Mix Market Model Capstone Project

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Business Understanding

ElecKart is an e-commerce firm based out of Ontario, Canada specialising in electronic products.

Over the last one year, they had spent a significant amount of money on marketing.

They are planning to create a marketing budget for the next year, which includes spending on commercials, online campaigns, and pricing & promotion strategies.

The company feels that the money spent over the last 12 months on marketing was not sufficiently impactful, and, they want to decide whether to cut on the budget or to reallocate it optimally across marketing levers to improve the revenue response.

Project Objective

- Develop a market mix model for 3 sub-categories product for the following –
  1. Camera accessory,
  2. Gaming accessory
  3. Home Audio
- **Observe impact of different marketing levers over sale of last year (From July 2015 to June 2016) and recommend the optimal budget allocation for different marketing levers for the next year.**

Data Understanding

Imported and cleaned the datasets (consumer , marketing , climate and holiday dataset) and finally, merged to created a common dataframe based on which further sub categories were derived (game , home and camera).

To understand the data some basic level EDA was done. Please refer to plots on next slides for details. (only the major trends are plotted.)

Some KPI were created. The major KPI's were:

Shelf InflationDiscount % on mrp

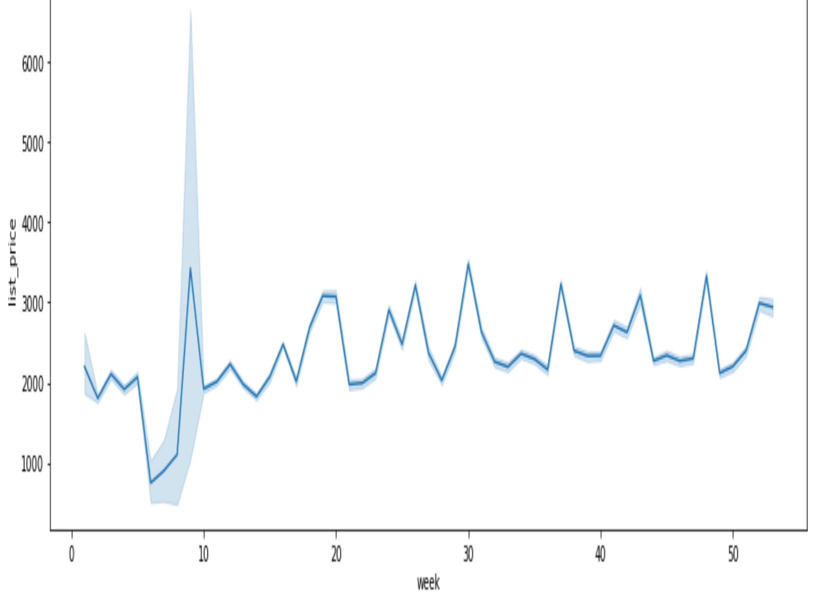
Discount % on list_price

List price

Lag variables for modelling

Brand perception KPI (Mass , Premium and Mid level) : Observation, the dataset was highly skewed towards Mass brand perception products.

Holidays and payday kpis.


list_price
1000
2000
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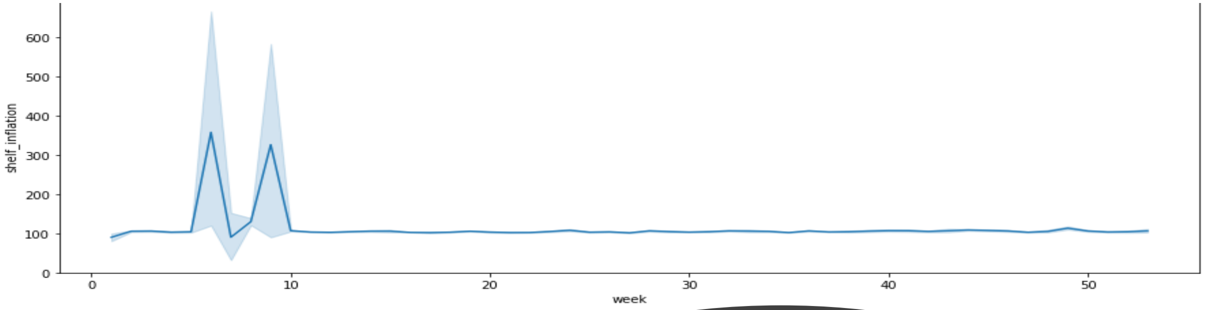
week


