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Demand Forecasting: An Open-Source Approach

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Demand Forecasting: An Open-Source Approach

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Abstract. In this paper, we compare demand forecasting methods used by the supply chain department at Bilports to open-source forecasting methods. The design and implementation of the open-source forecasting system also attempts to use several external datasets such as consumer sentiment, housing permit starts, and weather to improve prediction quality. Additionally, the performance of the forecast is evaluated by the reduction of shipment lead times from China, the company's primary vendor. The objective of our paper is to improve Bilports's forecasting capabilities. The primary motivation of this paper is to increase forecasting accuracy and identify the weaknesses of the methods used by the supply chain department. Our framework utilizes and compares both machine learning and statistical methods to generate a more cost effective and accurate forecast. We find that the modified open-source forecasting packages reduced the forecast error by 18 percent. Thus, the company's ability to improve fulfillment rates and increase customer satisfaction.

1 Introduction

Forecasting simply put, is a set of previously known observations ordered by time, predicting new outcomes[1]. On a cognitive level, intelligent life excels at it. Those who simply surrender to the "unpredictable" nature of events are vulnerable to it. The evolution of forecasting has spanned more than 2000 years. Babylonians around 650 BC used cloud patterns to predict the weather, as well as introduce some of the first set of astrological calculations. The more familiar statistically sophisticated forecasting methods however, have only been invented in the past century [1].

Forecasting is especially fundamental in businesses that survive on unit sales, and fulfilment of a product category in a timely manner. Manufacturers, distributers, and retailers routinely generate forecasts at different intervals for demand planning, inventory planning, production planning, and procurement planning. A company's Sales Inventory and Operations Planning team (SIOP) is responsible for coordinating between sales, finance, procurement, manufacturing, logistics, and the pricing teams

[1] "Time Series Analysis - Statistics Solutions", Statistics Solutions, 2018. [Online]. Available: https://www.statisticssolutions.com/time-series-analysis/. [Accessed: 05- Nov- 2018].

to generate an accurate demand forecast that supports downstream organizational wide planning activities[2]. The demand forecast produced by the SIOP team in a distribution company is especially important since profitability is highly dependent on margin optimization, responsive customer service with high fill rates, lower inventory, and reduced white space in distribution centers [3].

At Bilports, a commodity driven building products distributor, the SIOP team has taken rudimentary steps in adopting a demand-driven and commercialized supply chain system that moves away from subjective, judgmental, and experimental approaches to forecasting[3]. Judgmental and experimental approaches utilize sales force and customer surveys, as well as depend on a jury of experts such as Territory Managers and Field Specialists. Although, subject matter experts are invaluable to a forecast, the future of the business cannot depend on them methodically. Furthermore, Bilports is faced with a retiring employee population that significantly impacts the knowledge transfer between departments in the future.

Field research indicates that building products distribution companies have been changing their supply chain forecasting systems toward a more objective, relational, econometric models approach. These models consume leading indicators and input variables[4]. Bilports attempted to adopt this approach by purchasing a software package from SAP, the largest vendor of enterprise resource planning software in the world [2]. The software package, Advanced Planning and Optimization (APO), claims to deliver a myriad of solution to the Supply Chain Management (SCM) strategy of the company. Some include demand planning, supply network planning, production planning, data integrations, and so on [4].

The demand planning package offers a comprehensive demand forecasting tool-set that supports both top-down and bottom-up planning procedures. Additionally, the demand planning package has the ability to validate different univariate forecast models, validate different causal models, execute multiple linear regressions, and composite forecasting. Moreover, the most impressive function in the demand planning package is the Adaptive Forecasting feature. This function attempts to automatically find the best forecast model and parameters and determines the best profile for the assigned selection. The forecast profile is selected using the proprietary Automatic Model Selection Procedure strategy [5].

Although SAP's APO software solution comes highly recommended in the industry, Bilports SIOP team does not use it. The main reason is the fluctuating 60% Mean Absolute Percent Error (MAPE) that has resulted in higher import lead times. We suspect that the high error rate is associated with the lack of comprehensive

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[2] Ocw.mit.edu, 2018. [Online]. Available: https://ocw.mit.edu/courses/engineering-systems-division/esd-260j-logistics-systems-fall-2006/lecture-notes/lect6.pdf. [Accessed: 04- Nov-2018].

[3] Courses.edx.org, 2018. [Online]. Available: https://courses.edx.org/asset-v1:MITx+CTL.SC1x_1+2T2015+type@asset+block/w2l1_Forecasting1_v6_ANNOTATED.pdf. [Accessed: 01- Nov- 2018].

[4] "A Practitioner's Guide to Demand Planning - Supply Chain 24/7", Supplychain247.com, 2018. [Online]. Available: https://www.supplychain247.com/article/a_practitioners_guide_to_demand_planning. [Accessed: 01- Nov- 2018].

functional, technical testing, and training that is required to fully utilize this system[5]. Regardless, the SIOP team has lowered the MAPE score to 35% by utilizing a mixture of deterministic forecasting and shape modeling techniques.

To identify and understand the effectiveness of promising open-source probabilistic forecasting packages, we present a framework that attempts to predict the future as accurately as possible, using historical data sourced from Bilports and public datasets, including weather, housing starts, and consumer sentiment. Accurate forecasting is difficult in this industry due to recent tariff wars between the United States and China, national macroeconomic trends, and commodity driven competitiveness [6]. By discovering trends that improve accuracy of the forecast, Bilports can possibly use this feat to better purchase in larger quantities and capture larger market share.

