PREDICTION OF SALES BASED ON AN EFFECTIVE ADVERTISING MEDIA SALE DATA: A PYTHON IMPLEMENTATION APPROACH

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ABSTRACT

Sales forecasting is an essential task in the retail management field. Intelligent forecasting using machine learning techniques can help discover the selection of feature variables that influence prediction of sales growth. A Python program implementation is adopted to compute; develop and visualizing forecasting model of historical sales data based on advertising media opted to do the effective sales promotion. Python supports working on predictive algorithms through accessing from Python libraries. For this purpose, it relies on the past observations based transaction data set file as an input to produce output without worrying about the underlying mechanism. The results indicated that TV media is the feature variable that influences the prediction of sales of linear regression model. Regression results of OLS model type are displayed with coefficient values to substitute in the linear regression equation. Seaborne library of Python is used to generate the visualization of charts and graphs.

Keywords: Analyzing Sales Data, Linear Regression Model, Predictive Modeling, Predictive analytics, Python implementation, Sales Prediction

INTRODUCTION

Rapid development in the retail industry both in structure and growth in online-business is becoming the current marketing trends (Robert, Shaohui & Stephan, 2019). Sales forecasting is an important aspect of many business organizations today (Nguyen, Kedia, Snyder, Pasteur & Wooster, 2013). Sales forecasting is an essential task for the management of a store (Martin & Lopez, 2020). Sales prediction is used to predict sales of products at various stores and outlets of a big retail mart companies in different cities (Chandel, Dubey, Dhawale & Ghuge, 2019). Forecasting store sales can be categorized into: (i) forecasting existing store sales for distribution, setting target sales and its viability and controlling the finance and (ii) forecasting potential sales for the analysis of new store site selection (Robert, Shaohui & Stephan, 2019).. Predictive analytics is concerned with the prediction of future probabilities and trends. With predictive analytics, retailers are trying to enhance their product offerings, pricing models and service levels to create and enhance sustainable competitive advantage (Puri Seghal & Sharma, 2013). Intelligent forecasting can play significant role in the world of sales management. Intelligent forecasting uses the information of publicity of retail sales to forecast the effective media of advertising and thus predicting the growth of sales in terms of sales prediction. Though the process of forecasting tends

to be a complex, it is a straight forward technique to determine its accuracy (Pinki & Gupta, 2018). Machine learning can help us discover the factors that influence sales and estimate the number of sales that it will have in the near future (Martin & Lopez, 2020).

Many forecasting models use historical sales to predict future sales (Nguyen, Kedia, Snyder, Pasteur & Wooster, 2013; Lertuthai, Baramichai & Laptaned, 2009).

During the promotion period, purchasing behavior of the consumer partially influenced by the incentives offered through each promotion event. Consumers make their final purchase decisions based on their perceived values for these promotion events. The efficacy of promotion events depends on the duration of the advertisement medium and degree of advertisement medium. Every promotional event may have a different effect on the consumer's decision to increase their purchase (Lertuthai, Baramichai & Laptaned, 2009). Managers use analytical reports from sales to find market opportunities and processes where they could increase volume and profit. By comparing the result of positive and negative evaluations of comments of consumers, retailers can better understand the outcomes from competitors' analysis (Pantano, Giglio & Dennis, 2018).

RESEARCH OBJECTIVE

In this research, we developed an innovative realistic predictive method that could take the advantage of the historical demand data from the previous promotional events to forecast future sales. For example, a customer can exhibit a history of increased sales over certain periods (leading India, undated).

A Python program implementation is adopted to compute develop and visualizing forecasting model of historical sales data based on advertising media opted to do the sales promotion. Further Literature review on forecasting method has been studied in Lertuthai, Baramichai & Laptaned (2009) in passing.

We measure the causal effects of offline advertising on sales using Python programming with corresponding transaction data file. We wanted to find out statistically significant impacts of the advertising on sales (Lewis & Reiley, 2011). TV advertising is still huge and growing, despite the severe competition from online advertising. As an example, by the end of the year 2016 it was estimated by the e-Marketer that TV spending will be 71.29 Billion USD in USA (Deng & Mela, 2018). So as per the transaction data file figures that is considered for data processing, thus TV based sales prediction is targeted to be computed. This paper describes and assesses the effects of promotions of three media such as TV, NEWS PAPER and RADIO.