shelf_inflation
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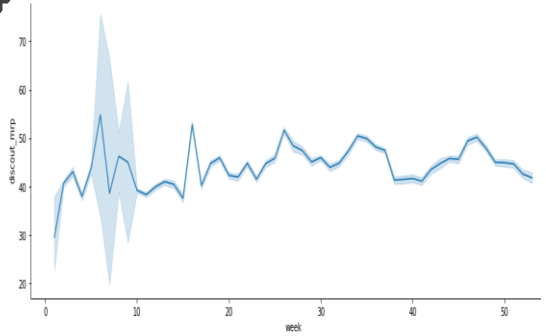
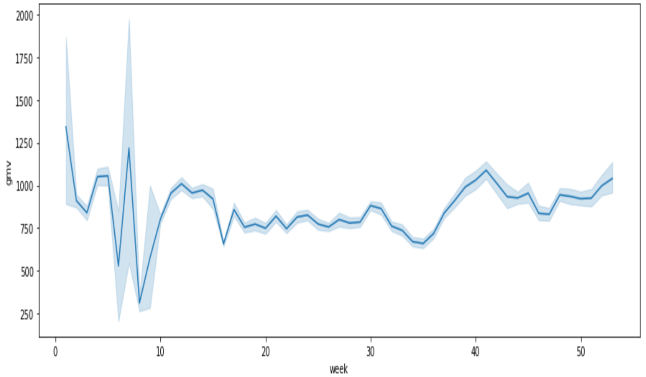
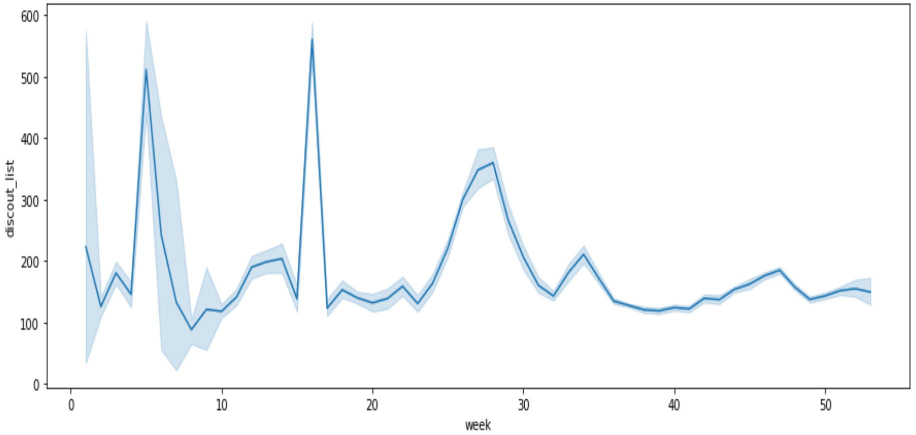

discout_mrp
week


gmv
week


discout_list
0
100
200
300
400
500
600
0
10
20
30
40
50
week

It quite evident from the above plots that there is some seasonality in data.

There were several factors that might lead to this seasonality. They might be

- Holidays
- Paydays
- Discount
- Offers (like Big Billion Sales)

Modelling result on next few slides will help us understand the Kpi where company needs to focus.

