

KPMG Data Analytics using python.

The Sporty Rocket Central Dataset

Developing a report that we can present to the client at our next meeting. Displaying the data summary and results of the analysis (see tools/references for assistance). Specifically, the presentation should specify who Sprocket Central Pty Ltd' should be targeting out of the new 1000 customer list using the Transactions Table.

Problem Outline SP Rocket Central is a company that specializes in high quality bikes and accessories. the Company is targeting 1000 new customers and is focused in Maximizing profit through Bike sales.

```
In [40]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.ticker as mticker
%matplotlib inline
```

```
In [22]: kpmg = pd.read_csv(r"C:\Users\user\Projects\BI-Analytics-Projects\KPMG Data Analytics (R
```

```
In [3]: kpmg
```

	transaction_id	product_id	customer_id	transaction_date	Recency	online_order	order_status	brand	pr
0	1	2	2950	2/25/2017	308	False	Approved	Solex	
1	2	3	3120	5/21/2017	223	True	Approved	Trek Bicycles	
2	3	37	402	10/16/2017	75	False	Approved	OHM Cycles	
3	4	88	3135	8/31/2017	121	False	Approved	Norco Bicycles	
4	6	25	2339	3/8/2017	297	True	Approved	Giant Bicycles	
...	
16715	19995	9	718	5/13/2017	231	True	Approved	OHM Cycles	
16716	19996	51	1018	6/24/2017	189	True	Approved	OHM Cycles	
16717	19997	41	127	11/9/2017	51	True	Approved	Solex	
16718	19998	87	2284	4/14/2017	260	True	Approved	OHM Cycles	
16719	20000	11	1144	9/22/2017	99	True	Approved	Trek Bicycles	

16720 rows × 30 columns

```
In [4]: kpmg.columns
```

```
Out[4]: Index(['transaction_id', 'product_id', 'customer_id', 'transaction_date',  
            'Recency', 'online_order', 'order_status', 'brand', 'product_line',  
            'product_class', 'product_size', 'list_price', 'standard_cost',  
            'product_first_sold_date', 'Profit', 'gender',  
            'past_3_years_bike_related_purchases', 'DOB', 'AGE', 'job_title',  
            'job_industry_category', 'wealth_segment', 'deceased_indicator',  
            'owns_car', 'tenure', 'address', 'postcode', 'state', 'country',  
            'property_valuation'],  
            dtype='object')
```

```
In [5]: kpmg.dtypes
```

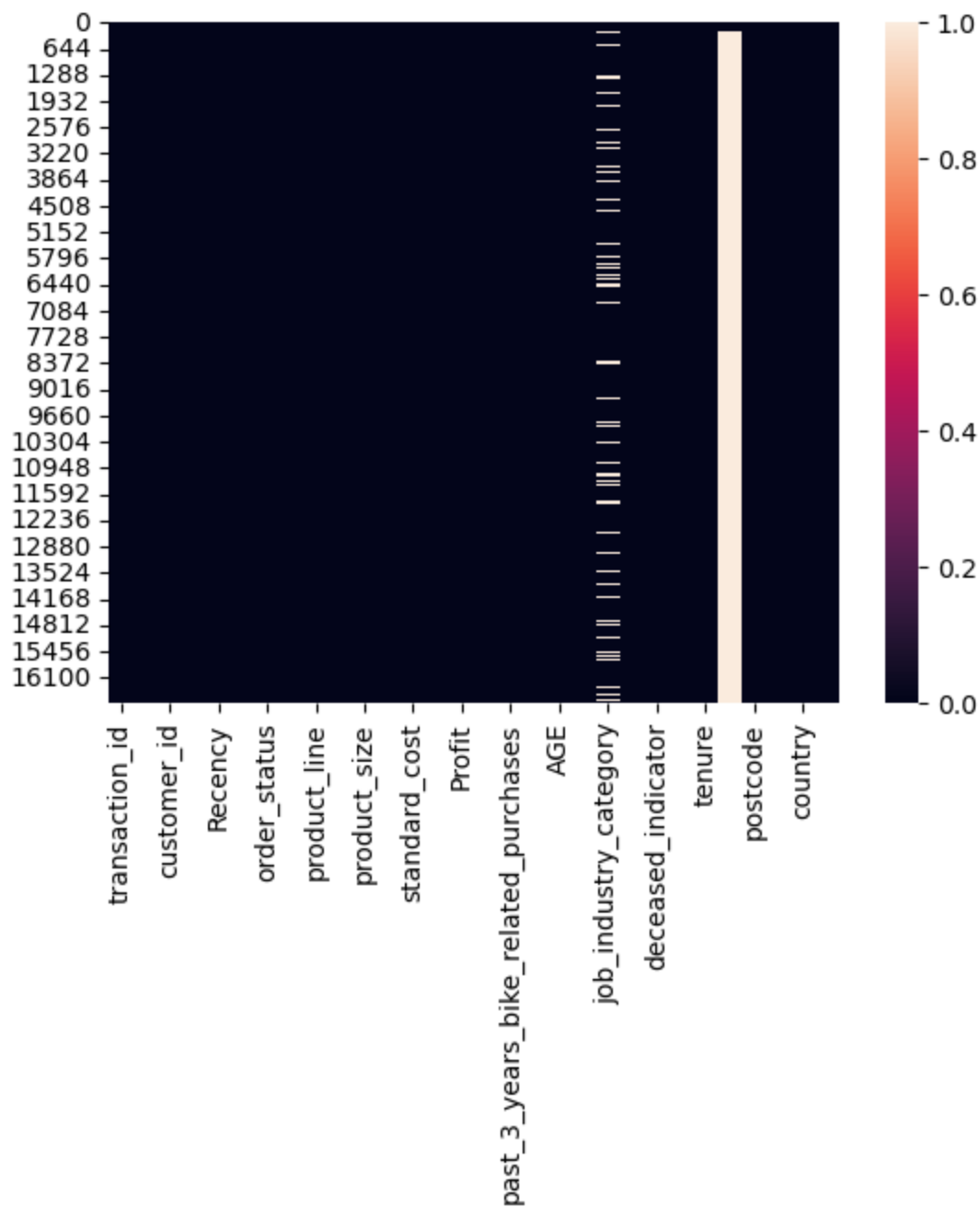
```
Out[5]: transaction_id      int64  
product_id      int64  
customer_id     int64  
transaction_date object  
Recency         int64  
online_order    bool  
order_status    object  
brand           object  
product_line    object  
product_class   object  
product_size    object  
list_price      float64  
standard_cost   float64  
product_first_sold_date object  
Profit          float64  
gender          object  
past_3_years_bike_related_purchases int64  
DOB            object  
AGE            int64  
job_title       object  
job_industry_category object  
wealth_segment  object  
deceased_indicator object  
owns_car        object  
tenure          int64  
address         object  
postcode        int64  
state          object  
country         object  
property_valuation int64  
dtype: object
```

```
In [7]: kpmg.Profit.describe()
```

```
Out[7]: count    16720.000000  
mean         551.874560  
std          493.450565  
min           4.800000  
25%         135.850000  
50%         445.210000  
75%         827.160000  
max         1702.550000  
Name: Profit, dtype: float64
```

```
In [23]: sns.heatmap(kpmg.isnull())
```

```
Out[23]: <Axes: >
```



```
In [24]: kpmg.isnull().sum()
```

```
Out[24]: transaction_id      0
product_id      0
customer_id     0
transaction_date 0
Recency         0
online_order    0
order_status    0
brand           0
product_line    0
product_class   0
product_size    0
list_price      0
standard_cost   0
product_first_sold_date 0
Profit          0
gender          0
past_3_years_bike_related_purchases 0
DOB             0
AGE             0
job_title       0
job_industry_category 2663
```