RESEARCH METHODOLOGY

A case study approach is adopted for research investigation, when realization of theoretical aspects becomes narrowed and complex with operational understanding and its synergies (Zamil & Vasista, 2020). In this paper, case study methodology and advertising media sales data processing with linear regression model are adopted. A case study is an empirical investigation that examines a current trend based phenomenon within its real-life context, especially when the boundaries between the research objects and contexts are not readily visible (Dul & Hak, 2008) as cited in Yin (2003); Ebneyamini, Reza & Moghadam (2018). The essence of case study is that it tries to illuminate decision or set of decisions, why they were taken, how they were implemented and with what results (Schramm, 1971) as cited in (Yin, 1984; Ebneyamini, Reza & Moghadam (2018).

Regression is an important machine learning model for these predicting sales kinds of problems, where we can fit a line of high sale and low sale product. It required significant amount

of data for training and testing of the model (Leading India, undated). We intended to use the historical sales data file from kaggle.com web site as a secondary data that captured the data of selected media and corresponding sales figures of store items purchased.

Today's advertisers are allocating budgets on different advertising platforms including TV, social media, online web display, catalogs, e-mail and many others (Zantedeschi, Feit & Bradlow, 2016).

Either product manufacturers or retail stores or both opt for various on-line and off-line promotional Medias such as Company Website, Television, Radio, News Paper, Brochure etc.

Each of the Medias is optimal in its own way facilitating the goods and service provides in promoting their sales. Electronic Word of Mouth communication such as social media often attracts new customers and is one of the contemporary practices to attract customers and to enhance customer decision making through E-word of mouth spread (AlSudairi, Vasista, Zamil & Algharabat, 2012). While newspaper media based sales in promotion items show growth steadily, radio retailers with vocal promotions and television retailers with visual effects attempt to promote selected stock keeping units with high discounts for shorter period (Lertuthai, Baramichai & Laptaned, 2009).

PREDICTIVE MODELING

As mentioned in Pattnaik & Behera (2016), predictive analytics is defined as generating predictive scores or probabilities of dependent variable(s) for individual organizational element and predicting at a more detailed level of granularity. Predictive analytics uses data mining techniques, which use analytical models to extract data and use it to predict trends and behavioral patterns of the unknown event of future interest. The basic process of creating analytical models involves use of one or more algorithms against a transactional data set having facts data by computationally determining the values of dependent variable, also called predicting variable. During this process, the data set get subjected to split into two where one data set is used to train the model and other data set to test the model. Predictive models may fail when business users ignore their results or when the model itself is found wrong. Further according to Pattnaik & Behera (2016), Sales and demand forecasting drives and number of merchandising, operational and financial processes such as replenishment, promotions, real estate, and budgeting and human resource related decision.

LINEAR REGRESSION MODEL

Models are a way to summarize data. Ainscough & Aroson (1999) cited that development of linear regression models are considered as primary tool for making data analysis. Linear regression models are a family of models that impose a linear function between predictor and response variables. There are two primary goals for using regression analysis: (i) inference about parameters (ii) Prediction. Examples of inference about parameters include: (a) how does advertising media (budget) affect sales? (b) Estimate effect of x or y, controlling for other explanatory factors. Examples of prediction include: (a) how accurately can sales be predicted given a certain sales media (budget) for promotion (b) what and how to use transformations or techniques to get better predictions (UoA, 2017).

The linear regression model is built to allow the prediction of value of new data, when given the training data used to train the model (Marwardi, 2017). It is a data modeling technique. In this the predicted value is determined using a straight line. The mathematical model of linear regression take the form as shown below:

$Y_i=ß_0+ß_1X_i+Ɛ_i$

Where: Y_i=Dependent variable
$ß_0$=Population Y intercept where X=0 and the line meets the Y-axis
$ß_1$=Population Slope Coefficient→ it is the amount of impact X has on Y
X_i=Independent variable→ it is the feature variable
$Ɛ_i$= Random Error term
$ß_0+ß_1X_i$ →this term is called the linear component.
Y_i= It is considered as response or dependent variable *i.e.*, we are predicting the sales

Prediction is determined by the value of the variable. Accuracy and fitness is measured by loss, R square, adjusted R square etc. Linear regression is a type of supervised machine learning algorithm (intellipat.com).

