Predicting Food Sales Using Social Media Mentions

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A Capstone Project

Submitted to the University of Chicago in partial fulfillment
of the requirements for the degree of

Master of Science in Analytics

Graham School of Continuing Liberal and Professional Studies

(March 2016)

The Capstone Project committee for (Insert your Official Names)
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Predicting Food Sales Using Social Media Mentions

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ABSTRACT

This project aimed to help retailers make accurate inventory decisions for products by using social media mentions to forecast sales volume. We were able to successfully integrate social media mentions into a vector autoregressive (VAR) forecast model for sales volume and found that it is superior in predicting sales volume than the benchmark autoregressive time series model.

KEYWORDS

Social Media
Food Sales
Food Trends
Facebook
Twitter
Blogs
Forums
Comments
Reviews

EXECUTIVE SUMMARY

Retailers are continuously faced with the difficult task of predicting consumer behavior, and food retailers are no exception. In fact, food retailers are continually surprised by sudden increase in demand for products. This analysis was initiated to assist food retailers in predicting food sales using social media mentions as predictors of upcoming demand.

We were given social media data for six different platforms including Facebook and Twitter, and national sales data for two items: cupcakes and clementines. We explored the relationship between the two data sets using a vector autoregressive model (VAR). Using this model, we used the co-integrated series to predict upcoming social media mentions and sales volume. We used lagged sales volume and social media mentions along with a constant and a trend component to predict sales volume.

We compared the VAR model with an autoregressive integrated moving average model (ARIMA). We deemed the ARIMA model as the benchmark model because sales volume is autoregressive. Using our benchmark model, we were able to compare the predicted values of the two forecasts VAR and ARIMA, and compare them to calculate the lift we gain by using social media as predictors. The comparison showed that the VAR model more accurately predicted clementines sales volume, and cupcakes sales volume was more accurately predicted by ARIMA.

We can conclude that social media is a good indicator of sales and has valuable insights. Different types social media data might yield better results (or be a better indicator of sales) for different foods. The VAR model can be used, but perhaps not for all food items.

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INTRODUCTION

Problem Statement

Retailers are continuously faced with the difficult task of predicting consumer behavior, and food retailers are no exception. In fact, food retailers are continually surprised by sudden increase in demand for products. This happens to certain items that gain popularity – usually on social media. Such sudden changes in demand can lead to a loss in sales (due to stock-outs) or a loss in profits (due to higher unit cost when demand is high). If the retailers were aware of what people were talking about on social media, they would be better equipped to handle the current or upcoming demand.

Research Purpose

Retailers can avoid missed sales opportunities by being aware of demand for a certain products in advance. Retailers can ultimately maximize shelf space and minimize unit costs by projecting the sales of a particular food. Our purpose is to provide this insight, by forecasting the weekly volume of units sold in the upcoming one-year time horizon, using frequency of social media mentions as predictors.

Variables and Scope

The dependent variable is weekly quantity of units sold for specified food products. The independent variable is total weekly social media mentions for food products across different platforms. These platforms include Facebook, Twitter, Blogs, Forums, Reviews and Comments.

Research Question

With what level of certainty can we predict the volume of food sales for the coming one-year time horizon, using frequency of social media mentions as predictors?

BACKGROUND

Social media refers to the vast network of websites and applications that enable users to create and share content or to participate in social networking. The percentage of Internet users who use social media is immense. According to an eMarketer™ report in 2013, nearly one in four people worldwide use social networks, which is estimated at about 1.73 billion people. By 2017, the global social network audience will total 2.55 billion[1].

Over the past several years, business executives have recognized social media as a driver for several functions including sales, marketing, public relations, and market research. While many executives are struggling to harness social media to its full potential, some of its key functions have been defined. Companies can use social media to monitor, respond, amplify, and lead consumer behavior. According to a survey created by McKinsey in 2012, 39% of companies use social media as a marketing tool. This number is expected to rise to 41% in 2016[2].

The rationality behind this movement is based on the belief that social media plays a key role in the "Consumer Decision Journey[3]," a framework developed by David Court and Dave Elzinga of McKinsey & Company. This framework describes the process in which a consumer decides to purchase a product. It consists five stages: 1) Awareness, 2) Familiarity, 3) Consideration, 4) Purchase, and 5) Loyalty. A consumer first considers a new purchase based on brand perception and exposure to recent touch points. He then adds or subtracts additional brands or consumer goods based on his own values, all of

1 Social Networking Reaches Nearly One in Four Around the World . (2013, June 18). In emarketer.com. Retrieved from http://www.emarketer.com/Article/Social-Networking-Reaches-Nearly-One-Four-Around-World/1009976

2 Roxane Divol, David Edelman, and Hugo Sarrazin. (2012, April). Demystifying Social Media . Retrieved from http://www.mckinsey.com/insights/marketing_sales/demystifying_social_media

3 David Court, Dave Elzinga, Susan Mulder, and Ole Jørgen Vetvik. (2009, June). The Consumer Decision Journey . Retrieved from http://www.mckinsey.com/insights/marketing_sales/the_consumer_decision_journey

which leads to the moment of purchase. After purchasing the good or service, the consumer builds expectations based on the experience that will inform the next decision journey.

The power of social media comes from its ability to impact consumers at any one of these stages. There are several companies that have successfully utilized social media to meet business goals such as creating brand awareness, developing consumer insights, and targeting customers. One of these companies is PepsiCo, who used social networks to gather customer insights via its Democracy promotions, which have led to the creation of new varieties of its Mountain Dew brand. Since 2008, the company has sold more than 36 million cases of them. It should be noted that social media and other digital platforms influence purchasing decisions both online and offline. According to a consumer behavior report from Deloitte, 80% of customers interact with products or services online before making an in-store purchase[4]. The customers will research the product online and identify which products they want to buy before arriving at a physical store. Traditionally, the consumer decisions journey took place largely in-store, but the rise of social media has changed this landscape significantly.

In response to the rise of social media marketing, several digital marketing companies have emerged that promise to help companies achieve business goals through social media. One particular company is Bottlenose, a company that formed in 2010 that is based out of Los Angeles, California. They provide a service that allows companies to spot upcoming trends in social media. This service tracks what instigated them, how long they will last, as well as what drives them. The existence of companies like Bottlenose

4 Lobaugh, Kasey, Jeff Simpson, and Lokesh Ohri. "NAVIGATING THE NEW DIGITAL DIVIDE." Deloitte. N.p., 2015.

suggest that there are valuable consumer insights within social media, although most of it is believed to be undiscovered.

