Machine Learning Based Product Price Inference Using Price Elasticity of Demand Approach

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Abstract

In India lot of production and manufacturing industries are there, every time the price fixing to any new or existing product is considered many factors. Many parameters are involved to fix the price of any product. In market price fixing consists of various parameters, before finalize price value of any product, that will be based on the market demand of any product, and customer behavior also may be vary based on the day of purchasing in this proposed work we need to optimization of price product using machine learning algorithm and how effectively increase the proof of any product.

Keywords: Machine Learning; Price Optimization; Data Analytics

1. Introduction

Machine learning is a type of Artificial Intelligence that allows software applications to become more accurate at predicting outcomes without being explicitly programmed to do so. Historical Data is provided as an input to machine learning algorithms which then predicts the output values. Basically ML can be classified into three categories, viz. Supervised Learning, Unsupervised Learning and Reinforcement Learning. In Supervised Learning we know the labels, i.e. the output, and we train the model knowing the output, the goal here is to learn the general rule that maps the inputs to outputs. The training is continued until the model reaches a desired level of accuracy, eg. Image Classification, Regression, etc. In Unsupervised Learning we have unlabelled data, i.e. we don't know the outputs. It is used for clustering population in different groups, e.g. Clustering. And the Reinforcement Learning works on the basis of a reward function. Generally used in gaming applications, the algorithm receives a reward if it performs well and a punishment if it doesn't, thereby contributing to the learning process.

Price optimization is the process of finding the optimal price point for a product or service. It maximizes profitability by using market and consumer data to find a balance between value and profit. There are various factors that need to be taken into account before deciding the price of a product, like customer survey, historic sales data, operating costs, inventories, demand fluctuations, lifetime value and churn data etc. One more factor to be considered is Price Elasticity of Demand, it is the measurement of the change in the consumption of a product in relation to a change in its price. Mathematically it can be represented as:

Price Elasticity of Demand = % Change in Quantity Demanded / % Change in Price

This equation is used to understand how price change affects the supply and demand of a product or service, if demand stays the same when its price changes, it means the commodity is inelastic. This information can be a key to successful price optimization; it helps to know how customers will react to changes in price.

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To decide an optimal price for a product or service, we first need data, i.e Quantitative and Qualitative Data. Quantitative data includes information on demographics, inventory, supply and demand, historical data, churn rate, price sensitivity, etc. While qualitative data includes customer surveys and opinions. Knowing the right value metric is also as important, because it showcases how customers value the product or service and what can be charged for the value offered. Continuous price monitoring is also required to know whether the value offered aligns with customers' need and pricing expectations and if it does not, then the pricing can be changed accordingly.

Some of the factors that determine the pricing of a product are:

1. **Cost of Production**: A company cannot sell a product at a price lower than its production cost and hence it must be taken into account before fixing the price.
2. **Demand for the Product**: Depending upon the demand price of a product can vary, i.e. if demand for a product is high the price is also higher.
3. **Price of Competing Firms**: The product prices of competing firms must be considered before fixing the price.
4. **Purchasing Power of the Customer**: Things like at what price and how much the customer can purchase should also be taken into consideration
5. **Government Regulations**: Price of a commodity has to be ascertained on the basis of government norms and regulations
6. **Marketing Method used**: The method used for marketing of product along with the commission provided to the middleman or retailers as well as 'after sale service' facility provided or not must be considered before fixing the price

2. Related Work

As referred to in the past piece of this article, energy research fundamentally focuses on the exceptional assessing on online business sectors, while blocking the necessity for a suitable portrayal of the methodologies used. The going with regions are based on the crucial confirmation in the field of online business in the neighborliness business and the portrayal of assessing models used to match the clients' necessities and their expense affirmation characteristics.
Pricing a product is a crucial aspect in any business. Alot of thought process is out into it. There are different strategies to price different kinds of products. There are products whose sales are quite sensitive to their prices and as such a small change in their price can lead to noticeable change in their sales. While there are products whose sales are not much affected by their price - these tend to be either luxury items or necessities (like certain medicines). This notebook will focus on the former type of products.

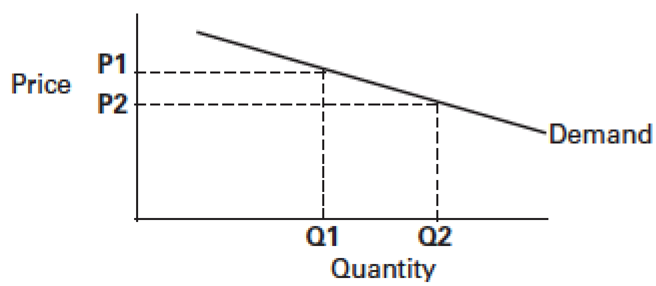

Figure 1: Example for Elastic Demand

The figure represents the example of computing elasticity of demand, using the formula is show as price is decreasing \$10 to \$8, the quantity of the product sales are increasing 30 unit to 50 unit, then elasticity coefficient is 2.25.