The best fit line for the data points is nothing but the line that best expresses the data point relationship. Residual Sum of Squares (RSS) is computed to find the best-fit line, such line will have the lowest value of RSS.

$$RSS=\sum_{k=1}^{n}(Actual-Predicted)^2$$

In simple linear regression, if the coefficient of x is positive, it can be concluded that the relationship between independent variable and dependent variables is positive.

i.e., in $Y_i=ß_0+ß_1X_i+Ɛ_i$,
if $ß_1>0$ the relationship is positive.
if $ß_1<0$ the relationship is negative.

PYTHON IMPLEMENTATION OF SALES PREDICTION

Python supports working on predictive algorithms through accessing from Python libraries by relying on the past observations based transaction data set file as an input to produce outputs without worrying about the underlying mechanism (Bradlow, Gangwar, Kopalle & Voleti, 2017).

```
In [3]: import warnings
        warnings.filterwarnings('ignore')

In [4]: import numpy as np
        import pandas as pd

        import matplotlib.pyplot as plt
        import seaborn as sns

In [6]: advt = pd.DataFrame(pd.read_csv("SalesPredictionAdvertisingKaggle.csv"))
        advt.head()

Out[6]:
```

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9

```
In [7]: advt.shape
Out[7]: (200, 4)
```

FIGURE 1
IMPORTING PYTHON LIBRARIES AND READING & DISPLAYING TRANSACTION DATA SET

```
Out[7]: (200, 4)

In [8]: advt.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   TV         200 non-null    float64
 1   Radio      200 non-null    float64
 2   Newspaper  200 non-null    float64
 3   Sales      200 non-null    float64
dtypes: float64(4)
memory usage: 6.4 KB

In [9]: advt.describe()
Out[9]:
```

	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	15.130500
std	85.854236	14.846809	21.778621	5.283892
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	11.000000
50%	149.750000	22.900000	25.750000	16.000000
75%	218.825000	36.525000	45.100000	19.050000
max	296.400000	49.600000	114.000000	27.000000

FIGURE 2
DESCRIBING THE AGGREGATED STATISTICAL FIGURES OF MEDIA TRANSACTIONAL AND SALES COUNT

```
In [10]: advt.isnull().sum()*100/advt.shape[0]
Out[10]: TV           0.0
         Radio        0.0
         Newspaper    0.0
         Sales        0.0
         dtype: float64

It means there are no NULL values present in the data set. Hence the data is clean

Outlier Analysis

In [14]: fig, axs = plt.subplots(3, figsize = (6,4))
         plt1 = sns.boxplot(advt['TV'], ax = axs[0])
         plt2 = sns.boxplot(advt['Newspaper'], ax = axs[1])
         plt3 = sns.boxplot(advt['Radio'], ax = axs[2])
         plt.tight_layout()
```

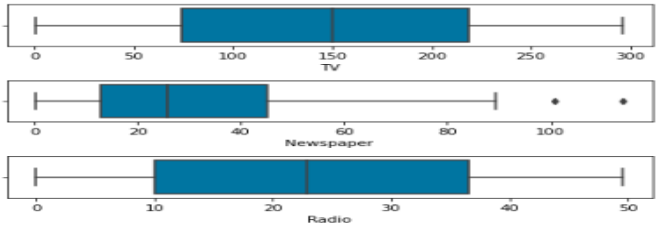


FIGURE 3
DATA CLEANSING AND OUTLIER ANALYSIS

Exploratory Data Analysis - Univariate Analysis - Sales is the Target Variable

```
In [15]: sns.boxplot(advt['Sales'])
         plt.show()
```

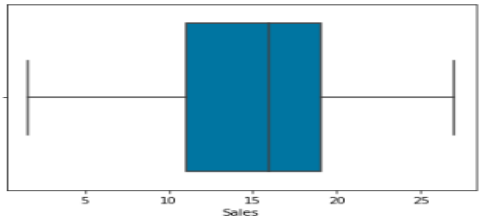


FIGURE 4
EXPLORATORY ANALYSIS – SALES IS THE TARGET VARIABLE

Seeing how Sales are related to other variables using scatter plot

```
In [19]: sns.pairplot(advt, x_vars=['TV', 'Newspaper', 'Radio'], y_vars ='Sales', height=4, aspect=1, kind='scatter')
         plt.show()
```