Using the data previously mentioned, we present methods that not only reduce the MAPE score in the current forecast, but assess whether 3rd party datasets are useful for that goal. Many companies bring outside consulting agencies to create "a quality forecast that can capture relationships and patterns from the data. Moreover, quality forecasts have the ability to discriminate among random fluctuations, or noise, that should be ignored and an actual pattern or shift that should be modeled and possibly extrapolated." [6]. This allows companies to verify the quality of their forecasts and increase confidence in their decision-support that is based on it.

The first stage of the framework is to determine which of Bilports SCM features should be included for analysis. In addition, whether or not 3rd party datasets contribute to the accuracy of the forecast. The Master Data repository contains invoice level line item transactions for the last four years. It is comprised of 125 fields with quantitative and descriptive categories. We eliminate most of the fields since they are certainly irrelevant to our framework. Fields like discounts, rebates, weight, and unit of measure cannot empirically improve the forecast. Useful fields such as unit quantity, time stamps, customer segmentations, and product segmentation can provide a wealth of insight into a possible trend of pattern. Customer segmentation for example is critical in improving demand forecast because Bilports has already determined that the purchasing behavior of their customers are three tiered. The three general customer segments are national accounts, major accounts, and independent accounts. National accounts are considerably more consistent in their purchasing behavior and in higher volumes than independently owned shops.

The second stage of the framework utilizes Prophet, a Facebook's open-source time series package to get a base level MAPE score in addition to the one the SIOP team has produced. This method also gives insight into the feasibility and efficiency of adding more features to a basic but accurate forecasting tool. The overwhelming consensus is that this library inside R or Python can produce forecasts that are often as accurate as those produced by skilled forecasters. This is because Prophet uses a fitting additive regression model where non-linear trends are fit with yearly and weekly seasonality. It is also robust to shifting trends, large outliers, and missing

[5] "What key components help ensure SAP APO upgrade success?", SearchSAP, 2018. [Online]. Available: https://searchsap.techtarget.com/answer/What-key-components-help-ensure-SAP-APO-upgrade-success. [Accessed: 09- Aug- 2018].

[6] R. Hyndman and G. Athanasopoulos, Forecasting. [Heathmont, Vic.]: OTexts, 2018.

data[7]. Although missing data is not a problem in Bilports's dataset, large outliers and purchasing volatilities are present. The Prophet forecast model results in a MAPE score of 22% using 16 months of data for training and 8 months of data for testing. The widely accepted industry standard for an optimal demand forecast is at 20% MAPE.

The third stage of the framework involves attempts at further reducing the MAPE score for our unit demand forecast using several statistical and machine learning methods. The weakness of Prophet's methodology is that it only accepts two features, but with machine learning methods, we can add multiple features that can possibly improve the forecast. It is assumed that a method like Artificial Neural Nets is a superior demand forecasting technique due to its ability to accommodate non-linear data and model complex relationships between inputs and outputs [7]. However, we find that statistical methods are not only easier to implement but more accurate as well. After implementation, our lowest MAPE score reduced to 17.52%.

In Section 2 we present the current research into Bilports supply chain management methods and present the first step of the framework, data collection and research. In Section 2 we also explore deterministic forecasting philosophies and include background research on demand planning fundamentals. In Section 3 we discuss the second stage, using Facebook's Prophet package in R programming language to produce a demand forecast superior to that of the current SIOP team's output. In Section 3 we also report on several additional statistical and machine learning methods. The results are discussed in Section 4. In Section 5 we discuss the ethical implications of our findings. Section 6 details our conclusions.

2 A Background on Bilports and Forecasting Fundamentals

2.1 Bilports Product Segmentation

Bilports has over 40,000 active building products sold in the United States. Over 33% of those products are imported and distributed in wholesale or in packages to wholesalers or retail outlets. As a distribution company, the range and variety of products adds a strain on any broad analysis conducted. Thus, we found it necessary to isolate the demand forecast to a product level, although, a product group can work but not as accurately.

The products fall under three hierarchies. Product group 1 is split into the following: Anchors, Building Materials Group (BMG) Primary, BMG Secondary, Bolts, Building Accessories, Collated Fasteners, Commodity Wood Products, and Miscellaneous. Further detailed, product group 2 branches as follows: BMG, Building Accessories, Collated Fasteners, Miscellaneous, Nail & Screws, Non-Core Products, Other Fasteners, and Unknowns. Product group 3 is less descriptive, but gives more meaningful insight into product groups: Fasteners, BMG, and All-Other. The

[7] "Prophet", Prophet, 2018. [Online]. Available: https://facebook.github.io/prophet/. [Accessed: 22- Aug- 2018].

challenge in demand planning is the aggregation of the forecast which is necessary for increasing accuracy[8]. However, in this case, products in the Fastenal group behave very differently than in the BMG group. Thus, we focus on the top ten revenue items for Bilports which happen to all be under Fastenal.

2.2 Bilports Customer Segmentation

It is no secret that the objective of every business is to increase their size whether it be sales or market share which is indicative of growth. Only recently did we hear that Apple has hit a company valuation of one trillion Dollars[9]. One colossal driver for that success is the behind-the-scenes market analytics that researches the consumers' willingness to spend thousands of dollars on tech products. This is why consumer data is probably one of the most sought after and inaccessible type of data category in the world.

