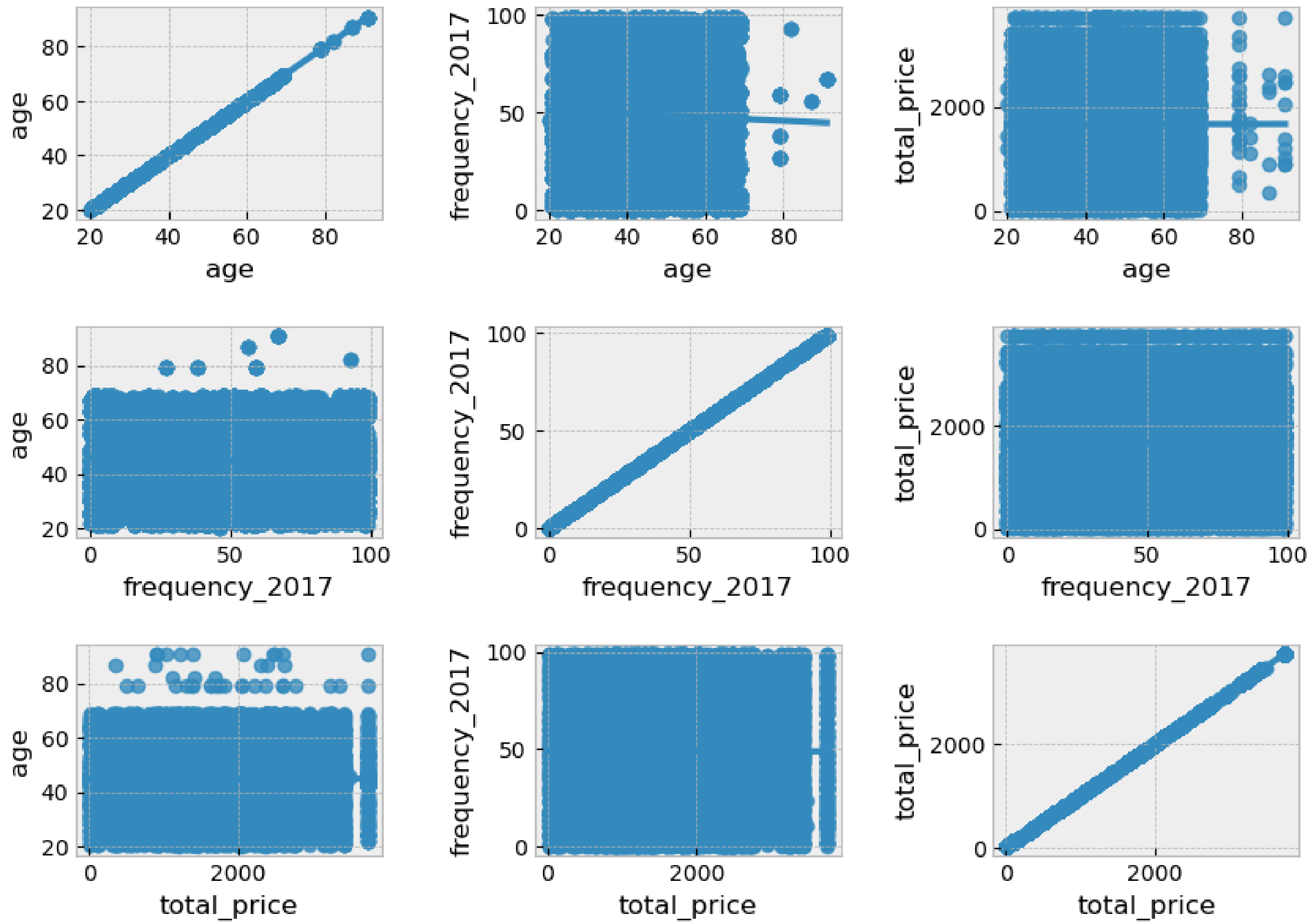
Observations:

- There are more female customers than Male and Other
- Manufacturing and Financial Services are the main industries customers are from
- Mass Customers more than double the High Net Worth or Affluent Customers
- The bulk of customers are based in NSW

Bivariate Analysis

Expolore relationships between 'age', 'frequency_2017' and 'total_price'

In [42]:
```
plt.figure(1 , figsize = (10 , 7))
n = 0
for x in ['age' , 'frequency_2017' , 'total_price']:
    for y in ['age' , 'frequency_2017' , 'total_price']:
        n += 1
        plt.subplot(3 , 3 , n)
        plt.subplots_adjust(hspace = 0.5 , wspace = 0.5)
        sns.regplot(x = x , y = y , data = df)
        plt.ylabel(y.split()[0]+' '+y.split()[1] if len(y.split()) > 1 else y )
plt.show()
```



Observations: There are no evident relationships present in these features.

In [43]:
```
df1 = df.copy()
```

In [44]:
```
df1.drop(['customer_id'], axis=1, inplace=True)
```

6. Statistics of Data

In [45]:
```
df1.describe()
```

Out[45]:

	frequency_2017	age	tenure	property_valuation	online_order	list_price	standard_cost
count	20325.000000	20325.000000	20325.000000	20325.000000	20325.000000	20325.000000	20325.000000
mean	48.816482	44.996064	10.676212	7.515031	0.478819	1107.714036	563.344223
std	28.613997	12.501186	5.610084	2.824812	0.499563	575.697431	404.233514
min	0.000000	20.000000	1.000000	1.000000	0.000000	12.010000	7.210000
25%	24.000000	36.000000	6.000000	6.000000	0.000000	586.450000	230.090000
50%	48.000000	45.000000	11.000000	8.000000	0.000000	1151.960000	513.850000
75%	73.000000	54.000000	15.000000	10.000000	1.000000	1577.530000	820.780000
max	99.000000	91.000000	22.000000	12.000000	1.000000	2091.470000	1759.850000

Observations: On avearge, our customers are of 44 years of age, frequent our store 49 times in 2017, and spent around $1671.

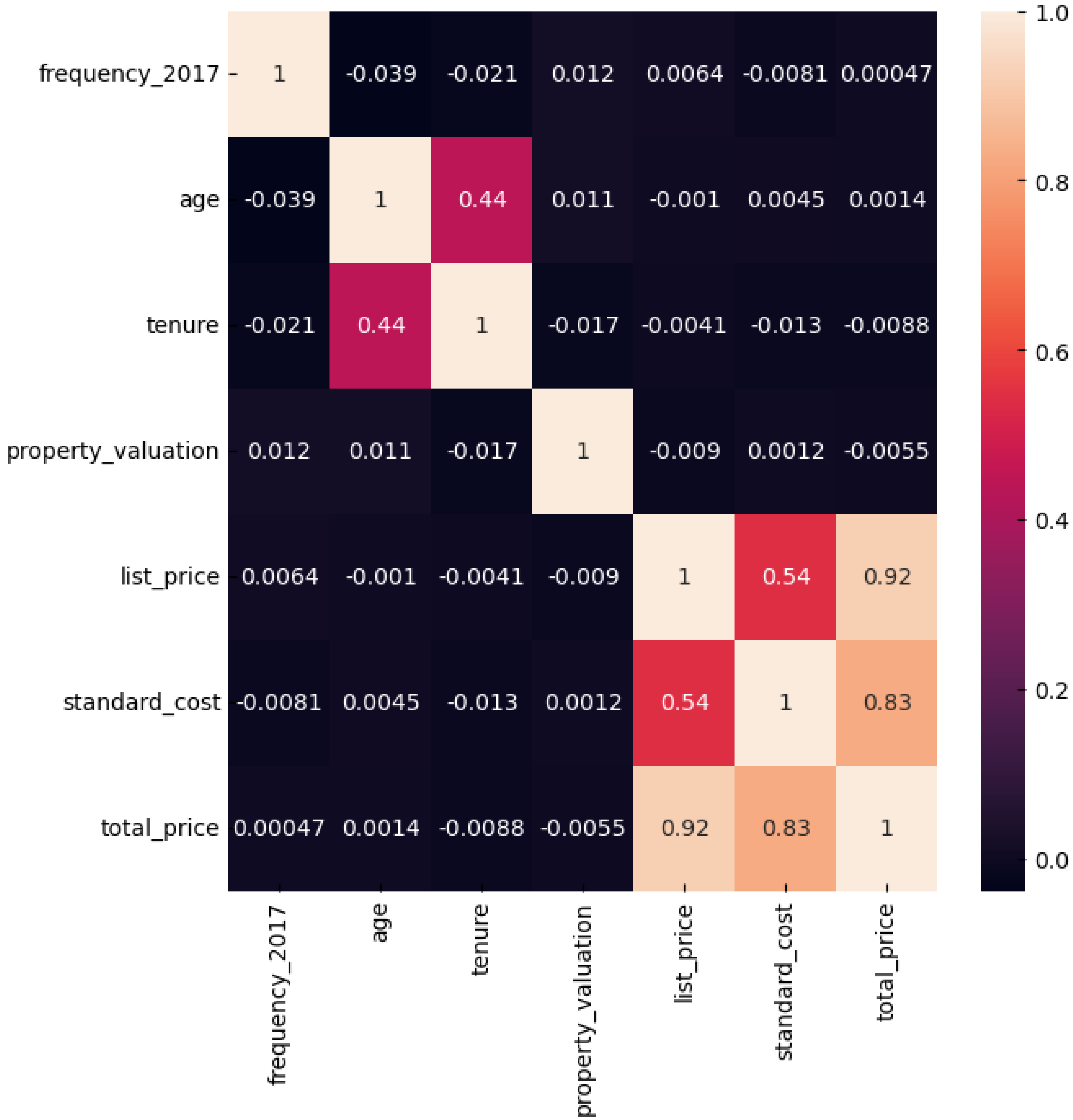
Correlations of Numerical Columns

In [46]:

```
# view the correlation of "int64" or "float64" dtype columns

df2 = df1[['frequency_2017', 'age', 'tenure', 'property_valuation', 'list_price', 'stand
```

In [47]:

```
plt.figure(figsize=(7,7))
sns.heatmap(df2.corr(), annot=True)
plt.show()
```



Observations:

- 0.44 relationship between 'age' and 'tenure', indicating the higher age range will have a higher tenure value
- 'list_price', 'standard_cost' and 'total_price' have a relationship as they've been feature engineered together

