Strategic Sourcing Analytics: Role of Data Science

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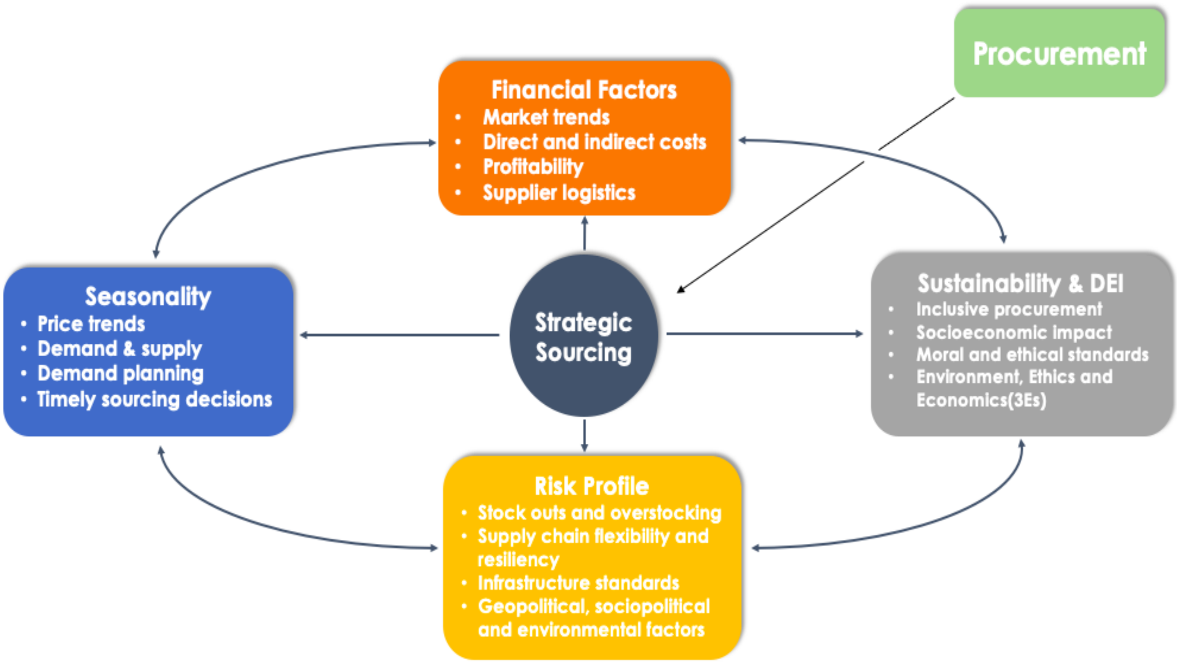
Introduction

The objective of this assignment was to research how data science techniques can be incorporated into the process of strategic sourcing analytics, which can potentially lead to enhancements and optimizations in supply chain operations. More precisely, it was centered around the question, "What is the optimal time for taking sourcing decisions like negotiating with the supply chain vendors?".

To begin with, what is Strategic Sourcing? It is a very exhaustive and comprehensive study of different vendors or sources available in the marketplace for availing goods and services. It allows a firm to have a bird's-eye view of the whole supply chain landscape and take intelligent decisions which can lead to a lower total operating cost, in the long run, rather than a simple lowering of the purchase cost for the materials in question. In the following sections, we will look at some of the most dominant factors which influence strategic sourcing decisions, what are the benefits of considering them as factors in our strategic sourcing portfolio, and how top firms like Unilever and Pfizer take care of these factors in their strategic sourcing operations and finally how data science can be of help to take these factors into account to provide solutions.

1 Influencers of Strategic Sourcing

These are 4 of the most dominant factors which influence strategic sourcing decisions and the points noted below them are some of the features of these influencers; they indicate the context in which they contribute to strategic sourcing decisions.



1.1 Financial Factors

Following and keeping up with contemporary market trends like advancements in technology and manufacturing methodologies and investing in them can be crucial for competitive sourcing. Then direct and indirect costs can be sectors of great concern since transparency is important to be established in order for a firm to work smoothly. Profitability, or the amount that a firm makes after all the transactions are done, needs to be considered and planned for as well; suppliers should follow practices that maximize profitability. Lastly, supplier logistics like negotiations, scalability, flexibility, lead times, OTIF scores, etc. are crucial for forming a budget, hence it is a huge factor to be considered as well.

1.2 Seasonality

The second factor considered is seasonality. Seasonality is essentially a pattern in time series data that gets repeated after regular intervals of time, this time frame can be anything from a day, week, month, year, or even decades. The idea behind seasonality being a factor for strategic sourcing is that if we can capture the essence of these patterns using statistical or machine learning algorithms, we can have foresight regarding what to expect in terms of demand and supply, and we can plan demand production which can ultimately lead to timely decisions, better inventory management, less wastage and an overall increase in optimization.

1.3 Risk Profiling

Risk profiling is another important factor that must be accounted for in strategic sourcing, these are scenarios you'd like to anticipate and be prepared for in order to avoid losses. Problems like stockouts and overstocking can lead to huge losses and a decline in the company's face value since flexibility and resiliency of your supply chain to external factors come under question. Infrastructure standards are important to be maintained for a smooth flow of transactions. And geopolitical and sociopolitical factors like wars, famines, earthquakes, etc. should also be prepared for in advance by assessing current events.

1.4 Sustainability and DEI

This is quite a prevalent factor in the industry right now, although not the focus of this task, inclusive procurement has proved to have commercial benefits and positive socioeconomic impacts; so much so that the investors are very keen on investing in firms that promote diversity and pursue an environment-friendly approach in their operations. The values of ethics and morals in terms of providing equal opportunities and benefits are becoming more and more important in the industry now.

2 Benefits of considering these factors in Strategic Sourcing

In the following sections, we will explore the benefits of considering the above-mentioned factors in Strategic Sourcing.

2.1 Benefits of Strategic Sourcing: Financial Factors

Monitoring all the direct and indirect costs like Labor, freight distribution, machinery and technology, rent, staff training, administrative expenses, etc. is a crucial process since transparency in all the affairs concerned with finance is of great importance. Strategically considering these factors can lead to greater control over spend and returns for the business.

Supplier logistics are also important to be considered since they are the backbone of the entire supply chain. Features like scalability, flexibility, lead times, and reliability(or OTIF) scores need to be monitored. Since the process of acquiring trustworthy suppliers is a drawn-out and difficult process that may go on for months worth of research, negotiations, RFP drafting, etc. it is considered that building up good relationships with the vendors is very important. It can also lead to better negotiations and opportunities for collaborations in the future.

2.2 Benefits of Strategic Sourcing: Seasonality

Here we will look at some questions which would make you think about seasonality in terms of demand and supply, historical price trends, and ultimately how demand forecasting can help you in answering these questions.

1. How often do you project to replenish your warehouse needs supply? This depends, of course, on the demand and supply of the product in question and since the process of warehouse replenishment is very time-consuming and costly(involves labor, rent, transportation, planning, etc.), it would be beneficial if we could have some sort of foresight regarding what the demand could be in the next life cycle. We can be better prepared for things if we can anticipate them. The next question would be 2. How can we use this information that we already have, in terms of the historical records of price trends and all the patterns in them, like seasonality, up trends, down trends, etc. how can we use that to cut costs and make the whole process more efficient? And 3. Do you know, what is the right time to capitalize on these things by taking sourcing decisions like negotiations with your suppliers? These things can be addressed by demand forecasting. Demand forecasting is essentially an exercise to determine what is likely to happen given the historical data(in terms of demand).

Thus benefits of demand forecasting are better operational efficiencies which ultimately lead to good customer experience, preparedness for risks, improved lead times, financial savings, better use of resources and overall spending, and also better production planning via inventory management.

2.3 Benefits of Strategic Sourcing: Risk Profiling

The benefits of risk profiling, as already mentioned before are more focused on avoiding the problems of inventory build-up (dead stock which leads to a lot of wastage) and stock-outs(which can lead to a bad reputation for the company). The resiliency and flexibility of the supply chain to changing needs need to be optimized and having foresight in terms of forecasts can help here as well. Identifying areas which need process optimization cost-cutting and avoiding losses by anticipating some anomalies or risks early on can lead to a better supply chain flow.

