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Demand Forecasting In Wholesale Alcohol Distribution: An Ensemble Approach

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Abstract. Demand forecasting is a vital part of the sale and distribution of many goods. Accurate forecasting can be used to optimize inventory, improve cash flow, and enhance customer service. However, demand forecasting is a challenging task because of the many variables and unknowns that can impact sales, such as weather and the state of the economy. In this study, historical data from a wholesale alcoholic beverage distributor was used to forecast sales demand. While many studies focus effort only on modeling consumer demand and endpoint retail sales, this study focused on demand forecasting from the distributor perspective. An ensemble approach was applied using traditional statistical univariate time series models, multivariate models, and contemporary deep learning-based models. The final ensemble models for the most sold product and highest revenue grossing product were able to significantly reduce sales forecasting error in comparison to a statistical naïve model. Additionally, this study determined that there is no "one size fits all" demand model for all products sold by the distributor. To attain the smallest forecasting error, each product needs an individually tuned model.

1 Introduction

In retail distribution and sales of beer and alcohol, demand forecasting is an integral and necessary part of supply chain management. Ideally, a distributor should not only have enough inventory to satisfy customer demand but also be able to minimize the expense of purchasing and warehousing inventory [16]. Robust and accurate forecasting can positively affect many aspects of a company's performance: it can assist in maximizing profits, managing product life cycles, and fostering collaboration between supplier and distributor [3, 4]. Conversely, poor demand forecasting can cause difficulties throughout the supply chain. Overstocks of inventory can incur excess costs caused by the necessity of surplus storage and stock expiration, while an undersupply of stock results in lost sales and poor customer rapport [16]. Additionally, if the demand forecast is too low, suppliers may have to perform costly unscheduled production runs, which require additional labor for the supply chain [4].

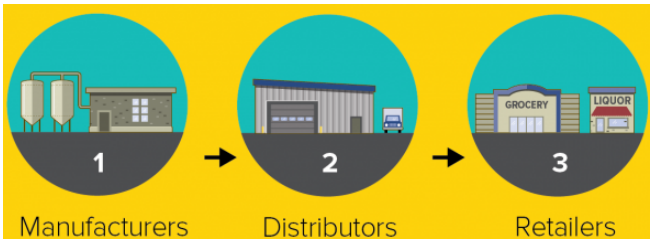


Fig. 1: The Three Tier Distribution System [7]

Demand forecasting is a notoriously challenging task for any company. Beer and alcohol sales can be affected by myriad factors such as weather conditions, supplier's price promotions and price variations, holidays and sporting events, the state of the economy, and many more [4]. Also, companies must invest time and resources into developing a forecasting technique and management style that best works for their specific needs and position in the supply chain. Management of demand forecasting includes making decisions about what information to gather, how to gather the information, who should be conducting the forecasting, what tools to use for forecasting, and what measures will be used to evaluate the forecasting [3].

Demand forecasting is, of course, not new to the alcohol distribution industry. However, in the past, forecasting has been complicated, slow, and dependent on a few employees with extensive domain expertise and experience [4]. The emergence of new forecasting methodologies has distributors and suppliers looking to advanced data analytics for more useful models. Many attempts at demand forecasting begin with traditional time series approaches that predict demand based on historical, sequential data points. Popular times series approaches include autocorrelation models such as Autoregressive Integrated Moving Average (ARIMA) and multivariate models such as Vectorized Autoregressive model (VAR). The development of machine learning advanced efforts concerning the demand prediction problem. Machine learning can harness big data that comprises more features and apply more advanced algorithms to make predictions. More recently, deep learning methods and neural networks have been applied to supply chain predictions, delivering improved results [8].

In this paper, historical data from a beer and alcohol distributor was used to forecast demand. An ensemble approach using traditional univariate time series models, multivariate models, and deep learning-based models was applied. The overall goal was to create more accurate forecasting in order to optimize inventory, improve cash flow, and enhance customer service for the distributor.

The remainder of this paper is organized as follows: In section 2, related academic works are reviewed. In section 3, the details of the methods of evaluation are presented. Section 4 has the Methods of Evaluation described, with the data and exploratory data analysis (EDA) in Section 5. In Section 6, the Experimental setup is explained, and in Section 7, we have the results and the performance

of all the models for one of the products. Section 8 describes work to test the generalization of models described in the previous section for another product. Lastly, in Section 9, this work concludes with consideration for future related studies.

2 Related Work

Traditionally, demand forecasting was dominated by time series and linear methods as they were well understood and effective on most of the problems. Deep learning models are black box but are able to learn arbitrary complex mappings from inputs to outputs automatically. In this paper, an ensemble of best of traditional models and newer deep learning models were explored and created.

Dejan Mircetic et al., in 2016, [11] created several forecasting models of beverage consumption for one of the market leaders in South-East Europe. They used an S-ARIMA model to forecast consumer beverage demand patterns because of its flexibility and ease of understanding. Root means square error (RMSE), mean absolute percentage error (MAPE), mean absolute scaled error (MASE), among others, were used as the evaluation criteria for comparing multiple models. For their weekly forecasting model, S-ARIMA$(5,0,1)(1,0,0)_{52}$ emerged as the best performing model. Their study found that models that included only autoregressive and moving average components were more successful than models that also included seasonal differencing. Surprisingly, they also found that the simple average naive forecast model outperformed S-ARIMA models that included seasonal components. They concluded that this result should be tested on other beverage companies to determine if this was particular to the company in their study, or whether it could be generalized to the entire industry. While Mircetic et al. provided a useful outline for testing and evaluating S-ARIMA in the beverage supply chain, their focus was on consumer demand instead of distributor demand, and a different result could be expected for the forecasting models in this study.