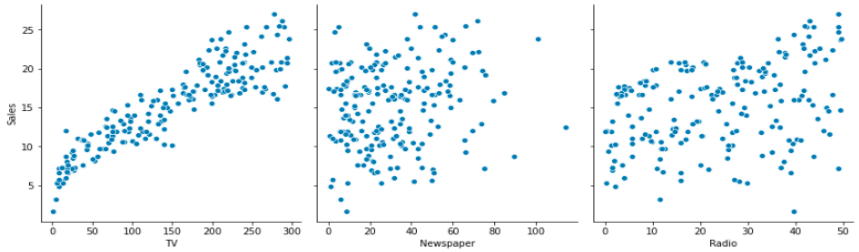


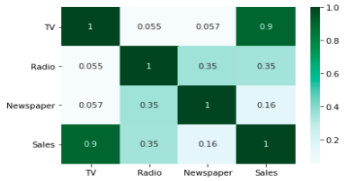
FIGURE 5
SCATTER PLOT SHOWING HOW TARGET VARIABLE SALES IS RELATED TO OTHER VARIABLES

Though from the figure 5, it is appearing that TV data set seems to be more linear as compared to other variable dispersion of values, let us confirm it through observing correlation values by generating a heat map.

Though it is appearing from the plot that TV data set seems to be more linear as compared to other variable dispersion of values

However let's see the correlation between different variables with heatmap

```
In [21]: sns.heatmap(advt.corr(), cmap="BuGn", annot = True)
         plt.show()
```



As seen from the pairplot and the heat map the Correlation factor for TV Variable is 0.9 It is means it is highly correlated with Sales. So now sales prediction is performed in TV as our feature varaible

FIGURE 6
HEATMAP SHOWING CORRELATION BETWEEN DIFFERENT VARIABLES

Building Simple Linear Regression Model for the TV as a feature variable

Building Simple Linear Regression Model: Sales = c+m1*TV

```
In [26]: X = advt['TV']
         y = advt['Sales']
```

Now the data is split for both training and testing data sets It is done by importing train_test_split from sklearn.model_selection library Usually 70% of the data as training set data and 30% is kept for the test data set

```
In [27]: from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7, test_size = 0.3, random_state = 100)

In [28]: X_train.head()

Out[28]: 74     213.4
         3      151.5
         185    205.0
         26     142.9
         90     134.3
         Name: TV, dtype: float64

In [29]: y_train.head()

Out[29]: 74     17.0
         3      16.5
         185    22.6
         26     15.0
         90     14.0
         Name: Sales, dtype: float64
```

FIGURE 7
BUILDING LINEAR REGRESSION: SHOWING TRAINING DATA

```
In [30]: import statsmodels.api as sm

In [31]: #Add a constant to get an intercept
         X_train_sm = sm.add_constant(X_train)

In [32]: # Fit the regression line using 'OLS'
         lnr = sm.OLS(y_train, X_train_sm).fit()

In [33]: lnr.params

Out[33]: const    6.948683
         TV       0.054546
         dtype: float64

In [34]: print(lnr.summary())

                            OLS Regression Results
==============================================================================
Dep. Variable:                  Sales   R-squared:                       0.816
Model:                            OLS   Adj. R-squared:                  0.814
Method:                 Least Squares   F-statistic:                     611.2
Date:                Mon, 22 Jun 2020   Prob (F-statistic):           1.52e-52
Time:                        14:31:35   Log-Likelihood:                -321.12
No. Observations:                 140   AIC:                             646.2
Df Residuals:                     138   BIC:                             652.1
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          6.9487      0.385     18.068      0.000       6.188       7.709
TV             0.0545      0.002     24.722      0.000       0.050       0.059
==============================================================================
Omnibus:                        0.027   Durbin-Watson:                   2.196
```

FIGURE 8
BUILDING LINEAR MODEL: IMPORTING STATSMODELS. API LIBRARY AND DISPLAYING REGRESSION RESULTS OF OLS MODEL

```
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

The values that are of interest to us are: (i) The coeffs and p-val (ii) R-square val (iii) F statistic and its significance

(i) The conefficient for TV is 0.0545 ---- > OK So association is not by chance (ii) R- sqaure = 0.816 = 81.6% of the variance is explained by TV (iii) F signfiince is considerably low --- means model fit is statistically significant. the linear equation will be as follows Sales = 6.9487 + 0.0545XTV

