2020 DubStech Datathon

Grocery Retail Store Prompt

Team UWO

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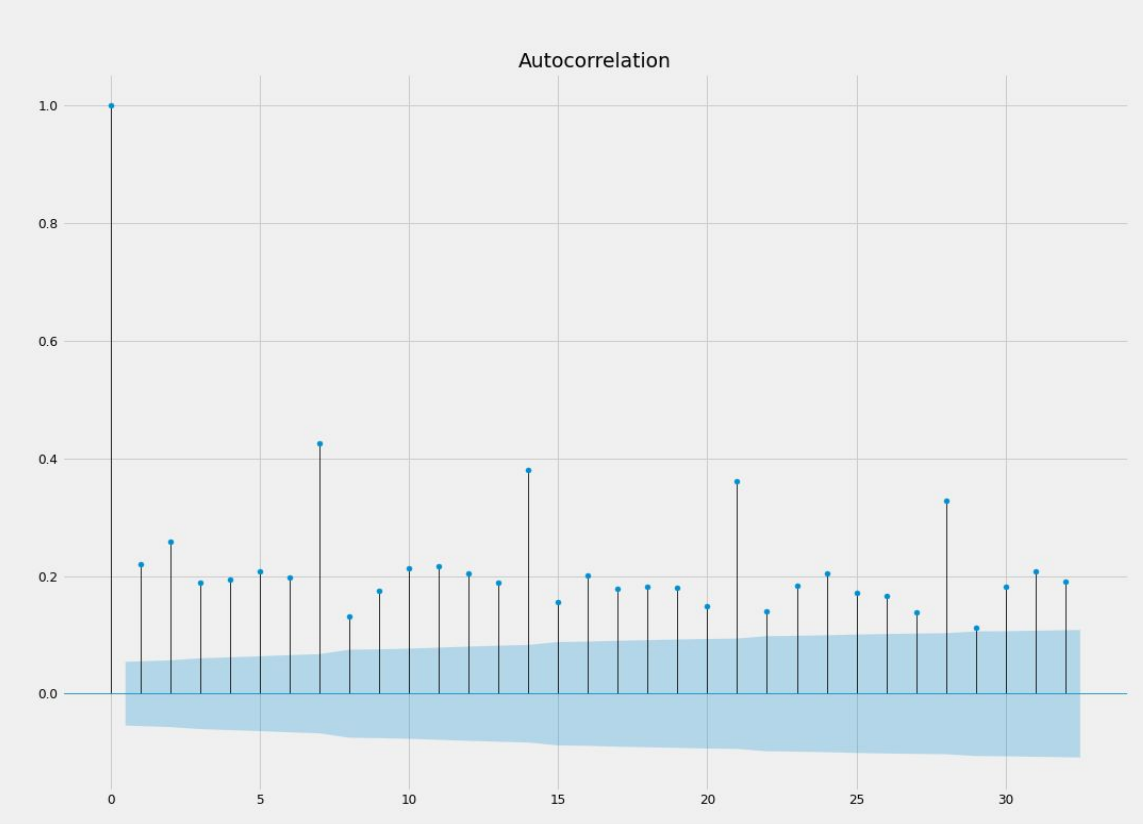
Setup

To start off with this problem, we first defined the metric we wanted to predict. In our case, it is known as cumulative sales for the next 91 days. We segmented the data on CATEGORY of product sold. This gave us all the receipts for a given group of goods (such as markdown bags). We then summed all the receipts on a given day, giving us a day by day look at the revenues a category of product brings into the store.

Time Series:

To determine the validity of using a time series we first performed STL decomposition on TOTAL_PRICESELL for all categories as well as the store wide revenue observed at a daily frequency. This led us to conclude that the time series did exhibit seasonality in quarters, and it is something we would have to account for when using a classical time series model.

To accompany our STL decomposition we also plotted the Autocorrelation function of the total store revenue time series to observe and pick which lags will have the most predictive power. As we can see lags 7, 14, 21 and multiples of 7 have predictive power.This agrees with anecdotal evidence that people buy groceries on a weekly time frame.



This led us to test the time series of TOTAL_PRICESELL, adjusted for a 1-day frequency, for stationarity. We opted to use the SARIMA model, as a benchmark to other models as this model takes into account seasonality and had the lowed AIC out of other models compared such as ARIMA, ARMA.

Feature Engineering:

In order to build robust models for time series prediction, we utilized multiple feature engineering techniques to extract most information from our given dataset.

