Assembling the Crystal Ball: Using Demand Signal Repository to Forecast Demand

By

Ahmed Rashad
B.S. Mechanical Engineering, Ain-Shams University, 2004

Santiago Spraggon
B.S. Industrial Engineering, Buenos Aires Institute of Technology 2006

Submitted to the Engineering Systems Division in Partial Fulfillment of the Requirements for the Degree of

Master of Engineering in Logistics

at the

Massachusetts Institute of Technology

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Signature of Author...
Master of Engineering in Logistics Program, Engineering Systems Division
May 10, 2013

Signature of Author...
Master of Engineering in Logistics Program, Engineering Systems Division
May 10, 2013

Certified by...
Dr. Shardul Phadnis
Postdoctoral Research Associate
Center for Transportation and Logistics
Thesis Supervisor

Accepted by...
Prof. Yossi Sheffi
Elisha Gray II Professor of Engineering Systems, MIT
Director, MIT Center for Transportation and Logistics
Professor, Civil and Environmental Engineering, MIT

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ABSTRACT

Improving forecast accuracy has positive effects on supply chain performance. Forecast accuracy can reduce inventory levels, increase customer service levels and responsiveness, or a combination of the two. However, the further upstream in the supply chain, the more difficult it becomes to forecast accurately. Demand for consumer products might be subject to factors that are hard to identify and quantify. One way to overcome this is to observe external factors or predictors that might help explain demand.

The purpose of this thesis is to explore the factors that potentially influence the demand of a fast-moving consumer product (bottled water), and build a demand signal repository for these factors to help the manufacturer generate more accurate forecasts. We identified more than 30 such factors that might affect demand, using interviews and industry research. We tested more than 200 causal models of the relationship between observed demand and the predicting factors.

The resulting model explained almost 60% of demand for two out of three customers using daily buckets and over 85% using weekly buckets compared to less than 50% using time-series techniques. Using the results of this extensive analysis, we propose a new forecasting model. We also identified additional factors that could not be included this analysis due to the lack of data; adding these to the model may further improve the forecast accuracy.

Thesis Supervisor: Dr. Shardul Phadnis

Title: Postdoctoral Research Associate, Center for Transportation and Logistics

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Chapter 1: Introduction and Motivation

"Forecasts are always wrong" is one thing that comes to mind whenever demand forecasts (or any other type of forecast for that matter) are mentioned, and for good reasons. A forecast is basically what we expect is going to happen in the future. And unless we have a crystal ball that works or develop time travel technology, forecasts will always be wrong. However, there are tools that can help create more accurate demand forecasts, and **Demand Signal Repository (DSR)** is one of them.

We wish to implement DSR in a simple, extensible, and replicable manner. We believe implementing DSR could improve demand management and supply chain performance.

1.1 What is DSR?

A Demand Signal Repository (DSR) is a pool of data that has influence on demand in some way and is collected from multiple sources. Once this data is collected, it needs to be normalized and used to create models that help predict how demand is affected by causal factors. The final result is a model that helps predict demand better (Moon, 2009). Some definitions of DSR restrict data sources to points of sale (POS) such as the one used by Margaret Rouse (Rouse, 2010), while others state that signal sources are not limited to POS (Gartner, 2013). We prefer the latter.

Like any other forecasting or demand management technique, DSR is part science, part art. What drives DSR is the art of coming up with potential causal factors and imagining the probable relationships between the product demand and seemingly unrelated events. Only then can specialized software such as Oracle's Demantra or SAP's Demand Planning -- or even free, general software such as SAS' JMP – be used to find causality and create a model.

1.2 Why not use conventional forecasting methods instead of DSR?

Some of the most commonly used forecasting methods such as Holt-Winters and moving average are discussed extensively in many supply chain references (Silver, Pyke,

& Peterson, 1998; Arnold, Chapman, & Clive, 2011) as well industry publications and certification material (The Association for Operations Management, APICS, 2012). These methods and other time series methods rely on historical data and use that data to forecast the future, so does DSR.

However, while most techniques rely on identifying a few factors that affect demand, such as seasonality and growth trends, and ignore or attribute everything else to random events. While one of the main purposes of forecasting is to improve predictability of demand and actually attributing the behavior to some factors, a major challenge is to identify these factors in the first place. While computers are capable of performing statistical calculations, they are still incapable of the investigative thinking required to discover such causal factors and are limited to solving the problems that we give them using the variables and tools we program them to use.

In time-series forecasting, we can think of demand as a number of layers on top of each other: the first layer being the base demand, then trend, then seasonality, and finally other factors that are usually attributed to randomness (Figure 1).

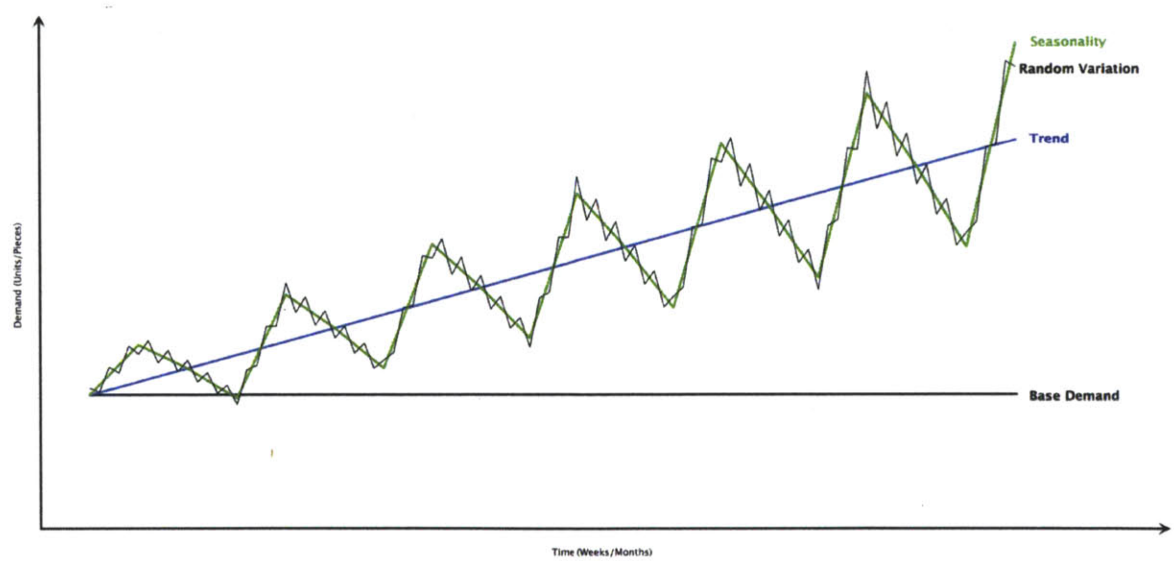

Figure 1 Demand Layers (figure illustrates the demand layers and is not representative of the actual data)

The base is what the demand would be if absolutely nothing changed between the current period and future periods. Trend is the overall growth or decline of demand over a period of time. Seasonality is the change of demand over different time periods (could be weather seasons, months, weekdays, or even time of the day). Random variation (true randomness) is variation that is due to chance.

However, there usually is another layer, un-explained behavior (Figure 2). These are variations in demand that could possibly be quantified but are currently not. All layers except for random variation and un-explained behavior have well established and simple forecasting methods to calculate them fairly accurately such as moving average and exponential smoothing. Even though random variation works against accurate forecasts by introducing variability, it is difficult to predict chance. Furthermore, these variations are usually small in amplitude and the normal approach of trend and seasonality could be used. That leaves un-explained behavior.

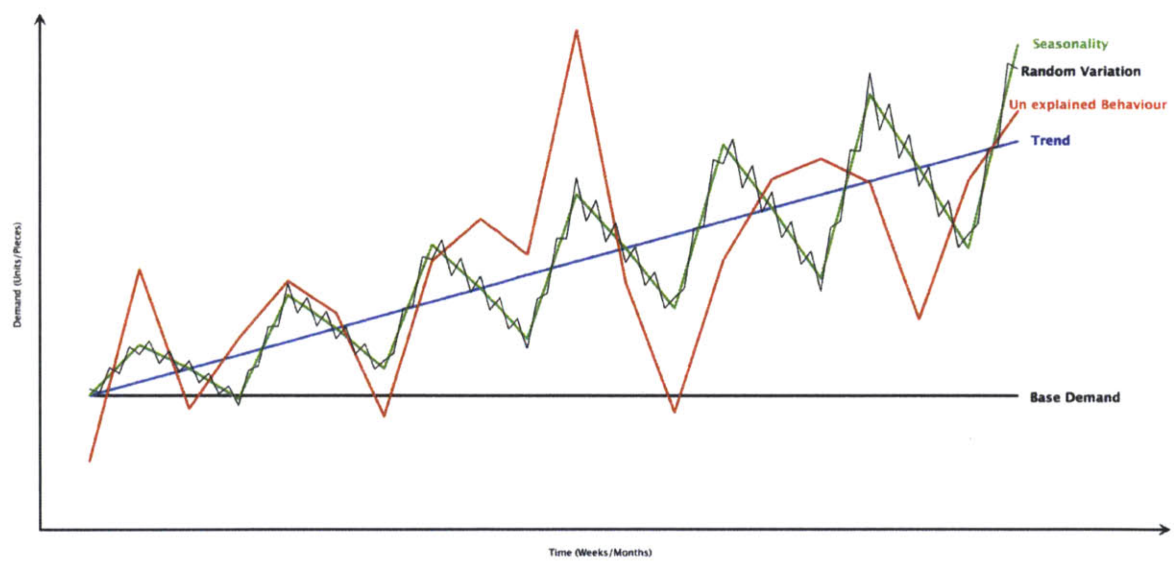

Figure 2 Demand Layers with un-explained behavior (figure illustrates demand layers and is not representative of the actual data)

Our objective is to introduce another layer into the demand hierarchy, causal factors, and move as much of the demand as possible from the un-explained behavior domain into the quantifiable domain (just like seasonality and trend). We believe (DSR) is one of the ways to achieve this.

1.3 The Company and Motivation

The research in this thesis was motivated by a practical challenge at Niagara Bottling, LLC (henceforth, "Niagara"), who sponsored this project. Niagara is a family owned company based in Southern California that was started in 1963. Currently, the company operates in all 50 states and exports to several countries including Japan and Mexico bottling water for both Niagara brand and private labels. Niagara operates 12 plants around the United States and is currently the largest family owned bottled water company in the country. Revenues are close to 1 billion dollars annually.

Niagara focuses on high customer service, quality, environmentally responsible production, and controlling costs. The market they operate in is very price conscious, as clearly expressed to us by several Niagara top executives and supply chain professionals during interviews such as the EVP of Sales, and the EVP of Manufacturing. Currently, the company uses ERP from a top vendor and already use an off the shelf statistical forecasting package from another vendor for time series analysis to forecast its demand. They also mentioned that pressure is high from the competition and mild price wars are not uncommon. This has led to great pressure to improve forecast quality in order to remain competitive. Niagara believes it can retain a competitive edge by reducing finished product inventory, getting a better mix of finished products, improving customer service levels and fill rates, and planning production more efficiently.

Niagara believes that DSR and the subsequent modeling will enable the company to achieve these goals by increasing forecast accuracy through analyzing some of the random factors and moving them into the predictable causal factors bin. This motivates our research question:

How can we develop a Demand Signal Repository (DSR) to better predict demand?

Chapter 2: Literature Review

In this section we will first explore a method used to choose a forecasting technique. Then, we will explore the bottled water industry, and finally, we will discuss if DSR is a good fit for Niagara.

