



Data Analytics - Fall 2021

Final Project presentation



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Sales & Marketing Dataset (Bike-selling Company)

About the project



06/12/2021

Dataset - Customer Details, Transaction Details, Customer Demography
(One Excel file in different sheets)

Problem - Exploratory Data Analysis - future planning for promotional sales and marketing for existing products

Libraries used - NumPy, Pandas, Matplotlib, Geocoder, Plotly, datetime, missingno

Process and Planning



Cleaning and
Manipulating



Analysis and
Visualization



Conclusion



Presentation



```

df_demo = df_demo.dropna()
df_demo['gender'] = df_demo['gender'].fillna('Female', 'Femal'], 'F', inplace=True)
df_demo['gender'] = df_demo['gender'].fillna('Male', 'M', inplace=True)

df_demo.isnull().sum()
customer_id      0
first_name       0
last_name      125
gender           0
past_3_years_bike_related_purchases  0
DOB             87
job_title        0
job_industry_category  0
wealth_segment   0
owns_car         0
dtype: int64

# merging first name and last name as new 'name' column
df_demo['name'] = df_demo['first_name'] + ' ' + df_demo['last_name']
df_demo['name'] = df_demo['name'].fillna('others')
df_demo.drop(['first_name', 'last_name'], axis=1, inplace=True)
df_demo.columns

```

To check duplicay or any null value in the dataframe

```

duplicate_data = df_demo.duplicated()
df_demo[duplicate_data].sum()

```

```

0]: customer_id      0.0
gender             0.0
past_3_years_bike_related_purchases  0.0
job_title          0.0
job_industry_category  0.0
wealth_segment     0.0
owns_car           0.0
name               0.0
age                0.0
age_range          0.0
dtype: float64

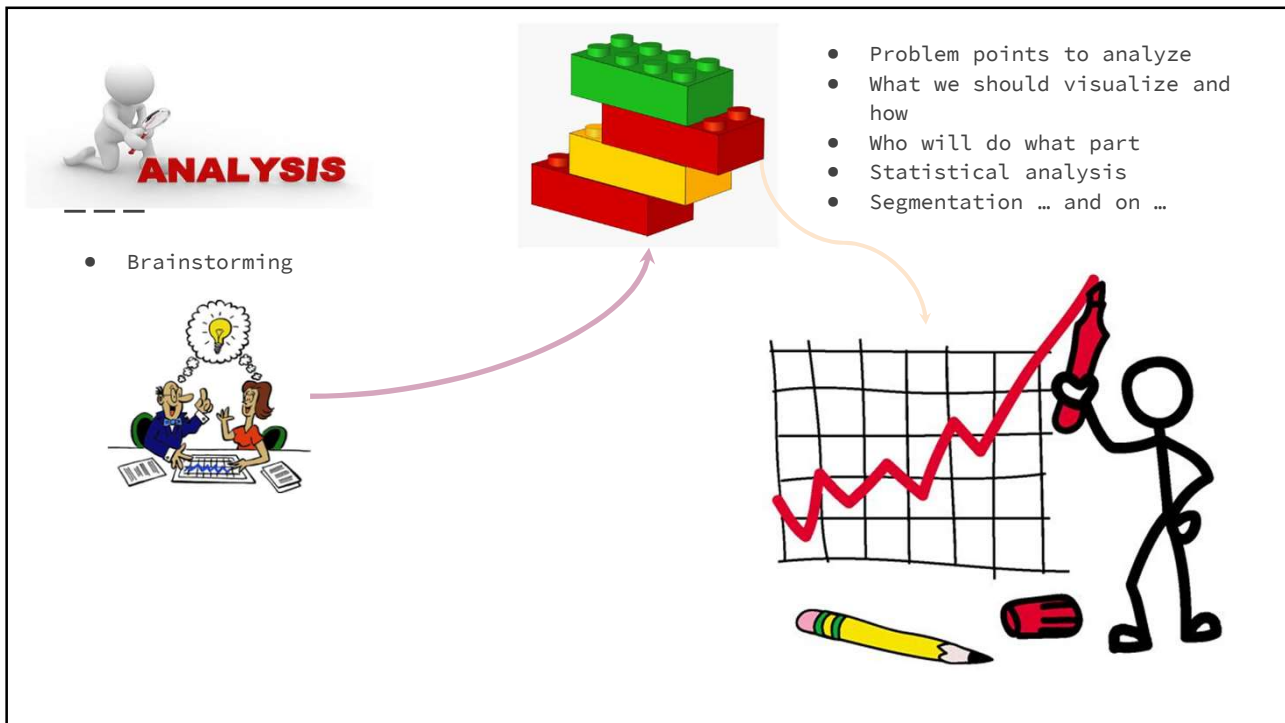
```

