TheAnalyticsTeam

Sprocket Central Pty Ltd

Data analytics approach

[Division Name] - [Engagement Manager], [Senior Consultant], [Junior Consultant]

Agenda

1. Introduction
2. Data Exploration
3. Model Development
4. Interpretation

Introduction

Finding Target Customers from New Customer Datset.

Problem:

Sprocket Central Pty Ltd, a medium size bikes & cycling accessories organisation has approached KPMG. Their marketing team is looking to boost there business by analysing their existing customer dataset to find trends and patters. They have provided us with a list of 1000 potential customer, with their demographics and attributes with no prior transaction with the company before.

Solution:

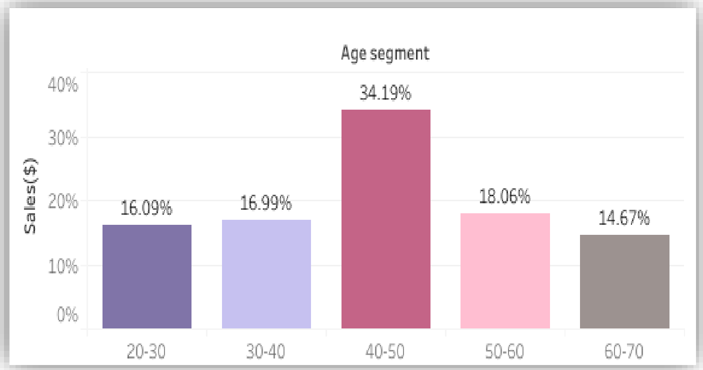
1. Analyse the data of the existing customer data set
2. Finding trends and patterns with different attributes like gender, job industry category, wealth segment, etc.
3. Calculate RFM score to recognise customer value and train our machine learning model.
4. Predict RFM score with the help of the model for the New Customer list.

Data Exploration

Age-Segment

Insights:

- Customers between the age of 40 to 50 are responsible for 34.2% of over-all Sales.
- Other age segments contribute to fairly same kind of figures for Sales
- Negligible sales for ages below 20 and above 70.

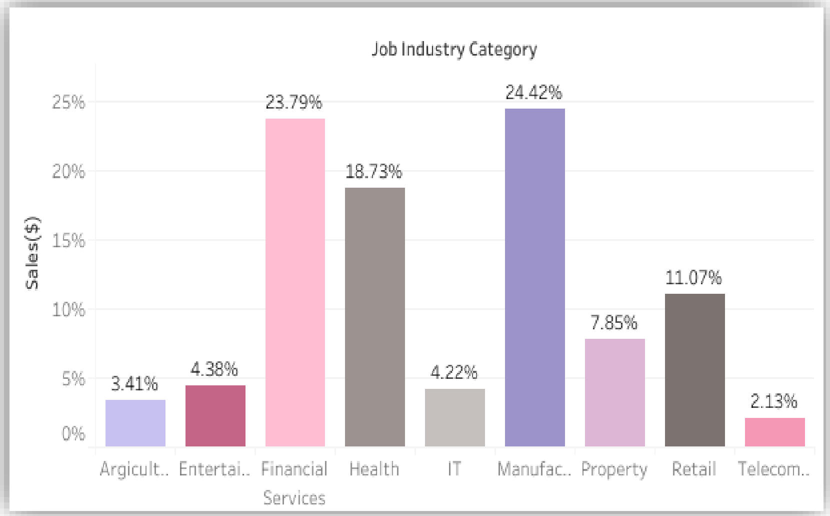


Data Exploration

Industry

Insights:

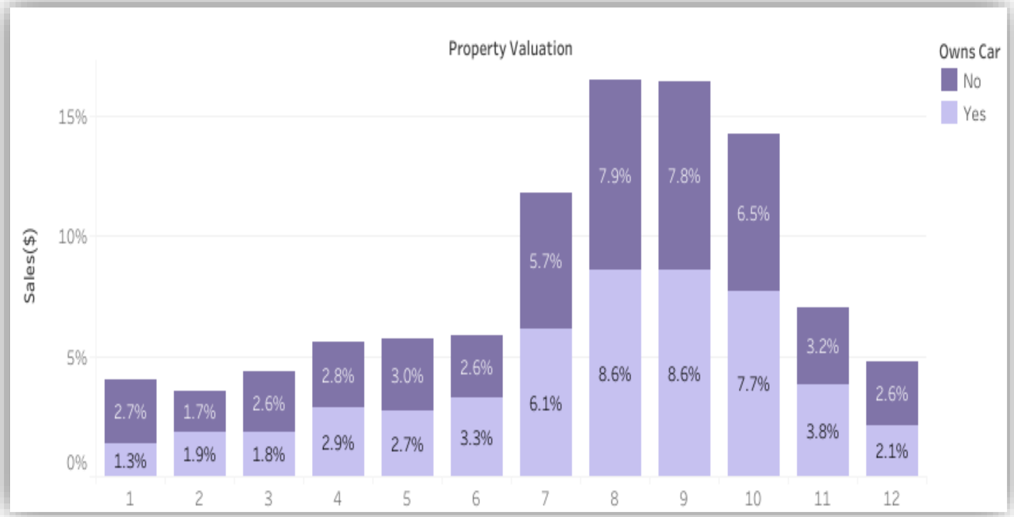
- Customer from financial services and Manufacturing contribute nearly same and combine for almost half of the sales(48.21%).
- Health sector follows with 18.73% of the sales.
- These three industries are responsible for almost 2/3rd of the total sales



