Sprocket Central Pty Ltd Market Analysis

Background Information

Sprocket Central Pty Ltd , a medium size bikes & cycling accessories organisation.

Primarily, Sprocket Central Pty Ltd needs help with its customer and transactions data. The organisation has a large dataset relating to its customers, but their team is unsure how to effectively analyse it to help optimise its marketing strategy.

Strategy is believed to be the key to future growth. The following steps will be followed: Ask, Prepare, Process, Analyze, Construct, Share, Act.

In [1]:
```
### 1. Ask Phase
```

Project aim

The aim of this project is to identify top customers Sprocket Central Pty Ltd should target.

2. Prepare phase

Provided with three datasets: Customer Demographic,Customer Addresses and Transactions data, here i made sure the datasets are reliable, original, comprehensive,current and cited to feel confident in them.

In [2]:
```
#    importing necessary python packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import datetime
import matplotlib as mpl
import seaborn as sns
from scipy import stats
```

In [3]:
```
#    import datasets
Customer_address_df0 = pd.read_excel("Customeraddress.xlsx")
Customer_demographic_df0 = pd.read_excel("Customerdemographic.xlsx")
Transactions_df0 = pd.read_excel("Transactions.xlsx")
```

3. Process Phase

In [4]:
```
Customer_address_df0.head(10) #    Display first ten row of customer address dataframe
```

Out[4]:

	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5
0	customer_id	address	postcode	state	country	property_valuation
1	1	060 Morning Avenue	2016	New South Wales	Australia	10
2	2	6 Meadow Vale Court	2153	New South Wales	Australia	10
3	4	0 Holy Cross Court	4211	QLD	Australia	9
4	5	17979 Del Mar Point	2448	New South Wales	Australia	4
5	6	9 Oakridge Court	3216	VIC	Australia	9
6	7	4 Delaware Trail	2210	New South Wales	Australia	9
7	8	49 Londonderry Lane	2650	New South Wales	Australia	4
8	9	97736 7th Trail	2023	New South Wales	Australia	12
9	11	93405 Ludington Park	3044	VIC	Australia	8

In [5]:
```
Customer_address_df0.tail(10) #    Display last ten row of customer address dataframe
```

Out[5]:

	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5
3990	3994	2918 Summer Ridge Hill	3030	VIC	Australia	2
3991	3995	613 Erie Lane	2088	NSW	Australia	12
3992	3996	0 Transport Center	3977	VIC	Australia	6
3993	3997	4 Dovetail Crossing	2350	NSW	Australia	2
3994	3998	736 Roxbury Junction	2540	NSW	Australia	6
3995	3999	1482 Hauk Trail	3064	VIC	Australia	3
3996	4000	57042 Village Green Point	4511	QLD	Australia	6
3997	4001	87 Crescent Oaks Alley	2756	NSW	Australia	10
3998	4002	8194 Lien Street	4032	QLD	Australia	7
3999	4003	320 Acker Drive	2251	NSW	Australia	7

In [6]:
```
Customer_address_df0.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4000 entries, 0 to 3999
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Unnamed: 0  4000 non-null   object
 1   Unnamed: 1  4000 non-null   object
 2   Unnamed: 2  4000 non-null   object
 3   Unnamed: 3  4000 non-null   object
 4   Unnamed: 4  4000 non-null   object
 5   Unnamed: 5  4000 non-null   object
dtypes: object(6)
memory usage: 187.6+ KB
```

In [7]:
```
Customer_address_df0.iloc[0:,4].unique()  #    Display country
```

Out[7]:
```
array(['country', 'Australia'], dtype=object)
```

In [8]:
```
Customer_address_df0.iloc[0:,3].unique()#    Display state
```

Out[8]:
```
array(['state', 'New South Wales', 'QLD', 'VIC', 'NSW', 'Victoria'],
      dtype=object)
```

In [9]:
```
Customer_address_df0.iloc[0:,5].describe(include = "all") #   property_valuation Statistics
```

Out[9]:
```
count     4000
unique      13
top          9
freq       647
Name: Unnamed: 5, dtype: int64
```

In [10]:
```
Customer_address_df0.to_csv("Customer_address_df0", index = False)
```

In [11]:
```
Customer_address_df = pd.read_csv("Customer_address_df0", header = None)
```

In [12]:
```
Customer_address_df.head()
```

Out[12]:

	0	1	2	3	4	5
0	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5
1	customer_id	address	postcode	state	country	property_valuation
2	1	060 Morning Avenue	2016	New South Wales	Australia	10
3	2	6 Meadow Vale Court	2153	New South Wales	Australia	10
4	4	0 Holy Cross Court	4211	QLD	Australia	9

In [13]:
```
Customer_address_df = Customer_address_df.drop([Customer_address_df.index[0]])
```

In [14]:
```
1 Customer_address_df.head()
```

Out[14]:

	0	1	2	3	4	5
1	customer_id	address	postcode	state	country	property_valuation
2	1	060 Morning Avenue	2016	New South Wales	Australia	10
3	2	6 Meadow Vale Court	2153	New South Wales	Australia	10
4	4	0 Holy Cross Court	4211	QLD	Australia	9
5	5	17979 Del Mar Point	2448	New South Wales	Australia	4

In [15]:
```
1 Customer_address_df = Customer_address_df.rename(columns={0: 'customer_id', 1: 'address', 2: "postcode", 3:"state", 4:"count
```

In [16]:
```
1 Customer_address_df
```

Out[16]:

	customer_id	address	postcode	state	country	property_valuation
1	customer_id	address	postcode	state	country	property_valuation
2	1	060 Morning Avenue	2016	New South Wales	Australia	10
3	2	6 Meadow Vale Court	2153	New South Wales	Australia	10
4	4	0 Holy Cross Court	4211	QLD	Australia	9
5	5	17979 Del Mar Point	2448	New South Wales	Australia	4
...	...	...	...	...	...	...
3996	3999	1482 Hauk Trail	3064	VIC	Australia	3
3997	4000	57042 Village Green Point	4511	QLD	Australia	6
3998	4001	87 Crescent Oaks Alley	2756	NSW	Australia	10
3999	4002	8194 Lien Street	4032	QLD	Australia	7
4000	4003	320 Acker Drive	2251	NSW	Australia	7

4000 rows × 6 columns

In [17]:
```
1 Customer_address_df = Customer_address_df.drop(1, axis = 0).reset_index(drop =True) # drop second row
```

In [18]:
```
1 Customer_address_df.head()  #    validate
```

Out[18]:

	customer_id	address	postcode	state	country	property_valuation
0	1	060 Morning Avenue	2016	New South Wales	Australia	10
1	2	6 Meadow Vale Court	2153	New South Wales	Australia	10
2	4	0 Holy Cross Court	4211	QLD	Australia	9
3	5	17979 Del Mar Point	2448	New South Wales	Australia	4
4	6	9 Oakridge Court	3216	VIC	Australia	9

In [19]:
```
1 Customer_address_df.property_valuation.describe()
```

Out[19]:
```
count     3999
unique      12
top          9
freq       647
Name: property_valuation, dtype: object
```

In [20]:
```
1 max(Customer_address_df.property_valuation)
```

Out[20]:
```
'9'
```

In [21]:
```
1 min(Customer_address_df.property_valuation)
```

Out[21]:
```
'1'
```

In [22]:
```
1 Customer_address_df.property_valuation.unique()
```

Out[22]:
```
array(['10', '9', '4', '12', '8', '6', '7', '3', '5', '11', '1', '2'],
      dtype=object)
```

In [23]:
```
Customer_address_df.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   object
 1   address             3999 non-null   object
 2   postcode            3999 non-null   object
 3   state               3999 non-null   object
 4   country             3999 non-null   object
 5   property_valuation  3999 non-null   object
dtypes: object(6)
memory usage: 187.6+ KB
```