2.1 Demand Signal Repository: When to use it?

Forecasting techniques can be classified into 3 main categories: (Chambers, Mullick, & Smith, 1971)

1. Qualitative techniques
2. Time Series and Projections
3. Causal Models

DSR is simply an application of causal models. It uses the same techniques of causal modeling, but:

- Uses a larger set of data that reflects consumer requirements (Demand),
- Consolidates the data into a single large pool (Repository),
- And updates frequently from different sources (Signal). (Makridakis, Hogarth, & Gaba, 2010)

We found that there are 4 questions that need to be addressed when choosing a forecasting method:

1. What are we forecasting?
2. What data is available?
3. What stage in the product lifecycle is the product in?
4. Is the investment in more sophisticated techniques worth it?

We will address these questions one by one.

Question 1: What are we forecasting?

Qualitative or judgmental techniques are used for forecasting when little data is available or when forecasting special events. There are several variations of such techniques such as expert opinion methods or role-playing (Armstrong, 2001). These methods rely on intuition and experience of people.

Unfortunately these methods should not be taken at face value as they are often biased (Armstrong, 2001). For this reason, in a stable system, even the most basic quantitative forecasting techniques outperform qualitative techniques (Georgoff & Murdick, 1986). Time series or extrapolation techniques are used for steady or somewhat predictable patterns and rely heavily on history (Armstrong, 2001). However, these methods are not effective when there is anything but stable demand that follows a pattern. When a special event occurs (such as an act of nature or a one-time large sale) these methods are incapable of predicting the effects of such events. Furthermore, such events distort the forecast for future periods as well (Makridakis, Hogarth, & Gaba, 2010).

Finally, casual models lie somewhere in between. Like qualitative techniques, they are used for special events, but they use history to develop an understanding of these events (Chambers, Mullick, & Smith, 1971).

Question 2: What Data is available?

Qualitative techniques are best used when data is not available, time series are best used when there is enough history to enable reliable statistical analysis, and casual models are best used when data is available and enough analysis has been done using time series techniques. Causal models are used to improve accuracy once time series has been used (Evans, 2003). DSR is an extension of causal methods and the same logic could be used (use DSR after time series has been used.)

Furthermore, the fact that data is available and patterns of statistical significance could be deduced does not imply demand predictability (Makridakis, Hogarth, & Gaba, 2010). This further challenges the accuracy of time series models and calls for dynamic models that require more real time inputs from the business and market environment.

Question 3: What stage in the product lifecycle is the product in?

Qualitative methods work best in the early stages of a product's lifecycle (Development and Introduction), time series and Prediction to work best during the growth and maturity phases, and causal models to work best with a product in the steady state or mature phase on top of time series (Chambers, Mullick, & Smith, 1971). Figure 3 below, shows the different stages of a product lifecycle and the corresponding forecasting methods to use.

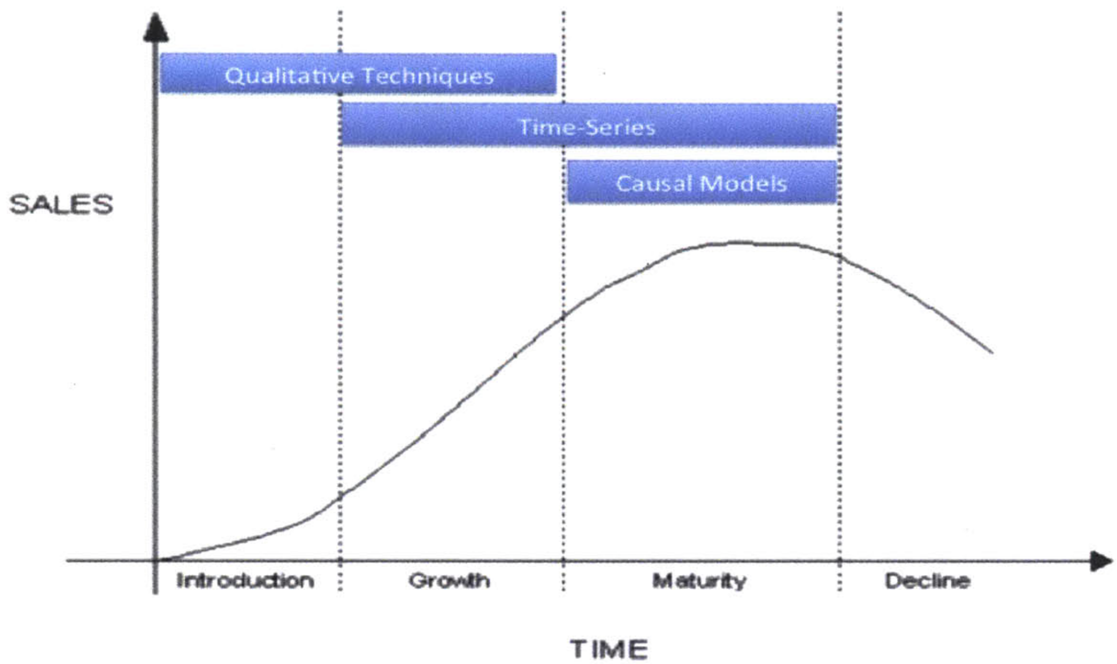

Figure 3 Product Life-Cycle Stages and corresponding forecasting methods to use.

Question 4: Is the investment in more sophisticated techniques worth it?

To answer this question, we need to calculate the cost of creating a forecast and compare it to the expected savings or the cost of inaccuracy. As forecast accuracy increases, variability decreases, and we are able to maintain our service levels with less inventory and costs. However, as we invest more resources to gain the extra forecast accuracy, cost of generating the forecast will increase. Theoretically, we can achieve near 100% forecast accuracy if we invest enough resources. However, the question becomes, are near 100% accurate forecasts worth the investment.

The simplest way to achieve this is to calculate the cost of inventory reduced by reducing variability while maintaining the same customer service levels.

The relationship between inventory and service levels is discussed in a lot literature. We used (Silver, Pyke, & Peterson, 1998) as a reference. One way to calculate such inventory costs is to calculate the cost of buying and holding the extra inventory. There are two components to these costs, first the change in safety stock required, and second, the reduction in holding costs due to the reduction in inventory. (Chambers, Mullick, & Smith, 1971) also address this issue of balance between cost to generate the forecast and cost of inaccuracy. Figure 4, below, shows their graph of the relationship.

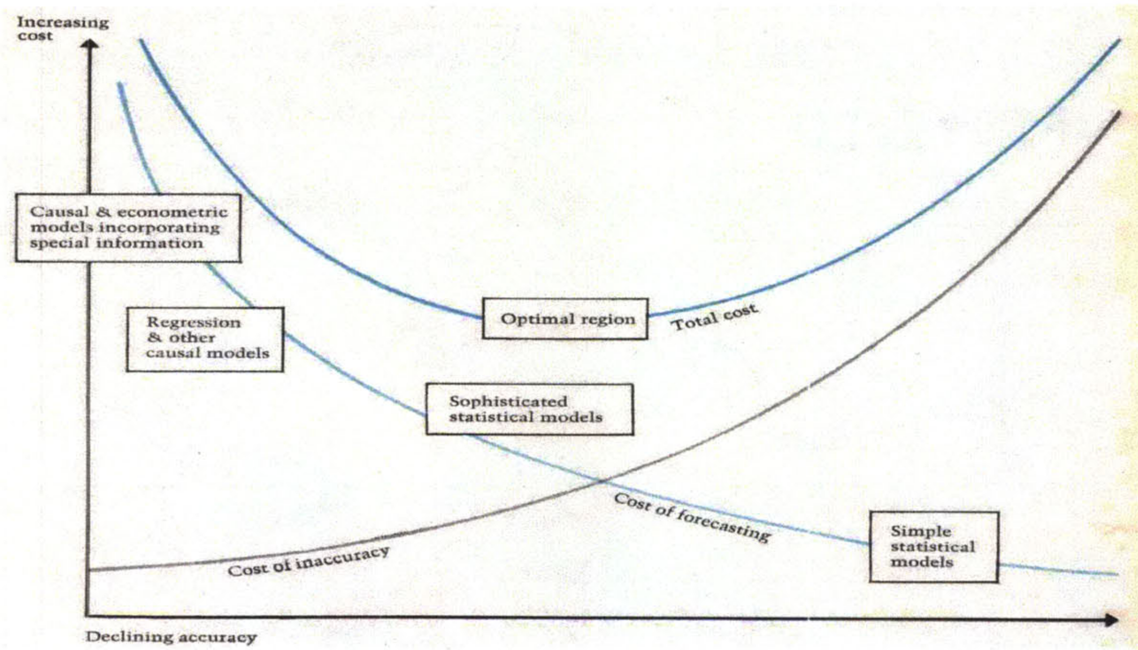

Figure 4 Cost of forecasting versus cost of inaccuracy for a medium-range forecast, given data availability *(Chambers, Mullick, and Smith, 1971)*

As we can see from Figure 4, investing in creating more accurate forecasts reduces overall system costs at first. But, returns diminish and costs to improve forecasts increase exponentially until any further investment in forecast accuracy actually increases system costs, as the returns no longer offset the investment. Table 1, below, summarizes the discussion above about which forecasting method to use given the four questions discussed.

Table 1 Decision Matrix for Choosing Forecasting Techniques

Decision Point	Forecasting Technique		
	Qualitative	**Time Series**	**Causal (Including DSR)**
Demand Type	Special events	Trends and patterns	Special events + some trends
Data Availability	Little or no Data	Sufficient History	Sufficient History

Product Lifecycle Stage	Early (Development and Introduction)	Mid (Growth and Maturity)	Mid (Growth and Maturity)
Costs	Relatively low	Low to high	Medium to High

By answering the four questions above we can decide which forecasting technique to use and whether (DSR) would be worth the investment. We can safely conclude that an investment in (DSR) would be justified if:

1. We are trying to forecast demand for product that has complex patterns and trends.
2. We have sufficient data (Demand Signals) to build the repository.
3. If the product is in the mature stage.
4. If the financial benefits from increase in forecast accuracy will offset the costs of implementing and maintaining (DSR)

We identified three key areas to implementations of (DSR), Data, Technology, and Organization. The **data** is used to determine relationships, correlations, and causation between demand and predictors using **technology**, which could be basic spreadsheets or sophisticated software packages and is to be collected, processed, and used by **people** (organization). (Makridakis, Hogarth, & Gaba, 2010)

DSR, if successfully implemented, will have great impact on improving forecast accuracy and all the perks and possibilities that accompany better forecasts such as reduction in inventory and improved customer service levels. It is also an exercise in data collection and analysis discipline (Hitachi Consulting Corporation, 2010)

2.2 The Bottled Water Industry

The bottled water industry has seen a 10% compounded growth globally between 1998 and 2003 (Packaging Magazine, 2004) and 6.7% compounded growth between 2004 and 2008 (Brei & Bohm, 2011). Brei and Bohm also mention that in 2008 this was a $77.6 Billion industry and according to (Marketline, 2011) it is expected to reach $126 billion by 2015. The United States' bottled water market was estimated at $17 billion in 2010 with Niagara holding about $1 billion worth of that market.

Part of this growth might be due to the overall population growth in the United States, but it also might be due to the increase in consumption of bottled water per person. Average bottled water consumption in the United States rose from 3.6 Gallons in 1983, to 6.4 gallons in 1987, to 10.4 Gallons in 1994 (Beverage Marketing Corporation, 1996) and has reached 30.8 Gallons in 2012 (Latif, 2013). This growth can be attributed to an increase in awareness of the health benefits of being hydrated (Packaging Magazine, 2004). Another factor mentioned in the report is concern about availability of safe water, which drives consumers to use bottled water, which they consider as a safer alternative.

According to the International Bottled Water Association (IBWA), 2013, "Domestic, non-sparkling water is the largest and strongest part of the US bottled water market". The IBWA breaks down the bottled water market into two main segments, home and office delivery (20% of the market) and retail bottled water (80% of the market). In this thesis, we focus on retail bottled water because that is the segment of most concern to Niagara.

The IBWA also mentions that the market is mostly fragmented with a lot of small family owned businesses and only a few major players who compete heavily, not only among themselves, but also to consolidate the industry. DATAMONITOR® supports this assessment: It reports that the largest global players (such as Coca-Cola, Nestle, and Groupe Danone) collectively hold only 36% of the market volume.