```
In [36]: plt.scatter(X_train, y_train)
         plt.plot(X_train, 6.9487 + 0.0545*X_train, 'r')
         plt.show()
```

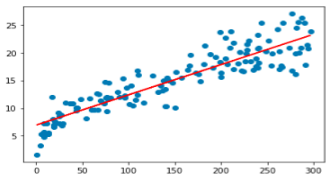


FIGURE 9
LINEAR REGRESSION EQUATION IS: SALES=6.9847+0.0545*TV AND VISUALIZING FIT ON THE TRAINING DATA

Residual Analysis and Distribution of Errors

```
In [37]: y_train_pred = lnr.predict(X_train_sm)
         resid = (y_train - y_train_pred)

In [40]: fig = plt.figure()
         sns.distplot(resid, bins = 15)
         fig.suptitle('Error Terms', fontsize=15)
         plt.xlabel ('y_train - y_train_pred', fontsize =15
         plt.show()
```

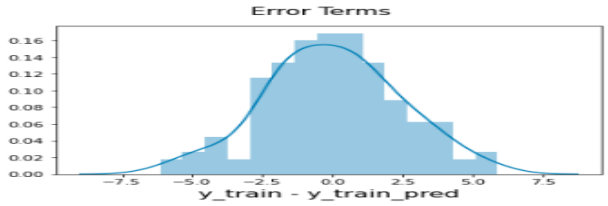


FIGURE 10
RESIDUAL ANALYSIS AND DISTRIBUTION OF ERRORS

Predictions on the Test data set

```
In [42]: X_test_sm = sm.add_constant(X_test)
         y_pred = lnr.predict(X_test_sm)

In [43]: y_pred.head()
Out[43]: 126      7.374140
         104     19.941482
         99      14.323269
         92      18.823294
         111     20.132392
         dtype: float64

In [47]: from sklearn.metrics import mean_squared_error
         from sklearn.metrics import r2_score

In [48]: np.sqrt(mean_squared_error(y_test, y_pred))
Out[48]: 2.019296008966233

In [ ]: Checking the R-squared value on the test data

In [49]: r_squared = r2_score(y_test, y_pred)

In [50]: r_squared
Out[50]: 0.792103160124565 7
```

FIGURE 11
TEST DATA RESULTS

Visualizing the fit on the test data

```
In [52]: plt.scatter(X_test, y_test)
         plt.plot(X_test, 6.9487+0.0545*X_test, 'r')
         plt.show()
```

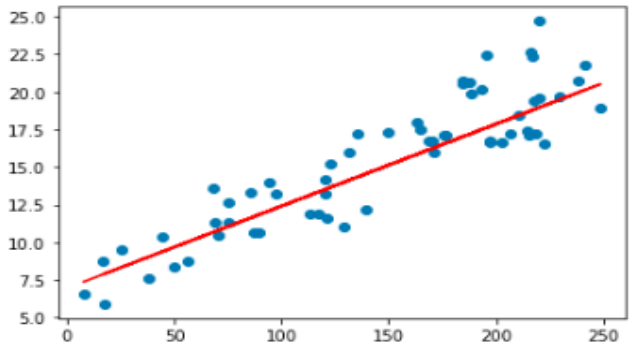


FIGURE 12
VISUALIZING THE FIT ON THE TRAINING DATA

CONCLUSION

Even though many technical advances are happening in Information Technology fields such as Artificial Intelligence, Machine Learning and Predictive Algorithms, Decision-Making-process of a retail manager will be far away from fully automated outcomes. Predictive analytics in retail management is only a part of business intelligence. It deals with forecasting what lies ahead through exploration processes. So, as a standalone it does not contribute to the firms in understanding integrated semantic insights that they need (Bradlow, Gangwar, Kopalle & Voleti, 2017). Companies should be able to evaluate the costs and benefits of each model with appropriate forecasting tool (Alon, Qi & Sadowski, 2001; Morgan & Chintagunta 1997) suggested that ordinary linear regression equation ignores self-selectivity. It produces inferior forecasting results, instead truncated regression model provides the most accurate and parsimonious fit to the data. From the perspective of selecting media of advertisement to improve sales, Mulcahy & Riedel (2020) indicated that touch senses mobiles can strengthen more purchase intention.

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