MARKETING ANALTYICS

With an aim to improve product management

OUR COMPANY

Kinship Coffee Roasters is a B2C chain of a third wave **coffee** shop in an around New York, which caters to all sorts of life. Products are coffee and snacks ,with additional merchandise too! It came into existence in the year 2014 and now successfully owns 4 stores.

OBJECTIVES

Customer Segmentation

Modelling Purchase Incidence

Modelling Product Choice

CUSTOMER ANALYTICS

A process by which data from customer behaviour is used to help make key business decisions via market segmentation and predictive analytics. This information is used by businesses for direct marketing, site selection, and customer relationship management.

CUSTOMER DATA

Customer ID

2000 unique entries

Sex

Male/Female

Marital Status

Single/Married

Age

18 -76

Education

Unknown
High School
University
Graduate School

Income

35K-450K

Occupation

Unemployed
Skilled Employee
Management

Settlement Size

Small city
Mid-sized city
Big city

SEGMENTATION

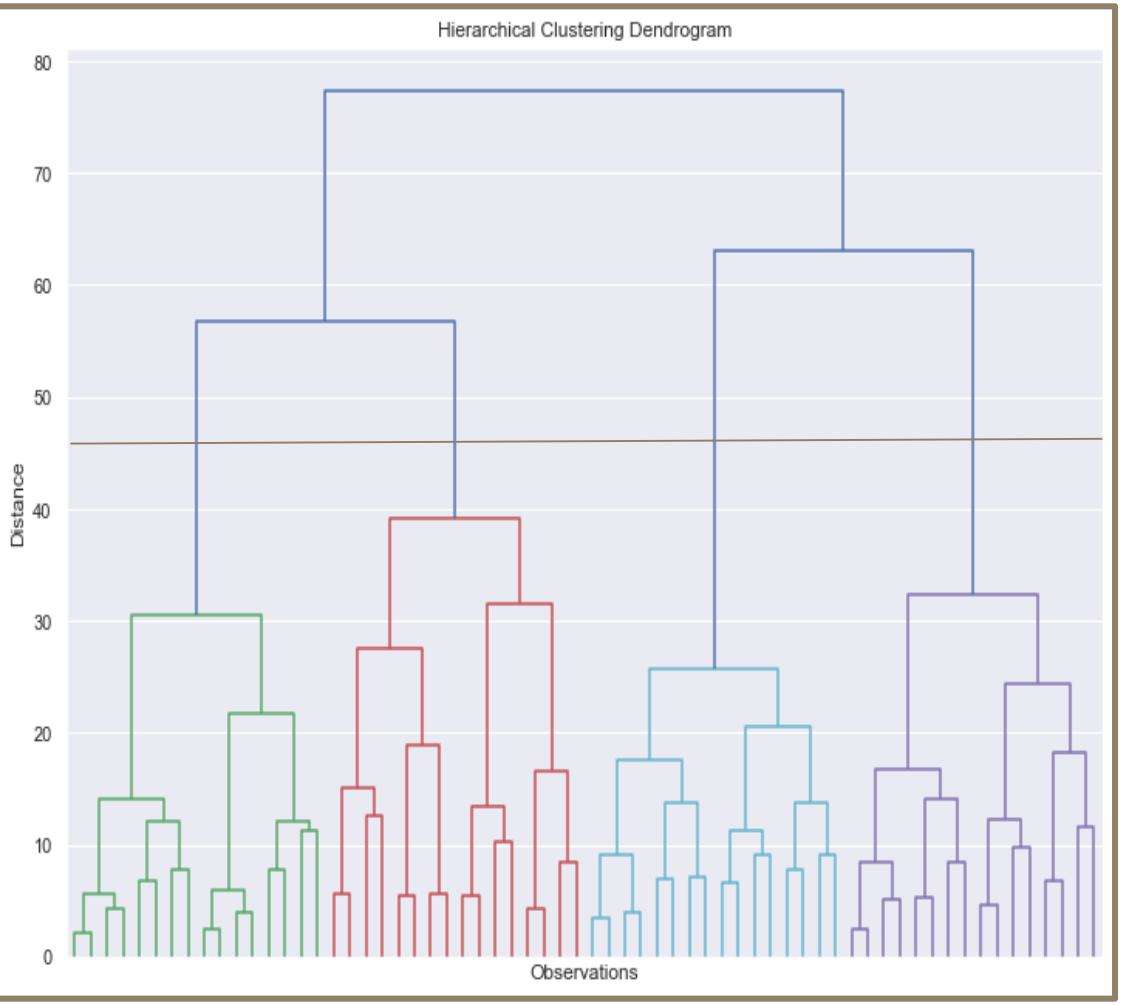
To divide the market into smaller categories

Iterative Distance-Based Clustering :