In [24]:
```
Customer_demographic_df0.head()    # first five rows
```

Out[24]:

	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unnar
0	customer_id	first_name	last_name	gender	past_3_years_bike_related_purchases	DOB	job_title	job_industry_category	wealth_segment	deceased_in
1	1	Laraine	Medendorp	F	93	1953-10-12 00:00:00	Executive Secretary	Health	Mass Customer	
2	2	Eli	Bockman	Male	81	1980-12-16 00:00:00	Administrative Officer	Financial Services	Mass Customer	
3	3	Arlin	Dearle	Male	61	1954-01-20 00:00:00	Recruiting Manager	Property	Mass Customer	
4	4	Talbot	NaN	Male	33	1961-10-03 00:00:00	NaN	IT	Mass Customer	

In [25]:
```
Customer_demographic_df0.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4001 entries, 0 to 4000
Data columns (total 13 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Unnamed: 0   4001 non-null   object
 1   Unnamed: 1   4001 non-null   object
 2   Unnamed: 2   3876 non-null   object
 3   Unnamed: 3   4001 non-null   object
 4   Unnamed: 4   4001 non-null   object
 5   Unnamed: 5   3914 non-null   object
 6   Unnamed: 6   3495 non-null   object
 7   Unnamed: 7   3345 non-null   object
 8   Unnamed: 8   4001 non-null   object
 9   Unnamed: 9   4001 non-null   object
 10  Unnamed: 10  3699 non-null   object
 11  Unnamed: 11  4001 non-null   object
 12  Unnamed: 12  3914 non-null   object
dtypes: object(13)
memory usage: 406.5+ KB
```

In [26]:
```
Customer_demographic_df0.to_csv("Customer_demographic_df0", index = False) # save dafaframe to csv
```

In [27]:
```
Customer_demographic_df1 = pd.read_csv("Customer_demographic_df0", header = None) # read csv file
```

In [28]:
```
Customer_demographic_df1.head()
```

Out[28]:

	0	1	2	3	4	5	6	7	8	
0	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unnam
1	customer_id	first_name	last_name	gender	past_3_years_bike_related_purchases	DOB	job_title	job_industry_category	wealth_segment	deceased_indi
2	1	Laraine	Medendorp	F	93	1953-10-12 00:00:00	Executive Secretary	Health	Mass Customer	
3	2	Eli	Bockman	Male	81	1980-12-16 00:00:00	Administrative Officer	Financial Services	Mass Customer	
4	3	Arlin	Dearle	Male	61	1954-01-20 00:00:00	Recruiting Manager	Property	Mass Customer	

In [29]:
```
Customer_demographic_df1 = Customer_demographic_df1.rename(columns={0: 'customer_id', 1: 'first_name', 2: "last_name", 3:"ge
```

In [30]:
```
Customer_demographic_df1.head()  # validate
```

Out[30]:

	customer_id	first_name	last_name	gender	past_3_years_bike_related_purchases	date_of_birth	job_title	job_industry_category	wealth_segment	de
0	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	
1	customer_id	first_name	last_name	gender	past_3_years_bike_related_purchases	DOB	job_title	job_industry_category	wealth_segment	d
2	1	Laraine	Medendorp	F	93	1953-10-12 00:00:00	Executive Secretary	Health	Mass Customer	
3	2	Eli	Bockman	Male	81	1980-12-16 00:00:00	Administrative Officer	Financial Services	Mass Customer	
4	3	Arlin	Dearle	Male	61	1954-01-20 00:00:00	Recruiting Manager	Property	Mass Customer	

In [31]:
```
Customer_demographic_df1 = Customer_demographic_df1.drop(0, axis = 0).reset_index(drop =True) # drop first row
Customer_demographic_df1.head() # validate
```

Out[31]:

	customer_id	first_name	last_name	gender	past_3_years_bike_related_purchases	date_of_birth	job_title	job_industry_category	wealth_segment	dece
0	customer_id	first_name	last_name	gender	past_3_years_bike_related_purchases	DOB	job_title	job_industry_category	wealth_segment	dece
1	1	Laraine	Medendorp	F	93	1953-10-12 00:00:00	Executive Secretary	Health	Mass Customer	
2	2	Eli	Bockman	Male	81	1980-12-16 00:00:00	Administrative Officer	Financial Services	Mass Customer	
3	3	Arlin	Dearle	Male	61	1954-01-20 00:00:00	Recruiting Manager	Property	Mass Customer	
4	4	Talbot	NaN	Male	33	1961-10-03 00:00:00	NaN	IT	Mass Customer	

In [32]:
```
Customer_demographic_df1 = Customer_demographic_df1.drop(0, axis = 0).reset_index(drop =True) # drop first row
```

In [33]:
```
Customer_demographic_df1.head()   #    validate
```

Out[33]:

	customer_id	first_name	last_name	gender	past_3_years_bike_related_purchases	date_of_birth	job_title	job_industry_category	wealth_segment	dece
0	1	Laraine	Medendorp	F	93	1953-10-12 00:00:00	Executive Secretary	Health	Mass Customer	
1	2	Eli	Bockman	Male	81	1980-12-16 00:00:00	Administrative Officer	Financial Services	Mass Customer	
2	3	Arlin	Dearle	Male	61	1954-01-20 00:00:00	Recruiting Manager	Property	Mass Customer	
3	4	Talbot	NaN	Male	33	1961-10-03 00:00:00	NaN	IT	Mass Customer	
4	5	Sheila-kathryn	Calton	Female	56	1977-05-13 00:00:00	Senior Editor	NaN	Affluent Customer	

In [34]:
```
Customer_demographic_df1.past_3_years_bike_related_purchases.describe()
```

Out[34]:
```
count     4000
unique     100
top         16
freq        56
Name: past_3_years_bike_related_purchases, dtype: object
```

In [35]:
```
Customer_demographic_df1.deceased_indicator.value_counts()
```

Out[35]:
```
N    3998
Y       2
Name: deceased_indicator, dtype: int64
```

In [36]:
```
Customer_demographic_df1.owns_car.unique()
```

Out[36]:
```
array(['Yes', 'No'], dtype=object)
```

In [37]:
```
Customer_demographic_df1.tenure.describe()
```

Out[37]:
```
count     3913
unique      22
top          7
freq       235
Name: tenure, dtype: object
```

In [38]:
```
Transactions_df0.head() #    first five row
```

Out[38]:

	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unnamed: 9	Unnamed: 10	Unnamed: 11
0	transaction_id	product_id	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	list_price	standard_cost
1	1	2	2950	2017-02-25 00:00:00	False	Approved	Solex	Standard	medium	medium	71.49	53.62
2	2	3	3120	2017-05-21 00:00:00	True	Approved	Trek Bicycles	Standard	medium	large	2091.47	388.92
3	3	37	402	2017-10-16 00:00:00	False	Approved	OHM Cycles	Standard	low	medium	1793.43	248.82
4	4	88	3135	2017-08-31 00:00:00	False	Approved	Norco Bicycles	Standard	medium	medium	1198.46	381.1

In [39]:
```
Transactions_df0.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20001 entries, 0 to 20000
Data columns (total 13 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Unnamed: 0   20001 non-null  object
 1   Unnamed: 1   20001 non-null  object
 2   Unnamed: 2   20001 non-null  object
 3   Unnamed: 3   20001 non-null  object
 4   Unnamed: 4   19641 non-null  object
 5   Unnamed: 5   20001 non-null  object
 6   Unnamed: 6   19804 non-null  object
 7   Unnamed: 7   19804 non-null  object
 8   Unnamed: 8   19804 non-null  object
 9   Unnamed: 9   19804 non-null  object
 10  Unnamed: 10  20001 non-null  object
 11  Unnamed: 11  19804 non-null  object
 12  Unnamed: 12  19804 non-null  object
dtypes: object(13)
memory usage: 2.0+ MB
```