Correlations of All Attributes

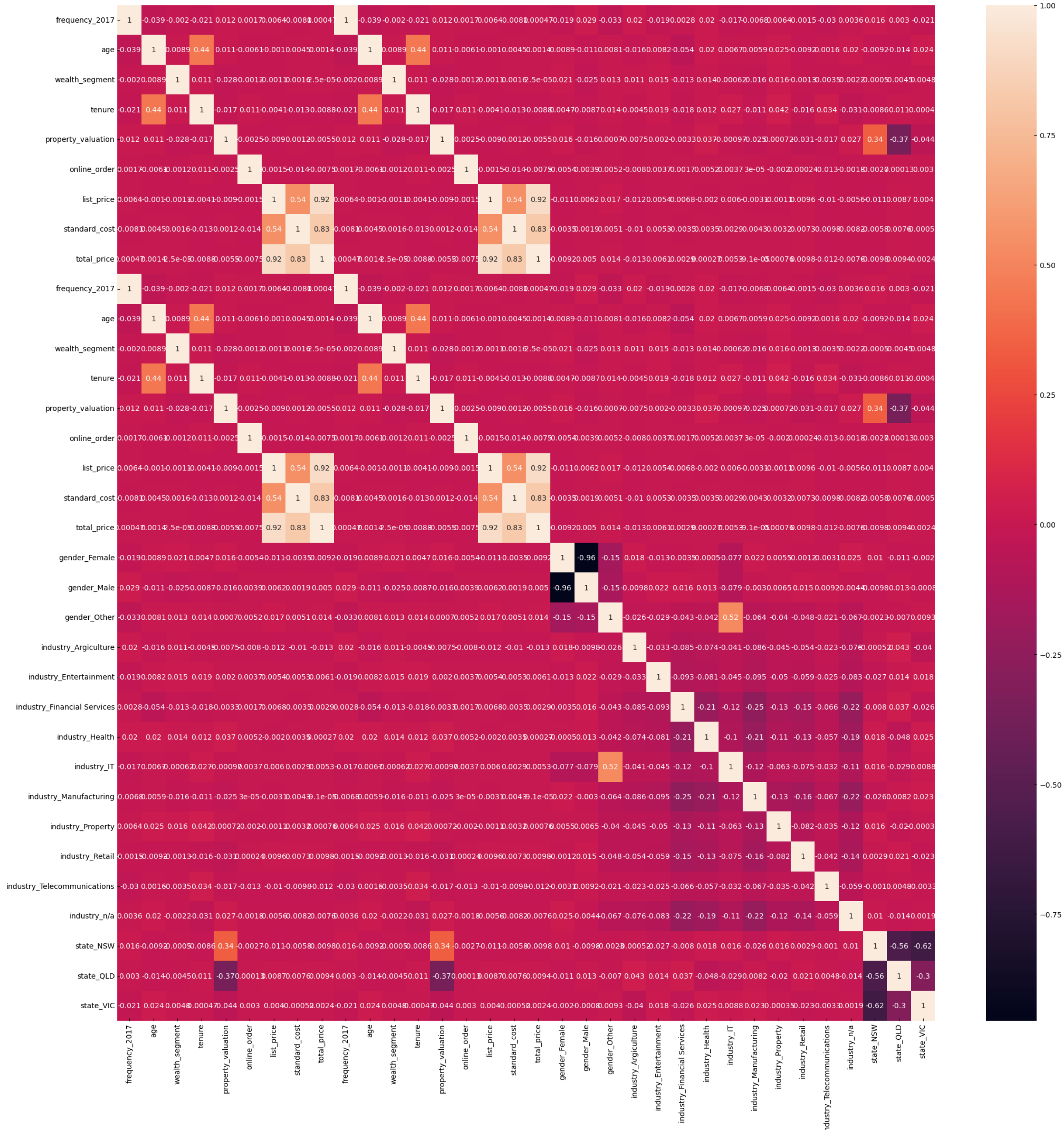
Feature Scaling

Let's scale our ordinal values using LabelEncoder which encodes ordinal data with values between 0 and n_classes-1, where n is the number of distinct labels. For nominal data, we apply the pandas .get_dummies() function to convert object datatypes into numerical data for statistical analysis.

In [48]:
```
from sklearn.preprocessing import LabelEncoder #preProcessing data
import os
```

In [49]:
```
# feature scale attributes using LabelEncoder and .get_dummies()

df1['wealth_segment']=LabelEncoder().fit_transform(df1["wealth_segment"])

dummies = pd.get_dummies(df1, columns=['gender','industry', 'state'])
df1 = pd.concat([df1, dummies], axis=1)
```

In [50]:
```
plt.figure(figsize=(25,25))
sns.heatmap(df1.corr(), annot=True)
plt.show()
```



Observation:

- state_NSW has a correlation of 0.34 to 'property_valuation', which implies NSW has a higher property valuation
- state_NSW is also strongly correlated to state_VIC, with a correlation of -0.62
- 'gender_Other' has a correaltion of 0.52 to 'industry_IT' which indicates that the IT industry has many gender_Other

7. Recency Frequency Monetary (RFM) Analysis

Here, we will apply the RFM model to identify our best customers, based on their Recency and Frequency of patroning the Sprocket Central shops, and according to their spending value (Monetary). RFM analysis allows us to segment our customers according to their spending, demographic and geographical behaviour, by sampling convinience of our customer database. Businesses can benefit from customer segmentation which fine tunes target marketing campaigns,improves resource allocation, and improves sales.

Customer segmentation models are usually built using unsupervised machine learning algorithms such as K-Means clustering or hierarchical grouping. These models can pick up on similarities between user groups that often go unnoticed by the human eye, by reducing the distortion of our dataset.

Our best customers will have the following attributes:

- Lowest Recency
- Highest Frequency
- Highest Monetary Value

Drawing

i. Calculate dates for analysis

In [51]:
```
# first order date

print("The first date of transaction is:", df['transaction_date'].min())
```

```
The first date of transaction is: 2017-01-01 00:00:00
```

In [52]:
```
# last order date

print("The last date of transation is:", df['transaction_date'].max())
```

```
The last date of transation is: 2017-12-30 00:00:00
```

In [53]:
```
# recency is calculated as a point in time, so based on the last transaction_date we'll

Now = dt.datetime(2017,12,31)
df['transaction_date'] = pd.to_datetime(df['transaction_date'])
```

ii. Create RFM Table

In [54]:
```
# create RFM Table

rfmTable = df.groupby('customer_id').agg({'transaction_date': lambda x: (Now - x.max()).
                                          'frequency_2017': 'first', 'total_price': lambd

rfmTable['transaction_date'] = rfmTable['transaction_date'].astype(int)

rfmTable.rename(columns={'transaction_date': 'recency',
                         'frequency_2017': 'frequency',
                         'total_price': 'monetary_value'}, inplace=True)
```

In [55]:
```
# view our RFM table

rfmTable
```

Out[55]:

	recency	frequency	monetary_value
customer_id			
1	8	93	15150.81
2	129	81	6071.88
3	103	61	16413.65

4	196	33	1874.87
5	17	56	9411.46
...	...	...	...
3996	292	8	1982.61
3997	292	87	1982.61
3998	292	60	1982.61
3999	292	11	1982.61
4000	292	76	1982.61

3999 rows × 3 columns

Below, we can check for accuracy of the RFM table. Let's inspect the first customer:

- Her last purchase was 8 days from 31 Dec 2017, meaning her last 'transaction_date' was on 23 Dec
- She has shopped 93 times in 2017
- She has spent a total of $15,150.81

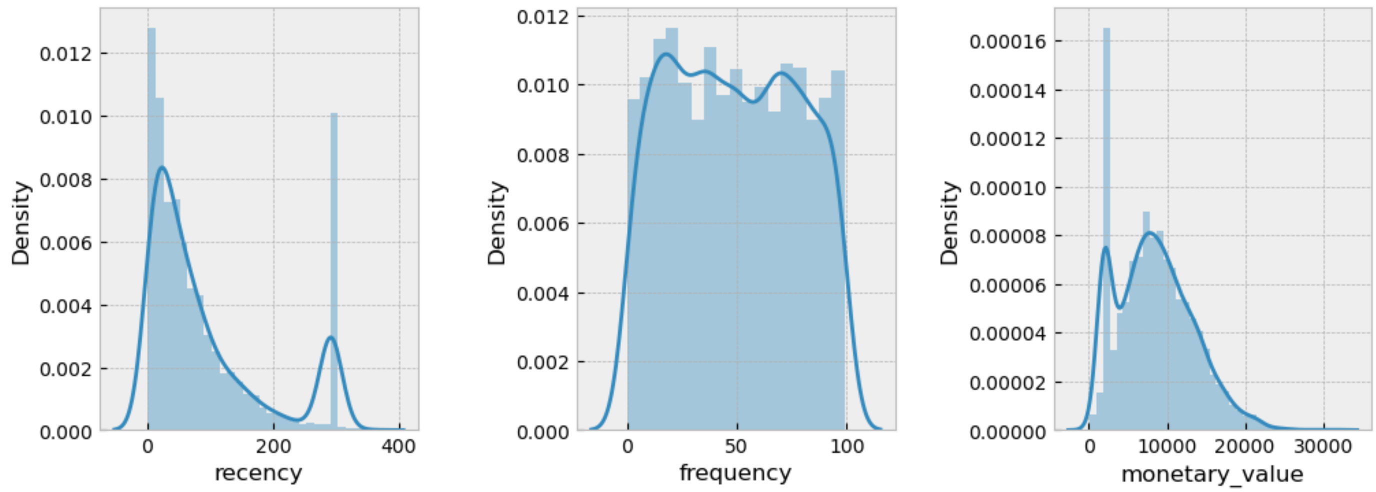
In [56]:
```
# check accuracy of rfmTable against our first customer

cust_1 = df[df['customer_id'] == 1]
cust_1.head()
```

Out[56]:

	customer_id	gender	frequency_2017	age	industry	wealth_segment	tenure	state	property_valuation	trans
0	1	Female	93	69	Health	Mass Customer	11.0	NSW	10.0	
1	1	Female	93	69	Health	Mass Customer	11.0	NSW	10.0	
2	1	Female	93	69	Health	Mass Customer	11.0	NSW	10.0	
3	1	Female	93	69	Health	Mass Customer	11.0	NSW	10.0	
4	1	Female	93	69	Health	Mass Customer	11.0	NSW	10.0	

iii. Visualise RFM Distribution

In [57]:
```
plt.style.use('bmh')
plt.figure(figsize=(12,4))
plt.subplot(1,3,1); sns.distplot(rfmTable['recency'])
plt.subplot(1,3,2); sns.distplot(rfmTable['frequency'])
plt.subplot(1,3,3); sns.distplot(rfmTable['monetary_value'])
plt.subplots_adjust(hspace =0.5 , wspace = 0.5)
plt.show()
```