2.4 Benefits of Strategic Sourcing: Sustainability and DEI

Diversity in inclusion is beneficial for the following reasons:

It provides better opportunities for creativity and problem-solving via a diverse workforce because diversity brings a wide variety of people with different experiences, skills, perspectives, and insights together to solve problems. Then we have the advantage of having access to new markets because the more diverse your suppliers are, the more diverse your reach would be via these suppliers, and that can get you access to new avenues in terms of markets. And naturally, with all these benefits, you will have a competitive advantage compared to the conventional homogeneous workplace.

And the following are some facts and trends in the industry right now showcasing the advantages of having an environment-friendly approach. Investors actually eliminate prospects based on criteria like Environmental, Social, and Governance(ESG score is a measure of a company's exposure to long-term environmental, social, and governance risks.) and Socially responsible investing(SRI) scores.

3 Strategic Sourcing practices by top firms

Here we'll look at how firms like Unilever and Pfizer(direct competitors to JNJ) are taking advantage of strategic sourcing, particularly by taking care of the above-discussed factors.

3.1 How Industries are doing it: Seasonality and Demand Forecasting at Unilever

Unilever USA is considered to be one of the most complex and biggest companies under Unilever and until recent times, they were using statistics-based naive approaches for forecasting and demand planning. Hence the process was not as accurate and robust. So they decided to incorporate data science into the whole forecasting process and they made use of advanced deep learning based forecasting algorithms for predictions. They haven't mentioned which algorithm has been used in particular, however, it is mentioned that they have used features like the point of sale sales, seasonality, promo investments, and national holidays as input features, so it is obviously a multivariate time series model and since we are talking about Unilever, it is safe to assume that they must've had a lot of data to train these models. So most likely it must've been a deep learning model with LSTM-based architectures like the DeepAR. And the platforms that they used to develop this model were Domo and Anaplan. Domo is similar to PowerBI and Tableau, it is primarily used for dashboarding and visualizations. Anaplan is a Web-based enterprise platform for developing applications very similar to Dataiku.

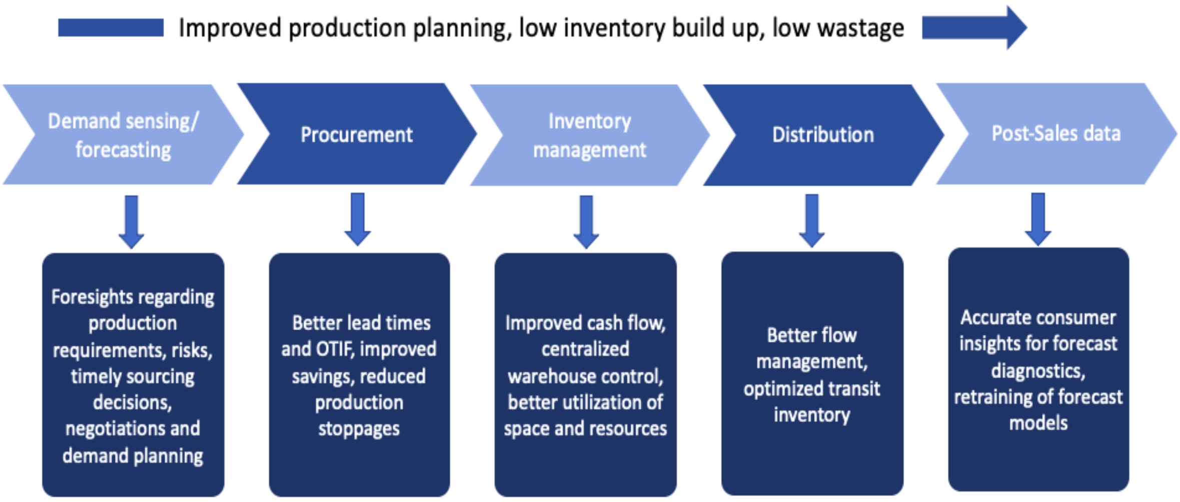
3.2 How Industries are doing it: Finance planning at Pfizer

Pfizer has this portal developed called the "Supplier Network Collaboration" or SNC, it allows collaboration between Pfizer and its trading partners from all over the world for demand proposals. Primarily it has two modules: Purchase Order Collaboration(POC), which is used for the MRP planning process, basically creates and releases Purchase Orders with all the key procurement information like forecasts, budget, time frames, and inventory level requirements to all the suppliers; basically like a request for proposal draft. Then the suppliers can make use of the "Supplier Managed Inventory" or SMI module to analyze the requirement and propose a replenishment plan. It is basically like the whole RFP process, just that it happens internally within Pfizer. This makes the whole process very streamlined, centralized, and transparent.

3.3 How Industries are doing it: Risk Profiling at Pfizer

This is another instance where forecasting was put to good use by a company which led to a successful outcome. The risk management team at Pfizer, when they witnessed all the problems that they had to face in Asia during the early stages of the pandemic, they prepared themselves for the 1st wave which was about to hit Europe in the spring of 2020. They devised a comprehensive preparedness plan which enabled their outlets to handle the tremendous increase in demand(which was more than 200 percent) for some ICU medicines. So they manufactured and shipped these materials at around 150 percent of the forecasted values. Following were the areas of focus: effective forward planning or demand forecasting, agility in reallocating supply, regulatory flexibility, and efficient inventory replenishment. Basically, these come under inventory management which relies a lot on demand forecasting. This led to the successful handling of demand in Europe via efficient forecasting.

4 Strategic Sourcing Value Stream: Demand Forecasting



The figure above depicts the value stream for demand forecasting. Each step mentions what value is being derived from that step and how it is contributing to the whole process(given the previous step is implemented correctly). The overall aim of demand forecasting is the optimization of production planning and avoiding losses due to inventory build-up or stockouts.

Stage 1: So to begin with, we have demand forecasting as the first stage. What do we get out of it? Foresights regarding production/replenishment requirements, risk assessments, sourcing decisions(like negotiations) to be taken, and demand planning that can be done thereafter. These foresights lay the foundation for an intelligent procurement plan.

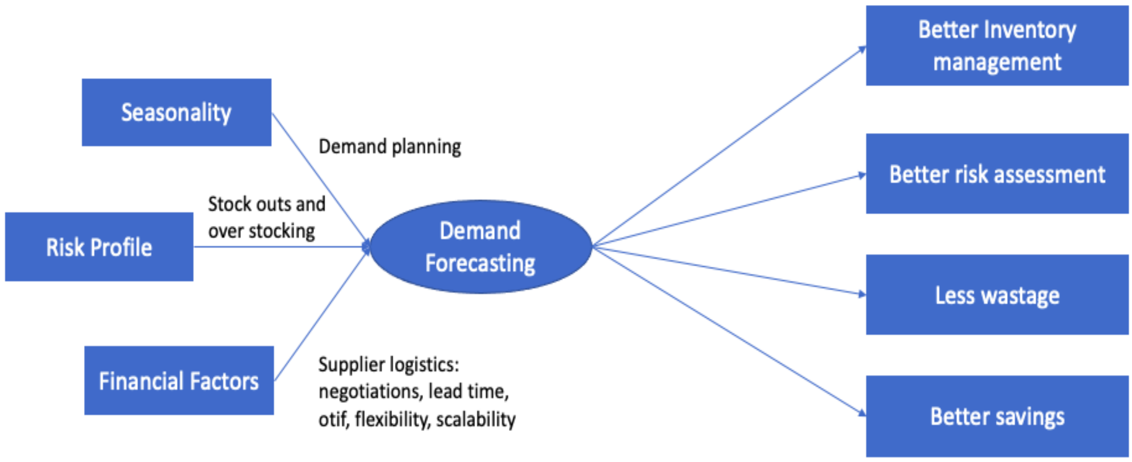
Stage 2: Then we go for procurement, if the estimates from the previous step were proven to be correct, and we achieve the goal of better negotiations, we can have a smooth procurement process which leads to better lead times, better OTIF scores, cost savings, and reduced production stoppages. This paves the way for better inventory management.

Stage 3: In the third stage, we have inventory management. Once we procure all the required products in their optimal quantities, management of inventory becomes easier and the benefits derived from it are improved cash flow, centralized warehouse control, and better utilization of space and resources. Inventory management is one of the most prevalent use applications of demand forecasting.

Stage 4: Then we have the distribution phase, here we get better flow management and an optimum amount of transit inventory. As the name suggests transit inventory is the inventory that has been shipped by the seller but has not yet reached the buyer's destination. Since the inventory is in-transit it is also called pipeline inventory. It is a crucial aspect of inventory management since it needs to be handled carefully taking into factors like ownership, safety, and other terms and conditions.