One particular industry that is interested to understand the impact of social media on sales is the food retail. This industry is highly innovative compared to most other industries; it has doubled its number of SKUs in just seven years[5]. This is especially important today as the food retail industry is losing market share to e-commerce websites. In 2014, e-commerce sales for food and consumables have increased by 13.5% in to $24.4 billion[6]. This leaves traditional brick-and-mortar grocery stores with the challenging task of maintaining customer retention with the rise in popularity of these sites.

While food retailers are on the cusp of understanding the correlation between social media and food sales, there have been studies to prove that social media does in fact play a role in the consumer decision journey. According to market research publisher Packaged Fact, 59% of grocery shoppers use social media for recipes. Among this segment of shoppers, the demographics that are strongly influenced by social media in purchasing decisions are males, Millennials, and parents. Millennial men are 165% more likely to say social media advertising from supermarkets influenced their decision to buy a grocery product in last 12 months. Research also shows that being a parent also has an impact on purchasing decisions. Millennial dads in particular shop at traditional stores about four times a week on average[7].

The rise of social media presents many challenges for traditional brick-and-mortar grocery stores but also some unique opportunities. Our research suggests that grocery

5 “Food Retailing Industry Speaks.” The Food Marketing Institute, 2010.
6 "The Future of Food Retailing ." Willard Bishop. N.p., 2015.

7 “Retail Food Marketing Trends in the U.S.: Technology, Mobile, and Social Media." Packaged Facts. N.p., 30 June 2015.

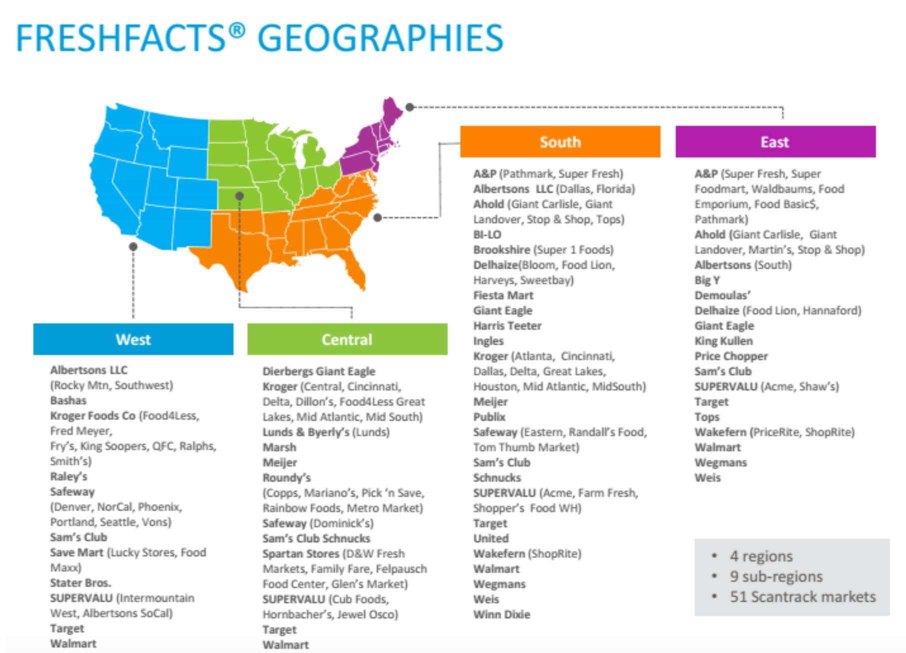
stores can use social media to their advantage. One particular avenue that grocery stores can advance to is using social media data to better understand consumer-purchasing decisions that will ultimately influence in-store sales. While this strategy is relatively unchartered territory, there is overwhelming evidence that social media does impact sales. This correlation will most likely become clearer in the upcoming years.

METHODOLOGY

Sales Data

The sales data used was retail census sales data for key food, club and mass/supercenter store chains in the United States, which was provided by [redacted] See Figure 1.1 below for more details.

Figure 1.1



Each store included in the data had more than $2 million in annual all commodity volume (or ACV) sales. This aggregated roughly 18,000 stores nationwide for a weekly total of dollar sales and volume (or units). The data provided was from January 2010 to June 2015 for two items: clementines and cupcakes. See Figures 1.2 and 1.3 below for plots of the raw volume data.

Figure 1.2

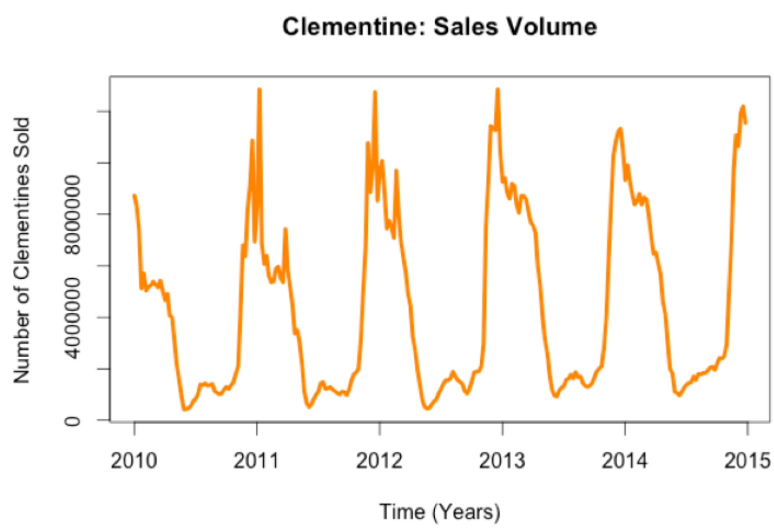
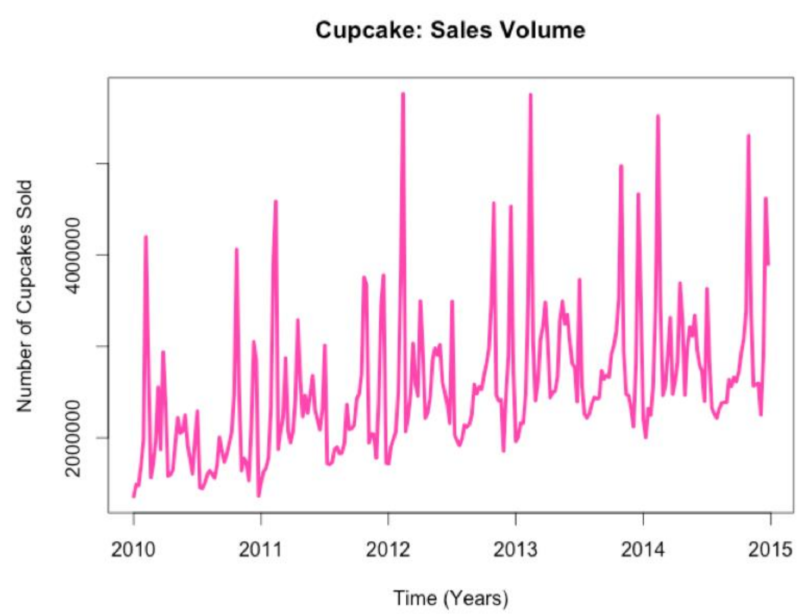


Figure 1.3



Social Media Data

Our social media data was weekly count of total social media mentions for cupcakes and clementines across six social media platforms: Facebook, Twitter, Blogs, Comments, Forums and Reviews from January 2010 to June 2015. Examples of several platforms can be seen below in Figures 1.4 and 1.5.