Check Skewness of RFM

In [58]:
```
rfmTable[['recency', 'frequency', 'monetary_value']].skew()
```

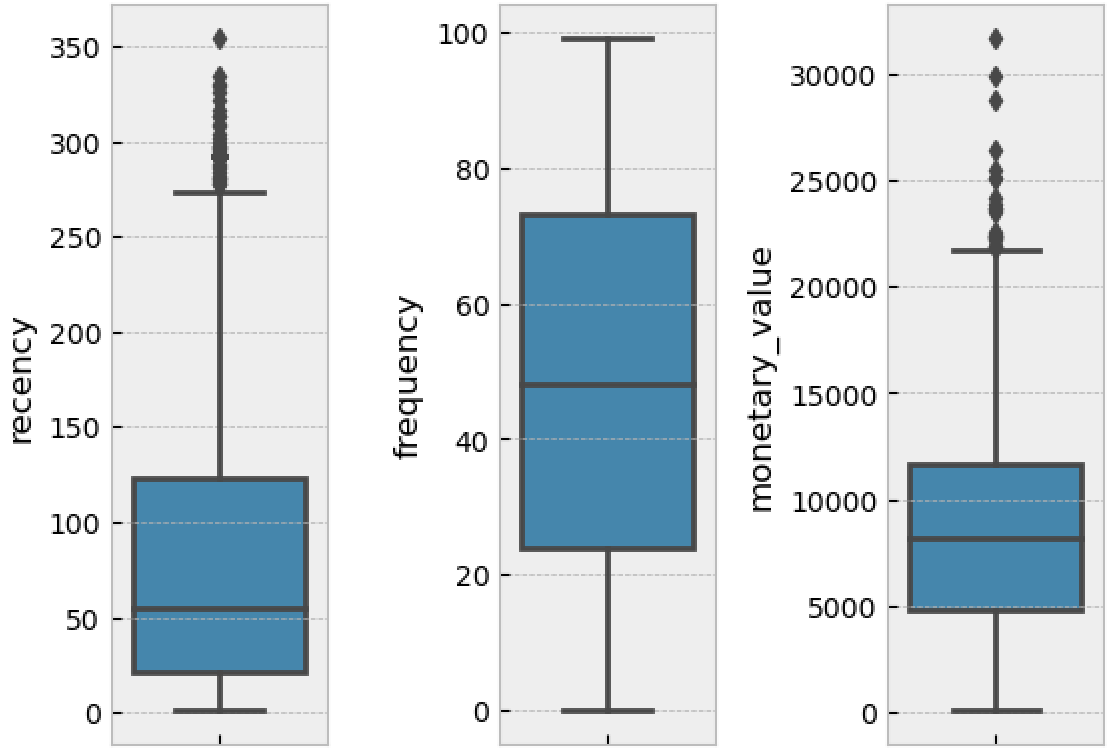
Out[58]:
```
recency           1.230968
frequency         0.045081
monetary_value    0.513079
dtype: float64
```

Observations:

- 'recency' presents skewness of 1.23 which reflects the distribution of having more 'Active Customers'
- 'frequency' is fairly evenly distributed across the range around the 9 mark

iv. Identify Outliers

In [59]:
```
f, axes = plt.subplots(1, 3)

sns.boxplot(  y= "recency", data=rfmTable,  orient='v' , ax=axes[0])
sns.boxplot(  y= "frequency", data=rfmTable,  orient='v' , ax=axes[1])
sns.boxplot(  y= "monetary_value", data=rfmTable,  orient='v' , ax=axes[2])
plt.subplots_adjust(hspace =0.5 , wspace = 0.8)
plt.show()
```



Observations:

- Outliers exists for 'recency' and 'monetary_value'
- As some bicycles are known to be valued in high price ranges, we can assume that 'Big Spenders' customers are serious biking hobbyists/connoisseurs who have the financial means for the luxury bike items
- There outliers in 'recency' represent the 'Lost Customers'

v. Calculate RFM Quartiles

Next, the RFM values will be split into 4 percentile groups using quantiles to divide the RFM values into 4 groups
1. This will allow us a starting point for analysis
2. Label value ranges from 1-4, where 4 is the best quantile score.

In [60]:
```
# define labels for RFM
r_labels = range(4, 0, -1); f_labels = range(1, 5); m_labels = range(1, 5)

# assign labels to 4 equal percentile groups
recency_group = pd.qcut(rfmTable['recency'].rank(method='first'), q=4, labels=r_labels)

frequency_group = pd.qcut(rfmTable['frequency'].rank(method='first'), q=4, labels=f_labe

monetary_group = pd.qcut(rfmTable['monetary_value'].rank(method='first'), q=4, labels=m_

# Create new columns R and F
rfmTable = rfmTable.assign(R = recency_group.values, F = frequency_group.values,  M = mo
rfmTable.head()
```

Out[60]:

	recency	frequency	monetary_value	R	F	M
customer_id						
1	8	93	15150.81	4	4	4

2	129	81	6071.88	1	4	2
3	103	61	16413.65	2	3	4
4	196	33	1874.87	1	2	1
5	17	56	9411.46	4	3	3

- The best customers segment will have a RFM score of 444
- 444 customers will have bought the most recently, shop more oftenly, and spent the most
- 444 customers can continue to thrive as a customer with loyalty programs and new products

vi. RFM Segments

In [61]:
```
def join_rfm(x): return str(x['R']) + str(x['F']) + str(x['M'])
rfmTable['RFM_Segment'] = rfmTable.apply(join_rfm, axis=1)
rfmTable.head()
```

Out[61]:

	recency	frequency	monetary_value	R	F	M	RFM_Segment
customer_id							
1	8	93	15150.81	4	4	4	4.04.04.0
2	129	81	6071.88	1	4	2	1.04.02.0
3	103	61	16413.65	2	3	4	2.03.04.0
4	196	33	1874.87	1	2	1	1.02.01.0
5	17	56	9411.46	4	3	3	4.03.03.0

In [62]:
```
# number of segment variations

print("Number of unique RFM_Segment variations:", rfmTable.RFM_Segment.nunique())
```

```
Number of unique RFM_Segment variations: 64
```

These 64 unique RFM Segment variations will need to be classified into groups to give a general description of the customer type. A RFM Score of the sum of the RFM quartiles will provide the scale of our RFM Score.

RFM Score

In [63]:
```
# Calculate RFM_Score

rfmTable['RFM_Score'] = rfmTable[['R','F','M']].sum(axis=1)
rfmTable.head()
```

Out[63]:

	recency	frequency	monetary_value	R	F	M	RFM_Segment	RFM_Score
customer_id								
1	8	93	15150.81	4	4	4	4.04.04.0	12
2	129	81	6071.88	1	4	2	1.04.02.0	7
3	103	61	16413.65	2	3	4	2.03.04.0	9
4	196	33	1874.87	1	2	1	1.02.01.0	4
5	17	56	9411.46	4	3	3	4.03.03.0	10

In [64]:
```
# remove the '.0' in the RFM_Segment values

rfmTable.RFM_Segment = rfmTable['RFM_Segment'].str.replace(".0","",regex=False)
```

In [65]:
```
rfmTable.RFM_Segment
```

Out[65]:
```
customer_id
1       444
2       142
3       234
4       121
5       433
       ...
3996    111
3997    141
3998    131
3999    111
4000    141
Name: RFM_Segment, Length: 3999, dtype: object
```

vii. Manually Grouping RFM Segments

In [66]:
```
def rfm_level(df):
    if df['RFM_Segment'] == '444':
        return 'Best Customers'

    elif df['RFM_Segment'] == '411':
        return 'New Customers'

    else:
        if df['M'] == 4:
            return 'Big Spenders'

        elif df['F'] == 4:
            return 'Loyal Customers'

        elif df['R'] == 4:
            return 'Active Customers'

        elif df['R'] == 1:
            return 'Lost Customers'

        elif df['M'] == 1:
            return 'Frugal Spenders'

        return 'Regular Customers'

# Create a new column RFM_Level
rfmTable['RFM_Level'] = rfmTable.apply(rfm_level, axis=1)
```

In [67]:
```
rfmTable.head()
```

Out[67]:

customer_id	recency	frequency	monetary_value	R	F	M	RFM_Segment	RFM_Score	RFM_Level
1	8	93	15150.81	4	4	4	444	12	Best Customers
2	129	81	6071.88	1	4	2	142	7	Loyal Customers
3	103	61	16413.65	2	3	4	234	9	Big Spenders
4	196	33	1874.87	1	2	1	121	4	Lost Customers
5	17	56	9411.46	4	3	3	433	10	Active Customers

Calculate Count and Percentage of RFM Segments

In [68]:
```
rfmTable.RFM_Level.value_counts()
```

Out[68]:
```
Big Spenders          911
Regular Customers     867
Loyal Customers       752
Lost Customers        701
Active Customers      479
Frugal Spenders       182
Best Customers         89
New Customers          18
Name: RFM_Level, dtype: int64
```

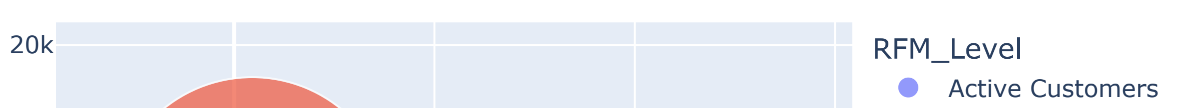
In [69]:
```
# calculate average and total values for each RFM_Level
rfm_agg = rfmTable.groupby('RFM_Level').agg({
    'recency': 'mean',
    'frequency': 'mean',
    'monetary_value': ['mean', 'count']}).round(0)

rfm_agg.columns = rfm_agg.columns.droplevel()
rfm_agg.columns = ['recencyMean','frequencyMean','monetaryMean', 'count']
rfm_agg['percent'] = round((rfm_agg['count']/rfm_agg['count'].sum())*100, 2)

# reset the index
rfm_agg = rfm_agg.reset_index()

# Print the aggregated dataset
rfm_agg
```