Artificial Neural Networks have been around for a long time, but with the advent of faster hardware and highly optimized open-source libraries, broad and deep neural networks have impressively and skillfully been applied to a range of problems. Deep Learning methods offer much promise for time series forecasting as well, and a lot of recent work in this area has been done on Deep Learning models.

Xinyu Hu et al. in Jan 2019 [5] proposed a regression-based Bayesian Neural Network (BNN) model to predict spatiotemporal quantities, such as hourly rider demand, with calibrated uncertainties. The paper has two contributions (i) A feed-forward deterministic neural network architecture that predicts cyclical time series data with sensitivity to anomalous forecasting events (ii) A Bayesian framework applying Stein variational gradient descent (SVGD) to train large neural networks capable of producing time series predictions, as well as, a measure of uncertainty surrounding the predictions. This BNN reduced average estimation error by 10% across 8 U.S. cities compared to a multilayer perceptron

(MLP), and 4% better than the same network trained without SVGD. Remaining interesting research questions explored different correlation structures to model time series data and investigation of the use of more structured prior distributions instead of prior independent assumptions made in the paper.

This use case is very similar to beverage demand predictions, which involve multivariate time series involving product, time, and location.

Predicting financial time series is another common use case in this problem area. Many researchers have used deep learning methods in recent years. Sangyeon Kim and Myungjoo Kang in March 2019 [9] compared various deep learning models such as MLP, one-dimensional convolutional neural networks (1D CNN), stacked long short-term memory network (LSTM), attention networks and weighted attention networks for financial time series prediction. Attention LSTM can be used not only to predict but also to visualize intermediate outputs for analysis on the mechanics of the prediction. It can help to understand why certain trends are predicted when accessing a given time series table. Their proposed model produced a 0.76 hit ratio, which was found to be superior to those of other methods. Their experiments considering 60 trading days as lookback days and 40 trading days as prediction days returned the highest hit ratio with the attention networks model. Moreover, the highest earn points were returned with weighted attention networks, as loss functions were minimized when improved at higher change ratios. These performed better with long sequential data.

Some researchers have successfully used hybrid or ensemble approaches that marry traditional time series methods with machine learning and deep learning. A study conducted by Islek and Oguducu in 2015 [6] sought to reduce demand forecasting error by clustering warehouses and sub-warehouses for a Turkish dried fruit and nut company according to their sales behavior. They then used a hybrid forecasting approach that combined a time series moving average model and a Bayesian Network machine learning algorithm and used separate models for each cluster. When using one model for all warehouses, the result was a 49% MAPE. After applying their specific models to each warehouse cluster, the researchers achieved 17% MAPE.

In 2019, Kilimci et al. [8] also used an ensemble approach for demand forecasting, this time for a Turkish retail grocery store. They integrated nine different traditional time series methods, a support vector regression (SVR) algorithm, and a deep learning multilayer feed-forward artificial neural network (MLFANN). They also created an integration strategy in an effort to combine the strengths of the different approaches into a "single collaborated method philosophy." The integration strategy considered weekly model performance and gave weight to predictions from the more accurate models for that week. They conducted forecasting on multiple product groups and found a reduction in MAPE for all groups when using their integration strategy, and further improvement was seen when their deep learning method was also employed with the integration strategy.

Hybrid models have also been employed successfully in the economic sector outside of retail distribution. In their 2018 study, M. E Nor et al. [12] merged an

S-ARIMA model with a non-linear artificial neural network (ANN) to forecast tourism demand in Malaysia. They used tourist arrival data and ran benchmarks for each individual model before equally weighting the two models for the hybrid. The ANN outperformed the SARIMA in terms of error, but the hybrid of the two reduced error by at 35.82% from the SARIMA model and at least 19.11% from the ANN model.

3 Methodologies

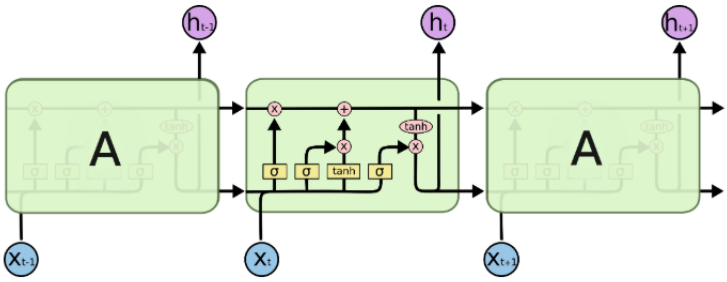
S-ARIMA: Autoregressive Integrated Moving Average (ARIMA) is one of the most widely used forecasting methods for univariate time series forecasting. ARIMA uses its own past values of the time series and has a treatment for the random factors through the use of moving averages [12]. However, it has certain limitations when it comes to seasonal data, i.e., a time series with a repeating cycle. Seasonal Autoregressive Integrated Moving Average (S-ARIMA or Seasonal ARIMA) is an extension of ARIMA that explicitly supports univariate time series data with a seasonal component. S-ARIMA model is formed by including additional seasonal terms in the ARIMA. The seasonal part of the model consists of terms that are very similar to the non-seasonal components of the model, but involve back shifts of the seasonal period.

Vector Auto-regression (VAR): VAR is a very useful statistical model that can capture linear interdependencies among multiple variables, or time series. In VAR, each time series is modeled as a function of past values and treats all variables as dependent. Unlike univariate models, VAR models are bi-directional, meaning that the model takes into account how variables influence each other. This makes VAR a standard means of modeling and forecasting in many fields, such as economics, that have a need to assess the subtleties and interrelationships between the variables of interest [10, 13].