Therefore, the steady growth in the industry, the dominance of a specific segment (domestic, non-sparkling water), the fragmented competition, and Niagara's well-established market position present both an opportunity and a challenge: An opportunity for rapid growth and a challenge to remain profitable in a highly competitive and fragmented market.

2.3 DSR at Niagara

Using the decision matrix for choosing forecasting techniques (Table 1) and the industry analysis in the previous section, we can conclude that (DSR) will fit the current situation at Niagara because bottled water is a product in its mature or growing phase and

Niagara is already utilizing time series methods to build forecasts using a significant amount of historical data. Now, the company is attempting to take forecasting to the next level by accounting for the effects of special events and causal factors.

2.4 Summary

In this section we discussed a method for choosing between three forecasting methods (Qualitative, Time series and projections, and Causal models). We found that there are four questions that need to be answered before deciding which method to use:

- What are we trying to forecast?
- What data is available?
- What stage in the product lifecycle are we currently in?
- Are the financial benefits from improving forecast accuracy worth the investment?

We also discussed the bottled water industry including market size, growth patterns, and market fragmentation. Finally, we discussed how DSR is probably a good fit at Niagara.

In the next chapter we will discuss the methods we used to build the demand signal repository for Niagara.

Chapter 3: Methods

In this section we will discuss the method used to create the demand signal repository (DSR) at Niagara. We will also discuss how we collected, prepared, and used the data for modeling.

3.1 Method Overview

The purpose of this thesis was to build a demand signal repository for Niagara. To achieve this, we took the following approach. We broke down our methodology into three main phases. First, we undertook initiation steps, then collected and validated the data, and finally developed and tested forecasting models. Figure 5, below, shows the progression through the different stages of the project.

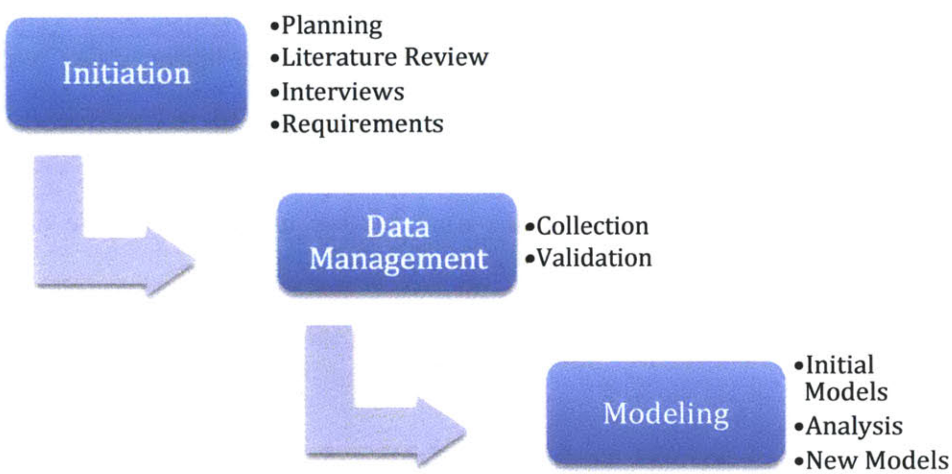

Figure 5 Process Steps

3.2 Initiation Steps

We started with industry and market research (please refer to the literature review, on page 15, for a summary) to get an understanding of the industry. Then, to generate ideas for factors in preparation for the meetings with Niagara personnel, we conducted brainstorming sessions together and with other classmates and faculty. About 25 people participated in brainstorming with group sizes ranging from 4 to 6. We asked each person 3 questions:

- Why would choose to buy bottled water?
- Why would you choose one brand over the other?
- How do you think other people make this decision?

There was no set target for ideas. Instead we encouraged participants to mention any factors they felt were relevant. We asked the questions one at a time and gave each participant, in turn, an opportunity to express his/her ideas. After that, we encouraged the group to interact freely and discuss their opinions. Finally, we would present participants with factors we got from other groups and ask them if they felt those factors were relevant. We repeated the process for each question and at the end asked participants if there were any other questions they think we should be asking.

Brainstorming sessions lasted about 20-30 minutes each and each person generated about 6-7 ideas. Over 60 individual causal factors were generated, 25 of which were unique and relevant. Table 3 lists the initial causal factors generated and their source (brainstorming sessions, interviews, or both).

We defined relevant as the causal factors that we believe could influence demand and could be quantified with enough lead time for us to be able to change inventory and production levels to match supply and demand. The final decision of which factors were relevant and which were not was reached after discussions with the project team at Niagara.

Following that, we began with the scoping and definition phase, in which we visited the company head quarters and met with company executives and several supply chain process owners (16 in total). A complete list of interviewees is in Appendix 1: . Those we couldn't meet with during the visit (regional sales managers), we arranged to have phone interviews or meetings with immediately after the visit. Some of the most critical interviews were those with Sales, Marketing, Supply Chain Planning, and Information Technology.

One key question we asked during the interviews was "What are the top causal factors you believe affect sales of bottled water to retailers at Niagara?" Table 2, below, displays the top 10 causal factors mentioned by the respondents during the interviews we conducted along with how many times they were mentioned. We also asked employees to rank the causal factors they believed affected Niagara sales the most (1 being most important). We then gave a score to each ranking (3 points for a rank of 1, 2 points for a rank of 2 and 1 point for a rank of 3) and summed up the scores.

Table 2 Causal Factor Scores (Niagara Employees)

Causal Factor	Number of Interviewees mentioning the factor			
	Rank 1	Rank 2	Rank 3	Total Score
Price to Retailers	4	2		16
Promotions & Merchandizing	3	3		15
Price to Consumers	4	1		14
Weather & Seasonality	1	4	2	13
Natural Disasters	1	2	4	11
Competition's Price	1	2		7
Promotions	1		1	4
Day of the Week			4	4
Macro Economic Factors (e.g. GDP)		1	1	3
Consumer's Environmental Awareness			1	1

After the initial scoping and problem definition process we were able to identify 9 new causal factors (we will refer to them later as predictors or independent variables) that could possibly help us explain some of the variability that we saw in demand. Causal factors are discussed further in the following section.

3.3 Data Management

After the initial kick-off phase, we moved into the second phase, which was data collection, validation, and review.

3.3.1 The Variables

Dependent Variables

The dependent variable is the variable we are trying to build a model to predict. This variable could be consumer demand, retailer orders, sales orders, or shipments.

Ideally we would have liked to use a variable as close to consumer demand as possible since this would help us almost eliminate the bullwhip effect and we no longer would need to account for retailer buying patterns, retailer inventory policies, delays in demand relay, delays in requirements realization, and other factors that would affect the quality of demand representative data. (Please refer to the section "Analysis and Models", page 31 to compare the results of using shipments versus point of sale data). However, due to the unavailability of data, we used shipments to retailers as our dependent variable. Figure 6, below, shows the data at each point in the supply chain and how many steps away from real demand the data collection point is.

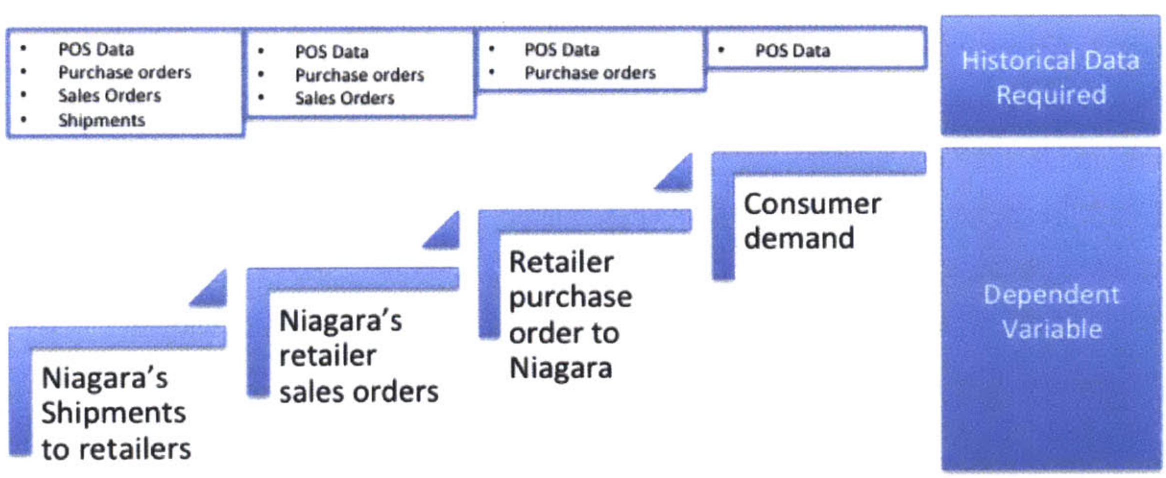

Figure 6 Data Lag behind actual consumer demand

We also chose to use liters shipped instead of cartons. This is because there is a lot of cannibalization and interchangeability between the different SKUs. For example, the same bottle could be packaged in 6, 12, 24, or 35 packs. Furthermore, the same bottle could be packaged with a different label for a different customer or a specific holiday. While this would be a different SKU, it still served to fulfill the same demand.

Independent Variables

From research, interviews, and brainstorming we created a list of possible causal factors or independent variables. Table 3, below, shows a list of those potential causal factors. We reviewed all the causal factors and categorized them using two criteria, **Horizon of effect** and **Magnitude of effect**.

Under Horizon we have 3 categories, A, B, and C.

Category A: Variables affecting the dependent variable at the tactical horizon (up to 3 months ahead)

Category B: Variables affecting the dependent variable at the strategic horizon (longer than 3 months ahead)

Category C: Variables affecting the dependent variable at both tactical and strategic horizons.

Under Magnitude we have three tiers, 1, 2, and 3.

Tier 1: Extreme causality.

Tier 2: Moderate causality (Decision to pursue these factors should be dependent on time and resources available)

Tier 3: Suspected or minor causality. (These factors should be monitored and reviewed regularly because of their potential to change.)

Below (Table 3) are all the potential factors and their classification along with an explanation of how we came to believe/suspect the causality.

We arrived at the results of this classification from interviews with Niagara personnel.