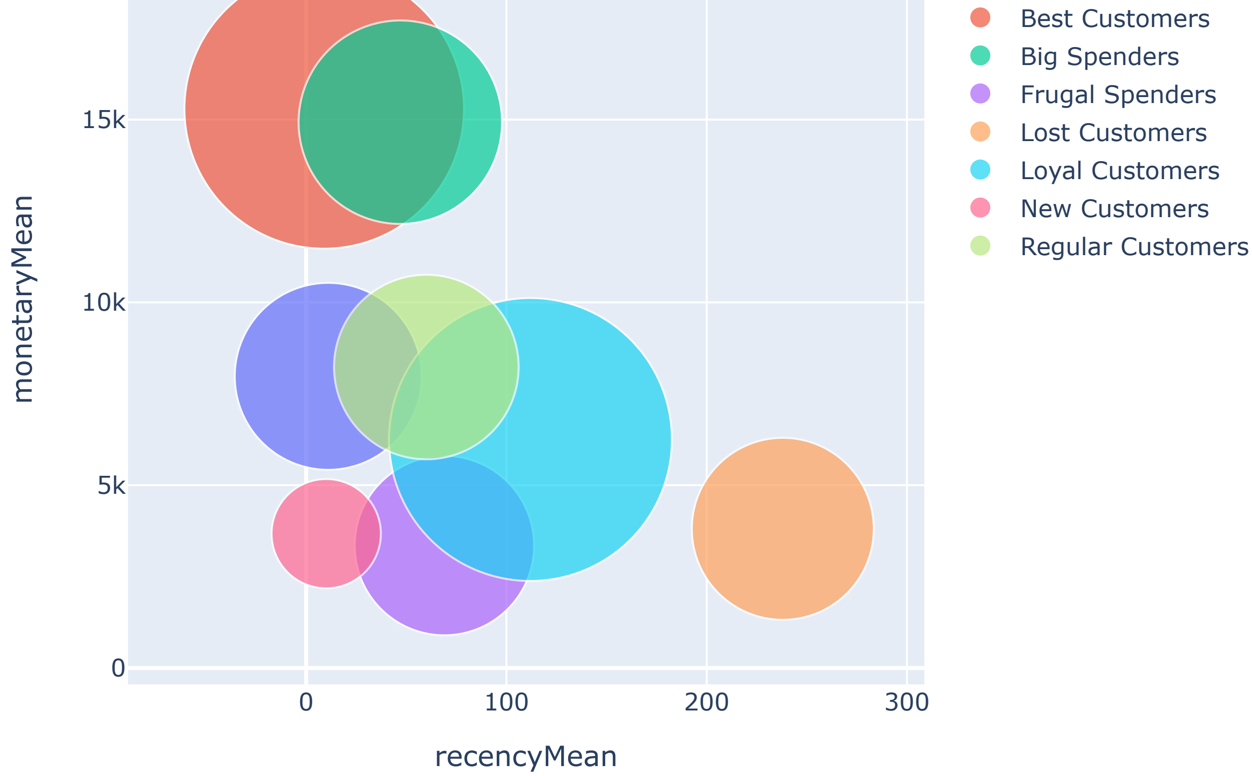
Out[69]:

	RFM_Level	recencyMean	frequencyMean	monetaryMean	count	percent
0	Active Customers	11.0	38.0	7977.0	479	11.98
1	Best Customers	9.0	85.0	15293.0	89	2.23
2	Big Spenders	47.0	45.0	14928.0	911	22.78
3	Frugal Spenders	69.0	35.0	3349.0	182	4.55
4	Lost Customers	238.0	36.0	3807.0	701	17.53
5	Loyal Customers	112.0	87.0	6250.0	752	18.80
6	New Customers	10.0	13.0	3674.0	18	0.45
7	Regular Customers	60.0	37.0	8233.0	867	21.68

viii. RFM Scatterplot

In [70]:
```
import plotly.express as px

fig = px.scatter(rfm_agg, x="recencyMean", y="monetaryMean", size="frequencyMean", color
           hover_name="RFM_Level", size_max=100)

fig.show()
```





Offline Scatterplot: data1rfmscatter

We are able to view the top 5 'Best Customers' with RFM Segment of 444

In [71]:
```
rfmTable[rfmTable['RFM_Segment']=='444'].sort_values('monetary_value', ascending=False).
```

Out[71]:

customer_id	recency	frequency	monetary_value	R	F	M	RFM_Segment	RFM_Score	RFM_Level
173	16	99	21573.45	4	4	4	444	12	Best Customers
2464	3	78	21331.02	4	4	4	444	12	Best Customers
2816	9	87	21246.99	4	4	4	444	12	Best Customers
3420	6	96	20962.72	4	4	4	444	12	Best Customers
2914	13	76	20813.10	4	4	4	444	12	Best Customers

Customer ID 173 is our top Best Customer, with recency 16 days, frequency of 99 days and spending total of $21,573.45 in 2017.

Concluding the RFM Model: When used alone, the RFM model may be too simplistic and may mislead. Notably, RFM models are not predictive and are easily skewed due to seasonal sales and subjective to product price. We can supplement the RFM model with another analytical model called K-Means Clusterring to get a fuller scope of our customers.

8. K-Means Clusterring Model

The unsupervised K-Means clustering algorithm segments unlabled data into non-overlapping sub-groups (k-clusters), that are distinct from each other. Each cluster has its own centroid and the main goal of this technique is to reduce the distortion between centroids, thus forming individual clusters according to their characteristics.

data1rfmscatter

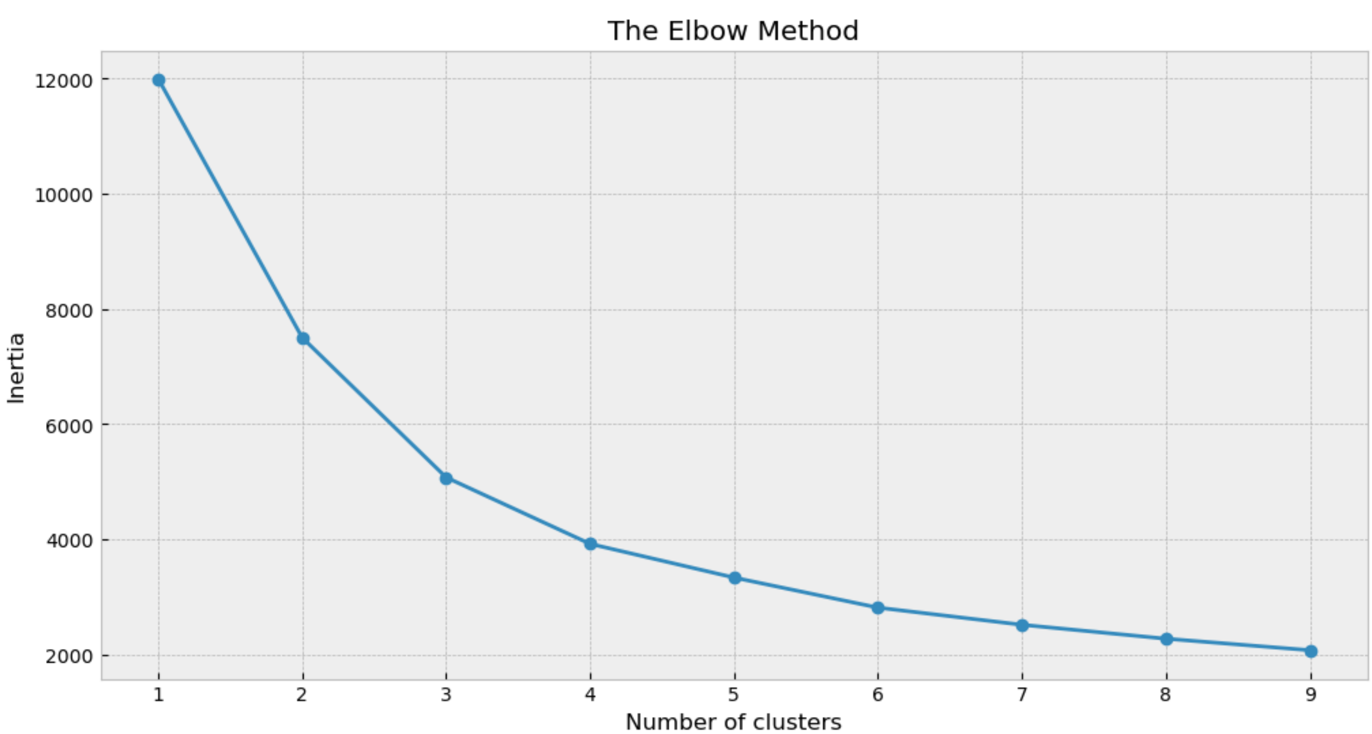
i. Elbow Method to predetermine K-clusters

The first step involves standardising the data (using StandardScaler) before predetermining the number of clusters the model will build, using the Elbow Method.

In [72]:
```
kmeans_rfm = rfmTable[['recency', 'frequency', 'monetary_value']]
```

In [73]:
```
from sklearn.preprocessing import StandardScaler
std_scaler = StandardScaler()
df_scaled = std_scaler.fit_transform(kmeans_rfm)
```

In [74]:
```
from sklearn.cluster import KMeans
SSE = []
for k in range(1, 10):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(df_scaled)
    SSE.append(kmeans.inertia_) #SSE to nearest clustter centroid

frame = pd.DataFrame({'Cluster':range(1,10), 'SSE':SSE})
plt.figure(figsize=(12,6))
plt.plot(frame['Cluster'], frame['SSE'], marker='o')
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')

plt.savefig("Elbow.png")
```



The graph indicates that the 'elbow' is on the number 3-cluster mark. Therefore, we will build our Kmeans model using 3 clusters.

In [75]:
```
model = KMeans(n_clusters=3, random_state=42)
```

```
model.fit(df_scaled)
```

Out[75]:

```
KMeans(n_clusters=3, random_state=42)
```

In [76]:

```
kmeans_rfm = kmeans_rfm.assign(ClusterLabel= model.labels_)
```

In [77]:

```
kmeans_rfm
```

Out[77]:

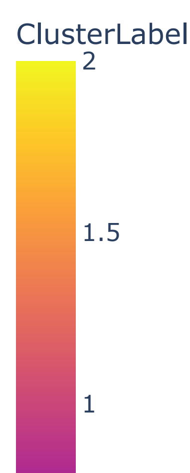
customer_id	recency	frequency	monetary_value	ClusterLabel
1	8	93	15150.81	2
2	129	81	6071.88	2
3	103	61	16413.65	2
4	196	33	1874.87	0
5	17	56	9411.46	2
...	...	...	...	...
3996	292	8	1982.61	0
3997	292	87	1982.61	0
3998	292	60	1982.61	0
3999	292	11	1982.61	0
4000	292	76	1982.61	0

3999 rows × 4 columns

ii. Visualising the K-Means Model

In [78]:

```
fig = px.scatter_3d(kmeans_rfm, x='recency', y='frequency', z='monetary_value',
                    color = 'ClusterLabel', opacity=0.5)
#fig.show()
fig.update_traces(marker=dict(size=5),

                  selector=dict(mode='markers'))
# tight layout
fig.show()
```



iv. Calculating the Mean, Count and Percentage of K-Mean Clusters

In [79]:

```
# create new df with cluster means, counts and percentage

agg_clusters = kmeans_rfm.groupby('ClusterLabel').agg({
    'recency': 'mean',
    'frequency': 'mean',
    'monetary_value': ['mean', 'count']}).round(0)

agg_clusters.columns = agg_clusters.columns.droplevel()
agg_clusters.columns = ['RecencyMean','FrequencyMean','MonetaryMean', 'Count']
agg_clusters['Percent'] = round((agg_clusters['Count']/agg_clusters.Count.sum())*100, 2)

# Reset the index
agg_clusters = agg_clusters.reset_index()

# Change ClusterLabel into discrete values
agg_clusters['ClusterLabel'] = agg_clusters['ClusterLabel'].astype('str')


agg_clusters
```

