Your Capstone Project Title

By

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A Capstone Project

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Certifies that this is the approved version of the following capstone project report:

Your Capstone Project Title

Approved by Supervising Committee:

Arnab Bose	Dr. Sema Barlas

Abstract

Abstract

Our research focus was on improving the forecast of tomato/bag sales for a company named Scholle by using social media conversation. We received Sales data from Scholle spanning period of 2010 to 2018.Lagged social media data sourced from Twitter and Google Trends was regressed on Scholle data using various time series model. Random Forest Model was found to be the most successful in predicting the Tomato bags Sales. From this study, we developed a set of analytical models when applied by Scholle improved the prediction of Tomato bag sales using social media data.

Keywords: Forecast, Social media data, Regression, Scholle data, time series model, Random Forest Model

Executive Summary

The executive summary is a maximum one page, double spaced summary of your report aimed at informing someone, who does not read the entire report, about your project. The executive summary is an extended version of the abstract with more space allocated to the key findings of the project and the conclusions and recommendations. You may want to write this section after writing the report.

Second Paragraph.

Third Paragraph.

NOTE: Like the abstract, do not use “#” or “##” symbols to start new sections in the executive summary section. Doing so will result in generating a table table of contents entry *prior* to the Introduction, which is not desirable.

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Preface

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Chapter 1

phoenixdown::capstone_gitbook: default

Placeholder

Problem Statement

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Results of descriptive analyses

1.0.1 Distribution of Quantity

Order quantity is typically less than 50,000, with a few orders significantly higher. Specifically, most order quantity are less than 30,000. See @ref(fig:Quantity_Histogram) below for histogram on the quantity distribution.

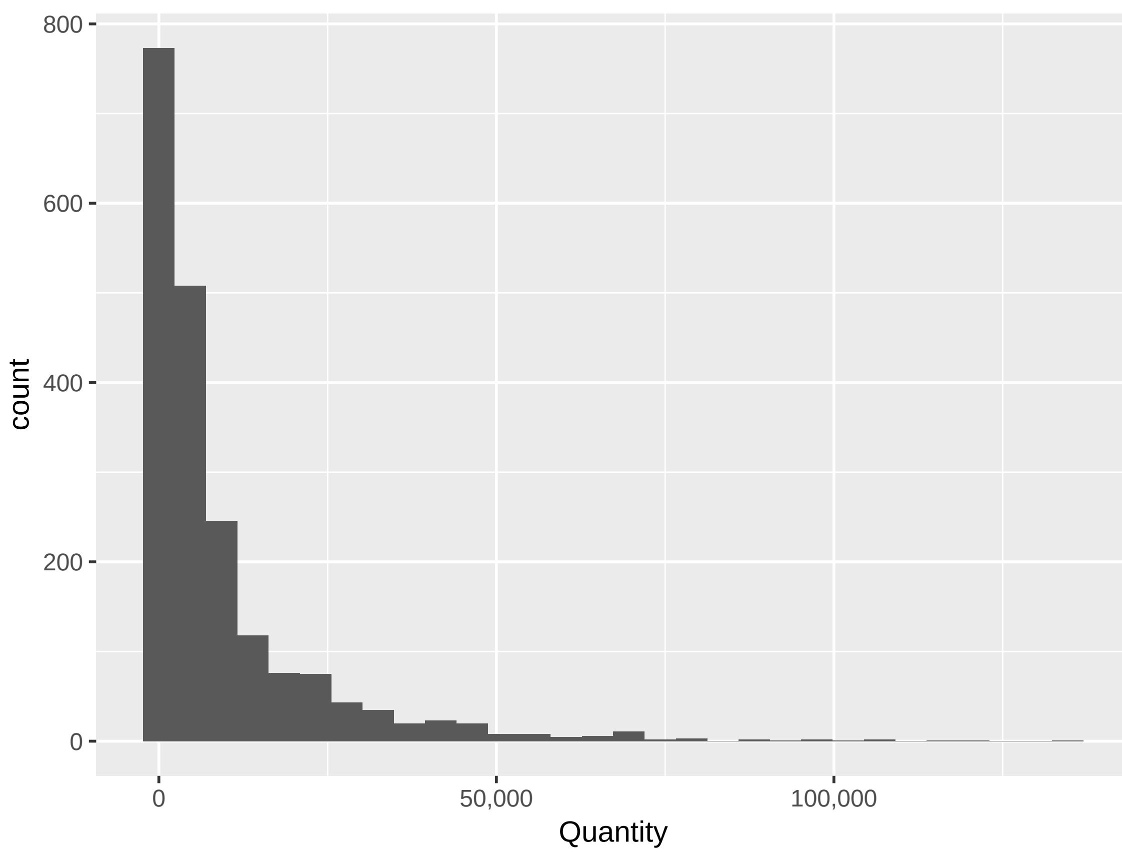


Figure 1.1: (#fig:Quantity_Histogram)Histogram of Quantity

1.0.2 Distribution of Quantity over time

The figure below breaks down shipments over time. There is a large degree of seasonal behavior. Tomato bag sales increase during summer time from June to August and begin to drop off in September and October. Quantity is very small during other months of the year.

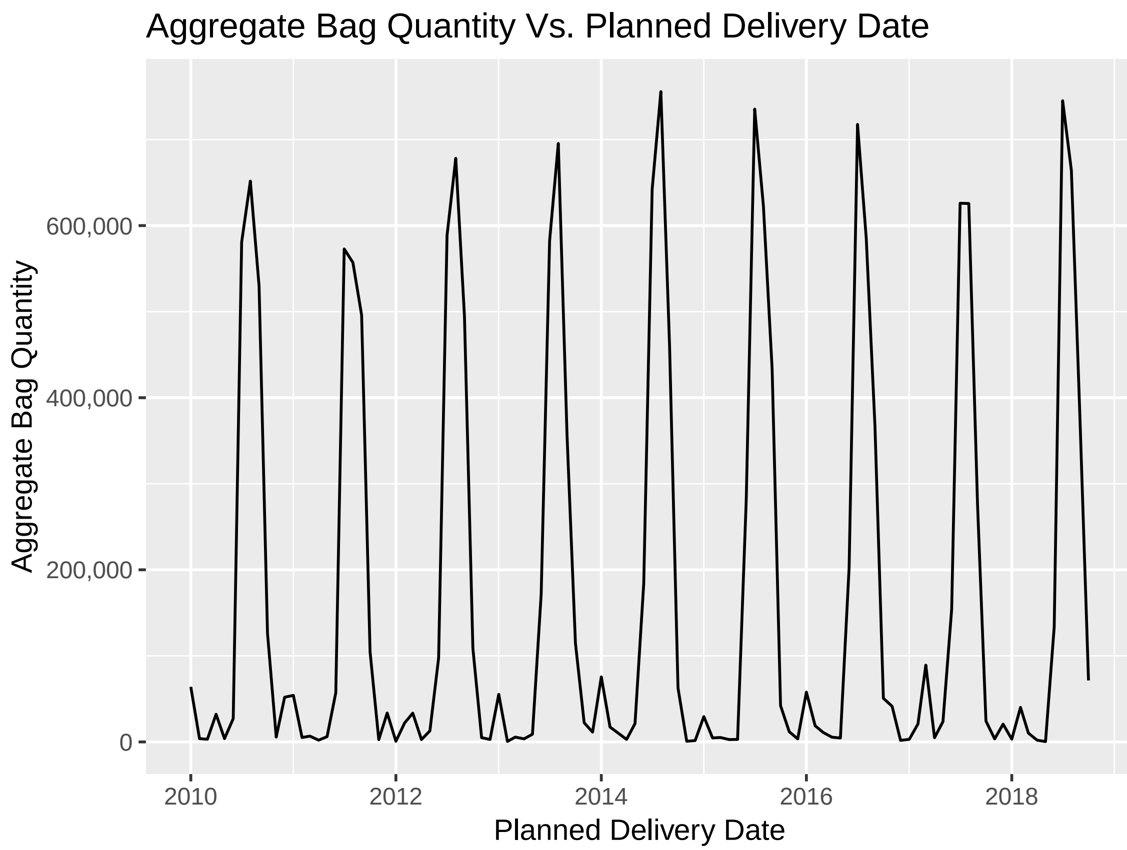


Figure 1.2: (#fig:Quantity_Time)Quantity over Time

1.0.3 Distribution of Quantity over Time

The figure below breaks down shipments over time. There is a large degree of seasonal behavior. Tomato bag sales increase during summer time from June to August and begin to drop off in September and October. Quantity is very small during other months of the year.