For the last 50 years, one extremely powerful method of understanding a business's market or customer base is through market segmentation[10]. Companies that try to market products to the masses or approach their marketing through a "one-size-fits-all" methodology eventually fail. Market segmentation divides the customer base into groups of individuals that are similar in specific ways.

The benefits of this practice are invaluable to the business and include: Marketing efficiency, identification and determination of new market opportunities, improved distribution strategies, and customer loyalty. The current customer segmentation methodologies implemented at Bilports are labeling customers with customer spending levels and domain industry.

Customer Level represents a static customer assignment based on what Distribution Center (DC) managers think the customer brings into the company. Customer Industry represents the main focus of what the customer sells, although, most overlap in more than one area. From this combination, the pricing department determines which customer gets which price point. In theory, because there are 5 different price points for each item sold, the customer that brings in the most sales receive the most discounted price and so on.

Several problems arise with this methodology. The DC Manager is biased, and often to increase sales, they change customer level attributes to give them better pricing. The customer segmentation is static. The only way to reclassify all the customers is to make the DC manager go through them all. The customer industry

[8] [11]"Measuring Forecast Accuracy: The Complete Guide | RELEX Solutions", RELEX Solutions, 2018. [Online]. Available: https://www.relexsolutions.com/measuring-forecast-accuracy/. [Accessed: 22- Aug- 2018].

[9] S. Salinas, "Apple hangs onto its historic $1 trillion market cap", CNBC, 2018. [Online]. Available: https://www.cnbc.com/2018/08/02/apple-hits-1-trillion-in-market-value.html. [Accessed: 22- Aug- 2018].

[10] "What is Market Segmentation? Different Types Explained | Qualtrics", Qualtrics, 2018. [Online]. Available: https://www.qualtrics.com/experience-management/brand/what-is-market-segmentation/. [Accessed: 22- Aug- 2018].

classification has a smaller purpose in methodology of choosing which customer is getting which price.

The band level customer segmentations are as follows: A($500K+), B($150K-500K), C($70K-150K), D($30K-70K), E($0K -30K). The customer industry classifications are as follows: Concrete, Gypsum, Farm & Ranch, Lumber, Hardware, Roofing, STAFDA, Retail, and Rental.

2.3 Bilports Deterministic Forecast

There are numerous methods when researching time series. This means that there are several philosophies regarding demand planning as well. One popular philosophy is deterministic forecasting. Determinism in general believes in a correlation between cause and effect[11]. This methodology is highly prevalent in weather forecasts. The events whether it be environmentally local or global inevitably result in a predecessor cause. A correction factor is added to a skilled observation which results in a forecast.

The trouble with deterministic forecasts is that they depend highly on the forecaster's ability in interpreting the observation and producing the result. There is a high level art and intuition involved. Those who believe categorically in deterministic forecasts seem to take pride in the additional hardships involved in producing an accurate forecast. Simply put, deterministic forecasting includes too many heuristic techniques which cannot successfully be replicated or transferred[12]. We did observe that the highest revenue pulling sales people at Bilports more often than not use deterministic forecasts based on industry news both local and abroad. However, our efforts of building a decision tree model based on their experience was not successful.

2.4 Demand Planning

One of the tougher and more frustrating aspects of SCM is demand planning. It is no wonder why SIOP teams have a sense of despair when approached with the topic. This is due to the fact that not only is demand planning the application with the greatest planned future spending, but it is often the function with the greatest gap between performance and satisfaction[13]. The SIOP team is often satisfied with other management processes, but demand planning continues to allude them.

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[11] "Deterministic vs Probabilistic Forecasting", Tornado.sfsu.edu, 2018. [Online]. Available: http://tornado.sfsu.edu/geosciences/classes/m698/determinism/determinism.html. [Accessed: 23- Aug- 2018].

[12] "Probabilistic verses deterministic in production forecasting -", Petrowiki.org, 2018. [Online]. Available: https://petrowiki.org/Probabilistic_verses_deterministic_in_production_forecasting. [Accessed: 23- Aug- 2018].

[13] "A Practitioner's Guide to Demand Planning - Supply Chain 24/7", Supplychain247.com, 2018. [Online]. Available: https://www.supplychain247.com/article/a_practitioners_guide_to_demand_planning. [Accessed: 23- Aug- 2018].

Supply chain management as a practice was first introduced in 1982 [14]. Organizations almost completely focused on optimizing their broad view logistical processes, procurement, and manufacturing. Integrations within the organization and across an ever-expanding global economy forced companies to invent more optimized approaches. At the heart of this optimization, demand planning came to be known as the use of market signals and analytics to predict future demand patterns[15].

The tactical planning processes, often with a forward period of somewhere from 10 months to 18 months vary by company. However, as companies became more mature, demand processing became more comprehensive across different organizational functions and achieving a holistic end-to-end status. The sometimes validated assumption is that the more developed the forecast becomes, the more likely a company can reduce costs by tightening inventories and speeding time of delivery.

As channels become more specialized and products proliferate, the company's supply chain process becomes more complex. Yet most companies do not evolve their methods because they don't understand the trade-offs between growth, costs, cycles, and complexity. It is merely expected that the SIOP team running the supply chain processes improve demand signals without affecting other mentioned trade-offs.

Additionally, most companies develop a top-down or bottom-up management approach, especially in distribution companies. Conversely, our research suggests that distribution companies must make their supply chain group central to other reporting relationships in order to increase effectiveness. Currently, Bilports historically positions its reporting relationships to the sales organization. Thus producing bias, since sales teams are notoriously known to be least interested in running structured routine processes and have lower quantitative skills compared to other departments. Though they have the highest level of contact with customers[16].

