Project Report

Sell-in Forecasting

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<tr><td>Project Name</td><td>Sell-in Forecasting</td></tr>
<tr><td>Date</td><td>31/07/2025</td></tr>
<tr><td>Project Overview</td><td>This project developed a model to predict primary sales to partners. Forecasts for August-December for Amazon and Flipkart have been made available through Excel. Predictions are currently made independent of prices but a method to predict sell-in for some combination of prices is proposed. The model is expected to be run no more than 2 weeks before the start of the Sellin forecast period.</td></tr>
<tr><td>Goals
& Objectives
Satisfied</td><td>
Forecasting Model:

<u>Goal</u>: Create model to forecast optimal sell-in units for the 3 next month at a given price.
<u>Progress</u>: Output of forecasting model includes predictions for sellin, sellout, and partner inventory for the next 3 months in units. Forecasts are independent of price and emphasize festive period, previous month sales, and other seasonal factors. The rationale for a price independent forecast is discussed in section xxx. For short time horizon, it may be assumed that predictions are made at most recent month's ASP during BAU month and an adjusted ASP for festive.

Incorporation of new data:

<u>Goal</u>: Implement automated processes for data transformation and incorporation into the model upon user upload.
<u>Progress</u>: Processes have been implemented to automate data transformations for use in the model. It is assumed that data will follow the same format in following months from varying sources including Flipkart monthly sellout, Amazon daily sellout, and stock allocation data. Obtaining forecasts for new month will either require manually updating data as originally expected or replacement with automated data upload process. It is emphasized that change in data source with different formats will break the model unless data preparation processes are also adjusted.

Create user-friendly interface:

<u>Goal</u>: Make output of model available to users. Also make any input assumptions available for adjustment if necessary.
<u>Progress</u>: Model output is automatically stored as an excel when forecasting program is run. Output for August-December forecasts have been sent to the team. Implementation of automating emailing forecasts to the relevant parties will be discussed with Center of Excellence. The model assumes festive months during a particular year for each platform upon consultation with the team. A method has not yet been deployed to allow team to directly adjust festive months.

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	• **Discrepancy Analysis: No**
	  ○ <u>Goal</u>: Quantify extent of discrepancy between forecasted sell-in and units received.
	  ○ <u>Progress</u>: A backward-looking discrepancy analysis to quantify lost sales per product was not performed due to time limitations. A direct comparison of forecasts for past months from model and sales at the product level is not recommended until model-level sales forecasts accuracy for future periods is verified upon deployment. Poor inventory data for all partners except Amazon and cross-product influences are challenges that must be considered for lost sales estimation.

Evaluating Project Success	• **Accuracy of sell-in forecasts, sell-out predictions, and discrepancy metric**
	  ○ Testing on past data indicates that sellout predictions are at most 75% accurate at the product level. Limited monthly data of individual products motivated assuming seasonal and festive influences affect all products equally.
	  ○ Discrepancy is expected to be particularly high during festive periods as many products
	• **Ease of use of interface**
	  ○ End-users will receive output of model as an Excel file. Implementation within a dashboard is also possible but not essential since model is expected to be run no more than once per month.
	• **Ability to incorporate new data**
	  ○ Model can automatically incorporate new model to provide updated forecasts assuming data formatting is consistent with past data.

Strategies to improve performance	• **Specification demand modelling**
	  ○ Advantages: The longer time horizon of sellout and sellin predictions immediately suggests that wider market demand may change dramatically over the time frame. Accurate specification data and groupings of products by specifications is expected to provide a more accurate view of these changes.
	  ○ Challenges: Attempts to predict sellout using specifications were unsuccessful due to unavailability of clean specification data. In particular, specification data available did not contain all models, model level matching to Flipkart and Amazon data proved unreliable algorithmically, and a particular specification variable may contain different formats and performance metrics across products (consider playback time measured at varying volumes, with or without case, etc.) as well as missing data for some product-spec combinations requiring manual lookup. Attempts were also made to extract specifications from product names but results were not found to improve model performance due to limited specs that could be reliably obtained.

	• **Data collection** ○ Inventory data for Flipkart is made available monthly at varying dates. The inventory data must be available at the time the forecasting model was run. Conversely, if the data is made available in the first half month, the accuracy of future inventory estimates will decline. Modifying model to predict inventory in case of unavailability is recommended to avoid model failure. Sellin forecasts rely on inventory data for the period immediately before the sellin forecast period. Beginning inventory for the next month is extrapolated from the last available inventory. The date at which this data is received varies for Flipkart.

Project: Price Optimization

Project Name	Price Optimization
Project Overview	Create an optimization model which recommends the BAU, DOTD, and Event prices of every product for the next month. The output of the optimization model is made available as an Excel file. The data required for the project will be transformed and incorporated by the model automatically upon upload. Initial price recommendations were made available for testing by the last week of July.