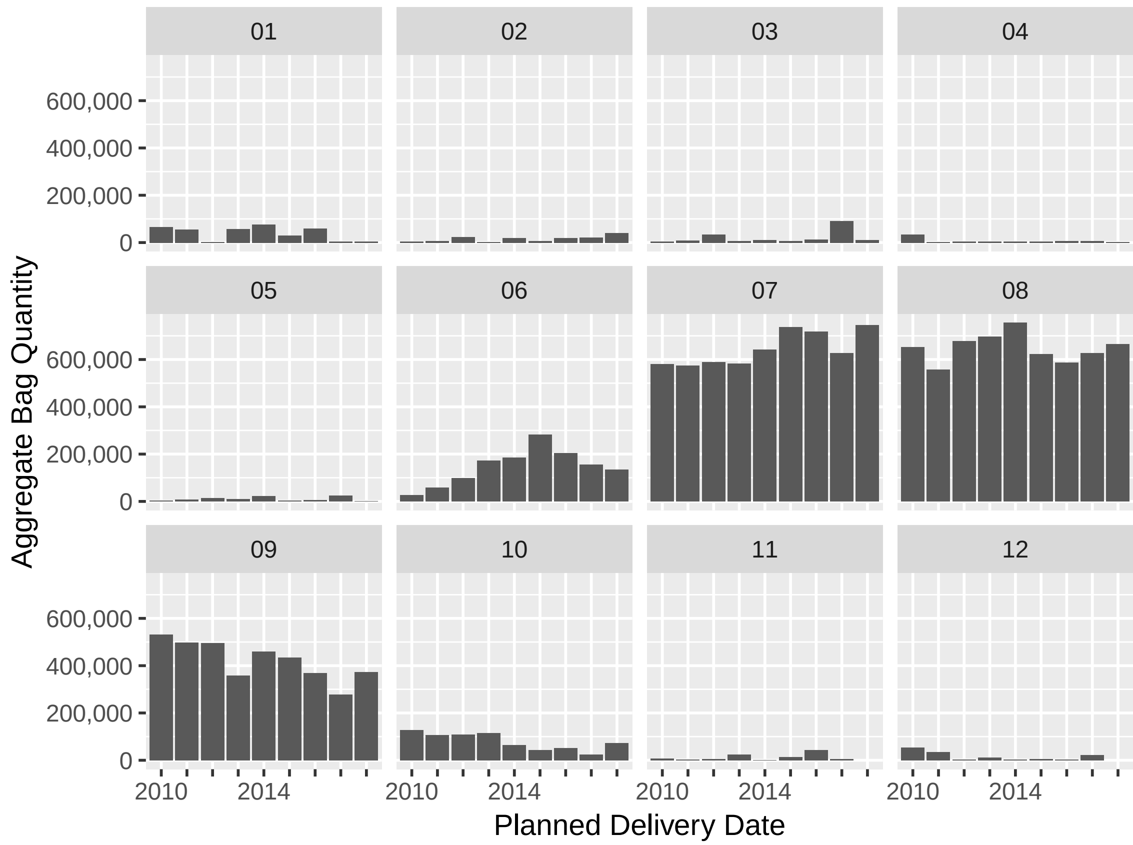
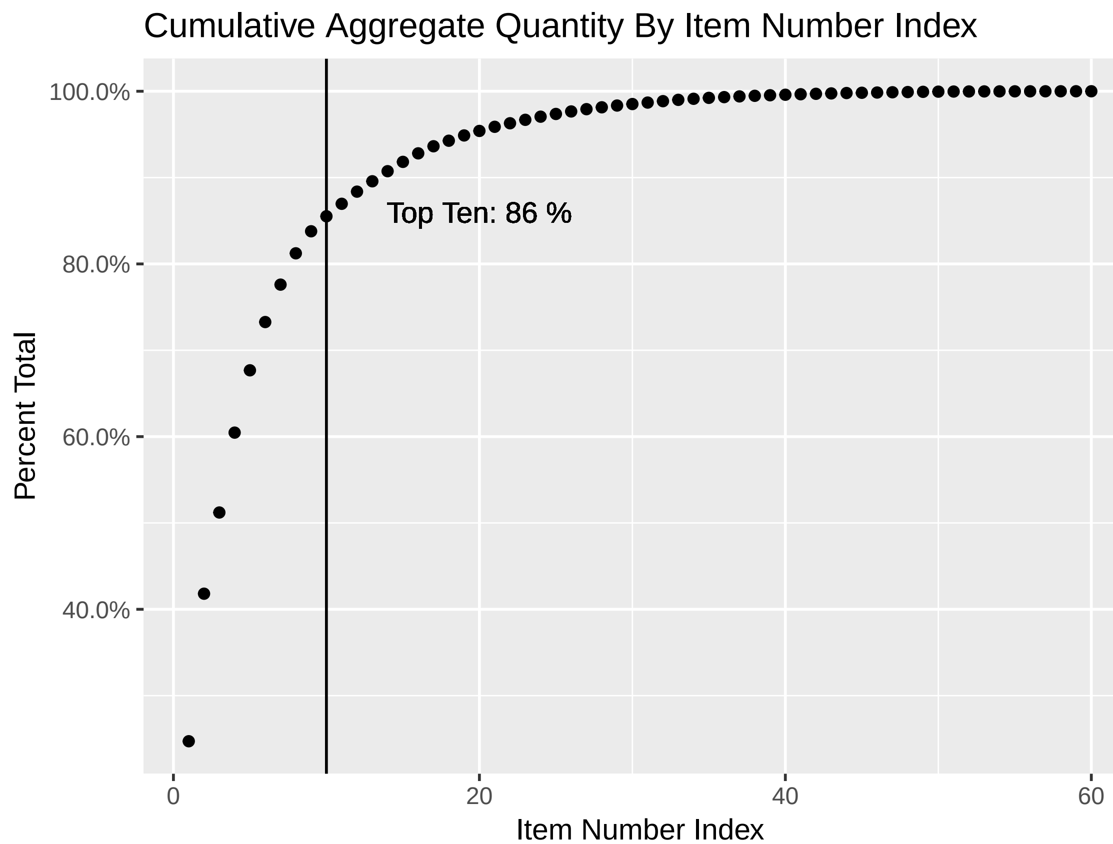


Figure 1.3: (#fig:Quantity_Month)Monthy Quantity by Year

1.0.4 Quantity by Item Number

In the figure below, total order quantity are aggregated by item number and then ordered by descending total quantity. Over 86% of bag quantities are driven by the top 10 out of a total of



60 item numbers.

1.0.5 Quantity by Top Business Partner

The figure below aggregates quantity by item number and then orders quantity descendingly. It suggests that over 93% of bag quantities are driven by the top 10 out of the 23 top business partners.

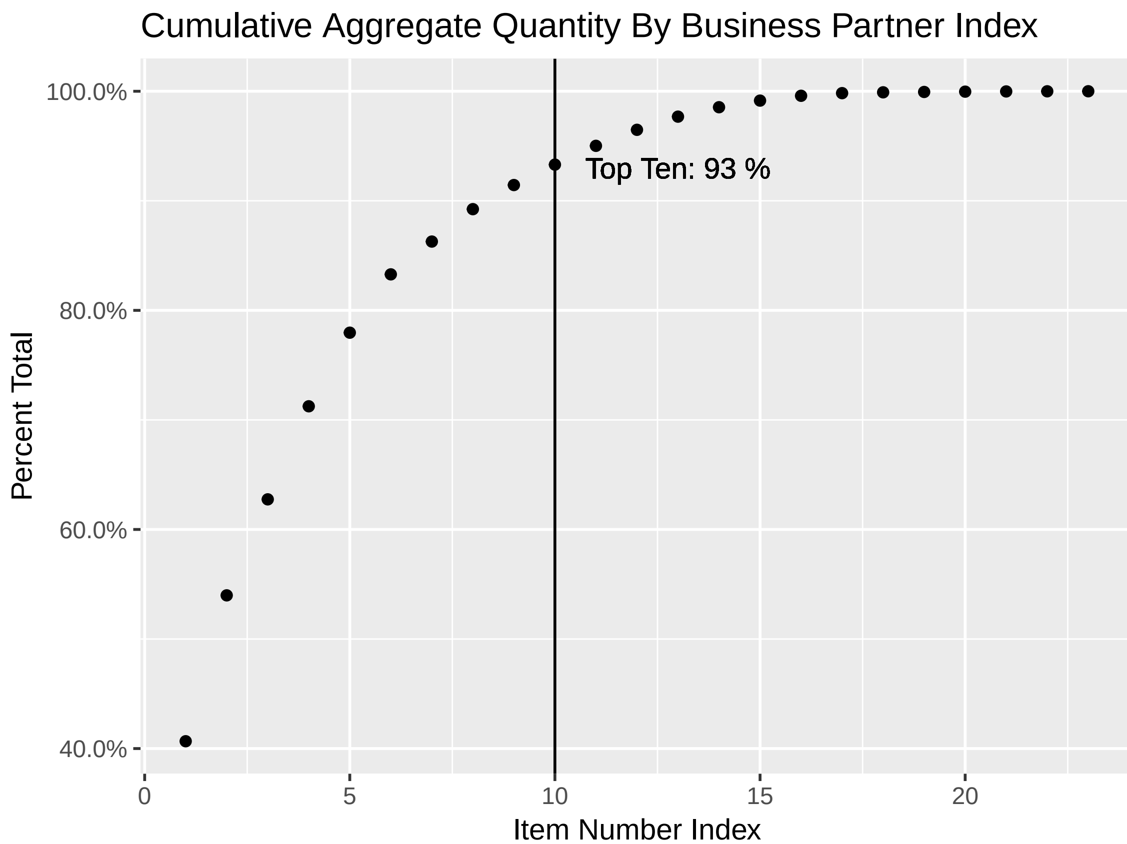


Figure 1.4: (#fig:BP_Cumulative)Cumulative Sales by Business Partner

1.0.6 External Data Collection

We collected Social Media data from two sources: Twitter and the Google Trends. Google Trends summarised US monthly search statistics from 2004 to 2019. The twitter data collected are of US users from 2007 to 2018.

Google Trends returns a single value showing how frequently a given search term (e.g. 'Tomato') goes in Google's search engine relative to its total search frequency for a given period.