Table 3 Initial Causal Factors

#	Causal Factor	Availability	Source (Brainstorming /Interviews)	Horizon	Magnitude
1	Juice & Juice Beverage Market	**Unavailable**. Information available from Nielsen, but claims of legal issues prevent Niagara from sharing the data	Brainstorming	C	1
2	Total Bottled Water Market	**Disregarded.** Acquirable, but this factor works on a Macro level and probably should not be part of the tactical process	Interviews	B	2
3	Total Bottled Beverage Market	**Disregarded.** Acquirable, but this factor works on a Macro level and probably should not be part of the tactical process	Interviews	B	2
4	Urban Water Supply	**Unavailable.** Difficult to acquire	Brainstorming	B	2
5	Pricing (Wholesale)	**Unavailable.** Data not provided by the company	Both	A	1
6	Pricing (Retail)	**Unavailable.** Data not provided by the company	Both	A	1
7	Holidays (Multiple)	**Available.** We researched US holidays and included them in a list of factors that we cross-referenced against possible outliers.	Both	A	1
8	Capacity Shortages	**Partially available.** We only have the capacity available at each location. Shortage data was not provided	Brainstorming	A	1
9	Temperature (Gradient)	**Available.** Access from national weather service.	Interviews	A	3
10	Temperature (Weekly Average)	**Available.** Access from national weather service	Interviews	A	3
11	Competitors' Pricing (Retail)	**Unavailable.** Information available from Nielsen, but legal issues prevent Niagara from sharing the data	Both	A	1
12	Competitors' Pricing (Wholesale)	**Unavailable.** Information available from Nielsen, but legal issues prevent Niagara from sharing the data	Both	A	1
13	Buyer Turnover	**Disregarded.** Data probably acquirable, but accuracy is challenged as records are not maintained	Brainstorming	A	3
14	NPI and Cannibalization	**Unavailable.** No data available	Brainstorming	A	2
15	# of Tourists In	**Disregarded.** Acquirable, but this factor works on a Macro level and	Brainstorming	A	3

		probably should not be part of the tactical process			
16	# of Tourists Out	**Disregarded.** Acquirable, but this factor works on a Macro level and probably should not be part of the tactical process	Brainstorming	A	3
17	Promotions	**Unavailable.** Data not Provided by the company	Both	A	1
18	Economic Indices	**Disregarded.** Acquirable, but this factor works on a Macro level and probably should not be part of the tactical process	Interviews	B	2
19	Natural Disasters	**Available.** We researched all natural disasters hitting the US since 2008.	Both	A	1
20	Food stamps and coupons	**Disregarded.** Ranked very low by Niagara.	Brainstorming	A	3
21	Day of the Week	**Available**	Interviews	A	1
22	Day of the Month	**Available.** Pay Day (Bi-Weekly, monthly, etc..)	Interviews	A	3
23	Week of the Month	**Available.**	Interviews	A	1
24	Week of the Year	**Available.**	Both	A	2
25	Region	**Available.**	Both	C	1
26	3-Digit Zip Code	**Available.**	Interviews	C	1
27	Customer	**Available.**	Both	C	1
28	Ship from location	**Available.**	Both	C	3
29	Rainy days (Precipitation)	**Disregarded.** Ranked very low by Niagara.	Brainstorming	A	3
30	Snow days	**Disregarded.** Ranked very low by Niagara.	Brainstorming	A	3
31	Lagged Demand -1 week	**Available.**	Brainstorming	A	1
32	Lagged Demand -2 weeks	**Available.**	Brainstorming	A	1
33	Retailer Inventory Policies	**Unavailable.** Specifically for Customer C where ordering is triggered automatically based on predefined and proprietary algorithms	Brainstorming	C	1
34	Retailer Inventory Positions	**Unavailable.** Specifically for Customer C where ordering is based on multiple Stores (Point of Sales) supplied from the same DC.	Brainstorming	C	1

3.3.2 Data Collection

We started with the data that we received from the sponsor company. We received several "raw" data files including the following:

1. A history of recorded shipments for 60 months.
2. A map of the company's production and storage facilities.
3. Capacity limits for each production facility.
4. Some Point of Sale data for one of the company's major customers.
5. Some promotional data for some of the very low volume/revenue clients

This data was extracted in an as-is form from the sources with no filtering or scrubbing. Furthermore, the data was spread across multiple spreadsheets, databases, and other online sources.

Second, we collected a history of all public holidays (U.S. Office of Personnel Management, 2013), natural disasters (Federal Emergency Management Agency (FEMA), 2013), and as many "special" events as we could from interviews with the Niagara employees.

Finally, we listed the data we believed was relevant but were not able to retrieve due to the lack of availability of data with the sponsor company, inability to share the data due to legal issues, inability to retrieve data from the company's database, or other similar reasons. For details, please refer to Appendix 2 on page 58

3.3.3 Data Validation

Since the data was spread across multiple spreadsheets, databases, and other sources, the first step was to aggregate the data into one database. To do this we created a database using Microsoft Access and Excel and manually mapped the fields from all sources to the fields that we created in the database. Then we imported the database into Tableau 8.0 for analysis.

Next, we classified the data into four categories (Customer, Geography, Product, and Time). Each category was aggregated at several levels. By choosing different aggregation levels for the different categories, we were able to view data from multiple perspectives. There was a total of 300 possible combinations, 40 of which were later used for analysis and modeling. *(see* Figure 7 *for a list of categories and levels of aggregation.)* Dimensions in red were excluded because customers exhibited different behaviors, not only from other customers, but also in different regions. Furthermore, SKUs were interchangeable; hence, we used the sum of liters sold instead of individual SKUs. We also excluded exports and donations since these were mostly outliers. Finally, we focused on the top 3 customers since they represented almost 50% of total demand.)

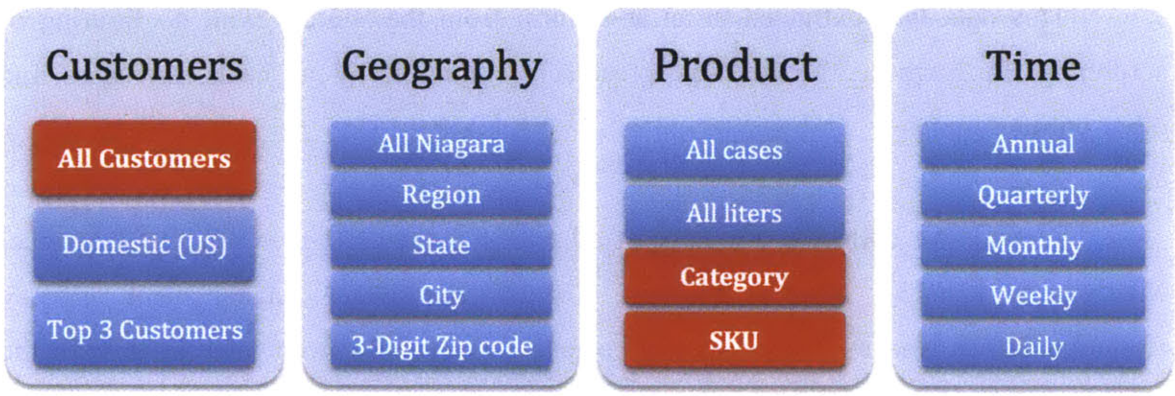

Figure 7 Data categories and aggregation levels

After that, we began scrubbing the data for outliers and other random factors. To do this we looked at different slices of data and analyzed each one individually and went through the following steps:

1. Removed exports and kept only information of shipments made to customers in the United States mainland because exports are less than 1 % of total revenue, irregular, and are often one time bulk orders that are made well in advance.
2. Broke the data into three categories, one for each of the top 3 customers (Customer A, Customer B, and Customer C). The top 3 customers constitute about 50% of the total revenue and by simple visual inspection we could see that they showed different demand patterns, hence the needed to look at each one independently.
3. Visually inspected the data for trends, peaks, and troughs across all 3 categories.

4. Overlapped the data with data from different slices to figure out if this was a one-time event or was consistent behavior. We then over-laid data from different years, customers, geographies, and products. For example, we examined how a certain customer behaved in a certain region and compared that to other regions, as well as other customers in the same region and over several years.
5. Created an outlier index where we examined each data point by comparing it to the mean of similar data points and how many standard deviations away was to help identify and isolate potential outliers through the 1 million records we had:
    a. (1 month) Each day compared the current calendar month
    b. (1 week) Each day compared to the current calendar week
    c. (3 + 3) Each day compared to the rolling week, the current day, 3 days before the current day and 3 days after.
    d. (14 + 14) Each day compared to the rolling month, the current day, 14 days before the current day and 14 days after.
    e. (Weekday) the current day (e.g. Monday) plus 2 similar weekdays before and two after.
6. Created a list of potential outliers and crosschecked them with the list of events that we had collected. If an event did occur on that day, we inspected similar data points to see if the behavior was consistent and probably could be explained. If not, we marked the data point as a suspected outlier.
7. Shared the list of potential outliers with the sponsor company for feedback. However, we have been advised by Niagara to aggregate the data into larger buckets to smoothen the outliers instead. So, we decided to proceed with their recommendations.
8. Created a new database with adjusted history.

The new database, which aggregated the data from all sources and all entries, followed the same format. (More than 1 million transactions in total)

3.4 Modeling

We only created models for the variables that were classified A1 or C1 and for which we had data available with the exception of temperature, because the company insisted it had significant effects. A summary of the causal factors used in the models we tested is listed below in Table 4. A list of all the models created and the results are in the (Analysis and Models) section below. We also included variables to account for trend, seasonality, and geographic locations. Below is a list of these variables.

1. Included the year as a causal factor to account for annual growth.
2. Included the month as a causal factor to account for monthly seasonality.
3. Included the Region, State, and 3-digit Zip Code to account for geographic locations.

Table 4 List of Causal Factors used in Final Models

#	Causal Factor	Horizon	Magnitude
1	Month	Seasonality	
2	Year	Growth	
3	Region	Geography	
4	State	Geography	
5	3 Digit Zip-Code	Geography	
6	Holidays & Public Events	A	1
7	Natural Disasters *	A	1
8	Day of the Week	A	1
9	Temperature (Gradient)	A	3
10	Temperature (Weekly Average)	A	3
11	Lagged Demand -1 week	A	1
12	Lagged Demand -2 weeks	A	1

* Tsunami Waves, Winter Storms, Flooding, Severe Winter Storms, Debris and Mudflows, Earthquake

We also included other "test" variables (temperature, point of sale, value of food stamps issued). For several variables we included, test or otherwise, we used variations of it such as using the average temperature of the past week or past three days instead of the absolute temperature for that day.

Table 5, below, lists all the factors and variations used.

Table 5 Key to variations and codes of Causal factors used

Causal Factor code used in models	Detail
Holiday Week	The week in which a holiday occurs (all 22 holidays aggregated as one predictor)
Holiday Week Detail	The week in which a holiday occurs (all 22 holidays as individual predictors)
Holidays (8 Individual)	The week in which a holiday occurs (8 significant holidays aggregated as one predictors)
Holidays, Weekly (8 Individual)	The week in which a holiday occurs (8 significant holidays as individual predictors)
Weekday	The week of the day
Previous 7 Days	The shipment in liters for the past 7 days
Previous Week	The average shipments in liters for the past week
Previous WeekdayWEnd	The average shipments in liters for the past 5 weekdays / past weekend
Food Stamps	Amount issued in food stamps
WeekNbr	The week number (1-52)
Avg Temp -7d	Average temperature for the past 7 days
Avg Temp -7d Diff	Variance between the current temperature and the average temperature for the past 7 days
Avg Temp -3d	Average temperature for the past 3 days
Avg Temp -3d Diff	Variance between the current temperature and the average temperature for the past 3 days
Temp-1	Temperature for the past day
Temp-1 Diff	Variance between the current temperature and the temperature for the past day
Temp +1	Forecast for the upcoming day
Temp +1 Diff	Variance between today's temperature and the next day's forecast
Temp +3	Average forecast for the next 3 days
Temp +3 Diff	Variance between today's temperature and the average forecast for the next 3 days
Lts -1	Shipments in liters for the past day
Lts -1/-3	Average shipments in liters for the past 3 days
Lts -1/-7	Average shipments in liters for the past 7 days
Lts -1/-14	Average shipments in liters for the past 14 days
Lts -7/-14	Average shipments in liters for 7 days, 7 days ago
POS Qty	POS quantity sold
POS Qty -1	POS quantity sold for the past day
POS Qty -3	POS quantity sold for the past 3 days
POS qty -7	POS quantity sold for the past 7 days
POS Revenue	POS revenue earned
POS Revenue -1	POS revenue earned for the past day
POS Revenue -3	POS revenue earned for the past 3 days
POS revenue -7	POS revenue earned for the past 7 days

3.4.1 Model Creation

To create the models we performed the following steps for each model:

1. Listed all dependent variables
2. Listed all independent variables (causal factors)
3. Provided a brief explanation of the factors and correlations (if any)
4. Listed the data sources and any assumptions
5. Created a model using regression analysis (for interval and ratio variables) and ANOVA (for categorical variable), using all the data except the last 6 months.
6. Used the model to attempt to predict the demand over the "hidden" 6 months and determine the effectiveness of the model.
7. Refine the model and repeat step 6.

3.4.2 Summary

In this chapter we discussed three main topics. First, the methods we used to collect, segment, and analyze the data. Second, the approach taken with choosing independent and dependent variables. Finally, the method causal factors are incorporated into models and the steps taken to create the models. In the next chapter we will present and discuss the results of the modeling process.