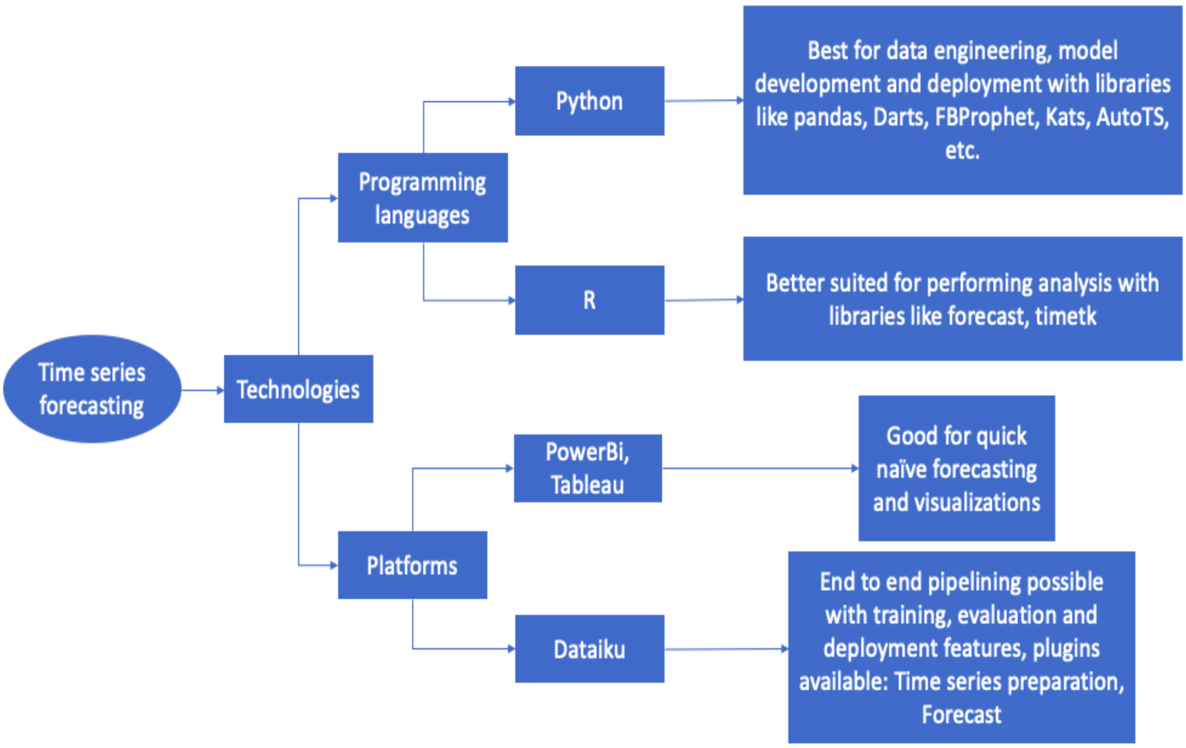
Stage 5: The last phase consists of post-sales data collection, we can make use of this data for forecast diagnostics(it is like feedback on the performance of our model). You need to look into areas like the accuracy of the model, the severity of the errors on your demand planning, do you need to add any extra external factors which may potentially increase the accuracy of our model, etc. This can be used for model retraining as well because forecasting is an iterative process.

5 Demand Forecasting Landscape



This is the landscape of the application, all the factors that are in discussion(except for sustainability and DEI), are considered(keeping in mind the mentioned key challenges in them) to build a demand forecasting solution, which can lead to a number of benefits like better inventory management, better savings, less wastage(dead stock) and better risk assessment.

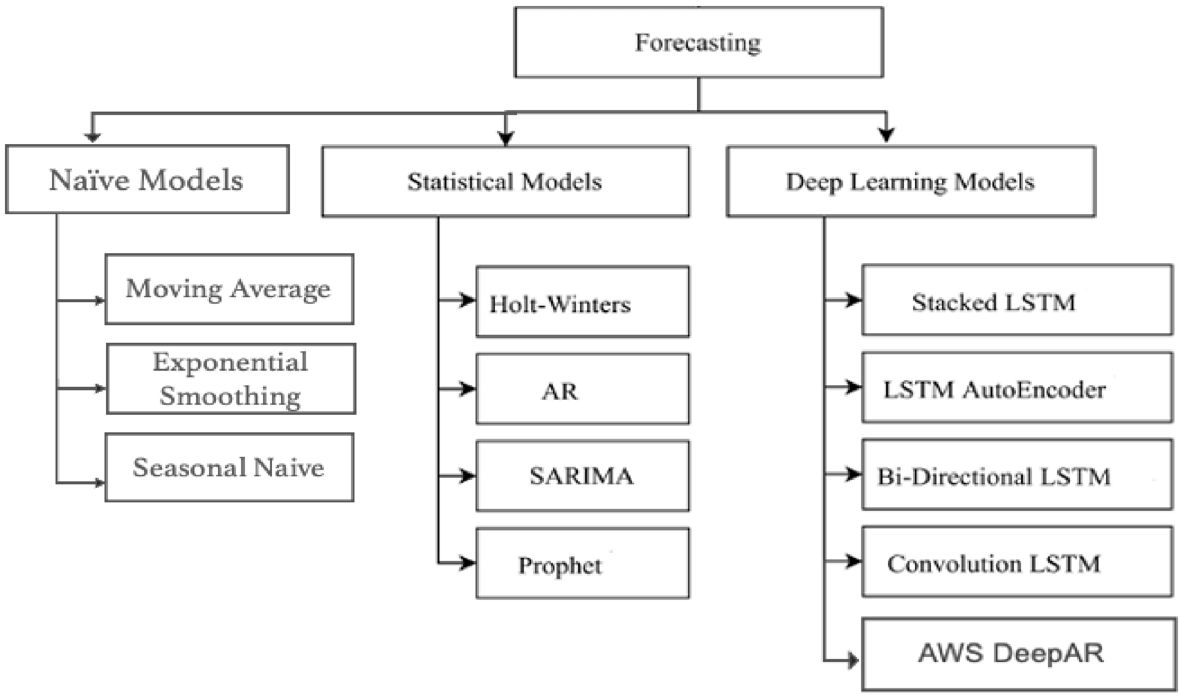
6 Data Science Applications - Technologies



Here, the most common technologies for performing time Series Forecasting have been explored. It is divided into two parts, 1. Programming languages used and 2. Platforms/tools for implementing the solution. In programming languages we have python and R. R is better suited for data exploration and statistical analysis. Statistical tests like stationary tests, seasonality tests, decomposition, auto-correlation/ partial auto-correlation tests, and others can be performed easily. On the other hand, python is good for data engineering, model training, and deployment. The libraries which can be used for these tasks are also mentioned in the figure.

Then we can take a look at the platforms available, we have dash-boarding platforms like PowerBI and Tableau for quick naive-based forecasting and visualizations and we have Dataiku for complete end-to-end pipe-lining. The most important plugins are Time series preparation and Forecast. Dataiku also provides the option of Visual Machine learning via the Dataiku lab. It is very convenient to use and has all the features included in the previously mentioned plugins.