Twitter data were gathered by collecting relevant tweets from Twitter using key search words as shown in Table __ below. We can grab a tweet based on defined keyword from Twitter by calling the Twitter API function. Subsequently, we can categorize opinions expressed in a piece of text, in order to determine opinion on our research (i.e, positive, negative, or neutral).

```
Attaching package: 'kableExtra'

The following object is masked from 'package:dplyr':
```

```
group_rows
```

External Data Source	Frequency Granularity	Range	Size	Data Type
Google Trend	Monthly	2004-2019	182	Numeric
Twitter	Monthly	2007-2019		Text, Numeric

Table __ above shows the description of the social media dataset. The google trend dataset based on relative search frequency is on a monthly basis. The monthly dataset at the time of reporting has 182 rows.

The Twitter data are sampled via a quasi-random approach that grabs data monthly over the entire period of 2007 - 2018. We had to employ this method of querying due to the nature of the Twitter API and its restrictions on total tweets returned. The Twitter API returns tweets in reverse chronological order. The total number of tweets that would mention one of our keywords would be vastly larger than the number we could collect over the course of our data collection period (January 2019 - March 2019). Limited in this way, we decided to strategically collect tweets from each month of the year between January 2007 and March 2019.

Assumptions & Limitation

Google Trends Assumptions We limited the Google Trends search to the United States. The keywords are independent of each other.

Limitation: The actual number of searches for the term being queried is not made available. Instead, the data are reported from 0-100, where 100 represents the maximum relative search frequency.

Resolution: Each term selected will be queried individually.

Twitter Datasets Assumptions We limited Twitter data to the United States. The frequency of tweets we collected for each keyword will be independent of the time period in which we collected them.

Limitations The demographic information of the twitter account user cannot be determined. With the limitation of our premium account API activity, we can only submit 100 requests to collect tweet per month. Per each request, we can get a maximum of 500 tweets back. The language associated with the Twitter account returned from the API does not guarantee the language of the Tweet. While we specified English language tweets, we received many tweets that were not in English. We subsequently dropped these tweets.

Plan for use

Twitter data We developed a sentiment index for all tweets using natural language processing techniques tilizing the textblob Library to analyze how similar or discrepant the meaning of tweets among each keyword

Google Trends Correlation analysis of frequency of individual search terms compared to quantity Subsequent seasonality & trend analysis to identify meaningful predictors

Twitter Data

We have collected tweets based on the keywords in Table 3 below. Tweets were aggregated on a monthly basis. The figure below shows how frequently the keywords appears in the returned tweets over time. Pizza is more frequently mentioned in Twitter than other keywords.

Google Trend Analysis

We collected Google Trend data consisting the same keywords as we did in Tweet collection. The Google Trends data was standardized and subsequently the cross correlation was found with respect to the Scholle bag sales. Figure __ displays the results of the cross correlation analysis.

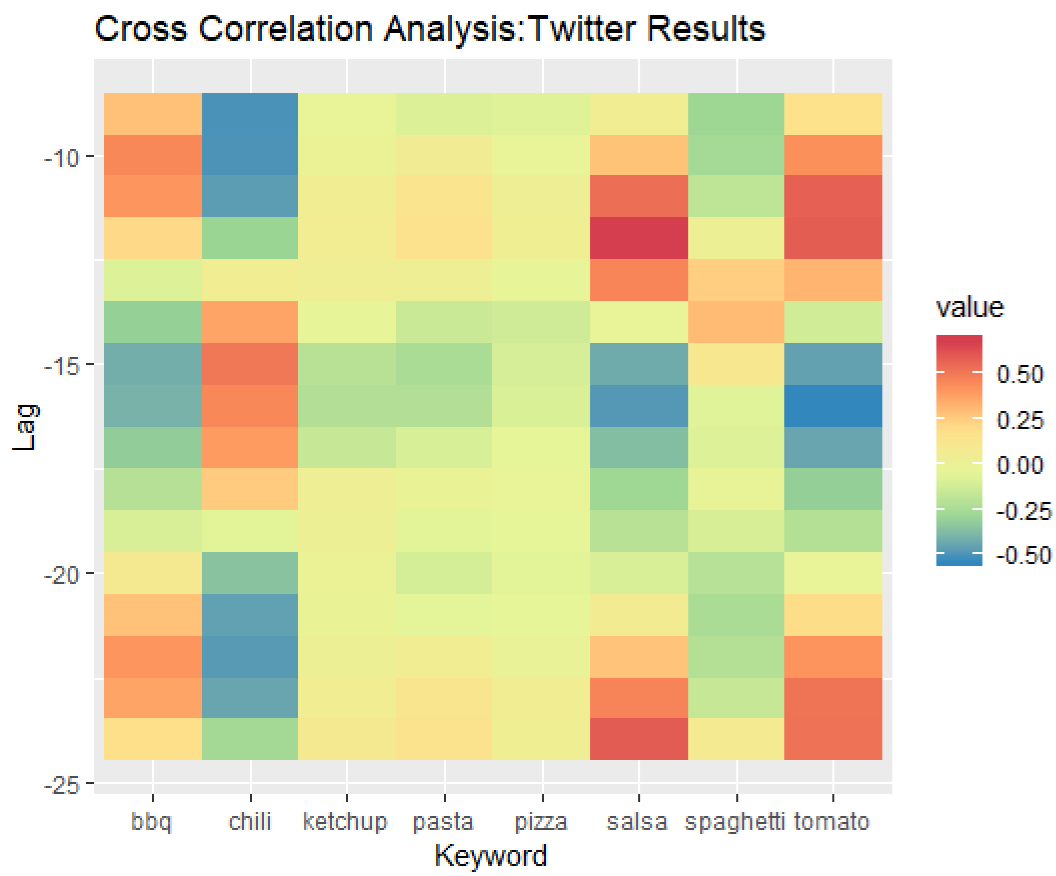


Figure 1.5: CCF Google

bbq	chili	ketchup	pasta	pizza	salsa	spaghetti	tomato
Lag 10	Lag 15	None	None	None	Lag 12	None	Lag 12

In Table 4 above, we highlight cross-correlations greater than 0.5 and with a time period of greater than 8 months. Since the Scholle bag sales data are records of the demand are placed well in advance of the desired delivery date, we would expect a long lag window in order for the trends of social media to drive market forces that would affect demand. Red indicates positive relations and blue indicates negative correlations. The deeper the color, the greater its correlation with Scholle's data.

Tweet Sentiment Analysis

We have conducted the following steps to conduct the sentiment analysis of the tweets.

Text Cleanup Pipeline: 1. Remove RT, URLs and non-text characters (except @ and punctuation symbols) 2. Handle mentions by replacing with upper case letters. 3. Remove all remaining non-text characters (including @ symbol and excluding punctuation symbols). 4. Check the language of the cleaned up tweet and drop any tweets that are not in English.

SpaCy Pipeline:

We used the spaCy English Core Web Large model to analyze each tweet to process into three data sets: 1. Tokenization - each tweet was broken into its component elements of words, punctuation, etc. 2. Dependency Parsing - Annotate the tweet to add the syntactic dependency within the tweet i.e. compare link verbs to their respective nouns. 3. Named Entities - Each tweet was analyzed to identify the named entities in the tweet. These entities will include the mentions because they were capitalized in the Text Cleanup Pipeline. 4. Removal of stop words - all stop words identified were removed.

Vector Extraction:

Spacy includes vector representations for individual words as well as entire entire sentences. See Figure 22 below for the Keyword Distance using Spacy.These are represented as 300 dimension Numpy arrays. To begin, we confirmed that were was a reasonable cosine distance measure between each of the keywords.