wealth_segment	0
deceased_indicator	0
owns_car	0
tenure	0
address	16513
postcode	0
state	0
country	0
property_valuation	0
dtype: int64	

```
In [68]: kpmg.drop(columns= ['address'], axis=1, inplace=True)
```

```
In [26]: kpmg.isnull().sum()
```

```
Out[26]: transaction_id      0
product_id      0
customer_id     0
transaction_date 0
Recency         0
online_order    0
order_status    0
brand           0
product_line    0
product_class   0
product_size    0
list_price      0
standard_cost   0
product_first_sold_date 0
Profit          0
gender          0
past_3_years_bike_related_purchases 0
DOB            0
AGE            0
job_title       0
job_industry_category 2663
wealth_segment  0
deceased_indicator 0
owns_car        0
tenure          0
postcode        0
state           0
country         0
property_valuation 0
dtype: int64
```

```
In [27]: kpmg.isnull().sum()
```

```
Out[27]: transaction_id      0
product_id      0
customer_id     0
transaction_date 0
Recency         0
online_order    0
order_status    0
brand           0
product_line    0
product_class   0
product_size    0
list_price      0
standard_cost   0
product_first_sold_date 0
Profit          0
gender          0
past_3_years_bike_related_purchases 0
DOB            0
```

```

AGE 0
job_title 0
job_industry_category 2663
wealth_segment 0
deceased_indicator 0
owns_car 0
tenure 0
postcode 0
state 0
country 0
property_valuation 0
dtype: int64

```

```
In [28]: kpmg.AGE.describe()
```

```

Out[28]: count    16720.000000
mean         46.192045
std          12.592445
min          22.000000
25%          37.000000
50%          46.000000
75%          55.250000
max          92.000000
Name: AGE, dtype: float64

```

```

In [29]: # Group the AGE in bins of 10 years
labels = ["{0} - {1}".format(i, i + 9) for i in range(1, 70, 10)]

kpmg['age_group'] = pd.cut(kpmg.AGE, range(1, 80, 10), right=False, labels=labels)

```

```
In [30]: kpmg.age_group.value_counts()
```

```

Out[30]: 41 - 50    5749
51 - 60    2975
31 - 40    2888
61 - 70    2634
21 - 30    2447
1 - 10      0
11 - 20     0
Name: age_group, dtype: int64