Chapter 4: Analysis and Models

In this section we will discuss the resulting models and insights from using the methodology discussed above for the specific case study.

4.1 The Models

First, we refined the data used for the models. Figure 8 below shows the shipments over time for the top three customers (solid lines) and the trend lines for the shipments to these customers (hashed lines). As we can see from the figure, both Customer A and Customer B had relatively very stable overall growth and trends, while Customer C has a sudden increase in activity after 2010 because of new agreements made over the past three years. Therefore; we have decided to use the entire data set for Customer A and Customer B, while only using data starting 2011 for Customer C. This decision was made to exclude data and trends that were no longer relevant to predict the future demand for Customer C. We also decided to restrict the Customer A models to California, Customer B models to Ohio, and Customer C models to Texas as these are the most well-established and stable markets and represent roughly 50% of the total volume shipped in 2012. Furthermore, the goal of this thesis is to demonstrate the concept. The method can be replicated for other customers, regions, and geographies easily.

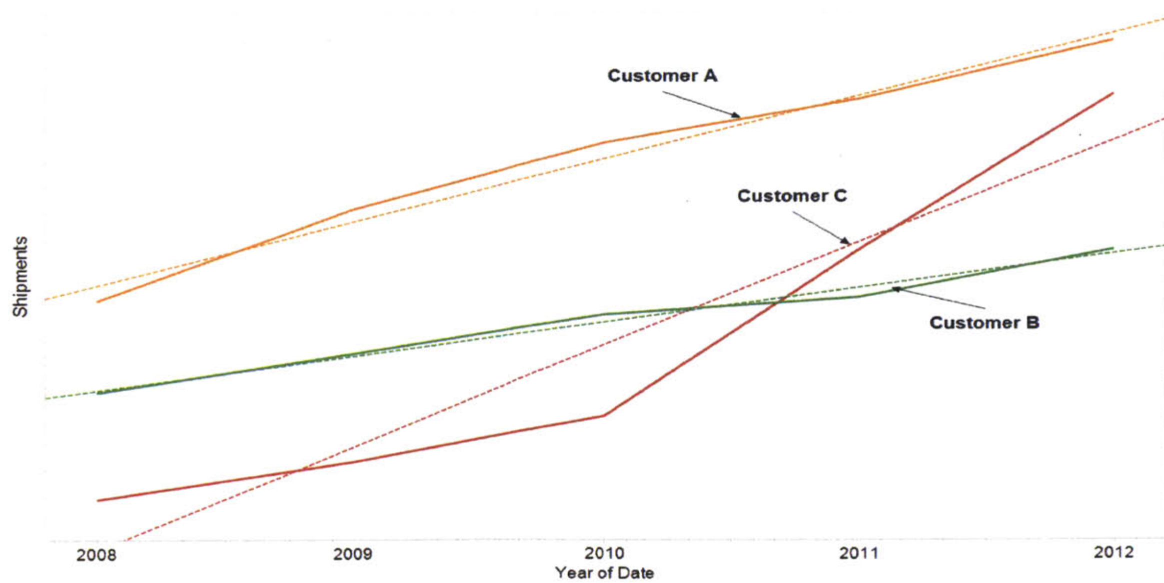

Figure 8 Trends over time per customer for U.S. Mainland

Then, we created basic models to test each of the variables independently. We started with only one variable (Weekday) and added one variable in each subsequent model. We also created models to test the effect of each of the 22 holidays (Table 6) on the dependent variable. The result was that several holidays proved to have little or no effect on the dependent variable. We chose to include the top 8 significant holidays in all subsequent models.

Table 6 Models created to test the effects of individual holidays

Customer/Region: Customer A / California

Dependent Variable: Shipments made to customers in liters

#	Aggregation	Independent 1	Adjusted R^2	Holiday	Comments
1	Daily	H1	0.0168	New Year's Day	**INCLUDED**
2	Daily	H2	Negative	Martin Luther King Day	Insignificant
3	Daily	H3	0.0035	Super Bowl	Not Included
4	Daily	H4	0.000091	Valentine's Day	Insignificant
5	Daily	H5	0.001	Presidents Day	Not Included
6	Daily	H6	0.0011	Mardi Gras Carnival	Not Included
7	Daily	H7	Negative	St. Patrick's Day	Insignificant
8	Daily	H8	0.0225	Easter Sunday	**INCLUDED**
9	Daily	H9	Negative	Mother's Day	Insignificant
10	Daily	H10	0.0183	Memorial Day	**INCLUDED**
11	Daily	H11	0.01	Independence Day	**INCLUDED**
12	Daily	H12	0.0185	Labor Day	**INCLUDED**
13	Daily	H13	0.0029	Patriot Day 2013	Not Included
14	Daily	H14	Negative	Columbus Day	Insignificant
15	Daily	H15	Negative	Halloween	Insignificant
16	Daily	H16	Negative	Veterans' Day	Insignificant
17	Daily	H17	0.0197	Thanksgiving	**INCLUDED**
18	Daily	H18	Negative	Black Friday	Insignificant
19	Daily	H19	0.0009	Christmas Eve	Insignificant
20	Daily	H20	0.0215	Christmas Day	**INCLUDED**
21	Daily	H21	0.0081	New Year's Eve	**INCLUDED**
22	Daily	H22	Negative	Cesar Chavez Day	Insignificant

We also found that natural disasters (fortunately) are too few and far apart to present significant coefficients. Hence, we excluded them from our models. We would recommend treating such events as outliers instead. Finally, we used multiple variables together to create more comprehensive models (243 in total). Table 7, Table 8, Table 9, Table 10 and Table 11 (below) provide a summary of the models created, predictors used, and corresponding values of R^2 for Customer A in California, Customer B in Ohio, and Customer C in California and Texas respectively.

We created models using different combinations of variables. Most of the models used shipment data that was aggregated daily. However, Niagara currently forecast on a monthly basis and plan to move soon to a weekly forecast. Hence, we created some models using weekly data so that Niagara can compare the model quality with their future forecasting practices.

Table 7 Summary of Models Created for Customer A in California

Customer/Region: Customer A / California

Dependent Variable: Shipments made to customers in liters

Data Aggregation: 2008 - 2012

#	Aggregation	Independent Variables	Observations	Adj R2
1	Daily	Weekday;	1825	13.98%
2	Daily	Month	1825	12.18%
3	Daily	Weekday	1825	12.79%
4	Daily	Month	1825	15.24%
5	Daily	Year	1825	13.16%
6	Daily	Holidays (22 Aggregate)	1825	7.77%
7	Daily	Weekday; Month	1825	28.19%
8	Daily	Weekday; Year	1825	26.07%
9	Daily	Month; Year	1825	28.56%
10	Daily	Weekday; Holidays (22 Aggregate)	1825	19.56%
11	Daily	Weekday; Holidays (22Individual)	1825	26.83%
12	Daily	Weekday; Month; Year	1825	41.64%
13	Daily	Weekday; Month; Year; Holidays (22 Individual)	1825	54.39%
14	Daily	WeekNbr	1816	10.52%
15	Weekly Average	WeekNbr	1816	19.13%
16	Weekday/Weekend	WeekNbr	1816	14.64%
17	Weekday/Weekend	WeekNbr; Weekday	1816	28.28%
18	Weekly	WeekNbr	260	30.97%

19	Weekly	Year	260	32.50%
20	Weekly	WeekNbr; Year	260	72.20%
21	Weekly	WeekNbr; Weekday/Weekend	519	87.04%
22	Daily	WeekNbr; Year	1816	55.09%
23	Weekly Average	WeekNbr; Year	1816	92.57%
24	Weekday/Weekend	WeekNbr; Year	1816	73.05%
25	Weekday/Weekend	WeekNbr; Year; Weekday	1816	86.87%
26	Daily	WeekNbr	1815	14.89%
27	Weekly Average	WeekNbr	1815	41.70%
28	Weekday/Weekend	WeekNbr	1815	33.18%
29	Weekday/Weekend	WeekNbr; Weekday	1815	36.16%
30	Daily	WeekNbr; Year	1815	29.19%
31	Weekly Average	WeekNbr; Year	1815	77.46%
32	Weekday/Weekend	WeekNbr; Year	1815	62.23%
33	Weekday/Weekend	WeekNbr; Year; Weekday	1815	65.26%
34	Daily	Weekday	1825	12.79%
35	Daily	Month	1825	15.24%
36	Daily	Year	1825	13.16%
37	Daily	Previous Day	1825	13.87%
38	Daily	Previous 7 Days	1825	25.14%
39	Daily	Previous Week	1815	21.87%
40	Daily	Previous WeekdayWEnd	1820	11.28%
41	Daily	Previous WeekdayWEnd; Weekday/Weekend	1820	23.03%
42	Daily	Weekday; Previous 7 Days	1825	38.06%
43	Daily	Weekday; Previous 7 Days; Month	1825	38.87%
44	Daily	Weekday; Previous 7 Days; Month; Year	1825	42.22%
45	Daily	Weekday; Previous 7 Days; Year	1825	33.04%
46	Daily	Weekday; Holidays (8 Individual)	1825	26.83%
47	Daily	Weekday	1825	12.79%
48	Daily	Month	1825	15.24%
49	Daily	Year	1825	13.16%
50	Daily	Previous Day	1825	13.87%
51	Daily	Previous 7 Days	1825	25.14%
52	Daily	Previous Week	1815	17.56%
53	Daily	Previous WeekdayWEnd; Weekday/Weekend	1815	19.82%
54	Daily	Weekday; Previous 7 Days	1825	38.06%
55	Daily	Weekday; Previous 7 Days; Month	1825	38.87%
56	Daily	Weekday; Previous 7 Days; Month; Year	1825	42.22%
57	Daily	Weekday; Previous 7 Days; Year	1825	38.79%
58	Daily	Weekday; Holidays (8 Individual)	1825	26.83%
59	Daily	Weekday; Holidays (8 Individual)	1825	25.90%
60	Daily	Weekday; Month; Year	1825	41.64%
61	Daily	Weekday; Previous 7 Days; Food Stamps	1825	38.16%

62	Daily	Weekday; Month; Food Stamps	1825	28.64%
63	Daily	Weekday; Month; Food Stamps; Year	1825	42.11%
64	Daily	Weekday; Month; Year; Holidays (8 Individual)	1825	54.39%
65	Daily	Weekday; Month; Year; Holidays (22 Individual)	1825	54.36%
66	Daily	Weekday; Month; Year; Holidays (8 Individual); Food Stamps	1825	54.56%
67	Daily	Weekday	1825	12.79%
68	Daily	Month	1825	15.24%
69	Daily	Year	1825	13.16%
70	Daily	Holidays (8 Individual)	1825	7.77%
71	Daily	Holidays (22 Aggregate)	1825	14.95%
72	Daily	Holiday Week	1825	5.54%
73	Daily	Holiday Week Detail	1825	5.56%
74	Daily	Holidays (8 Individual)	1825	14.54%
75	Daily	Holidays, Weekly (8 Individual)	1825	4.15%
76	Daily	Weekday; Month; Year; ;	1825	41.64%
77	Daily	Weekday; Month; Year; Holidays (22 Aggregate)	1825	54.39%
78	Daily	Weekday; Month; Year; Holidays (8 Aggregate)	1825	54.39%
79	Daily	Lts -1	1825	13.87%
80	Daily	Lts -1/-3	1825	15.96%
81	Daily	Lts -1/-7	1825	25.20%
82	Daily	Lts -1/-14	1825	25.87%
83	Daily	Lts -7/-14	1825	20.56%
84	Daily	Lts -1; Lts -1/-7	1825	25.76%
85	Daily	Lts -1/-7; Lts -7/-14	1825	26.33%
86	Daily	Weekday; Month; Year; Holidays (22 Aggregate); Lts -1/-7	1825	55.06%
87	Daily	Weekday; Month; Year; Holidays (8 Individual); Lts -1/-7	1825	55.04%
88	Daily	Weekday; Month; Year; Holidays (22 Aggregate); Lts -1/-14	1825	54.60%
89	Daily	Weekday; Month; Year; Holidays (8 Individual); Lts -1/-14	1825	54.60%
90	Daily	Weekday; Month; Year; Lts -1/-7	1825	42.22%
91	Daily	Avg Temp -7d; Avg Temp -7d	1825	12.48%
92	Daily	Avg Temp -7d Diff; Avg Temp -7d Diff	1825	0.68%
93	Daily	Avg Temp -3d; Avg Temp -3d	1825	9.61%
94	Daily	Avg Temp -3d Diff; Avg Temp -3d	1825	0.26%
95	Daily	Temp-1; Temp-1	1825	7.49%
96	Daily	Temp-1 Diff; Temp-1 Diff	1825	0.04%
97	Daily	Temp +1; Temp +1	1825	5.48%
98	Daily	Temp +1 Diff; Temp +1 Diff	1825	neg
99	Daily	Temp +3; Temp +3	1825	5.92%
100	Daily	Temp +3 Diff; Temp +3 Diff	1825	0.08%
101	Daily	Weekday; Month; Year; Holidays (8 Individual)	1825	54.40%
102	Daily	Weekday; Weekday; Month; Year; Avg Temp -7d	1825	44.02%
103	Daily	Weekday; Month; Year; Holidays (8 Individual); Avg Temp -7d	1825	56.61%