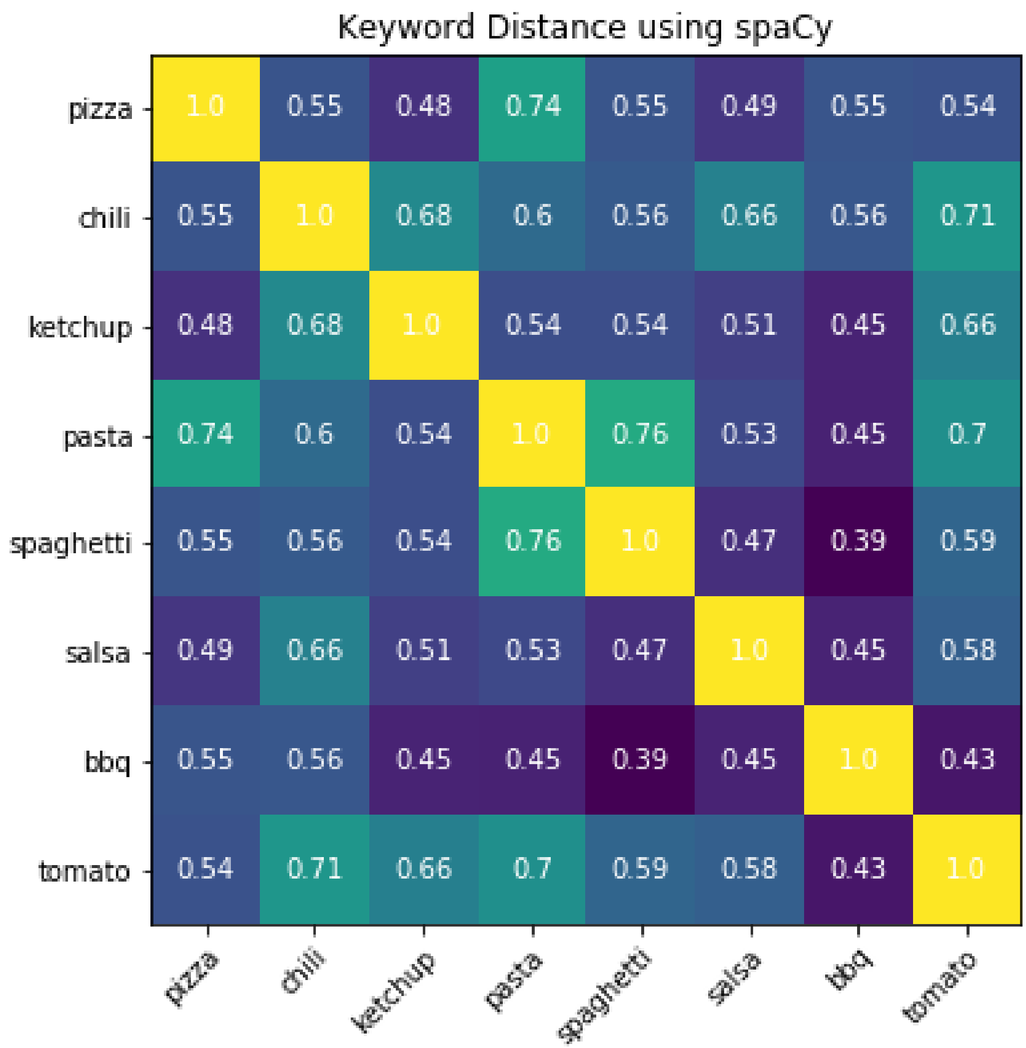


Figure 1.6: Spacy Keyword Distance

There is a reasonable distance between each of the keywords with the exception of bbq and barbecue but this is to be expected since they reference the same thing.

In addition, vectors representations of each tweet can be extracted. For each tweet keyword we summarised all vectors by finding their mean values for each dimension. We then found the pairwise distance measures for these ‘average’ tweets. See in the figure below

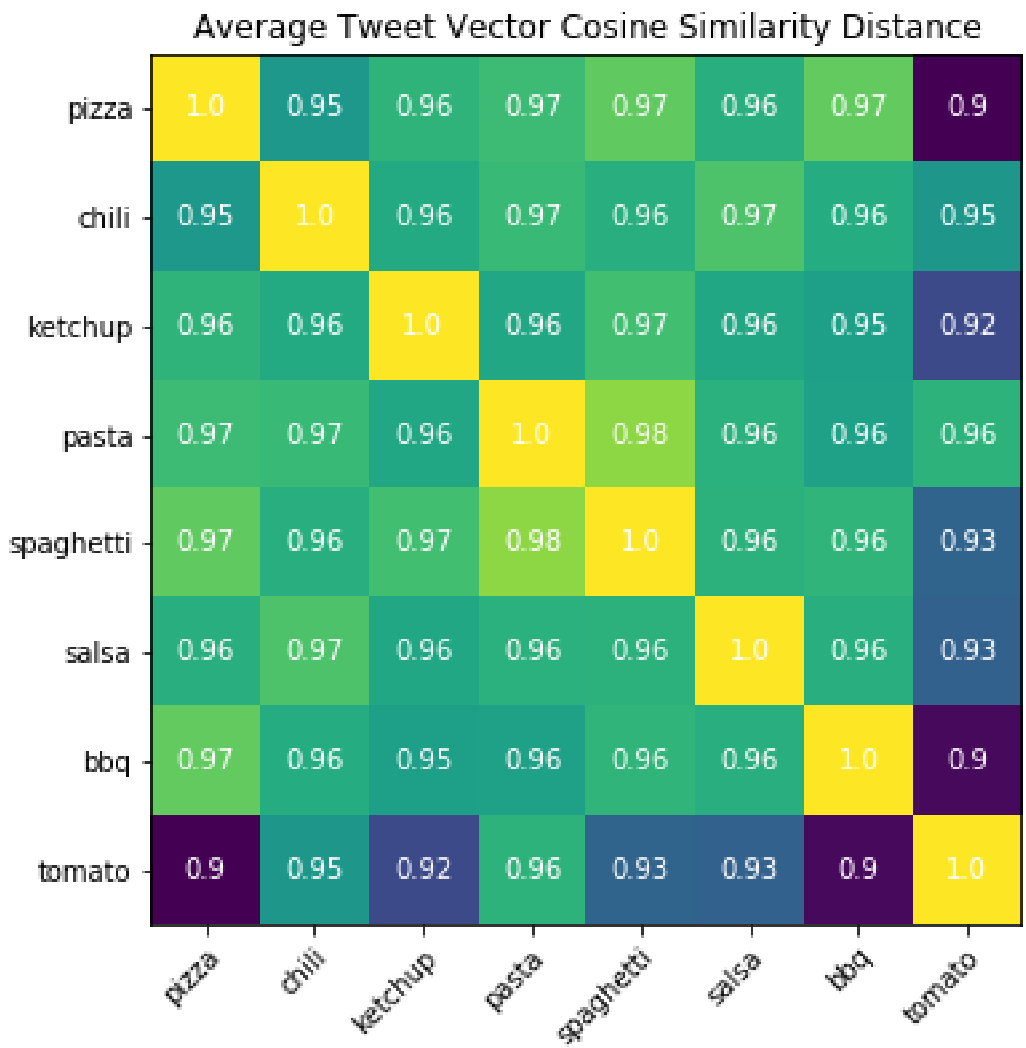


Figure 1.7: Spacy Mean Vector Distance

Here, the “average” tweets are rather similar to each other with the greatest distance from tomato to salsa.

In future work we will leverage these vector representations of the tweets to conduct transfer learning to identify tweet sentiment.

Sentiment Analysis using TextBlob

TextBlob is an open source Python library for conducting natural language processing. It has a built in sentiment analyzer that utilizes two axes of analysis Polarity and Subjectivity. Polarity refers to a positive or negative sentiment and ranges from positive one to negative one respectively. Subjective expresses the subjectivity or objectivity of the text. See Figure 24 below for the Tweet Polarity. The subjectivity axis ranges from zero to positive one where

0 is very objective and 1 is very subjective. See Figure 25 below for the Tweet Subjectivity
.