In [40]:
```
Transactions_df0.iloc[0:,5].unique() #    order_status categories
```

Out[40]:
```
array(['order_status', 'Approved', 'Cancelled'], dtype=object)
```

In [41]:
```
Transactions_df0.iloc[0:,6].unique()     #    brand categories
```

Out[41]:
```
array(['brand', 'Solex', 'Trek Bicycles', 'OHM Cycles', 'Norco Bicycles',
       'Giant Bicycles', 'WeareA2B', nan], dtype=object)
```

In [42]:
```
Transactions_df0.iloc[0:,7].unique()   #    product_class
```

Out[42]:
```
array(['product_line', 'Standard', 'Road', 'Mountain', 'Touring', nan],
      dtype=object)
```

In [43]:
```
Transactions_df0.iloc[0:,8].unique()  #    product_size
```

Out[43]:
```
array(['product_class', 'medium', 'low', 'high', nan], dtype=object)
```

In [44]:
```
Transactions_df0.head(3)
```

Out[44]:

	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unnamed: 9	Unnamed: 10	Unnamed: 11
0	transaction_id	product_id	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	list_price	standard_cost
1	1	2	2950	2017-02-25 00:00:00	False	Approved	Solex	Standard	medium	medium	71.49	53.62
2	2	3	3120	2017-05-21 00:00:00	True	Approved	Trek Bicycles	Standard	medium	large	2091.47	388.92

In [45]:
```
Transactions_df0.to_csv("Transactions_df0", index = False) # save dafaframe to csv
Transactions_df1 = pd.read_csv("Transactions_df0", header = None)

```

In [46]:
```
Transactions_df1.head()
```

Out[46]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unnamed: 9	Unnamed: 10	Unnamed: 11
1	transaction_id	product_id	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	list_price	standard_cost
2	1	2	2950	2017-02-25 00:00:00	False	Approved	Solex	Standard	medium	medium	71.49	53.62
3	2	3	3120	2017-05-21 00:00:00	True	Approved	Trek Bicycles	Standard	medium	large	2091.47	388.92
4	3	37	402	2017-10-16 00:00:00	False	Approved	OHM Cycles	Standard	low	medium	1793.43	248.82

In [47]:
```
Transactions_df1 = Transactions_df1.rename(columns={0: 'transaction_id', 1: 'product_id', 2: "customer_id", 3:"transaction_d
Transactions_df1.head(3)  #    validate
```

Out[47]:

	transaction_id	product_id	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	list_price	standa
0	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unnamed: 9	Unnamed: 10	Unna
1	transaction_id	product_id	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	list_price	standa
2	1	2	2950	2017-02-25 00:00:00	False	Approved	Solex	Standard	medium	medium	71.49	

In [48]:
```
Transactions_df1 = Transactions_df1.drop(0, axis = 0).reset_index(drop =True) # drop first row
```

In [49]:
```
Transactions_df1.head() #    validate
```

Out[49]:

	transaction_id	product_id	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	list_price	standard_
0	transaction_id	product_id	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	list_price	standard
1	1	2	2950	2017-02-25 00:00:00	False	Approved	Solex	Standard	medium	medium	71.49	
2	2	3	3120	2017-05-21 00:00:00	True	Approved	Trek Bicycles	Standard	medium	large	2091.47	3
3	3	37	402	2017-10-16 00:00:00	False	Approved	OHM Cycles	Standard	low	medium	1793.43	2
4	4	88	3135	2017-08-31 00:00:00	False	Approved	Norco Bicycles	Standard	medium	medium	1198.46	

In [50]:
```
Transactions_df1 = Transactions_df1.drop(0, axis = 0).reset_index(drop =True) # drop first row
```

In [51]:
```
Transactions_df1.head(3) # validate
```

Out[51]:

	transaction_id	product_id	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	list_price	standard_
0	1	2	2950	2017-02-25 00:00:00	False	Approved	Solex	Standard	medium	medium	71.49	
1	2	3	3120	2017-05-21 00:00:00	True	Approved	Trek Bicycles	Standard	medium	large	2091.47	3
2	3	37	402	2017-10-16 00:00:00	False	Approved	OHM Cycles	Standard	low	medium	1793.43	2

4. Analyze phase

In [52]:
```
Sprocket_df0 = Transactions_df1.merge(Customer_demographic_df1, on = "customer_id", how = "inner")
```

In [53]:
```
1 Sprocket_df0.head(3)
```

Out[53]:

	transaction_id	product_id	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	...	gender	past_3_
0	1	2	2950	2017-02-25 00:00:00	False	Approved	Solex	Standard	medium	medium	...	Male	
1	11065	1	2950	2017-10-16 00:00:00	False	Approved	Giant Bicycles	Standard	medium	medium	...	Male	
2	18923	62	2950	2017-04-26 00:00:00	False	Approved	Solex	Standard	medium	medium	...	Male	

3 rows × 25 columns

In [54]:
```
1 Sprocket_df0.shape
```

Out[54]: (19997, 25)

In [55]:
```
1 Sprocket_df = Sprocket_df0.merge(Customer_address_df, on = "customer_id", how = "inner")
```

In [56]:
```
1 Sprocket_df.head(3)
```

Out[56]:

	transaction_id	product_id	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	...	wealth_segment
0	1	2	2950	2017-02-25 00:00:00	False	Approved	Solex	Standard	medium	medium	...	Mass Customer
1	11065	1	2950	2017-10-16 00:00:00	False	Approved	Giant Bicycles	Standard	medium	medium	...	Mass Customer
2	18923	62	2950	2017-04-26 00:00:00	False	Approved	Solex	Standard	medium	medium	...	Mass Customer

3 rows × 30 columns

In [57]:
```
1 Sprocket_df.shape
```

Out[57]: (19968, 30)

In [58]:
```
1 Sprocket_df.dtypes
```

Out[58]:
```
transaction_id                       object
product_id                           object
customer_id                          object
transaction_date                     object
online_order                         object
order_status                         object
brand                                object
product_line                         object
product_class                        object
product_size                         object
list_price                           object
standard_cost                        object
product_first_sold_date              object
first_name                           object
last_name                            object
gender                               object
past_3_years_bike_related_purchases  object
date_of_birth                        object
job_title                            object
job_industry_category                object
wealth_segment                       object
deceased_indicator                   object
default                              object
owns_car                             object
tenure                               object
address                              object
postcode                             object
state                                object
country                              object
property_valuation                   object
dtype: object
```

In [59]:
```
missing_values_count = Sprocket_df.isnull().sum()
missing_values_count
```

Out[59]:
```
transaction_id                         0
product_id                             0
customer_id                            0
transaction_date                       0
online_order                         359
order_status                           0
brand                                195
product_line                         195
product_class                        195
product_size                         195
list_price                             0
standard_cost                        195
product_first_sold_date              195
first_name                             0
last_name                            642
gender                                 0
past_3_years_bike_related_purchases    0
date_of_birth                        446
job_title                           2379
job_industry_category               3222
wealth_segment                         0
deceased_indicator                     0
default                             1451
owns_car                               0
tenure                               446
address                                0
postcode                               0
state                                  0
country                                0
property_valuation                     0
dtype: int64
```

In [60]:
```
# how many total missing values do we have?
total_cells = np.product(Sprocket_df.shape)
total_missing = missing_values_count.sum()

# percent of data that is missing
percent_missing = (total_missing/total_cells) * 100
print(percent_missing)
```

```
1.6885349893162391
```

In [61]:
```
# remove all the rows that contain a missing value since percentage missing is relatively small
Sprocket_df = Sprocket_df.dropna()
```