```

```
In [19]: kpmg.columns
```

```

Out[19]: Index(['transaction_id', 'product_id', 'customer_id', 'transaction_date',
'Recency', 'online_order', 'order_status', 'brand', 'product_line',
'product_class', 'product_size', 'list_price', 'standard_cost',
'product_first_sold_date', 'Profit', 'gender',
'past_3_years_bike_related_purchases', 'DOB', 'AGE', 'job_title',
'job_industry_category', 'wealth_segment', 'deceased_indicator',
'owns_car', 'tenure', 'address', 'postcode', 'state', 'country',
'property_valuation', 'age_group'],
dtype='object')

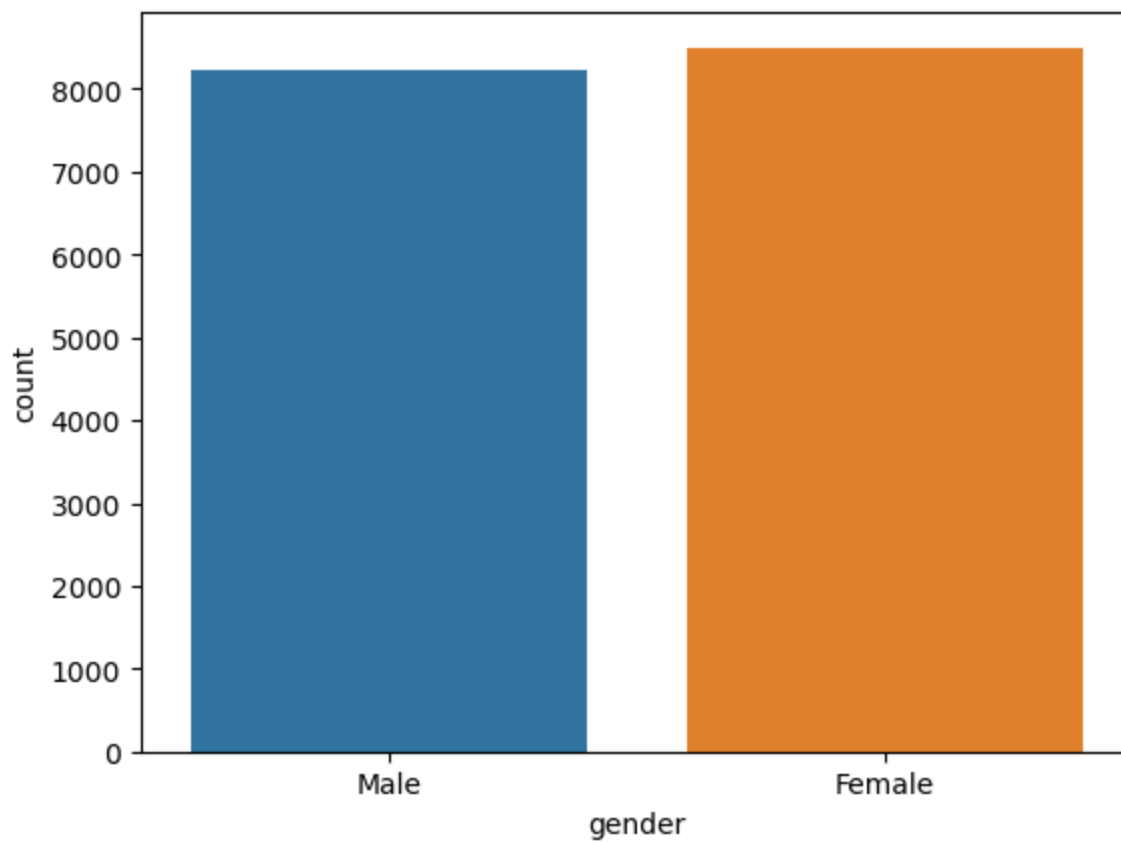
```

```
In [31]: sns.countplot(kpmg, x = 'gender')
```

```

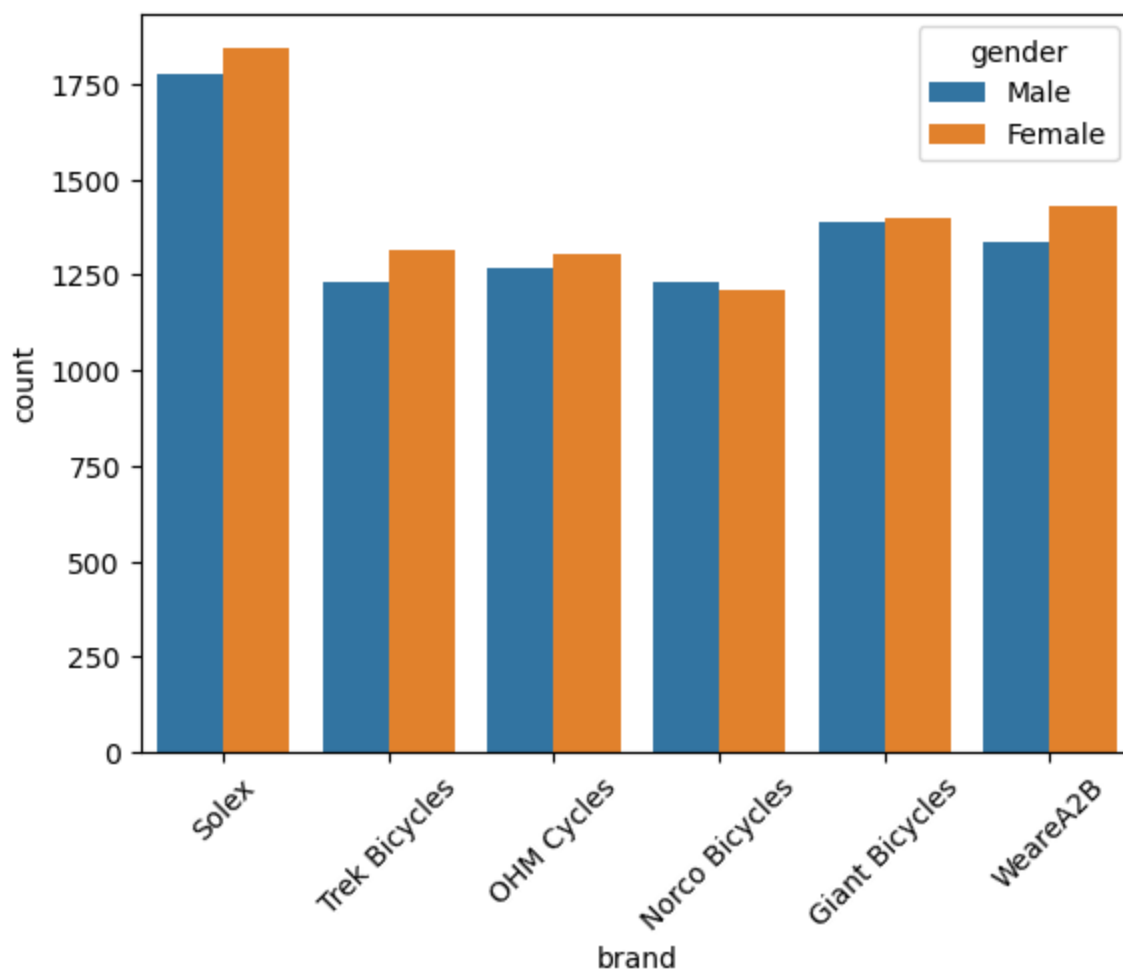
Out[31]: <Axes: xlabel='gender', ylabel='count'>