Table 8 Summary of Models created for Customer B in California

Customer/Region: Customer B / Ohio

Dependent Variable: Shipments made to customers in liters

Data Aggregation: 2008 - 2012

#	Aggregation	Independent Variables	Observations	Adj R^2
104	Daily	Weekday	1760	14.18%
105	Daily	Month	1760	2.76%
106	Daily	Year	1760	6.20%
107	Daily	Previous Day	1760	18.48%
108	Daily	Previous 7 Days	1760	12.41%
109	Daily	Previous Week	1760	3.91%
110	Daily	Previous WeekdayWEnd; Weekday/Weekend	1750	12.82%
111	Daily	Weekday; Previous 7 Days	1760	27.22%
112	Daily	Weekday; Previous 7 Days; Month	1760	27.41%
113	Daily	Weekday; Previous 7 Days; Month; Year	1760	28.81%
114	Daily	Weekday; Previous 7 Days; Year	1760	28.25%
115	Daily	Weekday; Holidays (22 Individual)	1760	16.18%
116	Daily	Weekday; Holidays (8 Individual)	1760	15.61%
117	Daily	Weekday; Month; Year	1760	24.28%
118	Daily	Weekday; Previous 7 Days; Food Stamps	1760	27.19%
119	Daily	Weekday; Month; Food Stamps	1760	17.24%
120	Daily	Weekday; Month; Food Stamps; Year	1760	24.25%
121	Daily	Weekday; Month; Year; Holidays (22 Individual)	1760	25.88%
122	Daily	Weekday; Month; Year; Holidays (8 Individual)	1760	25.86%
123	Daily	Weekday; Month; Year; Holidays (8 Individual); Food Stamps	1760	25.85%

Table 9 Summary of models created for Customer B in Ohio

Customer/Region: Customer B / Ohio

Dependent Variable: Shipments made to customers in liters

Data Aggregation: 2008 - 2012

#	Aggregation	Independent Variables	Observations	Adj R^2
124	Daily	Weekday	1787	2.61%
125	Daily	Month	1787	6.45%
126	Daily	Year	1787	7.89%
127	Daily	Holidays (8 Individual)	1787	0.39%
128	Daily	Holidays (22 Aggregate)	1787	0.28%
129	Daily	Holiday Week	1787	0.58%
130	Daily	Holiday Week Detail	1787	2.36%
131	Daily	Holidays (8 Individual)	1787	Negative
132	Daily	Holidays, Weekly (8 Individual)	1787	1.00%
133	Daily	Weekday; Month; Year	1787	17.35%
134	Daily	Weekday; Month; Year; Holidays (22 Aggregate)	1787	17.33%
135	Daily	Weekday; Month; Year; Holidays (8 Individual);	1787	17.24%
136	Daily	Lts -1	1787	19.40%
137	Daily	Lts -1/-3	1787	22.55%
138	Daily	Lts -1/-7	1787	20.25%
139	Daily	Lts -1/-14	1787	12.78%
140	Daily	Lts -7/-14	1787	2.54%
141	Daily	Lts -1; Lts -1/-7	1787	24.55%
142	Daily	Lts -1/-7; Lts -7/-14	1787	20.42%
143	Daily	Weekday; Month; Year; Lts -1/-7	1787	24.79%
144	Daily	Weekday; Month; Year; Lts -1	1787	27.21%
145	Daily	Weekday; Month; Year; Lts -1/-3	1787	28.59%
146	Daily	Weekday; Month; Year; Lts -1; Lts -1/-7	1787	28.79%
147	Daily	Avg Temp -7d	1787	5.62%
148	Daily	Avg Temp -7d Diff	1787	0.84%
149	Daily	Avg Temp -3d	1787	4.63%
150	Daily	Temp-1	1787	4.44%
151	Daily	Temp +1	1787	4.35%

152	Daily	Temp +3	1787	4.27%
153	Daily	Weekday; Month; Year; Avg Temp -7d	1787	17.28%
154	Daily	Weekday; Month; Year; Lts -1; Avg Temp -7d	1787	27.28%
155	Daily	Weekday; Month; Year; Lts -1/-3; Avg Temp -7d	1787	28.68%
156	Daily	Weekday; Month; Year; Lts -1/-7; Avg Temp -7d	1787	24.94%
157	Daily	Weekday; Month; Year; Lts -1; Lts -1/-7	1787	28.89%

Table 10 Summary of Models creates for Customer C in California

Customer/Region: Customer C / Texas

Dependent Variable: Shipments made to customers in liters

Data Aggregation: 2008 - 2012

#	Aggregation	Causal Factors	Observations	Adj R^2
158	Daily	Weekday	1085	12.93%
159	Daily	Month	1085	10.92%
160	Daily	Year	1085	0.64%
161	Daily	Previous Day	1085	6.62%
162	Daily	Lts -7	1085	13.76%
163	Daily	Previous Week	1085	12.19%
164	Daily	Previous WeekdayWEnd; Weekday/Weekend	1075	14.35%
165	Daily	Weekday; Previous 7 Days	1085	26.74%
166	Daily	Weekday; Previous 7 Days; Month	1085	28.17%
167	Daily	Weekday; Previous 7 Days; Month; Year	1085	28.26%
168	Daily	Weekday; Previous 7 Days; Year	1085	26.66%
169	Daily	Weekday; Holidays (22 Individual)	1085	13.02%
170	Daily	Weekday; Holidays (8 Individual)	1085	13.04%
171	Daily	Weekday; Month; Year	1085	24.93%
172	Daily	Weekday; Previous 7 Days; Food Stamps	1085	26.67%
173	Daily	Weekday; Month; Food Stamps	1085	24.16%
174	Daily	Weekday; Month; Food Stamps; Year	1085	24.89%
175	Daily	Weekday; Month; Year; Holidays (22 Individual)	1085	25.00%
176	Daily	Weekday; Month; Year; Holidays (8 Individual)	1085	25.47%
177	Daily	Weekday; Month; Year; Holidays (8 Individual)	1085	24.93%

Table 11 Summary of Models created for Customer C in Texas only for 24 pack of 0.5L bottles

Customer/Region: Customer C / Texas

Dependent Variable: Shipments made to customers in liters (24 Pack only)

Data Aggregation: 2008 - 2012

#	Aggregation	Independent Variables	Observations	Adj R^2

178	Daily	Weekday	1056	1.96%
179	Daily	Month	1056	9.14%
180	Daily	Year	1056	46.98%
181	Daily	Holidays (8 Individual)	1056	0.76%
182	Daily	Holidays (22 Aggregate)	1056	Negative
183	Daily	Holiday Week	1056	0.56%
184	Daily	Holiday Week Detail	1056	2.62%
185	Daily	Holidays (8 Individual)	1056	Negative
186	Daily	Holidays, Weekly (8 Individual)	1056	1.45%
187	Daily	Weekday; Month; Year	1056	59.96%
188	Daily	Weekday; Month; Year; Holidays (22 Aggregate)	1056	59.99%
189	Daily	Weekday; Month; Year; Holidays (8 Individual)	1056	59.93%

We also created a few models to test the effects of including POS data as a predictor for the expected shipments. To do so, we aggregated the data from all the retail locations that are being served by one of Niagara's locations. Then we created several models using the POS data and others without. Table 12, below, shows the results of the modeling process.

Table 12 Summary of Models created for Customer C in Texas using point of sale data and only for 24 pack of 0.5L bottles

Customer/Region: Customer C / Texas

Dependent Variable: Shipments made to customers in liters for 24 Pack/0.5L bottles

Data Aggregation: 2011 - 2012

#	Aggregation	Independent Variables	Observations	Adj R^2
190	Daily	Weekday	1041	2.31%
191	Daily	Month	1041	3.86%
192	Daily	Year	1041	46.01%
193	Daily	Holidays (8 Individual)	1041	0.48%
194	Daily	Holidays (22 Aggregate)	1041	Negative
195	Daily	Holiday Week	1041	0.18%
196	Daily	Holiday Week Detail	1041	2.31%
197	Daily	Holidays (8 Individual)	1041	0.04%
198	Daily	Holidays, Weekly (8 Individual)	1041	1.40%
199	Daily	Weekday; Month; Year	1041	53.80%
200	Daily	Weekday; Month; Year; Holidays (22 Aggregate)	1041	53.82%
201	Daily	Weekday; Month; Year; Holidays (8 Individual);	1041	53.83%

202	Daily	POS Qty	678	15.68%
203	Daily	POS Revenue	678	32.91%
204	Daily	POS Qty -1	678	16.30%
205	Daily	POS Revenue -1	678	30.34%
206	Daily	POS Qty -3	678	16.55%
207	Daily	POS Revenue -3	678	38.06%
208	Daily	POS qty -7	678	17.58%
209	Daily	POS revenue -7	678	47.02%
210	Daily	POS qty; POS Revenue	678	37.29%
211	Daily	POS Qty -1 ; POS Revenue -1	678	35.41%
212	Daily	POS Qty -3 ; POS Revenue -3	678	41.34%
213	Daily	POS qty -7 ; POS revenue -7	678	48.80%
214	Daily	Week; Month	678	10.18%
215	Daily	Week; Month; POS qty -7 ; POS revenue -7	678	55.11%
216	Daily	Avg Temp -7d	678	8.23%
217	Daily	Avg Temp -3d	678	8.28%
218	Daily	Temp-1	678	7.20%
219	Daily	Temp +1	678	5.66%
220	Daily	Temp +3	678	5.38%
221	Daily	Weekday; Month; ; Avg Temp -7d;	678	11.32%
222	Daily	Weekday; Month; POS qty -7 ; POS revenue -7 ; Avg Temp -7d	678	55.63%
223	Daily	Lts -1	678	52.57%
224	Daily	Lts -1/-3	678	47.30%
225	Daily	Lts -1/-7	678	49.40%
226	Daily	Lts -1/-14	678	12.80%
227	Daily	Lts -7/-14	678	9.28%
228	Daily	Lts -1; Lts -1/-7	678	57.42%
229	Daily	Lts -1/-7; Lts -7/-14	678	49.41%
230	Daily	Weekday; Month; Lts -1	678	56.23%
231	Daily	Weekday; Month; Lts -1/-3	678	54.42%
232	Daily	Weekday; Month; Lts -1/-7	678	53.17%
233	Daily	Weekday; Month; Lts -1; Lts -1/-7	678	60.35%
234	Daily	Lts -1; POS revenue -7	678	59.34%
235	Daily	Lts -1; POS revenue -7 ; Weekday	678	62.38%
236	Daily	Lts -1; POS revenue -7 ; Weekday; Month	678	63.23%
237	Daily	Lts -1/-3; POS revenue -7	678	53.33%
238	Daily	Lts -1/-7; POS revenue -7	678	52.63%
239	Daily	Lts -1; POS qty -7 ; POS revenue -7	678	59.80%
240	Daily	Lts -1/-3; POS qty -7 ; POS revenue -7	678	53.86%
241	Daily	Lts -1/-7; POS qty -7 ; POS revenue -7	678	52.98%
242	Daily	Lts -1; Lts -1/-7; POS qty -7 ; POS revenue -7	678	59.98%
243	Daily	Lts -1; Lts -1/-7; POS qty -7 ; POS revenue -7 ; Weekday	678	63.50%