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Figure 2: Price Elasticity of Demand

The figure which represents the changes of price values based on the demand in the market, if any product having more demand in the market, definitely people can purchase without having concern with price value.

$$E_Y = \frac{\frac{\text{Change in Quantity Demanded}}{\text{Average Quantity Demanded}}}{\frac{\text{Change in Income}}{\text{Average Income}}} = \frac{\frac{\Delta Q}{Q_1+Q_2/_2}}{\frac{\Delta Y}{Y_1+Y_2/_2}}$$

$$E_Y = \frac{\Delta Q}{\Delta Y} \times \frac{\frac{Y_1+Y_2}{2}}{\frac{Q_1+Q_2}{2}} \qquad \therefore E_Y = \frac{\Delta Q}{\Delta Y} \times \frac{Y_1+Y_2}{Q_1+Q_2}$$

Where,

ΔQ= Change in quantity demanded

ΔY= Change in income

Y_1= Initial income

Y_2= Final income

Q_1= Initial quantity demanded

Q_2= Final quantity demanded

Figure 3: Income elasticity of Demand

The figure with represent the income elasticity demand based on the various parameters of the product both price demand and income demand plays major role, for changing the price of any product based on the market demand. If the curve is more elastic, then small changes in price will cause large changes in quantity consumed. Graphically, elasticity can be represented by appearance of the supply or demand curve. A more elastic curve will be horizontal

3. Result and discussion

In this session we are going to discuss about how data is extracted from various dataset, from which we need to perform the data cleaning operation first followed by machine learning algorithm to optimization of the price. In this model data is collected from three different source files such as MetaData, Transaction and Dateinfousinf pandas library function all the data is loaded in one variable.

```
sold = pd.read_csv('MetaData.csv')
transactions = pd.read_csv('Transaction.csv')
date_info = pd.read_csv('DateInfo.csv')
```


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In which first step of every problem solving to load the required dataset and apply pre-processing methods to remove the noise values from the dataset, in our problem statement taken three different data set such as Metadata, Transaction and Date info, each dataset having unique row and columns.

	SELL_ID	SELL_CATEGORY	ITEM_ID	ITEM_NAME
0	1070	0	7821	BURGER
1	3055	0	3052	COFFEE
2	3067	0	5030	COKE
3	3028	0	6249	LEMONADE
4	2051	2	7821	BURGER
5	2051	2	5030	COKE
6	2052	2	7821	BURGER
7	2052	2	6249	LEMONADE
8	2053	2	7821	BURGER
9	2053	2	5030	COKE
10	2053	2	3052	COFFEE

Figure 4: Sold Dataset

The figure sold dataset consist of 4 columns such as Sell_id, Sell_category,Item_ID,Item_name which having 11 rows.

	CALENDAR_DATE	PRICE	QUANTITY	SELL_ID	SELL_CATEGORY
0	01/01/12	15.50	46	1070	0
1	01/01/12	12.73	22	2051	2
2	01/01/12	12.75	18	2052	2
3	01/01/12	12.60	30	2053	2
4	01/02/12	15.50	70	1070	0
5	01/02/12	12.73	22	2051	2
6	01/02/12	12.75	16	2052	2
7	01/02/12	12.60	34	2053	2
8	01/03/12	15.50	62	1070	0
9	01/03/12	12.73	26	2051	2
10	01/03/12	12.75	12	2052	2

Figure 5: Transaction table

The figure 5 Transaction table consists of 5 columns such as calendar_ date, price, quantity, sell_id and sell_category with 5404 rows.

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	CALENDAR_DATE	YEAR	HOLIDAY	IS_WEEKEND	IS_SCHOOLBREAK	AVERAGE_TEMPERATURE	IS_OUTDOOR
0	1/1/12	2012	New Year	1	0	24.8	0
1	1/2/12	2012	New Year	0	0	24.8	0
2	1/3/12	2012	New Year	0	0	32.0	1
3	1/4/12	2012	NaN	0	0	32.0	1
4	1/5/12	2012	NaN	0	0	24.8	0
5	1/6/12	2012	NaN	0	0	23.0	0
6	1/7/12	2012	NaN	1	0	26.6	0
7	1/8/12	2012	NaN	1	0	26.6	0
8	1/9/12	2012	NaN	0	0	23.0	0
9	1/10/12	2012	NaN	0	0	24.8	0
10	1/11/12	2012	NaN	0	0	21.2	0

Figure 6: Date_Info table

The Figure 6 which consists of following columns like Calendar _Date, Year, Holidy,Is_Weekend,Is_Schoolbreak,Average _tempature and Is_Outdoor with 1349 rows of data.