Goals
& Objectives Satisfied
	• **Develop optimization model:**
	  ○ Goal: Create model to recommend optimal BAU, DOTD, and Event product prices for the next month to maximize revenue subject to constraints.
	  ○ Progress: Model recommends BAU, DOTD, and Event prices which maximize revenue subject to minimum net margin by product and platform.
	• **Incorporation of new data**:
	  ○ Goal: Implement automated processes for data transformation and incorporation into the model upon user upload. Provide a platform to the user to upload data.
	  ○ Progress: The price optimization model uses the same data preparation method as the sell-in forecasting project.
	• **Create user-friendly interface**:
	  ○ Goal: Make output of model available to users. Also make any input assumptions available for adjustment if necessary.
	  ○ Progress: Output made available as excel file. Model does not require any inputs not obtained algorithmically.
	• **Limit Bias**:
	  ○ Goal: Quantify bias, test for instances of bias, and reduce to an acceptable level.
	  Model framework impacting bias:
	  ○ Model recommends identical prices for all platforms, eliminating bias associated with price variations across different platforms. However, prices are recommended using elasticity estimates for each product-platform combination and revenue maximization involves providing a higher weight to platforms with a higher share of

	sales of a product. Both aspects were deemed essential to accurately model price sensitivity differences across platforms and to estimate revenue. However, this implies that o <u>Lopsided Sales Split</u>: Model incorporates independent net margin constraints for each product and platform. This means that net margin must exceed a threshold for each product if it is sold on that platforms. However, if a product has a highly lopsided sales split such as 98%-2%, the platform with 2% sales will exclude prices which do not meet profitability constraint.
Model Constraints	• Minimum net margin per product per platform • Minimum % deviation from MOP to DOTD and from DOTD to Event prices. • Maximum % deviation from MOP to DOTD and from MOP to Event prices. The latter 2 constraints are employed to obtain 3 distinct prices and counterbalance the model's preference for the lowest possible event price and identical MOP and DOTD prices. If no feasible price is found under original net margin and minimum % deviations constraints, constraints are iteratively loosened. Under the existing approach, for each minimum % deviation threshold, the net margin constraint is weakened from 23% to 13%. If no price is found, the minimum % deviation constraint is weakened and so on. The reverse order of precedence may also be used and the functionality has been implemented in the model.
Project Scope	• **Prices are recommended for audio products only**. • **Partners considered: Amazon, Flipkart** o QC partners were not considered as price sensitivity estimates could not be reliably obtained using the same methods as Flipkart and Amazon. Adding QC specific profitability constraints was also deemed unnecessary due to lack of binding margin commitments and stronger control over support. • **Price types: BAU, DOTD, Event** o Mega-sale prices are not directly considered but can be obtained by lowering profitability requirements.
Success Criteria	• Accuracy of price recommendations o To be evaluated upon pilot deployment and consultation with Category and e-Sales team. • Channel Bias Limitation o No direct intervention taken to correct potential biases. The lopsided sales share may be corrected by weakening per-platform requirements and adding a blended net margin constraint. • Ease of use of interface o Recommendation provided as Excel file • Ability to incorporate new data o Elasticity estimates and platform shares in total sales automatically updated upon upload of new data when program is run.
Recommended expansions	• **Net margin correction**: Net margin is not adjusted for non-price support costs. Net margin used in the model approximates Revenue-COGS-Price Support and does not consider marketing and inventory support. • **Sellin-Sellout correction**: The model assumes that sell-in in the next month will be equal to sellout. Note that Net Revenue is ordinarily calculated using sell-in while support is calculated using sellout. The two primarily differ due

