ABInBev

Hackathon 2025

Problem Statement

Evaluation KPIs

Data Dictionary

Submission Guidelines

To ensure your submission is accepted without errors, please adhere to the following rules strictly:

1. All column names in your submission must exactly match those in the provided submission template.
2. Column names are case-sensitive, so ColumnName and columnname are considered different.
3. The total number of rows in your submission must exactly match the number of rows in the submission template.
4. Your submission must not contain any duplicate rows.
5. All primary key columns from the submission template must be present in your submission.
6. Ensure that all data types in your submission match the format in the template (e.g., numeric fields should not contain text).
7. Submit the file in the .csv format only

Pricing Optimization

Problem Statement

Build data-driven models to optimize portfolio pricing by understanding price elasticity and cannibalization—maximize MACO with smarter pricing!

Round 1 Price Elasticity Model

1. Build a SKU elasticity model using ML or statistical models to predict the impact on volume due to price changes
2. Derive own and cross price elasticities and analyze cannibalization.

Round 2 Pricing Optimizer

1. Build and optimization engine to find the optimal prices for the SKUs in the portfolio based on the PINC maximizing the MACO (Margin OF Contribution) at the country level using the Price Elasticity Model
2. Build an optimizer that can be integrated with the BrewVision tool
3. Submit Github repo for AI evaluation

Round 1 Price Elasticity

Problem Statement

Your task is to develop a statistical or machine learning model that quantifies the **own-price** and **cross-price elasticities** for our product portfolio in one of ABI's market.

- **Own-Price Elasticity:** Model the change in volume for each product in response to a change in its own price. The model should reflect the expected market behavior of negative elasticity (i.e., as price increases, volume decreases).
- **Cross-Price Elasticity:** Quantify how a change in the price of one product affects the demand for other products in the portfolio. Your model should identify and quantify cannibalization, particularly between substitutable products (e.g., within the same brand, beer type, or similar pack sizes). We expect a positive cross-elasticity, indicating that an increase in the price of one product drives an increase in demand for its substitutes.

IMPORTANT: Your model must provide own-elasticity for each SKU in the data. Additionally, each of these SKUs should have cross-elasticities with at least 2-3 other ABI SKUs and 1-2 Competition (Non- ABI) SKUs.

SKU Name Identifier = CONCAT(Brand, Sub-brand, Package, Package Type, Capacity Number, "cc")

Deliverables

Your submission for Round 1 must include:

1. **Volume Predictions:** The output from your elasticity model for the volume prediction on the test data
2. **Elasticity Matrix:** Pairwise SKU own and cross price elasticities for all SKUs in the test data

Evaluation Criteria

1. **Score = 0.25 * Adj R2 + 0.25 * wMAPE + 0.5*Elasticity Adherence**
2. **Elasticity Adherence Criteria:**
   - Own Elasticity should be negative
   - Cross Elasticity should be positive
   - Every SKU should have cross elasticities for atleast 2 other ABI SKUs and 2 non-ABI SKUs

Round 2 Pricing Optimizer (1/3)

In this round, you'll leverage your elasticity matrix to create a powerful **pricing optimizer**. The goal is to move from analysis to action by designing a new pricing structure that maximizes our Margin of Contribution (MACO) while adhering to key business constraints.

Problem Statement

Using the own and cross-price elasticities from Round 1, your task is to **build a pricing optimization engine** that recommends an optimal set of prices for the entire product portfolio at a **SKU** level for different PINCs (Price Increases) at a national level. The primary objective is to **maximize the overall MACO** for the market.

User Inputs

The optimization must be performed on the full portfolio based on these **user inputs**:

- **A National PINC (Price Increase)** that needs to be reallocated across SKUs
- **Price Bounds:** Bounds for the recommended price changes at SKU level

  Example -

  - **MIN:** Current PTC (Price to Consumer) - 300
  - **MAX:** Current PTC + 500

Some important formulae:

- MACO = NR - VILC
- NR = NR/unit * Sales units
- Discount% = Discount/GTO
- Excise% = Excise/GTO
- NR/unit =((PTC/(1+markup))*(1-Discount%-Excise%))/(1+VAT) *[Assume VAT as 19%]*
- Sales unit = (volume * 100000)/ Pack Size
- Target VILC = Base VILC (1+ VILC Growth Rate) *[Assume VILC Growth Rate as 3.78%]*