Figure 1.4

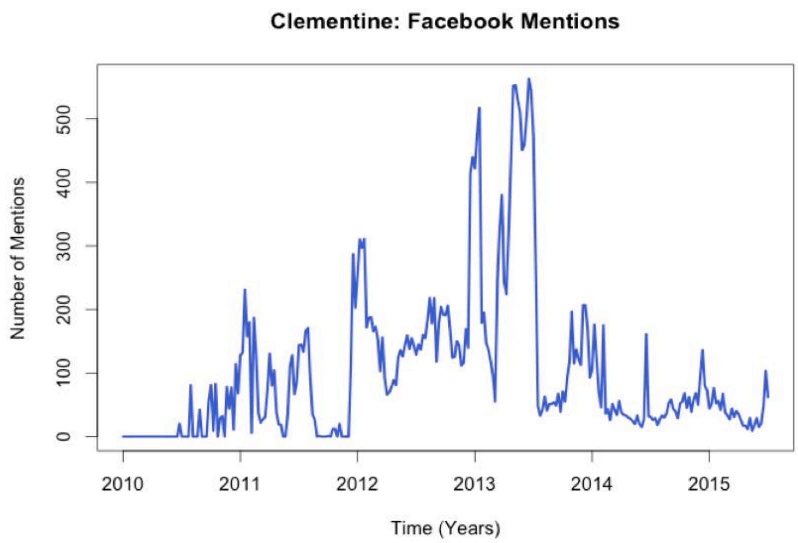
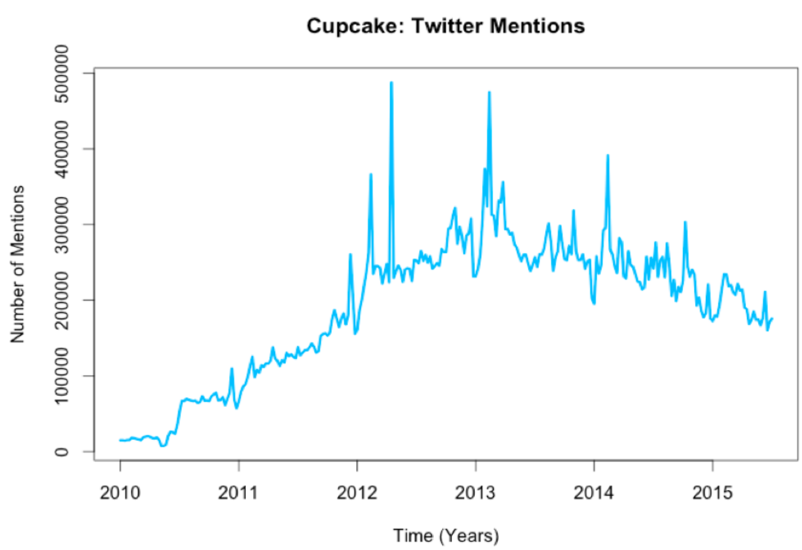


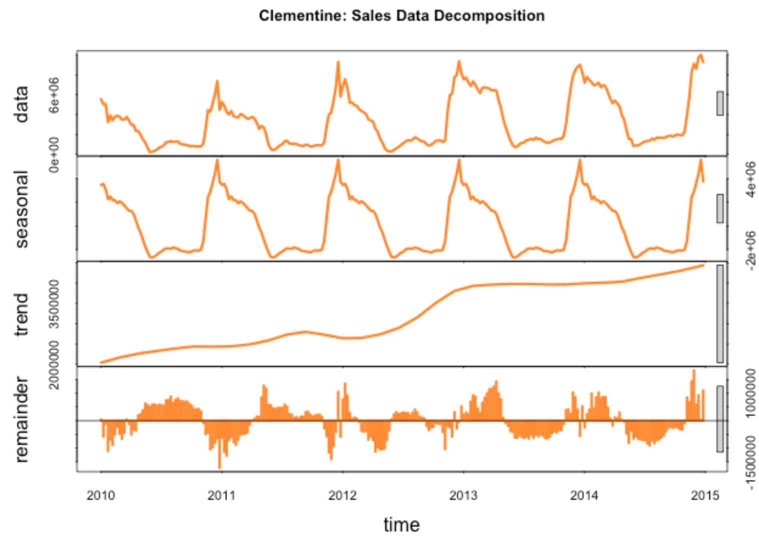
Figure 1.5



Descriptive Analyses

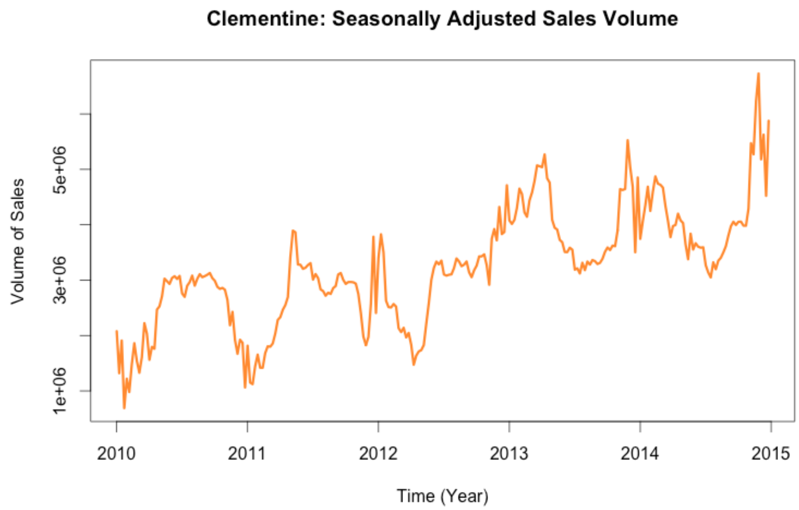
The first step of the analysis we explored was data manipulation. This process involved seasonally adjusting both the social media data and sales data. We first looked at the components of the sales data (see Figure 1.6).

Figure 1.6



After seeing the decomposition, we determined that this data would need to be seasonally adjusted since the seasonal component was a major factor in the data. This was done in order to understand the true underlying trend. We seasonally adjusted it by taking the raw data, and subtracting the seasonal component obtained from the time series decomposition above. We then analyzed at the seasonally adjusted sales data for clementines and cupcakes (see Figure 1.7 for clementines example).