	to existing partner inventory. It is proposed that sell-out in the model be adjusted by multiplying by the ratio of sell-in and sell-out obtained from the forecasting model. However, this cannot be implemented until the accuracy of the forecasting model on a product level is assured.
Modelling Decisions	• <u>Elasticity-based optimization</u>: It is assumed that sellout when price changes from price p to p' changes from x to $x(\frac{p'}{p})^{\epsilon}$ where epsilon is elasticity of a product for a given channel. • <u>Sellout and Sellin</u>: It is assumed that total sell-out is equal to total sell-in for a product across all channels the next month. This decision was taken due to the unreliability of models tested to predict sell-out and sell-in. The assumption when combined with the consistent share in sales allows us to avoid using any value of sellout and treat it as 1. • <u>Consistent shares in sale</u>: It is assumed that platforms will continue to have the same share in sales as their weighted share over the past 3 weeks. These shares are adjusted for differences in ASP. For example, if the weighted unadjusted share of Amazon and Flipkart are 60% and 40% with ASPs 1000 and 950, respectively. Then the share of Amazon will be reduced and that of Flipkart increased using estimated elasticities at weighted ASP of 980. • <u>Previous price</u>: It is assumed that immediately before the model was run, each platform has the same price: the adjusted ASP calculated in the previous step. • <u>Order of Prices</u>: The order in which MOP, DOTD, and Event prices are run matters since the change in sale depends on the ratio of new and previous price. We assume that in a 30 day month: MOP (6) -> DOTD (10) -> Event (8) -> MOP (6) MOP price period was split to include the spike in price that will occur when price rises after event prices. • <u>Elasticity estimation</u>: It is assumed that all products in a category have the price elasticity. This assumption was made due to instability of elasticity estimates when obtained for each product. However, grouping products by any method including model was also observed to consistently lower elasticities. These estimates may need to be scaled up while preserving order in relation to each other.

Appendix: 3-Price Product Optimization Model

Sets and Parameters

- $i \in \{1, 2, 3, 4\}$: price levels
- p_i: price at level i
- $p_1 = p_4 = \text{MOP}$ (fixed)
- C: COGS
- J: Billing MOP (Flipkart only)
- $\epsilon_{\text{fk}}, \epsilon_{\text{az}}$: elasticities for Flipkart and Amazon
- $w_{\text{fk}}, w_{\text{az}}$: weights for Flipkart and Amazon
- $d_i^{\text{fk}}, d_i^{\text{az}}$: days per price
- $M_{\text{fk}}, M_{\text{az}}$: Margin
- K: net margin (hyperparameter)
- n_0, n_1: minimum deviation (hyperparameters)
- m_0, m_1: maximum deviation (hyperparameters)

Decision Variables

$$\begin{aligned} z_2, z_3 &\in \mathbb{Z} \\ b_2, b_3 &\in \{0, 1\} \\ p_i &\in \mathbb{R}^+ \quad \forall i \in \{1, 2, 3, 4\} \end{aligned}$$

Recursive Demand Function

Let $p_0 = \text{MOP}$. Then, for each level i:

$$s_i(p, \epsilon, d) = \left(\prod_{k=1}^{i} \frac{p_k}{p_{k-1}} \right) \left(\frac{p_i}{p_{i-1}} \right)^{\epsilon} d_i$$

Platform Demands

$$\begin{aligned} D_{\text{fk}} &= \sum_{i=1}^{4} s_i(p, \epsilon_{\text{fk}}, d^{\text{fk}}) \\ D_{\text{az}} &= \sum_{i=1}^{4} s_i(p, \epsilon_{\text{az}}, d^{\text{az}}) \end{aligned}$$

Objective Function (Maximize Revenue)

$$\max_{p_2,p_3,z_2,z_3,b_2,b_3} \quad \text{MOP} \cdot [(1-M_{\text{fk}})w_{\text{fk}}D_{\text{fk}} + (1-M_{\text{az}})w_{\text{az}}D_{\text{az}}]$$

Constraints

Amazon Profitability Constraint:

$$w_{\text{az}}\left(\frac{(1-K)(1-M_{\text{az}})\cdot \text{MOP}}{1.18}\cdot D_{\text{az}} - CD_{\text{az}} - \frac{1}{1.18}\sum_{i=1}^{4} s_i(p,\epsilon_{\text{az}},d^{\text{az}})(1-M_{\text{az}})(\text{MOP}-p_i)\right) \geq 0$$

Flipkart Profitability Constraint:

$$w_{\text{fk}}\left(\frac{(1-K)(1-M_{\text{fk}})\cdot \text{MOP}}{1.18}\cdot D_{\text{fk}} - C\cdot D_{\text{fk}} - \frac{1}{1.18}\sum_{i=1}^{4} 0.75\cdot s_i(p,\epsilon_{\text{fk}},d^{\text{fk}})\cdot(-0.66p_i - 0.06\cdot \text{MOP} + 0.81\cdot J)\right) \geq 0$$

Price Bound Constraints

$$\begin{aligned}
p_3 &\leq p_2 \\
p_2 &\geq \text{MOP} * m_0 \\
p_3 &\geq 1.1C \\
p_3 &\geq \text{MOP} * m_1 \\
\frac{\text{MOP}-p_2}{\text{MOP}} &\geq n_0 \\
\frac{p_2-p_3}{p_2} &\geq n_1
\end{aligned}$$

Integer Constraint (price must end in 49 or 99)

$$\begin{aligned}
p_2 &= 100z_2 + 50b_2 + 49 \\
p_3 &= 100z_3 + 50b_3 + 49
\end{aligned}$$