

# Agenda

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# Problem Statement

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## Company Background

ElecKart is an e-commerce firm based out of Ontario, Canada specialising in electronic products. Over the last year, they had spent a significant amount of money on marketing. Occasionally, they had also offered big-ticket promotions (similar to the Big Billion Day). They are about to create a marketing budget for the next year, which includes spending on commercials, online campaigns, and pricing & promotion strategies. The CFO feels that the money spent over the last 12 months on marketing was not sufficiently impactful, and, that they can either cut on the budget or reallocate it optimally across marketing levers to improve the revenue response.

## Task in Hand

Imagine that you are a part of the marketing team working on budget optimisation. You need to develop a market mix model to observe the actual impact of different marketing variables over the last year. Using your understanding of the model, you have to recommend the optimal budget allocation for different marketing levers for the next year.

## Input Data Sets

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Core

Add Ons

Order Level Data  
[Order, GMV]

Investment Data Set  
[ Advertising Spend]

Climate  
[ Ontario]

Holiday  
[ Canadian]

Pay Day  
[ Canadian]

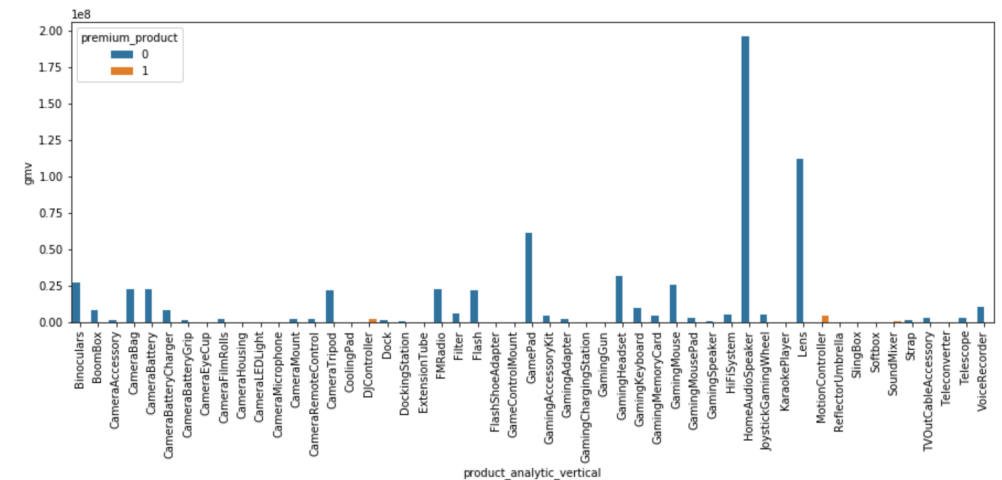
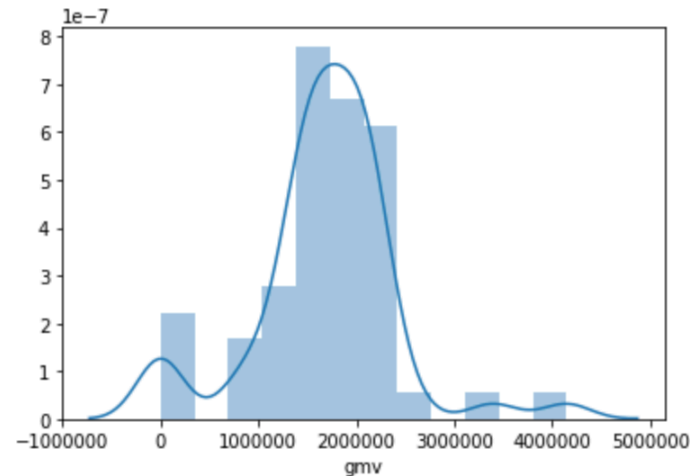
## Data Prep – Key Filters

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- Removing Duplicates
- Removing wherein GMV is null
- Removing values with 0 MRP, since it is not possible to have 0 MRP
- Deriving New Variable : gmv\_per\_unit , listing\_price , discount
- Outlier treatment on Product procurement sla and sla
- Reducing Data from July 2015 to June 2016
- Convert the data from day wise to week wise by taking the mean value for various KPIs
- Filter data into 3 product subcategories - camera accessory, home audio and gaming accessory
- Create separate columns if Pay date (if 1st or 15th of the month) and holidays by creating a flag as a 0 or 1.  
For eg. if Holiday is there, the value will be 1.