We'll save merged file to keep the data safe

```

df_demo.to_csv('Data/CustomerDemoAddTrans.csv')

```

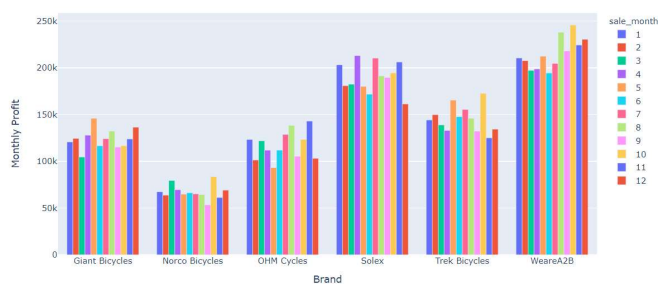


Sale of the brand and product line analysis

a) Which brand is most profitable ?

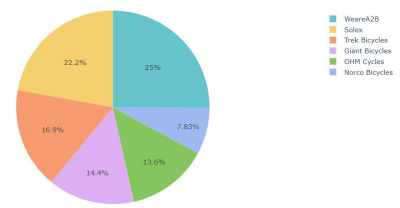


Monthly Profit of each brand

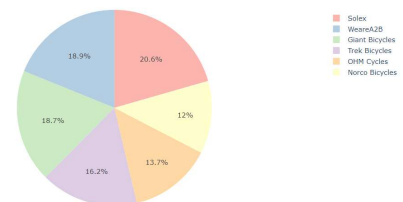


sale_month	brand	1	2	3	4	5	6	7	8	9	10	11	12
Giant Bicycles	120719.80	124478.99	104599.55	127888.69	146007.33	116562.20	124142.16	132296.42	115150.93	116862.07	123896.37	136474.07	
Norco Bicycles	67371.95	63711.91	79455.58	69549.67	64825.52	66263.30	65115.27	64361.79	53358.55	83541.67	61182.56	69074.27	
OHM Cycles	123322.74	101334.20	121840.47	111855.60	93196.94	111895.56	128738.02	138325.14	105387.79	123335.93	143031.34	103103.90	
Solex	203231.88	180857.54	182480.39	213091.94	180178.39	171810.80	210367.06	191407.14	189655.38	194571.81	209211.75	161324.15	
Trek Bicycles	144203.43	148818.50	138915.80	132952.03	165402.02	147687.99	155493.59	146037.22	132219.83	172633.06	125088.25	134355.52	
WeareA2B	210533.02	207644.43	187193.32	198802.33	212454.12	194481.27	204685.58	238065.16	218065.05	245764.50	224436.95	230533.37	

Profit % generated by different brands



Revenue % generated by different brands

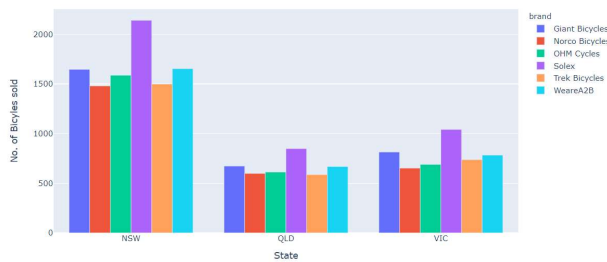


c) How each brand is performing in different states?

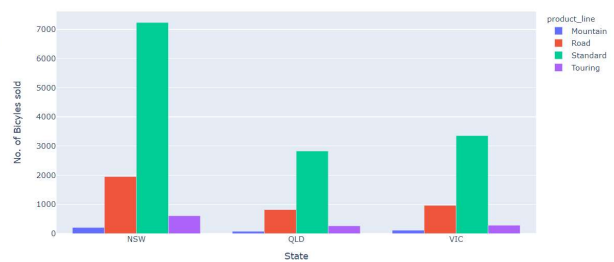


brand	Giant Bicycles	Norco Bicycles	OHM Cycles	Solex	Trek Bicycles	WeareA2B
state						
NSW	1646	1479	1587	2140	1499	1653
QLD	673	598	612	848	586	668
VIC	814	652	689	1041	737	783

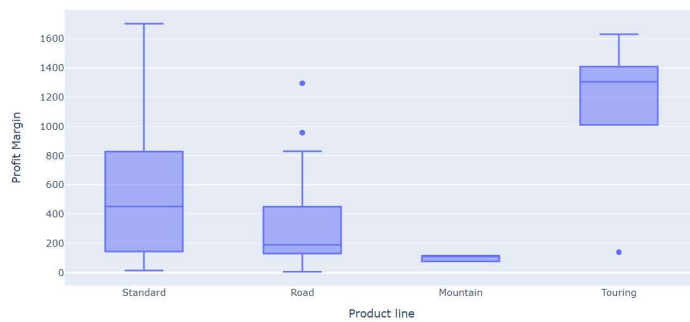
How each brand is performing in different states?