- Basic features:
    - Three features that will be used are TOTAL_PRICEBUY, TOTAL_PRICESELL, and PROFIT for each day.
- Time series features:
    - According to our autocorrelation tests, we noticed that past data do have predictability into the future. We computed rolling sum, mean, and standard deviation of the three basic features listed above, with different lookback periods such as 7, 14, 21 and 91 (approximately 3 months) days.
- Seasonality features:
    - According to our seasonality analysis, we noticed it plays a significant effect in our data. To allow regression models to take into account seasonality, we incorporated month and day-of-the-month as our features.

Regression Models:
We utilized various linear, ensemble, and tree models to determine the one that best predicts future sales. The models included in our research are listed below:

- Linear Regression
- Ridge
- SGD Regression
- Elastic Net
- Lars Regression
- Lasso
- Bayesian Ridge Regression
- Decision Tree Regression
- Extra Tree Regression
- Bagging Regression
- Random Forest Regression

Feature Selection:
For feature selection for each of the models (where applicable) we used recursive feature elimination with cross validation (k=5) to provide us a feature ranking that would then be applied on the data frame to keep the most relevant features. Because recursive feature elimination is a model-dependent algorithm we are able to extract the optimal set of features for each model.

Model Selection:
This set up our data to be inputting into various regression models in order to determine the one that best predicts future sales for each category of items. Given the range of various models, we computed in sample and out of sample MSE, using the out of sample value as the performance metric on which we selected our model.

	In-Sample MSE	Out-of-Sample MSE	Predicted 3 Month Sales
Linear	134482.3418	273567.2983	1941.498967
Ridge	41288.18429	45753.8628	2735.799055
SGD	**3.25E+30**	**2.25E+30**	**1.8345E+15**
ElasticNet	45669.75735	40093.75823	2641.328022
Lars	211769.5893	132275.9037	2318.161204
Lasso	43570.01305	44714.13031	2714.33088
BayesianRidge	33297.70668	98160.4781	2968.389355
DecisionTreeRegressor	0	226804.0091	3100.9175
ExtraTree	0	184168.1455	1593.84274

Bagging	296.2699099	198498.0669	2887.674672
RandomForest	161.985887	137338.1096	2533.270298
SARIMA	9619.349431	415010.4158	1880.91423

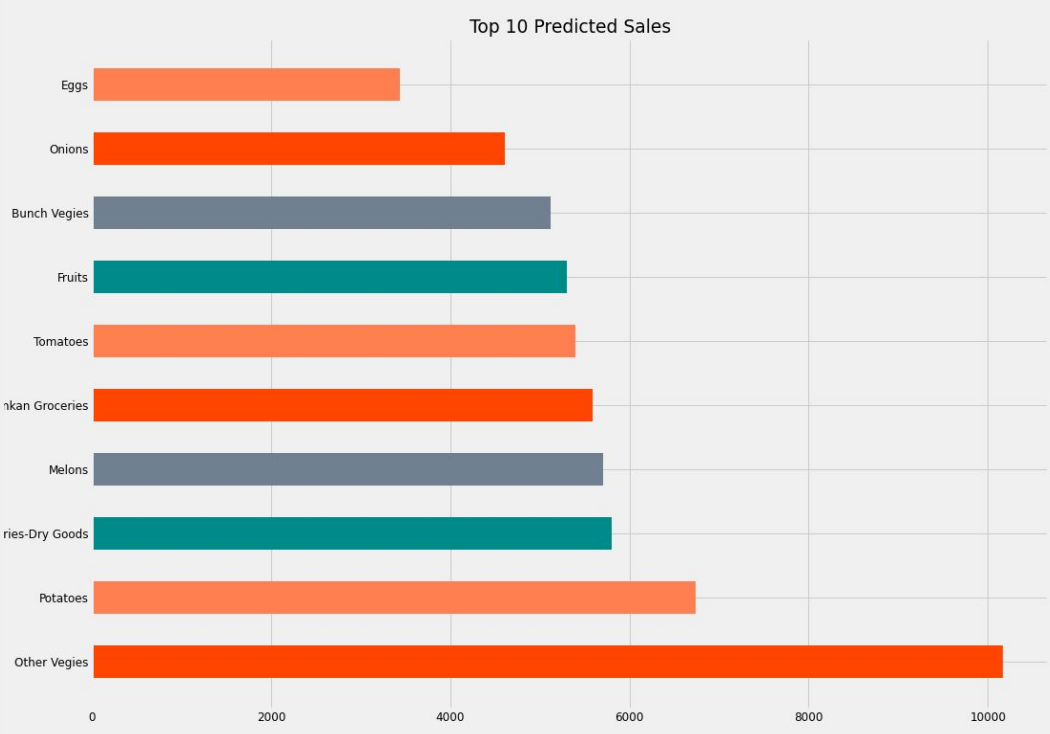
Table 1: Pumpkin Category regression models and their in-sample and out-of-sample MSE.