# Observations From Camera Sub Category , Gaming Sub Category & Home Audio Sub Category

- COD is preferred more than Prepaid order payment type
- Maximum revenue is generated through mass products like HomeAudioSpeaker, Lens, GamingPad, etc and not premium products that contribute quite less towards revenue. The company hence should focus more on mass products than premium products.
- GMV in range of 10 Lakhs to 25 lakhs

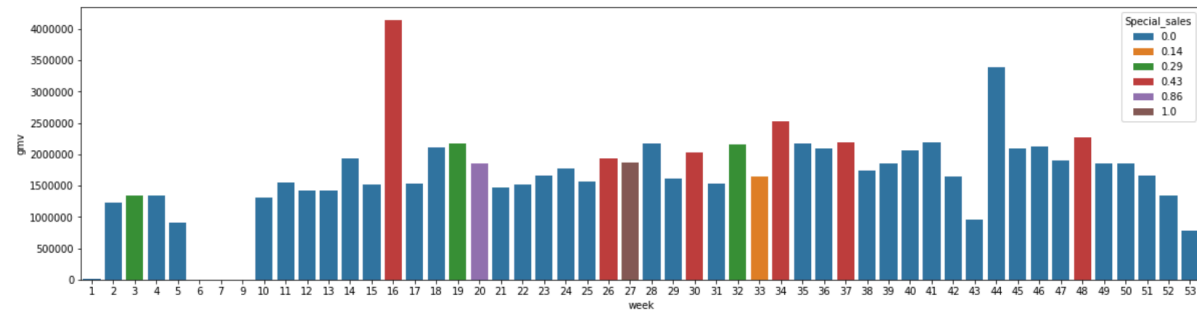


# Observations – Camera Category

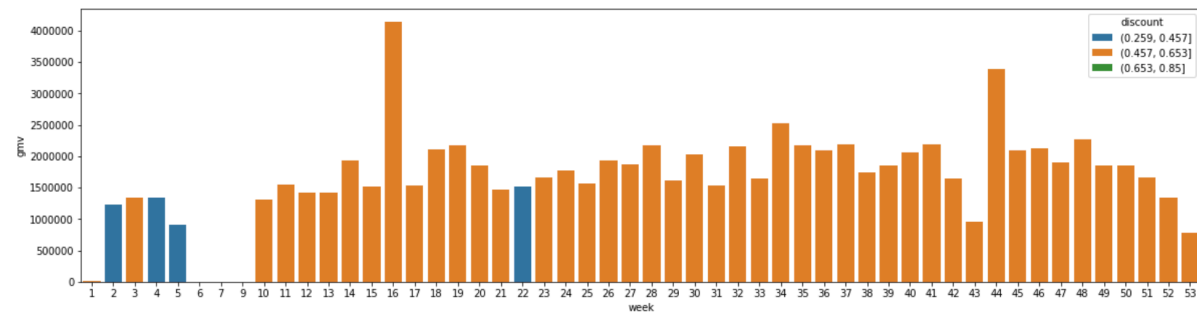
- COD is preferred more than Prepaid order payment type

#Bivariate Analysis

```
In [156]: plt.figure(figsize=(20, 5))
sns.barplot(x= ca_week_viz['week'], y =ca_week_viz['gmv'], hue = ca_week_viz['Special_sales'], dodge = False)
plt.show()
```



```
In [157]: plt.figure(figsize=(20, 5))
sns.barplot(x= ca_week_viz['week'], y =ca_week_viz['gmv'], hue = pd.cut(ca_week_viz['discount'],3), dodge = False)
plt.show()
```



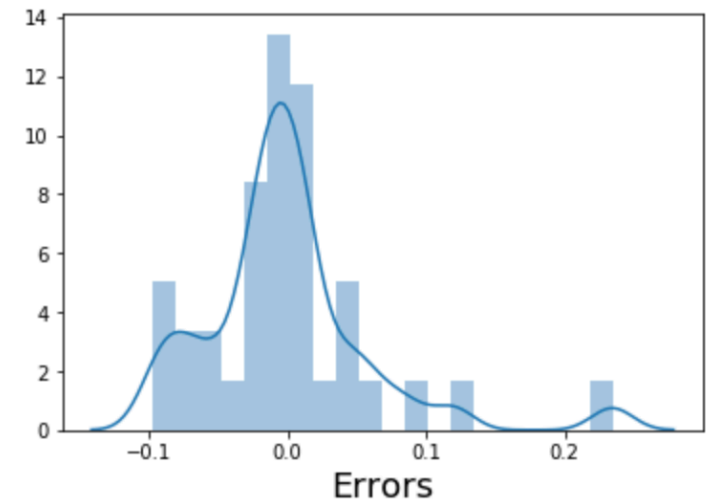
## Model Outputs

- Key Variables
  - Order pAyment Type
  - Online Order
  - Special Sales
  - MA4 Listed Price
- Error terms seem to be approximately normally distributed, so the assumption on the linear modeling seems to be justified and fullfilled

```
checkVIF(X_train_new)
```

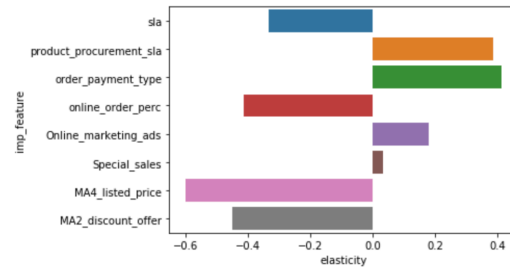
	Features	VIF
0	const	7.97
1	order_payment_type	1.66
2	online_order_perc	1.64
3	Special_sales	1.16
4	MA4_listed_price	1.15