4.2 Discussion of Model Results

4.2.1 Key Observations

- Using point of sale data increased the R^2 of the models. However, there are a couple of practical considerations:
  - The Customer C retail locations that are served by specific Niagara warehouses/distribution centers changes from month to month. Furthermore, some cross shipments and inventory-balancing activity takes place within Customer C that will difficult to keep track of.
  - Using both shipments and POS data (both are proxies for demand) might present the challenge of multi co-linearity. While this will not affect the overall quality of the model, it will compromise the reliability of individual coefficients.
- Using weekly buckets instead of daily buckets dramatically increased the R^2 of the models. However, there were fewer observations to build the models on and that might reduce reliability in less extensive data sets (newer regions and customers for example.)
- The same customers produced different models for different regions.
- Different customers have shown different demand patterns in the same region.
- The day of the week has significant effects on the models.
- Monthly seasonality and annual growth have significant effects on the models

4.2.2 Effects of temperature on the models

We created several models to test the effects of temperature. We collected government temperature records for 2008 through 2012 (National Weather Service, 2013). We also focused on a few stations that are closest to the retail locations where the water is eventually sold.

We chose the models that created very high or the highest R^2 without temperature and then added several variations of temperature to the model till we got the highest possible R^2. By comparing the models with the highest R^2 with and without the temperature variables (Table 13), we can see that including any of the variations of temperature as a variable had little effect on the model. This is evident in the low improvement or even decline in the value of R^2. Furthermore, weather stations do not necessarily align well with retail locations. This could present a modeling challenge. Also, Weather information would need to be updated almost daily. This might require investment in partnerships and technology, which presents an implementation challenge. Therefore, we recommend against using temperature as a predictor.

Table 13 Effects of temperature on Model Results

Customer	Highest R^2 with temperature	Model #	Highest R^2 without temperature	Model #
Customer A	56.61%	103	55.06%	86
Customer B	28.68%	155	28.59%	145
Customer C	55.63%	222	59.98%	242

4.3 Final Model Results

4.3.1 Model Selection Criteria

After running more than 240 models for four customer/state combinations, we had to decide which model to use for each. To do so, we followed the logic below:

- For each customer/state combination filter out the 10 models that yielded the highest R^2.
- For the selected models, identify the models that have the lowest number of independent variables and select the one with the highest value of R^2. We did not count factors that represent time (year, month, weekday, and weekend) because of their relative ease of acquisition and manipulation.
- Compare the model with the highest R^2 and the one with lowest number of independent variables.
- Repeat for other customer/location combinations.

From observation, we found that the difference in R^2 between the models selected was minor in 2 out of 5 cases (less than 0.5%). When that was the case, we chose the model with the fewer factors. In the other three cases, the difference was more than 3% in favor of the more extensive model. In those cases we chose to go with the model that had the higher R^2.

Finally, we believe choosing models is subjective as it is not always possible to quantify the effort required to add an extra independent variable to the model. It will also vary from industry to industry. In the bottled water industry where unit cost is low, we would recommend models that are easier to build and maintain. In industries with high inventory and holding costs, we would recommend more extensive models. In conclusion, the decision on which model to choose is left to the judgment of the demand management professionals implementing DSR.

4.3.2 The Final Models

Table 14 (below) shows the results of the final models created for all three customers in their respective regions (Customer A/California, Customer B/Ohio, Customer B/California, Customer C/California, Customer C/Texas, Customer C/Texas with POS data.

Table 14 Final Model: The effects of multiple causal factors on liters of water shipped

Predictor variable	**Liters Shipped**					
	Customer A in California	**Customer B in Ohio**	**Customer B in California**	**Customer C in California**	**Customer C in Texas**	**Customer C in Texas with POS Data**
Intercept	-799,519 **	373,869 ***	804,745***	364,655***	543,161***	221,522***
Weekday						
Monday	-115,335 ***	-35,822***	-123,477***	-29,365***	-20,258**	-45,039***
Tuesday	-86,575 ***	-43,462***	-126,500***	-30,834***	-36,482***	-49,228***
Wednesday	-104,544 ***	-37,231***	-77,429***	-48,510***	-51,575***	-62,193***
Thursday	-141,365 ***	-31,354***	-78,623***	-47,390***	-50,055***	-49,756***
Friday	-208,711 ***	-39,005***	-58,463***	-72,566***	-51,497***	-54,248***
Saturday	-166,072 ***	-11,668*	-25,358**	-35,892***	-31,190***	-19,879*

Month					
January	-4,861	6,745	-17,144	-1,837	35,754***
February	-5,683	7,769	4,502	4,148	13,758
March	-63,486 ***	2,726	-7,836	3,763	13,889
April	-90,437 ***	-10,621	-18,499†	-8,030	-6,939
May	-124,020 ***	-12,995†	-25,231**	-13,906*	-14,243
June	-138,793 ***	-24,444**	-24,654**	-18,180*	-25,808**
July	-182,810 ***	-18,195*	-20,486†	-30,143***	-34,628***
August	-183,081 ***	-16,289*	-41,943***	-16,140*	-44,766***
September	-182,790 ***	-6,108	-27,268*	-2,798	-27,332**
October	-101,044 ***	2,745	-20,620†	-3,409	-12,730
November	-65,022 ***	985	-20,308†	5,574	707
Year					
2009	28,168 **	-8,287*	-24,329***		
2010	-23,986 **	-15,537**	-41,583***		
2011	-73,999 ***	-20,069***	-41,827***		-35,892***
2012	-152,329 ***	-32,548***	-38,872***		-155,207***
Holidays & Events					
New Year's Day	426,553 ***				
M.L.K. Day	-61,897				
Super Bowl	11,830				
Valentine's Day	29,252				
Presidents Day	47,128				
Mardi Gras	33,818				
St. Patrick's Day	57,119				
Cesar Chavez Day	380,185 ***				
Easter Sunday	-31,152				

Mother's Day	487,746 ***					
Memorial Day	465,099 ***					
Independence	548,152 ***					
Labor Day	-93,429 †					
Patriot's Day	6,157					
Columbus Day	-30,193					
Halloween	46,262					
Veterans' Day	470,662 ***					
Thanksgiving	121,665 *					
Black Friday	69,436					
Christmas Eve	456,434 ***					
Christmas Day	249,783 ***					
New Year's Eve	21,716					
Others						
Avg. lts. day -1 / -3		0.4995***				
Lts previous day						0.4832***
Lts previous 7days			0.0630***	0.0669***		
POS Sales-7						1.7615***
n	**1825**	**1787**	**1759**	**1084**	**1041**	**678**
df	**43**	**22**	**22**	**18**	**19**	**8**
R^2	**55.47%**	**29.52%**	**29.70%**	**29.36%**	**54.62%**	**63.28%**
Adjusted R^2	**54.40%**	**28.64%**	**28.81%**	**28.17**	**53.78%**	**62.84%**

† $p < .10$; * $p < .05$; ** $p < .01$ *** $p < .001$

4.4 Summary

In this chapter we discussed the models created using the methodology created in the previous section. Then, we explored the results of the models and effects of different independent variables (such as temperature, point of sale data, and previous demand) and data aggregation methods on the outcome of the models. We also discussed the criteria we used for model selection. Finally, we presented the results of modeling efforts and the models we chose to forecast demand at Niagara for four customer/state combinations. In the next section we will discuss the conclusions of our finding and summarize the key take away points.

Chapter 5: Conclusion

In this chapter we will summarize our findings from the project. We will also discuss the practical implications of these findings and how they can be applied as well as some limitations of application and implementation. Then we will present some suggestions for maintaining the current project and for future expansion.

5.1 Summary of Findings

- **Effect of causal factors on demand has changed from year to year.**

The effect some factors have on demand has changed over the past 5 years. This can be seen from the values of R^2 of the models that used only the factor in question as an independent variable when these models were run for individual years and for the entire data set.

We have observed this trend with the following factors:

- Week of the day
- Monthly seasonality
- Holidays and Public Events
- Natural Disasters

This pattern was clearly evident in Table 6, where we ran the analysis with using years. The resulting coefficients and R^2 varied significantly from year to year.

- **Temperature is not a major causal factor**

As we can see from (Table 14) the extremely low R^2 and the low significance levels have lead us to the conclusion that temperature is not a strong causal factor contrary to the common perception. It also has practicality limitations as discussed in section 4.2.2 Effects of temperature on the models). Furthermore, absolute temperature seems to have higher effects (still minor) than temperature differentials. It was perceived that how "hot" consumers felt would drive demand. However, it seems that seasonality is more of a driver.

We suspect temperature is not a strong causal factor is because we were predicting demand of bottled water cases from retailers. This is completely different than the single serving bottles that a consumer would normally purchase on a hot day. These were more calculated purchases. Hence the daily and even weekly temperatures had very little effects on the sales of the large packs. Seasonality provided a better explanation of demand than simply temperature.

- **Factors that we found were most significant**

The following factors have shown the most significance and data regarding these factors is also relatively easy to collect and manipulate before using in models.

- Year
- Month
- Weekday
- Holidays

Factors that include lag (previous days'/week's demand) perform well for Customer B and Customer C, but not Customer A. This might be because Customer A is replenished by Niagara directly to stores and not to distribution centers or warehouses. In the case of direct store delivery (DSD), customers do not place orders or hold inventory other than what is on the shelves and Niagara representatives visit the retail locations and replenish inventory almost every day. This means that there is no lag between realizing demand, placing and order, and shipping to retail locations. This might reduce the effects of overbuying, bulk purchases, as well as delays in replenishment.

- ***Point of sale quantity and revenue are major predictors***

Using point of sale data as a predictor for shipments has significantly improved model quality (Table 12). By comparing the models with the highest R^2 created with shipment and point of sale data, we can see that using point of sale data yields an R^2 of 55.11% (model 215) Vs. 10.18% (model 214) without using point of sale data.

5.2 Challenges faced and anticipated in the project

Demand Signal Repository (DSR), like any major technology or business project, is not without its challenges. (DSR) requires investment and commitment in people, time, software, and relationships. There are also a few common issues that usually result in the less favorable results. Below we discuss some of these issues or challenges that we faced or anticipated during the project.

- ***Over estimating the capabilities of DSR***

(DSR) involves investment of time, money, and resources. Hence, it is logical to try and get the highest return on investment. However, this could be a reason for the implementation not to achieve its objectives. In an attempt to maximize ROI and get the most out the investment, both we and Niagara felt tempted at first to include as many causal factors as possible and to create a model that is as detailed as our imaginations allowed. We soon found out that this made the models very complicated and challenging to create and implement and we soon shifted our efforts to simpler, more usable models. At the same time, focusing on a few factors that contributed the most to the variation in demand (such as weekdays and POS data), yielded satisfactory results.

- ***Over estimating the capabilities of DSR***

We believe (DSR) is more about quality and not quantity. However, as discussed in the literature review section, we need to make sure the extra accuracy is worth the investment. As we attempted to use better data sources (Point of sale or sales order data), the effort and investment required collecting data and creating the models proved challenging. An example of this was our attempt to acquire and use point of sale or sales order data instead of the data we currently had (shipment data). We found that using sales order data would require change in the way orders are booked and processed in the ERP and would require training and change management efforts. Using point of sale data required having long-term collaborative relationships with all major clients, paying fees in some cases to get access to the data, and investing in mapping the data onto our database. This would have put the entire project on hold. We choose to proceed with what we had and make adjustments to compensate for the data lag as much as possible. We discuss this part in more detail in Chapter 3: Methods.