Through the aforementioned process, we were able to determine the best fitting models for each category and therefore able to compute total predicted sales effectively.

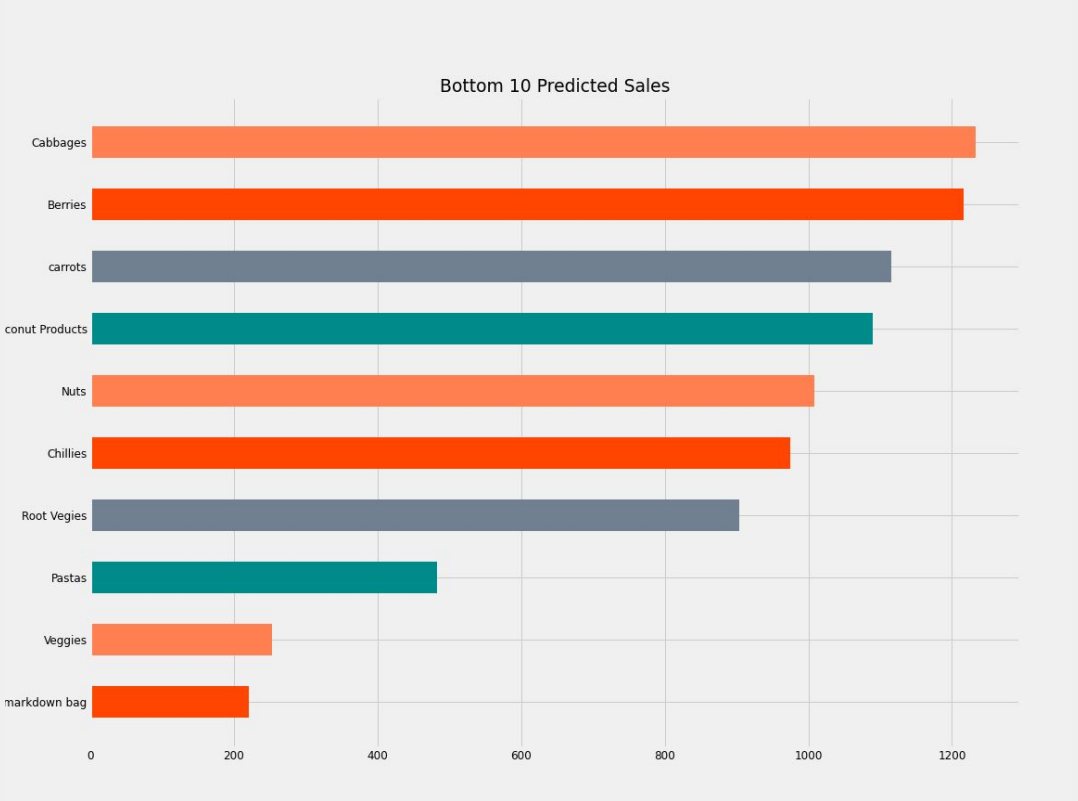
Results

Attached below are the results from the analysis. We ranked the predicted sales for each category of items in order to infer the optimal decisions.

As we see from the plot below. *other veggies* ranked highest in terms of predicted sales, this should be ignored in our decision since it is just a bracket of miscellaneous items. Ranked second and third are *potatoes* and *groceries-dry goods*. Hence, it is recommended for the store to increase the inventory of these items in order to have enough supply to fulfill customer's demands.



As we see from the plot below. *Markdown bag, veggies* and *pastas* are expected to have the lowest predicted sales over the upcoming months. Hence it is recommended for the store to not allocate excess resources on these products in terms of both inventory and marketing expense.



To further support our analysis. We plotted the percentage of item sales for each category with 100% margin. Note that the reason behind 100% margin is that these items are grown on the farm of the grocery so their acquisition cost of these items is $0.00. We note the *potatoes* category, which was predicted to have the highest sales, also has a significant percentage of items with 100% margin. The *veggies* category, which was predicted to have the lowest sales, also consists of a low percentage of items with 100% margin.