	SELL_ID	SELL_CATEGORY	ITEM_ID
count	11.000000	11.000000	11.000000
mean	2235.000000	1.272727	5906.909091
std	598.728653	1.009050	1830.217170
min	1070.000000	0.000000	3052.000000
25%	2051.500000	0.000000	5030.000000
50%	2053.000000	2.000000	6249.000000
75%	2540.500000	2.000000	7821.000000
max	3067.000000	2.000000	7821.000000

Figure 7: Statistical Description of Sold Table

The Fig.7 describes the statistical information about sold table, which does not contain any error values.

```
date_info.isnull().sum()
```

```
CALENDAR_DATE            0
YEAR                     0
HOLIDAY               1244
IS_WEEKEND               0
IS_SCHOOLBREAK           0
AVERAGE_TEMPERATURE      0
IS_OUTDOOR               0
dtype: int64
```

Figure 8: Before Pre-processing of Date Info Table

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```
date_info.isnull().sum()
```

```
CALENDAR_DATE          0
YEAR                   0
HOLIDAY                0
IS_WEEKEND             0
IS_SCHOOLBREAK         0
AVERAGE_TEMPERATURE    0
IS_OUTDOOR             0
dtype: int64
```

Figure 9: After Pre-processing of Date_Info Table

he Fig 8 shows the before pre-processing of Date_info table and Fig.9 Shows after pre-processing same table. The price of the product every day will not change, based the product and manpower involved for the product price will be vary or based the season, due to peak season the price of the product may be vary or because of huge demand in market also another reason the price of the product may be change. Every price will associated with sell_id, quantity is numerical value that is associated with product sold, Sell_Id is unique variable for each product.

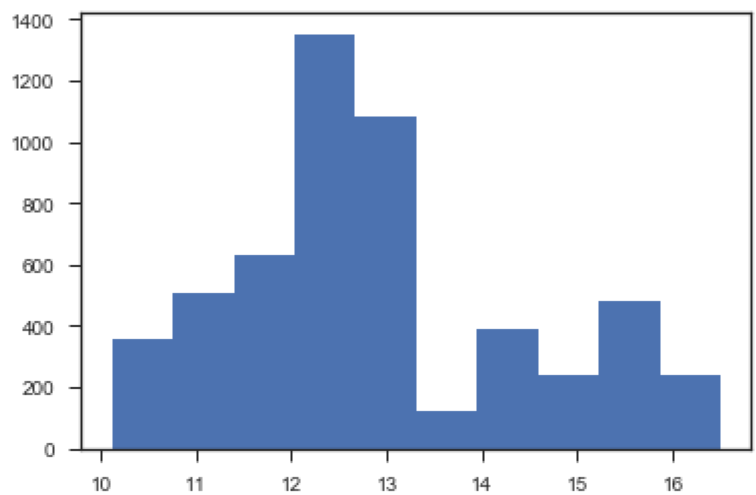

Figure10: Transaction of sales

	YEAR	IS_WEEKEND	IS_SCHOOLBREAK	AVERAGE_TEMPERATURE	IS_OUTDOOR
count	1349.000000	1349.000000	1349.000000	1349.000000	1349.000000
mean	2013.375093	0.285397	0.204596	56.326019	0.862120
std	1.073073	0.451771	0.403556	20.227597	0.344902
min	2012.000000	0.000000	0.000000	14.000000	0.000000
25%	2012.000000	0.000000	0.000000	35.600000	1.000000
50%	2013.000000	0.000000	0.000000	60.800000	1.000000
75%	2014.000000	1.000000	0.000000	75.200000	1.000000
max	2015.000000	1.000000	1.000000	87.800000	1.000000

Figure11: Statistical information about Date_ Info Table

Algorithm for Find Optimal Price:

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```
deffind_optimal_price(data, model, buying_price):
start_price = data.PRICE.min() - 1
end_price = data.PRICE.min() + 10
test = pd.DataFrame(columns = ["PRICE", "QUANTITY"])
test['PRICE'] = np.arange(start_price, end_price,0.01)
test['QUANTITY'] = model.predict(test['PRICE'])
test['PROFIT'] = (test["PRICE"] - buying_price) * test["QUANTITY"]
plt.plot(test['PRICE'],test['QUANTITY'])
plt.plot(test['PRICE'],test['PROFIT'])
plt.show()
ind = np.where(test['PROFIT'] == test['PROFIT'].max())[0][0]
values_at_max_profit = test.iloc[[ind]]
returnvalues_at_max_profit
```