- ***Models that explain demand better are not necessarily practical***

Assuming that we managed to create an excellent model with 50 causal factors or predictors, it will be more challenging and time and money consuming to maintain such a complicated model than it would maintaining a model that only had the top 4 or 5 of the 50 factors. So, we focusing only on the top factors that we could collect data for.

- ***Fully outsourcing the implementation with minimal time and internal personnel investment***

While the challenges make outsourcing the (DSR) implementation to external consulting firms attractive, there still remains the fact that no one knows a company's business, customers, and products like they do. Hence the question becomes, not whether to outsource the implementation or not, but who to assign to the project even if we decide to outsource it. As Jim Collins mentions several times in his book "Good to Great", it is all about finding the right people. Even if the effort is outsourced, significant contribution and internal commitment are required and not just for project management, but also for data collection and cleansing, hunting for causal factors, communicating with customers, and handling change management issues.

- ***Over relying on technology***

While (DSR) is all about using technology to collect and analyze data, at its core we believe it is a demand management project. Sales, marketing, production, and other company functions all need to be involved in this effort with varying degrees. Since computers (for now) cannot perform the key tasks required for implementing and maintaining (DSR) such as brainstorm and figure out the factors that might affect demand, make sure that data is collected from the correct sources, or investigate outliers and compensate, that makes human intuition and continuous involvement a must.

5.3 Practical Implications of Findings

- The resulting models explained almost 60% of demand for Customer A and Customer C and about 28% for Customer B while using daily buckets. When weekly buckets were used, the numbers went up higher than 85%. Under current forecasting practices, these numbers are barely achieved for monthly buckets.
- Some factors did slightly increase model quality. However, the question of whether including the higher level of detail is worth the effort, is a question best answered by the company implementing DSR.
- Natural disasters might have significant effects on sales and shipments. However, fortunately, there are relatively few and far apart natural disasters. Hence, it is more practical to treat such events as outliers and be prepared for supply chain disruptions instead.

5.4 Limitations

- Trends change over time. The models created require regular maintenance and tweaking to make sure they do not become obsolete.
- Causal models are not a replacement for time series models. Instead, they are supposed to complement each other.
- Certain factors might be challenging to implement because of the way they are applied to the models. For instance, temperature and point of sale data needs to be applied to retail locations, while Niagara currently does not have access to data from all point of sale locations.
- It is easier and more practical to create models for geographic regions that are aggregate by state or sales region. However, retailers' networks might not be segregated geographically in a way similar to Niagara's.
- Some variations in recorded data exist for accounting adjustments and end of month sales rushes. While these events could be considered as outliers as they do not represent demand, they are a part of daily business. Changing such practices to have records match demand are beyond the scope of this thesis.

5.5 Recommendations to the Firm

After analysis and reflection on the process and the results, we listed, below, our recommendations for future implementation at Niagara.

- ***Use the data closest to the point of consumption:***

Using data that is farther away from the consumer amplifies the bullwhip effect. This issue requires not only that the data closest to the consumer be available, but also that it can be mapped to our supply chain echelons.

- ***Record pricing and promotions:***

Pricing and promotional activities are the only causal factors that have been cited by all company personnel when we asked them to list the top 3 factors. Hence, we recommend collecting and centralizing this information. We would also recommend recording competitors pricing and promotional activities as well. These two factors have been identified as major causal factors, however, no data regarding them is recorded or the data is available but is not used in a systematic way.

- ***Understand retailer-ordering policies:***

Instead of simply fulfilling orders, we believe it would be better if are able to understand retailer ordering policies. These policies can dramatically affect the orders seen at the manufacturer, especially since no reliable data is currently available closer to the consumer than shipments to retailers. For example, if we manage to push sales this month, the retailer might have more stock than they need and will not buy as much next time. Furthermore, there are policies in place that incentivize bulk purchases and these policies further amplify the bullwhip effect. While this is no substitute for using point of sale data, it is probably better solution than using shipment data. Another option could be to implement Direct Store Delivery (DSD) programs

- ***Maintaining support after the initial implementation.***

Implementing (DSR) successfully now does not necessarily mean that we are done, especially since new factors might be introduced that might have great effects on demand such as new technology, new competitors, or more environmentally friendly consumers. Hence, we believe that continuously monitoring the models and investigating causal factors is necessary to maintain the models and (DSR) updated and relevant.

(DSR) is a huge ongoing effort that involves creating models that predict the future by looking at and analyzing demand signals. The quality of these models depends on the quality of the signals. Hence, we need to invest enough effort to cleanse and normalize the signals and make sure that quality does not decline over time.

- ***Use specialized demand signal repository software:***

Implementing (DSR) involves collecting, normalizing, and analyzing huge amounts of data on a daily basis. While this effort could be done using spreadsheets and basic database and statistical packages, we believe using a specialized package that is designed to perform this tasks might be worth the investment. Some generic packages and business intelligence software might also be capable of performing such tasks. Such software is provided from specialized companies as well software and ERP giants. Doug Henschen, executive director of Information week, created a summary including some of the software packages available on the market today. Below is a list of some of these packages.

Vendor	Package Name	Comments
CAS	CPWerx	
IBM	Cognos	
Oracle	Demand Signal Repository	
Relational Solutions	POSmart	
SAP	Vision Chain	Partnership with a 3rd party
Shiloh Technologies		Designed specifically around Customer C's Retail Link. Could be adapted to link with other retailers
Teradata	Demand Signal Repository	
TrueDemand		Partners with IBM and Vision Chain

Vision Chain		Partners with Microsoft, Microstrategy, SAP, Teradata, Tibco Software, and TrueDemand

From our experience, we believe that using a specialized package in contrast to generic software is a better option for the following reasons:

- Possibly shorter implementation time because that is the software's primary function.
- More experienced implementation consultants who supposedly have done DSR implementations before in contrast to business intelligence or generic package consultants who need to adapt to the new environment.
- Possibly easier integration with ERP packages since fewer custom fields will need to be created. This is especially true for packages offered by large ERP vendors such as Oracle and SAP.
- Specialized software is usually packaged with key performance indicators and capabilities to quickly collect and transform the data.

Furthermore, we believe choosing software should be done carefully and planned ahead of time. Some software packages might look attractive today, but there are other factors to consider such as:

- Integration capabilities with ERP
- Ease of expansion and limitations on the number of causal factors (if any)
- Data collection and manipulation capabilities
- Level of detail in forecasts the package is capable of creating
- Reports and Key Performance Indicators available and building capabilities
- Financial stability of the company offering the package
- Availability of support and partners capable of implementing the software
- Ecosystem size and quality of customers, experts, and consultants for the given package
- User friendliness and training time required

5.6 Future Work

Moving forward, the model needs to be expanded to other customers or customer groups as well as other geographical regions. However, it should be noted that Demand Signal Repository works best when the market and product are in the late growth or maturity phases. Regions that are currently facing rapid changes in market share are not good candidates for rollout. As for causal factors, building models that incorporate pricing, promotions, and merchandising activities would take the highest priority for this industry. Also, natural disasters, while few and far apart, might warrant further investigation due to the huge impact they might have on demand.

Closing Comments

Demand Signal Repository (DSR) might sound challenging, and we believe it is, but the rewards in our opinion could be worth the risk. We were able to create models that explained about 60% of demand for the top customers (on a daily basis) using only shipments data while using the most basic software tools. This leads us to believe that if we had access to better data such as point of sale instead of shipments and access to more causal factors such as pricing and promotions, we could have improved model even further. Furthermore, the use of specialized, corporate software might have significantly reduced the time required to collect, cleanse, sort, and analyze the data. However, the final decision whether to pursue a full-scale (DSR) implementation or not would depend on whether the savings from increased forecast accuracy can offset the costs of implementing and maintaining (DSR). Finally, in today's competitive market and pressure to increase service while reducing costs, a well timed, well implemented demand signal repository could mean survival and prosperity.

Appendix 1: List of Interviewees

Table 15 List of Interviewees

Interview #	Position of Interviewee
1	Sales Manager 1
2	Sales Manager 2
3	Sales Manager 3
4	Sales Manager 4
5	Marketing Director
6	CFO
7	Finance Director
8	EVP of Manufacturing
9	Sourcing Manager
10	Operations Manager
11	Customer Service Manager
12	EVP of Supply Chain
13	S&OP Manager
14	Planning Manager
15	Supply Chain Analyst 1
16	Supply Chain Analyst 2

Appendix 2: List of data believed relevant, but excluded due to inaccessibility

A list of that data is presented below:

1. Point of Sale data for the top 3 customers.
2. Pricing history offered by the manufacturer to the retailers.
3. Shelf price history offered to the end consumers.
4. Pricing history offered by competing manufacturers to the retailers.
5. Shelf price history offered to the end consumers.
6. Promotion history offered by the manufacturer to the retailers.
7. Promotion history offered by the retailers to the end consumers for our products.
8. Promotion history offered by competing manufacturers to the retailers.
9. Promotion history offered by the retailers to the end consumers for competing products.
10. History of stock-outs and capacity shortages.
11. History of original retailer purchase orders.
12. History of sales orders made to the retailers.
13. History of new product introductions.

Appendix 3: List of Holidays and Public Events used in modeling

Table 16 List of holidays and public events

Year		2009	2010	2011	2012
Holiday / Event	Event Code	Date	Date	Date	Date
New Year's Day	H01	1-Jan-09	1-Jan-10	1-Jan-11	1-Jan-12
Martin Luther King Day	H02	19-Jan-09	18-Jan-10	17-Jan-11	16-Jan-12
Super Bowl	H03	1-Feb-09	7-Feb-10	6-Feb-11	5-Feb-12
Valentine's Day	H04	14-Feb-09	14-Feb-10	14-Feb-11	14-Feb-12
Presidents Day	H05	16-Feb-09	15-Feb-10	21-Feb-11	20-Feb-12
Mardi Gras Carnival	H06	24-Feb-09	16-Feb-10	8-Mar-11	21-Feb-12
St. Patrick's Day	H07	17-Mar-09	17-Mar-10	17-Mar-11	17-Mar-12
Cesar Chavez Day	H08	31-Mar-09	31-Mar-10	31-Mar-11	31-Mar-12
Easter Sunday	H09	12-Apr-09	4-Apr-10	24-Apr-11	8-Apr-12
Mother's Day	H10	10-May-09	9-May-10	8-May-11	13-May-12
Memorial Day	H11	25-May-09	31-May-10	30-May-11	28-May-12
Independence Day	H12	4-Jul-09	4-Jul-10	4-Jul-11	4-Jul-12
Labor Day	H13	7-Sep-09	6-Sep-10	5-Sep-11	3-Sep-12
Patriot Day 2013	H14	11-Sep-09	11-Sep-10	11-Sep-11	11-Sep-12
Columbus Day	H15	12-Oct-09	11-Oct-10	10-Oct-11	8-Oct-12
Halloween	H16	31-Oct-09	31-Oct-10	31-Oct-13	31-Oct-12
Veterans' Day	H17	11-Nov-09	11-Nov-10	11-Nov-11	11-Nov-12
Thanksgiving	H18	26-Nov-09	25-Nov-10	24-Nov-11	22-Nov-12
Black Friday	H19	27-Nov-09	26-Nov-10	25-Nov-11	23-Nov-12
Christmas Eve	H20	24-Dec-09	24-Dec-10	24-Dec-11	24-Dec-12
Christmas Day	H21	25-Dec-09	25-Dec-10	25-Dec-11	25-Dec-12
New Year's Eve	H22	31-Dec-09	31-Dec-10	31-Dec-11	31-Dec-12

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