Figure 1.7



We repeated this process for each of the social media predictors. Figure 1.8 shows the clementines Twitter decomposition, and Figure 1.9 shows the seasonally adjusted Twitter clementine data.

Figure 1.8

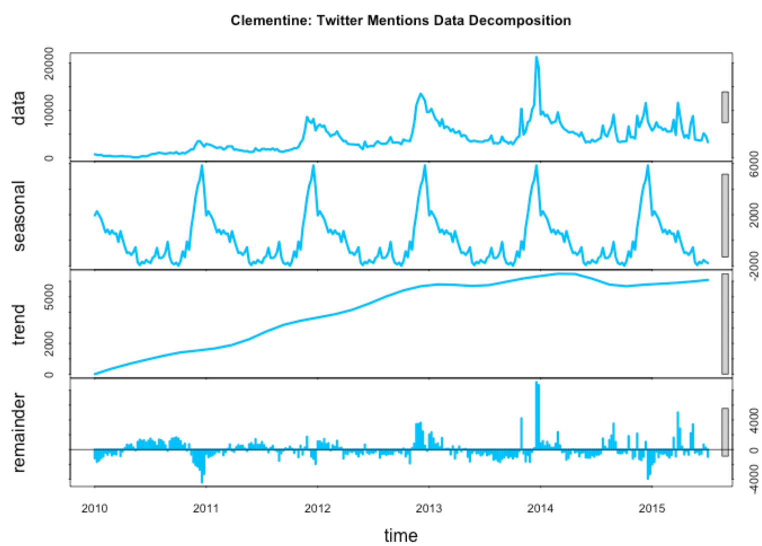
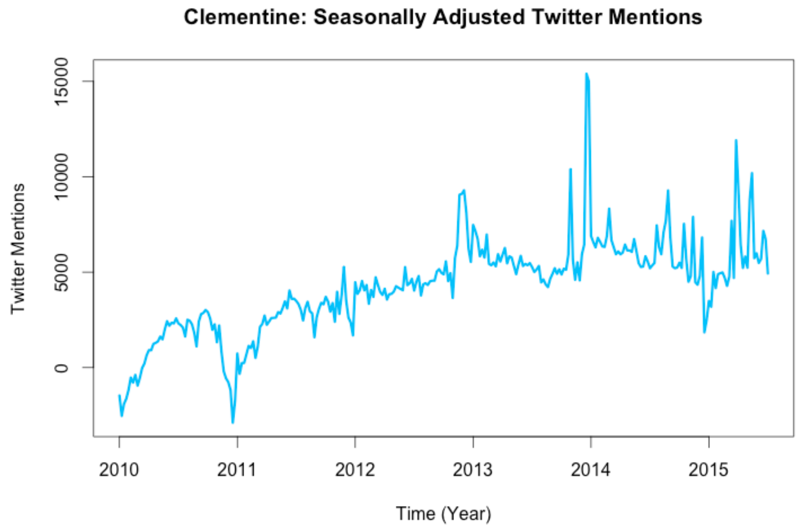
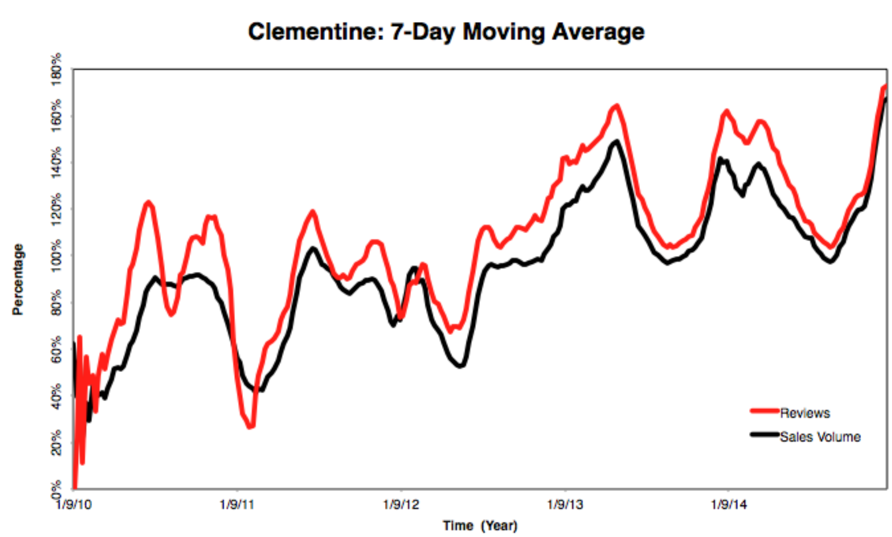


Figure 1.9



Once we had our seasonally adjusted data, we calculated the seven-day moving averages of each social media platform along with sales data. We plotted these moving averages against each other. See Figure 1.10 for an example of clementine reviews and sales.

Figure 1.10



The second part of the analysis was to create a vector autoregressive model (VAR). This model would allow us to forecast each type of variables: social media and sales volume as endogenous variables, concurrently. By using this method, the model takes into consideration lagged values of both variables before making a forecast for either one. For this model, we would use the seasonally adjusted sales data and a seasonally adjusted sum of social media mentions across all platforms.

To see if the VAR model would be a viable option, we tested the seasonally adjusted data (both sales volume and social media) for stationarity. We performed two tests: the Augmented Dickey-Fuller (ADF) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The results of tests were that in fact, all datasets were non-stationary with a drift / linear trend and did not show a tendency to return back to the mean. This shows the VAR model would be a viable option. See Figure 1.11 for further details.

Figure 1.11

Tests		**Clementines p-value**		**Cupcakes p-value**	
Test	**Null Hypothesis**	**Sales**	**Social Media**	**Sales**	**Social Media**
ADF Test	Non-Stationary	0.07494	0.4398	0.01*	0.9835
KPSS Test	Stationary	0.1*	0.01	0.01	0.01

*This suggests we should reject the null hypothesis, however we tested for trend. Trend is stationary, the series is not.

Next, we needed to test for co-integration between the sales data and social media mentions for both clementines and cupcakes. We did this by performing the Johansen test. The Johansen test looks at the test statistic in comparison to the critical value at different confidence intervals. If the test statistic is lower than a critical value, we accept the given null at that particular confidence level. If the test statistic is higher than a critical value, we reject the given null at that particular confidence level.

The results of the test were favorable. For cupcakes (at 1% critical value) we accept the r <=1 null and reject the r=0 null, meaning we can conclude there may be co-integration between the datasets. For clementines (at 10% and 5% critical values) we accept the r <=1 null and reject the r = 0 null, implying there is likely co-integration between the datasets. See Figure 1.12 for more details.