Table 1: Items sales details

Name of Items	**PRICE**	**QUANTITY**	**PROFIT**
burger_1070	17.22	71.259194	585.751
burger_2051	15.02	21.782193	131.129
burger_2052	14.34	15.259215	81.4842
burger_2053	14.57	34.329951	191.218
coke_2051	15.02	21.782193	131.129
lemonade_2052	14.34	15.259215	81.4842
coffee_2053	14.57	34.329951	191.218

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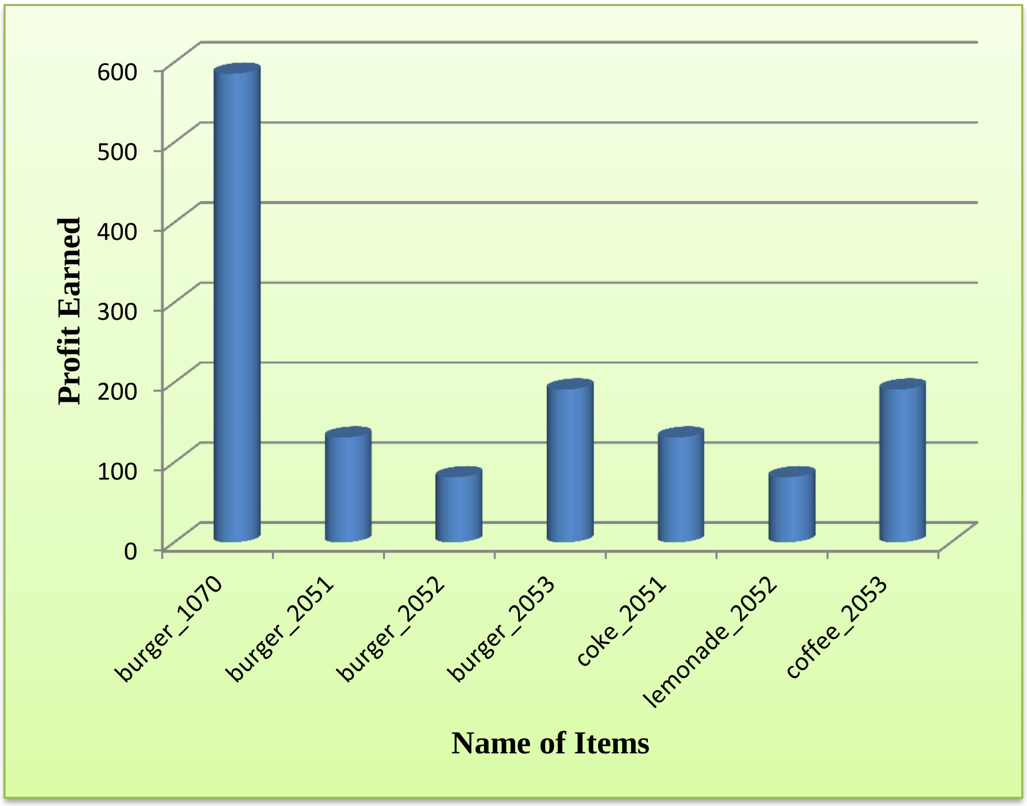

Figure 12: Profit Earned by items

```
burger2052_data = bau2_data[(bau2_data['ITEM_NAME'] == "BURGER") & (bau2_data['SELL_ID'] == 2052)]
elasticities['burger_2052'], model_burger_2052 = create_model_and_find_elasticity(burger2052_data)
```

```
Price elasticity of the product: -2.856702984559962
                            OLS Regression Results
==============================================================================
Dep. Variable:               QUANTITY   R-squared:                       0.433
Model:                            OLS   Adj. R-squared:                  0.432
Method:                 Least Squares   F-statistic:                     316.5
Date:                Sat, 20 Jun 2020   Prob (F-statistic):           5.32e-53
Time:                        15:03:02   Log-Likelihood:                -1014.7
No. Observations:                 416   AIC:                             2033.
Df Residuals:                     414   BIC:                             2041.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     56.2243      1.927     29.177      0.000      52.436      60.012
PRICE         -2.8567      0.161    -17.790      0.000      -3.172      -2.541
==============================================================================
Omnibus:                      139.808   Durbin-Watson:                   1.864
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               21.201
Skew:                           0.025   Prob(JB):                     2.49e-05
Kurtosis:                       1.895   Cond. No.                         171.
==============================================================================
```

Figure 13: OLS Regression result of Burger_2052 Product id

4. Conclusion

This is the price the cafe should set on it's item to earn maximum profit based on it's previous sales data. It is important to note that this is on a normal day. On 'other' days such as a holiday, or an event taking place have a different impact on customer buying behaviours and pattern. Usually an increase in consumption is seen on such

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days. These must be treated separately. Similarly, it is important to remove any external effects other than price that will affect the purchase behaviours of customers including the data points when the item was on discount.

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