In [62]:
```
Sprocket_df.shape
```

Out[62]:
```
(12970, 30)
```

In [63]:
```
Sprocket_df = Sprocket_df.drop_duplicates()
```

In [64]:
```
Sprocket_df.shape
```

Out[64]:
```
(12970, 30)
```

In [65]:
```
Sprocket_df.gender.unique()
```

Out[65]:
```
array(['Male', 'Female', 'F', 'Femal'], dtype=object)
```

In [66]:
```
# convert to lower case
Sprocket_df['gender'] = Sprocket_df['gender'].str.lower()
```

In [67]:
```
Sprocket_df.gender.unique()
```

Out[67]:
```
array(['male', 'female', 'f', 'femal'], dtype=object)
```

In [68]:
```
d = {'f':'female','femal':'female'}
Sprocket_df['gender'] = Sprocket_df['gender'].replace(d)
Sprocket_df.gender.unique()
```

Out[68]:
```
array(['male', 'female'], dtype=object)
```

In [69]:
```
Sprocket_df.state.unique()
```

Out[69]:
```
array(['VIC', 'NSW', 'QLD', 'Victoria', 'New South Wales'], dtype=object)
```

In [70]:
```
# convert to lower case
Sprocket_df['state'] = Sprocket_df['state'].str.lower()
# remove trailing white spaces
Sprocket_df['state'] = Sprocket_df['state'].str.strip()
```

In [71]:
```
Sprocket_df.state.unique()
```

Out[71]:
```
array(['vic', 'nsw', 'qld', 'victoria', 'new south wales'], dtype=object)
```

In [72]:
```
d = {'vic':'victoria','nsw':'new south wales','qld':'queensland'}
Sprocket_df['state'] = Sprocket_df['state'].replace(d)
Sprocket_df.state.unique()
```

Out[72]:
```
array(['victoria', 'new south wales', 'queensland'], dtype=object)
```

In [73]:
```
Sprocket_df[["date_of_birth","product_first_sold_date","transaction_date"]]
```

Out[73]:

	date_of_birth	product_first_sold_date	transaction_date
0	1955-01-11 00:00:00	41245	2017-02-25 00:00:00
1	1955-01-11 00:00:00	37659	2017-10-16 00:00:00
2	1955-01-11 00:00:00	40487	2017-04-26 00:00:00
3	1979-02-04 00:00:00	41701	2017-05-21 00:00:00
4	1979-02-04 00:00:00	40649	2017-10-05 00:00:00
...	...	...	...
19960	1975-08-31 00:00:00	38991	2017-11-13 00:00:00
19962	1997-07-18 00:00:00	40649	2017-10-15 00:00:00
19963	1997-07-18 00:00:00	40410	2017-02-02 00:00:00
19964	1992-11-30 00:00:00	35378	2017-12-06 00:00:00
19965	1992-11-30 00:00:00	42226	2017-06-20 00:00:00

12970 rows × 3 columns

In [74]:
```
Sprocket_df["list_price"] = Sprocket_df[["list_price"]].astype('float64')  #    format to float datatype
Sprocket_df["standard_cost"] = Sprocket_df[["standard_cost"]].astype('float64')  #    format to float datatype
Sprocket_df["property_valuation"] = Sprocket_df[["property_valuation"]].astype('int')  #    format to int datatype
Sprocket_df['date_of_birth'] = pd.to_datetime(Sprocket_df['date_of_birth'], format="%Y/%m/%d") #    format to datetime datat
Sprocket_df['transaction_date'] = pd.to_datetime(Sprocket_df['transaction_date'], format="%Y/%m/%d") #    format to datetime
Sprocket_df["profit"] = Sprocket_df.list_price - Sprocket_df.standard_cost #    create profit column
```

In [75]:
```
Sprocket_df['date_of_birth'].head(3)   #   first few row of date  of birth
```

Out[75]:
```
0   1955-01-11
1   1955-01-11
2   1955-01-11
Name: date_of_birth, dtype: datetime64[ns]
```

In [76]:
```
Sprocket_df['transaction_date'].head(3) #   first few row of transaction date
```

Out[76]:
```
0   2017-02-25
1   2017-10-16
2   2017-04-26
Name: transaction_date, dtype: datetime64[ns]
```

In [77]:
```
#    create year column
Sprocket_df['year_of_birth'] = Sprocket_df['date_of_birth'].dt.year
Sprocket_df['transaction_year'] = Sprocket_df['transaction_date'].dt.year
```

In [78]:
```
Sprocket_df['transaction_year'].head(4)
```

Out[78]:
```
0    2017
1    2017
2    2017
3    2017
Name: transaction_year, dtype: int64
```

In [79]:
```
Sprocket_df['transaction_year'].unique()    #     transaction year category
```

Out[79]:
```
array([2017], dtype=int64)
```

In [80]:
```
Sprocket_df['year_of_birth'].head(4)

```

Out[80]:
```
0    1955
1    1955
2    1955
3    1979
Name: year_of_birth, dtype: int64
```

In [81]:
```
Sprocket_df['age'] = Sprocket_df['transaction_year'] - Sprocket_df['year_of_birth']
# create age column
```

In [82]:
```
Sprocket_df.dtypes #    validate
```

Out[82]:
```
transaction_id                          object
product_id                              object
customer_id                             object
transaction_date                datetime64[ns]
online_order                            object
order_status                            object
brand                                   object
product_line                            object
product_class                           object
product_size                            object
list_price                             float64
standard_cost                          float64
product_first_sold_date                 object
first_name                              object
last_name                               object
gender                                  object
past_3_years_bike_related_purchases     object
date_of_birth                   datetime64[ns]
job_title                               object
job_industry_category                   object
wealth_segment                          object
deceased_indicator                      object
default                                 object
owns_car                                object
tenure                                  object
address                                 object
postcode                                object
state                                   object
country                                 object
property_valuation                       int32
profit                                 float64
year_of_birth                            int64
transaction_year                         int64
age                                      int64
dtype: object
```

In [83]:
```
def group(age):
    ''' group age '''
    if age > 80:
        age_group = "old"
    elif age > 60:
        age_group = "old_adult"
    elif age > 40:
            age_group = "middle_adult"
    elif age > 20:
            age_group = "early_adult"
    else:
        age_group = "adolescent"
    return age_group

```

In [84]:
```
Sprocket_df["age_group"] = Sprocket_df["age"].apply(group)
```

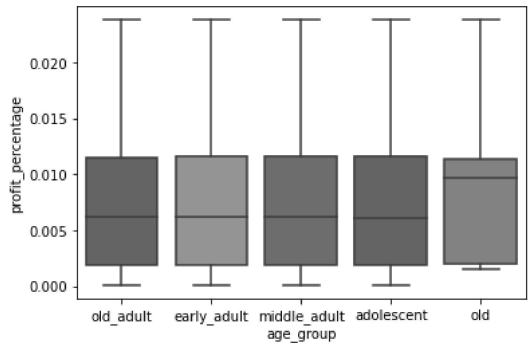
In [85]:
```
Sprocket_df['age_group'].unique()
```

Out[85]:
```
array(['old_adult', 'early_adult', 'middle_adult', 'adolescent', 'old'],
      dtype=object)
```

In [86]:
```
total_profit = Sprocket_df.profit.sum()
```

In [87]:
```
Sprocket_df["profit_percentage"] = (Sprocket_df.profit/total_profit) * 100  # create profit percentage column
# Create boxplot to show distribution of profit percentage by age group
sns.boxplot(x = "age_group", y = "profit_percentage", data = Sprocket_df)
```