Hierarchical Clustering

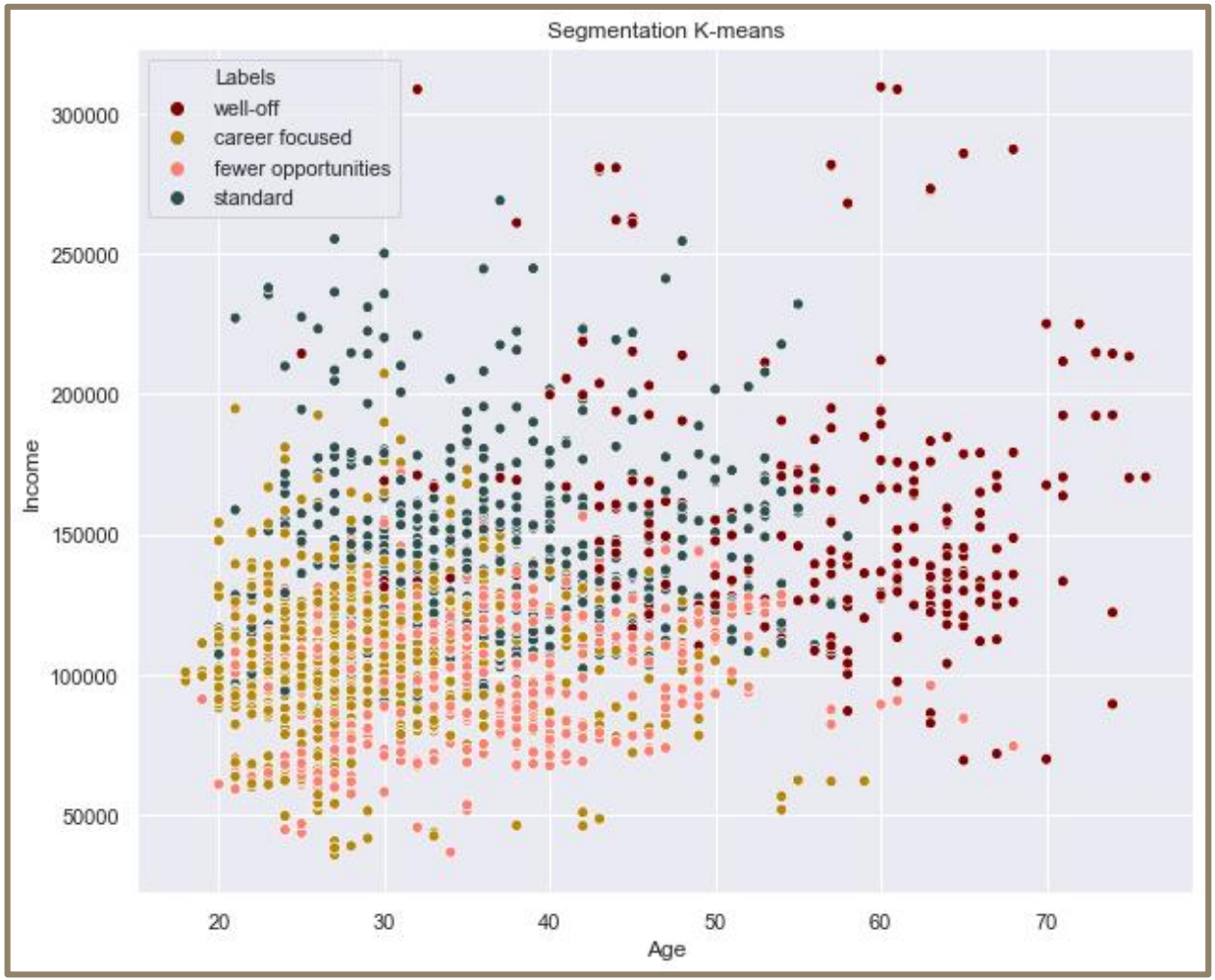
K-means Clustering

K-means with PCA



Hierarchical Clustering

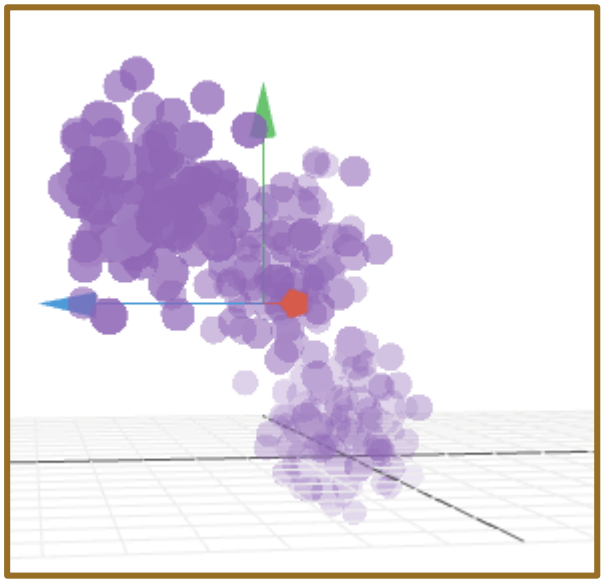
K-Means Clustering



K-Mean Clusters

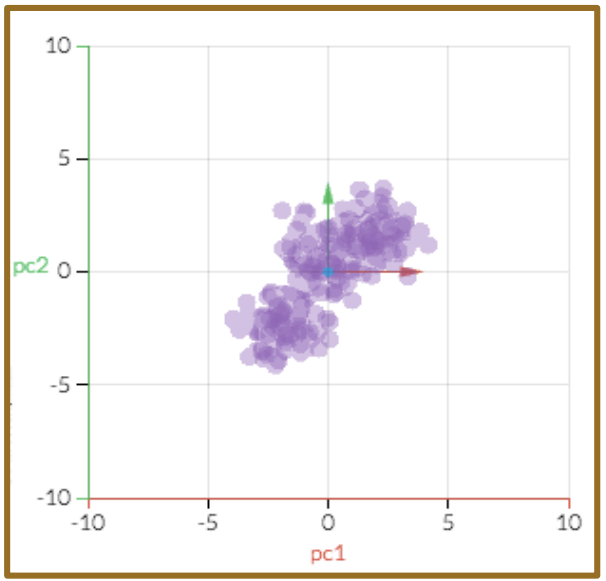
	Sex	Marital status	Age	Education	Income($)	Occupation	Settlement size	N Obs	Prop Obs
Well-Off	Equal	Married	55	University	1,58,338	Skilled	Mid-sized	263	0.1315
Fewer Opportunities	Female	Married	35	High School	97,859	Unemployed	Small City	462	0.231
Standard	Male	Single	34	High School	1,41,218	Skilled	Big City	570	0.285
Career Focused	Male	Married	29	Graduate School	1,05,759	Management	Mid-sized	705	0.3525

