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**PREDICTING SALES FOR MULTIPLE WAL-MART STORES**

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**Abstract**

Walmart is one of the oldest shopping marts in the US and now has international branches. It is a big name in the retail industry and provides services to a huge population.Data pertaining to 45 different Walmart stores was downloaded, then extracted, manipulated and analyzed using Python. Exploratory Data Analysis yielded the correlation of various featured and the weekly sales. On implementing machine learning models, using Python, the Random Forest model was found to be the most suited, amongst the K- Nearest Neighbor and Extra Trees models. The Random Forest model was then used for predicting the sales with an accuracy of ~ 98%.

**Introduction**

Walmart also known as Walmart Supercenter was founded by Sam Walton in 1962. It is headquartered in Bentonville, Arkansas, US. It is a Multinational Retail Corporation and comprises of many departments offering an astonishing range of merchandise – grocery, hardware, electronics, clothing, etc. As of January 31, 2020, Walmart has 11,503 stores and clubs in 27 countries, operating under 56 different names. Being a giant in the retail industry predicting sales can be amazingly useful for budget forecasting, scrupulous management of revenue, inventory control, planning growth and making intelligent business decisions.

**Goal**

The goal of the project is to predict the sales for multiple Walmart stores and the date of its occurrence – in the test.csv file. Part of the challenge was to build a model to cater for markdowns on the given holidays, where ideal/complete historical data was absent. In addition, Walmart runs several promotional markdown events throughout the year, and we had other features like store and department sizes affecting the weekly sales.

**Similar Research Projects**

Electronic Devices Sales Prediction Using Social Media Sentiment Analysis [1] - In this project they predicted the sales of electronic devices based on the sentiment of the comments made about the products, before their release, on Twitter. Data used was pertaining to social media content and product sales. The sentiments of the comments were predicted using a machine learning framework based on recursive autoencoders (RAE) for sentence-level prediction of sentiment label distributions *(semi-supervised)*, further using 70/30 cross-validation on this data, settling on classification accuracy of 83%. They, then used linear regression with four features to predict sales of the products based on the sentiment analysis. Predicting sales in a food store department using machine learning [2] - Their study aimed to compare three machine learning methods for sales prediction in the food industry - Multilayer Perceptron (MLP), Support Vector Machine (SVM) and Radial Basis Function Network (RBFN). The performance of the models was determined using the performance measures: Mean Average Percentage Error (MAPE) and Root Mean Squared Error (RMSE). Based on the results, the SVM performed with lower error measures than the other two methods and was concluded to be the best. The data consisted of sales data provided by a Swedish food company; pertaining to one department in one store from year 2012 to year 2016. Each validation set then consists of 180 daily sales in a department. Drugs store sales forecast using Machine Learning [3] - For this project, training data of 1115 of Rossmann stores’ daily sales dated back to 2013, with 1,017,209 entries in total, including features of promotion and competitors’ information was used. Since they had no access to the real sales amount for testing during Kaggle competition, so they used 70% of the contest given training data as the training set for their model, the rest 30% as test set for cross validation. They established an auto regression (AR) model and tested it using order numbers and calculated the test errors. Random forest (RF) and Support regression vector (SVR) were used, to help identify the most apt feature/factor influencing sales. They made good predictions based on the adoption of the above-mentioned models.

**Data Source Details**

Historical sales data for 45 Walmart stores located in different regions, containing several departments was been downloaded [1]. It was a huge data set consisting of 4 csv files - stores.csv, file containing anonymized information about the 45 stores, features.csv, containing additional data pertaining to the stores like store number, date*(week)*,temperature *(average temp. in the region)*, fuel price in the region, CPI *(consumer price index)*, unemployment rate, markdown1-5 *(promotional markdowns values)*,is holiday week *(whether a week is a special holiday week or not)*, train.csv**,** containing historical training data, from Feb'2010 to Nov'2012 and test.csv, identical to train.csv, excluding the weekly sales and dates from Nov’2012 to Jul’2013

**Methodology**

To fulfil the goal, I used csv files for storage on the local machine. Then I carried out data extraction, transformation, cleaning/ manipulation using Python, which included replacing missing values for markdowns, temperature and fuel price with zero and consumer price index and unemployment with their average values, respectively. I further changed the datatype of attributes ensuring they were in integer or float format. I then manipulated the date splitting it into day, month and year. The train and test datasets were merged with features as well to understand the effect of features on sales. Exploratory data analysis (EDA) was done using Python, which further assisted me in visualizing the results. Python was also used for building machine learning models, K nearest neighbor (KNN), Random Forest (RF), Extra Trees (ET) and train them, using 80/20 train/test split. Validation metrics used were Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), which made me settle with the (RF) model. The (RF) model was made accurate by tuning it’s hyperparameters [2] – estimators, max depth, min split and min leaf, which was then used for predicting the result (i.e.) sales.