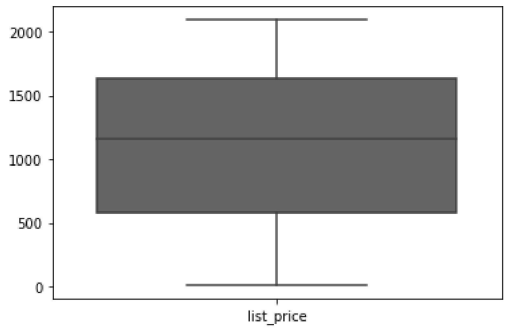
Out[87]: <AxesSubplot:xlabel='age_group', ylabel='profit_percentage'>



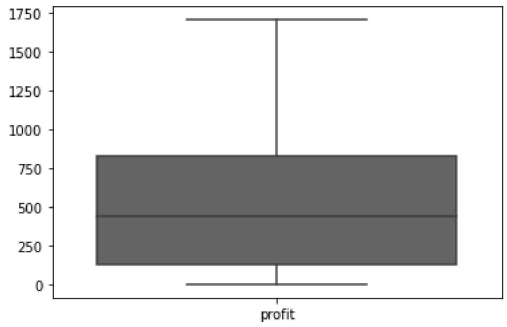
Apart from the old category, the means of other categories are nearly equal

Chect for outliers

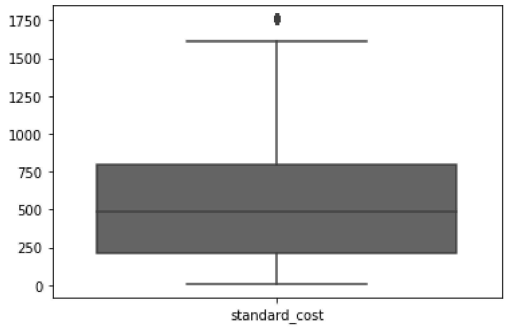
In [88]:
```
sns.boxplot(data = Sprocket_df[["list_price"]], showfliers = True);
```



In [89]:
```
sns.boxplot(data = Sprocket_df[["profit"]], showfliers = True);
```



In [90]:
```
sns.boxplot(data = Sprocket_df[["standard_cost"]], showfliers = True);
```



In [91]:
```
Sprocket_df["z_score"] = stats.zscore(Sprocket_df["standard_cost"]) #   z_score column
```

In [92]:
```
#  select rows where corresonding z score is less than 3 or greater than -3
Sprocket_df = Sprocket_df[(Sprocket_df["z_score"] < 3) | (Sprocket_df["z_score"] > -3)]
```

5. Construct

Run two-way ANOVA

In [93]:
```
# Import statsmodels and ols function
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

In [94]:
```
Sprocket_test_df = Sprocket_df[["profit", "state","age_group"]]
```

In [95]:
```
Sprocket_test_df.head()
```

Out[95]:

	profit	state	age_group
0	17.87	victoria	old_adult
1	448.68	victoria	old_adult
2	179.44	victoria	old_adult
3	1702.55	new south wales	early_adult
4	451.65	new south wales	early_adult

In [96]:
```
# Construct a multiple linear regression with an interaction term between color and cut
model = ols(formula = "profit ~ C(age_group) + C(state) + C(age_group):C(state)", data = Sprocket_test_df).fit()
```

In [97]:
```
# Get summary statistics
model.summary()
```

Out[97]:

OLS Regression Results

Dep. Variable:	profit	**R-squared:**	0.001
Model:	OLS	**Adj. R-squared:**	-0.000
Method:	Least Squares	**F-statistic:**	0.7446
Date:	Sun, 20 Aug 2023	**Prob (F-statistic):**	0.720
Time:	11:40:16	**Log-Likelihood:**	-98864.
No. Observations:	12970	**AIC:**	1.978e+05
Df Residuals:	12956	**BIC:**	1.979e+05
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	526.8216	21.372	24.650	0.000	484.930	568.714
C(age_group)[T.early_adult]	32.8963	23.108	1.424	0.155	-12.399	78.192
C(age_group)[T.middle_adult]	20.3765	23.258	0.876	0.381	-25.213	65.966
C(age_group)[T.old]	194.3954	157.920	1.231	0.218	-115.151	503.942
C(age_group)[T.old_adult]	0.6418	35.128	0.018	0.985	-68.214	69.497
C(state)[T.queensland]	17.9801	40.777	0.441	0.659	-61.949	97.909
C(state)[T.victoria]	55.7610	39.746	1.403	0.161	-22.148	133.670
C(age_group)[T.early_adult]:C(state)[T.queensland]	-20.4787	43.871	-0.467	0.641	-106.471	65.514
C(age_group)[T.middle_adult]:C(state)[T.queensland]	-27.5258	44.287	-0.622	0.534	-114.335	59.283
C(age_group)[T.old]:C(state)[T.queensland]	9.489e-13	4.85e-13	1.958	0.050	-1.1e-15	1.9e-12
C(age_group)[T.old_adult]:C(state)[T.queensland]	32.8144	64.162	0.511	0.609	-92.953	158.582
C(age_group)[T.early_adult]:C(state)[T.victoria]	-65.4712	42.767	-1.531	0.126	-149.302	18.359
C(age_group)[T.middle_adult]:C(state)[T.victoria]	-38.5845	42.907	-0.899	0.369	-122.688	45.519
C(age_group)[T.old]:C(state)[T.victoria]	-527.9240	273.908	-1.927	0.054	-1064.825	8.977
C(age_group)[T.old_adult]:C(state)[T.victoria]	-45.1069	60.666	-0.744	0.457	-164.021	73.807

Omnibus:	1336.549	**Durbin-Watson:**	1.957
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1661.050
Skew:	0.854	**Prob(JB):**	0.00
Kurtosis:	2.606	**Cond. No.**	2.91e+17

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.41e-31. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Null Hypothesis (age group)

$H0$:$p$rofit adolescent=$p$rofit early adult=$p$rofit middle adult=$p$rofit old adult=$p$rofit old

There is no difference in profit based on age group.

Alternative Hypothesis (age group)

There is a difference in profit age group.

Null Hypothesis (state)

There is no difference in profit based on state.

Alternative Hypothesis (state)

There is a difference in profit based on state.

Null Hypothesis (Interaction) $H0$:The effect of age group on profit is independent of the state, and vice versa.

Alternative Hypothesis (Interaction) $H1$:There is an interaction effect between age group and state on profit.

In [98]:
```
sm.stats.anova_lm(model, typ = 1)
```

Out[98]:

	df	sum_sq	mean_sq	F	PR(>F)
C(age_group)	4.0	3.085021e+05	77125.532344	0.315029	0.868099
C(state)	2.0	1.236038e+05	61801.884994	0.252438	0.776908
C(age_group):C(state)	8.0	2.242839e+06	280354.827687	1.145147	0.328974
Residual	12956.0	3.171889e+09	244820.052031	NaN	NaN

Since all of the p-values (column PR(>F)) are greater than 0.05, we can fai to reject all three null hypotheses.

In [99]:
```
# Import Tukey's HSD function
from statsmodels.stats.multicomp import pairwise_tukeyhsd
```

In [100]:
```
# Run Tukey's HSD post hoc test for one-way ANOVA
tukey_oneway = pairwise_tukeyhsd(endog = Sprocket_test_df["profit"], groups = Sprocket_test_df["age_group"], alpha = 0.05)
# Run Tukey's HSD post hoc test for one-way ANOVA
tukey_onewaystate = pairwise_tukeyhsd(endog = Sprocket_test_df["profit"], groups = Sprocket_test_df["state"], alpha = 0.05)
```

In [101]:
```
# Get results (pairwise comparisons)
tukey_oneway.summary()
```

Out[101]:

Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
adolescent	early_adult	13.486	0.9358	-33.5436	60.5156	False
adolescent	middle_adult	6.2263	0.9965	-41.0951	53.5478	False
adolescent	old	20.4917	0.9999	-330.7572	371.7405	False
adolescent	old_adult	-1.3433	1.0	-70.0783	67.3917	False
early_adult	middle_adult	-7.2597	0.9362	-32.6212	18.1018	False
early_adult	old	7.0056	1.0	-341.9638	355.975	False
early_adult	old_adult	-14.8293	0.9512	-70.7613	41.1027	False
middle_adult	old	14.2653	1.0	-334.7435	363.2742	False
middle_adult	old_adult	-7.5696	0.9961	-63.7473	48.608	False
old	old_adult	-21.835	0.9998	-374.3862	330.7163	False

In [102]:
```
# Get results (pairwise comparisons)
tukey_onewaystate.summary()
```

Out[102]:

Multiple Comparison of Means - Tukey HSD, FWER=0.05

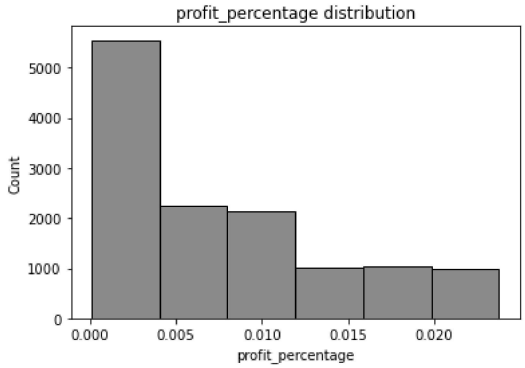
group1	group2	meandiff	p-adj	lower	upper	reject
new south wales	queensland	-1.2161	0.9933	-27.1244	24.6923	False
new south wales	victoria	6.5482	0.809	-18.1959	31.2922	False
queensland	victoria	7.7642	0.8157	-22.1669	37.6954	False

The observed difference in profit by state and age group is statistically insignificant.

6. Share phase

In [103]:
```
sns.histplot(data=Sprocket_df, x= "profit_percentage", bins = 6)