Figure 1.12

Johansen-Procedure					
			Critical Values		
Item	**Null Hypothesis**	**Test Statistic**	**10%**	**5%**	**1%**
Cupcakes	r <= 1	10.48	6.5	8.18	11.65
Cupcakes	r = 0	36.06	15.66	17.95	23.52
Clementines	r <= 1	6.06	6.5	8.18	11.65
Clementines	r = 0	18.87	15.66	17.95	23.52

Lastly, we would use the autoregressive integrated moving average model (ARIMA) on sales volume to create a benchmark model. An ARIMA model has six components: p, d and q (autoregressive, integrated and moving average terms respectively) for non-seasonal component and P, D and Q (which represent the same characteristics) for the seasonal component of the model. Each component gets assigned a number to reflect the different attributes of the model after preliminary analyses.

Modeling Framework

The first step before we could begin modeling the VAR model was to create a benchmark prediction of sales data, using the ARIMA process. This was to calculate incremental lift that would be used in comparison to our VAR model. To do this, we first examined the seasonally adjusted sales volume data. We tested many combinations of ARIMA and settled on two models:

Cupcakes: ARIMA (2, 1, 2) (0, 0, 0)

Clementines: ARIMA (1, 2, 1) (0, 0, 0)

Mathematic structure of ARIMA when d = 1: $y_t = \Upsilon_t - \Upsilon_{t-1}$ where the residuals resemble white noise for each. Using the order of models above forecasted both clementines and cupcakes 52 weeks. We did a training (208 weeks) and holdout (52 weeks) set. Below, in Figure 1.13 and 1.14 are the results of our forecasts that would be used as benchmarks.

Figure 1.13

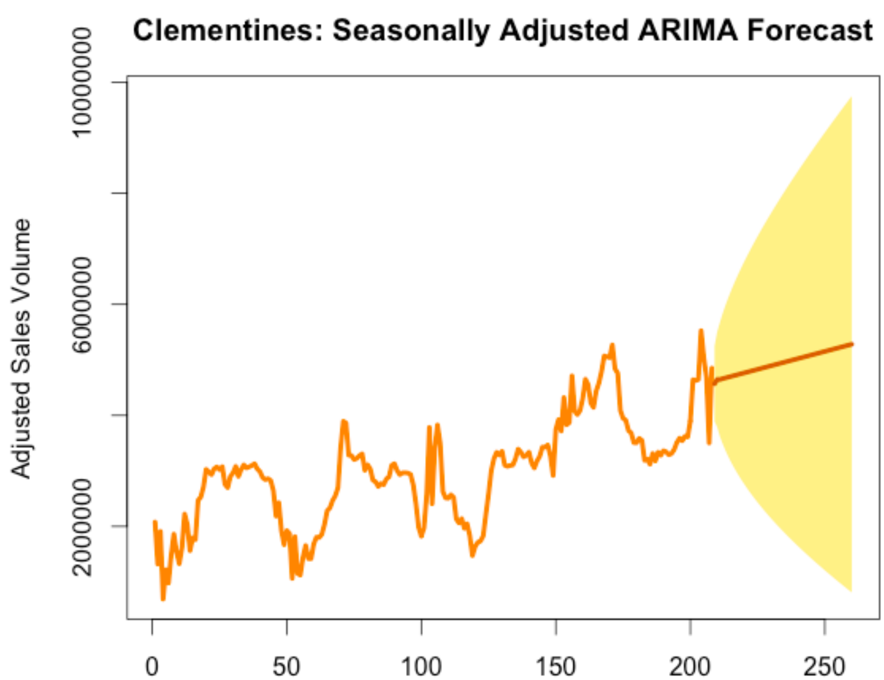
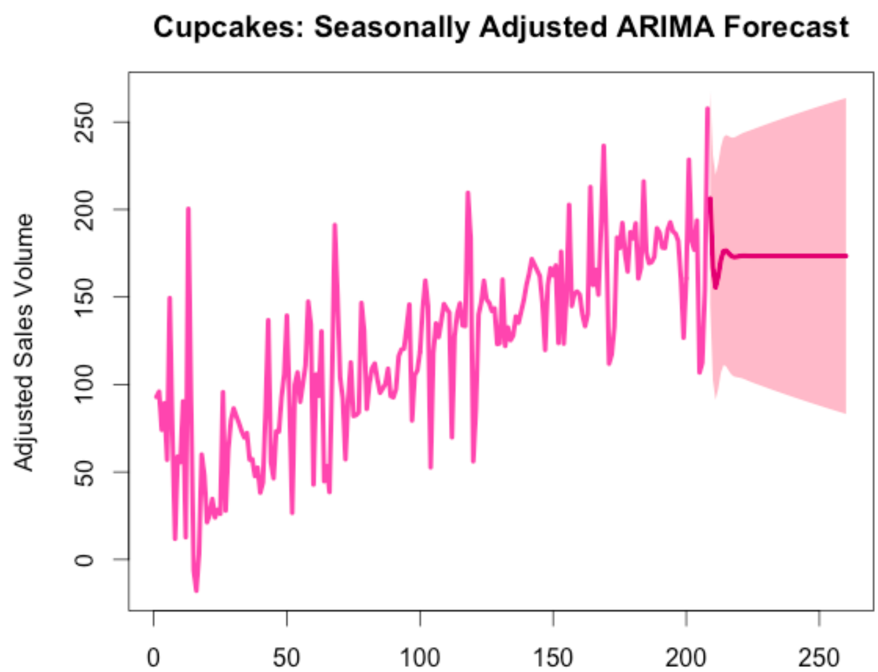


Figure 1.14



The next step was to begin the VAR model. First, we created two matrices (for clementines and cupcakes) and combined: seasonally adjusted sales volume, and a sum of all seasonally adjusted social media mentions per week.

Once we had our matrices of endogenous variables, we split the data into training (208 weeks) and validation (52 weeks) sets. We used the VARselect function to determine what the optimal number of lags should be for each food item. Based on Akaike Information Criterion (AIC) and Schwarz Criterion (SC) Values obtained and using our best judgment, we determined the optimal lag for our prediction was 9 for clementines, and 7 for cupcakes. Given the problem of over / under stocking and maintaining optimal level of inventory for these products (cupcakes and clementines), optimal lag essentially translates as number of weeks prior to expected lift in sales volume that the retailers need to starting planning that inventory levels based on our prediction. Once the lag was determined, we could then create the VAR model.

Using the VAR function in R, we specified the data (in this case the training set) and specified the lags (chosen above by function VARselect). We looked at the output, which tested sales volume as the dependent variable. The r-squared for clementines is relatively high indicating social media is a strong predictor of sales. In contrast, the r-squared for cupcakes is not sufficient to prove a strong relationship between sales and social media. However, it does not indicate there is no relationship. Please reference Figure 1.15 for r-squared results, and Appendix A and B for full coefficient tables.