7 Data Science Technologies: Most used algorithms and techniques in Demand Forecasting



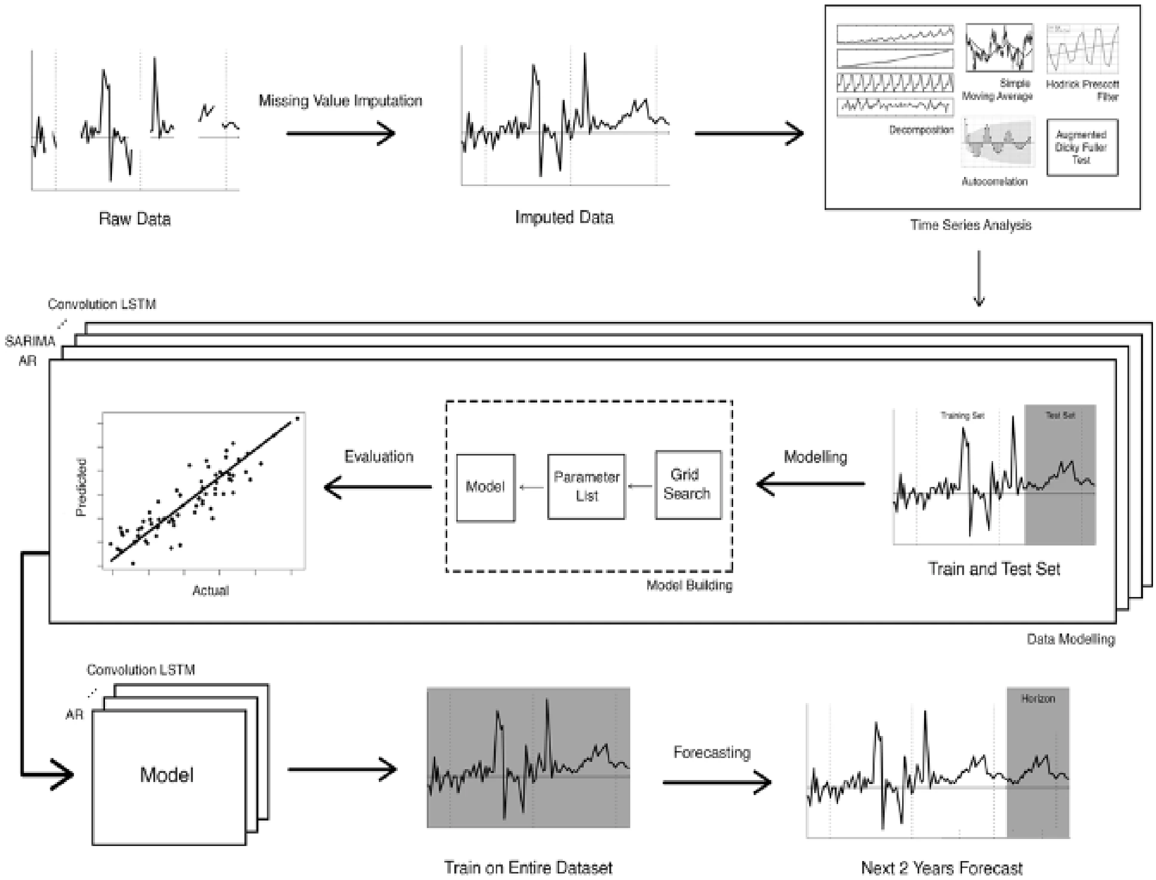
This is a list of some of the most commonly used time series models. It is divided into statistical-based and deep learning-based models(and statistical-based naive forecasting as well but they are deprecated as of now). In a statistical-based approach, we try to model our algorithm according to statistical tests and assumptions like the ones we consider during linear regression for eg. it tries to look at the distribution of the data and models the parameters accordingly. On the other hand, deep learning makes use of complex optimization techniques to learn the parameters or weights to closely replicate the data. Deep Learning can learn the data very well, but since it needs to perform complex computations, it requires a lot of records and it can also run into problems like over-fitting. These are some of the most commonly used time series models in the industry right now: (S)ARIMA, FBProphet, and LSTMs.

ARIMA or Autoregressive Integrated Moving Average is a very popular method used in time series forecasting. Autoregression is nothing but the relation of the current state data points with the previous data points. And moving average is the rolling average, so the model tries to quantify both of these properties to model the data and give predictions. It is fairly simple to interpret, but it only works best for short-horizon forecasts. Since, at its core, it works on the concept of regression, it is not suitable for volatile data, or data with a lot of outliers. And the process for selecting the best variant of ARIMA is the Box-Jenkins methodology.

FBProphet is a very powerful library for time series problems, developed by Facebook in 2017. It works very well with data that has different levels of seasonality in it, hence it is preferred for sales/retail data. It can also work with multi-variate data and it gives you a lot of choice in terms of tunable parameters, like holidays, trends, frequencies of different scales, etc.

Lastly, we will discuss the deep learning based Long Short Term memory(LSTM) models. Since it works on the concept of deep learning, it can give you very good results, but it can also run into the problems like overfitting, and getting rid of that can be difficult. Again, since deep learning is the concept being used, we need to have a lot of data for training which can be a constraint for small-scale firms. It is available in different variants like the plain and simple Vanilla LSTM, the Bidirectional LSTM(which takes into account the context vector), or Stacked LSTM which is just vanilla LSTM stacked on top of each other for more memory. Each of these variants has its own unique pros and cons.

8 Data Science Technologies: Time Series modelling process



Here we will look into some of the technical aspects of training a time series forecasting model.

Time series forecasting or modelling is the process of training a model on sequential historical data so that it can forecast future values. The figure above shows the whole process of time series modelling in a brief manner. In the initial stage, we have data in its raw form, with all its imperfections like in this case we have missing values. Whatever the issue with our raw data is, we get it fixed by performing some feature engineering, like in this case they had to implement missing value imputation and re-sampling. Then, once the data is in a proper format, we take it forward for time series analysis. Time series analysis is a drawn-out process, we take our time to really understand the nature of the data at hand, we run a lot of tests and find out what the decomposed version of our data looks like, whether it showcases stationarity, whether it is seasonal, what kind of trends is it following, what is the amount of auto-correlation present, etc. because these findings can help us narrow down our choices for the models that we are planning train the data with. Then the second stage is quite common for all machine learning projects, we take the list of models that were considered after the analysis, and we run the following process on each of those models: train and test split of the data series, then select a model to train on and perform hyper-parameter tuning, then evaluate the predictions vs actual values. Once this process is done, we get our best among the bunch model, which has the highest accuracy score (or least error score). The performance can be evaluated on any of these metrics: forecast bias, mean absolute deviation, and mean absolute percentage error. Then finally, the best model is used to perform forecasting for the desired time frame.

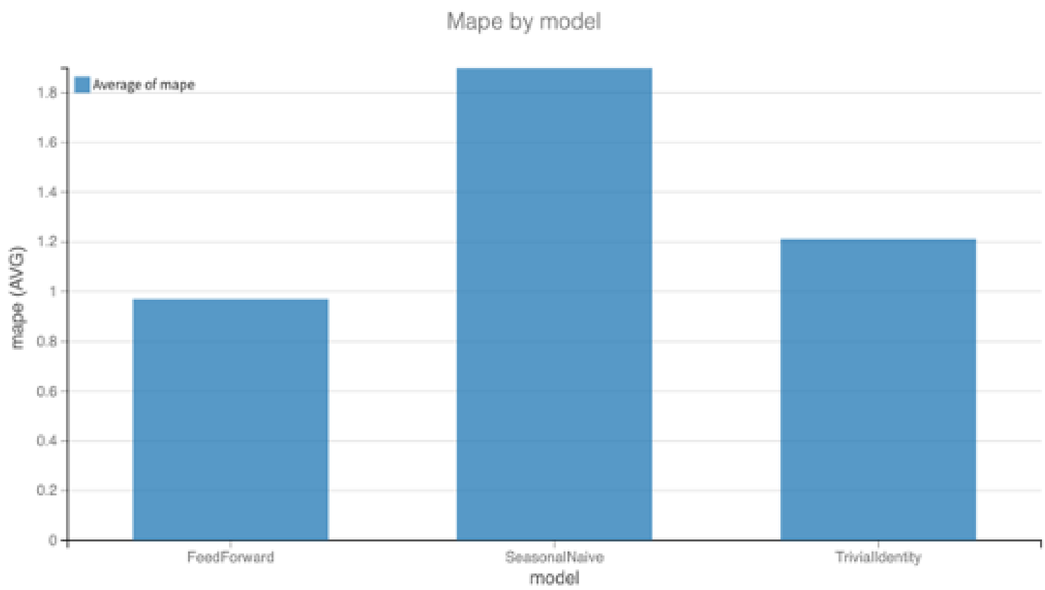
9 Case Studies

This research has two case studies implemented exploring the two main methods of time series forecasting: univariate and multivariate forecasting. Case study 1 focuses on univariate forecasting using Dataiku plugins like Time series Preparation and Forecast, while case study 2 is based on multivariate forecasting using the visual ML feature available in Dataiku Lab.