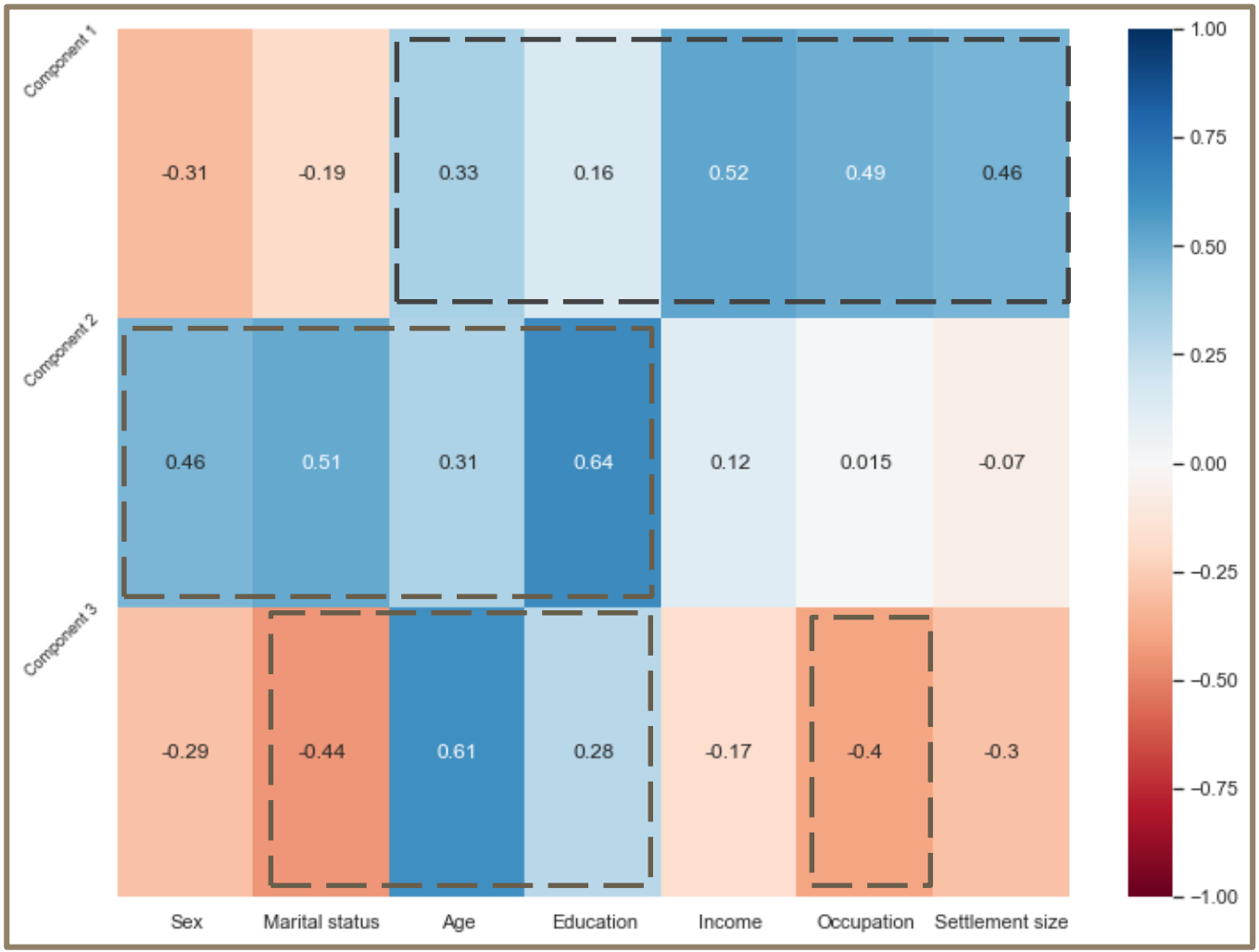
7 Factors



PRINCIPAL COMPONENT ANALYSIS

3 Components





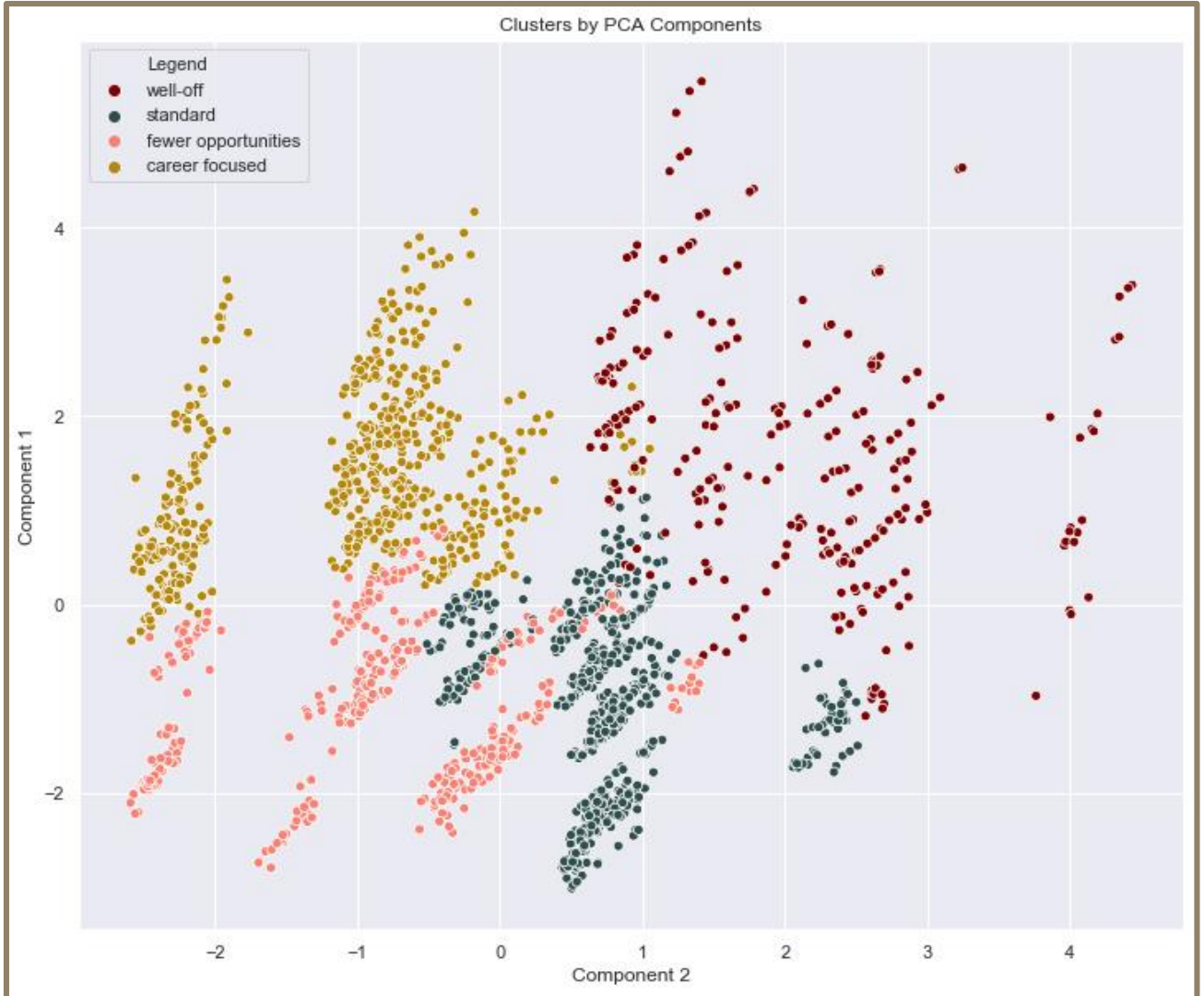
Career

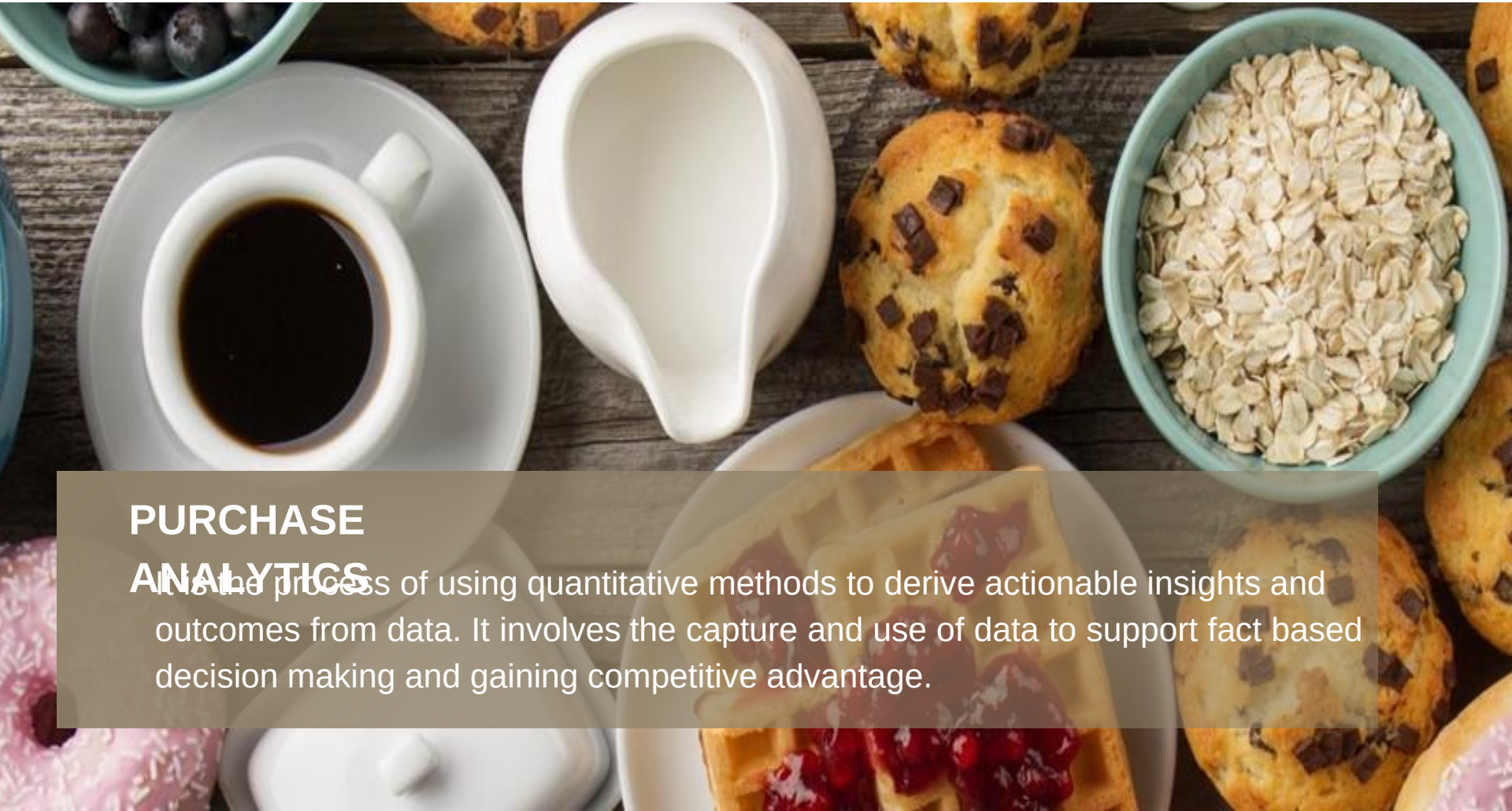
Educational & Lifestyle

Experience

SEGMENTATION WISE COMPONENT

	Component 1 **(CARRER)**	Component 2 **(EDUCATION & LIFESTYLE)**	Component 3 **(EXPERIENCE)**	N Obs	Prop Obs
Well-Off	**1.697646**	**2.029427**	**0.841953**	264	13.2%
Fewer Opportunities	-1.04761	-0.904856	**1.005493**	459	22.5%
Career Focused	**1.372663**	-1.046172	-0.248046	583	29.1%
Standard	-1.106034	**0.7053**	-0.776925	694	34.7%


Clusters by PCA Components
Legend
well-off
standard
fewer opportunities
career focused
Component 1
Component 2
4
2
0
−2
−2
−1
0
1
2
3
4



PURCHASE ANALYTICS

It is the process of using quantitative methods to derive actionable insights and outcomes from data. It involves the capture and use of data to support fact based decision making and gaining competitive advantage.