# Add title
plt.title("profit_percentage distribution")
```

Out[103]: Text(0.5, 1.0, 'profit_percentage distribution')



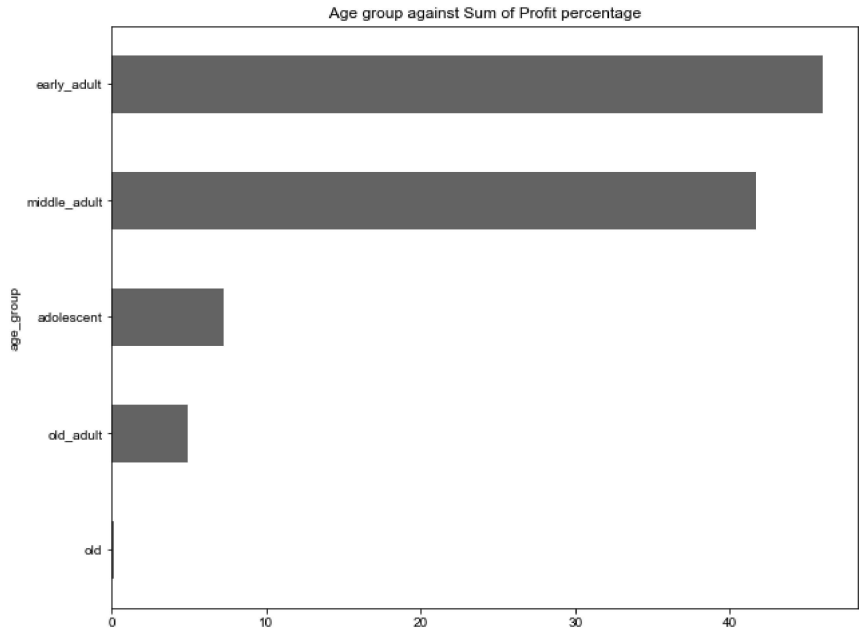
The districbution of the histogram is skewed to the right i.e count decreses as the profit percentage increases

In [104]:
```
Sprocket_df.groupby('age_group').profit_percentage.sum().sort_values()
```

Out[104]:
```
age_group
old              0.118118
old_adult        4.889938
adolescent       7.262026
middle_adult    41.699803
early_adult     46.030116
Name: profit_percentage, dtype: float64
```

middle_adult and early_adult contribute about 92% of the profit

In [105]:
```
Sprocket_df.groupby('age_group').profit_percentage.sum().sort_values().plot(kind='barh',figsize=(10,8));
sns.set_style("darkgrid")
plt.title(" Age group against Sum of Profit percentage ");
```



In [106]:
```
Sprocket_df.groupby('online_order').profit_percentage.sum().sort_values()
```

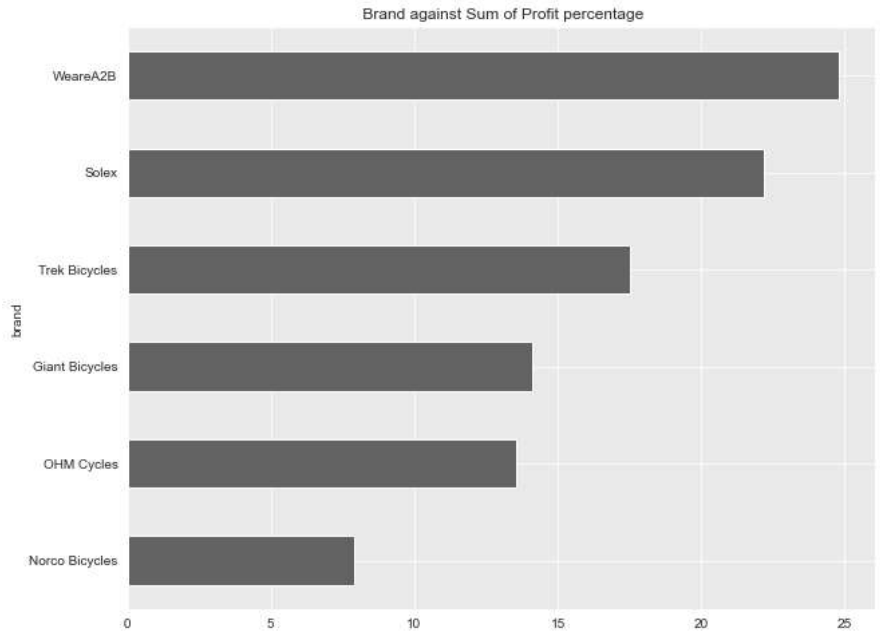
Out[106]:
```
online_order
True     49.336272
False    50.663728
Name: profit_percentage, dtype: float64
```

Onine order and non online order are nearly equal

In [107]:
```
Sprocket_df.groupby('brand').profit_percentage.sum().sort_values()
#    How product brand contribute to profit
```

Out[107]:
```
brand
Norco Bicycles     7.919267
OHM Cycles        13.542690
Giant Bicycles    14.088296
Trek Bicycles     17.497087
Solex             22.160707
WeareA2B          24.791953
Name: profit_percentage, dtype: float64
```

In [108]:
```
Sprocket_df.groupby('brand').profit_percentage.sum().sort_values().plot(kind='barh',figsize=(10,8));
sns.set_style("darkgrid")
plt.title(" Brand against Sum of Profit percentage");
```

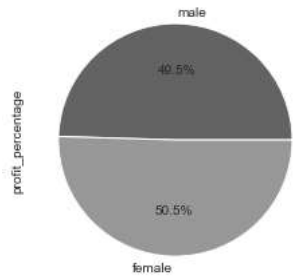


In [109]:
```
Sprocket_df.groupby('gender').profit_percentage.sum().sort_values()
#    How product gender contribute to profit
```

Out[109]:
```
gender
male      49.524477
female    50.475523
Name: profit_percentage, dtype: float64
```

The difference in profit generates from gender can be ignored

In [110]:
```
plt.figure(figsize=(4,4))
Sprocket_df.groupby('gender').profit_percentage.sum().sort_values().plot.pie(autopct="%1.1f%%")
plt.show()
```

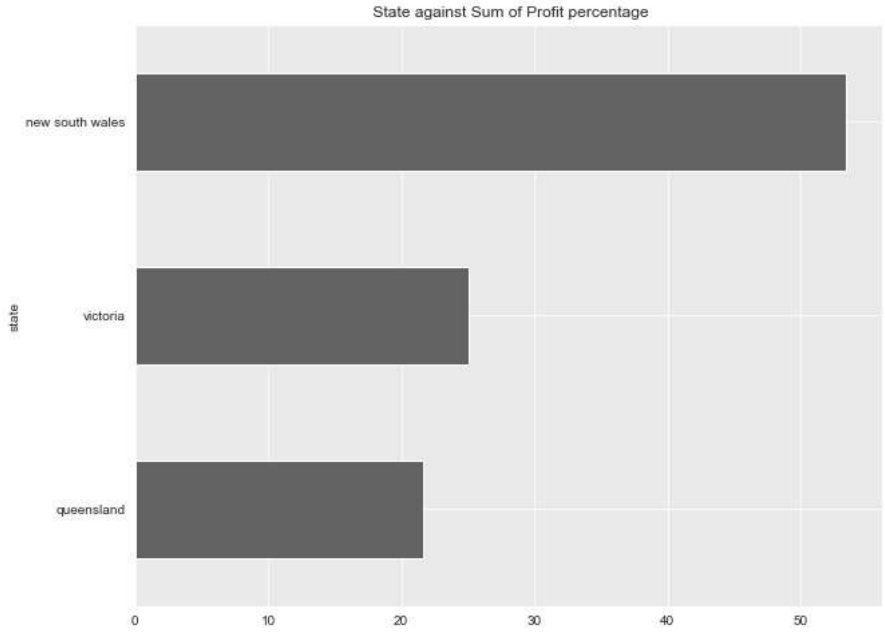


In [111]:
```
Sprocket_df.groupby('state').profit_percentage.sum().sort_values()
```

Out[111]:
```
state
queensland         21.618061
victoria           25.013210
new south wales    53.368729
Name: profit_percentage, dtype: float64
```

About 54% of the profit being generated is from customers from new south wales

In [112]:
```
Sprocket_df.groupby('state').profit_percentage.sum().sort_values().plot(kind='barh',figsize=(10,8));
sns.set_style("darkgrid")