Long Short-Term Memory Networks (LSTM): [2] Recurrent neural networks (RNN), like the Long Short-Term Memory network, or LSTM, can explicitly handle the order between observations when learning a mapping function from inputs to outputs. This works very well with sequence data, which is the case for time series input. Where standard RNNs fail to learn in the presence of time lags greater than 5-10 discrete time steps between relevant input events and target signals, LSTM can learn to bridge minimal time lags in excess of 1000 discrete time steps by enforcing constant error through "constant error carousels" (CECs) within special units, called cells. LSTMs solve both the problems of vanishing gradient and exploding gradient. A basic LSTM Network architecture is shown in below Figure 2. [14]

The first step in LSTM is the "forget gate layer", that decides what information will be thrown away from the cell state. It looks at $h_{t\text{-}1}$ and x_t, and outputs a 0 representing "get rid of this" and a 1 representing "keep this"

Next is the "input gate layer", which decides which values will be updated. A *tanh* layer creates a vector of new candidate values, $C_t^{\text{-}}$, that could be added to the step. These two are combined to create an update to the state.



The repeating module in an LSTM contains four interacting layers.

Fig. 2: Basic LSTM Architecture

New Cell state C_t is created by multiplying the old state, i.e. C_{t-1}, by the forget gate layer f_t and puts the cell state through **tanh**, C_t^-, so that it would output only the parts that were desired.

4 Method of Evaluation

Different evaluation criteria were used during different phases of model building to evaluate the model performance.

For Intermediate models, the following criteria were used:

Akaike Information Criterion (AIC): AIC is an estimator of overall model quality and widely used for model selection. It measures the relative information loss by a given model. Thus, less information loss by a model, better the model quality.

$$\mathbf{AIC} = 2k - 2\ln(\widehat{L})$$

Bayesian Information Criterion (BIC): BIC is closely related to AIC, but imposes a larger penalty for a higher number of parameters in a model as compared to AIC. Thus, models with lower BIC scores are preferred.

$$\mathbf{BIC} = \ln(n)k - 2\ln(\widehat{L})$$

where

- $\widehat{L}$ = the maximized value of the likelihood function of the model M, i.e. $\widehat{L} = p(x \mid \widehat{\theta}, M)$, $\widehat{\theta}$ are the parameter values that maximize the likelihood function;
- x = the observed data;
- n = the number of data points in x, the number of observations or equivalently, the sample size;
- k = the number of parameters estimated by the model. For example, in multiple linear regression, the estimated parameters are the intercept, the q slope parameters, and the constant variance of the error: thus, $k = q + 2$.

Forecasting errors were evaluated in terms of Average Square Error (ASE) or Root Mean Squared Error (RMSE). Lower ASE or RMSE yielding models are preferred.

$$ASE = mean((Forecasted\ Value - Observed\ Actual\ Value)^2)$$

$$RMSE = \sqrt{ASE}$$

Quality of Residuals: The models that tend to whiten the residuals the most are considered to model the trend and pattern in the dataset. Hence, models that whiten the residuals to a higher degree are preferred.

Forecasting Characteristics: Some models perform better on short term forecasts, whereas some models perform better for long term forecasts. Hence, the forecast duration also plays a vital role in the model evaluation phase. Preferred models would be those that perform better with forecast duration specified by Company A.

For evaluating the final models, both **forecasting errors**, in terms of ASE and **forecasting characteristics** of forecasts produced from the model, was used in a sequenced cross-validation manner to obtain the best fitting final model.

5 Dataset

The data set for this study was from a large American wholesale alcohol distribution company (Company A), which deals in beer, spirits, wine, and a few other alcohols. Initial data contained the total number of standard (STD) cases sold per month for different beverage types "spirit" at a distribution warehouse located in South Texas. There were different products with varying quantities for each beverage category in the dataset. The goal was to predict, given the current dataset, the number of STD cases for six months horizon into the future, and the predictions should be updated monthly.

As the testing progressed, several other factors that could affect the demand for alcohol in a month were considered and added to the dataset. These additional predictors were:

- Local weather
- Price promotions
- Marketing campaigns
- Holidays and special events (festivals, sports, concerts, etc.)

5.1 Exploratory Data Analysis

The sales and pricing data provided by Company A was for seven years (84 months), from January 2013 to December 2019. It included the target variable: the number of STD Cases ordered per month by different customers for a certain product ID. Each product ID is unique for a product of a particular size. There were no missing values in the received dataset. However, a close examination

revealed that if there was no demand for a product in a particular month, then data for that product is not recorded for that particular month.

The distributor provided us a list of attributes and metrics it has. The primary focus was to predict the demand for STD Cases. Additional sales information that the client maintains and that was not shared was Makeup Cases, House Goals, Free Goods, and Credit cases. All of these factors could impact the demand or could themselves be by-products of previous sales.

The dataset received contained 375K observations and 29 features for monthly sales and pricing data. Company A has seven distributors in Texas alone, distributing four different types of beverages, including beer, wine, spirits, and others. The alcoholic beverage considered for this study was spirits. Spirits alone had 54 different types of products, such as whiskey, flavored, vodka, etc. which had a total of 405 different brands. These brands include Jack Daniel's, 1800 Tequila, 360 Vodka, etc. All of these brands combined to 4017 unique products. Each product came in different sizes like 1L, 200M, 750M, etc. There were a total of seven sizes available. Orders were maintained as cases where a case is a unit of measure equal to a case of beer or 24 12-ounce bottles (2.25 gallons).

Based on the EDA conducted for all the spirits in the given dataset, Taaka Vodka 80 1L was found to be the most sold product in the last seven years and Jack Daniel's Black Whiskey 1L was found to be the highest revenue grossing product for the last seven years. The prediction analysis was focused on these two products, since forecasting these products accurately would benefit distribution house the most. Vodka and Scotch are two very different products with different flavors and customer appeal. The times series for cases sold for Taaka Vodka (Fig. 3) and Jack Daniel's (Fig. 4) were very different so it was expected that there would be varying factors that affect the orders from year to year; and that one demand model may not generalize to both products.

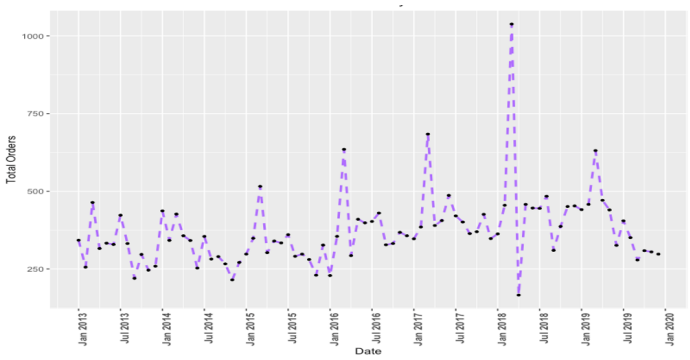


Fig. 3: Taaka Vodka 80 1L - Total Cases Sold Per Month

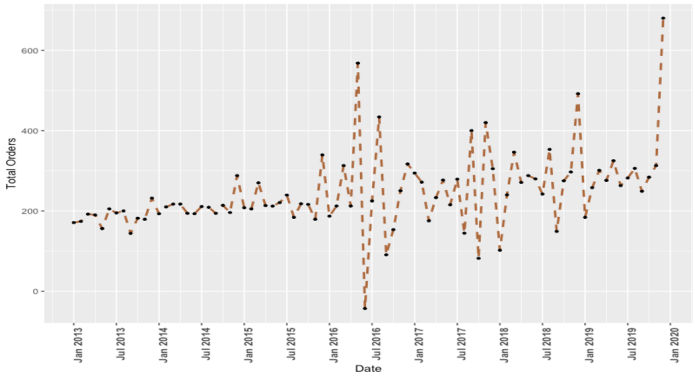


Fig. 4: Jack Daniel's Black Whiskey 1L - Total Cases Sold Per Month

6 Experimental Setup

Individual models for a particular product ID. This study began by developing a proof-of-concept model for demand forecasting for the distribution center's best selling product: Taaka Vodka 80 1L. Univariate, multivariate, and deep learning models were created and a rolling window cross-validation strategy was used to identify the best models.

The rolling window cross-validation is a technique that implements cross-validation while accounting for the sequenced nature of the time series [17]. Rolling windows, a variation of back testing, also called sliding windows, have long been used in forecasting financial data. Elements of a rolling window model include the window size, the horizon, and the rolling steps. Fig 5 graphically explains this logic. The window size is the number of data points in the training set; for our research, we used 36 months of past STD case sales data. The horizon is the forecasting window size for unseen data, which was chosen to be six months for our study. The rolling steps are the number of data points skipped on each pass [17]. The step size we applied was six so that forecasts at each step do not overlap. Each model's performance was judged on average of ASEs from the eight, six month sliding windows.

Create ensemble model Once best models from the individual model types i.e., Univariate, multivariate, and deep learning models, were identified, they were combined into a simple average or weighted average ensemble model, depending upon the relative credibility of obtained models.

Feasibility study. Next, a feasibility study was conducted to investigate whether the developed hybrid model on Taaka Vodka could be generalized to different products of the same type "spirit", but different beverage types. The other product chosen was Jack Daniel's Black 1L, the highest-grossing product for the distribution center in question.

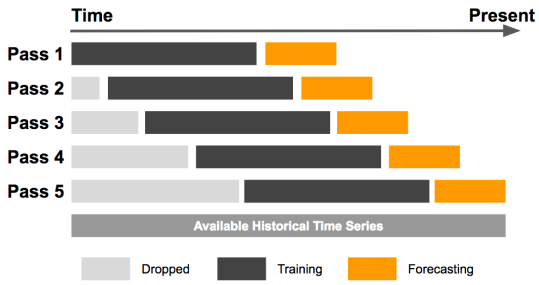


Fig. 5: Rolling Window Technique: Cross Validation Strategy For Model Selection

7 Results - Taaka Vodka

All of the model fitting began with total cases of the Taaka Vodka 80 1L product, the most sold product for this particular distribution center.

Naive Model: As a benchmark to judge the more sophisticated models, a statistical naive model was created. As per this model, predictions for a given month of a year were calculated as a simple average of the same month for the previous three years. The average ASE of all rolling windows for Taaka Vodka was found to be 12631.85. Using the naïve ASE as a benchmark allowed a better understanding of the value that was added by the more intelligent models being tested later. Figure 6 displays the forecast for the last four years with the actual sales.

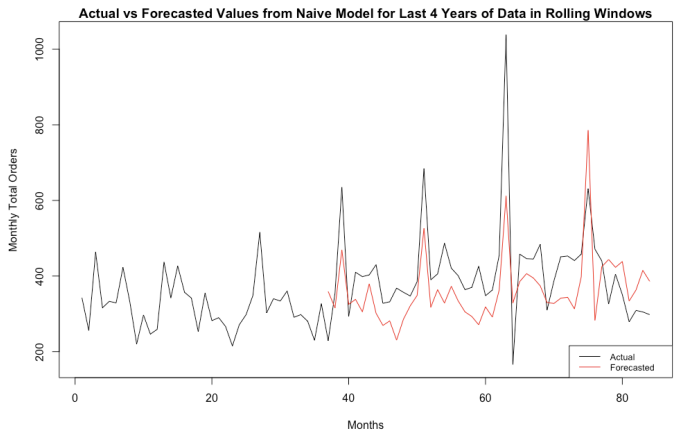


Fig. 6: Naive Model - Forecast of Total Cases per Month for Last Four Years for Taaka Vodka

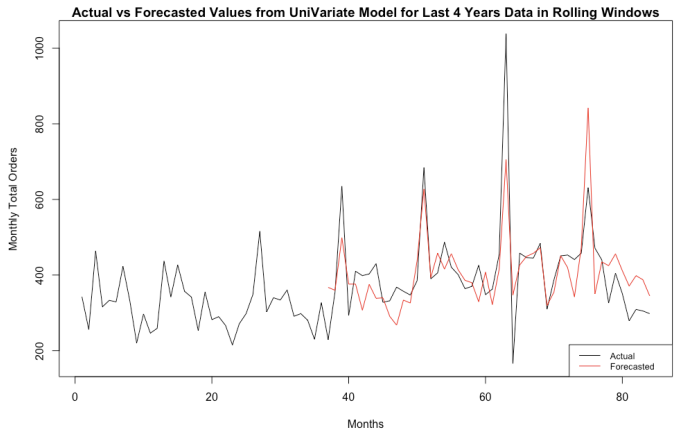


Fig. 7: Univariate Model - Forecast of Total Cases per Month for Last Four Years for Taaka Vodka

S-ARIMA: The S-ARIMA model sought to improve upon the Naive Model by exploiting any autocorrelation structure that might be present in the data. 116 univariate models were created and tested. ARIMA(12, 0,0) with a seasonality of 12 was found to have the smallest ASE of 7619.15 among these 116 univariate models, a 40% improvement from the Naive model. It was not surprising that the data showed a monthly seasonality as the number of cases per month is often similar to that of the same month in previous years. Fig 7 displays the forecast of the last four years with the actual sales using the univariate model

Vector Auto-Regression (VAR): The VAR modeling began with a bivariate approach using the number of cases sold and the average price per case for the Taaka Vodka with various seasonality and lag. Then, to improve forecasting further, weather data was added to the model. Weather conditions have been found to influence retail sales and the type of goods purchased by consumers [15]. This weather data was obtained for the distribution center's region from the National Oceanic and Atmospheric Administration's (NOAA) Climate Data Online service [1]. After cleaning the data, the average monthly temperature and average monthly rainfall were added to the monthly time series. However, we found out that, for this product, the addition of the weather data lead to increased noise in predictions, and hence, these weather predictors were subsequently removed. The final multivariate model, a VAR(lag=3), displayed monthly seasonality and attained an ASE of 9852.90. This was a 22% improvement over the Naive Model. Figure 8 displays the forecast for the last four years with the actual sales using the VAR model.

Long Short-Term Memory Networks (LSTM): LSTMs, amongst the deep learning models, are known to be well-suited for making predictions based on time-series data. Each of the LSTM models was run on 36 different lookback window sizes, or lag, i.e., how many previous inputs were used to predict the

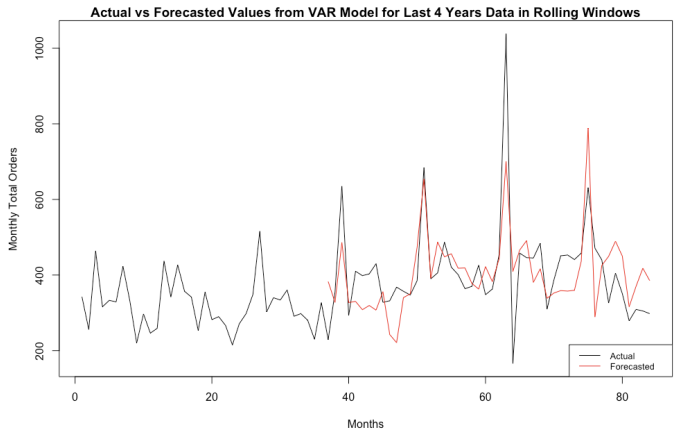


Fig. 8: VAR Multivariate Model - Forecast of Total Cases per Month for Last Four Years for Taaka Vodka

next value. The initial approach was to apply a base LSTM model to the time series data in a univariate fashion. The best rolling window ASE obtained was 4670.468 for a look back size of 10. As part of our study, we enhanced the LSTM model by adding other predictors as auxiliary inputs to the model. Based on the data received from the client, price was the only other predictor that could be used as an auxiliary input. It was also identified during the exploratory data analysis(EDA) that impending price changes could affect product sales. Because of this identified lagged relationship between sales and average product price, in which price changes in immediate past influence future sales, models with price difference instead of contemporary price performed better. During our literature review, it was found that holidays or football season could impact sales of alcohol. Company A did not supply this data, so additional variables were created to define the number of national holidays in a month; and the months that are the primary season for NFL or college football. These additional predictors were appended to the monthly sales data, and new models were created by adding a combination of these as auxiliary inputs. Auxiliary inputs were added as linear sequences to the output of LSTM. Based on the tests conducted, the model with auxiliary input from the last lagged input i.e., from t-1, gave the minimum rolling window ASE.

This model took an input of sales, the size of which was based on the lookback value, and passed through an LSTM layer with 32 hidden units. If there was an auxiliary input(s), it was concatenated with the LSTM output and then passed through 3 Dense layers with 64 hidden units and activation function as 'relu'. A final output layer was added with the number of outputs as six, representing the next six months' predictions and an activation function of 'sigmoid'. The model was compiled using mean_squared_error as the loss function and 'adam' optimizer.

Table 1: ASE of best models amongst different LSTM models for Taaka Vodka

LSTM Models	**#models**	**ASE of best model**	**lag**
tuned_baselstm	36	4670.468	10
lstm_price_last_lag_auxinput	72	7309.540	28
lstm_price_hol_games_auxinput	108	6668.175	34
lstm_pricediff_auxinput	36	2960.519	15
lstm_pricediff_avgTemp_avgRain	36	6934.131	26

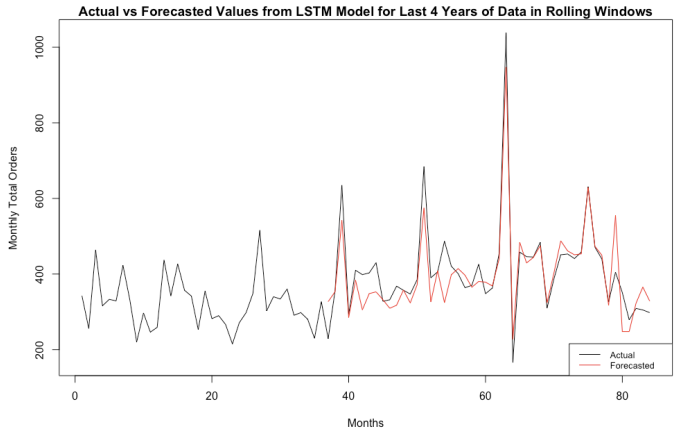


Fig. 9: LSTM Model - Forecast of Total Cases per Month for Last Four Years for Taaka Vodka

The best LSTM model used impending price change and achieved an ASE of 2960.519, a significant 76% improvement over the naive model ASE. The table below (Table 1) provides the summary of LSTM models created with corresponding ASEs obtained for the best model and the Figure 9 displays the forecast for Taaka Vodka using the model with the lowest ASE (lstm_pricediff_auxinput), which had the smallest ASE amongst the LSTM models tested.

Ensemble: Finally, an ensemble demand forecasting model was created integrating best identified univariate, multivariate, and LSTM models. An ensemble model could avoid possible over or under-fitting present in its constituent models. Any shortcomings of one model would be compensated by the rest of the models in the ensemble. For Taaka Vodka, a weighted ensemble was employed that combined the models in ratio to their accuracy. Weighting the ensemble allows the more accurate model (the LSTM in this case) to have more importance in prediction than a less accurate model. To create the weighted model, the mean ASE of the three models were summed to create the total error. This total error was used to weight each model individually using their mean ASE. The weight of the model was computed as ASE or the model divided by total ASE from all the models in the ensemble. These weights were then multiplied

by their corresponding model forecasts, and the result was summed. Lastly, this total was divided by the sum of the weighted ASEs. The weighted ensemble model achieved an average ASE over all rolling windows of 3633.82, a 71% improvement over the naive model ASE. A graph of the ensemble forecast and the actual monthly cases of Taaka Vodka sold is displayed in below Figure 10.

Table 2 provides a summary of the total number of models created and tested for Taaka Vodka and the best-identified model with the smallest ASE for each of the model types.

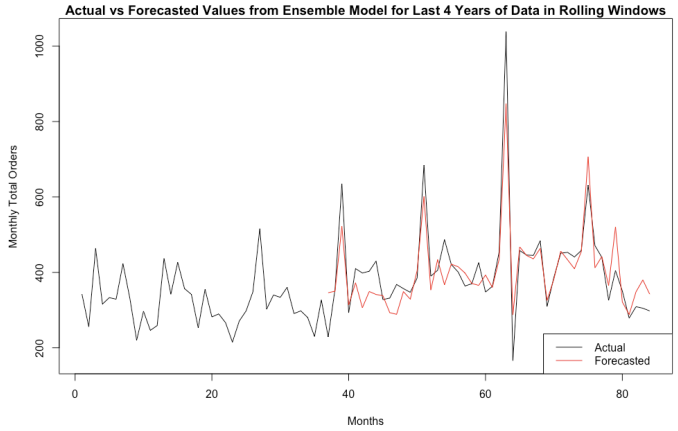


Fig. 10: Ensemble Model - Forecast of Total Cases per Month for Last Four Years for Taaka Vodka

Table 2: Summary of demand models tested and best ASE for Taaka Vodka

Model Type	**No. of Models Created and Tested**	**Best Identified Model ASE**
Intuition based Naïve Model: The Benchmark	1	12631.85
Univariate Model	116	7619.15
Vector Autoregressive Model , Multivariate	30	9852.90
LSTM	288	2960.52
Ensemble	2	3633.82

8 Results - Jack Daniels

Naive Model: As was done with the Taaka Vodka, a statistical naive model was created based on the averages of the same month from the previous three years. The average ASE of the all rolling windows was 14521.89. Figure 11 displays the forecast for the last four years in rolling windows with the actual sales using the naive model.

S-ARIMA: A univariate model was explored, but the time series had inconsistent variance that resembled a white noise pattern. It was decided to split the time series into two parts and then model each part as a separate process. However, even after splitting the series at the point of change in variance, the two obtained sub time series still resembled white noise pattern. It was then decided that a univariate model would not be an appropriate choice for this time series.

Vector Auto-Regression (VAR): For Jack Daniel's Whiskey, 52 different VAR models were explored, starting with the following predictors included in the model: the number of cases sold, the average price per case, the average monthly temperature and rainfall for the area with various different combinations of seasonality and lag. Later, interactions among these variables with different lag values were also added into the models. This was done to increase the complexity in the models as base VAR models, without interaction terms, demonstrated high bias. Time was also added as an exogenous variable. Best identified VAR model included the following variables as suitable predictors: Sales, Average Price, Average Rain, Average Temperature, Exogenous time variable, the interaction between rain and time, the interaction between price, temperature, and

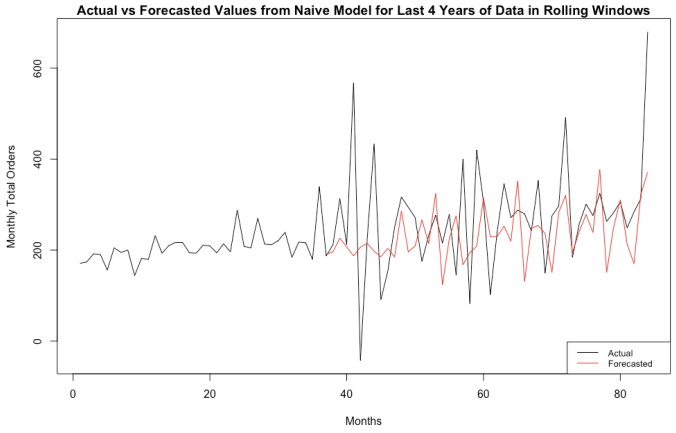


Fig. 11: Naive Model - Forecast of Total Cases per Month for Last Four Years for Jack Daniels

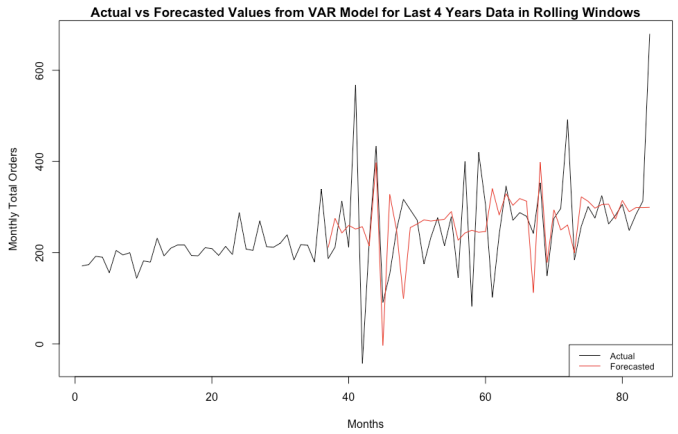


Fig. 12: VAR Multivariate Model - Forecast of Total Cases per Month for Last Four Years for Jack Daniels

time; and interaction between price, rain and time. This final multivariate model achieved an ASE of 14402.26. This was only a 1% improvement over the Naive Model for Jack Daniels product. Figure 12 displays the forecast for the last four years with the actual sales using the VAR model.

Long Short-Term Memory Networks (LSTM): Considering some of the learning from the models created for Taaka Vodka, a fewer number of models were tested for Jack Daniels. The top-performing LSTM models were the models with price difference and base LSTM model without any auxiliary input. For the first mode, the price difference for the last available month was considered. All LSTM models were tested for 36 lags or lookback values, so a total of 72 models were created and tested for Jack Daniel's product. The model with price difference gave the minimum ASE of 3893.45 at a lookback value of 28, meaning that for predicting the next six months of sales, 28 previous sales were considered. Figure 13 displays the forecast for the last four years with the actual sales using the LSTM model.

Ensemble: For Jack Daniel's ensemble model, a simple average ensemble approach was used. The difference in the results from VAR and LSTM models was significant. LSTM tends to overfit with the small amount of overall training data we had; hence a simple ensemble in which both models contributed an equal amount to the final prediction seemed fit. The ensemble model attained an average ASE overall rolling windows of 6413.11, a 56% improvement over the naive model ASE. A graph of the ensemble forecast and the actual monthly cases sold of Jack Daniel's Whiskey is displayed in below Figure 14.

Table 3 provides a summary of the total number of models created and tested for Jack Daniels and the best-identified model with the smallest ASE for each of the model types.

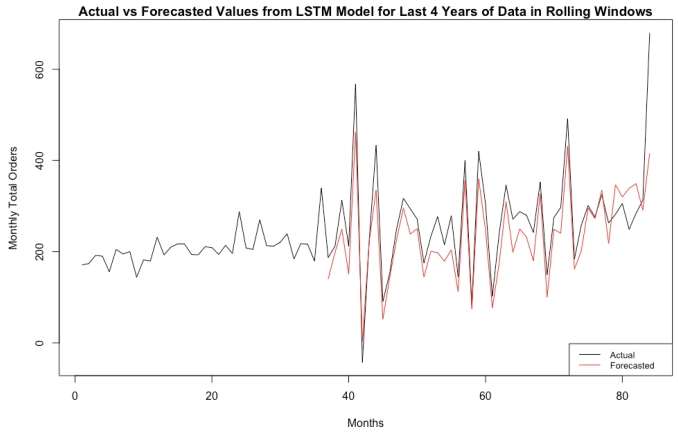


Fig. 13: LSTM Model - Forecast of Total Cases per Month for Last Four Years for Jack Daniels

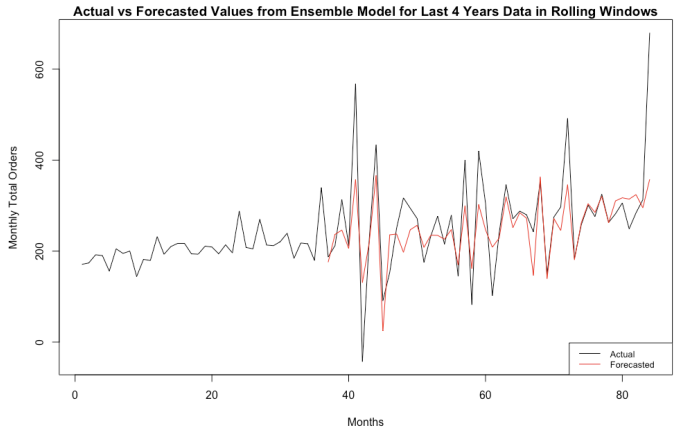


Fig. 14: Ensemble Model - Forecast of Total Cases per Month for Last Four Years for Jack Daniel's Whiskey

Table 3: Summary of demand models tested and best ASE for Jack Daniels Whiskey

Model Type	**No. of Models Created and Tested**	**Best Identified Model ASE**
Intuition based Naïve Model: The Benchmark	1	14521.89
Univariate Model	N/A	N/A
Vector Autoregressive Model , Multivariate	52	14402.26
LSTM	72	3893.45
Ensemble	1	6413.11

9 Conclusion

In this study, analysis and forecasting using the last seven years of available monthly sales data for two alcoholic beverages: Taaka Vodka and Jack Daniel's Whiskey, each with a different time series, was conducted. These products were the most sold and highest revenue grossing products, respectively, for the distribution center in question. Using ensemble models that harnessed naive, univariate, multivariate, and LSTM models, an overall reduction was achieved in the monthly forecasting error, as compared to the naive model for the total number of standard cases sold. The monthly forecasting error, in terms of RMSE, was reduced by nearly 50% for Taaka Vodka and nearly 33.5% for Jack Daniel's Whiskey. For the distributor, this improved forecasting translates to a real-world reduction in the error in the number of cases sold each month. For Taaka Vodka, the ensemble model reduced monthly error from $\pm$ 112 cases to only $\pm$ 60 cases. For Jack Daniel's Whiskey, the ensemble model reduced monthly error from $\pm$ 120 cases to only $\pm$ 80 cases.

Additionally, it was found that models created for Taaka Vodka could not be generalized to the Jack Daniel's Whiskey. This led to the conclusion that there is no "one size fits all" model for all products sold by the distributor. Different products can have widely varying demand patterns and hence, command different models for sales forecasting. Understanding the individual sales data for the different products sold should lead to better efficiency in stocking, storage, and sales for Company A's distributor.

9.1 Future Work

Looking at the distributor perspective, they would be interested in the aggregate demand of the product for a month, that would help them maintain inventory without over-housing products in their warehouse. However, each client could have different purchasing patterns, and hence, modeling demand at the individual retail customer level and not just at aggregate level could reveal different and interesting findings. Our study also lays the groundwork for the creation of an autoML framework that could create a slightly naive but useful model for each product and brand combination present in the dataset. Since these models would be generated in an automated fashion and not manually, these would provide significant value addition for the product house.

References

1. Climate data online - the national climatic data center, https://www.ncdc.noaa.gov/cdo-web/
2. Brownlee, J.: A gentle introduction to long short-term memory networks for the experts (May 2017), https://machinelearningmastery.com/gentle-introduction-long-short-term-memory-networks-experts

3. Danese, P., Kalchschmidt, M.: The role of the forecasting process in improving forecast accuracy and operational performance. International Journal of Production Economics **131**(1), 204–214 (2011), https://www.sciencedirect.com/science/article/pii/S0925527310003282
4. Eisenstein, M.: Hitting the mark. Nature methods **11**(9), 894 (Sep 2014), https://www.ncbi.nlm.nih.gov/pubmed/25317456
5. Hu, X., Szerlip, P., Karaletsos, T., Singh, R.: Applying svgd to bayesian neural networks for cyclical time-series prediction and inference. arXiv.org (2019), iD: proquest2168396692
6. Islek, I., Oguducu, S.G.: A retail demand forecasting model based on data mining techniques. pp. 55–60. IEEE (Jun 2015), https://ieeexplore.ieee.org/document/7281443
7. Johnson, S.: History, politics shape wisconsin's alcohol laws (May 2019), https://www.wpr.org/history-politics-shape-wisconsins-alcohol-laws
8. Kilimci, Z.H., Akyuz, A.O., Uysal, M., Akyokus, S., Uysal, M.O., Atak Bulbul, B., Ekmis, M.A.: An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain. Complexity **2019**, 1–15 (Mar 26, 2019), https://search.proquest.com/docview/2204833037
9. Kim, S., Kang, M.: Financial series prediction using attention lstm. IDEAS Working Paper Series from RePEc (2019), iD: proquest2188166324
10. Liu, Y., Roberts, M., Sioshansi, R.: A vector autoregression weather model for electricity supply and demand modeling. Journal of Modern Power Systems and Clean Energy **6**(4), 763–776 (Jul 2018), https://search.proquest.com/docview/1993572747
11. Mircetic, D., Nikolicic, S., Maslaric, M., Ralevic, N., Debelic, B.: Development of s-arima model for forecasting demand in a beverage supply chain. Open Engineering **6**(1) (Nov 4, 2016), http://www.degruyter.com/doi/10.1515/eng-2016-0056
12. Nor, M.E., Nurul, A.I.M., Rusiman, M.S.: A hybrid approach on tourism demand forecasting. Journal of Physics: Conference Series **995**, 12034 (Apr 2018)
13. Nyberg, H., Saikkonen, P.: Forecasting with a noncausal var model. Chemometrics and Intelligent Laboratory Systems **73**(2), 263 (2004), https://www.sciencedirect.com/science/article/pii/S0169743904001820
14. Olah, C.: Understanding lstm networks (August 2015), https://colah.github.io/posts/2015-08-Understanding-LSTMs
15. Starr-McCluer, M.: The effects of weather on retail sales (January 2000), https://ideas.repec.org/p/fip/fedgfe/2000-08.html
16. Thomopoulos, N.T.: Demand Forecasting for Inventory Control. Springer (2016)
17. Yang, R.: Omphalos, uber's parallel and language-extensible time series backtesting tool (Jan 24 2018), https://eng.uber.com/omphalos/