Customer ID
58693 transactions

Date
2017-2019

Incidence
Food/Top 5 Coffee

Quantity
1-4

Promotion
On promotion/Not on promotion

3.Cappuccino
3.74-4.28

2. Americano
2.52-3.8

4. Cold Brew
3.52-4.52

1. Drip Coffee
2.2-3.18

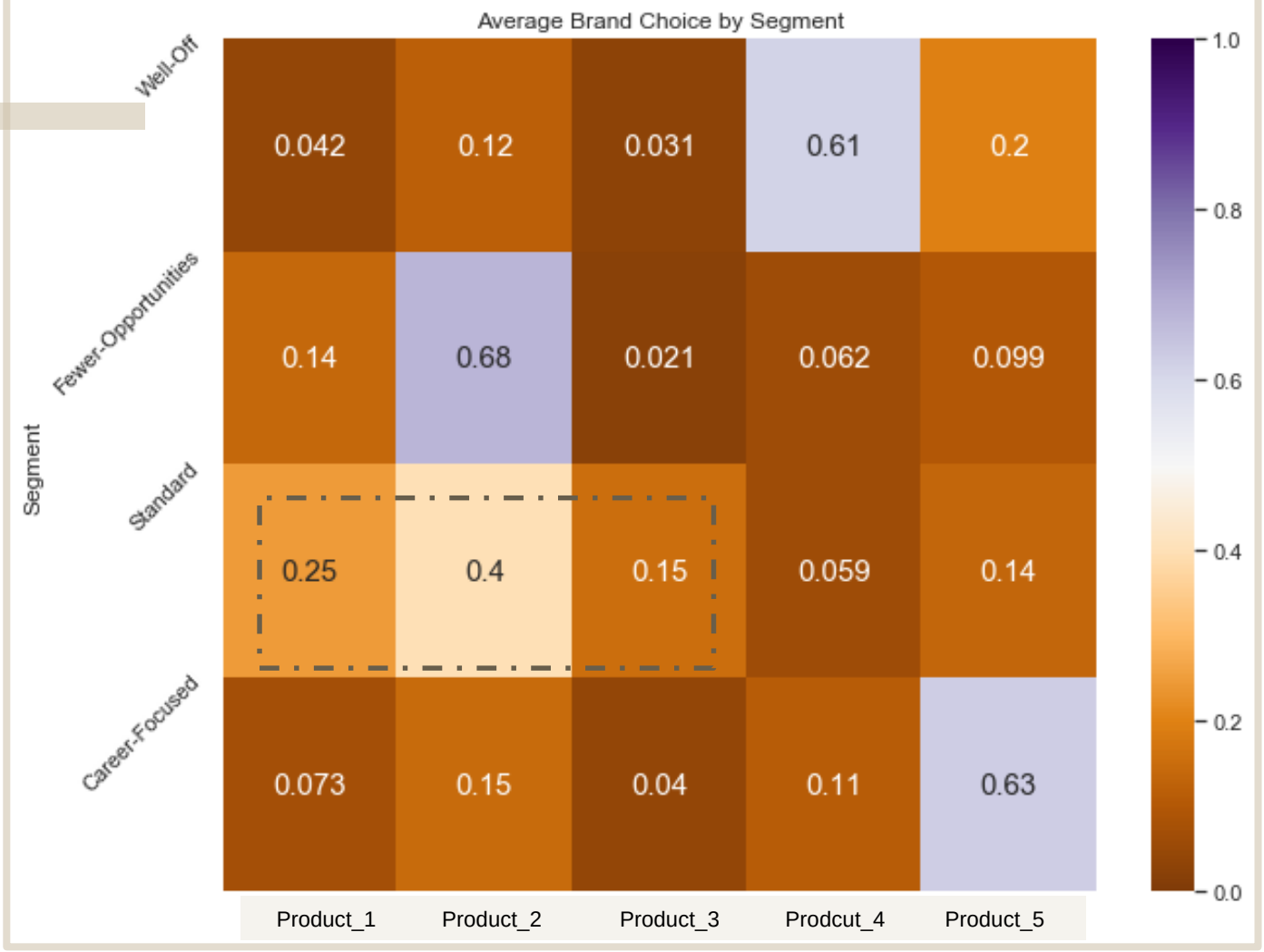
5. Mocha
4.22-5.6

SEGMENT WISE TRANSCATIONS

SEGMENT PROPORTION

WELL-OFF	19.6%
STANDARD	20.8%
CAREER FOCUSED	22.0%
FEWER OPP	37.6%

PRODUCTWISE SEGMENTATION



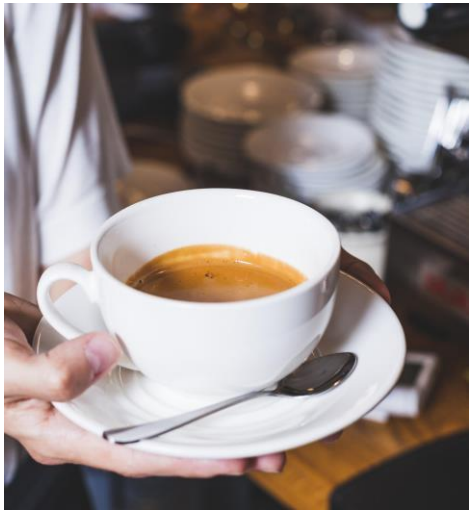
Revenue($)	Revenue P_1	Revenue P_2	Revenue P_3	Revenue P_4	Revenue P_5	Total Revenue	Segment Proportions
Career Focused	1,472.1	3,492.8	1,329.5	4,727.6	38,882.12	49,904.32	22%
Well-Off	1,398.9	2,596.4	1,462.7	28,371.1	11,019.38	44,848.62	19.6%
Fewer Opportunities	4,517.8	27,736.6	1,432.5	3,258.6	4,461	41,406.52	37.6%
Standard	5,222.3	9,710.7	7,818.3	1,722.7	4,879.5	29,353.7	20.8%

Insights