```



```
In [34]: sns.countplot(kpmg, x = 'brand', hue = 'gender')  
plt.xticks(rotation=45)
```

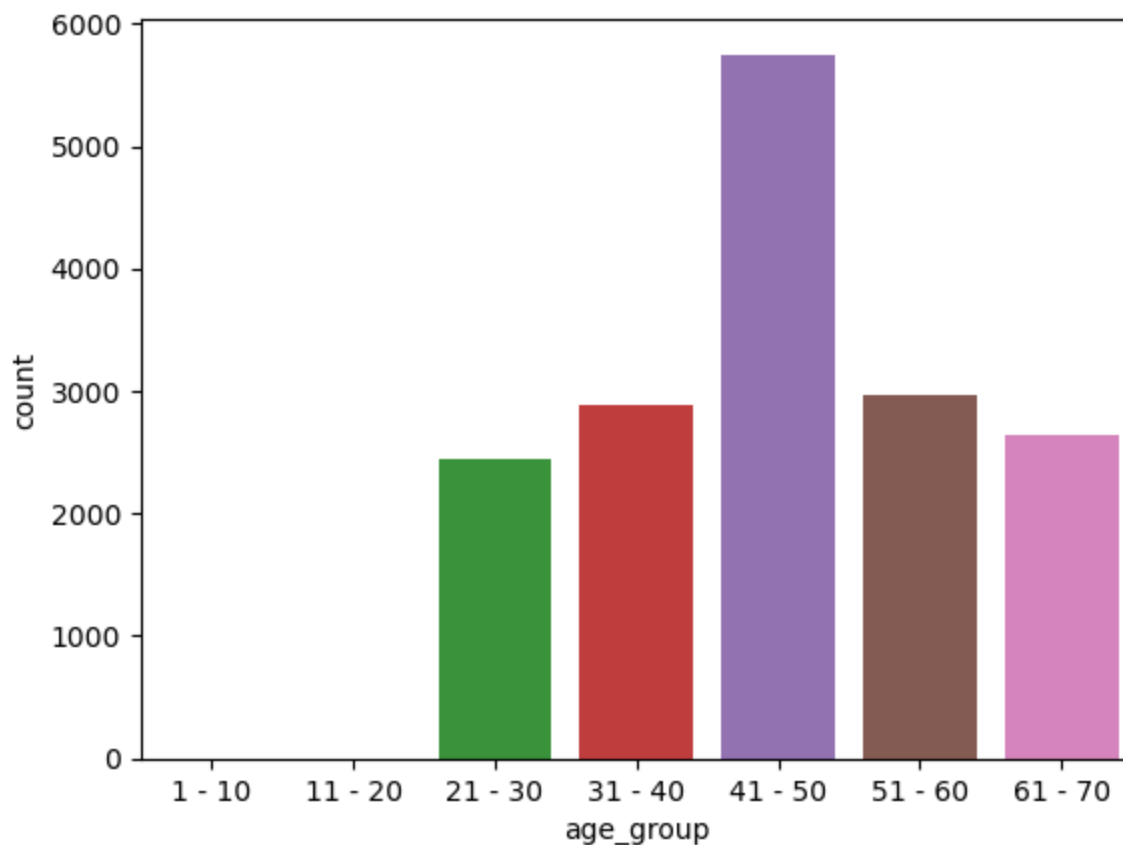
```
Out[34]: (array([0, 1, 2, 3, 4, 5]),  
 [Text(0, 0, 'Solex'),  
  Text(1, 0, 'Trek Bicycles'),  
  Text(2, 0, 'OHM Cycles'),  
  Text(3, 0, 'Norco Bicycles'),  
  Text(4, 0, 'Giant Bicycles'),  
  Text(5, 0, 'WeareA2B')])
```



```
In [50]: plt.close()
```

```
In [53]: sns.countplot(kpmg, x = 'age_group')
```

```
Out[53]: <Axes: xlabel='age_group', ylabel='count'>
```