Out[79]:

	ClusterLabel	RecencyMean	FrequencyMean	MonetaryMean	Count	Percent
0	0	263.0	49.0	2665.0	745	18.63
1	1	51.0	25.0	9842.0	1674	41.86
2	2	52.0	75.0	9813.0	1580	39.51

9. Interpreting the Cluster Labels:

Cluster 0: Lost or Low Spending Customers:

- On average Cluster 0 customers visit the store 49 times, and spent approximately $2665 in 2017.
- Cluster 0 make up 19% of the customer base. These customers shop during special promotions and prefer economical products.
- Using special marketing promotions can help bring these customers back to the store
- Promote cycling events, membership rewards and hold free training sessions to attract these customers back

Cluster 1: Infrequent Big Spenders:

- Cluster 1 customers has the lowest average frequency of 25 counts, a moderate recency average of 51 days and high spending mean amount $9842
- These customers have high spending power, despite not being frequent as other clusters. They may buy according to times of need over want, or are busy people with little time to shop
- Introduce premier loyalty membership reward programs, promote cycling events and training programs to encourage Cluster 1 customers to purchase more frequently.

Cluster 2: Best Customers:

- Sprocket Central's best customers spent $9813 on avegrage, has the highest frequency mean of 75, and recenecy mean of 52 days.
- Cluster 2 are loyal customers and are cycling hobbyists.
- They are always on the look out for the newest products and have a strong spending power.
- They will continue to thrive as customers with membership programs, marketing of new products, promotions and inivitations to cycling events.

II. NEW CUSTOMERS DATA ANALYSIS

Applying K-Means Model to the New Customer Data

Variable Descriptions (Assumptions of New Customer Data):

- gender: sex of customer - 'Female', 'Male' or 'Other'
- past_3_years_bike_related_purchases: count of purchases in the last 3 years - numbers ranging 0 to 99
- DOB: customers' date of birth
- wealth_segment: the wealth level the customer is recorded as - 'Mass Customer', 'Affluent Customer', 'High Net Worth'
- tenure: the duration of residence at customers' address, in years
- state: the state the customer is based in - 'QLD', 'NSW', 'VIC'
- property_valuation: the valuation score of customers' property - numbers from 1 to 12
- Rank: customers' ranking based on recency score - ranking numbers from 1 (most recent) to 1000 (least recent)
- Value: customers' perceived value score of Sprocket's products, services, benefits, and costs - numbers ranging from 0.34 (lowest) to 1.71875 (highest).

1. Importing Data

In [80]:
```
# import data
newdf = pd.read_excel('NewCustomerList.xlsx', header=1)
```

In [81]:
```
# view summary of data
newdf.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
```

In [82]:
```
# selecting relevant columns for analysis

newdf = newdf[['first_name', 'last_name', 'gender', 'past_3_years_bike_related_purchases
```

2. Data Wrangling

Check for Duplicates

In [83]:
```
newdf.duplicated().any()
```

Out[83]:
```
False
```

Missing Values

In [84]:
```
# % of missing values

round(newdf.isnull().sum().sort_values(ascending = False)/len(newdf)*100,2)
```

Out[84]:
```
last_name                              2.9
DOB                                    1.7
first_name                             0.0
gender                                 0.0
past_3_years_bike_related_purchases    0.0
wealth_segment                         0.0
tenure                                 0.0
state                                  0.0
property_valuation                     0.0
Rank                                   0.0
Value                                  0.0
dtype: float64
```

In [85]:
```
newdf.last_name = newdf['last_name'].replace([np.nan],['Not Applicable'])
```

In [86]:
```
newdf.gender = newdf.gender.replace(['U'],['Other'])
```

iii. Data Formatting

Concat first_name and last_name

In [87]:
```
newdf['fullname'] = newdf['first_name'] + '_' + newdf['last_name']
newdf = newdf.drop(columns=['first_name', 'last_name'])
```

Converting DOB to Age Values

In [88]:
```
newdf.fillna(value={'DOB':newdf['DOB'].mode()[0]},inplace=True)
```

In [89]:
```
def calculate_age(born):
    today = date.today()
    return today.year - born.year - ((today.month, today.day) < (born.month, born.day))

newdf.DOB = newdf.DOB.apply(calculate_age).astype('int')
```

Renaming Columns

In [90]:
```
newdf = newdf.rename(columns={'past_3_years_bike_related_purchases': 'count_purchase', '
```

In [91]:
```
newdf.head()
```

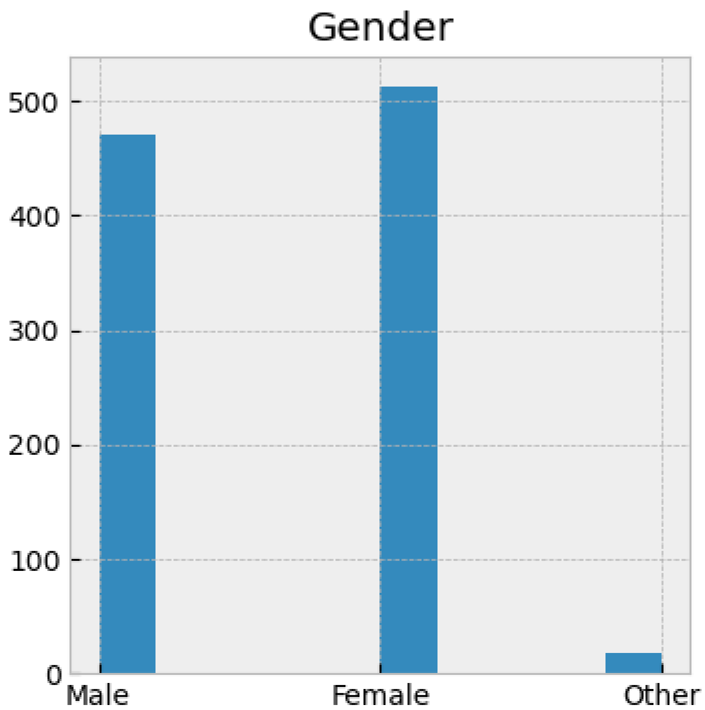
Out[91]:

	gender	count_purchase	age	wealth_segment	tenure	state	property_valuation	Rank	Value	fullna
0	Male	86	65	Mass Customer	14	QLD	6	1	1.718750	Chickie_Bri
1	Male	69	52	Mass Customer	16	NSW	11	1	1.718750	Morly_Ger
2	Female	10	48	Affluent Customer	10	VIC	5	1	1.718750	Ardelis_Forre
3	Female	64	44	Affluent Customer	5	QLD	1	4	1.703125	Lucine_S
4	Female	34	57	Affluent Customer	19	NSW	9	4	1.703125	Melinda_Hac

3. Data Exploration

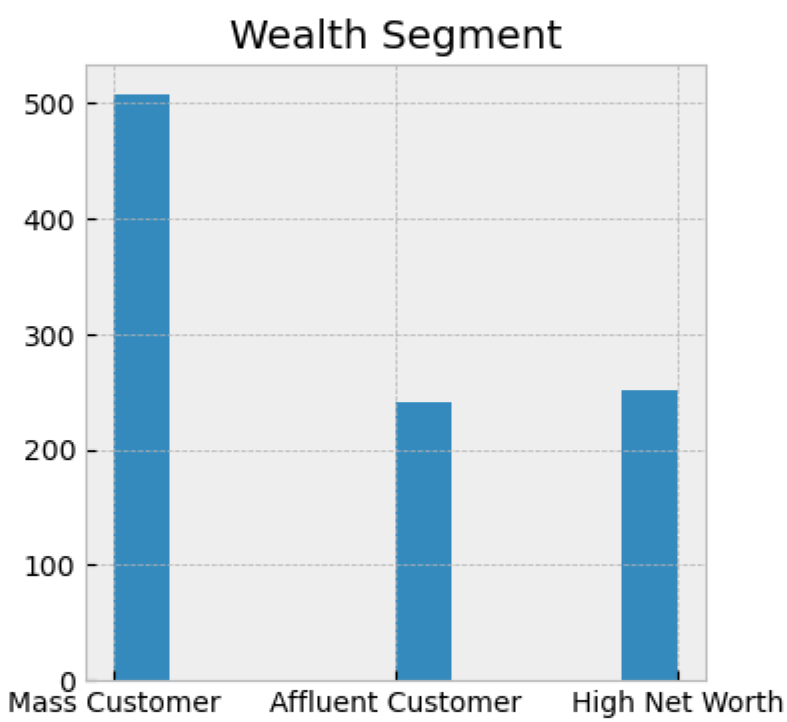
Univariate Analysis

In [92]:
```
plt.figure(figsize=(4, 4))
plt.hist(newdf['gender'])
plt.title('Gender')
plt.show()
```



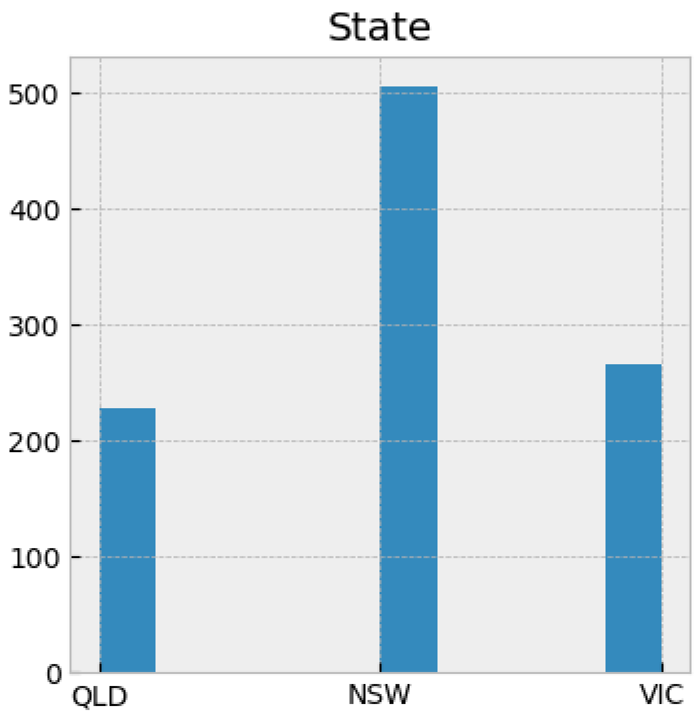
In [93]:

```
plt.figure(figsize=(4, 4))
plt.hist(newdf['wealth_segment'])
plt.title('Wealth Segment')
plt.show()
```