- The Well Off segment has the least number of customers but generates the second highest revenue
- The Standard segment doesn’t show loyalty to any product
- The price of product 4&5 can be increased

Purchase Incidence

To understand how each segment reacts to price change



Logistic Regression

Price Elasticity

Promotion Variable

PURCHASE PROBABILITY

Y
Incidence

X
Avg(Price_1 to Price_5)

Logistic Regression
Price Vs Incidence

Coefficient
-1.2039326

With Increase in Price ,the purchase probability decreases

PRICE ELASTICITY

$$P.E = \frac{\%\ change\ in\ Variable\ of\ Interest}{\%\ change\ in\ the\ Price}$$

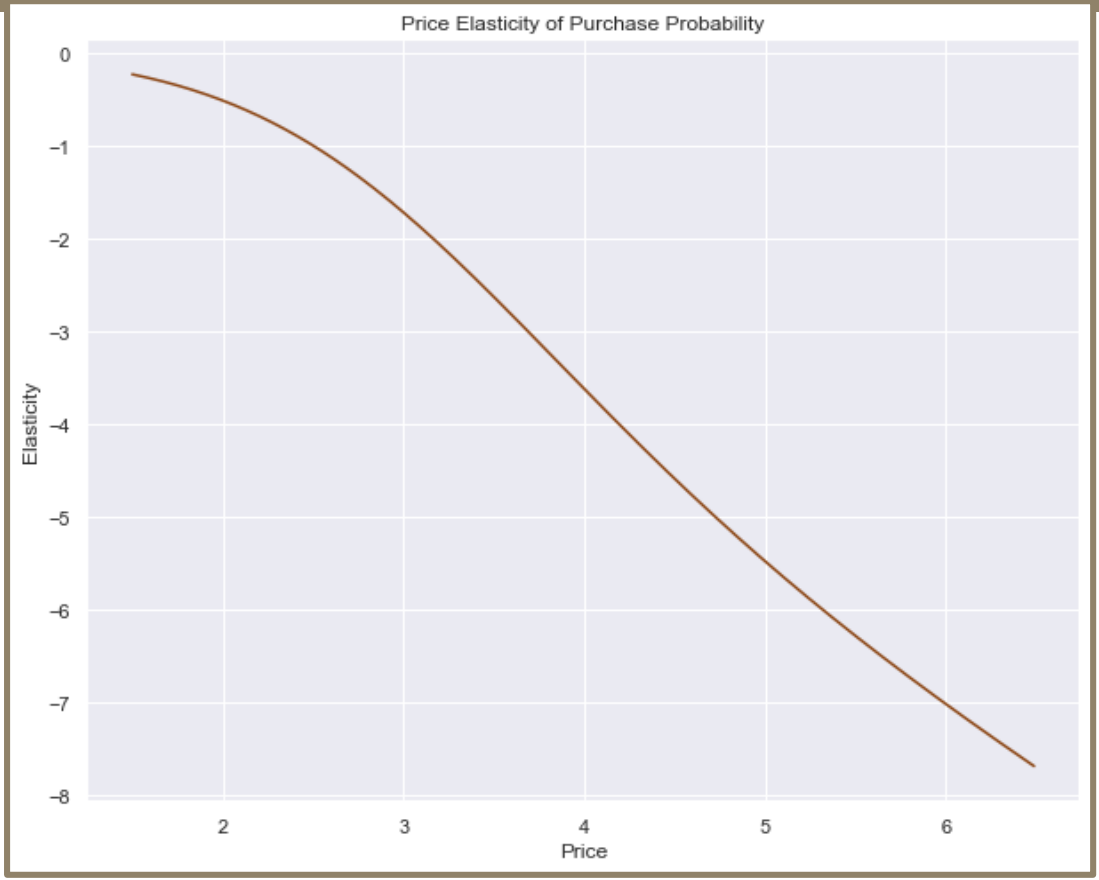
Own Price Elasticity

Price elasticity with respect to the same product

Cross Price Elasticity

Price elasticity with respect to the another product

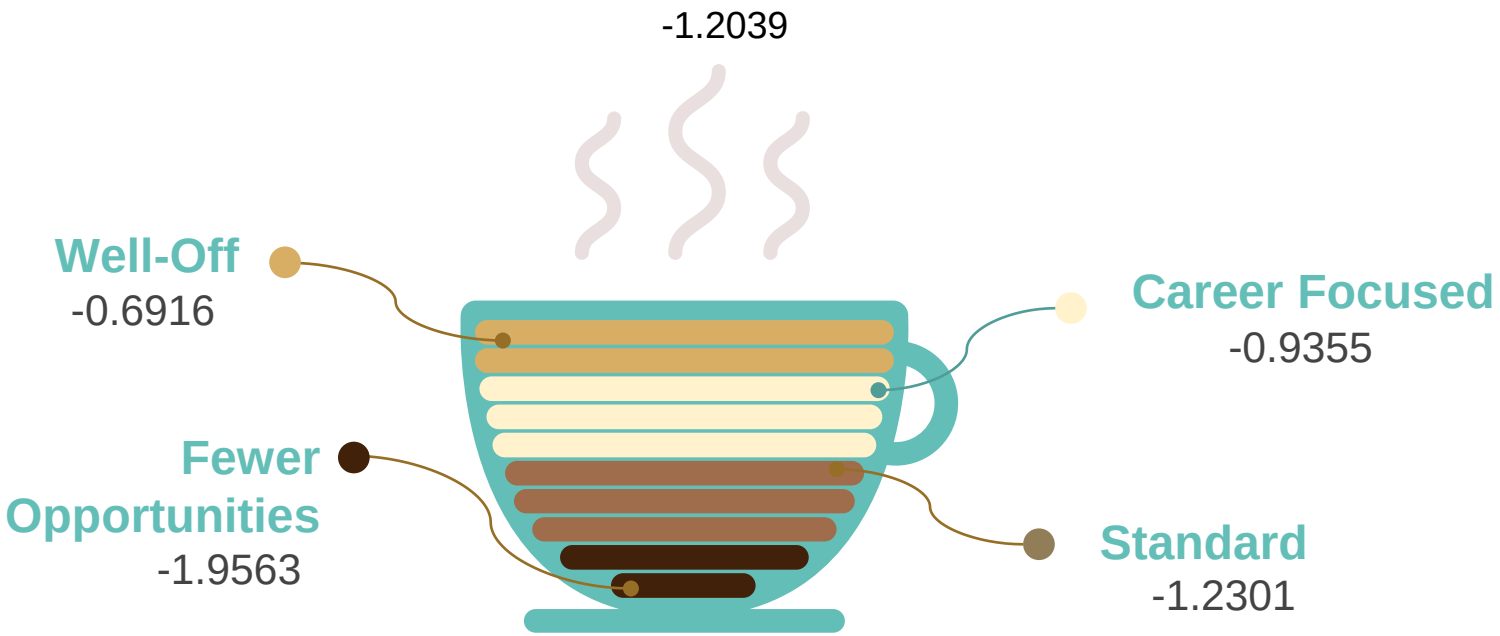
$$E = beta * price * (1 - Pr(purchase))$$