Analysis & Results Model Dashboard

- R-square values (without and with cross validation) on test data

Model/Category	Camera Accessory	Gaming Accessory	Home Audio
Linear Model	99 % , 75 %	99.95 % , 79 %	93 % , 78 %
Multiplicative Model	100% , 98 %	100% , 97 %	100 % , 95 %
Koyck Model	99% , 87 %	99 % , 80 %	100 % , 76 %
Distributed Lag Model	100 % , 77 %	99 % , 62 %	100 % , 66 %

Analysis & Results
Significant Variables

MODEL GAMING DATASET	SIGNIFICANT VARIABLES
Linear regression Model	list_price, NPS, Other, radio, SEM, TV, COD.
Multiplicative Model	units, list_price, product_type_mass
Koyck Model	list_price, NPS, Other, radio, TV, COD
Distributed Lag Model	Untis, list_price, digital, prodcut_type_mass

MODEL Camera Dataset	Significant Variables
Linear regression Model	Units,product_procurement_sla, list_price, other, radio, sponsorship,digital, tv
Multiplicative Model	Units,product_procurement sla, list_price, product_type_Mass
Koyck Model	Units,product_procurement sla, list_price, other, radio, sponsorship , digital, tv
Distributed Lag Model	Units, product_mrp, product_type_mass , max temp , mean temp, LP-1, LP-2 gmv-1 , gmv-2

Analysis & Results Significant Variables

Analysis & Results
Significant Variables

MODEL HOME DATASET	Significant Variables
Linear regression Model	units, list_price, other, Digital, product_type_mass
Multiplicative Model	Units, list_price, product_type_Mass , Total Rain(mm)
Koyck Model	Units, list_price, Affiliates, content Marketing, product_type_Mass, Max,Min and Mean Temp.
Distributed Lag Model	Units, list_price, Affiliates, content Marketing, product_type_Mass, Max,Min and Mean Temp.

Model Interpretation Variables – Elasticity

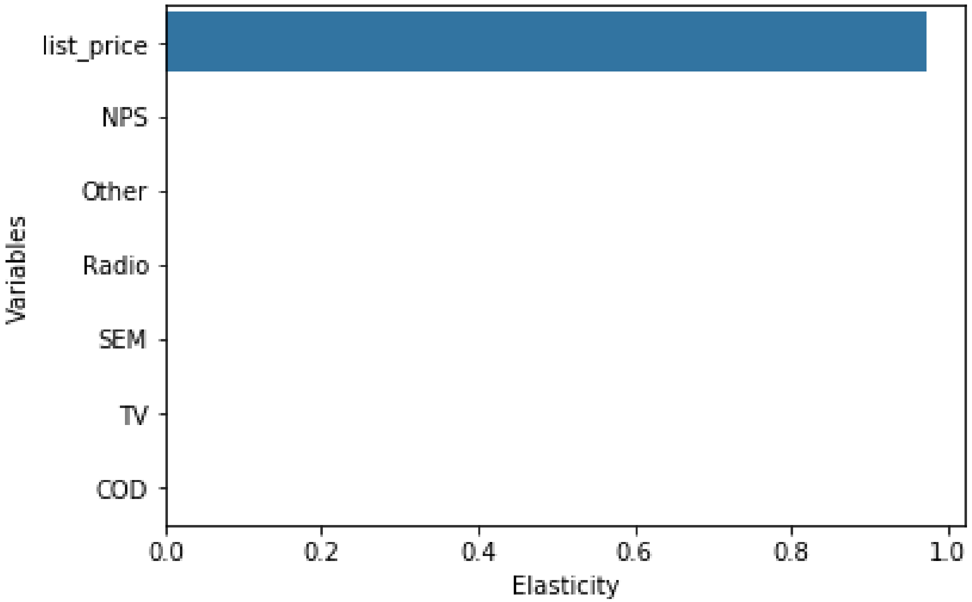
Elasticity: Since the model does not estimate the actual revenue, but its first derivative, which is the growth of revenue, the coefficients also reflect the 'elasticity' i.e. the rate of change of revenue with a change in advertising spending. There, we suggest this method to understand and optimize the budget allocation.