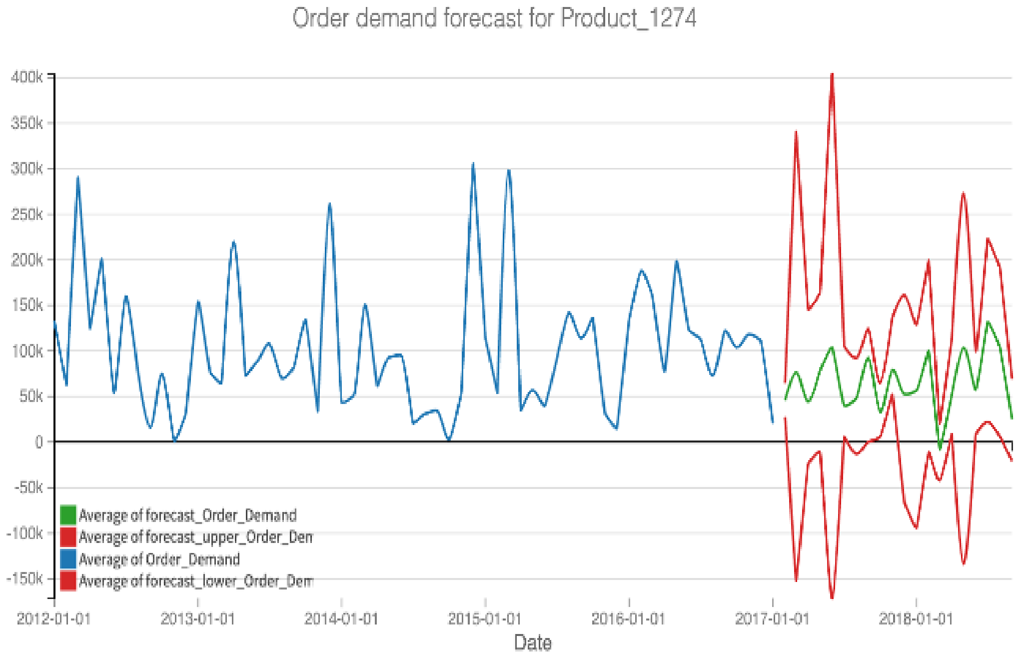
9.1 Case Study 1: Order Demand Forecasting

This first case study is univariate in nature, i.e. it uses only two variables in which one is the time feature(usually not counted as a variable, hence univariate) and the other one is the feature to forecast(order demand in this case). The dataset at hand contains information regarding order demands of thousands of products from an unnamed firm, from 2012 to 2017 aggregated on a monthly basis. For the sake of this research, one of those products has been selected in order to perform forecasting. The link to the dataset is as follows:https://www.kaggle.com/datasets/felixzhao/productdemandforecasting

The entire dataset(from 01-2012 to 01-2017) was taken as the training set and the forecast horizon was set to be 20 months or around 1.5 years. This case study makes use of the plugins available in Dataiku for preparing the data training model. The two plugins are time series preparation and forecast. Once you are done with the preparation of the data(by taking care of missing values and other issues), you can make use of this recipe called "forecast" for training your time series model. You just have to mention the time column(Date in our case), the frequency of your data(monthly in our case), and the forecast horizon which is the number of units of forecast that you want your model to predict(20 in our case). Then you need to select, what method you want to go with for the forecast training. In this case study, the "AutoML quick prototypes" option was selected. AutoML just takes your data and trains all the available models on it(the three models available are: Feedforward Neural Net, Seasonal Naïve and Trivial identity). Once the training is done, the recipe returns evaluation scores for all the trained models. You can choose the best one among them and go ahead with the forecasting. Other than Auto-ML Quick proto-types we have options like "Expert choose algorithm" and "Expert Customize algorithm". In both of these options, you'll just have to select certain parameters for the models like the learning rate, regularization parameters, forecast horizon, number of layers and neurons(for feed-forward network), etc. according to your data and you'll be good to go. After training, we have to store the evaluation values in a folder and the charts section can be used to visualize the data. In this case, the Mean Absolute Percentage Error(MAPE) (which is the average of the absolute percentage errors of forecasts) for all three models was plotted. And as you can see in the figure below, the feed-forward model also known as the simple neural network was the best performing model for this use case. It has the lowest MAPE of 0.96.



For forecasting, you'll need to use the Forecast recipe again(this time using the Forecast Future Values option). The settings in this recipe are pretty straightforward, you can either select a trained model(from the list of models available after training) manually, or the Auto-Select option automatically selects the best model for you(based on the accuracy scores). Then you can set the desired confidence interval for your forecasts. As you can see in the figure below, we have the training data in blue, the forecast in green, and the 95 percent confidence interval lines in red. A confidence interval is the mean of your estimate added and subtracted by the variation in that estimate. This is the range of values you expect your forecast to fall between 95 percent of the time. Confidence, in statistics, is another way to describe probability.

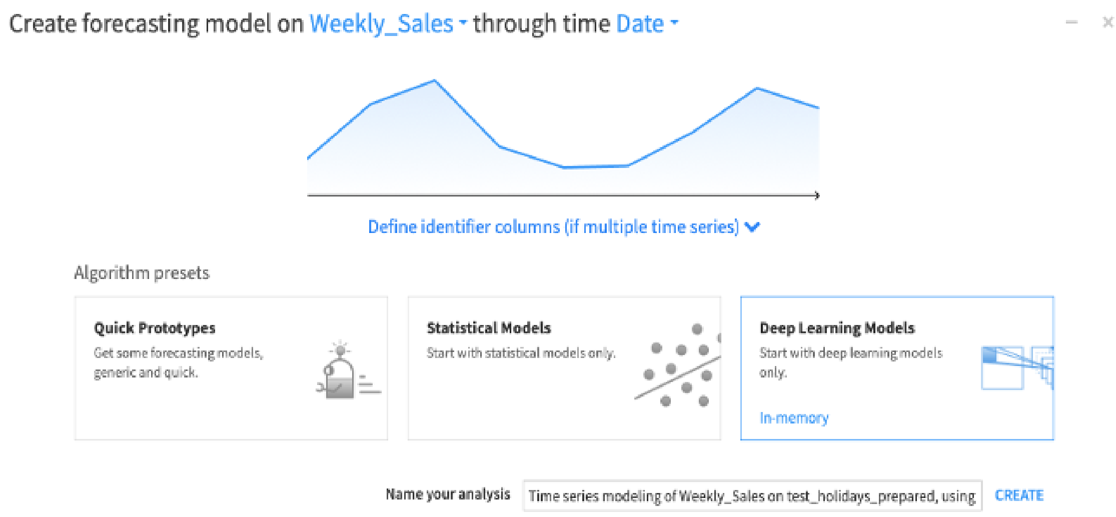


9.2 Case Study 2: Weekly Sales Forecasting

This case study deals with a multivariate dataset. Multivariate forecasting contains multiple variables: one variable being time, one being the target variable for forecasting and the rest are variables that have some correlation with the target variable. This is more commonly used in retail forecasting since a product's demand is usually dependent on multiple factors.

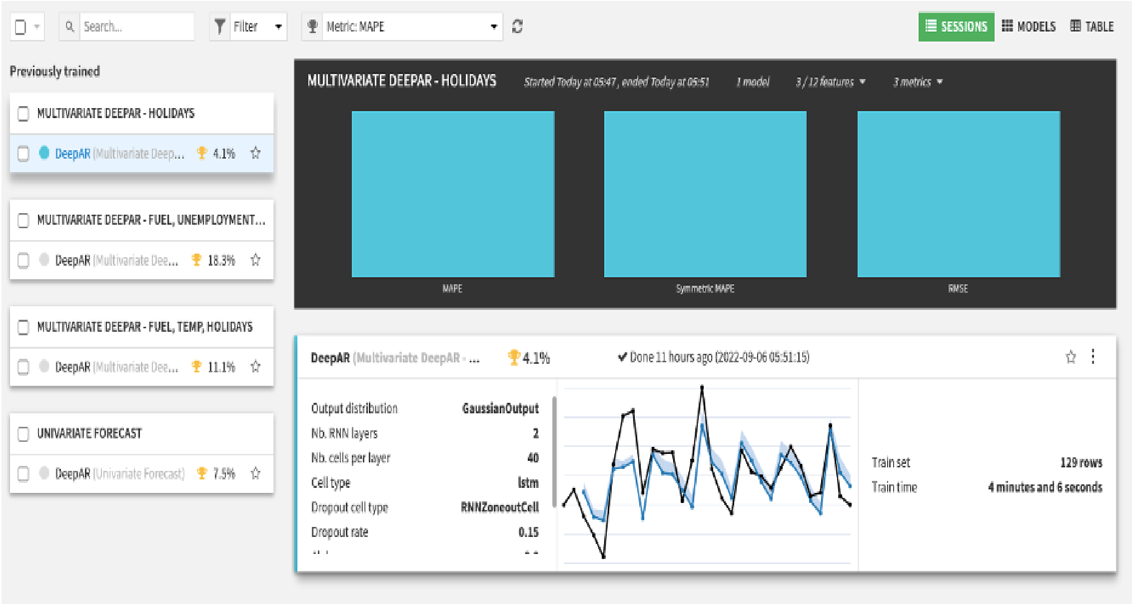
The dataset at hand contains weekly sales records of 45 Walmart outlets from May 2010 to July 2012 and this case study focuses on one of these stores. Along with weekly sales, which is the feature for forecasting, we have some independent external features as well like temperature, fuel prices, holidays, unemployment rate, and customer price index.