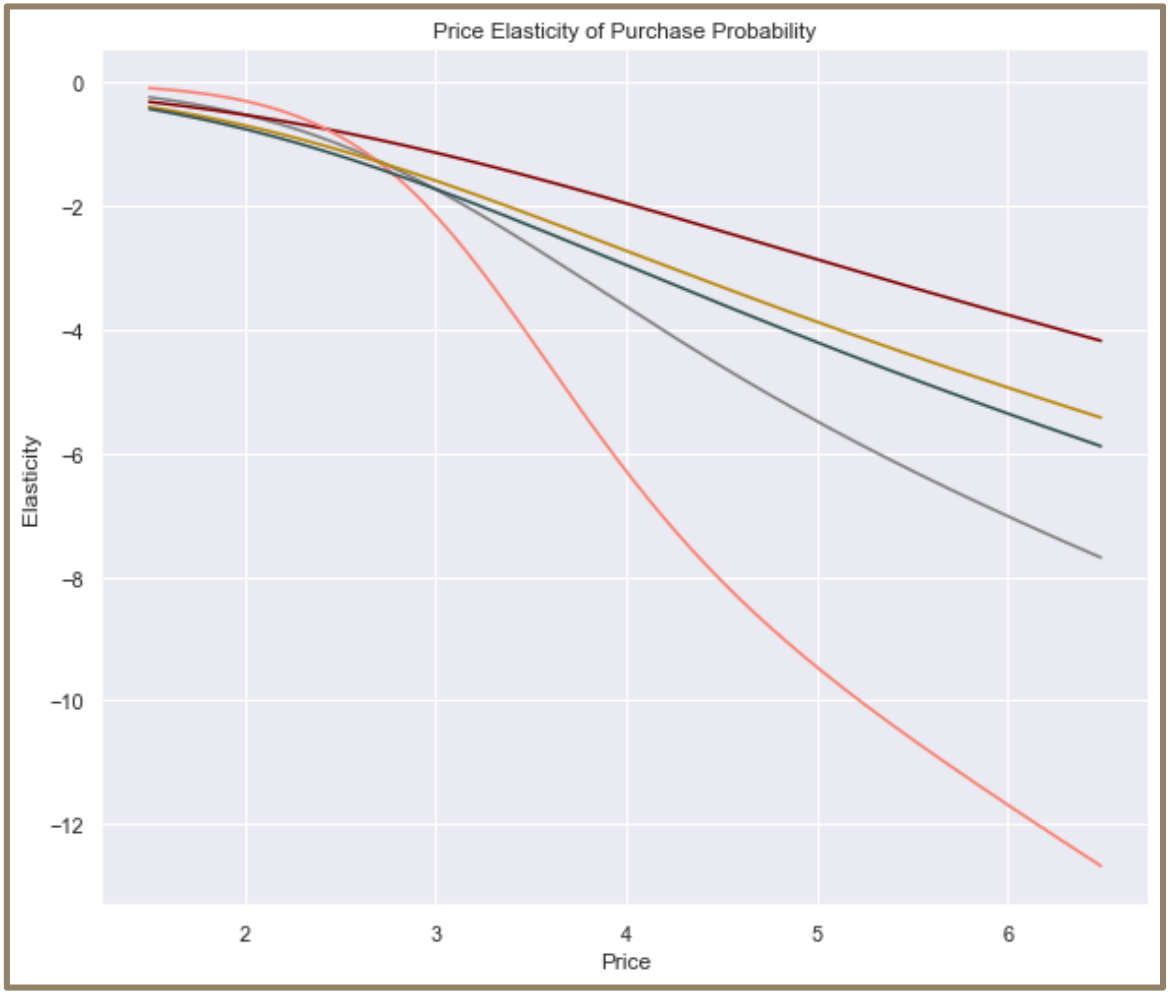


Inelastic |E| <1
Elastic Otherwise

Price Point	2.51

Segmentwise Coefficients





2.31

2.40

2.58

2.82

Promotion-Purchase Probability

X=Promotion

Y = Incidence

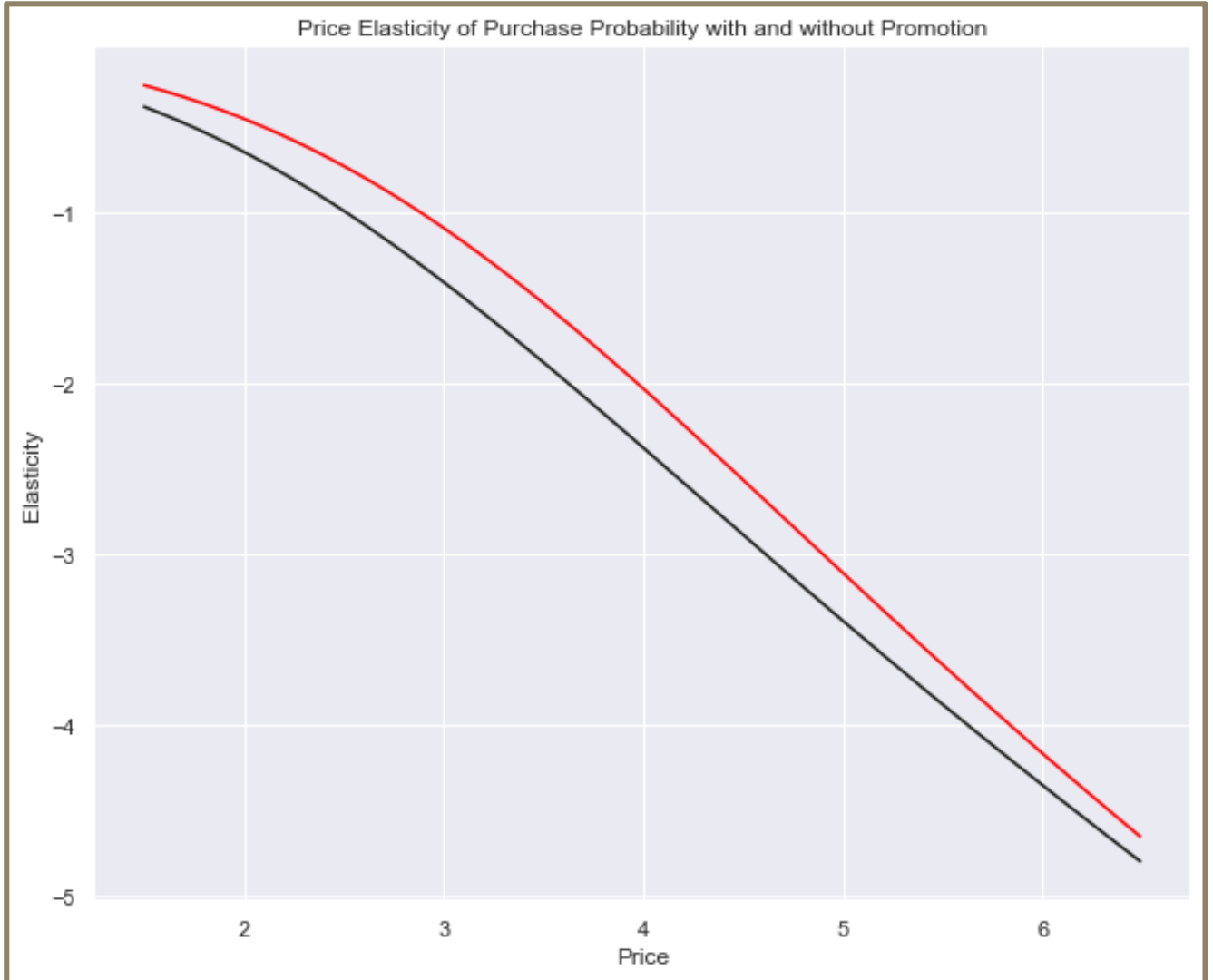
Logistic Regression

X&Y

Coefficient

0.5542825

Price Elasticity of Promotion

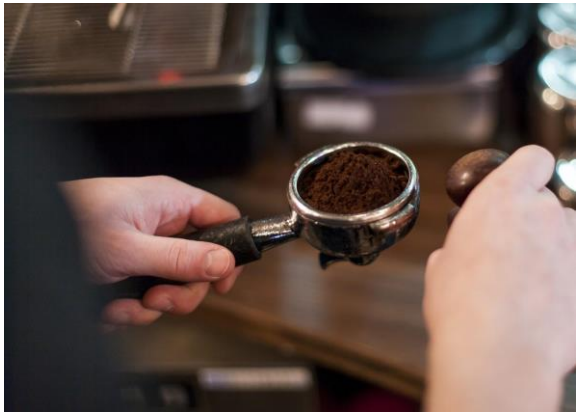


Insights

- Different segments of customer have different tipping points after which the purchase probability becomes elastic
- Customers are less price sensitive to price changes when there are promotion activities
