



WHITE PAPER

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Optimizing Facings On The Shelf Of A Retail Store

Managing shelf space is critical for retailers to attract customers and to optimize profit. The decisions relating to the products to be stocked among a large number of competing products and the amount of shelf space to allocate to those products is a question central to retailing. As shelf space is a scarce and fixed resource, and the number of potentially available products continually increases, retailers have a high incentive to make these decisions correctly. If customers were completely brand-loyal, they would look for a specific item and buy it if it were available or delay their decisions if it were not. Thus, space allocated to a product would have no effect on its sales. However, marketing research shows that most consumer decisions are made at the point of purchase.

Thus, customers' choice of product may be influenced by in-store factors including shelf space allocated to a product. With a well-designed shelf space management system, retailers can attract customers, prevent stock outs and, more importantly, increase the financial performance of the store while reducing operating costs. Further, close-to-optimal shelf space allocations provide the basis for distributing promotional resources among the different product categories. However, the optimization problem is very complex because products usually have different profit margins and widely varying space- and cross elasticities. This is compounded due to the fact that the product demand is a non-linear function of the facings.

Approach

Using Store level regression technique, models were developed for each product by controlling Price and Trade variables for own and selected competitors. Facings measures for all products were included in all models to capture own and competitor space elasticity. The facings or space elasticities are computed by a volumetric regression model. These elasticity values describe the effects of a unit change in product facings on demand for that product and other products. The elasticities are then used in the optimization model to come up with an optimal combination of facings which maximizes the revenue. The details of the linearized model are given in the appendix.

Assumptions

Some of the assumptions in our model are:

- The retailer's objective is to maximize product category profit
- The elasticity values are generally between -1 and 1
- Effects other than space (e.g., price discounts, special marketing efforts, etc.) are not considered

DSS for Facings Optimization

Store level POS data, in-store facings data and audit data are generally used to cluster stores either by geography or by structural similarity. This data is used to run statistical linear regression on the store clusters to estimate the space elasticity for each product and other products in that category. The linear regression model is implemented in SAS. Data is also converted to SAS data format. The optimization model was implemented in R statistical software for data preparation/presentation and GLPK (GNU Linear Programming Kit) libraries for optimization. We have also built a version of this tool using SAS- OR so that it is in sync with the regression model. The model is tested with various precision values to see the run time efficiency also.

DSS for Facings Optimization

- Assists decision maker with regard to optimal facings for each target product considering all self and cross elasticity effects
- Inputs and outputs are in readable comma separated flat files which enable data input (output) to be retrieved (flushed) to other systems or databases
- Mixed integer programming is a powerful technique as compared to other methods to obtain quick and accurate solutions

Input

Following are the file names and formats for input data required. This also includes the column names and their formats too. All files are comma separated flat files.

Product

COLUMN NAME	TYPE	DESCRIPTION	REMARKS
ID	Integer	Product identification number	Sequence starting from 1
Facings_lb	Integer	Facings lower bound	0.1 if lower bound is 0
Facings_ub	Integer	Facings upper bound	
Selling_price	Float	Selling price	
Base_facings	Float	Base facings	Average of facings on store level for a certain period
Base_volume	Float	Volume sales	Volume sales averaged across stores for a certain period
Width	Float	Linear width	

Elasticity

COLUMN NAME	TYPE	DESCRIPTION	REMARKS
ID1	Integer	Product 1 id	Refers to product table1
ID2	Integer	Product 2 id	Refers to product table1
Value	Float	Elasticity value	

Parameter

COLUMN NAME	TYPE	DESCRIPTION	REMARKS
Total_Shelf_Space	Float	Total available shelf space	Refers to product table1

Category

COLUMN NAME	TYPE	DESCRIPTION	REMARKS
CID	Integer	Category id	Sequence of integers from 1
Category_lb	Integer	Shelf space lower bound	
Category_ub	Integer	Shelf space upper bound	

Product-Category

COLUMN NAME	TYPE	DESCRIPTION	REMARKS
Pid	Integer	Product id	Reference to product table
Cid	Integer	Category id	Reference to category table

Output

Following are the file names and formats for input data required. This also includes the column names and their formats too.

Facings

COLUMN NAME	TYPE	DESCRIPTION	REMARKS
ID	Integer	Product id	Refers to product table
Facings	Integer	Optimal number of facings	Approximated in case it is float

Test Results

We have tested this model on a few sets of target products of a major soft drinks manufacturer and obtained consistently improved results. The number of products in the product groups ranged from 7 to 16. Our results were found to be superior compared to results from other techniques in maximizing revenues by as much as 20 – 40%. These results are obtained by setting one category and total available shelf space as a range between 55 to 95 units and assuming each product has unit width.

Some of the limitations of the current work are listed below. We also suggest a few enhancements and improvements to our model:

- Linearizing a non-linear model may affect accuracy. This can give near optimal solutions and not an optimal solution
- The regression model assumes that increasing the facings would always increase the demand which might not be always true beyond a limit in practice
- Incorporate the cost parameters like production costs, inventory holding costs, restocking costs etc into the model to optimize on profit instead of revenue

APPENDIX

Model

Terminology and notation

C	: Set of categories	U_i	: Upper bound on number of facings of product i ($i \in P$)
P	: Set of all products	SP_i	: Selling price of product i ($i \in P$)
T	: Set of all target products (T is subset of P)	BV_i	: Base volume of product i ($i \in P$) - Average volume sales
P_c	: Set of products in category c ($c \in C$) (P_c is a subset of P)	BF_i	: Base facings of product i ($i \in P$) - Average facings
S	: Total available shelf space	W_i	: Width of product i ($i \in P$)
S_c	: Total available shelf space for category ($c \in C$)	n_i	: Number of facings for product i ($i \in P$)
L_i	: Lower bound on number of facings of product i ($i \in P$)		

Non-linear model

Maximize:

$$\text{Revenue} = \sum_{i \in T} \left(SP_i \times BV_i \times \prod_{j \in P} \left[\frac{n_j}{BF_j} \right]^{\beta_{ij}} \right)$$

Subject to:

$$\sum_{i \in P} W_i \times n_i \leq S$$

(Total shelf space allocated for all products is not more than total available shelf space)

$$\sum_{i \in P_c} W_i \times n_i \leq S_c \quad : \text{ for all } c \in C$$

(Total shelf space allocated for all products in a category is not more than total available shelf space for that category)

$$L_i \leq n_i \leq U_i \quad : \text{ for all } i \in P$$

Upper and lower bounds for number of facings for a product) n_i is integer : for all $i \in P$

Non linear model

Maximize:

$$\text{Revenue} = \sum_{i \in T} \left(t_i \times SP_i \times BV_i \times \prod_{j \in P} \frac{1}{BF_j^{\beta_{ij}}} \right)$$

Subject to

$$\sum_{i \in P} W_i \times n_i \leq S$$

$$\sum_{i \in P_c} W_i \times n_i \leq S_c \quad : \text{ for all } c \in C$$

$$L_i \leq n_i \leq U_i \quad : \text{ for all } i \in P$$

$$l_i - B_i \times y_i \leq 0 \quad : \text{ for all } i \in P$$

$$A_i \times y_i + m_i - l_i \geq A_i \quad : \text{ for all } i \in P$$

$$l_i - A_i \times y_i \geq 0 \quad : \text{ for all } i \in P$$

$$B_i \times y_i + m_i - l_i \leq B_i \quad : \text{ for all } i \in P$$

$$e^{A_i} \leq t_i \leq e^{B_i} \quad : \text{ for all } i \in P$$

$$(D_i - D_i') \times l_i + (e^{A_i} - D_i \times A_i - e^{E_i} + D_i' \times E_i) \times y_i + D_i' \times m_i - t_i = D_i' \times E_i - e^{E_i} \quad : \text{ for all } i \in P$$

$$E_i \times y_i + m_i - l_i \geq E_i \quad : \text{ for all } i \in P$$

$$m_i - \sum_{j \in P} \left(\beta_{ij} \sum_{k=1}^{V_i} (\lambda_{jk} \times \ln(X_{jk})) \right) = 0$$

$$: \text{ for all } i \in P \text{ and } V_i = \frac{U_i - L_i}{\text{Precision}}$$

$$\sum_{k=1}^{V_i} (X_{ik} \times \lambda_{ik}) - n_i = 0$$

$$: \text{ for all } i \in P \text{ and } V_i = \frac{U_i - L_i}{\text{Precision}}$$

$$\sum_{k=1}^{V_i} \lambda_{ik} = 1$$

$$: \text{ for all } i \in P \text{ and } V_i = \frac{U_i - L_i}{\text{Precision}}$$

$$A_i \leq m_i \leq B_i$$

n_i is integer if L_i is integer else continuous

λ_{ik} is binary

Where

$$A_i = \sum_{\substack{j \in P \\ \beta_{ij} \geq 0}} (\beta_{ij} \times \ln(L_i)) + \sum_{\substack{j \in P \\ \beta_{ij} \leq 0}} (\beta_{ij} \times \ln(U_i))$$

: for all $i \in P$

$$B_i = \sum_{\substack{j \in P \\ \beta_{ij} \geq 0}} (\beta_{ij} \times \ln(U_i)) + \sum_{\substack{j \in P \\ \beta_{ij} \leq 0}} (\beta_{ij} \times \ln(L_i))$$

: for all $i \in P$

$$E_i = \ln \left(\frac{e^{A_i} - e^{B_i}}{A_i - B_i} \right)$$

: for all $i \in P$

$$D_i = \frac{e^{A_i} - e^{E_i}}{A_i - E_i}$$

: for all $i \in P$

$$D_i' = \frac{e^{B_i} - e^{E_i}}{B_i - E_i}$$

: for all $i \in P$

About Genpact

Genpact Limited (NYSE:G), a global leader in business process management and technology services, leverages the power of smarter processes, smarter analytics and smarter technology to help its clients drive intelligence across the enterprise. Genpact's Smart Enterprise Processes (SEPSM) framework, its unique science of process combined with deep domain expertise in multiple industry verticals, leads to superior business outcomes. Genpact's Smart Decision Services deliver valuable business insights to its clients through targeted analytics, reengineering expertise, and advanced risk management. Making technology more intelligent by embedding it with process and data insights, Genpact also offers a wide variety of technology solutions for better business outcomes.

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For More Information, Contact:

V Prem Kumar

prem.viswanathan@genpact.com