Property Valuation and Car Owner-Ship

Insights:

- Most sales came from customers with property valuation between 7 and 10.
- Almost 60% of sales were generated by these customers.
- Customers with car owner-ship are slightly more profitable

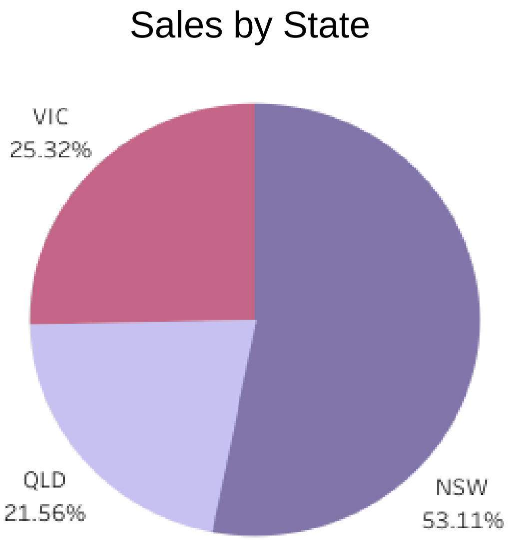


Data Exploration

State

Insights:

- More than half of the sales came from New South Wales(53.11%).
- As population in all these states are fairly same, it is not the factor for most sales in NSW.



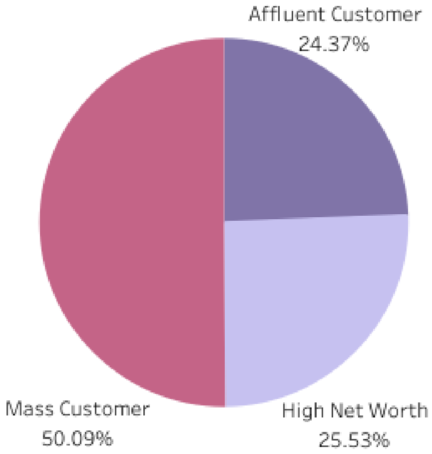
Data Exploration

Wealth Segment

Insights:

- Half of the sales came from Mass Customer segment(50.09%).
- Nearly same sales were generated from Affluent & High Net Worth Customer.

Sales by Wealth-Segment



Model Development

RFM Scoring System

An RFM analysis evaluates clients and customers by scoring them in three categories: how recently they've made a purchase, how often they buy, and the size of their purchases.

The RFM model is based on three quantitative factors:

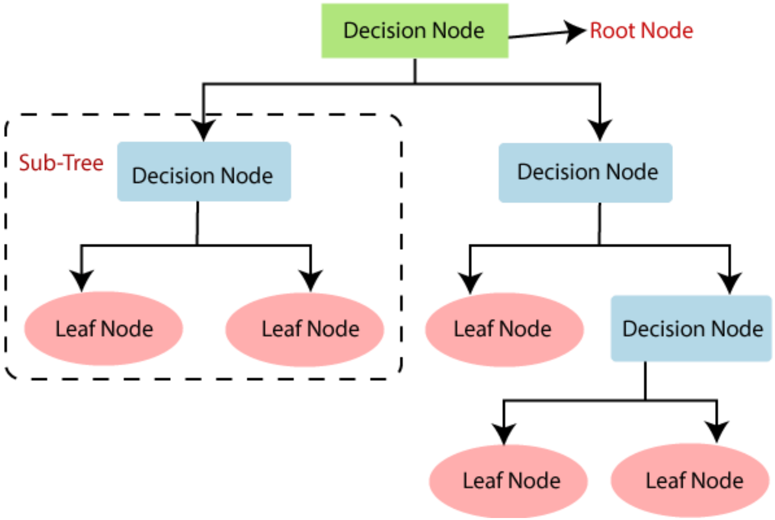
- **Recency**: How recently a customer has made a purchase.
- **Frequency**: How often a customer makes a purchase.
- **Monetary value**: How much money a customer spends on purchases.

