

Bigmart Sales Prediction Based on Voting Classifier Algorithm and Linear Regression

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ABSTRACT ;

Machine Learning is a technology that allows machines to become more accurate in predicting outcomes without being explicitly programmed for it. The basic premise of machine learning is to build models and deploy algorithms that can receive input data and use statistical analysis to predict an output while modifying outputs as the new data becomes available. These models can be used in different areas and trained to match the expectations so that accurate steps can be taken to achieve the organization's target. In this paper, the case of Big Mart Shopping Centre has been discussed to predict the sales of different types of items and for understanding the effects of different factors on the sales of different items. Taking various features of a dataset collected for Big Mart, and the methodology followed for building a predictive model, results with high levels of accuracy are generated, and these observations can be used to take decisions to improve sales.

Key words : Machine Learning, Sales Prediction, Big Mart, Voting classifier algorithm, Linear Regression.

I.INTRODUCTION

In modern times, huge shopping complexes such as big malls and marts are storing data related to sales of items or products with their various dependent or independent features as an important step to be helpful in prediction of inventory management and future demands. The big mart dataset is formed with independent and dependent. The data is processed and refined in order to get accurate predictions and gather new as well as the interesting results that will shed new lights on our knowledge with respect to the task's

data. This could further be used to predict the future sales by means of deploying machine learning algorithms such as the random forests and simple or multiple linear regression model.

1.1 Machine Learning

The volume of data is increasing day by day and such unprocessed data is needed to be analysed more precisely, as it could give very informative and accurate gradient results as per current standard requirements. Artificial Intelligence (AI) is evolved over the past two decades, Machine Learning (ML) is also on a fast pace of evolution. Machine Learning is an important pillar of IT sector and with that it becomes a rather important part of our life [1]. As the technology progresses further, the analysis and understanding of data to give good results will also increase as the data is very useful in current aspects. In machine learning, one deals with both supervised and unsupervised problems and generally a classification type of problem accounts as a source for knowledge discovery. It generates resources and deploys regression to make accurate predictions about the future, the main emphasis being laid on making the system self-efficient, to be able to do analysis and computations to generate more accurate and precise results [2]. By using statistics and probabilistic tools, data can be converted into knowledge.

In this paper, we have discussed various applications of Machine Learning and the types of data it could deal with. Now, the problem statement addressed through this work is stated in a formalized manner. This is followed by explaining the methodologies ensued and

the prediction results observed on implementation. Various machine learning algorithms include [3]:

- **Linear Regression:** It can be referred to as a parametric ML technique which is used to predict a continuous or dependent variable since a dataset of independent variables is provided. This technique is said to be parametric as different predictions are made based on the dataset.
- **K-Nearest Neighbors (KNN):** It is a machine learning algorithm which is based on instances and knowledge gained through them [4]. Unlike data mining in streams, cases where every sample could simultaneously belong to multiple classes in hierarchical multi-label classification problems, k-NN can produce results in a structured form [5].
- **Voting classifier algorithm:** A Voting Classifier is a machine learning model that trains on an ensemble of numerous models and predicts an output (class) based on their highest probability of chosen class as the output. It simply aggregates the findings of each classifier passed into Voting Classifier and predicts the output class based on the highest majority of voting. The idea is instead of creating separate dedicated models and finding the accuracy for each them, we create a single model which trains by these models and predicts output based on their combined majority of voting for each output class. [8].
- **Random Tree:** It is an efficient machine learning algorithm for achieving scalability and is used in identification problems for building approximation systems. The decisions are taken considering the choices made based on the possible consequences, the variables which are included, input factor. Other algorithms that could be employed are SVM, XG-Boost, logistic regression and so on [7].
- **K-means clustering:** This algorithm is used in unsupervised learning for creating clusters of related data based on their closeness to the centroid value [9].

1.2 EXISTING PROBLEM

“To build a framework that is able to predict future sales of Big Mart from given data using the Machine Learning Algorithms”. Auto-Regressive Integrated Moving Average, (ARMA) Auto-Regressive Moving Average, have been utilized to develop a few deals forecast standards. Be that

as it may, deals anticipating is a refined issue and is influenced by both outer and inside factors, and there are two significant detriments to the measurable technique as set out in A. S. Weigend et A mixture occasional quantum relapse approach and (ARIMA) Auto-Regressive Integrated Moving Average way to deal with every day food deals anticipating were recommend by N. S. Arunraj and furthermore found that the exhibition of the individual model was moderately lower than that of the crossover model.