Figure 1.15

Sales Volume as Dependent Variable in VAR Model		
	Clementines	**Cupcakes**
Adjusted R-Squared	88.12%	69.89%

Since clementines were a good fit and cupcakes required further exploration, we tested the residuals and fit. The diagrams of fit and residuals from the VAR models can be seen in Figures 1.16 and 1.17.

Figure 1.16

Cupcake: Sales Volume Fit and Residuals

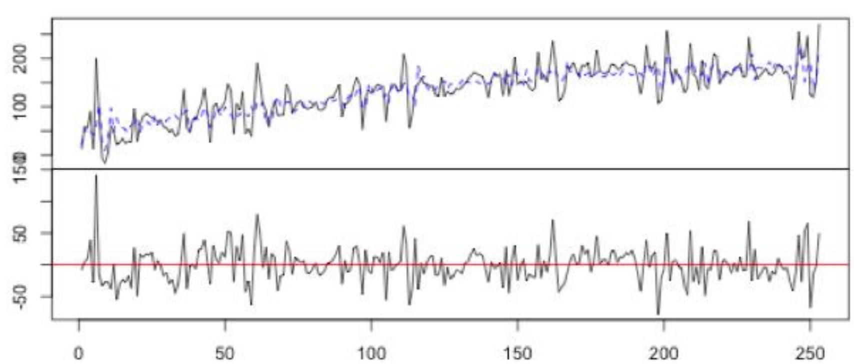
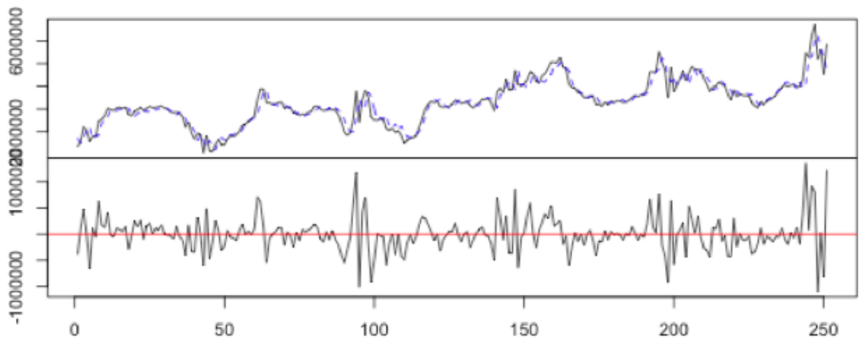


Figure 1.17

Clementine: Sales Volume Fit and Residuals



Looking at the plots above, the VAR model appears to be fit the data well. With these results we forecasted the sales volume and social media simultaneously for the validation period (52 weeks) using the VAR model. Figure 1.18 and 1.19 show the outcome.

Figure 1.18

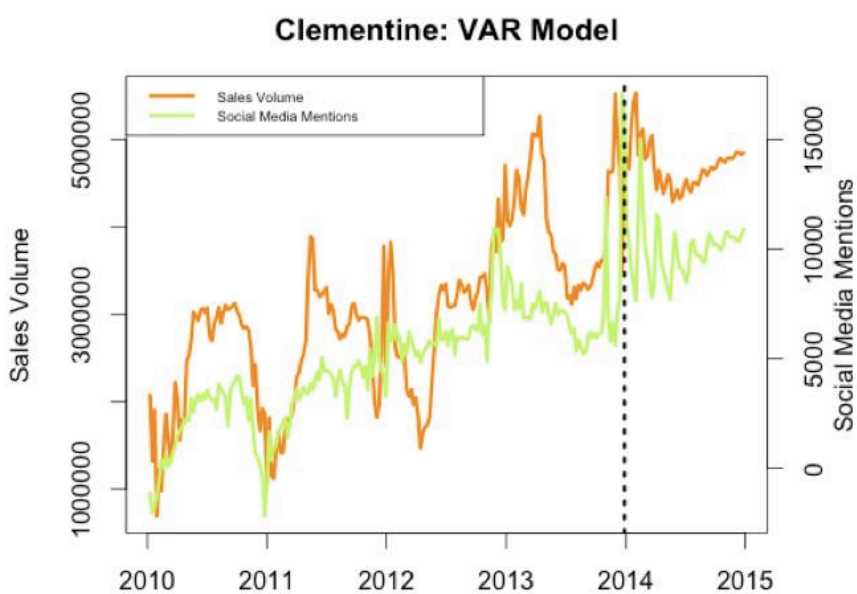
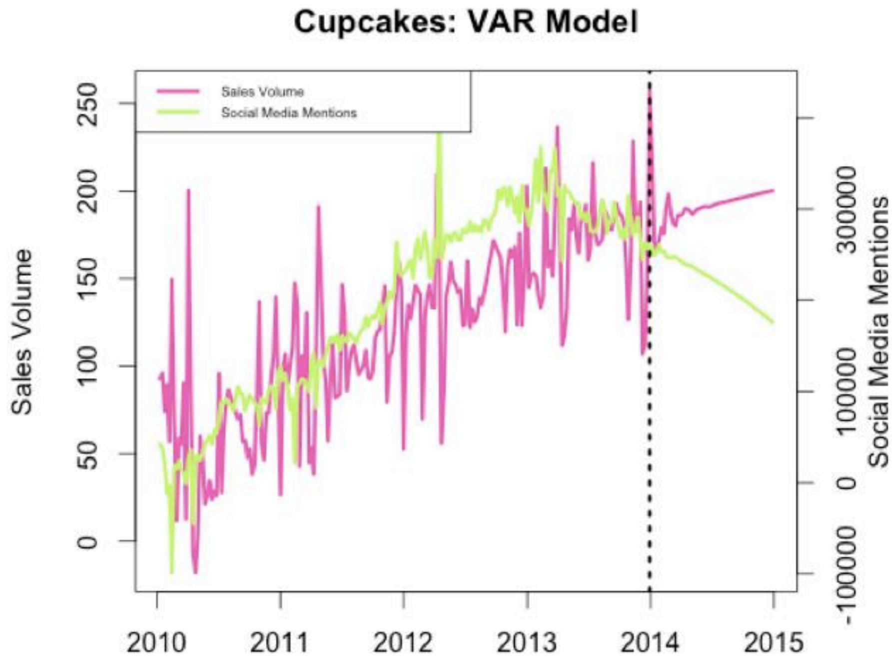


Figure 1.19



FINDINGS

Our overall goal was to use this method to be able to compare it to the benchmark ARIMA model on merely sales volume. Both clementines and cupcakes were highly seasonal with moderate trend, which make them perfect candidates for an autoregressive model to make predictions. However, our goal was to not only use the sales data provided, but to use social media to make predictions.