plt.title(" State against Sum of Profit percentage");
```

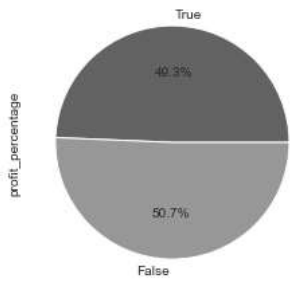


In [113]:
```
Sprocket_df.groupby('online_order').profit_percentage.sum().sort_values()
```

Out[113]:
```
online_order
True     49.336272
False    50.663728
Name: profit_percentage, dtype: float64
```

The difference in profit generates from mode order can be ignored

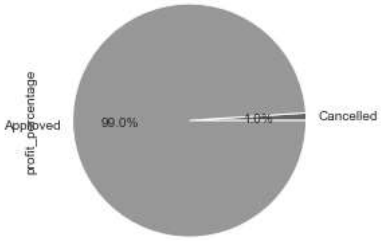
In [114]:
```
plt.figure(figsize=(4,4))
Sprocket_df.groupby('online_order').profit_percentage.sum().sort_values().plot.pie(autopct="%1.1f%%")
plt.show()
```



In [115]:
```
Sprocket_df.groupby('order_status').profit_percentage.sum().sort_values()
```

Out[115]:
```
order_status
Cancelled     1.037798
Approved     98.962202
Name: profit_percentage, dtype: float64
```

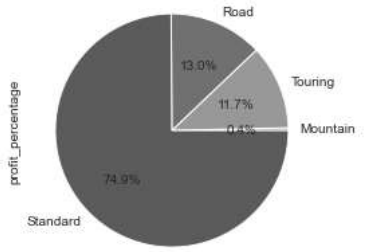
In [116]:
```
plt.figure(figsize=(4,4))
Sprocket_df.groupby('order_status').profit_percentage.sum().sort_values().plot.pie(autopct="%1.1f%%")
plt.show()
```



In [117]:
```
Sprocket_df.groupby('product_line').profit_percentage.sum().sort_values()
```

Out[117]:
```
product_line
Mountain     0.361666
Touring     11.731323
Road        13.000500
Standard    74.906511
Name: profit_percentage, dtype: float64
```

In [118]:
```
plt.figure(figsize=(4,4))
Sprocket_df.groupby('product_line').profit_percentage.sum().sort_values().plot.pie(autopct="%1.1f%%")
plt.show()
```



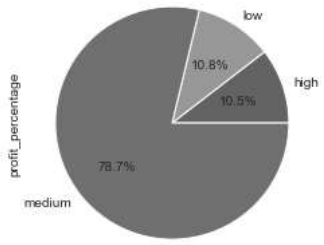
In [119]:
```
Sprocket_df.groupby('product_class').profit_percentage.sum().sort_values()
```

Out[119]:
```
product_class
high      10.470744
low       10.783299
medium    78.745958
Name: profit_percentage, dtype: float64
```

In [120]:
```
Sprocket_df.groupby('product_size').profit_percentage.sum().sort_values()
```

Out[120]:
```
product_size
small      3.747644
large     33.302844
medium    62.949512
Name: profit_percentage, dtype: float64
```

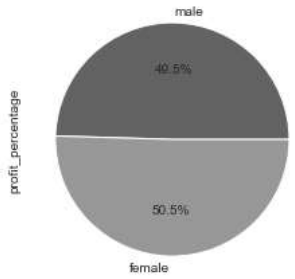
In [121]:
```
plt.figure(figsize=(4,4))
Sprocket_df.groupby('product_class').profit_percentage.sum().sort_values().plot.pie(autopct="%1.1f%%")
plt.show()
```



In [122]:
```
Sprocket_df.groupby('gender').profit_percentage.sum().sort_values()
```

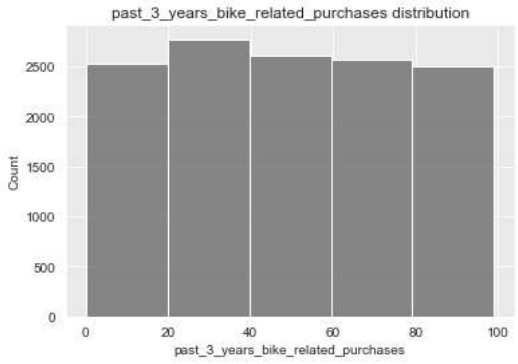
Out[122]:
```
gender
male      49.524477
female    50.475523
Name: profit_percentage, dtype: float64
```

In [123]:
```
plt.figure(figsize=(4,4))
Sprocket_df.groupby('gender').profit_percentage.sum().sort_values().plot.pie(autopct="%1.1f%%")
plt.show()
```



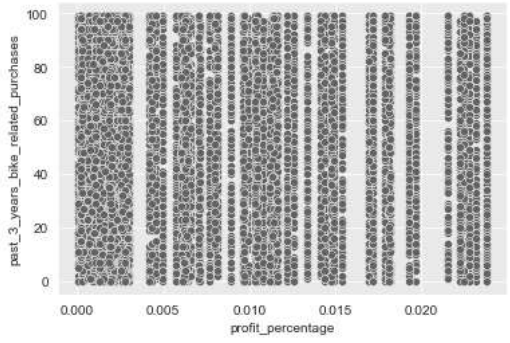
In [124]:
```
Sprocket_df["past_3_years_bike_related_purchases"] = Sprocket_df[["past_3_years_bike_related_purchases"]].astype('int64')
sns.histplot(data=Sprocket_df, x= "past_3_years_bike_related_purchases", bins = 5)