E. Hadavandi utilized the incorporation of “Genetic Fuzzy Systems (GFS)” and information gathering to conjecture the deals of the printed circuit board. In their paper, K-means bunching delivered K groups of all information records. At that point, all bunches were taken care of into autonomous with a data set tuning and rule-based extraction ability. Perceived work in the field of deals gauging was done by P.A. Castillo, Sales estimating of new distributed books was done in a publication market the executives setting utilizing computational techniques. “Artificial neural organizations” are additionally utilized nearby income estimating. Fluffy Neural Networks have been created with the objective of improving prescient effectiveness, and the Radial “Base Function Neural Network (RBFN)” is required to have an incredible potential for anticipating deals.

1.3 PROPOSED SYSTEM

The objective of this proposed system is to predict the future sales from given data using Voting classifier algorithm Another objective is to conclude the best model which is more efficient and gives fast and accurate result by using Decision Tree Regression. To find out key factors that can increase their sales and what changes could be made to the product or store's characteristics. Experts also shown that a smart sales forecasting program is required to manage vast volumes of data for business organizations. We are predicting the accuracy for Voting classifier algorithm. Our predictions help big marts to refine their methodologies and strategies which in turn helps them to increase their profit. The results predicted will be very useful for the executives of the company to know about their sales and profits. This will also give them the idea for their new locations or Centre’s of Bigmart.

2.METHODOLOGY

The steps followed in this task, beginning from the dataset preparation to obtaining results are represented in Fig.1.



Fig1: Steps followed for obtaining results

2.1 Pre-processing of Dataset

Big Mart’s data scientists have collected sales data of their 10 stores established at different locations with each store having 1559 different products as per 2013 data collection. Using all the observations it is deduced what role certain properties of an item play and how they cloud affect their sales. The dataset is displayed in Fig.2 on using head() function on the dataset variable.

```

In [7]: df.head()
understanding rows and column
Out[7]:
  Item_Identifier  Item_Weight  Item_Fat_Content  Item_Visibility  Item_Type  Item_MRP  Outlet_Identifier  Outlet_Establishment_Year  Outlet_Size  Outlet_Location_Type  Item_Outlet_Sales
0  FDO18          9.30          Low Fat          0.010947          Dairy          249.8992          OUt749          1999          Medium          Tier 1 Supermarket Type1          3735.1330
1  DRC01          8.82          Regular          0.019278          Soft Drinks          48.2862          OUt718          2009          Medium          Tier 3 Supermarket Type3          443.4228
2  FDO15          17.50          Low Fat          0.019790          Meat          141.9180          OUt749          1999          Medium          Tier 1 Supermarket Type1          2097.2700
3  FDO17          19.20          Regular          0.000000          Fruits and Vegetables          182.0690          OUt710          1999          NaN          Tier 3 Grocery Store          732.8800
4  NCD19          8.80          Low Fat          0.000000          Household          53.8614          OUt713          1987          High          Tier 3 Supermarket Type1          994.7082
  
```

Fig2: Screenshot of Dataset

The data set consists of various data types such as integer, float and, object as shown in Fig.3.

```

In [9]: df.dtypes
#tells datatype of column convert data type
Out[9]:
Item_Identifier          object
Item_Weight              float64
Item_Fat_Content         object
Item_Visibility          float64
Item_Type                object
Item_MRP                 float64
Outlet_Identifier        object
Outlet_Establishment_Year  int64
Outlet_size              object
Outlet_Location_Type     object
Outlet_Type              object
Item_Outlet_Sales        float64
dtype: object
  
```

Fig3: Various datatypes used in the Dataset

In the raw data, there could be various types of underlying patterns which also gives deeper knowledge about subject of interests and provides useful insights about the problem.

But caution should be observed while dealing with the data as it may contain null values, or redundant values, or ambiguity values, which also demands for pre-processing of data. Therefore data exploration becomes mandatory. Various factors that are important by statistical means like mean, standard deviation, median, count of values and maximum value etc. are shown in Fig.4 based on the numerical variables of our dataset.

```

In [10]: df.describe()
Out[10]:
  Item_Weight  Item_Visibility  Item_MRP  Outlet_Establishment_Year  Item_Outlet_Sales
count  7080.000000          8523.000000          8523.000000          8523.000000          8523.000000
mean     12.857845          0.089132          140.692782          1997.831887          2181.288914
std      4.843488          0.051598          62.275087           8.371760          1708.498818
min      4.855000          0.000000          31.290000          1885.000000          33.290000
25%     8.773750          0.028989          83.826500          1987.000000          834.247400
50%     12.600000          0.053931          143.012800          1999.000000          1794.331000
75%     16.850000          0.094585          185.843700          2004.000000          3101.298400
max     21.350000          0.328391          288.888400          2009.000000          13088.984800
  
```

Fig4: Numerical variables of the Dataset

Pre-processing of this dataset involves analysis on the independent variables like checking for null values in each column and then replacing or feeding supported appropriate data types, so that analysis and model fitting is carried out its way to accuracy. Shown above are some of the representations that are obtained using Pandas tools which gives information about variable count for numerical columns and model values for categorical columns. Maximum and minimum values in numerical columns, along with their percentile values for median, plays an important factor in deciding which value will be chosen at priority for future data exploration tasks and analysis. Data types of different columns are further used in label processing and one-shot encoding scheme during model building.

