Analyzing and Predicting Marketing Campaign Performance using Regression and Time Series Analysis

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Nestlé USA's Marketing Process

Nestle was founded in 1867 and is one the global leaders in food manufacturing. Nestle USA is one of Nestle's operation companies that is responsible for brands that sell their product in the US. Nestle USA's office located in Rogers, Arkansas manages Nestle's account with Walmart and its subsidiaries. The Rogers office primarily works on marketing Nestle's products throughout Walmart using the *every day low price* format. The process starts with Strategy & Planning which includes seeing the opportunity for an activation and defining the objective. Next, Activation Planning is when Nestle selects the tactic and develops a final plan. Third, Creative Development & Execution is when Nestle designs the ad. Finally, Billing, Measurement, & Analysis is when Nestle receives vendor recaps and analyzes the performance of the activation.

Analyses of Initial Dataset

We decided to move back a period to capture the effect of the ads on the next period's sales value. If you run ads in week 1, you would most likely see the impact in sales in the following week, not in the same week. In addition, after stakeholder analysis, we added a 2-week moving average on our sales to better capture the effect of the ads (Table on the left). After the initial data cleanup and re-formatting, we decided to start our high-level analyses with some simple graphing and correlation plots (Plot on the right). To our surprise, the Pearson correlation between these two came out to be very low so we moved on to our next, more complex analyses.

Date	1/13/19	1/20/19	1/27/19	2/03/19	2/10/19
Sales	27,705	27,978	29,477	28,551	23,711

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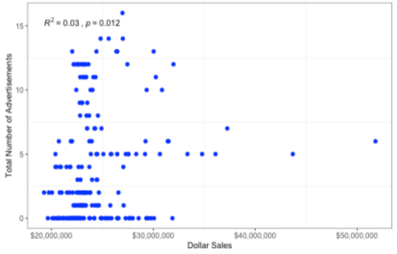
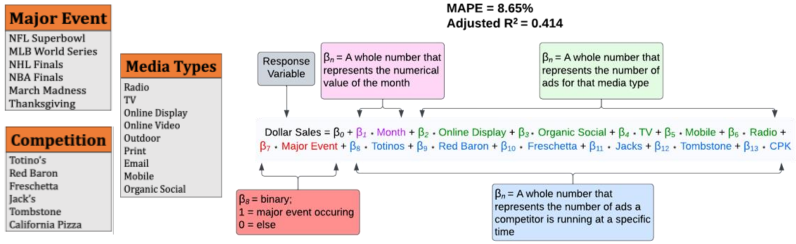
Sales	28,728	29,014	26,131



Initial Predictive Modeling

After removing variables with near zero variance, our team created a multiple linear regression model to predict weekly sales of DiGiorno. We used the month of the year and the week of the month as our timing predictors, 5 DiGiorno media types as our type predictor, a major event binary variable with 1 acting as a major event present and 0 otherwise, and 6 brands that compete with DiGiorno as our competition factor. By using multiple linear regression, the team was able to gain insights on the coefficients and the significance of each predictor. Each coefficient measures the amount by which the target variable changes for a one-unit change in the corresponding predictor variable, while holding all other predictor variables constant. This gives us an idea of the importance of each predictor when predicting sales. The multiple linear regression model produced a decent fit with an adjusted R-squared of 0.307 and a MAPE of 7.08%.



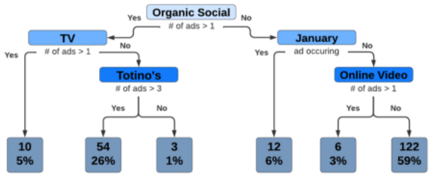
Comparing Accuracy of Tested Models

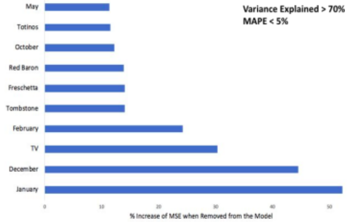
After creating our initial predictive model, we realized there were limitations to multiple linear regression. The results can often be difficult to interpret, especially when there are complex relationships within the data. Therefore, we wanted to test a variety of models to understand which predictive method would be the best for our team to utilize. We tested ridge regression, principal component regression, and LASSO regression in hopes to account for the multicollinearity in our data but found there was minimal improvement. Finally, we tested multivariate additive regression splines, or MARS, after discovering our data had many complex non-linear relationships. The MARS model outperformed the rest of the regression models that we have previously used to predict sales.

Predictive Model Used	MAPE (%)	R^2
Multiple Linear Regression	8.65	0.38
Ridge Regression	8.58	0.26
LASSO Regression	8.41	0.35
Principal Component Regression	8.78	0.31
Multivariate Adaptive Regression Splines	6.86	0.72

Ranking Predictors using Machine Learning

Due to the relatively high MAPE and low adjusted R-squared in our multiple linear regression model, we decided that a random forest regression model would be a much better fit. Random Forest Regression is a supervised learning algorithm that uses ensemble learning which is a technique that combines predictions from multiple decision trees to make a more accurate prediction. For our model, our optimal tunning parameters came out to be 1100 trees with 7 variables tested. Every tree in the forest will be different and will create different results. The result is unbiased since it is an average of all the random decision trees in the forest. From this model we were able to find the importance of each predictor by finding the increase in mean squared error when the predictor is removed from the model. The higher the MSE value the more important that predictor is for the model, since removing it would make the model less accurate.





Impactful Insights of Our Analyses

Our analyses strive to provide Nestle USA with insightful information related to the timing, media type, and impact of competition on activation performance in terms of dollar sales. Nestle USA will ideally be empowered with data-driven insights to boost sales and conduct more impactful ad campaigns in the future. Various predictive models including random forest and multiple linear regression were used to analyze the data provided by our industry partner and gather these insights.