In [65]: `kpmg['Profitss'] = kpmg.Profit.sum()`

In [69]: `kpmg`

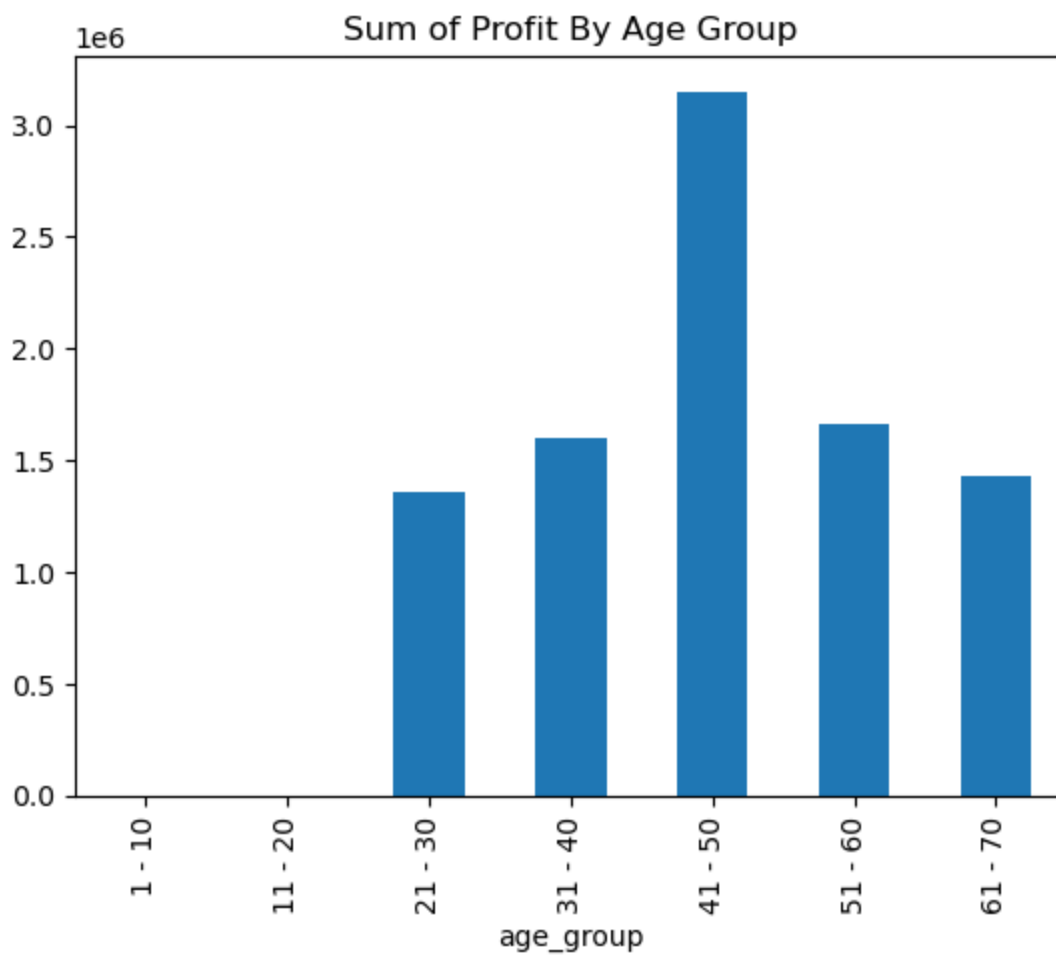
Out[69]:

	transaction_id	product_id	customer_id	transaction_date	Recency	online_order	order_status	brand	pr
0	1	2	2950	2/25/2017	308	False	Approved	Solex	
1	2	3	3120	5/21/2017	223	True	Approved	Trek Bicycles	
2	3	37	402	10/16/2017	75	False	Approved	OHM Cycles	
3	4	88	3135	8/31/2017	121	False	Approved	Norco Bicycles	
4	6	25	2339	3/8/2017	297	True	Approved	Giant Bicycles	
...
16715	19995	9	718	5/13/2017	231	True	Approved	OHM Cycles	
16716	19996	51	1018	6/24/2017	189	True	Approved	OHM Cycles	
16717	19997	41	127	11/9/2017	51	True	Approved	Solex	
16718	19998	87	2284	4/14/2017	260	True	Approved	OHM Cycles	
16719	20000	11	1144	9/22/2017	99	True	Approved	Trek Bicycles	

16720 rows × 30 columns

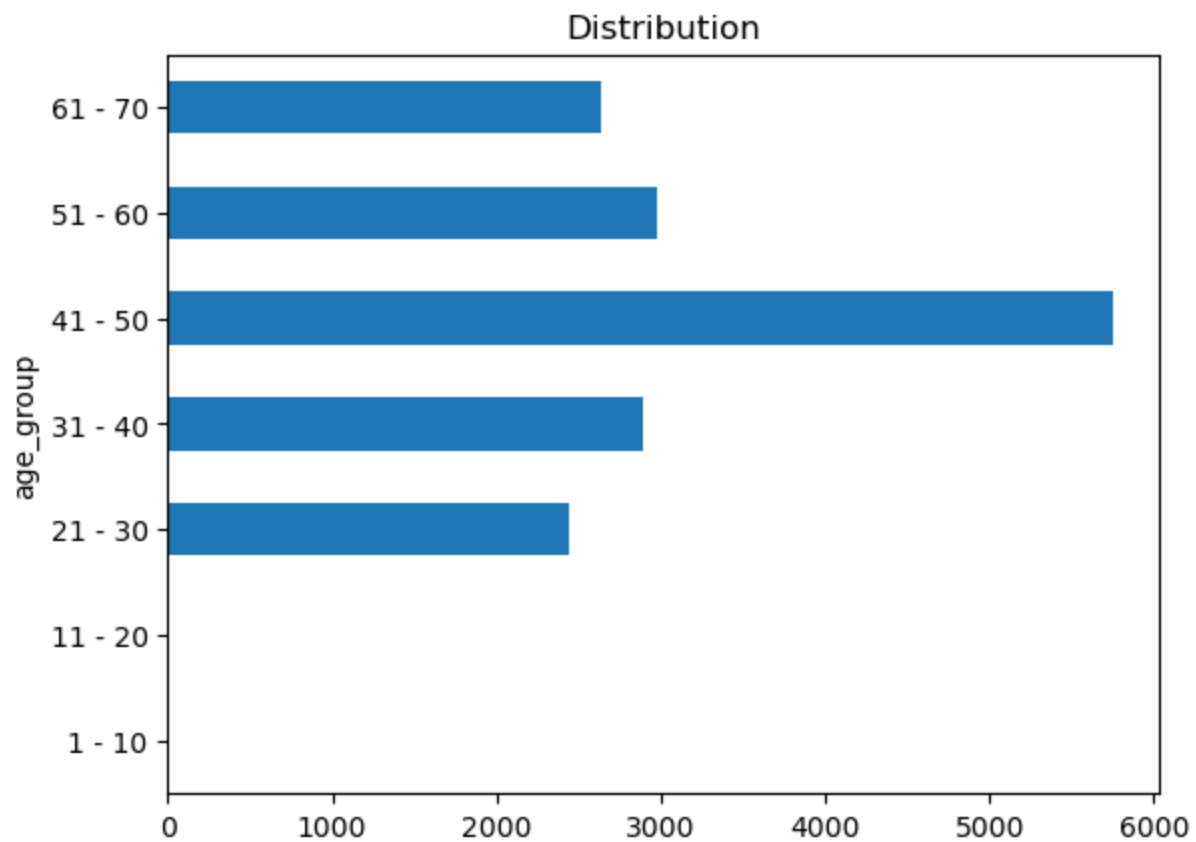
In [83]: `kpmg.groupby(kpmg.age_group).Profit.sum().plot(kind = 'bar')`
`plt.title("Sum of Profit By Age Group")`