2.2 Algorithms employed

Scikit-Learn can be used to track ML system on wholesome basis [12]. Algorithms deployed for predicting sales for this Big Mart dataset are discussed as follows:

Random Forest Algorithm

Random forest algorithm is an accurate machine learning algorithm which will be used for predicting sales. It is easy to use and understand for the purpose of predicting results of machine learning tasks. In sales prediction, random forest classifier is used because it has similar hyper parameters like decision tree. The tree model is same as decision tool. Fig.5 shows the relationship between random forest and decision tree. To solve regression tasks of prediction by virtue of random forest, the sklearn.ensemble library’s random forest

regressor class is used. The important role is played by the parameter labeled as $n_estimators$ which also comes under random forest regressor. Random forest could be referred to as a meta-estimator that is used to fit upon numerous decision trees by taking the different sub-samples of the dataset.

Linear Regression Algorithm

Regression is referred to as a parametric technique that is used to predict a continuous or dependent variable based on provided set of independent variables. This technique is said to be parametric as different predictions are made based on data set.

$$Y = \beta_0 + \beta_1 X + \epsilon \quad (1)$$

Equation shown in eq.1 is used for simple linear regression. These parameters can be said as:

Y – Dependent Variable X – Independent Variable β_0 - When $X=0$, it is termed as prediction value or can be referred to as intercept term β_1 - when there is a change in X by 1 unit it denotes change in Y . It can also be said as slope term

ϵ -The difference between the predicted and actual values is represented by this parameter and also represents the residual value. However efficiently the model is trained, tested and validated, there is always a difference between actual and predicted values which is irreducible error thus we cannot rely completely on the predicted results by the learning algorithm. Alternative methods given by Dietterich can be used for comparing learning algorithms [10].

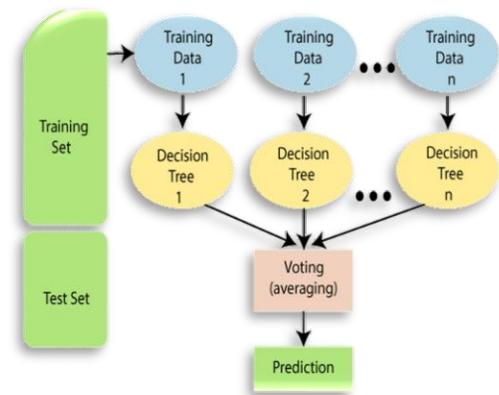
Voting classifier algorithm

A Voting Classifier is an ensemble learning method that combines the predictions of multiple base estimators (machine learning models) and predicts the class label by taking a vote. It's applicable to both classification and regression problems. Ensemble learning has gained significant traction in machine learning due to its ability to combine multiple base models to achieve superior predictive performance. One prominent ensemble method is the Voting Classifier, which leverages the wisdom of the crowd to make robust predictions. This article aims to provide a detailed understanding of Voting Classifiers, their variants, and practical applications.

- **Hard Voting** : In hard voting, each base estimator (model) predicts the class label, and the final prediction is determined by a majority vote. The class label with the most votes becomes the final

prediction. In the context of classification, the class that receives the most votes is chosen as the final predicted class label.

- **Soft Voting** : In soft voting, each base estimator predicts the probability distribution over all the classes. The final prediction is determined by averaging these probabilities and then selecting the class with the highest average probability. The final prediction is then determined by averaging these probabilities across all the base estimators and selecting the class with the highest average probability.



3.IMPLEMENTATION AND RESULTS

In this section, the programming language, libraries, implementation platform along with the data modeling and the observations and results obtained from it are discussed.

3.1 Implementation Platform and Language

Python is a general purpose, interpreted-high level programming language that is used extensively nowadays for solving domain problems instead of dealing with complexities of a system. It is also known as the „batteries included language“ for programming. It has various libraries that could be used for scientific purposes and enquiries along with number of 3rd-party libraries for making problem solving more efficient.

In this task, the Python library Numpy is used for scientific computation, and Matplotlib is used for 2D plotting. Along with this, Pandas tool of Python has been deployed for carrying out analysis of data.