**Exploratory Data Analysis (EDA) Results**

Stores file contained 45 and 3 columns/attributes - store, type, size. The 3 distinct store types were A, B, C *(figure 1)* with A being the largest and C the smallest. There was no overlapped area in the sizes of the stores *(figure 2)*. There was no missing data in this file. The features file contained 8190 rows and 12 attributes. The train dataset contained 421570 records and test data contained 115064 records. Sales on holidays was found to be a little bit more compared to non-holidays *(figure 3)*. The department with highest sales lies b/w 60 – 80 *(figure 4)*. On further correlating features to the weekly sales *(figure 5)* we found that the markdown values/ discounts didn’t have much effect on the sales, neither did consumer price index, unemployment, fuel price and temperature.

**Predictive Modeling and ML Results**

Train and test data sets were created, and 3 models were trained to predict the outcome. I picked (KNN,) as is simple to implement and is useful in classification and regression problems, (RF) as it is accurate and handles missing values and (ET) as it is equally robust and has a quick downtime. The scatter plots were plotted *(figure 6,7,8 respectively).* I then proceeded to validate these models using RMSE and MAE and calculated their accuracy *(figure 9)*. After a few runs, changing the K value in the (KNN) model it was found that its accuracy was maxing at ~49%, the (ET) model was giving a 100% accurate result, which seemed overfitting. The (RF) model gave an accuracy of ~94%, with high RMSE and ME values. I then proceeded with tuning the (RF) model. The hyperparameters in the (RF) model tuned were estimators *(figure 10)*, max depth *(figure 11)*, min split *(figure12)* and min leaf *(figure 13).*  The figures show the variation in accuracy with change in their respective values. On visual analysis and calculation, I took 100 estimators, max depth of 16, min split of 2 and min leaf as 1 ad final hyperparameter values and ran the (RF) model, which gave me an accuracy of ~98%. I then trained the model on 100% training dataset and predicted the final result. The plot showing the comparison between actual and predicted further justified the acceptance of hyperparameter values *(figure 14).*

**Conclusion**

It was found that department size and store size were positively correlated with the weekly sales and other features such as markdown values, holidays, consumer price index, unemployment, fuel price and temperature didn’t have much effect on the weekly sales (a very low correlation existed). The (RF) model proved to be the most suitable model for our dataset and assisted in predicting a near accurate prediction for sales from Nov’2012 to Jul’2013, taking into consideration features provided in the datasets.

**References**

**Similar Research Studies**

[1] Electronic Devices Sales Prediction Using Social Media Sentiment Analysis

<http://cs229.stanford.edu/proj2012/ZarghamNassirpourNasiri-ElectronicDevicesSalesPredictionUsingSocialMediaSentimentAnalysis.pdf>

[2] Predicting sales in a food store department using machine learning

<http://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1108597&dswid=5794>

[3]Drugs store sales forecast using Machine Learning

<https://s3.amazonaws.com/academia.edu.documents/59368319/191_report20190523-80443-dzybc.pdf?response-content-disposition=inline%3B%20filename%3DDrugs_store_sales_forecast_using_Machine.pdf&X-Amz-Algorithm=AWS4-HMAC-SHA256&X-Amz-Credential=AKIAIWOWYYGZ2Y53UL3A%2F20200302%2Fus-east-1%2Fs3%2Faws4_request&X-Amz-Date=20200302T021231Z&X-Amz-Expires=3600&X-Amz-SignedHeaders=host&X-Amz-Signature=07f88ef3f10d237291a4ae68c4935291b9f6de8be7cbb1dae1a90452aad42c24>

**Data Source Details**

[1] <https://www.kaggle.com/c/walmart-recruiting-store-sales-forecasting/data>

**Methodology**

[1] Validation Metrics

<https://medium.com/human-in-a-machine-world/mae-and-rmse-which-metric-is-better-e60ac3bde13d>

[2] Hyperparameter Tuning

<https://towardsdatascience.com/optimizing-hyperparameters-in-random-forest-classification-ec7741f9d3f6>