Since we were able to get predictions for both social media and sales volume, we wanted to compare the results of the VAR model with the ARIMA model predictions for the sales volume data. The results can be seen below in Figure 2.1 and 2.2.

Figure 2.1

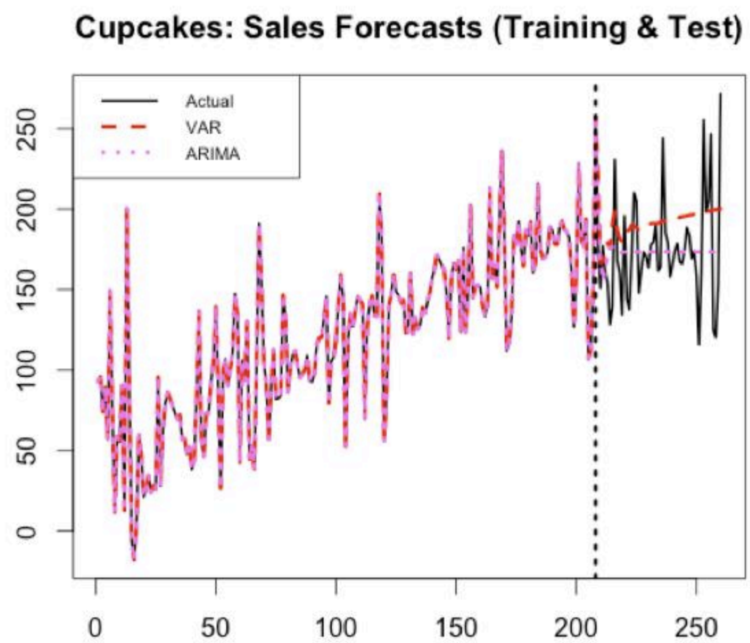
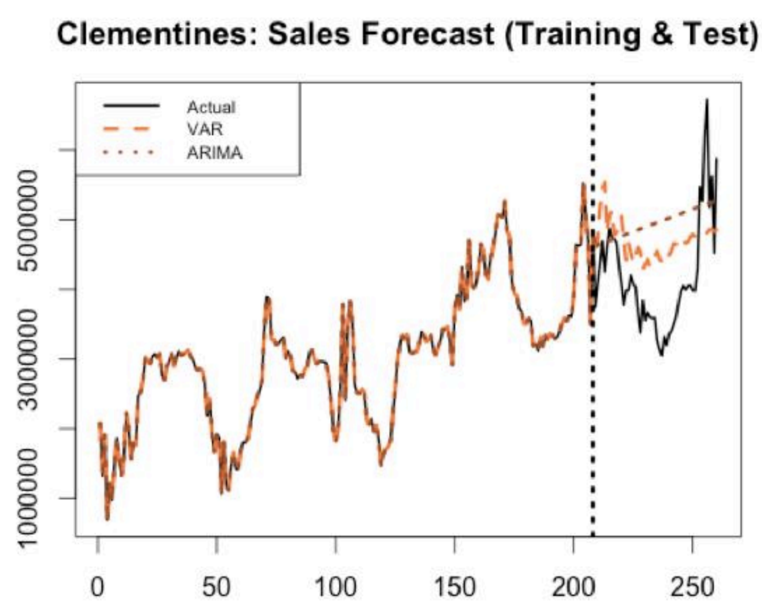


Figure 2.2



We found that in comparison the benchmark ARIMA model, VAR cupcake predictions were not as accurate because they had a negative lift. In contrast, VAR clementine predictions were more accurate than the ARIMA model as they had a positive lift. See Figures 2.3 and 2.4 below. The Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) were both lower for the VAR model and the opposite is true for cupcakes.

Figure 2.1

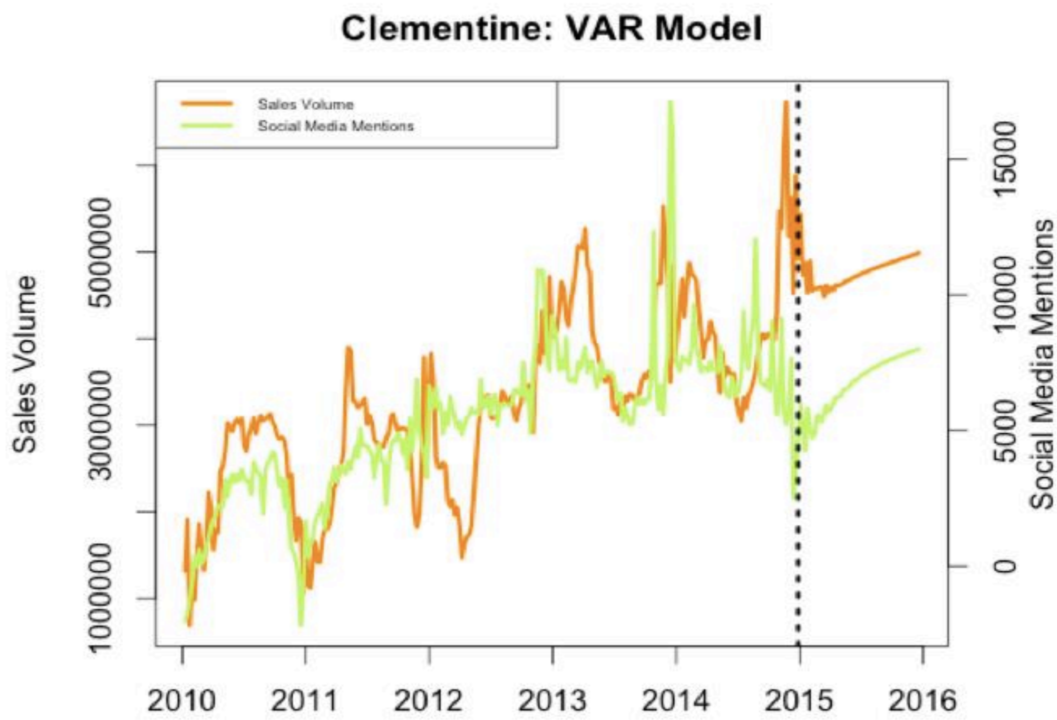
Cupcakes			
	ARIMA	**VAR**	**Lift in Prediction Accuracy**
RMSE	32.61	35.65	-9.33%
MAE	23.40	29.80	-27.34%

Figure 2.2

Clementines			
	ARIMA	**VAR**	**Lift in Prediction Accuracy**
RMSE	1,082,234.00	790,863.80	26.92%
MAE	934,652.20	672,441.00	28.05%

Since we found that the VAR model produced more accurate results than the benchmark model for clementines, we used all available data and forecasted clementines 52 weeks using our VAR model. The results of the clementines VAR model can be seen below in Figure 2.3. We are confident that this is the most accurate prediction of upcoming sales volume for clementines. The benchmark ARIMA model (Figure 1.13) would be our best prediction for upcoming sales volume of cupcakes, and therefore we did not predict further using the VAR model.