Random forest regressor is used to solve problems by using random forest method. As a development platform, Jupyter

Notebook, which has proven to work great due to its excellence in „literate programming“ scheme, where human-friendly code is punctuated within code blocks to make it more presentable and readable.

3.2 Prediction results and Conclusion

- The largest Big Mart store did not produce the highest number of sales. The location that produced the highest sales was the OUT027, which was a Supermarket Type3, having its size recorded as medium in Big Mart dataset. It can be said that this store’s performance was much better than any other store with any size provided in the considered dataset.
- The median of the target variable Item_Outlet_Sales was calculated to be 3364.95 for OUT027 location. The outlet with the second highest median score (OUT035) had a median value of 2109.25.
- Adjusted R-squared and R-squared values for Linear regression model are much higher than average. Therefore, the used model fits better and provides more accuracy.
- Also, model accuracy and score of regression model can reach nearly 61% if it is built with more hypothesis consideration and analysis, as represented by code snippet in Fig.13.

```
from sklearn.ensemble import RandomForestRegressor
X_train = ds.drop(['Item_Outlet_Sales', 'Item_Identifier', 'Outlet_Identifier'],axis=1)
Y_train = ds['Item_Outlet_Sales']
X_test = ds.drop(['Item_Identifier', 'Outlet_Identifier'],axis=1).copy()
rf = RandomForestRegressor(n_estimators=400,max_depth=6, min_samples_leaf=100,n_jobs=4)
rf.fit(X_train,Y_train)
rf_pred = rf.predict(X_test)
rf_accuracy = round((rf.score(X_train,Y_train)*100,2)
print('accuracy of random forest is : %.4g' %rf_accuracy)

accuracy of random forest is : 60.8
```

Fig 13. Code showing model score of random forest From this it can concluded that more locations should be switched or shifted to Supermarket Type3 to increase the sales of products at Big Mart. Any onestop shopping centres like Big Mart could benefit from this model by using it to predict the sales of its products on different locations.

4.CONCLUSION AND FUTURE SCOPE

In this paper, basics of machine learning and the associated data processing and modelling algorithms have been explained, followed by their applications for the task of sales prediction in Big Mart shopping centres at different locations. On implementation, the prediction result show s the correlation between different attributes considered and

how a particular location of medium size outlet recorded the highest number of sales, suggesting that other shopping locations should follow similar patterns for improving the sales.

Multiple instance parameters and various factors could be used to make the sales prediction more innovative and successful. Accuracy plays an important role in prediction-based systems. It used to significantly increase the number of parameters used. Also, a look into how the sub-models work can lead to increase in productivity of the prediction-system. The project could further be collaborated into a web application or in any device supported with an inbuilt intelligence by virtue of Internet of Things (IoT), to be more feasible for use. Various stakeholders concerned with sales information could also provide more inputs to help in hypothesis generation and more instances could be taken into consideration such that more accurate results that are closer to real world scenarios could be generated. When combined with effective data mining techniques and properties, the traditional means could be used to make a higher and positive effect on the overall development of organization’s task. One of the main highlights of this project is more expressive regression outputs, which are bounded with accuracy. Moreover, the flexibility of the proposed approach can be increased with variants at a very appropriate stages of regression model development. There is a further need of experiments for proper measurements of both accuracy and resource efficiency to assess and optimize correctly.

REFERENCES

- [1] Kadam, H., Shevade, R., Katekar, P. and Rajguru (2018). A Forecast of Big Mart Sales based on Random Forests and Multiple Linear Regression
- [2] Makridakis, S., Wheelwrigth.S.C., Hyndman. R.J (2008). Forecasting methods and applications [3] C.M. Wu, P.Patil and S. Gunaseelan (2018). Comparison of different machine learning algorithms for Multiple Regression on Black Friday Sales Data
- [4] MacKay, D. J., & Mac Kay, D. J. (2003). Information theory, inference and learning algorithms. Cambridge university press.
- [5] Daumé III, H. (2012). A course in machine learning. Publisher, ciml. info, 5, 69.

- [6] Quinlan, J. R. (2014). C4. 5: programs for machine learning. Elsevier.
- [7] Cerrada, M., & Aguilar, J. (2008). Reinforcement learning in system identification. In Reinforcement Learning. IntechOpen.
- [8] Welling, M. (2011). A first encounter with Machine Learning. Irvine, CA.: University of California, 12.
- [9] Learning, M. (1994). Neural and Statistical Classification. Editors D. Mitchie et. al, 350.
- [10] Mitchell, T. M. (1999). Machine learning and data mining. Communications of the ACM, 42(11), 30-36.
- [11] Downey, A. B. (2011). Think stats. " O'Reilly Media, Inc."
- [12] Géron, A. (2019). Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems. O'Reilly Media.