Out[83]: `Text(0.5, 1.0, 'Sum of Profit By Age Group')`



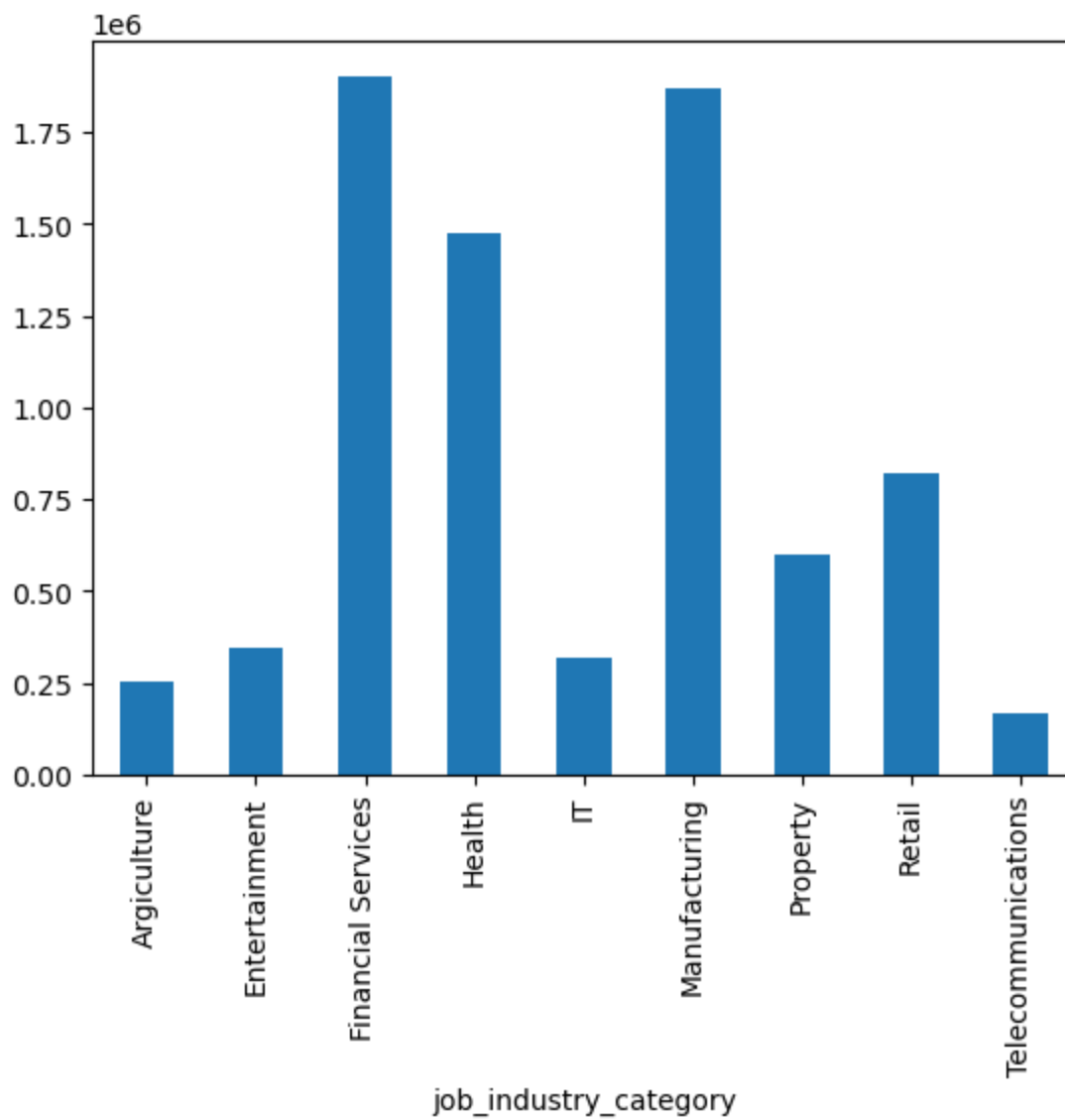
```
In [81]: kpmg.groupby(kpmg.age_group).past_3_years_bike_related_purchases.count().plot(kind = 'bar')
plt.title("Distribution")
```

```
Out[81]: Text(0.5, 1.0, 'Distribution')
```