- Fewer Opportunities are elastic to price changes

Product Choice

To analyse each product segment wise



Multinominal Regression

Cross Price Elasticity

Product Management

PRODUCT CHOICE

PRODUCT	PRICE	REGRESSION
Y	X	MULTINOMINAL

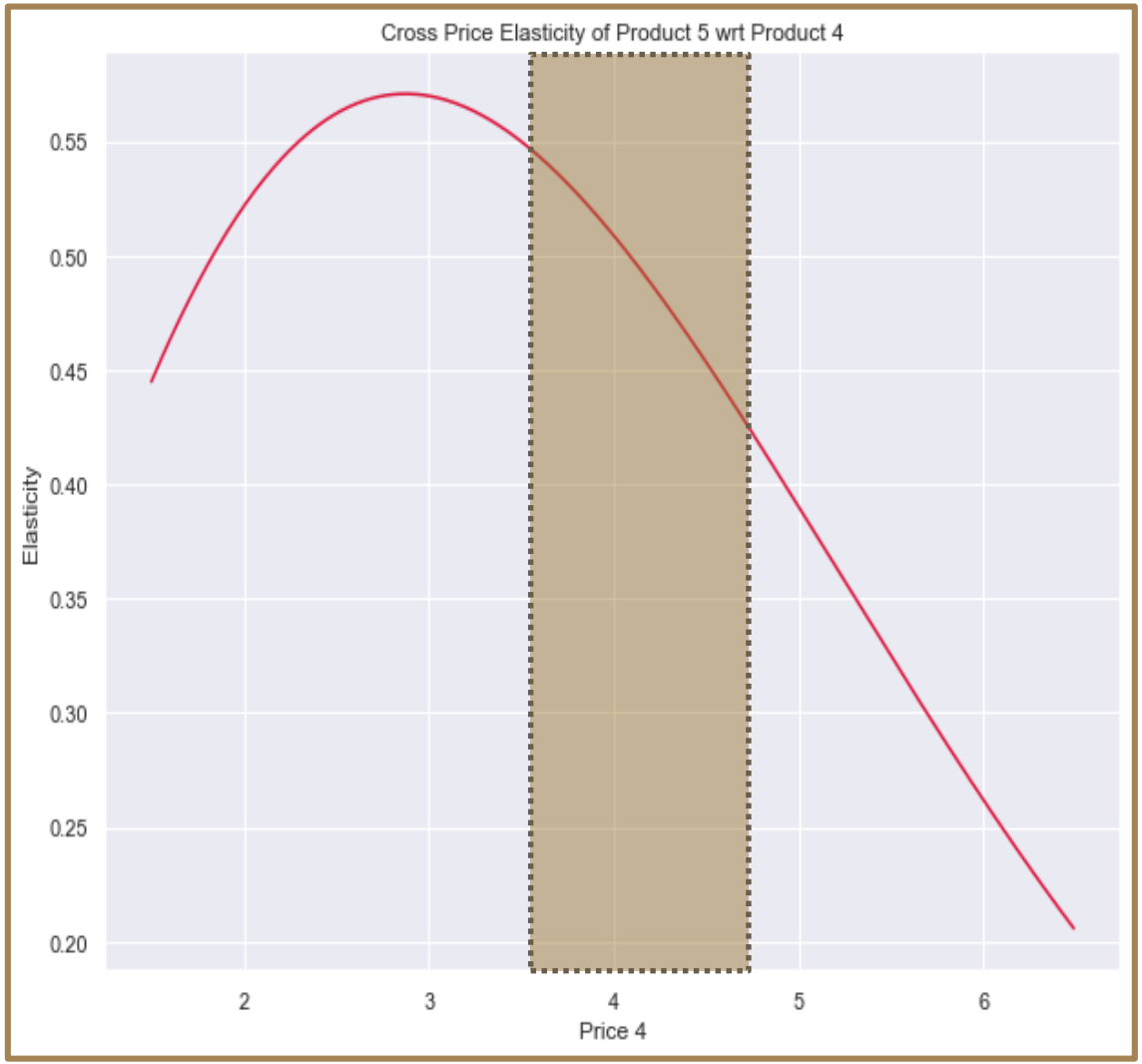
	Coef_Product_1	Coef_Product_2	Coef_Product_3	Coef_Product_4	Coef_Product_5
Price_1	-2.07	0.66	0.86	0.31	0.24
Price_2	0.34	-0.94	0.27	0.2	0.14
Price_3	1.56	-0.12	0.04	-0.77	-0.71
Price_4	0.27	-0.09	0.56	-0.61	-0.12
Price_5	-0.11	0.31	0.17	0.16	-0.54