In [94]:

```
plt.figure(figsize=(4, 4))
plt.hist(newdf['state'])
plt.title('State')
plt.show()
```



Observations:

- There are mostly Female customers, followed by Male then Other genders
- Weath Segment indicates that Mass Customers make up 50% of the customer data
- Most of the customers are from NSW

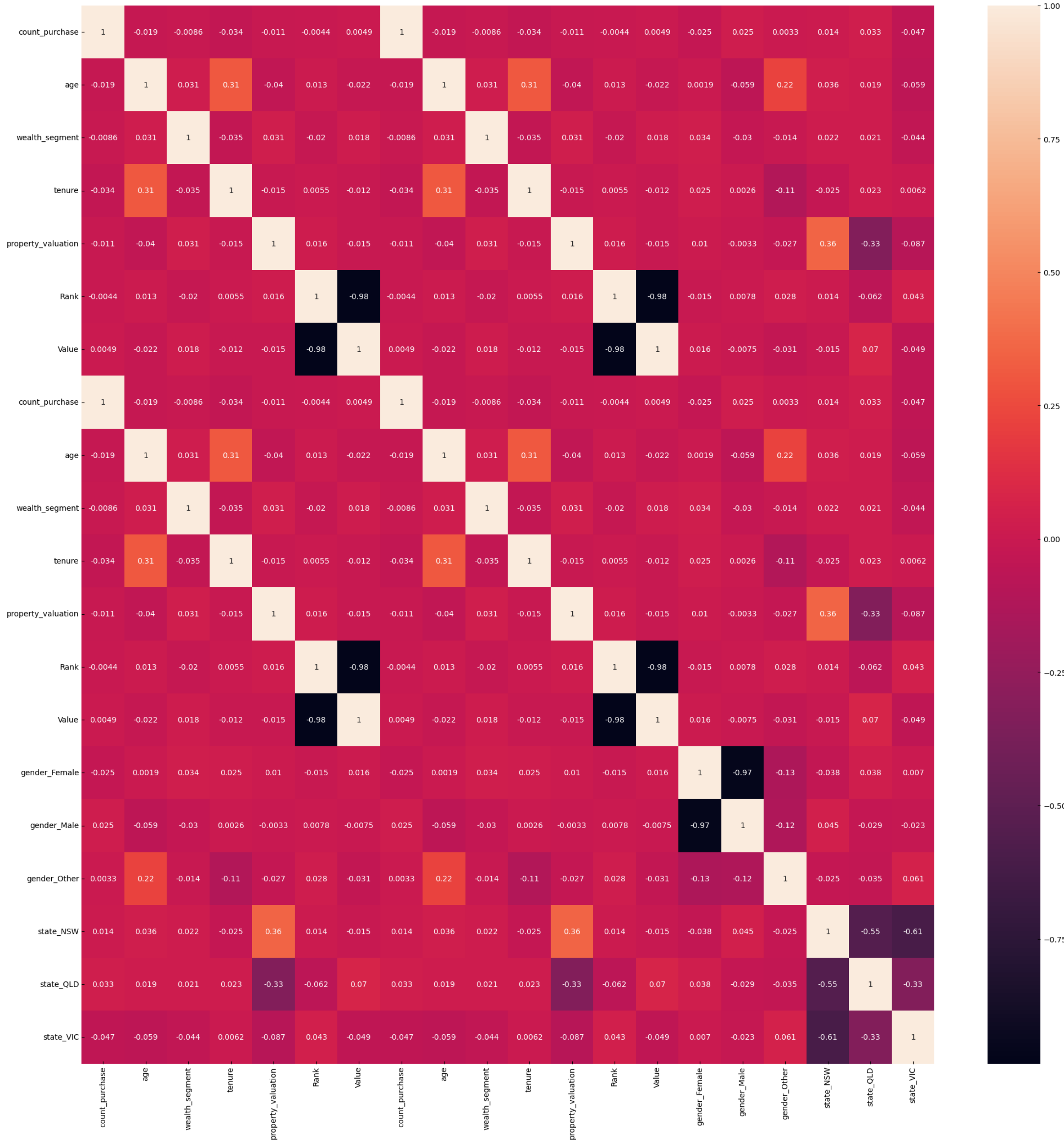
Feature Scaling

In [95]:
```
newdf.to_excel('NewDF.xlsx')
newdf_copy = newdf.copy()
```

In [96]:
```
# scale dataset before viewing correlations using LabelEncoder for ordinal column values
# and one-hot-encoding for nominal column values

newdf_copy["wealth_segment"]=LabelEncoder().fit_transform(newdf_copy["wealth_segment"])


dummies = pd.get_dummies(newdf_copy, columns=['gender', 'state'])
newdf_copy = pd.concat([newdf_copy, dummies], axis=1)
```

Correlations

In [97]:
```
plt.figure(figsize=(25,25))
sns.heatmap(newdf_copy.corr(), annot=True)
plt.show()
```



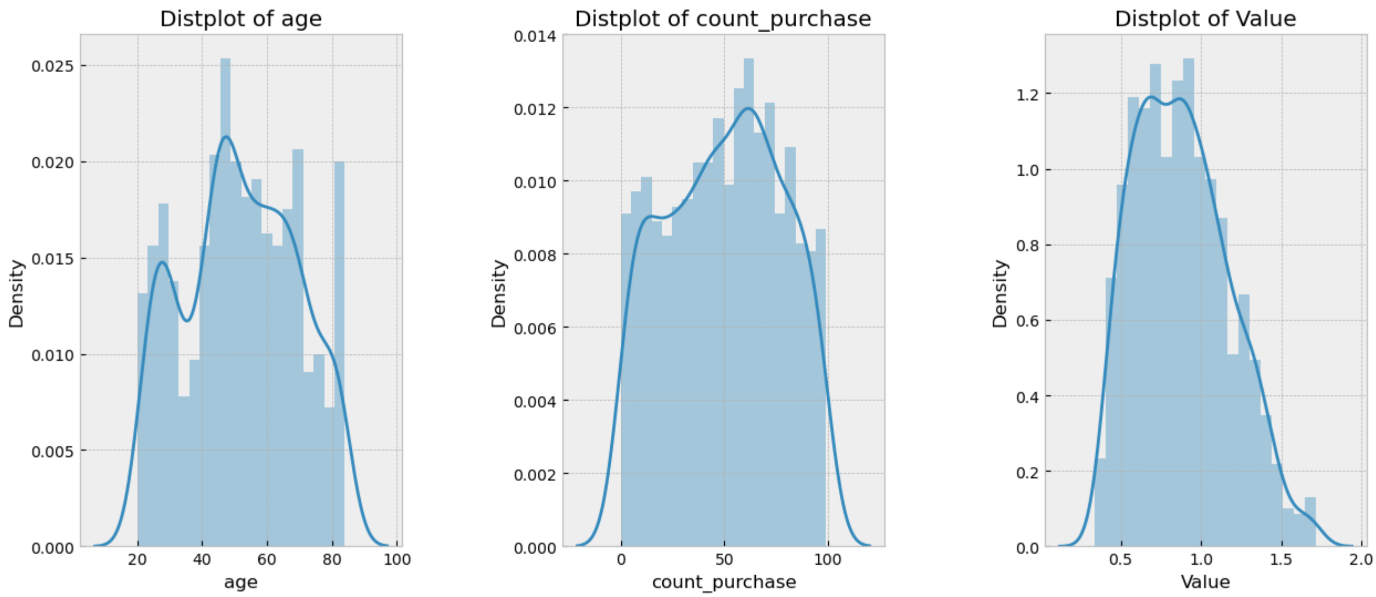
Observations:

- 'age' and 'tenure' have a correlation of 0.31. This implies the older customers have a longer tenureship of their residence
- 'property_valuation' has a correlation of 0.36 to 'state_NSW', suggesting that the valuation score for NSW is higher than other states
- 'Value' to 'Rank' has a correlation of -0.98, indicating a strong relationship.
- 'gender_Female' is strongly correlated to 'gender_Male', with a correlation of -0.97

Distribution Plots of Age, Rank and Value

In [98]:
```
plt.figure(1 , figsize = (15 , 6))
n = 0
for x in ['age' , 'count_purchase' , 'Value']:
```

```
    n += 1
    plt.subplot(1 , 3 , n)
    plt.subplots_adjust(hspace =0.5 , wspace = 0.5)
    sns.distplot(newdf[x] , bins = 20)
    plt.title('Distplot of {}'.format(x))
plt.show()
```



Skewnesss of Attributes

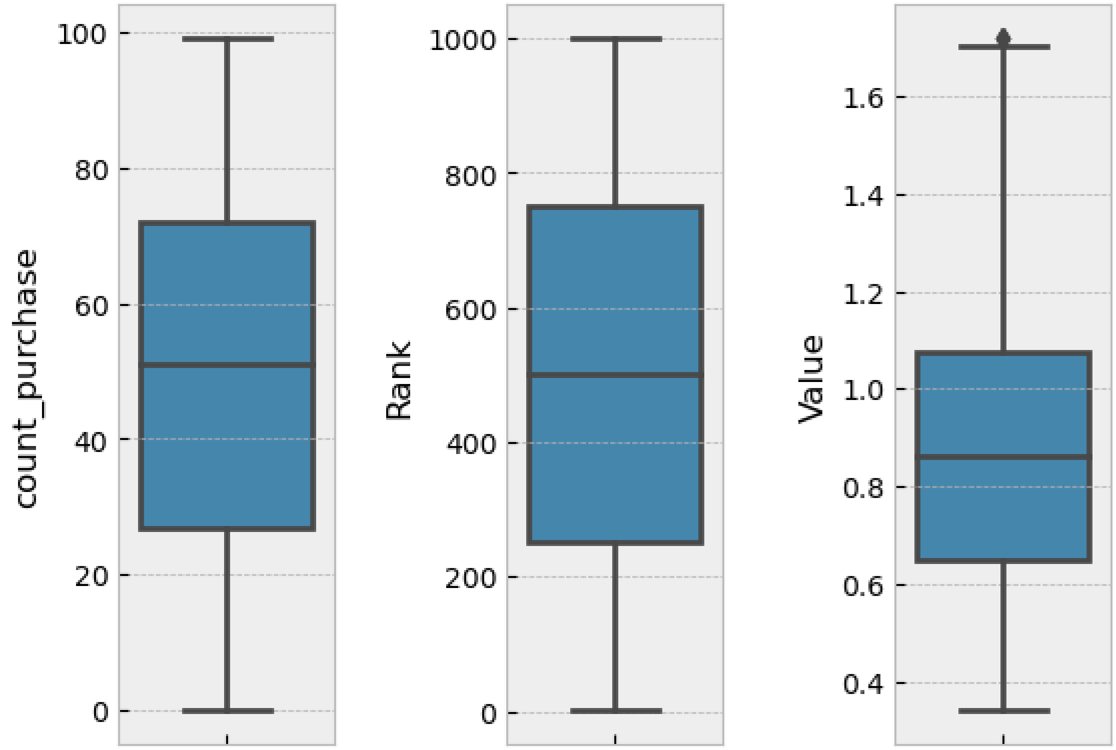
In [99]:
```
newdf.skew()
```

Out[99]:
```
count_purchase        -0.065622
age                    0.009349
tenure                 0.070891
property_valuation    -0.557611
Rank                   0.001246
Value                  0.429903
dtype: float64
```