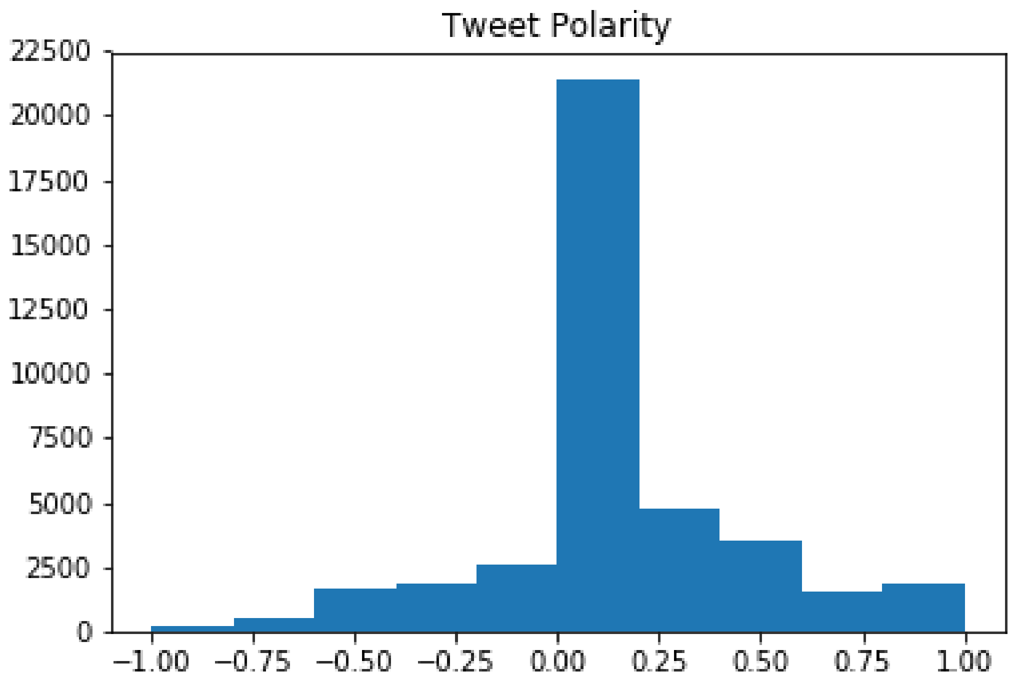


Figure 1.8: Tweet Polarity

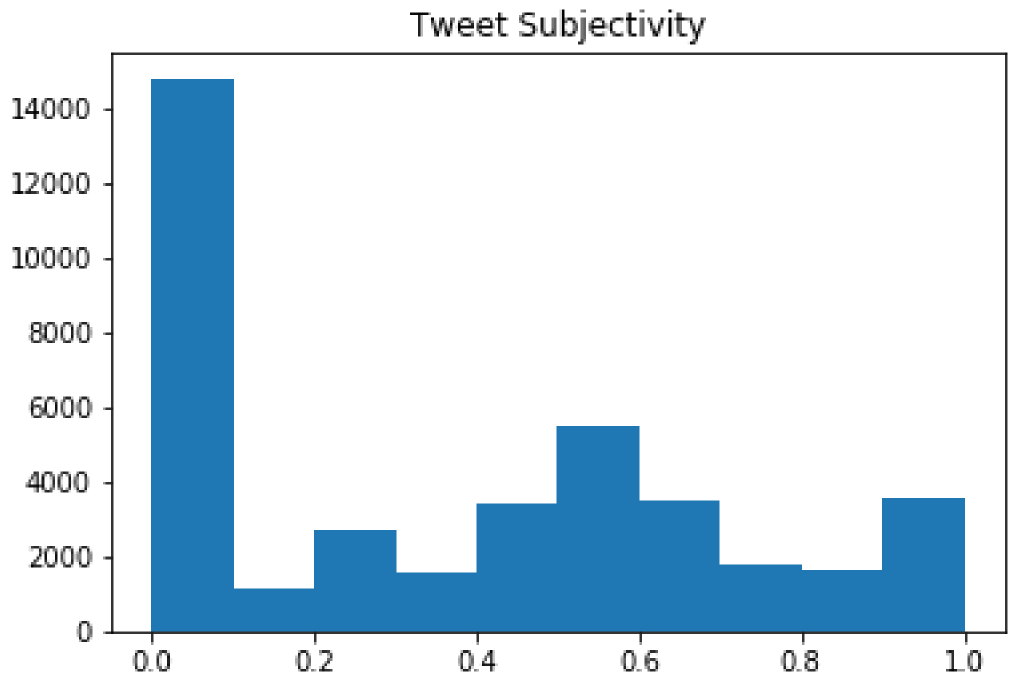


Figure 1.9: Tweet Subjectivity

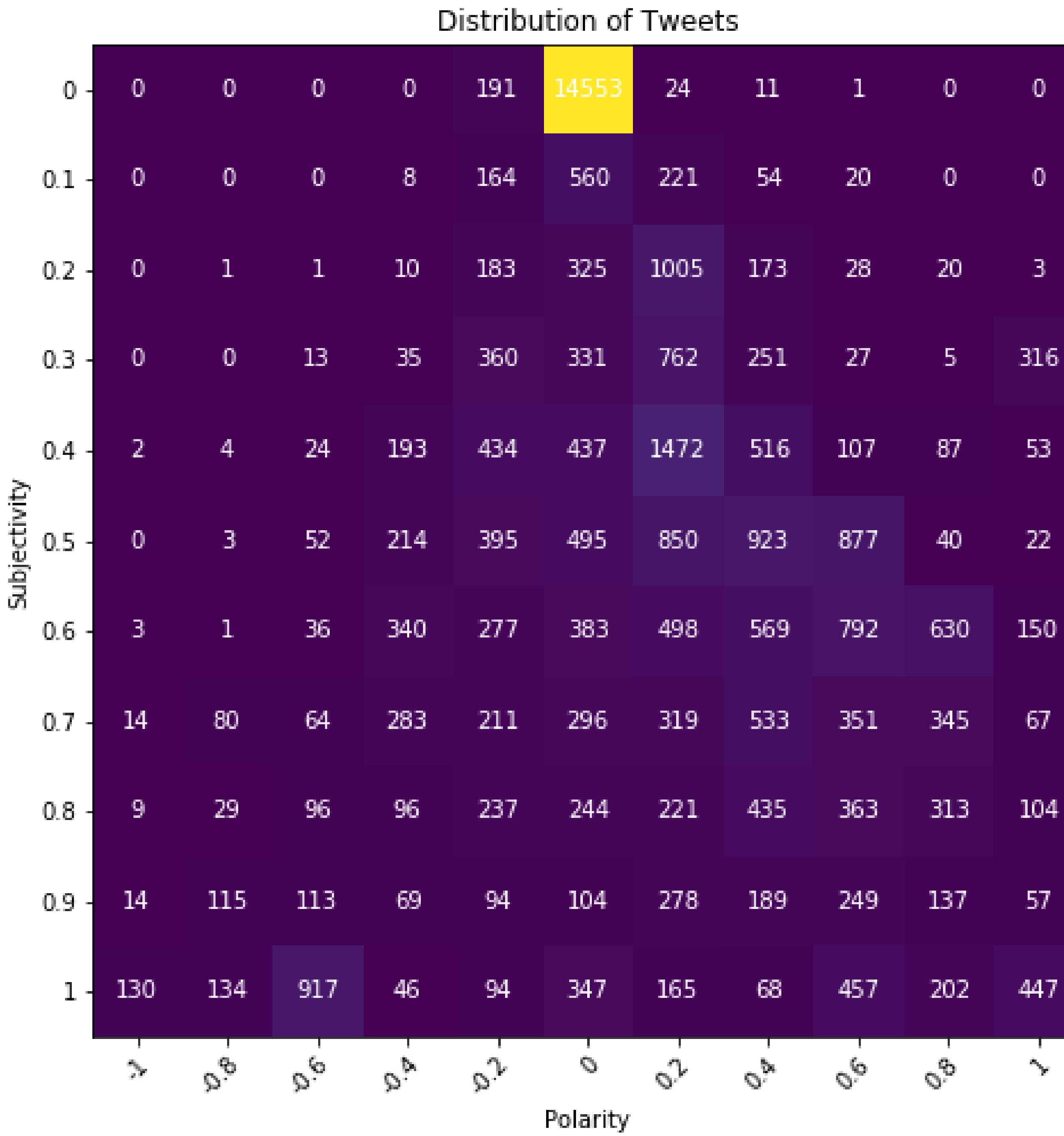


Figure 1.10: Tweet Distribution

TextBlob categorizes the vast majority of tweets as non-subjective non-polar.

With the tweets collected, we generated a sentiment index by taking each tweet's subjectivity & polarity and multiplied them by the retweet count for that tweet. We then aggregated the sentiment index at the monthly level for each keyword. The cross correlation between the Scholle data and the sentiment monthly index for the overall sentiment and for each keyword was calculated and the results displayed in the figure below.

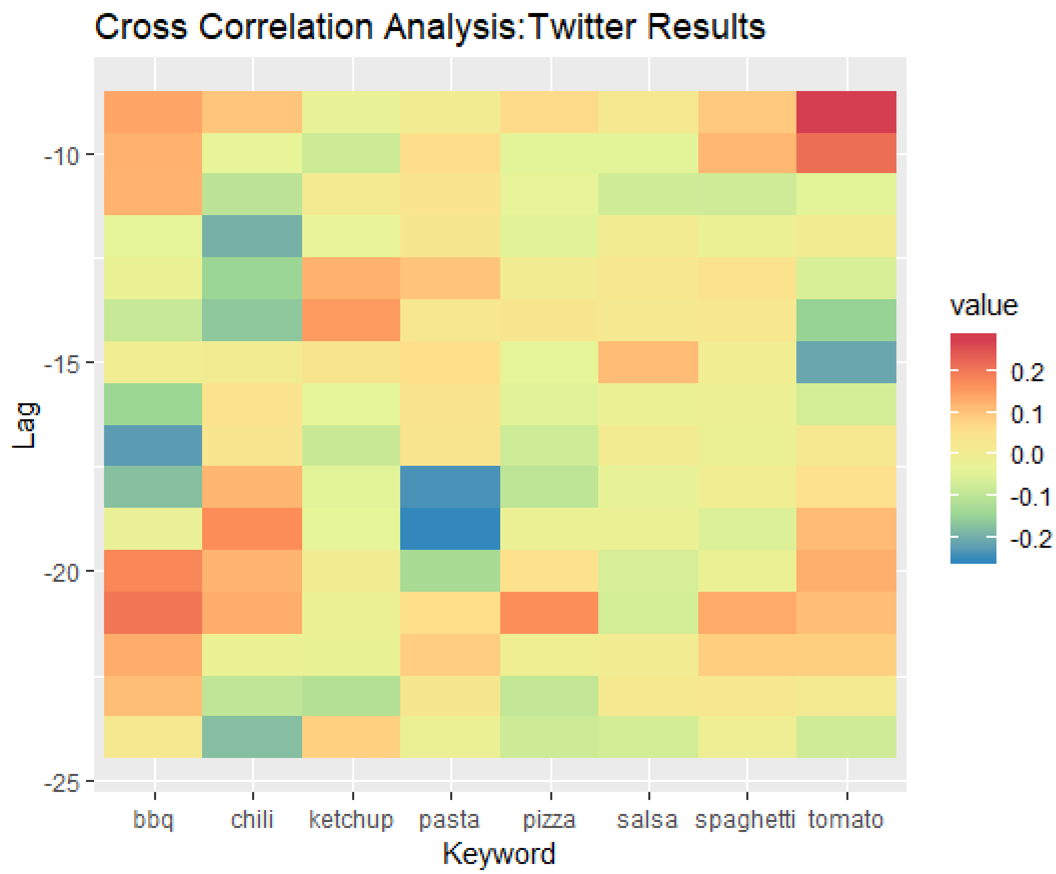


Figure 1.11: Twitter CCF

It is important to note the difference in scale relative to the Google Trends results; the correlations to the Twitter sentiment index are much weaker.

The table below compiles the list of lagged values used in our analysis.

bbq	chili	ketchup	pasta	pizza	salsa	spaghetti	tomato
Lag 17	None	None	Lag 18	None	None	None	Lag 15

Model Selection Metrics

Selection of Metrics

In order to determine the best model, we began by choosing selection metrics to test each model against. The following metrics outlined below will be used to measure the performance of each model. 1. SMAPE 2. RMSE 3. % bias – no of time above forecast vs below. 4. Accuracy

sMAPE -Symmetric Mean Absolute Percentage Error

Symmetric mean absolute percentage error (sMAPE) is an accuracy measure based on percentage (or relative) errors. It allows us to understand error independent of scale.

$$sMAPE = \frac{100\%}{n} \frac{|A_t - F_t|}{(|A_t| + |F_t|)/2}$$

sMAPE has a lower bound of 0% and an upper bound of 100%. The best value will be 0% while the worst value will be 100%.

The major limitation with sMAPE is that it gives more penalties to underestimates than overestimates.