Elasticity was plotted for each dataset. From all the models, **it was quite clear that list_price (pricing KPI) was quite significant**. Please refer to attached screenshots for reference. The screenshots are dataset wise:

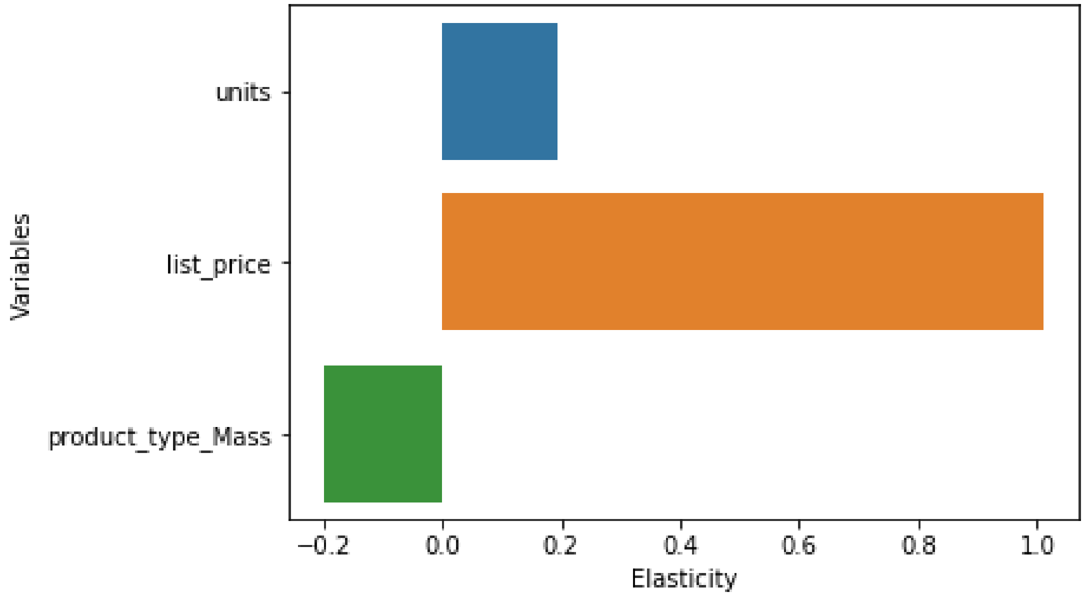
Gaming	Camera	Home

Elasticity - Game

- Linear model

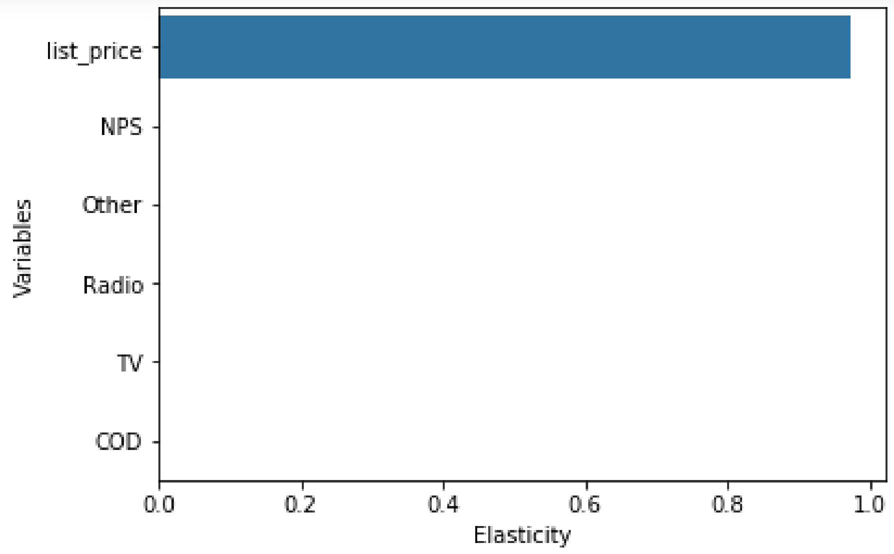


- Multiplicative Model

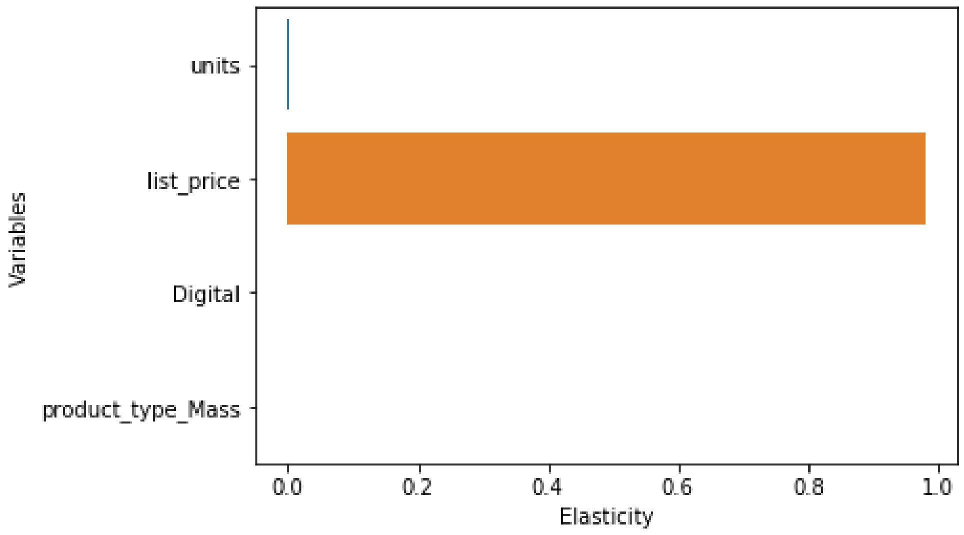


Elasticity – Game..