Figure 2.3



SUMMARY AND CONCLUSIONS

Based on the findings above, we can conclude that social media does impact sales. The seasonality and patterns of the datasets show they have similar characteristics and are co-integrated. For instance, as people buy more clementines during peak seasons, social media mentions about clementines also tend to rise.

The VAR model that was used to predict sales volume for clementines has a more accurate outcome than the ARIMA model, which means we can conclude that social media is a good predictor of sales volume and can improve the accuracy of predictions. We can also conclude that using social media mentions, we can 26-28% more accurately predict upcoming sales volume of clementines.

The reverse is true for cupcakes – ARIMA is a better predictor of upcoming sales volume. This would indicate that the cupcake sales are extremely autoregressive, and the social media predictors do not add substantial value to the predictions.

RECOMMENDATIONS

It is clear overall that social media can be a predictor of sales, which was the underlying goal of this project. We aimed to find whether food retailers can more accurately predict their upcoming sales using social media. Even though social media did not add accuracy to the cupcake predictions, we can see that cupcake mentions do have validity. The model used has limitations and perhaps a different prediction method could harness the social media data differently. We recommend gathering more social media data for different foods to test the VAR model on a larger scale and across different product categories. This would give you a better indication of social media influence.

Another recommendation for the social media data would be to use different social media platforms, specifically when analyzing the food industry. This is because discussion about food on social media is dominant on image-sharing platforms as opposed to text-sharing platforms. An example of an image-sharing social media platform is Pinterest and Instagram. Food & Drink is the most popular category on Pinterest, as this category makes up 57%[8] of total posts on the website. Both of these platforms were not part of our data, which may have weakened our results.

An even more robust analysis would require image data from social media platforms. This would enable the researcher to harness the data within the photo instead of relying on a caption or comment made. Photo posts account for roughly 75% of all

8 Dougherty, J. (2015, January 19). 25 Pinterest Stats, Facts & PR Best Practices. In Cision.

posts on Facebook, and 100% on Pinterest and Instagram[9]. Performing an analysis solely on textual data really does not paint an accurate picture of the impact of social media on sales.

Lastly, for social media data it would be helpful to categorize social media mentions by geographic region. It is likely that the popularity of certain food items vary by geographic region. Therefore, it may be helpful to evaluate each geographic region separately to obtain different results.

9 Photos Cluttering Your Facebook Feed? Here's Why (2014, April 21). In emarketer.com.

APPENDIX A – CLEMENTINE VAR RESULTS

VAR Estimation Results - Clementines

Endogenous Variables: Sales and Social Media Mentions
Deterministic Variables: Both
Sample Size: 199
Log Likelihood: -4440.46

Lag Type	Estimate	Standard Error	T Value	P-Value	Significance
Sales Lag 1	0.7824150	0.0743986	10.517	< 0.0000000000000002	***
Social Media Lag 1	61.9213764	22.4120775	2.763	0.00633	**
Sales Lag 2	0.0670740	0.0972770	0.690	0.49139	
Social Media Lag 2	-15.2176997	29.4991001	-0.516	0.60658	
Sales Lag 3	0.0840304	0.0986113	0.852	0.39528	
Social Media Lag 3	1.5080413	30.5420930	0.049	0.96067	
Sales Lag 4	-0.0003986	0.0985692	-0.004	0.99678	
Social Media Lag 4	37.8738262	30.5592585	1.239	0.21684	
Sales Lag 5	-0.0327493	0.1006215	-0.325	0.74521	
Social Media Lag 5	20.3766829	30.5374959	0.667	0.50546	
Sales Lag 6	0.0124848	0.0972799	0.128	0.89802	
Social Media Lag 6	-13.6852507	30.5267073	-0.448	0.65448	
Sales Lag 7	-0.1538542	0.0942053	-1.633	0.10419	
Social Media Lag 7	-87.9174710	31.2062961	-2.817	0.00539	**
Sales Lag 8	-0.0033756	0.0925183	-0.036	0.97094	
Social Media Lag 8	74.4549571	33.1058257	2.249	0.02573	*
Sales Lag 9	0.1187393	0.0751441	1.580	0.11584	
Social Media Lag 9	-44.6051934	29.6485585	-1.504	0.13422	
Constant	197421.8028591	95498.9624249	2.067	0.04015	*
Trend	174.7394694	832.8827007	0.210	0.83406	

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Residual standard error: 311100 on 179 degrees of freedom
Multiple R-Squared: 0.8926, Adjusted R-squared: 0.8812
F-statistic: 78.27 on 19 and 179 DF, p-value: < 0.00000000000000022

APPENDIX B – CUPCAKE VAR RESULTS

VAR Estimation Results - Cupcakes

Endogenous Variables: Sales and Social Media Mentions
Deterministic Variables: Both
Sample Size: 201
Log Likelihood: -3240.266

Lag Type	Estimate	Standard Error	T Value	P-Value	Significance
Sales Lag 1	0.32312258	0.07251035	4.456	0.0000144	***
Social Media Lag 1	-0.00008352	0.00009269	-0.901	0.368749	
Sales Lag 2	-0.25586878	0.07362081	-3.475	0.000635	***
Social Media Lag 2	0.00024064	0.00008789	2.738	0.006785	**
Sales Lag 3	-0.10760046	0.07722375	-1.393	0.165183	
Social Media Lag 3	-0.00022200	0.00009112	-2.436	0.015787	*
Sales Lag 4	0.01673850	0.07836051	0.214	0.831087	
Social Media Lag 4	0.00008206	0.00009263	0.886	0.376824	
Sales Lag 5	0.03800949	0.07686324	0.495	0.621534	
Social Media Lag 5	0.00007810	0.00009256	0.844	0.399897	
Sales Lag 6	-0.11210559	0.07392164	-1.517	0.131088	
Social Media Lag 6	0.00012317	0.00008968	1.373	0.171279	
Sales Lag 7	0.19048609	0.07044511	2.704	0.007489	**
Social Media Lag 7	-0.00011903	0.00008937	-1.332	0.184564	
Constant	39.72650620	9.10786410	4.362	0.0000214	***
Trend	0.47616440	0.15134569	3.146	0.001928	**

*Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

Residual standard error: 28.41 on 185 degrees of freedom
Multiple R-Squared: 0.7215, Adjusted R-squared: 0.6989
F-statistic: 31.95 on 15 and 185 DF, p-value: < 0.00000000000000022

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