The method used in this case study is the Visual ML option available in the Dataiku lab which is much simpler and intuitive as compared to using plugins.



This is what the interface for visual ml forecasting looks like in the beginning, we have to select the forecast feature and the time column(`"Weekly_Sales"` and "Date" respectively in our case study). Then you need to select what group of algorithms you want to use for training, there are three options: Quick Prototypes, Statistical Models, and Deep Learning Models. Quick Prototypes, as we saw in the previous case study, takes the dataset and performs the process of AutoML over it. The algorithms available are Feedforward Neural Net, Seasonal Naïve, and Trivial identity. The Statistical based models available are Trivial, Seasonal Naïve, AutoARIMA, and NPTS. And the Deep Learning models available are FeedForward, DeepAR, Transformer, and MQ-CNN. The DeepAR model, which was introduced by the AWS cloud services, was deemed fit for this problem. It is based on auto-regressive LSTMs for probabilistic forecasting. Probabilistic forecasting is a very commonly used method in retail businesses.

The following are the 5 settings offered by visual ML to tweak your forecasting process:
1. General settings: It includes variable parameters, time step parameters, forecasting parameters, and quantiles(confidence intervals).
2. Train/Test settings: This lets you set the split ratio of training and testing data.
3. External Features selection: This Lets you select the independent features for multivariate forecasting and tweak their properties.
4. Algorithms selection: This lets you select what algorithms you want to train your data with. For multivariate deep learning, we have DeepAR, Transformer, and MQ-CNN available. This case study uses the DeepAR model.
5. Runtime environment requirements (Select one of the "Visual Timeseries forecasting" packages presets in a code environment's Packages to install > Add sets of packages, depending on your architecture (CPU or GPU with CUDA) and update your code-env.)



Once you are done with the desired settings, you can start the training and view logs for updates. After the training is done, the dashboard looks like the figure above; on the left, you get a list of trained models and upon selection, you can view a panel that shows error scores(MAPE), the back-testing graph, and other details of the training job. In the case study, 4 DeepAR models were trained using different combinations of the external features, out of which we are going to discuss the top 2. The first model uses the holidays feature, which got an MAPE of 4.1 percent(the lowest error score of all models), then the third model which used fuel prices, temperature, and holidays got an MAPE of 11.1 percent. The first one had the smallest error score although the forecasts from the third one seemed the more sensible. The rest of the error metrics like Mean Squared Error(MSE), Mean Absolute Squared Error(MASE), Mean Absolute Quantile Loss(MAQL), etc. are shown in the images below for both the models.

Mean Absolute Percentage Error(MAPE) is the most commonly used error metric in forecasting. It is the average of the absolute percentage errors between forecasts and actual values.

$$\mathrm{M} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

where
n is the number of observations,
A_t is the actual observation,
F_t is the Forecast

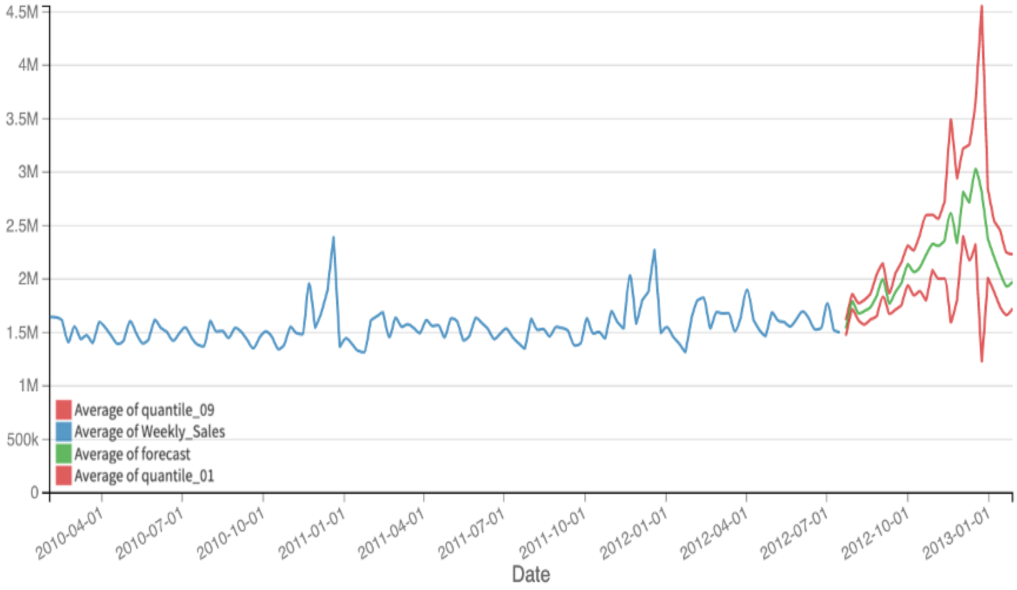
Error metrics and forecast for the DeepAR model trained on Holidays as an external feature:

Metrics

Detailed metrics

Mean Absolute Scaled Error (MASE)	0.38320	Mean Squared Error (MSE)	6.6659e+9
Mean Absolute Percentage Error (MAPE)	4.12%	Root Mean Squared Error (RMSE)	81645
Symmetric MAPE	4.15%	Mean Scaled Interval Score (MSIS)	1.1904
Mean Absolute Quantile Loss	1.7547e+6	Normalized Deviation	0.041237
Mean Weighted Quantile Loss	0.039040		

Weekly Sales Forecast(multivariate series with holidays)



The green line is the forecast and the red lines above and below it are the confidence intervals.

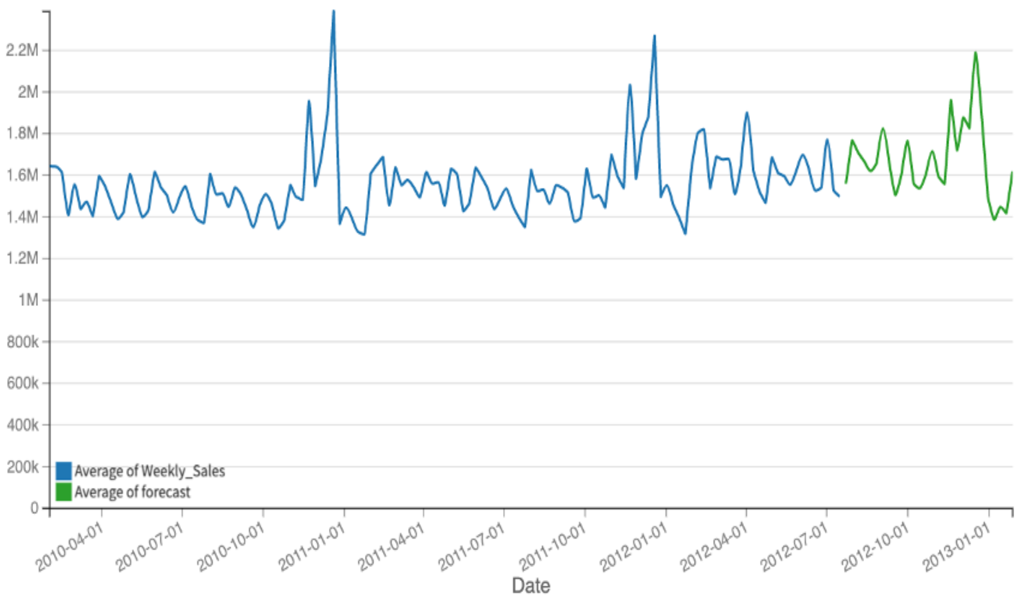
Error metrics and forecast for the DeepAR model trained on Holidays, Temperature and Fuel Prices as external features:

Metrics

Detailed metrics

Mean Absolute Scaled Error (MASE)	**1.0519**	Mean Squared Error (MSE)	**3.8369e+10**
Mean Absolute Percentage Error (MAPE)	**11.1%**	Root Mean Squared Error (RMSE)	**1.9588e+5**
Symmetric MAPE	**11.9%**	Mean Scaled Interval Score (MSIS)	**3.0950**
Mean Absolute Quantile Loss	**6.5085e+6**	Normalized Deviation	**0.11320**
Mean Weighted Quantile Loss	**0.14480**		