**Appendix**

Figure 1: Pie Plot of Stores

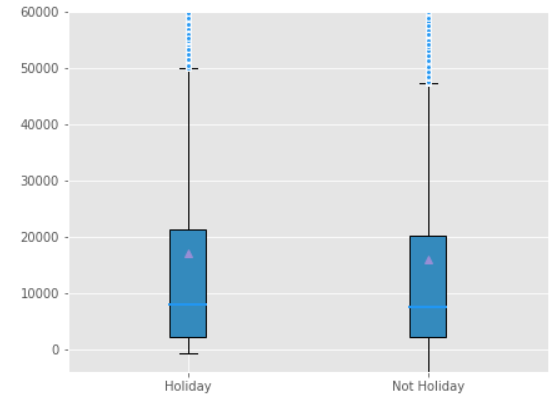
A picture containing umbrella

Description automatically generated

Figure 2: Box Plot of Store Size

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Figure 3: Effect of Holidays on Sales Figure 4: Effect of Department on Sales

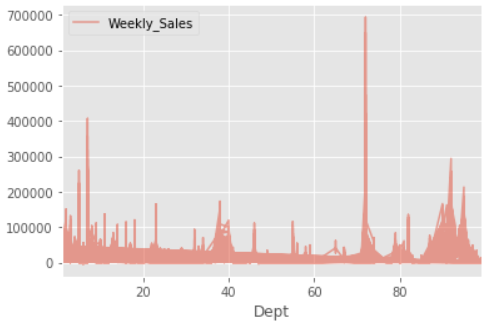
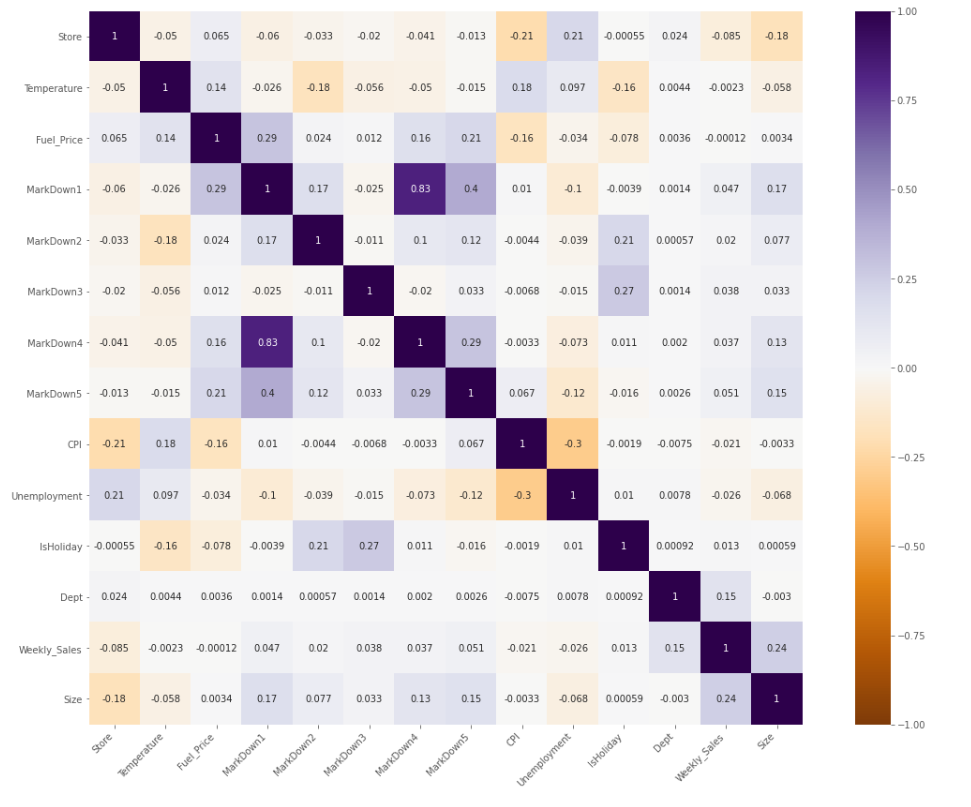
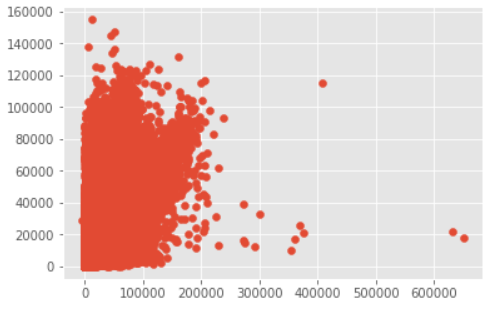
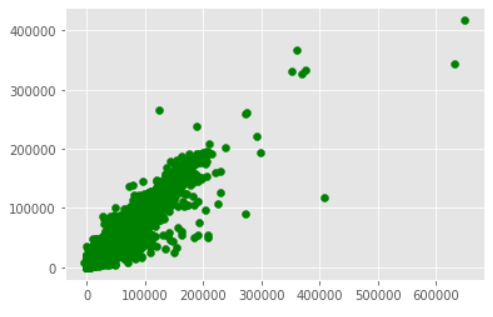