Many digitized companies opt-in for a supply chain center of excellence. These teams take responsibility for two key elements: Data governance, regional governance, and global governance of demand insights[17]. Thus, the core focus of this group is to improve the quality of demand insights, data integrity, and report quality market signals. Bilports currently lacks this initiative as well which further hinders the addition of a key success factor.

Another growing concern is the increasing demand volatility occurring across all industries participating in the global market. This is due to faster proliferation of

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[14] S. Kolenko, "A Brief History of Modern Supply Chain Management and Best Practices", Spend Culture, 2018. [Online]. Available: https://blog.procurify.com/2014/12/17/brief-history-modern-supply-chain-management-supply-chain-management-best-practices/. [Accessed: 06- Nov- 2018].

[15] M. Materials, "Elements of Demand Planning", Supplytechnologies.com, 2018. [Online]. Available: http://www.supplytechnologies.com/blog/elements-of-demand-planning. [Accessed: 22- Aug- 2018].

[16] "The Important Role of Sales In An Organisation | Oxford College of Marketing Blog", Oxford College of Marketing Blog, 2018. [Online]. Available: https://blog.oxfordcollegeofmarketing.com/2014/10/17/the-important-role-of-sales-in-an-organisation/. [Accessed: 24- Aug- 2018].

[17] [1]"How to create a supply chain center of excellence that <i>works</i> – Technology – CSCMP's Supply Chain Quarterly", Supplychainquarterly.com, 2018. [Online]. Available: https://www.supplychainquarterly.com/topics/Technology/20161021-how-to-create-a-supply-chain-center-of-excellence-that-works/. [Accessed: 06- Nov- 2018].

products, lower barrier to enter for competition, changing needs of customers, and stronger demands for faster fill rates. Traditional methods of analysis cannot adapt to rising demand volatility especially when data carries latency. A company's ability to respond is not as important as a company's ability to sense. Bilports seems to be aware of this problem, however, they have yet to introduce a system or a SCM team that's not only able to sense and respond, but is also able to manage volatility.

Furthermore assessing a company's past mistakes are critical for upgrading the SCM process. Although this tendency is well versed in most companies, one-number forecasting is well intentioned but naïve[18]. It is believed to decrease forecast error but operationally ends up doing the opposite. This is especially true in Bilports, where products are segmented, and the demand plan is focused around geographical and channel hierarchies. One-number forecasting restricts attributes that are important to the organization and becomes too constraining. Integration of other departments such as sales and marketing needs to be addressed in the model. To achieve this level of advanced forecasting requires a shift from traditional approaches to a system that is designed to consider role-based views. This implementation cannot be done in the Prophet forecast but certainly can be done in other forecast systems[19].

Other troublesome areas to focus on are manufacturing based forecasts and urgency-based forecasts. Bilports downstream forecasting application is meant to instruct what the manufacturing plants in China should make. This is based on what stock needs to be replenished. Conversely, predicting what the channels sell, reduces demand latency and gives the organization not only a more current signal but also improve forecast quality. This could be a riskier approach, since the possibility of deadstock accumulation increases. Ultimately, the reward must outweigh the risk.

The next subject cannot be discussed empirically, however, it is critical for the organization to discuss. The mindset change in bias and error reduction is a holistic approach introduced in the book "The Business Forecasting Deal: Exposing Myths, Eliminating Bad practices, Providing Practical Solutions." The author introduces steps such as the Forecast Value Add Analysis to add discipline to the demand management process. Our investigation suggests that forecasters carry on their biases into their work. Positive, pragmatic, and optimistic personalities tend to over-estimate the demand, while pessimistic characters under-estimate demand. To reduce volatility, the process has to be designed from the outside-in, which is a radical shift in traditional distribution and manufacturing SCM.

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[18] M. Gilliland and M. Gilliland, "Is one-number forecasting a new worst practice?", The Business Forecasting Deal, 2018. [Online]. Available: https://blogs.sas.com/content/forecasting/2013/04/02/is-one-number-forecasting-a-new-worst-practice/. [Accessed: 06- Nov- 2018].

[19] I. Slimani, I. El Farissi and S. Achchab, "Artificial neural networks for demand forecasting: Application using Moroccan supermarket data", 2015 15th International Conference on Intelligent Systems Design and Applications (ISDA), 2015.

3 Evaluating Forecasting Model

3.1 Methods of Forecasting

As discussed in the background section, accurate forecasting models contribute in a powerful way to the decision-making process in the business. Perhaps even more critical in the distribution business. Determining the inventory levels needed, not only forces a smaller lead time but reduces an unnecessary high inventory level called deadstock. We also discussed briefly different demand planning approaches. In this section we discuss these concepts further in the data science context.

Forecasting can be successfully implemented using empirical qualitative analysis, qualitative methods, or by using mathematical quantitative analysis, known as quantitative methods. According to Fildes and Lusk, no forecasting method can be established as ultimately the best model [11]. A forecaster must be knowledgeable enough to know the advantages and disadvantages of all methods and select the right one. Figure 1 displays the typical process for selecting a forecast model and Figure 2 displays a categorization hierarchy of some of the models available to the forecaster[20].