Weekly Sales Forecast(with holidays, temperature and fuel prices)

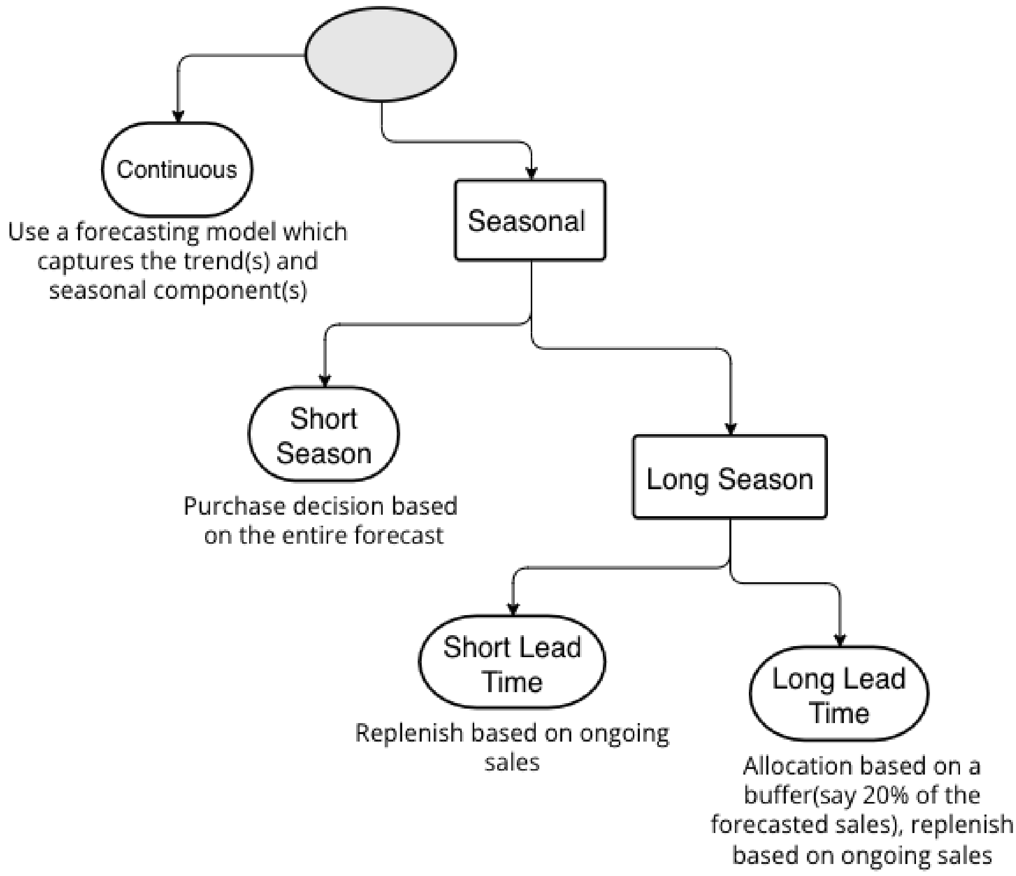


On paper, the first model with a 4.1 percent error is the better one, but if we look at the forecasts, the one with an 11.1 percent error makes more sense. So, the model with holidays, temperature, and fuel prices was finalized as the best model.

10 Decision-making factors and evaluation Key Performing Indicators in Demand Forecasting

10.1 Decision Making in Forecasting

As observed in the case studies, it is not always the model with the least error score that gets the nod, you need to consider other factors as well while finalizing your best model. Following is a flow chart depicting a decision-making process for selecting models taking into account factors like seasonality, length of seasons, and lead times.



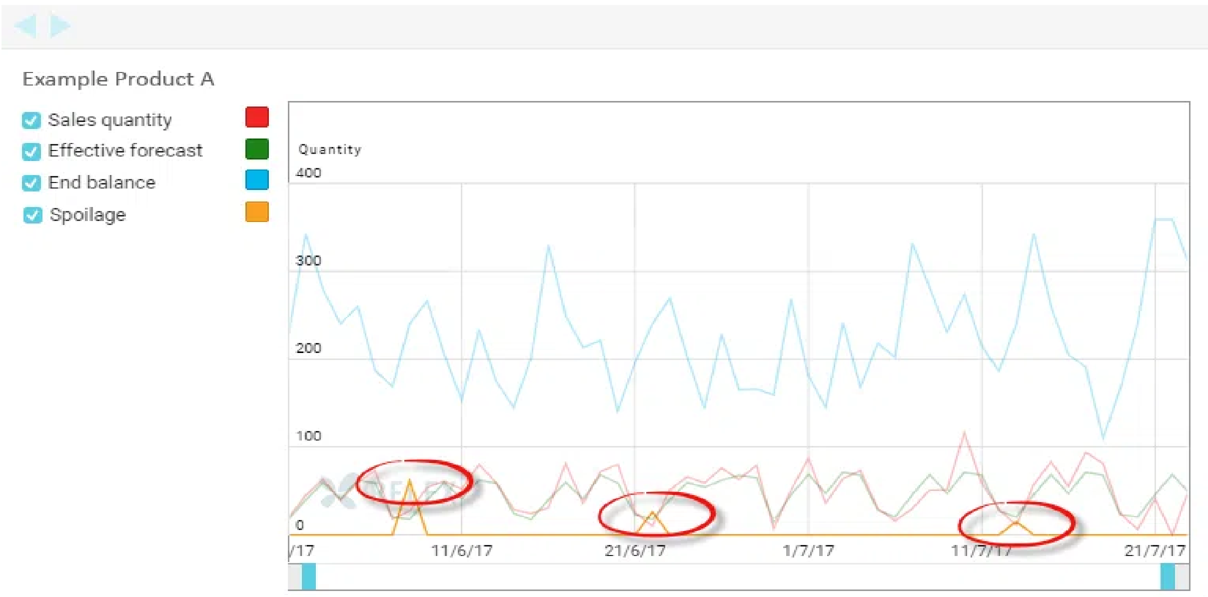
In the beginning, we try to identify whether the product in question has a continuous/perennial life cycle or a seasonal one. If it is continuous in nature, we can just make use of a simple forecasting model which takes into account the normal trends(and say maybe occasional seasons) and gives us a forecast. This forecast can be used then to take sourcing decisions. On the other hand, if the life cycle is seasonal or a mixture of seasonal and perennial components in nature, we need to identify whether the length of the season is short or long. If it is short, we must be equipped with the sourcing decisions quite early on(and the accuracy of forecasts is crucial in this case), since once we enter the season period, we won't have enough time to improvise on the decisions because of the short nature of the season. Then we have the products with longer seasons, which are further classified into commodities with either short or long lead times. For shorter lead times, since the time for production is very less, we can play it safe by just taking replenishing decisions based on the ongoing sales so that we don't end up with dead stock. On the other hand, if the lead time is large, we will have to deal with it tactfully by ordering a smaller amount, like say, 20 percent of the entire forecasted requirement which will act as a buffer for us to observe and take decisions. Since the lead time is large, once an order is placed and the manufacturing starts, we usually don't have the option to back out. But at the same time, we can't risk having a filled inventory and the forecast being off the margin leading to dead stocks. So we go ahead with 20 percent of the forecasted quantity, then take the sourcing decisions based on the ongoing sales.