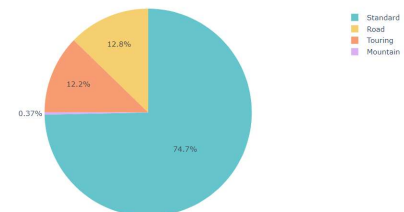
Is any Product-Line preferred over others in different states?



Which Product-line is generating most profit?



Profit % generated by different product-lines



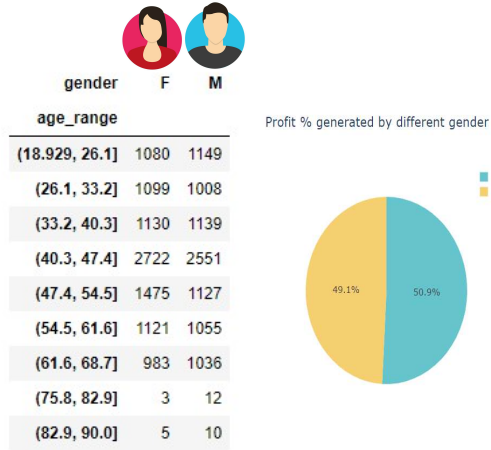
Product-Line sale by Post code

product_line	Mountain	Road	Standard	Touring
postcode				
2000	NaN	10.0	28.0	2.0
2007	NaN	1.0	10.0	2.0
2008	1.0	2.0	3.0	1.0
2009	1.0	6.0	19.0	1.0
2010	4.0	7.0	40.0	4.0

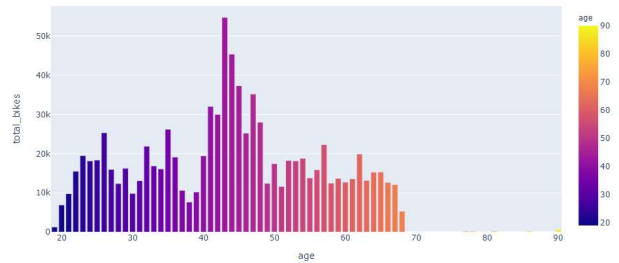
Customer behaviour analysis



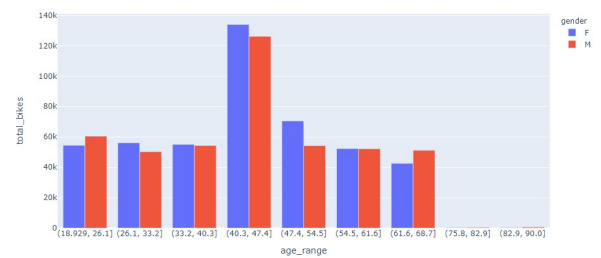
a) Which age-group is buying bicycles the most?



Age-wise bike purchase in past 3 years by existing customers

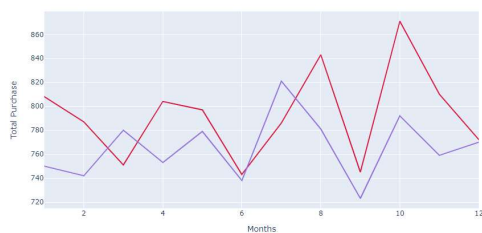


Gender-wise Total bike purchase in different age group



b) Customer's behaviour on purchasing mode i.e online/offline

Online vs Offline purchase (monthly)