Round 2 Pricing Optimizer (2/3)

Contraints

Your optimizer must adhere to the following **hard constraints**:

- **Volume should change in accordance with the Industry Volume model:** The final volume must be connected to the PCC model, using elasticities as inputs to determine the new volume mix across the different products in the country. Total Industry Volume should not decline by more than 1%.
  - New Industry Volume = (1-.56*price change) * Old Industry Volume
- **Financial Target:** The target MACO (model output) must be higher than the base MACO (current year).
- **Volume Target:** The target volume (model output) should not decrease by more than 1% or increase by more than 5% compared to the base volume(current year).
- **Total Price Increase (PINC):** The overall portfolio price increase can be between 0-6%, based on a user-defined input.
- **Market Share:** ABI's market share should not drop by more than 0.5%.
- **Pricing Multiples:** All recommended price changes must be in multiples of 50.

You must also consider **soft constraints** to maintain brand hierarchy:

- The Net Revenue per Hectoliter (NR/HL) of different segments must follow the established hierarchy: Value < Core < Core+ < Premium < Super Premium.
- The NR/HL architecture of size groups must follow the hierarchy: Small > Regular > Large.
  - **Small:** An SKU is considered small if the pack_size is less than 300.
  - **Regular:** An SKU is considered regular if its pack_type is 'CAN' and its pack_size is between 300 and 399 (inclusive), or if its pack_type is 'RB' or 'NRB' and its pack_size is between 300 and 599 (inclusive).
  - **Large:** An SKU is considered large if its pack_type is 'CAN' and its pack_size is greater than 399, or if its pack_type is 'RB' or 'NRB' and its pack_size is greater than 599.

Round 2 Pricing Optimizer (3/3)

Deliverables

Your submission for Round 2 must include:

1. **Pricing Optimizer:** The operational code for your optimization model. The model should take the elasticity matrix and user inputs (like PINC target and Price Bounds) and output the optimal pricing recommendations.
2. **Optimized Pricing Plan:** The final pricing recommendation plan and its impact.
    - **Overall Summary:** This table should clearly show the **old price, new price, and the projected impact on key performance indicators (KPIs)**, including:
        1. Volume
        2. Net Revenue (NR)
        3. NR per Hectoliter (NR/HL)
        4. MACO
        5. MACO per Hectoliter (MACO/HL)
    - **SKU level pricing architecture:** A visualization of the new and old prices across SKUs based on the recommendations from the optimizer for the user defined PINC
3. Build an **optimizer** front-end feature that can be integrated with the BrewVision tool

Please note : Additional data for the Pricing Optimizer shall be shared after completion of Round1

Evaluation Criteria

Round 1 Price Elasticity Model

Score = 0.25 * Adj R2 + 0.25 * wMAPE + 0.5*Elasticity adherence

Elasticity Adherence Criteria:

- Own Elasticity should be negative
- Cross Elasticity should be positive
- Every SKU should have cross elasticities for atleast 2 other ABI SKUs and 2 non-ABI SKUs

Round 2 Pricing Optimzier

1. Adherence with the hard constraints
2. Working dynamic visualization of the following :
    - Summary of PINC changes on the financial KPIs
    - SKU Price Architecture – Dynamic visualization of the old prices and the recommended new prices at a SKU level
- Github Repo for AI evaluation

Data Dictionary (1/2)

Sellout Data

Column Name	Description
• DATE	Date of the record
• MARKET	Market or region name
• MANUFACTURER	Name of the manufacturer
• BRAND	Product brand
• SUB_BRAND	Sub-brand or variant
• PACKAGE	Type of package (e.g., bottle, can)
• PACKAGE_TYPE	Descriptor of packaging (e.g., RETORNABLE, NO RETORNABLE)
• CAPACITY_NUMBER	Capacity per unit (usually in ml)
• SALES_VALUE	Total sales value
• SALES_HECTOLITERS	Total sales in hectoliters
• NUMERIC_DISTRIBUTION_STORES_HANDLING	Number of stores handling the product
• AVG_PRICE_PER_LITER	Average price per liter
• INVENTORY_HECTOLITERS	Inventory in hectoliters
• WEIGHTED_DISTRIBUTION_TDP_REACH	Weighted distribution (e.g., Total Distribution Points Reach)

Data Dictionary (2/2)