- Koyck

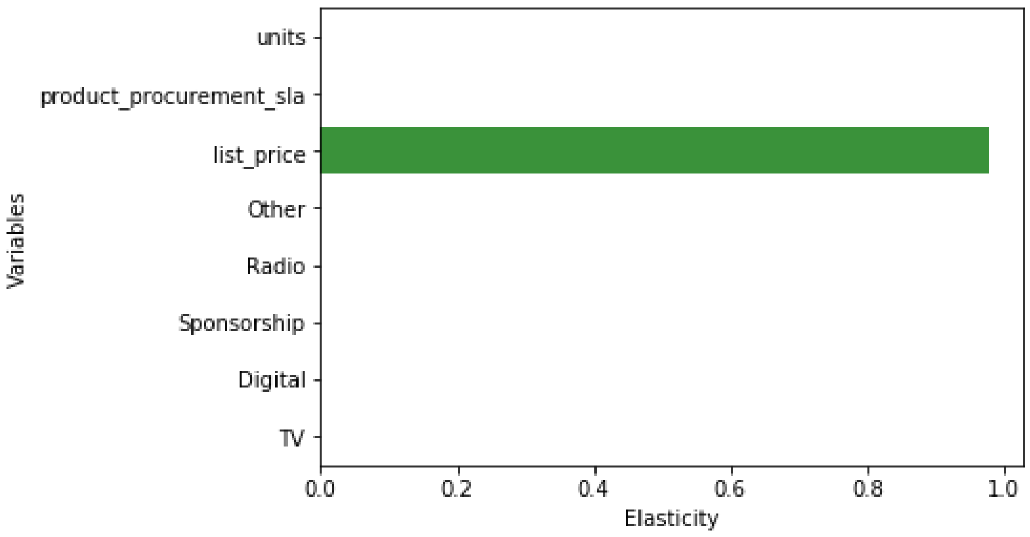


- Distributive Lag

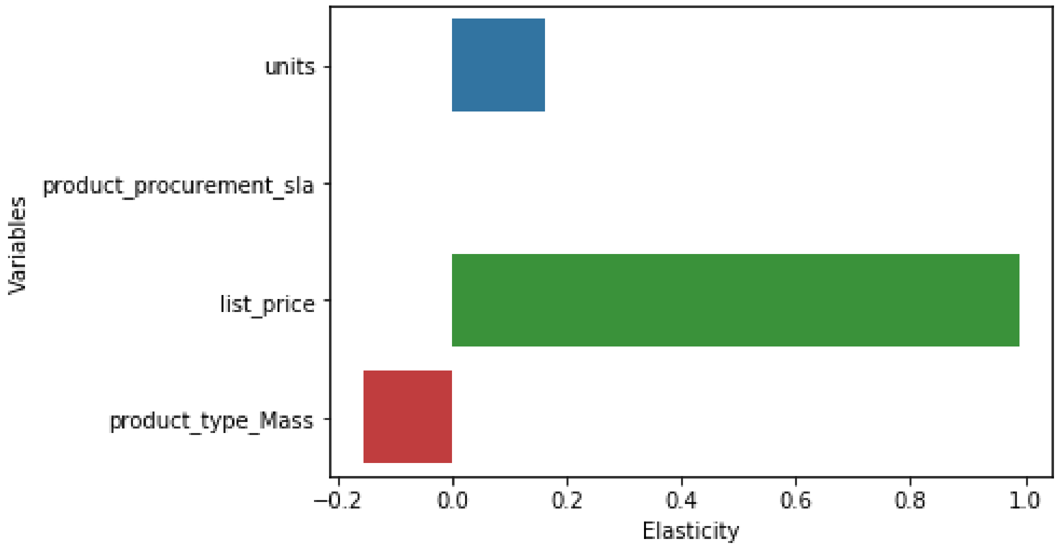


Elasticity - Camera