# Add title
plt.title("past_3_years_bike_related_purchases distribution")
```

Out[124]:
```
Text(0.5, 1.0, 'past_3_years_bike_related_purchases distribution')
```



In [125]:
```
sns.scatterplot(data=Sprocket_df, x="profit_percentage", y="past_3_years_bike_related_purchases")
#   No correlation
```

Out[125]:
```
<AxesSubplot:xlabel='profit_percentage', ylabel='past_3_years_bike_related_purchases'>
```



In [126]:
```
Sprocket_df.groupby('job_title').profit_percentage.sum().sort_values(ascending = False).head(15)
```

Out[126]:
```
job_title
Information Systems Manager    1.717418
Social Worker                  1.590804
Recruiting Manager             1.421926
Nuclear Power Engineer         1.356981
Internal Auditor               1.355069
General Manager                1.324777
Chemical Engineer              1.295316
Speech Pathologist             1.245013
Administrative Officer         1.207766
Registered Nurse               1.184907
Assistant Media Planner        1.180942
Food Chemist                   1.172929
Assistant Manager              1.163864
Marketing Manager              1.147413
Project Manager                1.144754
Name: profit_percentage, dtype: float64
```

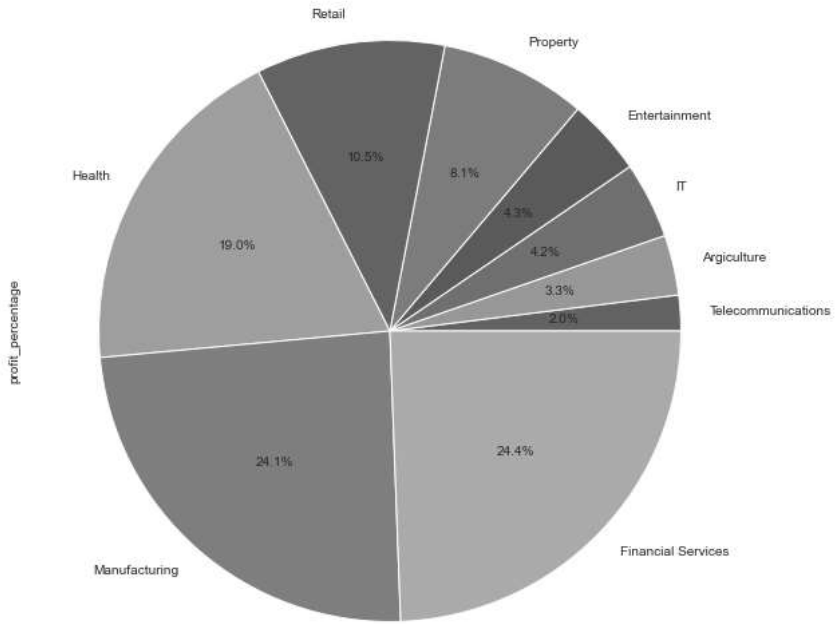
In [127]:
```
Sprocket_df.groupby('job_title').profit_percentage.sum().sort_values(ascending = False).tail(15)
```

Out[127]:
```
job_title
Accounting Assistant II         0.089983
Systems Administrator IV        0.088001
Health Coach III                0.087474
Human Resources Assistant IV    0.076379
Web Developer II                0.072734
Programmer Analyst I            0.071497
Geologist II                    0.065086
Geologist III                   0.064593
Automation Specialist IV        0.061198
Developer I                     0.060576
Office Assistant II             0.059511
Research Assistant III          0.055594
Administrative Assistant I      0.044153
Developer IV                    0.039761
Database Administrator II       0.037188
Name: profit_percentage, dtype: float64
```

In [128]:
```
Sprocket_df.groupby('job_industry_category').profit_percentage.sum().sort_values(ascending = False)
```

Out[128]:
```
job_industry_category
Financial Services    24.409255
Manufacturing         24.129211
Health                18.996776
Retail                10.499267
Property               8.138326
Entertainment          4.259811
IT                     4.242691
Argiculture            3.342727
Telecommunications     1.981936
Name: profit_percentage, dtype: float64
```

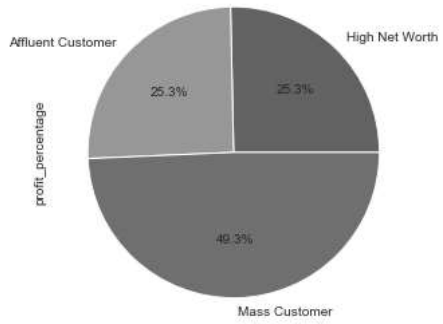
In [129]:
```
plt.figure(figsize=(10,10))
Sprocket_df.groupby('job_industry_category').profit_percentage.sum().sort_values().plot.pie(autopct="%1.1f%%")
plt.show()
```



In [130]:
```
Sprocket_df.groupby('wealth_segment').profit_percentage.sum().sort_values()
```

Out[130]:
```
wealth_segment
High Net Worth       25.340132
Affluent Customer    25.342887
Mass Customer        49.316981
Name: profit_percentage, dtype: float64
```

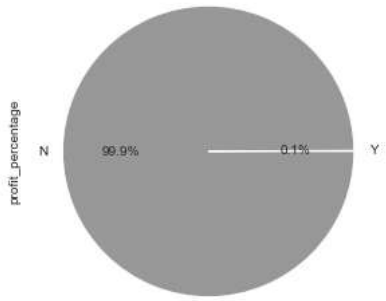
In [131]:
```
plt.figure(figsize=(5,5))
Sprocket_df.groupby('wealth_segment').profit_percentage.sum().sort_values().plot.pie(autopct="%1.1f%%")
plt.show()
```



In [132]:
```
Sprocket_df.groupby('deceased_indicator').profit_percentage.sum().sort_values()
```

Out[132]:
```
deceased_indicator
Y     0.107919
N    99.892081
Name: profit_percentage, dtype: float64
```

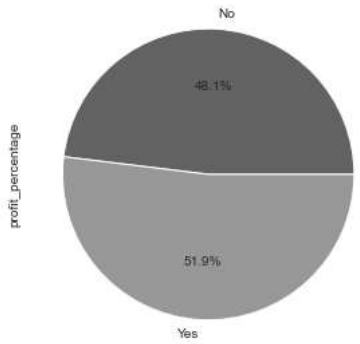
In [133]:
```
plt.figure(figsize=(5,5))
Sprocket_df.groupby('deceased_indicator').profit_percentage.sum().sort_values().plot.pie(autopct="%1.1f%%")
plt.show()
```



In [134]:
```
Sprocket_df.groupby('owns_car').profit_percentage.sum().sort_values()
```

Out[134]:
```
owns_car
No     48.068036
Yes    51.931964
Name: profit_percentage, dtype: float64
```

In [135]:
```
plt.figure(figsize=(5,5))
Sprocket_df.groupby('owns_car').profit_percentage.sum().sort_values().plot.pie(autopct="%1.1f%%")
plt.show()
```



7. Act phase

Key findings

1. About 88% of profit is generated from customers within the age 21 to 60.
2. About 53% of profit is generated from customers residing in new south wales.

Recommendations

Customers residing in new south wales and within the age of 21 to 60 should be top target

In [136]:
```
Sprocket_df.to_csv("Sprocket_df")
```

```
1
```