RMSE- Root Mean Squared Error

The root mean squared error (RMSE) of an estimator measures the average of the squares of the errors—that is, the average squared difference between the estimated values and what is estimated. The square root of this value is then taken to produce the RMSE.

$$RMSE = \sqrt{\frac{\sum^n (A_t - F_t)^2}{n}}$$

RMSE measures the variation between predicted and measured values and it provides us a basis for measuring the model variance on the same scale as the data.

The RMSE is a measure of the quality of an estimator. RMSE is always non-negative, as the process of squaring removes any negative signs. It also penalizes larger differences. The best value is zero while the worst value is unbounded.

In sum, the lower the RMSE, the smaller the error, the better the estimator.

Percent Bias – ratio of model high or low.

Bias refers to the propensity of a measurement process to over- or under-estimate the value of a population parameter. Percent bias (PBIAS) measures the average tendency of the predicted values to be larger or smaller than the actual values.

Percent Bias is calculated by taking the sign of the residual for each data point and setting positive values to 1 and negatives values to zero. These are then averaged and multiplied by 100 to produce a percentage. The best percentage bias is 50% - there are just as many over predictions as under predictions. The worst percentage bias is either 0% or 100% as the model is regularly over- or under-estimating the actual data.

Accuracy - Mean Accuracy between Model & Actual

Accuracy measures the closeness of a model prediction to the actual value. In our case we are measuring the mean accuracy for all model predictions versus actual values. The best accuracy measure is 1; the prediction and the actual are the same so their ratio is 1. Accuracies that diverge from 1 are bad; a value greater than 1 means the prediction was higher than the actual while a value below 1 is means the predictions was lower than the actual. We aggregate the accuracy measure for each data point and find the overall mean. One precaution to consider by using this procedure is it may mask an underlying trend in prediction of the accuracy in which the model could overestimate early and then underestimate late or other non-linear behavior.

Training and Forecasting Windows

In order to evaluate our model to avoid either overfitting or underfitting , we split our dataset into a training set and a test set. Based on our discussions with Scholle, the test set will be the subsequent 18 months. The length of the training period was chosen based on the evaluation of the model stability of our baseline model using a rolling window cross validation.

Rolling Window Cross Validation

Time series data present a unique challenge in analysis in that the data are not independent - they are collected at regular intervals over the course of time. We employed rolling window cross validation to generate multiple train and test sets from the overall data set. Initially we explored the model stability of our baseline model and used the best criteria from that in order to decide the length of the cross validation window.

Because of the highly seasonal nature of the data, we created a baseline model using only Scholle data. We used periods of 2-year, 4-year and 6-year windows, to identify the forecast window period with the greatest stability.

Results of model performance and validation

Baseline Model - Prophet

Prophet is an open-source tool developed by Facebook to conduct time series modeling. Prophet models data using a decomposable time series model with three main components: trend, seasonality, and holidays. The focus is to model the time series via regression instead of as a generative model like ARIMA would. This is done for flexibility, the ability to handle irregularly spaced data, speed, and interpretability.

Cross-Validation Window Selection

The figures below show results of the cross-validation analysis at 2, 4 and 6 year training windows using the Prophet Model.