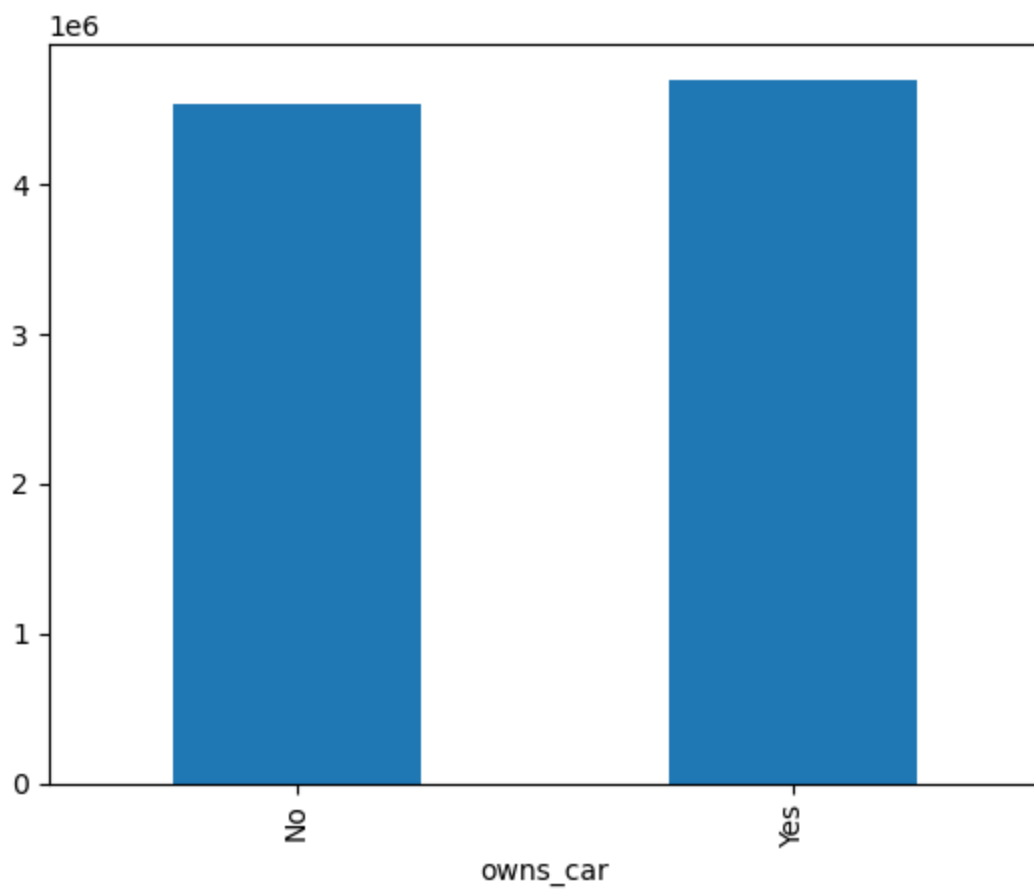
```
In [82]: kpmg.groupby(kpmg.job_industry_category).Profit.sum().plot(kind = 'bar')
```

Out[82]: <Axes: xlabel='job_industry_category'>



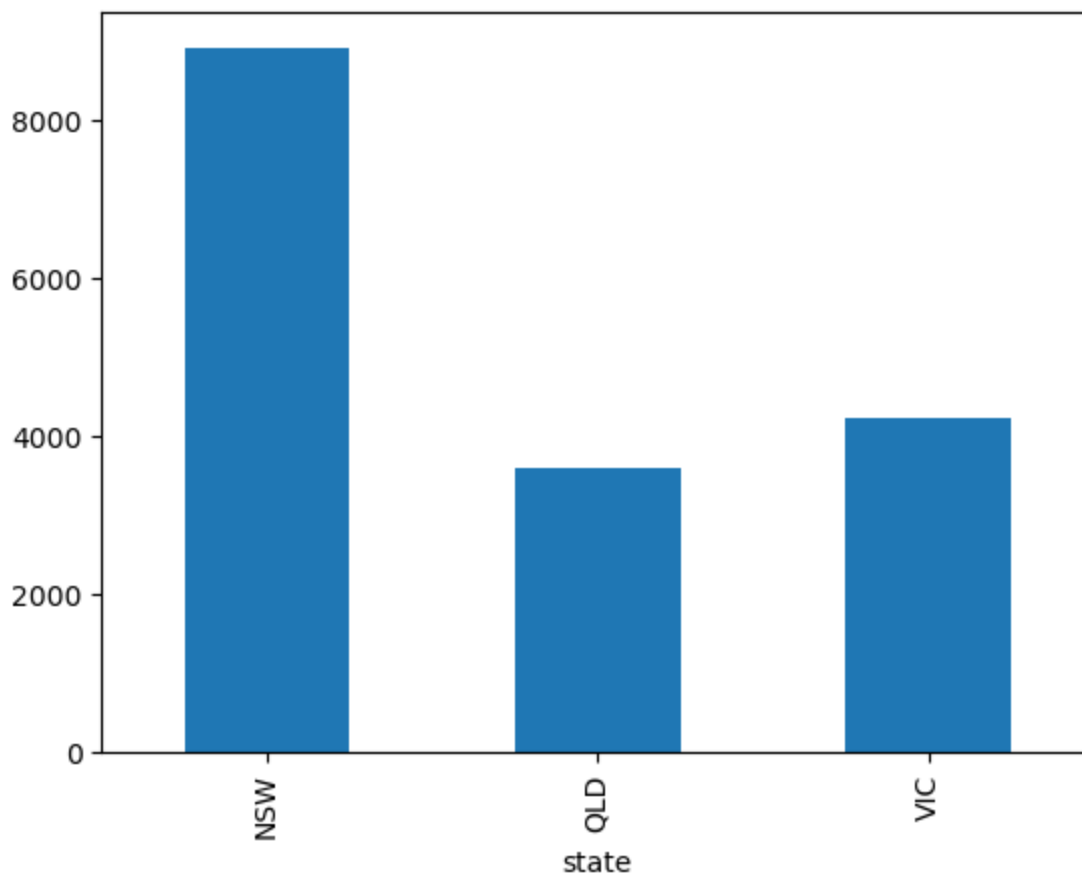
In [84]: `kpmg.groupby(kpmg.owns_car).Profit.sum().plot(kind = 'bar')`

