MCA ASSIGNMENT SOLUTIONS

by Group-02 - AMPBA[2025]

Question 1: Product Optimization Exercise

Answer: Given dataset has three different water bottles and their characteristics on five features - Price, Time Insulated, capacity, Cleanability, Containment and Brand Name.

- 311 Users preference ratings on these features and there inference ratings
- Cost of manufacturing Water bottle with different features per bottle
- We have calculated In utility matrix for five products. And calculated market share of each product.

Products	Market Share (%)
Product A	33.05
Product B	45.97
Product C	20.97

For Product C Expected Profit per Person is calculated as $ 4.69 & Revenue is $6.29

Sub Q1: Using the compensatory rule with logit adjustment: Calculated Product C Cost, EPP, Market Share and Revenue calculation for Product C is shown below:

```
LexicalDf.iloc[44,:]
✓ 0.0s

Price                               $30
TimeInsulated                     1 hrs
Capacity                          20 oz
Cleanbility                        Easy
Containment              Leak Resistant
TimeCost                         1.0000
CapacityCost                     2.6000
CleanabilityCost                 3.0000
ContainmentCost                  1.0000
TotalCost                        7.6000
TotalGM                         22.4000
MktShare                         0.2097
EPP                              4.6967
Revenue                          6.2902
Name: 44, dtype: object
```

Sub Q2: Discrete Optimization: I have generated Lexical table for all 243 products and calculated their Cost,Market Share, Expected Profit Per Person & Revenue.

Name of the file is: DiscreteOptimizationResults.csv

Details of Product 106:

```
LexicalDf.iloc[105,:]
✓ 0.0s

Price                            $10
TimeInsulated                0.5 hrs
Capacity                       32 0z
Cleanbility                     Easy
Containment          Slosh Resistant
TimeCost                      0.5000
CapacityCost                  2.8000
CleanabilityCost              3.0000
ContainmentCost               0.5000
TotalCost                     6.8000
TotalGM                       3.2000
MktShare                      0.2117
EPP                           0.6774
Revenue                       2.1170
Name: 105, dtype: object
```

Details of Product 230:

```
LexicalDf.iloc[229,:]
✓ 0.0s

Price                             $5
TimeInsulated                  3 hrs
Capacity                       20 oz
Cleanbility                     Fair
Containment          Spill Resistant
TimeCost                      3.0000
CapacityCost                  2.6000
CleanabilityCost              2.2000
ContainmentCost               0.8000
TotalCost                     8.6000
TotalGM                      -3.6000
MktShare                      0.5365
EPP                          -1.9314
Revenue                       2.6825
Name: 229, dtype: object
```

243 Product chart with MarketShare against EPP is shown below:

Sub Q3: Product with highest EPP is shown below:

```
LexicalDf.iloc[LexicalDf.idxmax(axis=0)['EPP'],:]
✓ 0.0s

Price                          $30
TimeInsulated                3 hrs
Capacity                     20 oz
Cleanbility                   Easy
Containment         Leak Resistant
TimeCost                    3.0000
CapacityCost                2.6000
CleanabilityCost            3.0000
ContainmentCost             1.0000
TotalCost                   9.6000
TotalGM                    20.4000
MktShare                    0.2827
EPP                         5.7671
Revenue                     8.4810
Name: 71, dtype: object
```

Sub Q4.1: See the characteristic of product with Highest Mkt Share:

```
LexicalDf.iloc[LexicalDf.idxmax(axis=0)['MktShare'],:]
✓ 0.0s

Price                          $5
TimeInsulated               3 hrs
Capacity                    20 oz
Cleanbility                  Easy
Containment        Leak Resistant
TimeCost                   3.0000
CapacityCost               2.6000
CleanabilityCost           3.0000
ContainmentCost            1.0000
TotalCost                  9.6000
TotalGM                   -4.6000
MktShare                   0.7505
EPP                       -3.4523
Revenue                    3.7525
Name: 233, dtype: object
```

Profit (P) = MarketSize x MarketShare(P) x [Price(P) - MarginalCost(P)] - FixedCost(P)

Profit of the product is multiples of market share. And follows linear relationship. And for a product - high market share gives strategic advantage because it already demonstrates strong consumer preference or product-market fit. And also imply widespread acceptance and greater visibility in the market.

Sub Q4.2: Product with highest Gross Margin:

```
LexicalDf.iloc[LexicalDf.idxmax(axis=0)['TotalGM'],:]
✓ 0.0s

Price                           $30
TimeInsulated               0.5 hrs
Capacity                      12 oz
Cleanbility               Difficult
Containment         Slosh Resistant
TimeCost                     0.5000
CapacityCost                 1.0000
CleanabilityCost             1.0000
ContainmentCost              0.5000
TotalCost                    3.0000
TotalGM                     27.0000
MktShare                     0.0170
EPP                          0.4590
Revenue                      0.5100
Name: 0, dtype: object
```

Product with highest gross margin gives below advantages: Gross Margin is revenue post deducting product raw material expenses. And this product has least expenses and highly priced gives option for discount promotion, though its at low market share. Higher GM gives good EPP from each dollar of revenue earned.

Sub Q4.3 Products with lowest Cost:

```python
LexicalDf[LexicalDf['TotalCost']==LexicalDf['TotalCost'].min()].T
```
✓ 0.0s

	0	81	162
Price	$30	$10	$5
TimeInsulated	0.5 hrs	0.5 hrs	0.5 hrs
Capacity	12 oz	12 oz	12 oz
Cleanbility	Difficult	Difficult	Difficult
Containment	Slosh Resistant	Slosh Resistant	Slosh Resistant
TimeCost	0.5000	0.5000	0.5000
CapacityCost	1.0000	1.0000	1.0000
CleanabilityCost	1.0000	1.0000	1.0000
ContainmentCost	0.5000	0.5000	0.5000
TotalCost	3.0000	3.0000	3.0000
TotalGM	27.0000	7.0000	2.0000
MktShare	0.0170	0.0836	0.1704
EPP	0.4590	0.5852	0.3408
Revenue	0.5100	0.8360	0.8520

Above shown products are Lowest Cost products with $3, however, the price of the products & their Market Share made Profit realisation different. So more than cost of product; market share and price helps in maximizing revenue and price. From marketing perspective- **lowest-cost product** can help penetrate price-sensitive markets or support aggressive pricing strategies. This approach works well in volume-driven markets where winning on affordability can lead to cumulative gains even if per-unit profits are low.

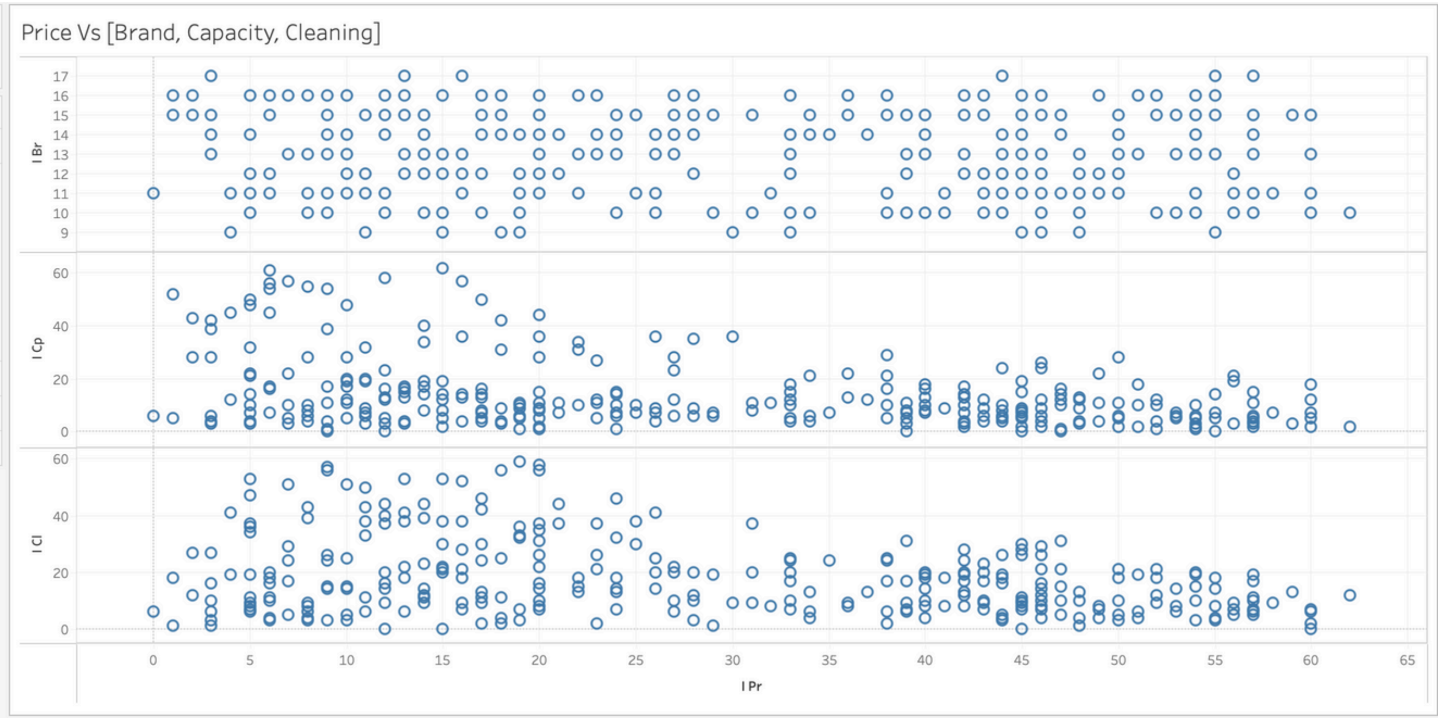
Sub Q4.4 Product with highest revenue per person:

```python
LexicalDf[LexicalDf['Revenue']==LexicalDf['Revenue'].max()].T
```
✓ 0.0s

	71
Price	$30
TimeInsulated	3 hrs
Capacity	20 oz
Cleanbility	Easy
Containment	Leak Resistant
TimeCost	3.0000
CapacityCost	2.6000
CleanabilityCost	3.0000
ContainmentCost	1.0000
TotalCost	9.6000
TotalGM	20.4000
MktShare	0.2827
EPP	5.7671
Revenue	8.4810

Product with highest revenue with help to monetise more money from each person in the market. This is achieved either with higher market share and modest price, or higher price with modest mkt share. Maximizing revenue is every product manufacturer dream. So he has to keep price higher and

Given 311 Customer Preference * Inference Matrix has been plotted on Scatter Plot below:



These parameters to be scaled for better customer segments visibility.

Question 2: Product Affinity based segmentation

Answer:There are three product segments in the provided customers

With our calculated data average within-segment mean values of inference parameters is below:

	ProductA	ProductB	ProductC
income	58.7130	50.7217	58.5110
age	46.2999	43.3833	46.4186
sports	0.4704	0.2025	0.4092
gradschl	0.3723	0.2971	0.3565
Price	20.4856	38.7165	21.7185
Insulation	13.5514	9.0576	10.6994
Capacity	14.3687	12.3397	14.5441
Cleaning	19.6418	14.5638	20.4457
Constalation	18.9232	12.4038	19.5518
Brand	13.0502	12.8947	13.0597

Price is the most important attribute with an average within-segment mean of 21.72 and that the most distinguishing demographic variable, where the log-lift is furthest away from zero, is gradschl with a log-lift of 0.0180.

Please find the segment description of each product.

Product	***Positioning Style***	***Segment Fit***	***Ideal Customer***
A	*Balanced Performer*	*Strong overall fit*	*Functional mainstream buyers*
B	*Value Outlier*	*Poor fit*	*Deep-discount shoppers/promos*
C	*Affordable Specialist*	*Good price-duration fit*	*Price-conscious but quality-seeking users*

Product A – The Balanced Performer

Positioning: Product A is ideal for **practical, quality-conscious customers** looking for an everyday solution with **reliable cleaning, capacity, and leak protection**. It's the **most balanced product**, appealing to the **core customer segment**.

Product B – The Value Outlier

Positioning: Product B targets **price-sensitive buyers** but misaligns with what the broader segment values. It's a **value option** with basic features but may be better suited for **budget or promotional campaigns**, not the core segment.

Product C – The Affordable Specialist

Positioning: Product C is a value-oriented alternative that aligns well with the price expectations of the target segment. While it doesn't outperform in cleaning or durability like Product A, it delivers adequate quality at a better-aligned price point, making it suitable for cost-conscious yet quality-aware buyers.

Question 3: Paid Search Bid Optimization

The workings of question is

Answer 3.a: Curve fitting is done in notebook and

Used custom function and reduced loss by training step and used optax optimizer to take the step towards optimization [reducing RMSE] and found less loss and best fit alpha and beta values; listed them below:

```
# ✅ Define model
class SaturationModel(nn.Module):
    def __call__(self, x, alpha, beta):
        return alpha * (1 - jnp.exp(-beta * x))
```

Result metrics of alpha and beta along with their RMSE:

KeyWord	RMSE	Alpha	Beta
kw8322228	5.053	74.0858	0.0395
kw8322392	13.1469	101.1043	0.3314
kw8322393	5.6378	90.9805	0.1031
kw8322445	32.0930	91.0318	1.1437

Answer 3.b: Optimal Bids have been found

Keyword	Optimal Bid	Max Profit
kw8322228	$ 34.119	$ 3952.6018
kw8322392	$8.6093	$4698.0386
kw8322393	$19.8118	$5153.7559
kw8322445	$3.2284	$3037.6401

Answer 3c: Budget Allocation across the keywords

Keyword	Optimized Bid ($)	Clicks	Cost ($)	Profit ($)	Budget Allocation (%)
kw8322228	18.010000	37.709999	679.049988	3325.669922	22.639999
kw8322392	8.560000	95.18000	814.659973	4697.990234	27.160000
kw8322393	16.370001	74.150002	1213.589966	5081.700195	40.450001
kw8322445	3.230000	88.760002	286.440002	3037.639893	9.550000

Question 4: <u>Display Advertising Assessment</u>

Answer 4.A: Five Product details successful clicks have been provided

Ad	1	2	3	4	5
Clicks	52	38	51	45	25
Exposures	1000	1000	1000	1000	1000
Higher CTR Wins [100,000]	4621	70246	25109	24	0
Mean Volume Wins per[100,000]	1346	13907	1627	4548	78572
CTR* Mean Volume wins [100,000]	17329	20449	17593	16582	28047

Rank Metrics of Ads

Adds	Rank Order as per Higher CTR	Rank Order as per Mean Volume	Rank Order as per CTR vs Mean Volume
Ad 1	3	5	4
Ad 2	1 -	2	2
Ad 3	2 -	4	3
Ad 4	4	3	5
Ad 5	5	1	1

Probabilities of these ads getting clicked or in the attached Ipython notebooks. Change in the ranks of Ads is shown in below graph. The probabilities have been normalized.

The add with less success clicks has been shown higher volume to generate mean value.


Probabilities of Campaign with CTR and Volume
Probabilities
CTR Prob
Volume Prob
Combined Score
0.8
0.6
0.4
0.2
0
Ad 1
Ad 2
Ad 3
Ad 4
Ad 5
Ad Campaigns
Probabilities