- Linear model

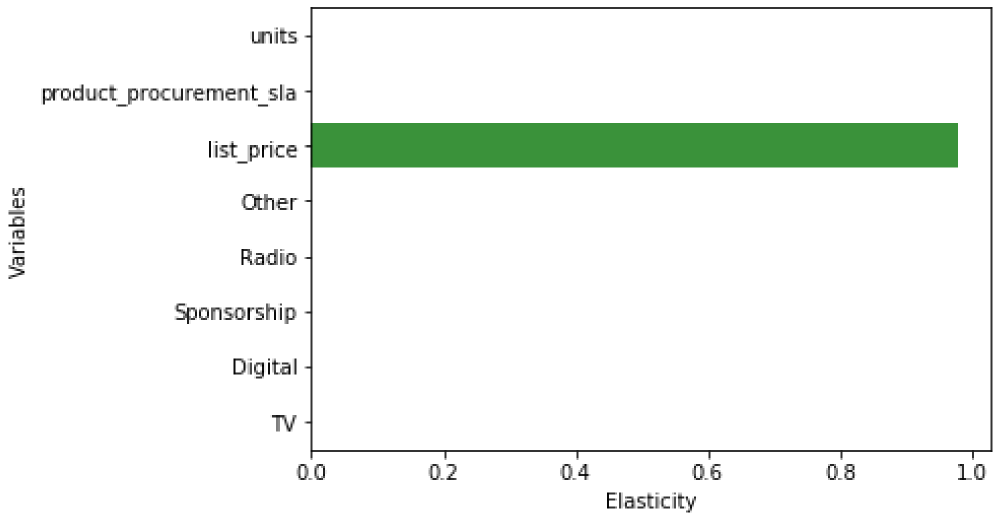


- Multiplicative Model

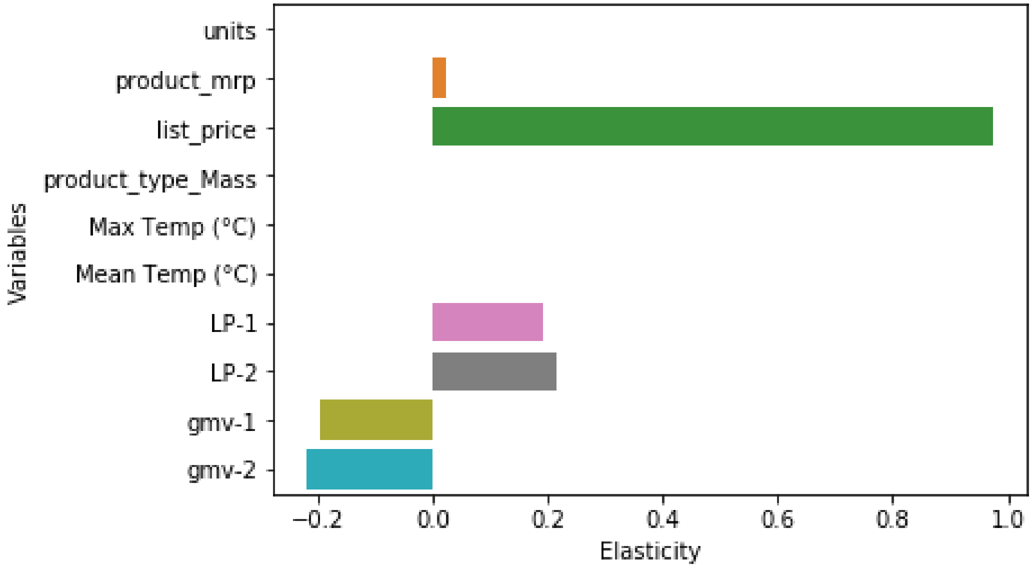


Elasticity – Camera..