IHS – Macroeconomic Data

Column Name	Description
• date	Date of the observation or forecast
• geography	Geographical focus of the data
• concept	Description of the economic concept measured
• historical_edge_date	Date marking the edge of historical data
• scale	Scale of measurement (e.g., unit, thousand)
• source	Original data source
• frequency	Frequency of data (e.g., annual, monthly)
• real_or_nominal	Whether the value is real or nominal (inflation-adjusted or not)
• value	Numeric value of the data point
• source_id	Identifier from the source
• bank_name	Name of bank or financial institution providing data
• adjustment_name	Type of adjustment applied (if any)
• base_period_name	Name or label of the base period
• base_period_end	End date of the base period
• base_period_start	Start date of the base period
• base_period_value	Value during the base period
• last_update	Timestamp of last data update
• actual_or_forecast	Indicates if the value is actual or forecast
• __insert_gmt_ts	GMT timestamp of data insertion
• __update_gmt_ts	GMT timestamp of last update

2. Long Term Equity

Long Term Equity

Problem Statement

Analyse the long-term impact of marketing activities on Brand Power

Background

Brand Power is a leading indicator of market share and a growing strategic metric, with many teams already setting Power targets. Today, most marketing is optimized for short-term sales, but sales alone don't reflect brand health. **This exercise shifts focus to long-term equity - understanding how marketing builds Brand Power and how long it takes to show measurable impact.** The goal is to guide smarter investments that drive both sales and sustainable brand strength.

Round 1

1. **Predict Brand Power**
2. **Clear articulation of how long it takes for each of the marketing actions to reflect in Power**

Round 2

1. **Optimize Marketing Investments to drive Power**
2. **Develop an interactive simulator tool for Power**
3. **Integrate a GenAI chatbot layer that explains results in simple, business-friendly language *(Good to have)***
4. **Submit Github repo for AI evaluation**

Evaluation KPI

Round1

Power Prediction Score (PPS) = 0.5 * RMSE Skill Score + 0.5 * Trend Hit Rate

where:

RMSE Skill Score = max (0, min (1, 1 - $\frac{RMSE}{\sigma_Y}$)) ;

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Trend Hit Rate = #cases ($\Delta Y = \Delta \hat{Y}$)/#cases total

Round2

For Optimization: Power uplift w.r.t. baseline power

For Simulation:

1. Accuracy of predictions - When inputs are changed, do the simulated Power values stay consistent with model outputs?
2. Do the simulated outcomes make business sense?
3. Does the simulator offer an optimal mix recommendation in addition to manual scenario testing?

Round2

Optimization Goal: **The goal for optimization is to drive power growth using the best marketing allocations**

Constraints:

1. Digital cannot be 100%
2. TV cannot be more than 50% of the total mix

Data Dictionary – Brand Guidance

BG Column	Description	Comment
Country	Name of the country	
Brand	Name of the brand. It can be ABI or Competitor	
Power	Prediction of volume share a brand can command based on consumer predisposition to choose the brand over others	Within a market, all brand power sums to 100
Meaning	Extent to which brands build an emotional connection and are seen to deliver against functional needs	Indexed at 100
Difference	Extent to which brands set themselves apart from the category by offering something others don't and by leading the way	Indexed at 100
Salience	How quickly and easily the brand comes to mind	Indexed at 100
Premium	Prediction of price index a brand can support based on consumer predisposition to pay more for the brand than for others	Indexed at 1

Data Dictionary - Marketing

S.No.	Data Set	Details
1	Sell-in	NR, MACO, VOL, discounts, GTO
2	Sell-out Data	National and Regional PTC trend, Price Index vs Competitor
3	Distribution	Simple / Average / Multiple Distribution / TDP / Weighted Distribution etc.
4	Promotions Calendar / PINC	Any branded promotion, PINC calendar by brand
5	Media Investments	Example - Facebook, OpenTV, Print, Radio etc.
6	All other Marketing investments	Sponsorship, Experiential
7	Sales Investments	Contracts, Trand off
8	Macroeconomics	Income, Unemployment rate, Inflation, etc.
9	Weather	Temperature, Precipitation
10	Holidays	Key holidays / festivals
11	Demographics	Total population trends, income groups, age groups, ethnicity, etc.
12	FX rate	–
13	Mapping files	For mapping Brand to PTC, Investments to Marketing or Sales

More detailed Data Dictionary: **Data_Dictionary - latest.xlsx**

If feasible can keep/attach this. Else the above table is fine.