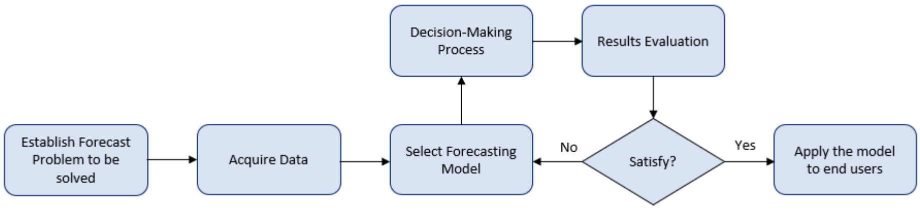

Figure 1. Forecasting process flowchart.

[20] S. Wang and W. Chaovalitwongse, "Evaluating and Comparing Forecasting Models", Wiley Encyclopedia of Operations Research and Management Science, 2011. Available: 10.1002/9780470400531.eorms0307 [Accessed 28 January 2019].

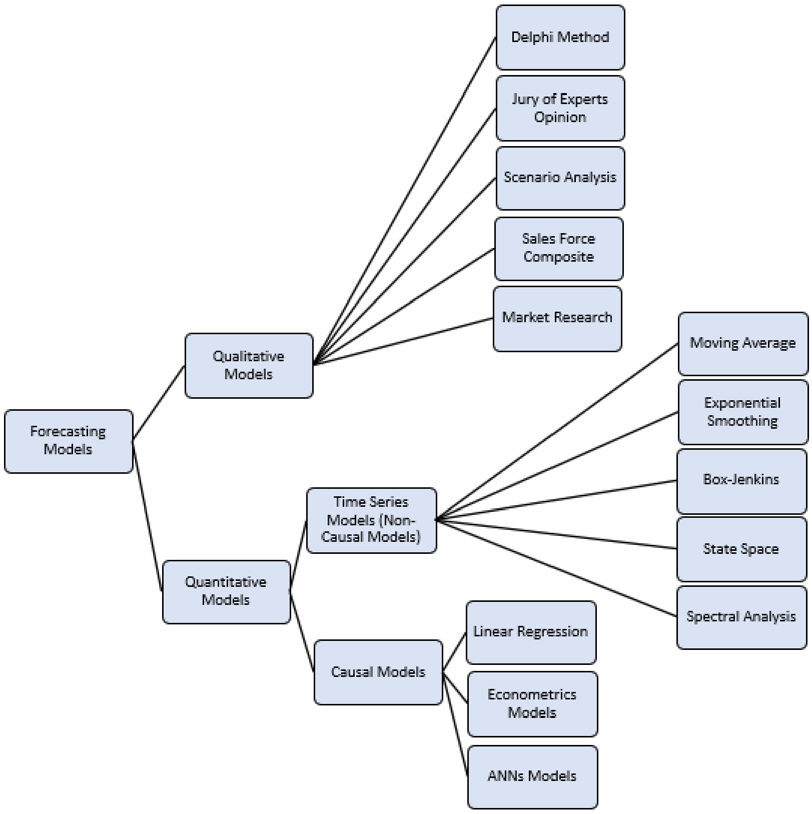

Figure 2. A sample of forecasting models categorized.

3.2 The Pillars of Time Series

Although we found extensive research on the fundamentals of time series, we summarized four important concepts. At the very core of time series is the assumption that future patterns are similar to historical patters. The four basic properties of time series are trend, seasonality, cycles, and randomness. Trend refers to the stability of the increase or decrease in the overall data. One can describe trend as the direction which can also be linear or non-linear. Seasonality refers to patterns observed in the time series at fixed repeated intervals. Cycles has a similar concept to seasonality with one exception, the pattern comes at varying intervals. Finally, randomness refers to the noise and sometimes outliers that make patterns difficult to establish.

3.3 Causal Models

Perhaps the most popular and the most common, cause-and-effect models establish a causal relationship between the forecasted variable and all other related variables. The most widely known model that applies this principle is the regression model. The previously mentioned forecast variable is known as the response or dependent variable, and the related variable is known as the independent or explanatory variable. Regression models are tremendously popular because they are based on a well studied mathematical relationship. Based on a visual approach, we have determined that an unsophisticated regression did not work for our dataset.

3.4 Artificial Neural Network

ANN has the ability to models complex relationships between inputs and outputs. As we can see in Figure 3[21], the model consists of a network of neurons, sometimes called single units or processing elements connected with coefficients (weights) [22]. The power of ANN comes from the connecting neurons into a network that gather knowledge by detecting patters through experience, rather than programming. This is often referred to as the statistical approach, rather than the symbolic approach to programming. Each neuron has a weighted input, a transfer function, and an output. The behavior is determined by the transfer function, the learning rule, and by the architecture itself. The forecaster can adjust the parameters by adjusting the weights, which as a sum constitute the activation of the neuron. The training of the network is done by minimizing the error in predictions in the inter-unit connections until the specified level of accuracy is reached. Perceptron learning and backpropagation are some of the various algorithms available to train ANNs.

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[21] K. Kandananond, "A Comparison of Various Forecasting Methods for Autocorrelated Time Series", International Journal of Engineering Business Management, vol. 4, p. 4, 2012. Available: 10.5772/51088 [Accessed 28 January 2019].

[22] S. Agatonovic-Kustrin and R. Beresford, "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research", Journal of Pharmaceutical and Biomedical Analysis, vol. 22, no. 5, pp. 717-727, 2000. Available: 10.1016/s0731-7085(99)00272-1 [Accessed 28 January 2019].