- Koyck

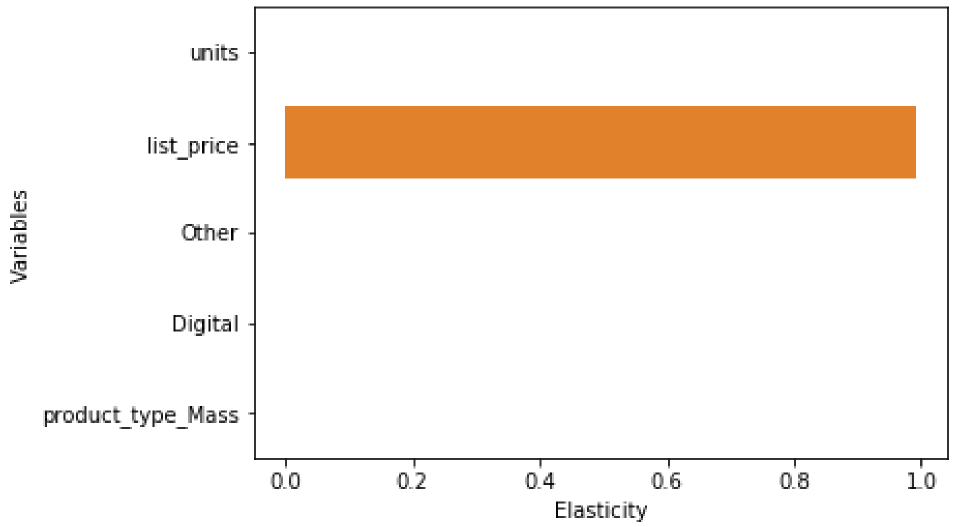


- Distributive Lag

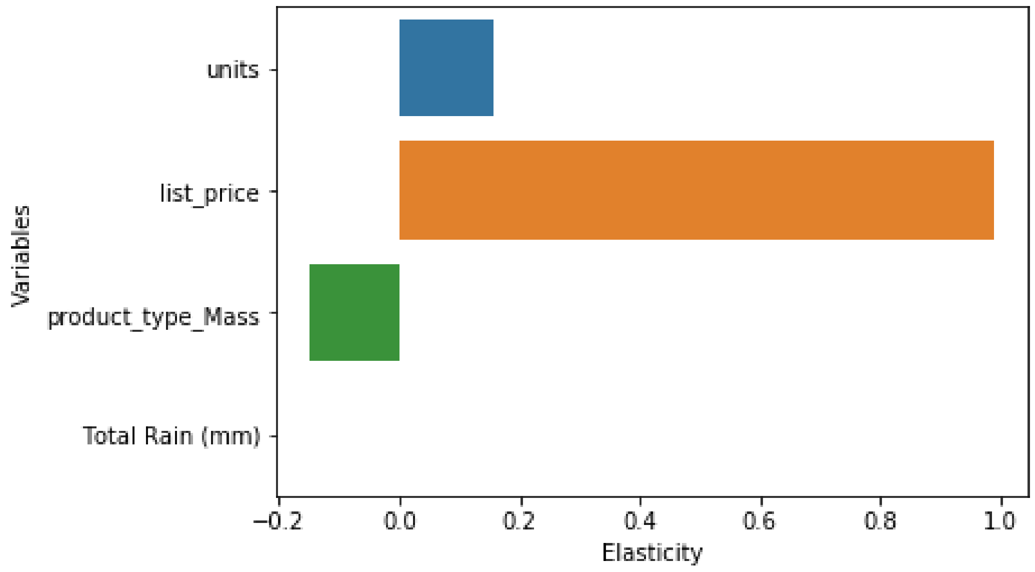


Elasticity - Home

- Linear model

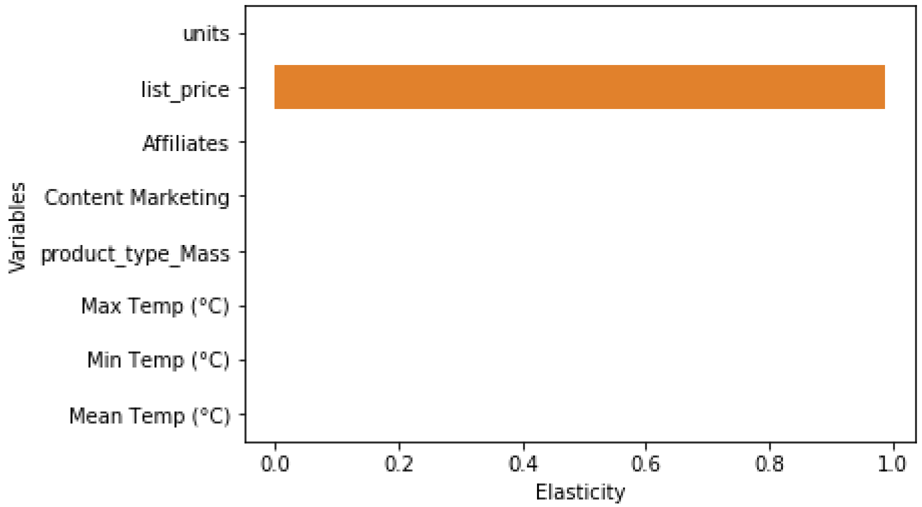


- Multiplicative Model

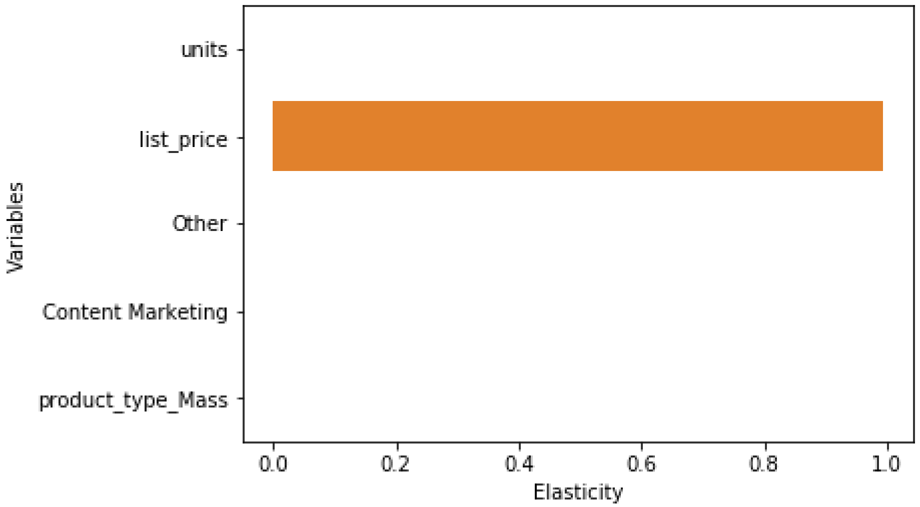


Elasticity – Home..

- Koyck



- Distributive Lag



Results

We suggest multiplicative model for gaming dataset. Also, the company should allocate their budget to price KPI (list price) **and they can cut budget from brand perception kpi (product_Type_Mass).**

We suggest Distributive Lag Model for Camera Dataset. Because this models covers a large variance of data and its highly likely that when tested on new dataset this model perform satisfactorily.

The elasticity interpretation for **Camera remains the same as gaming dataset that the company should allocate their budget to price KPI (list price) and they can cut budget from brand perception kpi (product_Type_Mass).**

We suggest multiplicative model for Home dataset. Also, the company should allocate their budget to price KPI (list price) and they can cut budget from brand perception kpi (product_Type_Mass).