Cross Price Elasticity

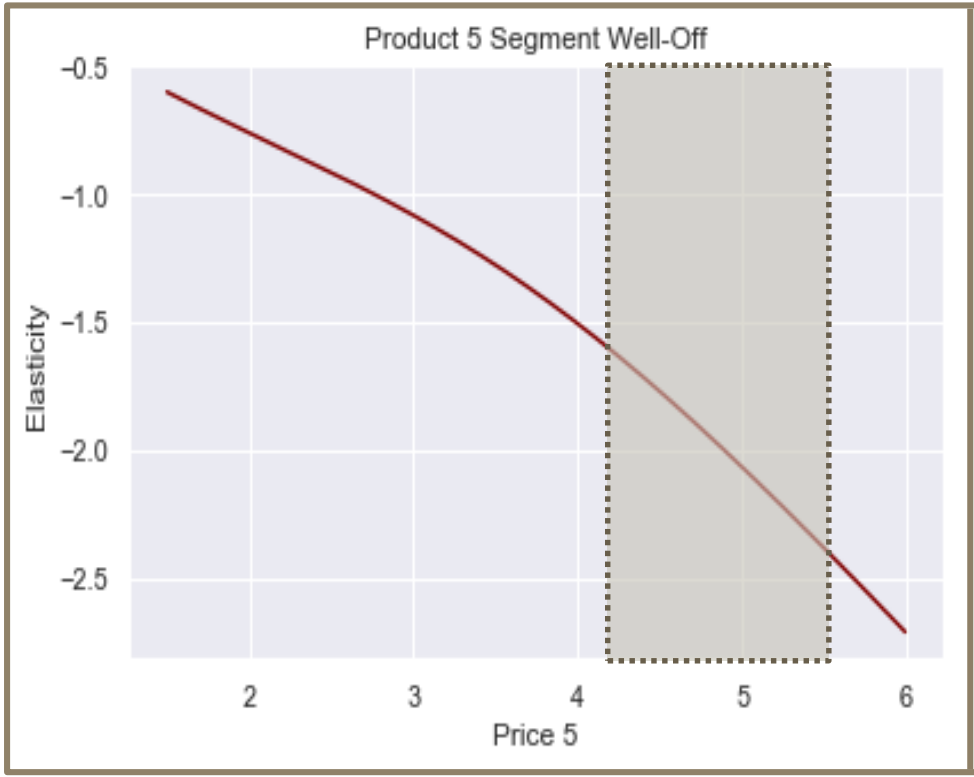
VS

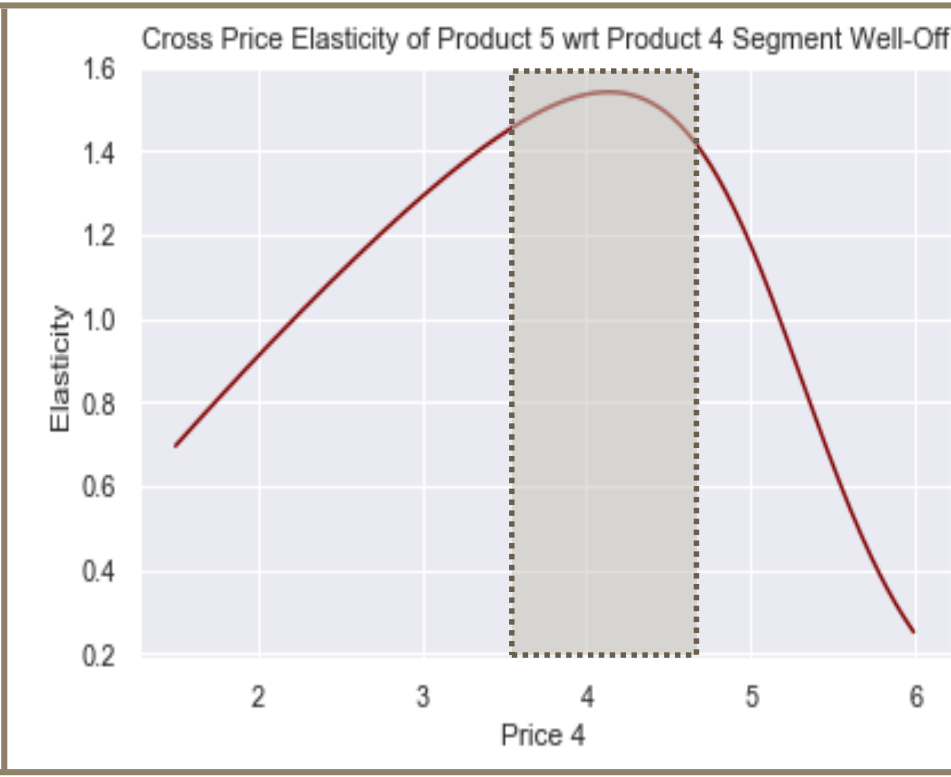
Product 4

$$E = -beta(own\ price) * price(cross\ brand) * Pr(cross\ brand)$$



E(Cross product) > 0
Substitute


Product 5 Segment Well-Off
Elasticity
−0.5
−1.0
−1.5
−2.0
−2.5
2
3
4
5
6
Price 5


Cross Price Elasticity of Product 5 wrt Product 4 Segment Well-Off
Elasticity
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
2
3
4
5
6
Price 4

Price_Point	Product 5	P_5_Cross_P_4
4.79	-0.5154	0.1564
4.8	**-0.5179**	0.1558
4.81	-0.5204	0.1553

Price_Point	Product 5	P_5_Cross_P_4
3.99	-0.3485	0.20187
4	-0.3503	**0.2013**
4.01	-0.3520	0.20074

Market Gain

Insights

- Product 1 and Product 2 are strong substitutes compared to 4&5
- Standard segment is more elastic than the average customer for product 5
- Career Focused segment are unlikely to switch any other product

Limitations

- The data available was only of two years
- Our analysis focused just on the top 5 coffee products of the shop
- Customer Lifetime Value was not taken into consideration
- Quantity factor was not taken into account

Future Scope

- Working on the analysis of all the products offered by the coffee shop
- Building a deep learning model to predict whether a customer will convert again or not
- To model the purchase quantity, thus manage supply
- Create a new variable and calculate Customer Lifetime Value

SUGGESTION
S

**Promotions to product 1,2,3 can pro
beneficial**

**Reducing the Price of Product 3,will
generate more revenue**

**Improving Customers experience for
Well_Off and Career_Focused segment**

Conclusion

- Customer segmentation provides a very beautiful insight in understanding the different types of customer, By modelling purchase incidence and product choice we can find out what price and product suits the best for customers in different segments.

- Applied holistically, marketing analytics allows for better, more successful marketing by enabling marketers to close the loop as it relates to your marketing efforts and investments.

CHALLENGES FACED

Acknowledgement

- A sincere thank you to our internal mentor Mr. Sunil Shirvaiker and Mr. Ketan Solanki for guiding us throughout our project.

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THANK YOU

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