Out[84]: <Axes: xlabel='owns_car'>



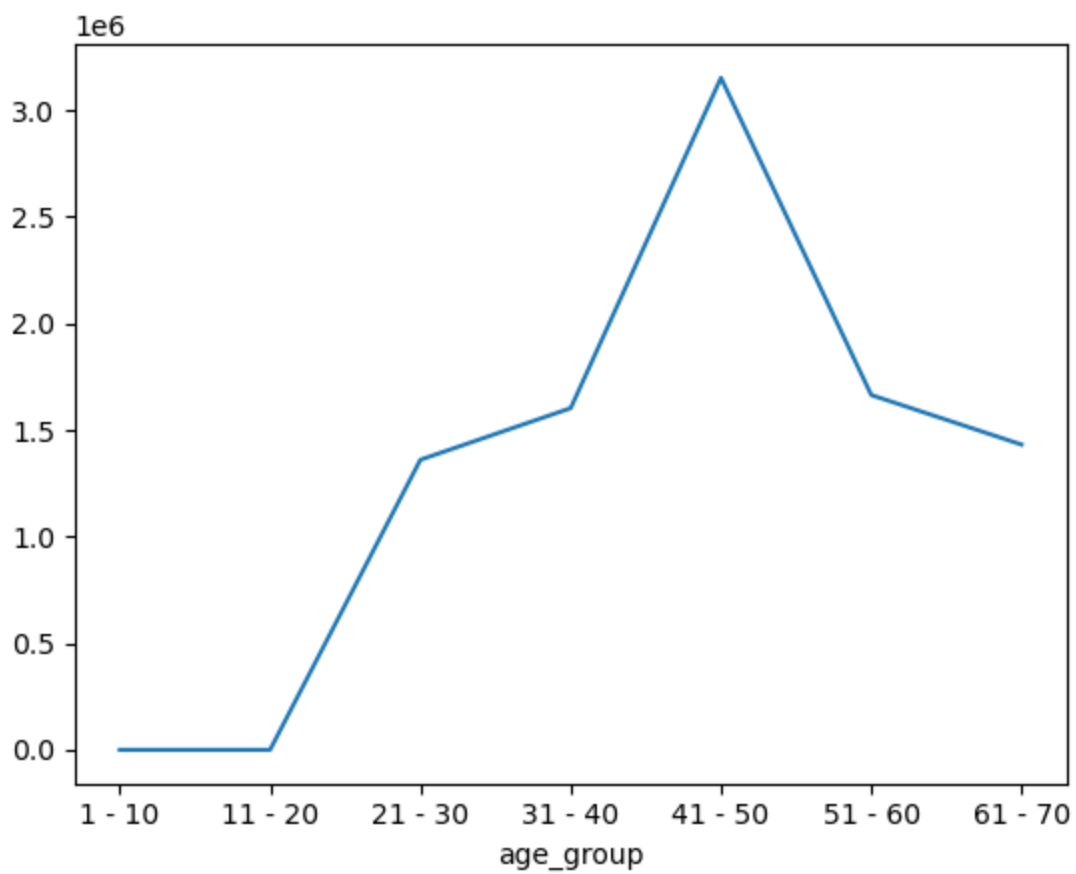
```
In [85]: kpmg.groupby(kpmg.state).customer_id.count().plot(kind = 'bar')
```

```
Out[85]: <Axes: xlabel='state'>
```



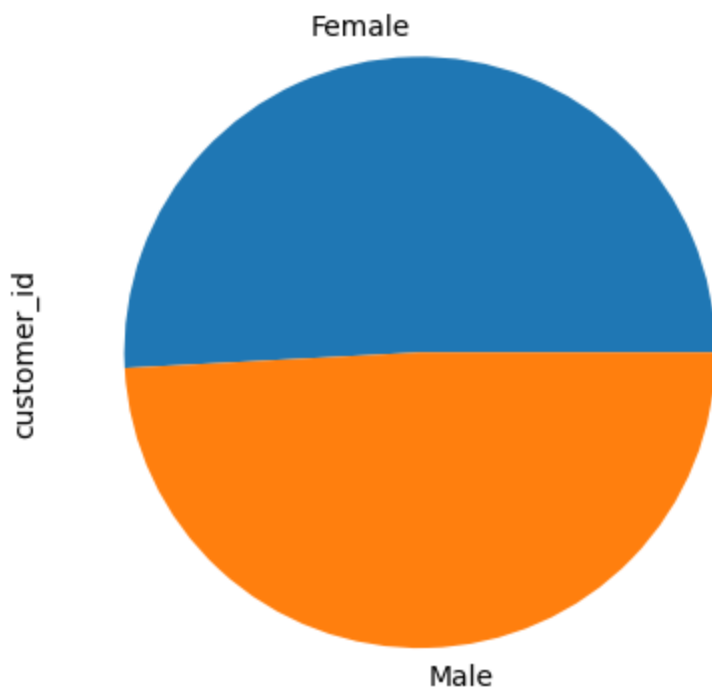
```
In [86]: kpmg.groupby(kpmg.age_group).Profit.sum().plot(kind = 'line')
```

```
Out[86]: <Axes: xlabel='age_group'>
```



```
In [87]: kpmg.groupby(kpmg.gender).customer_id.count().plot(kind = 'pie')
```

```
Out[87]: <Axes: ylabel='customer_id'>
```



```
In [88]: kpmg.gender.value_counts()
```

```
Out[88]: Female      8501
Male        8219
Name: gender, dtype: int64
```

DATA EXPLORATION

- Most of the Bike related Purchases were made by the age 40 and 49
- The Data shows that middle aged customers are the most potential Customers
- Finalcial Services, Health and Manufacturing Sector are the top Three Profit Generating industries, followed by Retail, IT and Property

In []:

In []: