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Price Elasticity Model for Fashion Products

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Abstract

The present study explains the advanced data preparation methodologies in the context of estimating the elasticity of demand in the fashion business. This study examines the way demand respond to the price changes and what such responsiveness implies the revenue in fashion goods industry. In the fashion industry, there are so many products and every product may have different elasticity behavior. One product might sell at different locations across the globe for a company. And the elasticity may change from region to region or place to place for a product. Elasticity can be estimated on geography-product combination to overcome issues as mentioned above. To estimate proper elasticity, data preparation is a very important aspect. In particular, we introduce and explain an important way of advanced data preparation methodology which uses in demand elasticity models.

Keywords: Fashion goods demand, Price elasticity of demand.

INTRODUCTION:

Elasticity is one of the important measure in the concept of demand. Elasticity is a measure of how one economic variable responds to the changes of another economic variable. Demand is an economic principle that explains a consumer behaviour to pay a price for a product. In particular, price and demand are inversely proportional to each other.

Elasticity can be estimated by using different types of methods such as Qualitative, Time Series, Causal and Simulation. Qualitative methods are subjective and they rely on human judgement to make a decision. These methods are useful when there is lack of sufficient historical data available. Time series methods uses historical demand to make a decision. These are based on the assumption that past demand pattern is a good indicator of future demand. These methods are useful when there is a stable and demand pattern does not change significantly from one time to other. These methods are broadly classified into two categories. They are Causal and simulation methods. Causal methods assume that demand is highly correlated with other economic factors in the environment. These models estimate correlation between demand and other economic factors. Based on that, these models estimate what economic factors will play key role in future demand. Simulation methods imitate the consumer choice that gives rise to demand to arrive at a demand estimate. Using these methods, a frim can combine time series and causal methods to answer such problems.

There are some important aspects in the area of demand estimation. They are, considering all the factors that are influencing demand and the way one prepares data. Advanced statistical models are also not able to estimate better elasticities without considering the above two aspects properly.

BACKGROUND:

A retail sale occurs when a business sells a product to end customer for their use. The transaction can occur through a number of different sales channels, such as online, offline, etc. There are four major categories in retail sector. They are Hardliners, Soft goods or Consumables, Food and Art. Products which comes under hardliners are things that tend to last a long life, such as appliances, vehicles and furniture. Products which comes under soft goods or consumables are clothing, shoes and toiletries. Products which comes under food are meat, cheese, produce and baked goods. Products which comes under art are fine arts, books and musical instruments.

There are different types of retail stores. They are, Departmental stores, Discount stores, Warehouses and E-retailors.

From above all the categories, the present study explains only about fashion goods in offline retailors (Factory outlets).

METHODOLOGY:

Retail business creates different plans on their products so that it will get maximum margin and minimum inventory. In fashion industry, there may be huge number of products and most of the products may sell at different locations across the globe depending on company's size. In retail business, data should be considered from two areas. They are, geography and product. At geography, there may be some hierarchies like Country, Region, State, District and Store. In this hierarchy, Country and Store are the highest and Lowest levels respectively. In Product, there may be certain hierarchies like Company, Department, Category, Sub category and Stock Keeping Unit (SKU). Here Company and SKU are the highest and lowest levels respectively. And the data should be considered in regular time intervals such as yearly, quarterly, monthly or weekly.

Geography Hierarchy

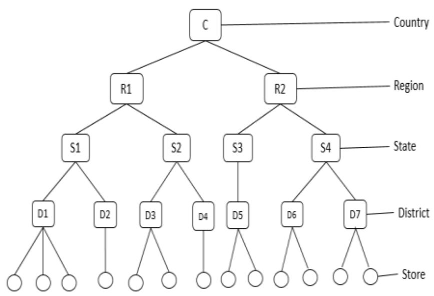

Figure 1.1

Product Hierarchy

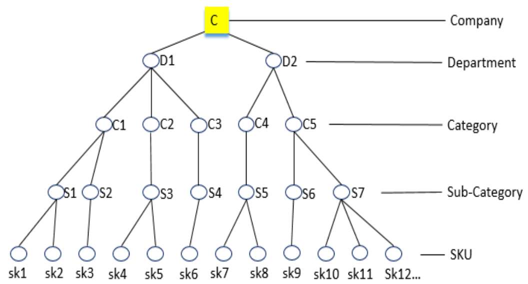

Figure 1.2

Figure 1: *Illustrate the hierarchies of geography and product.*

In geography hierarchy, Country is at top/first level. It divides in two leap nodes in the second level called R1 and R2 which comes under Region. Here Parent level is Country and Region is child to Country. In the third level, each region divides into two leap nodes called S1, S2, S3 and S4 which comes under States. Here Parent level is Region and State is child to Region. In fourth level, each state divides into some leap nodes called Districts. Again, District nodes divides into terminal nodes called Stores.

In product hierarchy, Company is at top/first level. It divides in two leap nodes in the second level called D1 and D2 which comes under Department. Parent and child relationship remains as same as geography hierarchy. Each Department node divides into multiple nodes called Category at third level. Again, Categories divide into sub-categories and then SKUs nodes.

Groups:

Group is defined as the subset of geography and product. To create a Group, select a parent level anywhere in the modelling hierarchy for geography and product. All of the child levels under the parent level are included in the Group. A Group can be created at any level of the geography and product but nodes can't be overlapped (i.e., one node can't be in more than one Group). All the nodes within the Group are homogeneous. For example, if a Group is created for men's apparel, then all the men's apparel related SKU's should come under that Group.

In the following figure 2, to create Groups we have chosen region as geography level and department as product level in the hierarchy. In geography level, there is only region and in product level there are three departments. So, total 3 Groups created. If we consider Figure 1, there are two nodes in the region level and 2 nodes in the department level. So, total 4 Groups can be created. In the current example, three Groups were created. They are Men's Apparel, Women's Apparel and Kid's Apparel. All these Groups are homogeneous (i.e., all the SKUs under Men's apparel will be included in this Group and these SKUs will not be overlap with other Groups).

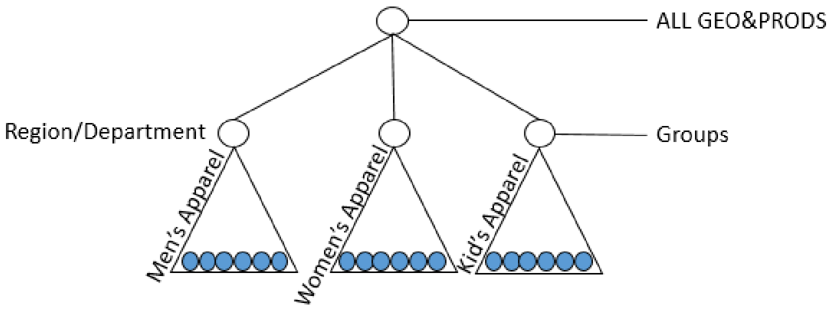

Figure 2: *Illustration of Group Creation*

In fashion business, sales units at SKU level will not follow any significant pattern. This insignificant pattern can be due to several reasons. One of the main and most prevalent reason is that data points are very low as product life span is very less. There are two different types of products in fashion business. They are, seasonal products and year over products. Seasonal products will have sales units in their respective seasons only. And year over products also will not have same sales pattern across the year. Due to these reasons, there will not be consistent pattern in the data.

If one consider data from store and SKU level, then there won't be any specific pattern in the data and it won't have significant sales units. So, data at lower level is very insufficient, inconsistent and not reliable to build a model. Even Advanced Statistical models are also not able to provide better elasticity estimates on this type of data.

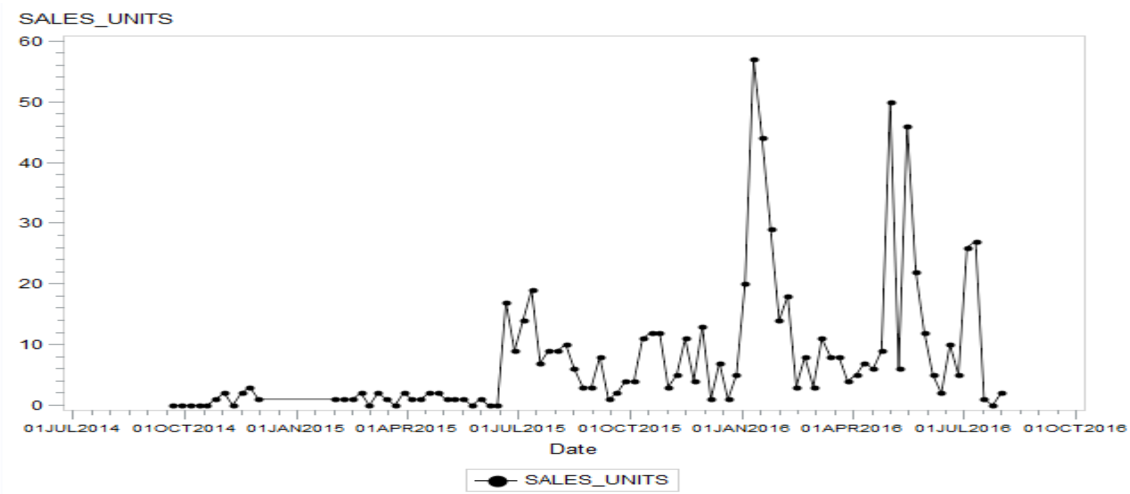

Figure 3: *Example of data pattern at Store-SKU level.*

In the above graph, line represents sales units by week. Most of the Geo-Prods exhibits the same pattern at very low level in the hierarchy called Store and SKU. Year over products might have good enough sales but there won't be any pattern.

To overcome these problems, we need to aggregate Store-SKU level data to higher level wherever we get significant pattern in the data.

In this case data aggregates into two stages, namely Stage1 and Stage2. Time series components and holiday effects estimation happens at Stage1, and elasticity estimation happens at Stage2.

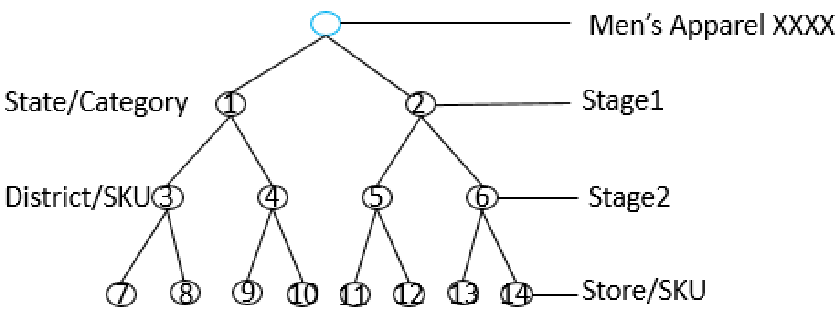

Figure 4: *Illustration of Group and its levels.*

Stage1: Time series components and holidays are estimated as part of Stage1. In the geography hierarchy, Stage1 is estimated at higher levels than the lowest level(Store). In product hierarchy, Stage1 is estimated at higher levels than lowest level(SKU). By aggregating above SKUs to higher levels, it enables one to get longer series. By aggregating above stores to higher levels, and it enables one to see the seasonal pattern more clearly. By doing as above aggregation, we can eliminate seasonal pattern from the data. In the above Figure 4, Stage1 aggregated to State and Category level and it has only two nodes(GPs) namely 1(GP1) and 2(GP2).

Stage2: Price, Promotion, Product Life Cycle and inventory effects are estimates as part of Stage2. Elasticity is estimated at lowest level in the product hierarchy and level higher than the lowest level in the geography hierarchy. First, we need to remove time series component effects from the data before estimating price, promotion, product life cycle and Inventory effects. In the above Figure 4, Stage2 aggregated to District and SKU level and it has four nodes(GPs) namely 3(GP3),4(GP3),5(GP5) and 6(GP6).

Data aggregation is very important aspect. At very high levels, data is sufficient but not consistent. At above low levels, data is consistent but not sufficient. To overcome this problem, need to aggregate data to a level which can provide both significant and consistent data.

Demand Model:

Demand of a product is influenced by various explainable and unexplainable factors like price changes, promotions, inventory levels, product life cycle, trend, seasonality, and so on. An ideal demand model is a function which reflects as measurable factors of a product demand. An absence of any given factor introduce bias in other factors estimation.

Additive model:

The mathematical form of the typical additive demand model is as follows.

Demand=trend+seasonality+ Price changes+ promotions+ inventory+ product life cycle.

Multiplicative model:

The mathematical form of the typical multiplicative demand model is as follows.

Demand=Price changes*trend*seasonal effect*promotions*inventory*Product life cycle.

$$Y_{ijt} = B.D*f(F1)*f(F2)*f(F3)*\text{-------}*f(Fn)*e$$

$$\mathbf{Y_{ijt} = B.D * \prod_{i=1}^{n} f(F_i)} \qquad \mathbf{i=1,2,3,\ldots n.}$$

F_i is the i^{th} demand factor.

Let's assume F1= Price factor

F2= Promotion factor

F3 =Holiday effects

$$\mathbf{Y_{ijt} = exp(\beta_0+\beta_1 * F_{1ijt}+\beta_2 * F_{2ijt}+\text{-----}+\beta_n F_{nijt}+e_t)}$$

$$\mathbf{= exp(\beta_0) * exp(\beta_1 * F_{1ijt}) * exp(\beta_2 F_{2ijt}) * \text{------} * exp(\beta_n F_{nijt}) * exp(e_t)}$$

Where Y_{ijt} is the demand of i^{th} product, j^{th} store at time period 't'.

i=1, 2, 3, …., p (Products)

j=1, 2, 3, …., G (Geography)

t=1, 2, 3, ….T (Time periods weeks/months/quarterly).

Each component in the demand model can be estimated at different stages in the Groups.

Time series components estimation:

To estimate time series components, first aggregate data to Stage1 as explained above. In this case, data is aggregated to Region in geography level and Category in product level. Time series components can be estimated by using several forecasting methods such as ARIMA, Classical Decomposition, Trend Seasonal decomposition by Loess method, etc. In this level, we estimate only trend, seasonality, cyclical and holiday effect. In the Stage1, there may be few GEO-PRODS as we are aggregating data to very high level in the hierarchy. We can estimate time series components at this level for all the geo-prods and use these estimated components at lower level, say Stage2, to deseasonalize the data.

To illustrate the above process, we have taken one Geo-prod (GP1) from Stage1 aggregated data and it has the following sales pattern.

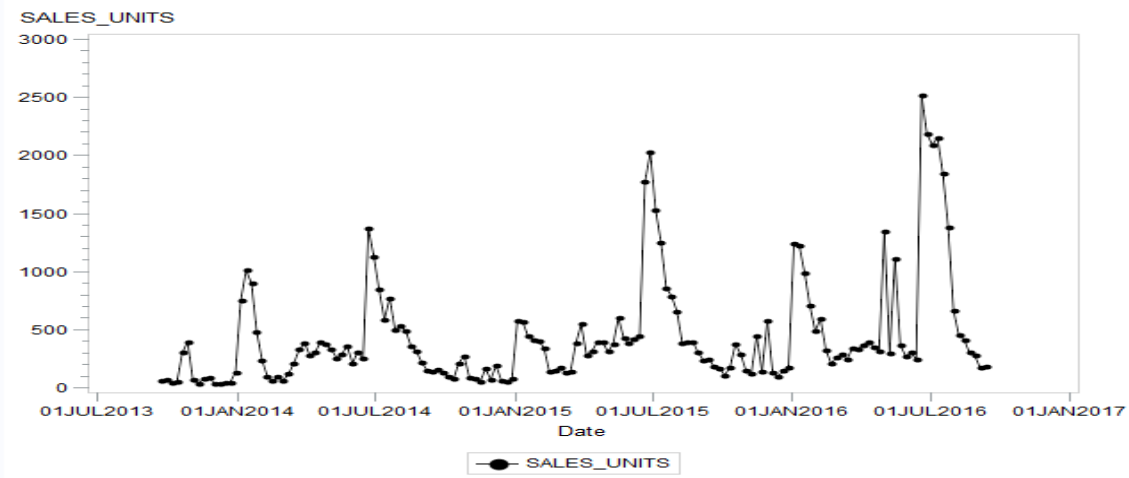

Figure 5: *Illustrate sales pattern of GP3.*

Based on this geo-prod data, we need to estimate time series components and holiday effect by using above mentioned models. As same as we need to estimate these effects to another node(GP2) in Stage1 data.

Once done with Stage1 components estimation, taken only one node (GP3) from Stage1 data. This Geo-Prod is at child level of Stage1 node (GP1). The GP3 which taken from Stage2 has the following sales pattern with respect to price ratio.

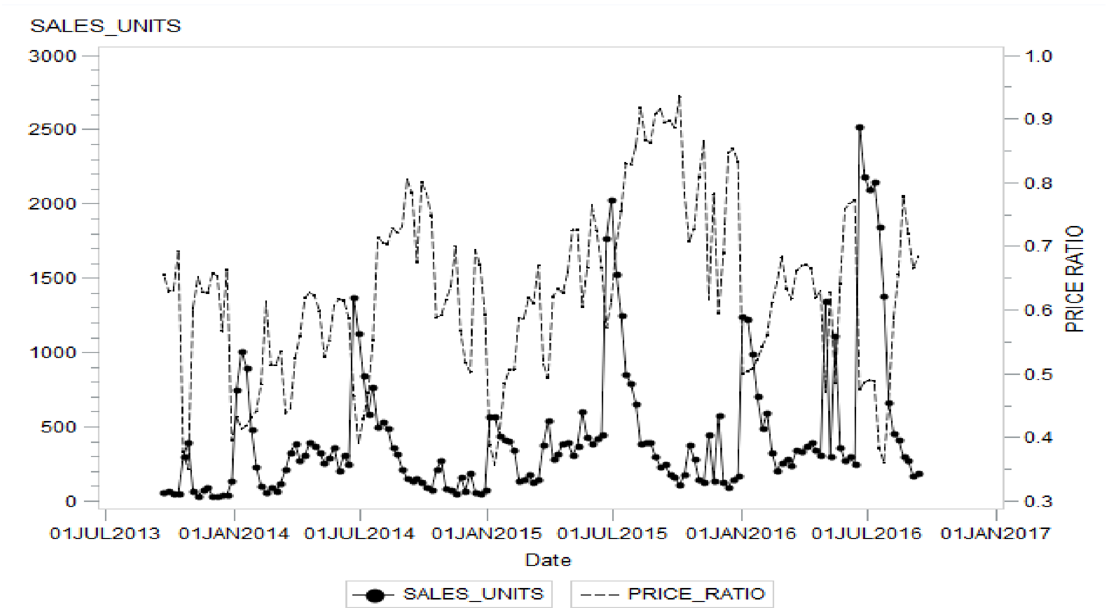

Figure 6: *Illustrate sales pattern with respect to Price Ratio for GP3.*

Dotted Line: Dotted line plotted along with right axis and represents Price Ratio.

Thick Line: Plotted along with left line and represents Sales pattern.

Here we make an assumption that, whatever components estimated at Stage1 for GP1 those effects inherited to all the GPs (GP3 and GP4) at Stage2. Then next step is to remove those Stage1 estimated effects from Stage2. That is, we are looking at GP3 and it has seasonal effects. To estimate elasticity for this GP3, first we need to remove inherited Stage1 components effects by using multiplicative model.

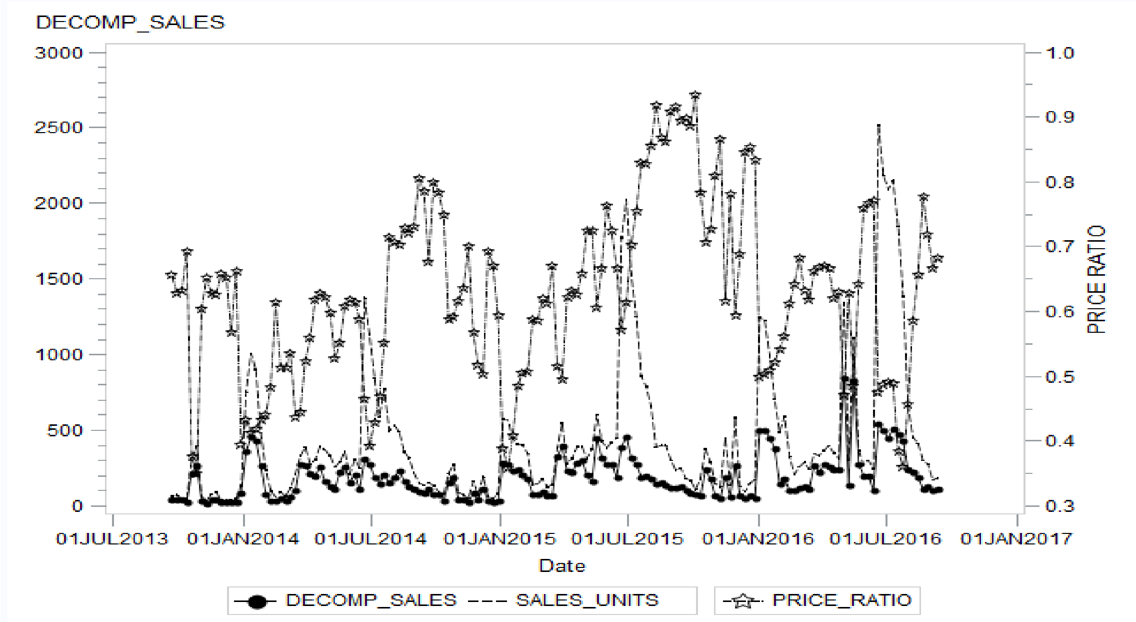

Figure 7: *Illustrate decomposed sales pattern for GP3.*

Figure 7 contain the following lines:

Dotted Line: This Line is plotted along with right vertical axis of the graph. This line represents the Price Ratio.

Thick Line: This line is plotted along with left vertical axis of the graph. This line represents actual sales values that are available at Stage2 for that geo_prod(GP3).

Star Line: This line is also plotted along with left vertical axis of the graph. This line represents sales values after decomposition at Stage2 for that geo_prod(GP3).

After data decomposition, need to estimate price effect. In particular, promotion data will not be available. So, we can exclude promotion effect from the demand model. And inventory values are also not accurate. It could be better to eliminate inventory effect from the model. Now we have only price effect which can be estimate at Stage2. Generally, we will have regular price and actual price for all the geo-prods. Discount can be calculated by using following formula. Price ratio can be can be calculated by sing discount.

Discount= (Regular Price-Actual Price)/Regular Price

Price Ratio=1-Discount

At this level, sales units can be considered as response variable and price ratio can be considered as control variable.

$$\text{Log } (Y_i) = \beta_0 + \beta_1 X_{1i} + \epsilon$$

$$\text{Log (Demand)}= \beta_0 + \beta_1 * Price\ Ratio + \epsilon$$

Solution for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	6.2774	0.2953	154	21.26	<.0001
PRICE_RATIO	-2.1161	0.4598	154	-4.60	<.0001

$$\text{Log (Demand)}= 6.2774 - 2.1161 * Price\ Ratio + \epsilon$$

From the model, we got outputs as shown above. Here price ratio effect is -2.1161.

exp (-(beta*0.2)) = 1.52687

Price lift is 1.52 if you give 20 % discount on this product.

CONCLUSION:

Price elasticity of demand plays a vital role in the business pricing strategies. Inaccurate price elasticity leads to wrong pricing decisions, which increase the unnecessary spend/cost. Especially in fashion products business, pricing decisions play crucial role in competing with competitors. Current paper recommends an ideal demand model, which can be used to estimate an accurate and unbiased price elasticity demand of a product or service. It also describes few information borrowing methods to overcome the data challenges during model fitting like data sufficiency and consistency. The demand equation will produce high accurate demand forecast through by estimating various measurable demand factors such as Price effect (Elasticity), promotions effect, Holidays effect, Seasonality and so on. This paper mainly focused on describing the methodology to estimate an accurate, reliable & unbiased price elasticity of demand of a product or service in fashion industry where the life cycle of the product is very short.

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