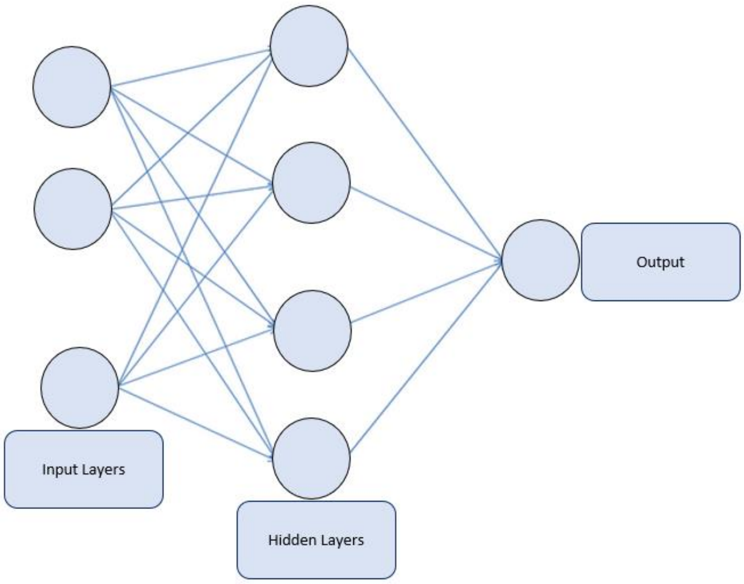

Figure 3. Artificial Neural Network Architecture.

3.5 Statistical Methods

We compare the forecasting outcomes of the SIOP team at Bilports to both statistical and machine learning methods. We chose the statistical methods based on popularity and the machine learning methods based on performance expectations. The following describes the five statistical methods performed [13]:

- Seasonal Naïve (SA)

  The Naïve method is used when all prediction of the future values are based on the last observation. Seasonal Naïve method is slightly different. All predictions in the SA are based on the last observed value on the same seasons of the previous year.

$$yT+h|T = yT \quad (1)$$

- Simple Exponential Smoothing (SES)

  The SES method uses weighted averages of previous observations. The user decides where more weight is given, usually either to the most recent observation. This decreases the relevance of older observation on the outcome of the forecast.

$$y_{T+1|T} = \alpha y_T + \alpha(1-\alpha)y_{T-1} + \alpha(1-\alpha)^2 y_{T-2} + \cdots \quad \textbf{(2)}$$

- Holt Exponential Smoothing (HES)

  This forecasting method captures trends by adding a second exponential modeling, hence the upward or downward predictions. Thus, this method takes into account the trend of the dataset.

$$\begin{aligned} &\text{Forecast equation:} && y_{t+h|t} = \ell_t + h b_t \\ &\text{Level Equation:} && \ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1}) \\ &\text{Trend Equation:} && b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*) b_{t-1} \end{aligned} \quad \textbf{(3)}$$

- Damped Exponential Smoothing (DES)

  This is an addition to the HES where we know that the increasing or decreasing trend does not follow indefinitely into the future. HES becomes weak in long forecast horizons. Thus a "dampener" was introduced that would include a parameter that added a flat line to the trend some time in the future.

$$\begin{aligned} &\text{Forecast equation:} && y_{t+h|t} = \ell_t + (\phi + \phi^2 + \cdots + \phi^h) b_t \\ &\text{Level Equation:} && \ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + \phi b_{t-1}) \\ &\text{Trend Equation:} && b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)\phi b_{t-1} \end{aligned} \quad \textbf{(4)}$$

- Autoregressive Integration Moving Average (ARIMA)

  Perhaps the most popular of all time series methods is the ARIMA model. While other models are based on either trends or seasonality, ARIMA correlates both and takes into account Holt's Winter's solution. The parameters of the ARIMA models take into account lag observations, degree of difference between the raw observations, and the size of the moving average window.

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad \textbf{(5)}$$

3.6 Measure of Forecast Error

By far the most popular measure for confirming high prediction accuracy is the following direct error measures:

Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2. \quad \textbf{(6)}$$

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}. \quad \textbf{(7)}$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad \textbf{(8)}$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{y_i - \hat{y}_i}{y_i}.| \quad \textbf{(9)}$$

Additionally, comparing forecasting models against each other is also done using the above measures. A forecaster wants to achieve the lowest error rate possible without overfitting which indicates higher accuracy. Typically overfitting is avoided using either a K-fold cross validation or our preferred method of repeated random partition validation. We partition several months together and test the level of fitness. If a model does not fit the validation data but fits the training data very well, that indicates overfitting [12].

4 Results & Analysis

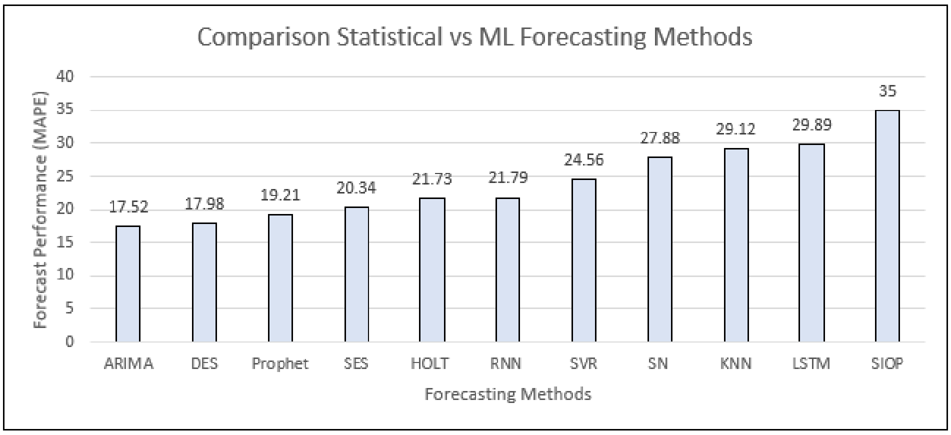

Figure 4. The statistical and ML forecasting methods are compared via MAPE scores against SIOP's team's performance.