	A	B	C	D	E
1	**Customers**	**Recency**	**Frequency**	**Monetary**	**RFM SCORE**
2	Customer A	5	4	5	14
3	Customer B	1	1	1	3
4	Customer C	2	1	1	4
5	Customer D	4	3	3	10
6	Customer E	3	5	5	13
7	Customer F	1	2	2	5
8	Customer G	3	2	2	7
9	Customer H	4	3	3	10
10	Customer I	2	4	4	10
11	Customer J	1	1	1	3
12	Customer K	1	2	1	4
13	Customer L	2	1	1	4
14	Customer M	3	2	2	7
15	Customer N	2	4	3	9

Model Development

Building Decision Tree Model for RFM Prediction.

- To predict the RFM score for New Customer Dataset we are going to use Decision Tree Regressor algorithm for multivariate linear regression.
- Features like age, gender, job industry , etc will be used as input variable (X).
- Output variable (Y) will be the RFM score to perform supervised learning.



Interpretation

Target Customer

- After predicting RFM score of the new customer data set and sorting them in order will give us the best customers to target
- We can take top 100 rows from the sorted table and if needed can filter the best in each category to further narrows down target customers
- List of top 20 potential Customer is on the right.

id	first_nam	last_name	gender	past_3_years_bike_	DOB	Age	job_industry_category	wealth_segment	deceased_	owns_car	country	property_valuation	rfm_pred
5634	Shellyshe	Bichard	M	96	06-01-1954	69	Financial Services	Mass Customer	N	Yes	Australia	5	9.965437
5554	Jacqui	Devey	F	79	01-10-1995	27	Financial Services	High Net Worth	N	Yes	Australia	8	9.887724
5783	Calhoun	Mussingto	M	98	13-10-1992	30	Health	Mass Customer	N	No	Australia	9	9.724772
5359	Pace	Clemonts	M	99	28-07-1990	33	Retail	High Net Worth	N	No	Australia	7	9.665261
5288	Giana	Staresmea	F	96	20-04-1976	47	Retail	Affluent Customer	N	Yes	Australia	7	9.637
5693	Patrice	Pariss	M	96	15-06-1954	69	Financial Services	Mass Customer	N	No	Australia	5	9.610345
5384	Palmer	Heaven	M	82	18-05-1995	28	Financial Services	Affluent Customer	N	Yes	Australia	6	9.577182
5447	Bunny	Leebetter	F	83	30-04-1966	57	Manufacturing	High Net Worth	N	Yes	Australia	4	9.542815
5871	Lotty	Loach	F	76	23-08-1961	61	Health	High Net Worth	N	Yes	Australia	3	9.5402
5727	Son	Varney	M	75	02-11-1993	29	Property	Mass Customer	N	Yes	Australia	7	9.535061
5517	Zabrina	Margram	F	87	15-05-1964	59	Manufacturing	High Net Worth	N	Yes	Australia	8	9.513102
5759	Flore	Cashen	F	79	21-06-1978	45	Health	High Net Worth	N	No	Australia	4	9.510282
5808	Davie	Blay	M	94	19-12-1985	37	Financial Services	Mass Customer	N	No	Australia	7	9.47251
5209	Tannie	Gambrell	M	92	25-05-1967	56	Financial Services	Affluent Customer	N	No	Australia	4	9.453046
5130	Aurie	Rhead	F	78	28-07-1962	61	Manufacturing	Affluent Customer	N	Yes	Australia	2	9.43325
5010	Rockwell	Matson	M	94	01-01-1995	28	Retail	High Net Worth	N	No	Australia	6	9.399905
5136	Malorie	Votier	F	90	29-05-1990	33	Manufacturing	Affluent Customer	N	No	Australia	5	9.383627
5513	Jodi	Lermit	F	94	30-01-1954	69	Health	Mass Customer	N	Yes	Australia	2	9.377451
5688	Renie	Fiveash	F	92	10-10-1992	30	Health	High Net Worth	N	No	Australia	4	9.372406
5802	Darlleen	Shalcras	F	77	14-09-1980	42	Health	Mass Customer	N	No	Australia	10	9.372222

Appendix