Observations: All columns are fairly normally distributed

Identifying Outliers

In [100…
```
f, axes = plt.subplots(1, 3)

sns.boxplot(  y= "count_purchase", data=newdf,  orient='v' , ax=axes[0])
sns.boxplot(  y= "Rank", data=newdf,  orient='v' , ax=axes[1])
sns.boxplot(  y= "Value", data=newdf,  orient='v' , ax=axes[2])
plt.subplots_adjust(hspace =0.5 , wspace = 0.8)
plt.show()
```



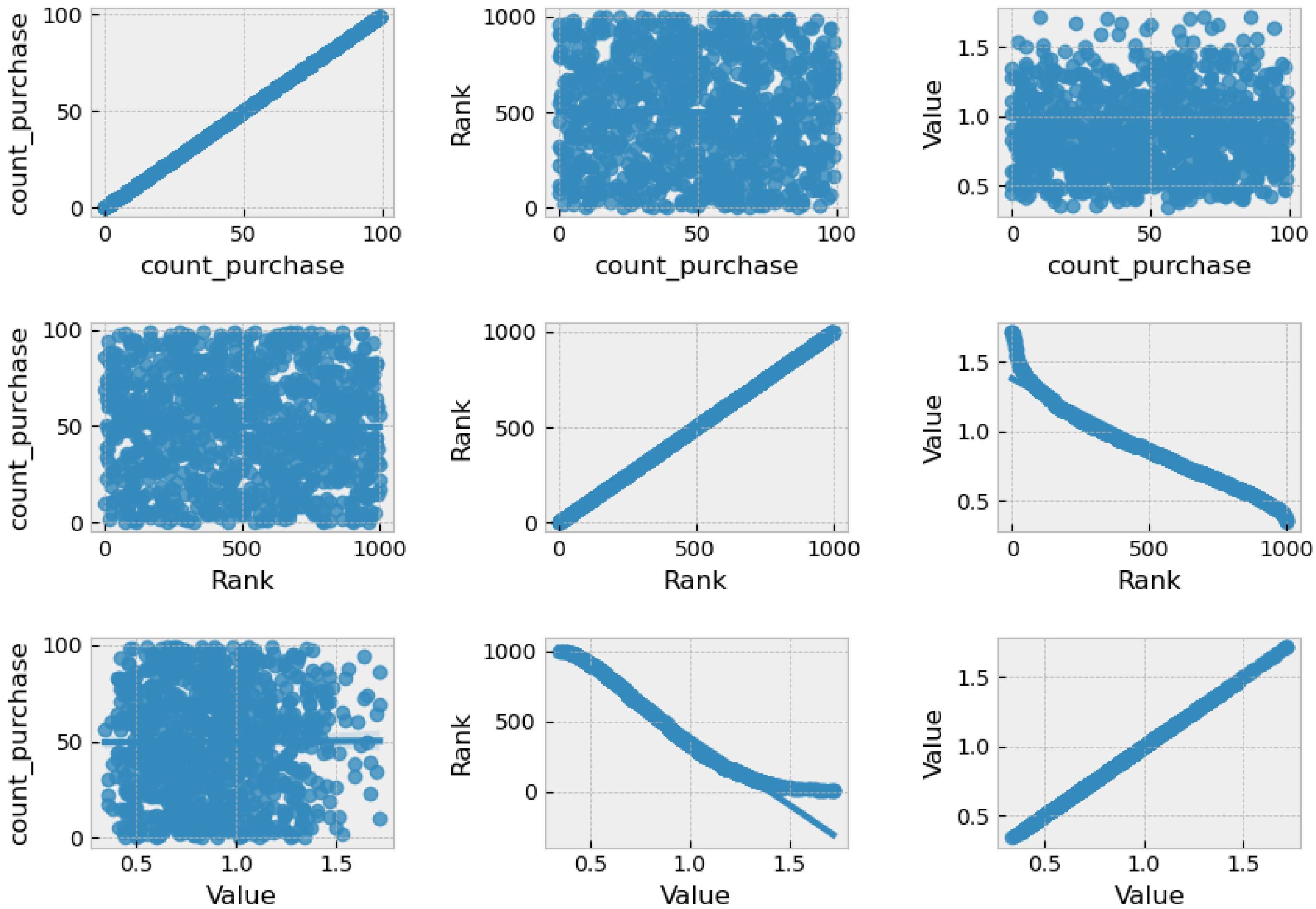
Observations:

- Value has a slight outlier, attributed to the high Value scores of above 1.7
- There are no outstanding outliers for 'Rank' and 'count_purchase'

Regression Plots of Frequency, Rank and Value

In [101…

```
plt.figure(1 , figsize = (10 , 7))
n = 0
for x in ['count_purchase' , 'Rank', 'Value']:
    for y in ['count_purchase' , 'Rank', 'Value']:
        n += 1
        plt.subplot(3 , 3 , n)
        plt.subplots_adjust(hspace = 0.5 , wspace = 0.5)
        sns.regplot(data = newdf, x = x , y = y)
        plt.ylabel(y.split()[0]+' '+y.split()[1] if len(y.split()) > 1 else y )
plt.show()
```



Observations: There is a relationship between Rank and Value. The lower the Rank level (measured for recency), the higher the Value score. We can attribute this to Rank score 1 being the best and most recent customers, which is in relation to a higher customers' perceived Value score, as content customers would patronage more recently.

4. Select Key Features for K-Means Analysis

In [102…

```
newKmeans = newdf[['count_purchase', 'Rank', 'Value']]
```

5. Standardise the Data

In [103…

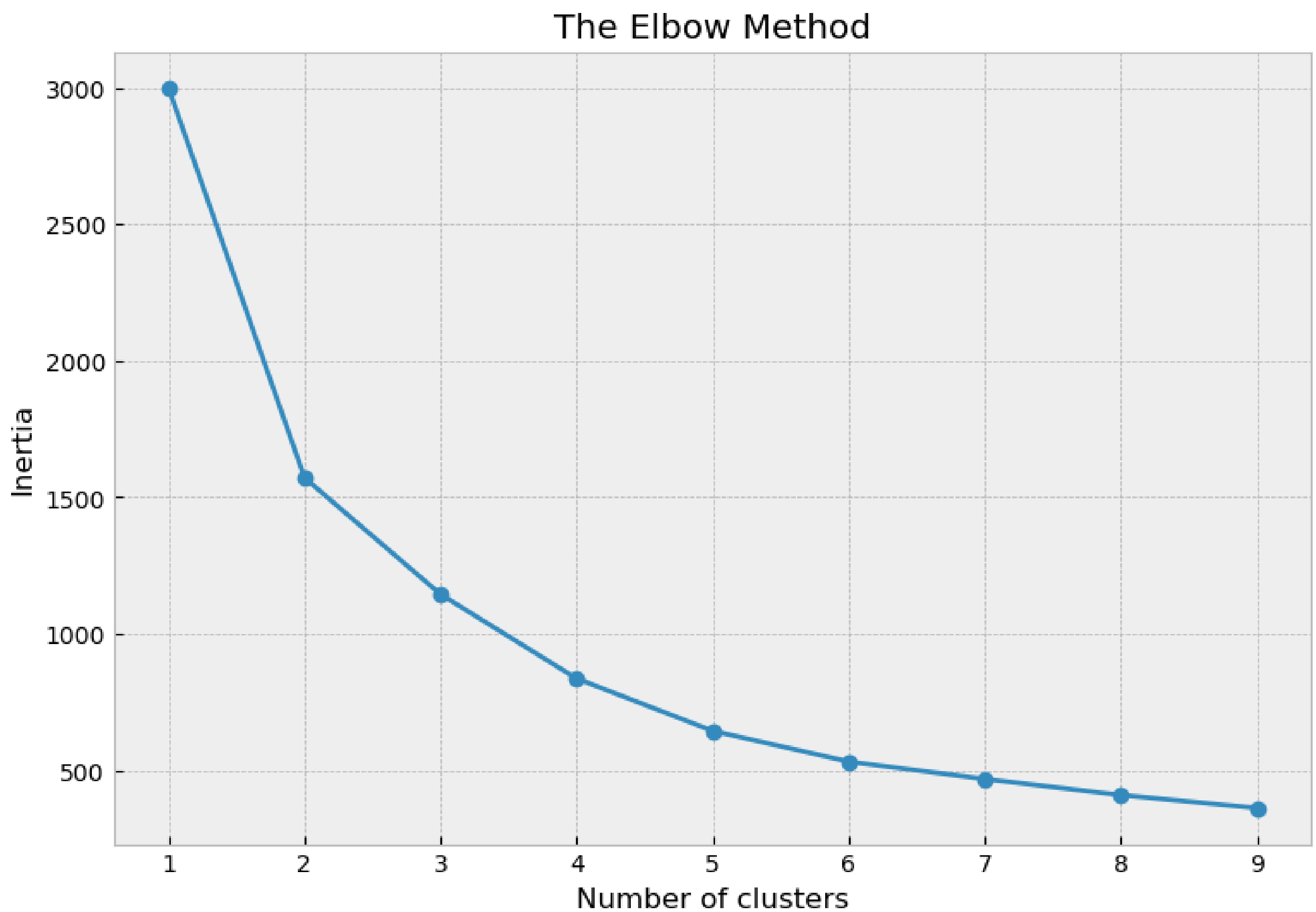
```
from sklearn.preprocessing import StandardScaler
std_scaler = StandardScaler()
scaled_newKmeans = std_scaler.fit_transform(newKmeans)
```

6. Predetermine the K-clusters with Elbow Method

In [104…

```
from sklearn.cluster import KMeans
SSE = []
for k in range(1, 10):
    kmeans2 = KMeans(n_clusters=k, random_state=42)
    kmeans2.fit(scaled_newKmeans)
    SSE.append(kmeans2.inertia_) #SSE to nearest clustter centroid

frame = pd.DataFrame({'Cluster':range(1,10), 'SSE':SSE})
plt.figure(figsize=(9,6))
plt.plot(frame['Cluster'], frame['SSE'], marker='o')
```

```
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')

plt.savefig("Elbow2.png")
```



The Elbow method graph indicates that the 'elbow' is on the number 2-cluster mark. This means that the optimal number of clusters to use in this K-Means algorithm is 2. We will build our Kmeans model using 2 clusters.