Error Terms



# Elasticity – Key features

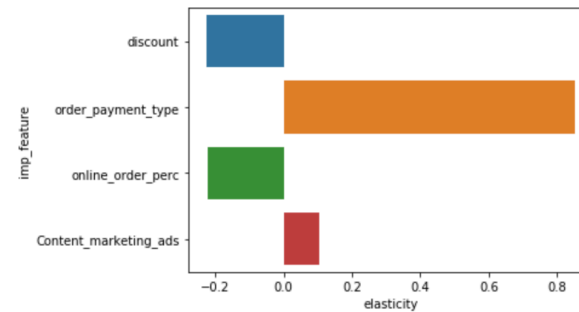
```
In [290]: elasticity(lm1,camera_train_lm)
```



```
Out [290]:
```

	imp_feature	coef	elasticity
0	sla	-0.22	-0.34
1	product_procurement_sla	0.31	0.39
2	order_payment_type	0.78	0.41
3	online_order_perc	-0.55	-0.41
4	Online_marketing_ads	0.12	0.18
5	Special_sales	0.11	0.03
6	MA4_listed_price	-0.42	-0.60
7	MA2_discount_offer	-0.53	-0.45

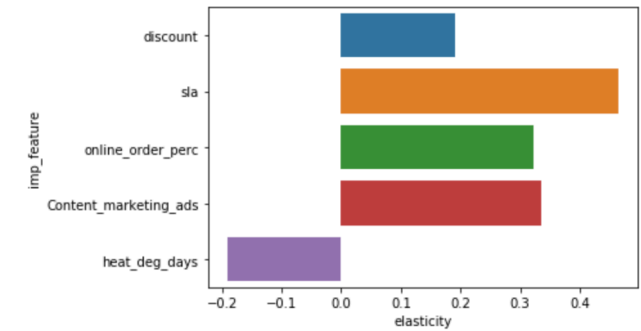
```
: elasticity(mm1,camera_train_mm)
```



```
:
```

	imp_feature	coef	elasticity
0	discount	-0.34	-0.23
1	order_payment_type	0.97	0.85
2	online_order_perc	-0.27	-0.22
3	Content_marketing_ads	0.12	0.10

```
: elasticity(mm1,gaming_train_mm)
```



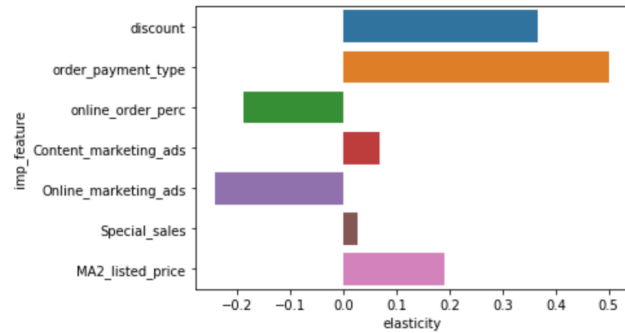
```
:
```

	imp_feature	coef	elasticity
0	discount	0.21	0.19
1	sla	0.49	0.47
2	online_order_perc	0.44	0.32
3	Content_marketing_ads	0.38	0.34
4	heat_deg_days	-0.21	-0.19



# Elasticity – Key features

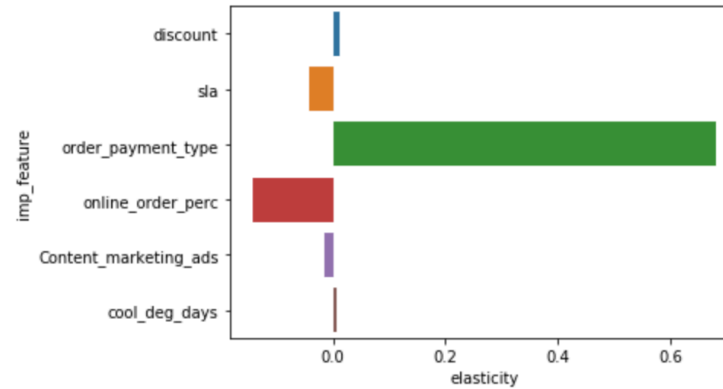
```
: elasticity(lm1,home_train_lm)
```



```
:
```

	imp_feature	coef	elasticity
0	discount	0.27	0.37
1	order_payment_type	0.52	0.50
2	online_order_perc	-0.34	-0.19
3	Content_marketing_ads	0.11	0.07
4	Online_marketing_ads	-0.11	-0.24
5	Special_sales	0.07	0.03
6	MA2_listed_price	0.09	0.19

```
elasticity(mm1,home_train_mm)
```



	imp_feature	coef	elasticity
0	discount	0.02	0.01
1	sla	-0.05	-0.04
2	order_payment_type	0.77	0.68
3	online_order_perc	-0.38	-0.14
4	Content_marketing_ads	-0.02	-0.02
5	cool_deg_days	0.01	0.01