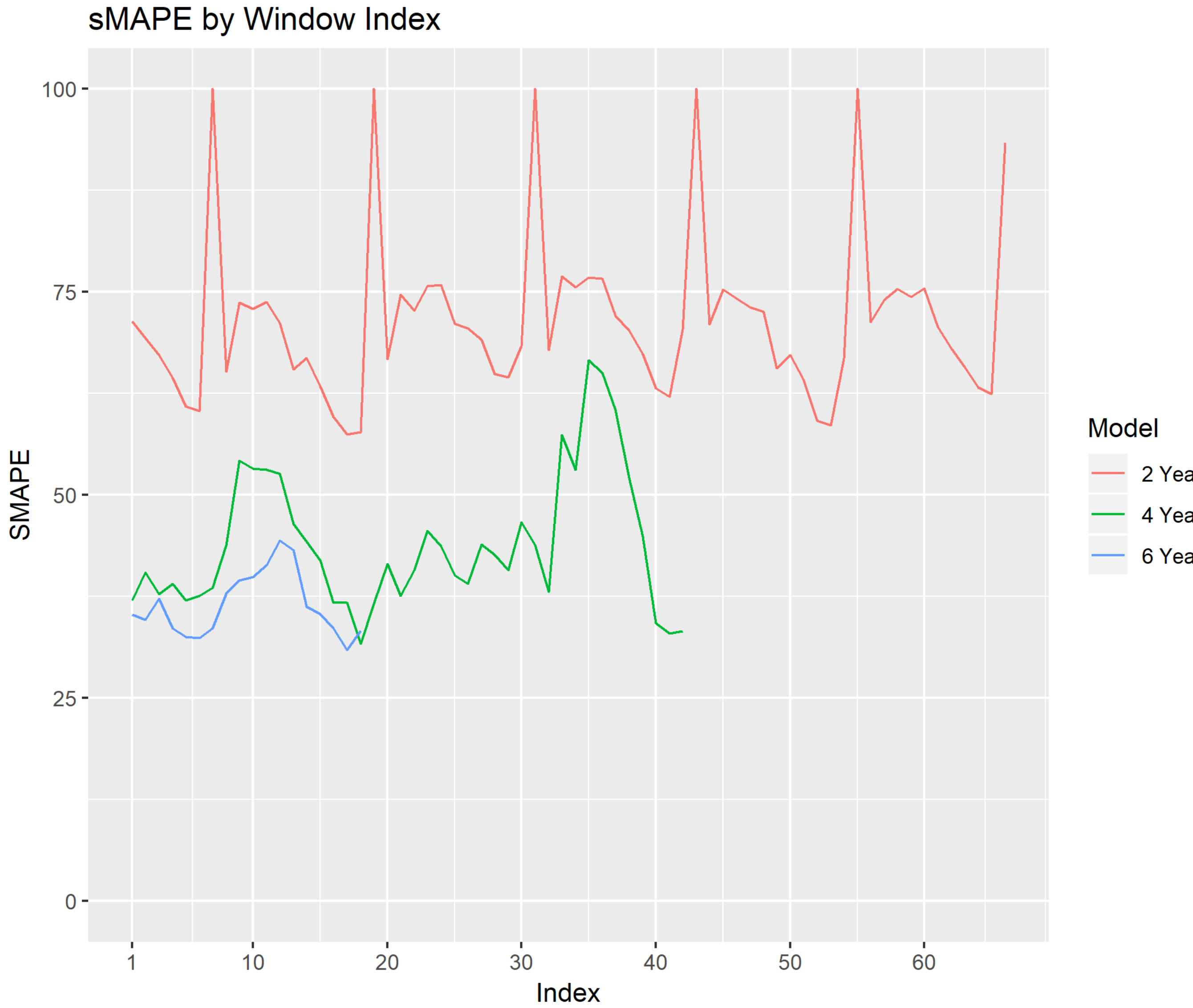


Figure 1.12: sMAPE CV Window Selection

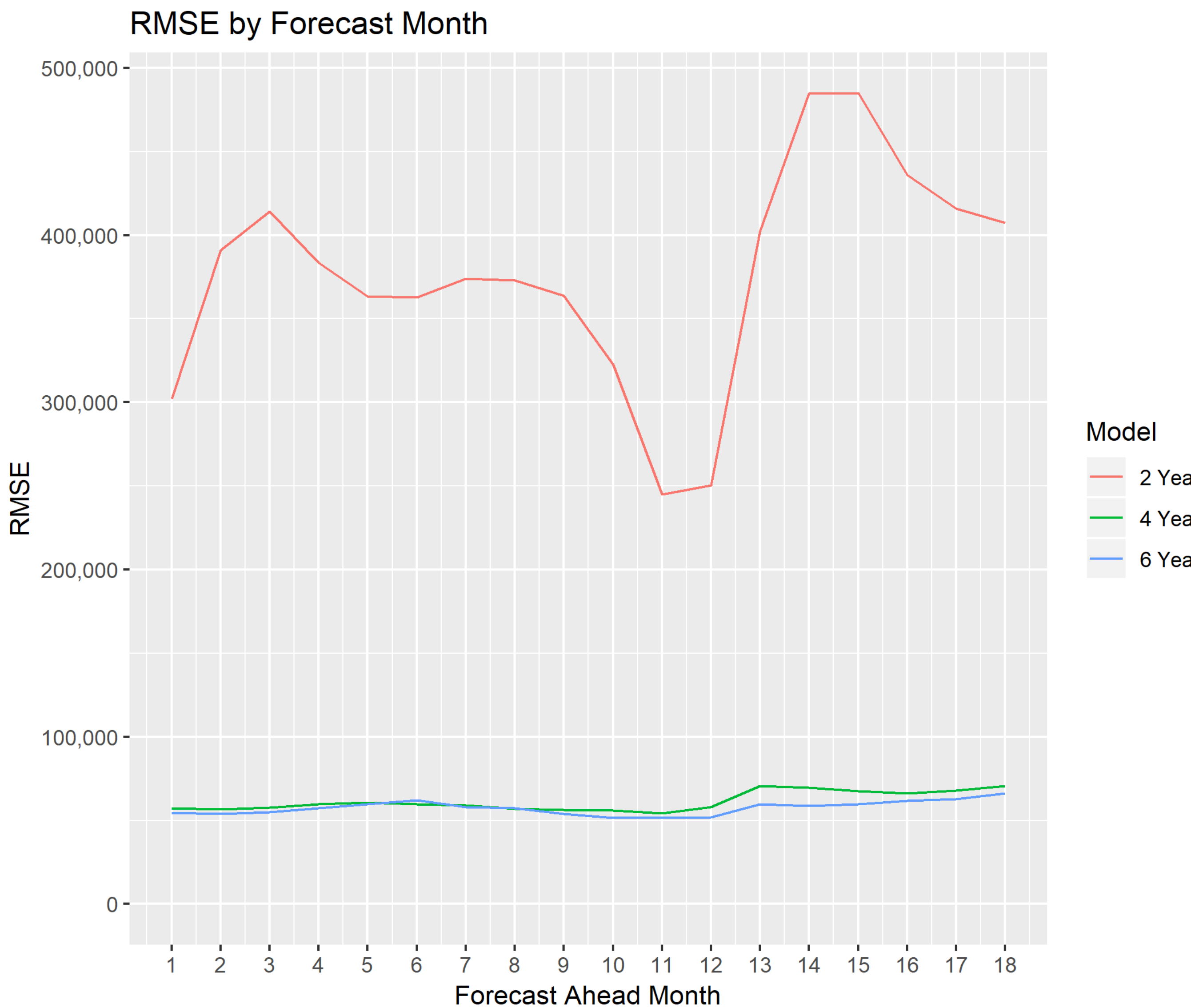


Figure 1.13: RMSE CV Window Selection

For both sMAPE and RMSE, the 2 year window shows much higher variability than the 4 or 6 year windows. Given the similarity of the 4 and 6 year windows RMSE, we chose the 4 year window to both reduce the data requirements of the model and allow for additional cross-validation of each other model. A 4 year cross validation allows us to generate 42 complete training and testing windows whereas A 6 year cross validation window only allows us to generate 18.

Baseline Model Results

The reported model metrics are the mean values for each of the cross validation periods collected.

X	sMAPE	RMSE	X..Bias	Accuracy
Train	30%	29896.68	22%	0.86
Test	43%	62625.69	67%	4.04

Challenger Model sARIMA

Seasonality is a key feature of the dataset, as it was observed that the Tomato bags sales increase significantly during summer time from June to August and drop in September and October while repeating this cycle annually.This key attributes in the dataset meant we deploy a model that uses differencing at a lag equalling the number of seasons to remove additive seasonal effect.

For this challenger, we split the data into two groupings; harvest months (June -October) and all months. In the Table 7 & 8 below, we summarise the result for the model:

X	sMAPE	RMSE	X..Bias	Accuracy
Train	9%	125522.0	19%	1.76
Test	68%	338725.3	100%	0.43

In the figure below, the mean forecast value is highlighted in blue and the actual value is captured in red, and the confidence interval ranging between 80%-95%. The actual values are represented in black.

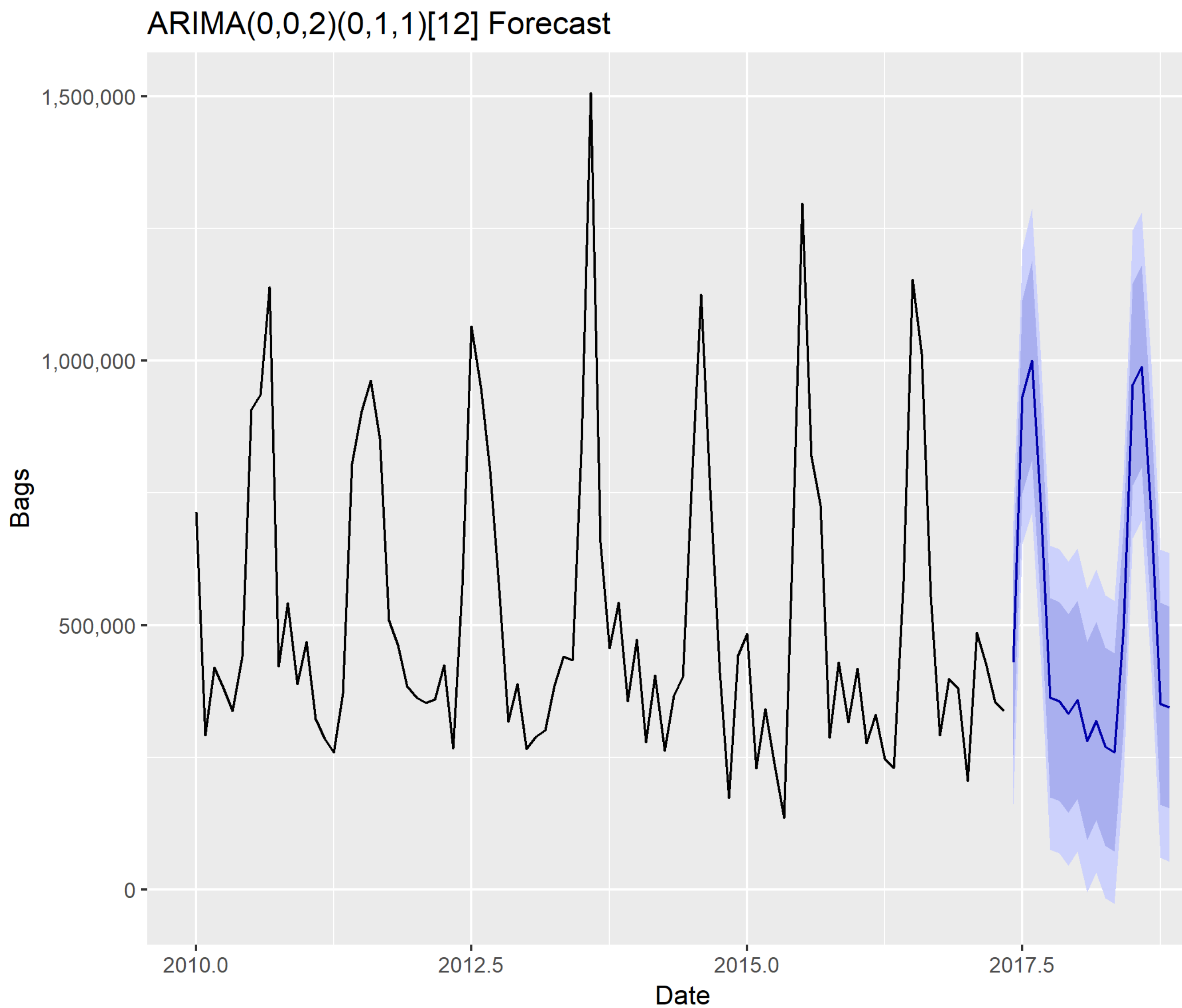


Figure 1.14: Arima(0,0,2)(0,1,1)12 with Drift

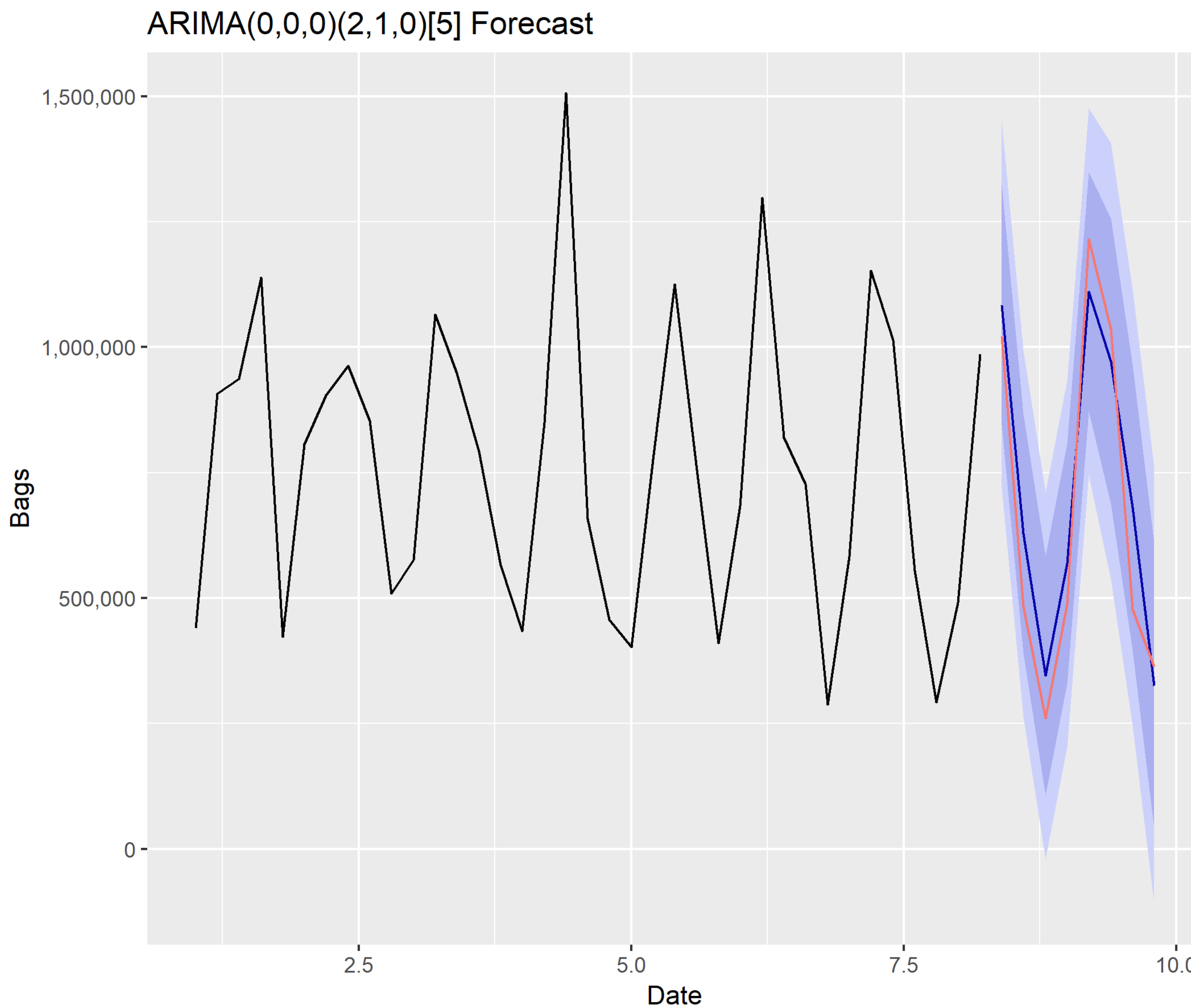


Figure 1.15: Arima(0,0,0)(2,1,0)5

1.0.7 Challenger Model - Regression with ARIMA Errors### {unnumbered}

The first challenger model we built is regression model with ARIMA errors. While the regression model allows for the inclusion of predictor variables, it does not allow for the subtle time series dynamics that can be handled with ARIMA models. The regression with ARIMA errors model solves this problem by fitting regression models with all the relevant variables first, and then applying ARIMA to the residuals of the regression to detect time series elements in the residuals.