For the majority of the methods, the statistical methods outperform ML methods in the horizons tested. ARIMA surprisingly performed the best. Figure 4 shows the line up of methods with their MAPE scores. The top five performers are the statistical methods that slightly outperform ML methods. Given the massive advances in other areas using ML, it is puzzling why the same advances are not prevalent in forecasting.

The ARIMA model is optimizing a set of weights in order to minimize error. That is generally what a neural network does. One would expect RNN and the LSTM to outperform all the models since they are more advanced versions of neural networks. However, we suspect that since there is no learning for the ML models involved, then the performance stagnates. The only way for this to happen is if the ML methods have a way to learn about unknown futures instead of fitting historical data.

The easiest model to run by far was the Seasonal Naïve and the Prophet model published by Facebook's elite data science team. The difference between the two is 8.67 percentage points. Which equals to a few thousand items ordered per product category. Naïve models are often called benchmark forecasts and a forecaster is expected to only be more accurate from there. Thus, we conclude that the difference between the SIOP's team and our efforts is not dependent on the methods used, but rather on how the data is processed, segmented, and tested.

5 Ethical Implications of Forecasting

The ethical considerations inherent in trying to predict future events, such as demand or supply planning for distribution centers are indeed negligible, in general. However, as sourcing became more global and competitive, the yearn for gaining an edge has pushed many businesses into instances of malpractice and exploitation. The ethical concerns assume the aggregation of our dataset with other datasets acquired through legal and illegal means[23]. The first ethical concern we discuss in this section are price collusion with suppliers or against suppliers leading to possible antitrust violations. The second concern is the unethical exploitation of forecasting in order to price gouge consumers in accurate anticipation of or during a weather-related natural disaster.

Antitrust laws came about after the phenomenon of large manufacturing conglomerates dominating one or multiple industries with excessive economic power[24]. These businesses were known as “Trusts” and they infamously controlled sectors of the economy like oil, railroads, and steel. The most famous trust of the 1900s is the Standard Oil Company founded by John Rockefeller. Rockefeller along with his partners established an oil-refining company in 1862 and for the next five years reaped extensive wealth. However, since the oil they were refining was only used for lighting, the market was limited, and pricing fluctuated dramatically. Rockefeller dissatisfied with this prospect, sought out the partnership of the largest oil refinery in Cleveland to hopefully fix prices and stabilize them. His intentions for monopolization became awfully clear in the next 10 years, when he either bought out his competition or aggressively drove them out of business by selling his oil for much cheaper. In 1978, Standard Oil controlled ninety percent of the oil refineries in the United States [8]. Since trade is essential for the overall economic health of the system, monopolizing an industry restricts it. Thus, reducing competition which diminishes innovation, controlling price which is bad for the consumer, and smothering the free market since one entity can become more powerful than the market [9].

The possibility that Bilports can leverage its large market share of the buildings products sector and engage in price fixing practices by strong arming manufacturers or vendors was raised by the company’s general counsel. By leveraging public data sets obtained from US customs at US ports, compiling Bill of Landing along with indexed Shipping Manifests, an analyst can potentially triangulate manufacturer-competitor links. Moreover, estimate the market share of the competition by estimating the volume of imports. Leveraging this information with manufacturers to either gain exclusivity or collusion could lead to smaller margins for the competition and drive them out of business. Similarly, obtaining illegal datasets from manufacturers or labor spies and honing the strategy of underselling efficiently, can also be detrimental to smaller suppliers. Hence, making it possible for the company to monopolize if that was intended.

The second ethical consideration is price gouging during natural disasters. In this case, we focus on wind related natural disasters such as tornadoes or hurricanes. Price gouging refers to a seller excessively increasing the prices of goods or services after

[23] C. Stenmark, A. Antes, C. Thiel, J. Caughron, X. Wang and M. Mumford, "Consequences Identification in Forecasting and Ethical Decision-Making", Journal of Empirical Research on Human Research Ethics, vol. 6, no. 1, pp. 25-32, 2011. Available: 10.1525/jer.2011.6.1.25 [Accessed 27 January 2019].

[24] Consumer.ftc.gov, 2019. [Online]. Available: https://www.consumer.ftc.gov/sites/default/files/games/off-site/youarehere/pages/pdf/FTC-Competition_Antitrust-Laws.pdf. [Accessed: 27- Jan- 2019].

an emergency has been declared by officials in authority[25]. In mainstream economic theory, price gouging can also be referred to as coercive monopoly pointing to the above market rate coercion that would otherwise not happen in a competitive environment. Thus, we have established a similar theme with the former ethical consideration.

Aggregating historical datasets of weather and climate patterns to create probabilistic models for which customers in the geographic areas likely affected by hurricanes and when can create a means of legally raising prices just before the emergencies are declared. Thus, benefiting from increased margins without facing public backlash. However, many economists do not agree with the premise that price gouging is unethical. Many argue that it could help people in disaster-prone areas to recovery faster and prevent looting by artificially reducing the depletion of supplies. Hence, when water costs seven dollars a gallon instead of one dollar, and the alarmed consumer can't afford to buy out the shelf, it minimizes interruptions in the supply that leads to the desperation that produces looting and panic. Furthermore, legal price gouging could entice businesses to forecast in anticipation of disaster more effectively, temporarily increasing supplies, since they can profit generously [10].