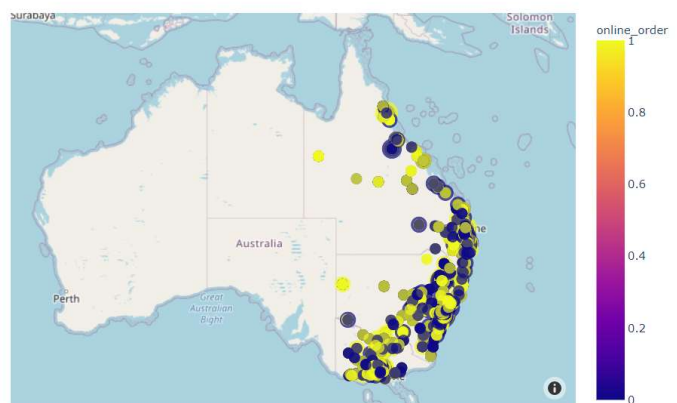


total transaction count 18705

Online/Offline

0.0	9188
1.0	9517

Online and Offline Transaction count



c) RFM (Recency, Frequency, Monetary) analysis and customer segmentation



```
rfm_df.groupby('customer_id').agg(['Recency': 'min', 'Product ID': 'count', 'Profit Margin': 'sum']).reset_index()

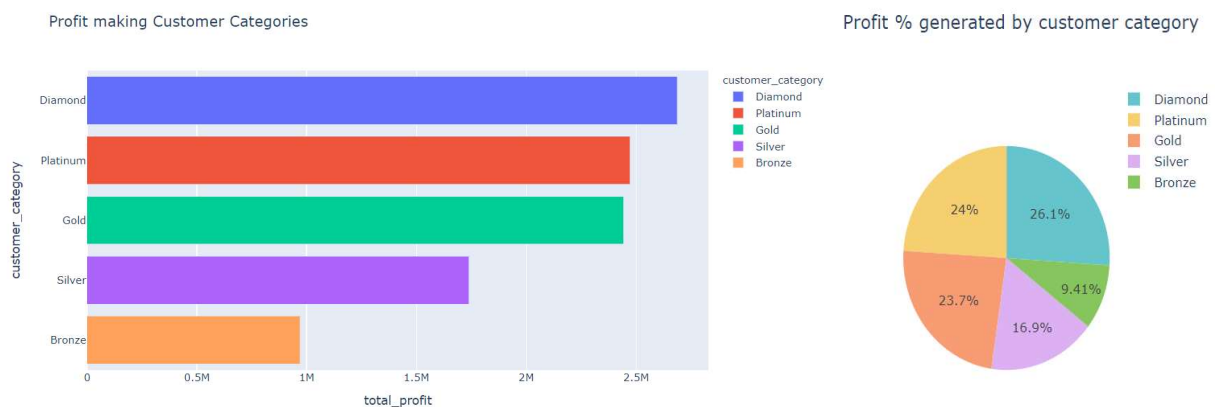
rfm_rfm_df['customer_category'] = pd.qcut(rfm_df['RFM_Score'], 5, ['Diamond', 'Platinum', 'Gold', 'Silver', 'Bronze'])
rfm_rfm_df.sort_values(by='Monetary', ascending=False, inplace=True)
# Showing customer category

cust_df = rfm_df.groupby('customer_category').agg({'customer_category': ['count'], 'Monetary': ['sum']}).reset_index()
cust_df.columns = ['customer_category', 'total_count', 'total_profit']
cust_df
```

	customer_category	total_count	total_profit
0	Diamond	681	2688322.06
1	Platinum	648	2473062.29
2	Gold	757	2443345.96
3	Silver	642	1739129.90
4	Bronze	575	970843.11

```
rfm_df.info()
```

c) Profit generated by segmented customer group

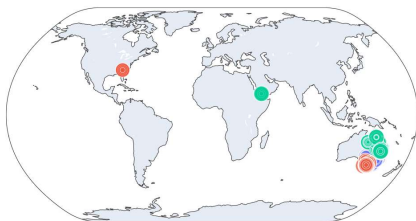




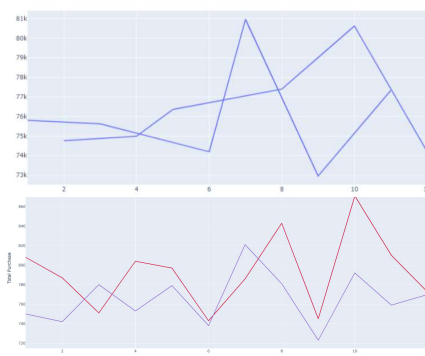
Conclusion

- Target state
- Target Product line
- Target Brand
- Target Selling mode – Online/Offline based on area
- Target segmented group
- Target Age group

Learned through error:



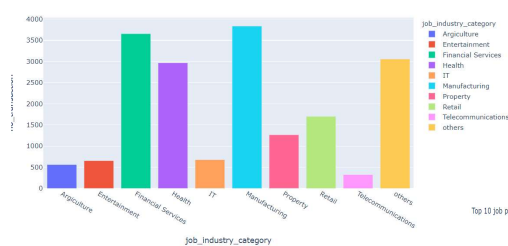
state
 ● NSW
 ● VIC
 ● QLD



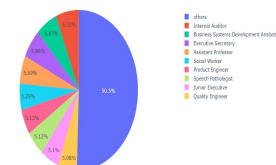
Extra work for fun



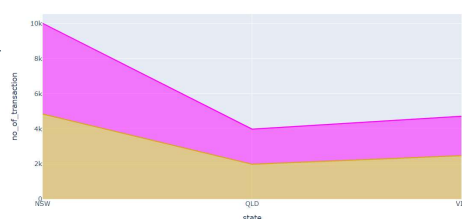
No. of transaction with job industry category



Top 10 job profile customers

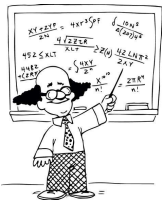


No. of transaction in each state with and without cars



Great Thanks to

Our talented and helpful teachers and ReDI School



TEACHERS