We explored the correlations of twitter data and Google trend Scholle tomato bag sales and found the keywords and lags in Table 4 and Table 6 tend to strongly correlated with tomato bag sales. Since the regression with ARIMA errors is based on linear regression, we first build a linear regression model these keywords and lags. Results are shown in below Table 10. Significant variables are highlighted in green.

Based on the variables significant in the linear model, we built the regression model with ARIMA errors. The parameters and accuracy are shown below in Table 11 and Table 12.

Keyword...Lag	Estimate	P.Value
Google bbq lag 10	-39516	0.137173
Google chili lag 15	-42963	0.017008
Google salsa lag 12	92606	0.000366
Google tomato lag 12	122522	0.000145

Based on the variables significant in the linear model, we built the regression model with ARIMA errors. The parameters and accuracy are shown below in Table and Table 12.

Keyword...Lag	Estimate	P.Value
Google bbq lag 10	-39516	0.137173
Google chili lag 15	-42963	0.017008
Google salsa lag 12	92606	0.000366
Google tomato lag 12	122522	0.000145

Positive coefficients imply that for a unit increase in the variable, there is a corresponding positive increase in the Scholle bag sales. Negative coefficients imply that for a unit increase in the variable, there is a corresponding negative decrease in the Scholle bag sales.The negative coefficient shows there is an inverse relationship between the variable and Scholle bag sales.

X	sMAPE	RMSE	X..Bias	Accuracy
Train	25%	93857.76	20%	0.38
Test	44%	68342.19	58%	-0.93

The above results indicate that Google trend data tend to have a greater influence in the predictions than twitter data, because the count in google searches is more direct in measuring the importance of the keywords and lags, compared to twitter data which might lose some information both due to the limitations in gathering tweet data and due to the complicated natural language preprocessing process. The ARIMA errors is (0,0,0), indicating our model has extracting enough informations and there's no time series dynamics in the residuals.

Challenger Model - Random Forest Regression

The second challenger model we built was a Random Forest Regression Model. Random Forest leverages many regression trees to build a consensus model in addition to bootstrap aggregation or bagging to generate additional augmented data. Bagging simply builds additional training sets by sampling with replacement from provided training data. Each individual tree uses the bagged training data and selects a random subset of features at each branching point rather than all features available to build the regression. This restriction forces the model to create a more robust estimator.

One useful feature when using tree-based approaches for regression is the ability to use categorical or ordinal predictors without the need for one-hot-encoding. In our model we represented the date as a pair of categorical variables, one for year and a second for month. We chose to do this because of the seasonal nature of the data.

In addition, we decided to challenge the model by only using lags that we thought to be have a reasonable explanation for their effect. To this end we chose to use lags greater than 9 months. Our logic was that it would take time for an increase or decrease in the social media presence of one of the keywords selected to go from an uptick in interest of consumer products to be captured by Scholle's bag sales.

The table below displays the results of our Random Forest model.

X	sMAPE	RMSE	X..Bias	Accuracy
Train	38%	66560.6	64%	2.94
Test	37%	61758.7	28%	5.54

An important feature of Random Forest modelling is its ability to generate rank-ordered summaries of variable importance. The model's feature importance is displayed in the figure below.

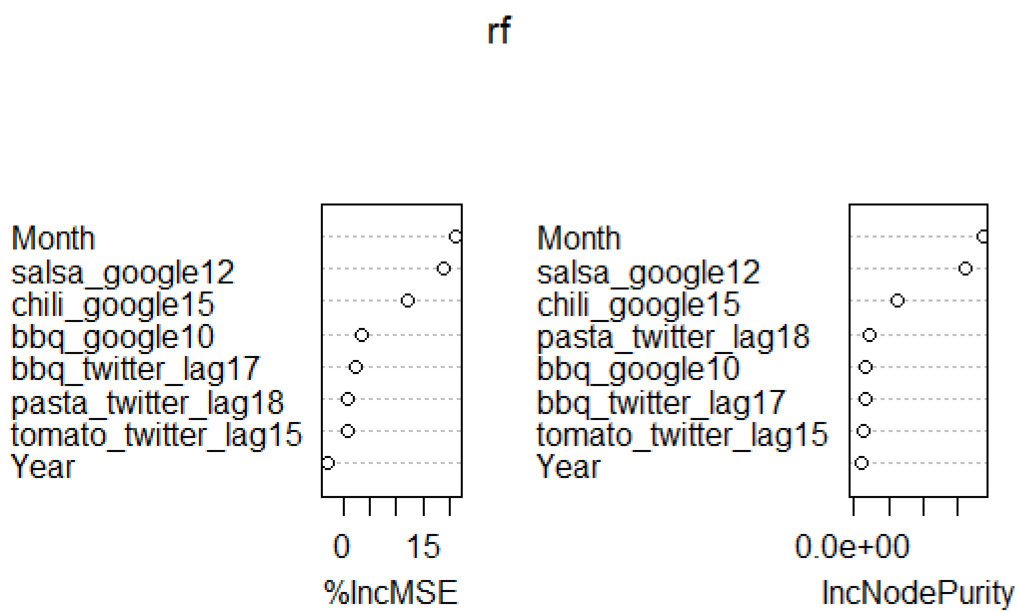


Figure 1.16: Random Forest Importance

The most important features are displayed at the top of this chart, in this the month was the most important predictor followed closely by google salsa data at lag 12. This agrees with the importance of monthly seasonality that we observed in the other models.

Challenger Model - XGBoost

XGBoost is an implementation of gradient boosted decision trees designed for speed and performance. It build trees one at a time, where each new tree helps to correct errors made by previously trained tree.

X	sMAPE	RMSE	X..Bias	Accuracy
Train	15%	55311.64	11%	0.52
Test	35%	88097.99	44%	2.00

Stacking Forecasts

Our project focuses only on the ship-to date sales number. The overall time range from people speaking about keywords on social media, to its influence on tomato demand, and then to the whole order, manufacture and ship process takes place for at least 9 months. So we think it's more meaningful to exclude lags shorter than 9 months. We explored the correlations between Scholle tomato bag sales and twitter data as well as Google trend with lags from 9 months up to 24 months, and built regression with ARIMA model using only the keywords and lags exhibiting strongly correlations.

Based on discussions with Scholle, we limited the scope to simply the months of June through October, the months when tomatoes become ripe in California. We refer to these months as the harvest months.

The stacking method is used to create an additional consensus model by using the results of trained models. There are two approaches we used for stacking, simple averaging and creation of a linear model.

We then combined our forecast results from all models mentioned prior in this report, including the ARIMA model built only on the more stationary harvest months, the regression with ARIMA errors model using on strong correlated keywords and lags, random forest model, XGBoost model and Prophet model. We averaged the forecasts of all combinations of the models. We found that we were able to improve the model predictions by combining the Random Forest and Regression with Arima Error models predictions using a simple average.

The second approach to stacking we attempted was to build a linear model using the results of all our other models. This model was trained on all the harvest month data for 2014-2018. The fitted values produced a better estimate of the actual than the simple average of Random Forest and Regression with Arima Error. However, we must consider the amount of information the additional variables add to the regression. When we applied the step function we achieved a minimized AIC for a linear model composed of just arima with Regression Error & Random Forest. The linear combination of the two slightly weighs more towards the Random Forest over the Regression with Arima Error.

Conclusion

This section includes a concise summary of the findings. Your summary might be organized by the research objectives or hypotheses. Make sure you address the extent to which research objectives are achieved, and if they are not achieved, explain why. Make sure to interpret your findings in a way that acknowledges the limitations of the research. That is, do not extrapolate the insights derived from your research to situations you have not examined.

While increasing dosage leads to larger incisor length, the choice of delivery mechanism between Orange Juice and Vitamin C does not seem to make a difference. However, at very low levels, Orange Juice appears more effective, displaying higher average growth.

Recommendations

Includes guidelines as to ways in which your results should or could be used in practice. You may discuss other uses of your results, if there are any. The ways to extend your analysis and the benefits of doing so might be included in this section as well.

Appendix A

The First Appendix

This first appendix includes all of the R chunks of code that were hidden throughout the document (using the `include = FALSE` chunk tag) to help with readibility and/or setup.

In section 1:

In section 1:

Appendix B

A Second Appendix, for example

References

Placeholder