6 Conclusion

This framework provides evidence towards the importance of holistic data cleansing. The insights drawn from using different models and comparing MAPE scores not only benefits the overall demand planning outcome but gives us an opportunity to dig deeper into the quality of the data. This was only revealed when we compared statistical models against the ML models, with the expectation that ML models would significantly outperform the statistical ones. Furthermore, we only focused on the top 10 revenue items that also happen to be imports following an overall similar purchasing pattern. To establish an even cleaner pattern, we picked our biggest customers for the abundance of data which also happen to be consistent in pattern. These parameters would not have been possible without earlier, large scale interventions into segmenting and reclassifying the customers and products. Thus, our decision to keep the data simple. Testing sophisticated models should not have been preemptive, though it was the basis for our original hypothesis. Further preliminary testing does indicate that ML models produce superior forecasts when aggregating additional levels of data.

In terms of next steps, we recommend that the SIOP team rethink their strategic approach towards modeling, and not follow a one size fits all approach. Our research indicates that product demand at Bilports follow several different patterns depending on the customer or product classification. Thus, it is probably necessary to run several different models to cover all customers and products achieving higher accuracy forecasts. Seasonal Naïve models should be run on customers with scarce order

[25] "How to Spot and Report Price Gouging | Office of the Attorney General", Texasattorneygeneral.gov, 2019. [Online]. Available: https://www.texasattorneygeneral.gov/consumer-protection/disaster-and-emergency-scams/how-spot-and-report-price-gouging. [Accessed: 27- Jan- 2019].

history. The more complex ML models, such as RNNs, should be implemented on customers that order from the disordered product category "All Other", and so on. For future recommendation, the SIOP team should isolate the top 10 revenue items which bring in close to half the overall revenue for Bilports and immediately generate new forecasts.

References

1. S. Ren, "Predict the weather like Babylonians – Scientific Scribbles", *Blogs.unimelb.edu.au*, 2018. [Online]. Available: https://blogs.unimelb.edu.au/sciencecommunication/2017/08/17/predict-the-weather-like-babylonians/. [Accessed: 05- Nov- 2018].
2. "What is SAP? - Definition from WhatIs.com", SearchSAP, 2018. [Online]. Available: https://searchsap.techtarget.com/definition/SAP. [Accessed: 05- Nov- 2018].
3. R. Niraj, M. Gupta and C. Narasimhan, "Customer Profitability in a Supply Chain", *Journal of Marketing*, vol. 65, no. 3, pp. 1-16, 2001.
4. "SAP Library - Demand Planning Process", Help.sap.com, 2018. [Online]. Available: https://help.sap.com/saphelp_scm700_ehp03/helpdata/en/15/3cc95360267614e10000000a174cb4/frameset.htm. [Accessed: 06- Nov- 2018].
5. "SAP Library – Automatic Model Selection Procedure 2", Help.sap.com, 2018. [Online]. Available: https://help.sap.com/saphelp_scm700_ehp03/helpdata/en/1e/3bc95360267614e10000000a174cb4/frameset.htm. [Accessed: 06- Nov- 2018].
6. G. Hall and J. Rust, "Econometric Methods for Endogenously Sampled Time Series: The Case of Commodity Price Speculation in the Steel Market", 2002.
7. Chiu, M., & Lin, G. (2004). Collaborative supply chain planning using the artificial neural network approach. Journal of Manufacturing Technology Management, 15(8), 787–796. Choy, K. L., Lee, W. B., & Lo, V. (2003). Design of an intelligent supplier relationship management system: A hybrid case based neural network approach. Expert Systems with Applications, 24, 225–237.
8. "Standard Oil Company - Ohio History Central", Ohiohistorycentral.org, 2019. [Online]. Available: http://www.ohiohistorycentral.org/w/Standard_Oil_Company. [Accessed: 27- Jan- 2019].
9. "Why Monopolies Are Bad for the Economy – Sam Yang – Medium", Medium, 2019. [Online]. Available: https://medium.com/@stufffromsam/why-monopolies-are-bad-for-the-economy-d5cc96aa6ab7. [Accessed: 27- Jan- 2019].
10. A. Mill and A. Mill, "Why Price-Gouging Helps People Recover Faster From Natural Disasters", The Federalist, 2019. [Online]. Available: http://thefederalist.com/2018/09/13/price-gouging-helps-people-recover-faster-natural-disasters/. [Accessed: 27- Jan- 2019].
11. R. Fildes and E. Lusk, "The choice of a forecasting model", Omega, vol. 12, no. 5, pp. 427-435, 1984. Available: 10.1016/0305-0483(84)90042-2 [Accessed 28 January 2019].
12. S. Wang and W. Chaovalitwongse, "Evaluating and Comparing Forecasting Models", Wiley Encyclopedia of Operations Research and Management Science, 2011. Available: 10.1002/9780470400531.eorms0307 [Accessed 29 January 2019].
13. Hyndman, R.J., & Athanasopoulos, G. (2018) *Forecasting: principles and practice*, 2nd edition, OTexts: Melbourne, Australia. OTexts.com/fpp2. [Accessed 29 January 2019].