Figure 5: Correlational Plot (Features – Weekly Sales)



Figure 6: KNN Regression: Scatter Plot

Figure 7: Random Forest Regression: Scatter Plot

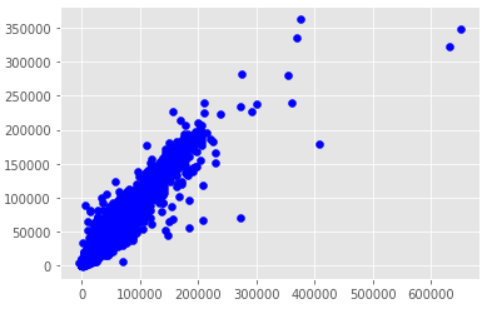
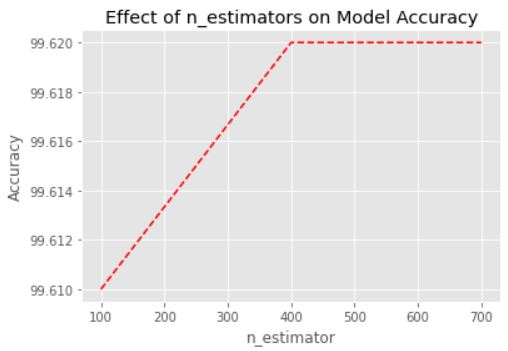
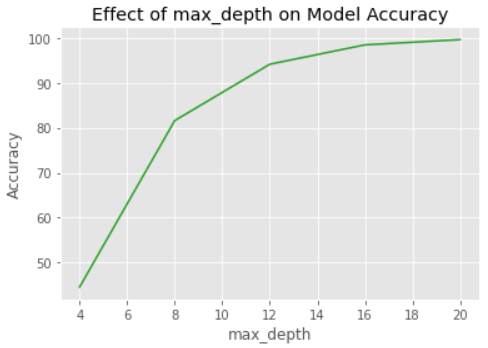
Figure 8: Extra Trees Regression: Scatter Plot

Figure 9: Validation Metrics: Comparison of ML Models

![A screenshot of a cell phone

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAeAB4AAD/4RDsRXhpZgAATU0AKgAAAAgABAE7AAIAAAALAAAISodpAAQAAAABAAAIVpydAAEAAAAWAAAQzuocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAERhdmlkIEdpbGwAAAAFkAMAAgAAABQAABCkkAQAAgAAABQAABC4kpEAAgAAAAM2MwAAkpIAAgAAAAM2MwAA6hwABwAACAwAAAiYAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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Figure 10: Effect of Estimators on Model Accuracy

Figure 11: Effect of Max Depth on Model Accuracy

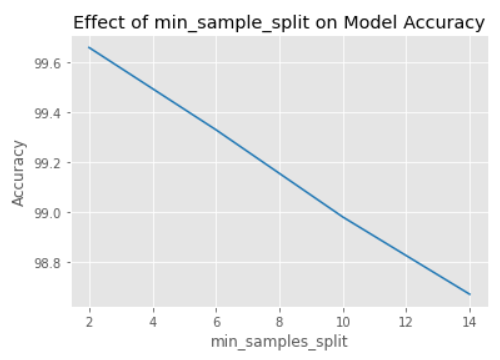
Figure 12: Effect of Min Split on Model Accuracy

Figure 13: Effect of Min Leaf on Model Accuracy

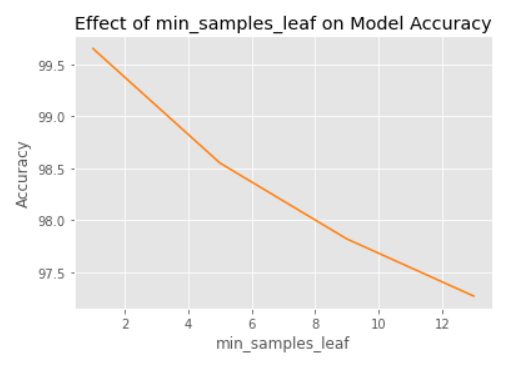


Figure 14: Predicted Vs Actual