6.a Applying Knee-Locator to Determine Optimal Cluster

In [105…

```
from kneed import KneeLocator
kl = KneeLocator(x = range(1, 10),
                 y = SSE,
                 curve="convex",
                 direction="decreasing")
print('The optimal number of clusters is: ' + str(kl.elbow))
```

```
The optimal number of clusters is: 3
```

6b. Evaluate 3 cluster seperation

Comparison picture:

threeclusterssilhouettescore

7. Fit the Model onto our Data

In [106…

```
model = KMeans(n_clusters=2, init='k-means++', random_state=42)

# fit our model int
model.fit(scaled_newKmeans)
```

Out[106]:

```
KMeans(n_clusters=2, random_state=42)
```

In [107…

```
newKmeans = newKmeans.assign(Cluster= model.labels_)
newKmeans
```

Out[107]:

	count_purchase	Rank	Value	Cluster
0	86	1	1.718750	0
1	69	1	1.718750	0
2	10	1	1.718750	0
3	64	4	1.703125	0
4	34	4	1.703125	0
...	...	...	...	...
995	60	996	0.374000	1
996	22	997	0.357000	1
997	17	997	0.357000	1
998	30	997	0.357000	1
999	56	1000	0.340000	1

1000 rows × 4 columns

8. Evaluate the K-cluster Seperation

In [108…

```
from sklearn.metrics import silhouette_score

print(silhouette_score(scaled_newKmeans, model.labels_, metric='euclidean'))
```

```
0.40577971695251722
```

The silhouette coefficient of this model is 0.40, indicating reasonable cluster separation.

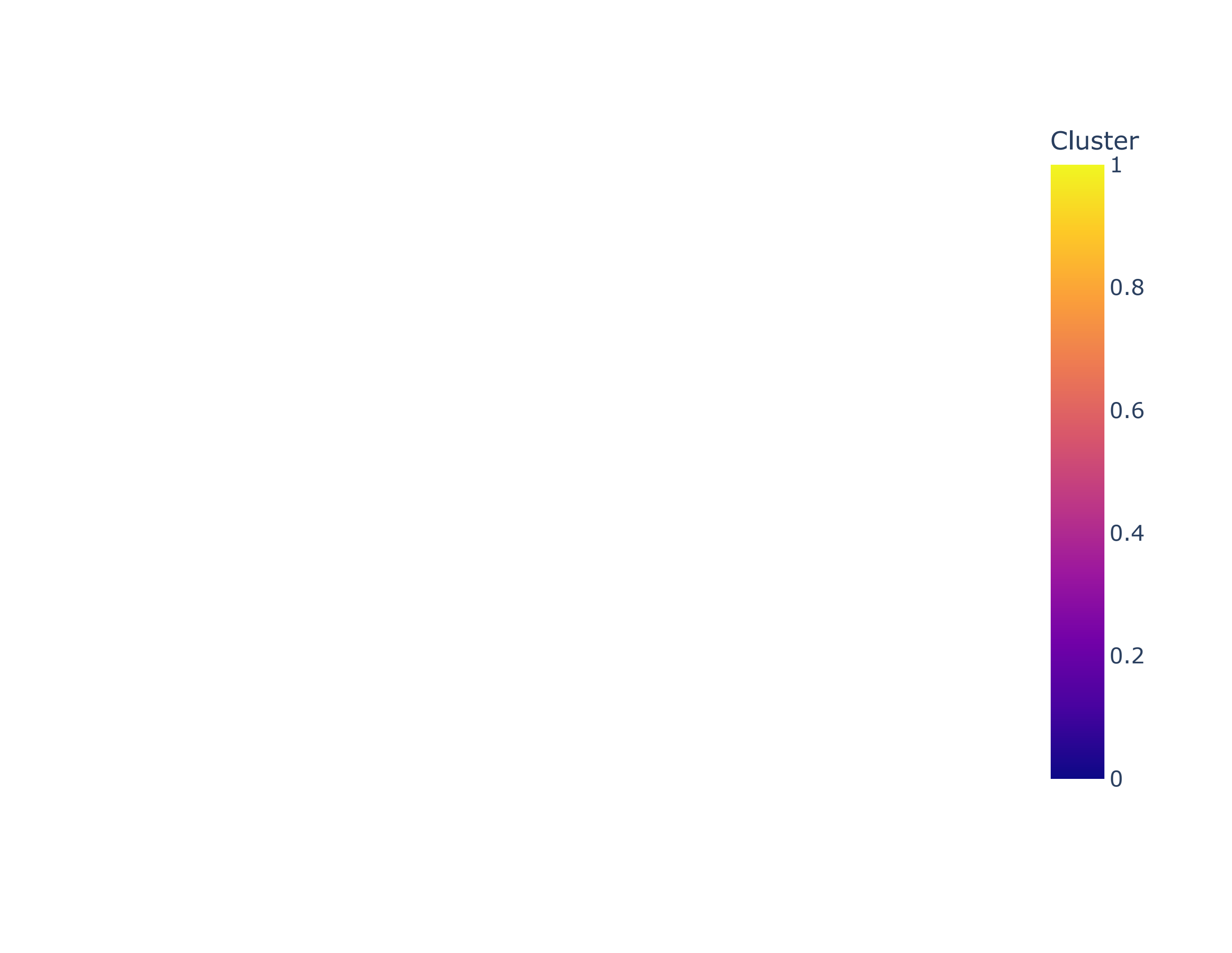
"The best value is 1 and the worst value is -1. Values near 0 indicate overlapping clusters. Negative values generally indicate that a sample has been assigned to the wrong cluster, as a different cluster is more similar." - source: scikit-learn.org

9. Visualising K-Means Model

In [109…

```
# 3D scatterplot of model

fig = px.scatter_3d(newKmeans, x='count_purchase', y='Rank', z='Value',
                    color = 'Cluster', opacity=0.5)

fig.update_traces(marker=dict(size=5),

                  selector=dict(mode='markers'))
```

```
fig.show()
```



10. Calculating the Mean, Count and Percentage of K-Mean Clusters

In [110…

```
# create new df with cluster means, counts and percentage

agg_newKmeans = newKmeans.groupby('Cluster').agg({
    'count_purchase': 'mean',
    'Rank': 'mean',
    'Value': ['mean', 'count']}).round(0)

agg_newKmeans.columns = agg_newKmeans.columns.droplevel()
agg_newKmeans.columns = ['count_purchase_Mean','Rank_Mean','Value_Mean', 'Count']
agg_newKmeans['Percent'] = round((agg_newKmeans['Count']/agg_newKmeans.Count.sum())*100,

# Reset the index
agg_newKmeans = agg_newKmeans.reset_index()

# Change Cluster into discrete values
agg_newKmeans['Cluster'] = agg_newKmeans['Cluster'].astype('str')


agg_newKmeans
```

Out[110]:

	Cluster	count_purchase_Mean	Rank_Mean	Value_Mean	Count	Percent
0	0	49.0	237.0	1.0	477	47.7

1	1	50.0	737.0	1.0	523	52.3

In [111…

```
newKmeans.describe()
```

Out[111]:

	count_purchase	Rank	Value	Cluster
count	1000.000000	1000.000000	1000.000000	1000.000000
mean	49.836000	498.819000	0.881714	0.523000
std	27.796686	288.810997	0.293525	0.499721
min	0.000000	1.000000	0.340000	0.000000
25%	26.750000	250.000000	0.649531	0.000000
50%	51.000000	500.000000	0.860000	1.000000
75%	72.000000	750.250000	1.075000	1.000000
max	99.000000	1000.000000	1.718750	1.000000

11. Interpreting the Clusters

Cluster 0: Active, Regular & Satisfied Customers:

- Cluster 0 customers have a better Rank in recency score.
- These are active and regular customers, who have made approximately 50 purchases in the last 3 years.
- There are 477 Cluster 0 customers and they make up 48% of the new customer list.
- These customers also consists of new customers
- Cluster 0 customers have higher customer perceived Value (max= 1.718), indicating they are saistfied customers

Recommendated Action:

- Introducing premier loyalty programs, marketing of new products, premier promotions and inivitations to cycling events, can encourage these customers to be lifelong customers

Cluster 1: Lost, Low Purchase or Irregular Customers

- Cluster 1 customers comprises of customers who've made none to several purchases in the past.
- They are termed Lost, Low Purchase or Irregular customers as they have low Rank in recency, implying they haven't shopped at Sprocket Central's platform recently
- They score low in customers' perceived Value, indicating either customer disappointment with Sprocket Central goods and services, switching to a competitor platform, or lost interest in the products.
- Cluster 1 Customers make up 52% of the customer database and account for 523 customers in total

Recommendated Action:

- Using special marketing promotions can help bring these customers back to the store
- Promote cycling events, membership rewards and hold free training sessions to attract these customers back

Top 10 Cluster 0 Customers

In [112…

```
top = newdf.sort_values(['Rank']).head(10)
top
```

Out[112]:

	gender	count_purchase	age	wealth_segment	tenure	state	property_valuation	Rank	Value	fullna
0	Male	86	65	Mass Customer	14	QLD	6	1	1.718750	Chickie_Bri
1	Male	69	52	Mass Customer	16	NSW	11	1	1.718750	Morly_Ger
2	Female	10	48	Affluent Customer	10	VIC	5	1	1.718750	Ardelis_Forre
3	Female	64	44	Affluent Customer	5	QLD	1	4	1.703125	Lucine_S
4	Female	34	57	Affluent Customer	19	NSW	9	4	1.703125	Melinda_Hac
5	Female	39	71	High Net Worth	22	QLD	7	6	1.671875	Druci_Bra
6	Male	23	46	Mass Customer	8	NSW	7	6	1.671875	Rutledge_H
7	Female	74	50	Mass Customer	10	QLD	5	8	1.656250	Nancie_\
8	Male	50	50	Mass Customer	5	NSW	10	8	1.656250	Duff_Karlov
9	Male	72	37	Mass Customer	17	QLD	5	10	1.640625	Barthel_Doc