10.2 Model Evaluation

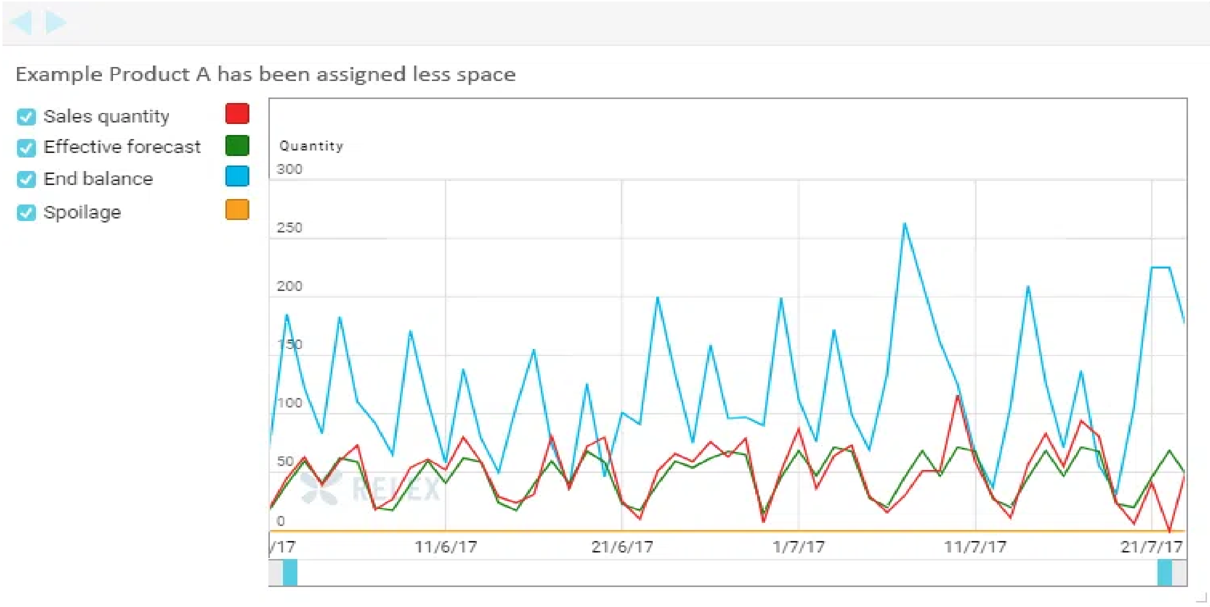
The evaluation phase is where we need to take a step back and look at the whole process in terms of the value it is bringing to the table, what are some of the key performing indexes that we need to pay special attention to in order to make the most of it and how is it enabling us to take better decisions? It is a bit complicated when it comes to forecasting because unlike other machine learning applications like classification and regression, where the output directly corresponds to the end product, it is usually not the case with forecasting, because forecasting is essentially just a small part of a long process, it is just an educational guess regarding what the future might be because there is a limit to what you can consider while modelling your data. It is by no means a factor you can rely completely on to take business decisions.

The most important question to be asked in order to judge the quality of your forecasting model is: What is the role of demand forecasting in attaining your business results? You need to define it carefully, in our case it is about finding the optimal time for taking sourcing decisions, but different scenarios may have different measures of success. Most commonly, the goal is to increase profitability, improve inventory management, reduce waste and assess risk. Depending on the scenario, we may have to use different metrics with different levels of aggregation for different models to get optimum results. For eg. Forecast accuracy is crucial when managing short shelf-life products, such as fresh food. However, for other products, such as slow-movers with long shelf-life, other factors of your planning process may have bigger impacts on your business results. In such a case, you shouldn't invest a lot in developing a forecasting model with the best accuracy; rather you should go for something which gives you a baseline or a reference to what you can expect in terms of demand and use it as a small yet contributing factor in your decision-making process. Furthermore, if the forecast error is identified to be caused by essentially a random variable in demand, any attempt to further increase forecast accuracy will be fruitless.

The following is an example that solidifies this point. The figure below is an example of using forecasting to drive replenishment forecasts for grocery stores.



Although the forecast accuracy for the example product and store is quite good, there is still systematic waste due to product spoilage. When they dug deeper into the matter, it turned out that the main problem behind the excessive waste was the product's presentation stock, i.e. the amount of stock needed to keep its shelf space sufficiently full to maintain an attractive display. So all they had to do was assign less space to the presentation stock for this particular product and lower the inventory levels. This allowed 100 percent availability with no waste.



This, of course, holds true for any planning process. If you only focus on forecasts and do not spend time on optimizing the other elements such as safety stocks, lead times, batch sizes, etc. you will reach a point, where additional improvements in forecast accuracy will no longer improve business results.

Another important question to ask while evaluating a model's performance is: What factors affect the attainable forecast accuracy? There are a few basic rules of thumb to answer this question:

1. Forecasts are more accurate when sales volumes are high: a technical explanation for this is quite intuitive if you think about it, more sales mean more number of records or data points we have to train our model on, and that usually translates to better performing models in the realm of machine learning.

2. Forecast accuracy improves with the level of aggregation: the concept of aggregation in terms of grouping together products or different time frames is very crucial in forecasting as it can lead to a lot of misinterpretations if not defined correctly(explored more in the next session). Aggregating can lead to the elimination of the effects of certain random variables in the overall accuracy calculation. This means that forecast accuracy measured on products grouped together or for a chain of stores is higher than that of individual products in specific stores. Likewise, the forecast accuracy measured on a monthly or weekly basis is usually higher compared to that calculated on a daily basis.

3. Short-term forecasts are more accurate than long-term forecasts: A longer forecasting horizon significantly increases the chances of random variables or noise infiltrating the process resulting in undesired outcomes.

10.3 Usage of different forecasting metrics at different scenarios

The most commonly used forecast error metrics are: forecast bias, mean average deviation (MAD), and mean average percentage error (MAPE). Depending on the chosen metric, level of aggregation, and forecasting horizon, you can get very different results on forecast accuracy for the exact same data set, hence it is important to understand the properties of each metric.

Forecast bias is the difference between forecast and sales. If the forecast overestimates actual sales, it is a positive value, and negative if it underestimates. In many cases, it is useful to know if demand is systematically being over- or under-estimated. Because, even if a slight forecast bias would not have a noticeable effect on store replenishment, it can have a notable effect at the warehouse or distribution center level. To make that point clear, and to also show the importance of aggregation, let's have a look at the following scenario.

Forecast bias = Σ(Forecast - Sales)   Forecast bias % = $\frac{\Sigma \text{Forecast}}{\Sigma \text{Sales}}$

	Sales	Forecast	Bias	Bias %
Product A	28	14	-14	50%
Product B	81	112	+31	138%
Product C	222	196	-26	88%
Group	331	322	-9	97%

In the table above, for Product A and C, the model has underestimated the sales by 50 and 12 percent respectively and for Product B it has over-estimated by 38 percent. But if you aggregate together these products and consider them as a group of products, you'll notice that the bias now is just an under-estimated 3 percent. Now, this begs the question, what is the right approach, should we go for aggregations or not? The answer to that question depends on what business problem are you trying to solve, if say, you are interested in optimizing the replenishment figures at your store, it is important to pay attention to products as individual commodities and not go for aggregation, so as to avoid dead stock in the case of Product B and under-stocking in the cases of Products A and C. So in this case you may want to improve the accuracy of your model. On the other hand, if the forecast is used for business decisions on a more aggregated level, like planning a picking process at your distribution center(which is a very labor-intensive and time-consuming task), the aggregated error of 3 percent is actually a great result and there is no need to work on the accuracy of your model any further.

Mean absolute deviation (MAD) is another commonly used forecasting metric. This metric shows how large an error, on average, you have in your forecast. However, as the MAD metric gives you the average error in units, it is not very useful for comparisons. Mean absolute percentage error (MAPE) is similar to the MAD metric but expresses the forecast error in relation to sales volume. Basically, it tells you by how many percentage points your forecasts are off, on average. This is probably the most commonly used forecasting metric in demand planning(hence used in the previous case studies). So,

1. Forecast bias tells you whether you are systematically over- or under-forecasting. The other metrics do not tell you that.
2. MAD measures forecast error in units. It can, for example, be used for comparing the results of different forecast models applied to the same product.
3. MAPE is better for comparisons as the forecast error is put in relation to sales.

To summarize, the key principles to bear in mind when measuring forecast accuracy:
1. Primarily measure what you need to achieve, such as efficiency or profitability. Use this information to focus on situations where good forecasting matters. Ignore areas where it will make little or no difference.
2. Understand the role of forecasts in attaining business results and improve forecasting as well as the other parts of the planning processes in parallel. Optimize safety stocks, lead times, planning cycles, and demand forecasting in a coordinated fashion, focusing on the parts of the process that matters the most.
3. Choose the right aggregation level and horizon for each purpose. Often the best insights are available when you use more than one metric at the same time.

11 DEI Dashboarding in Strategic Sourcing

A DEI dashboard shows you the status of your supplier workforce in areas like gender representation, age distribution, race and ethnicity factors and growth opportunities, retention rates, turnover rates, etc. Basically, it is graphs, charts, and other visuals that are intuitive and simple to comprehend. An organization can use these insights to monitor and improve its DEI efforts and actions.

For example, it can help you answer questions like:

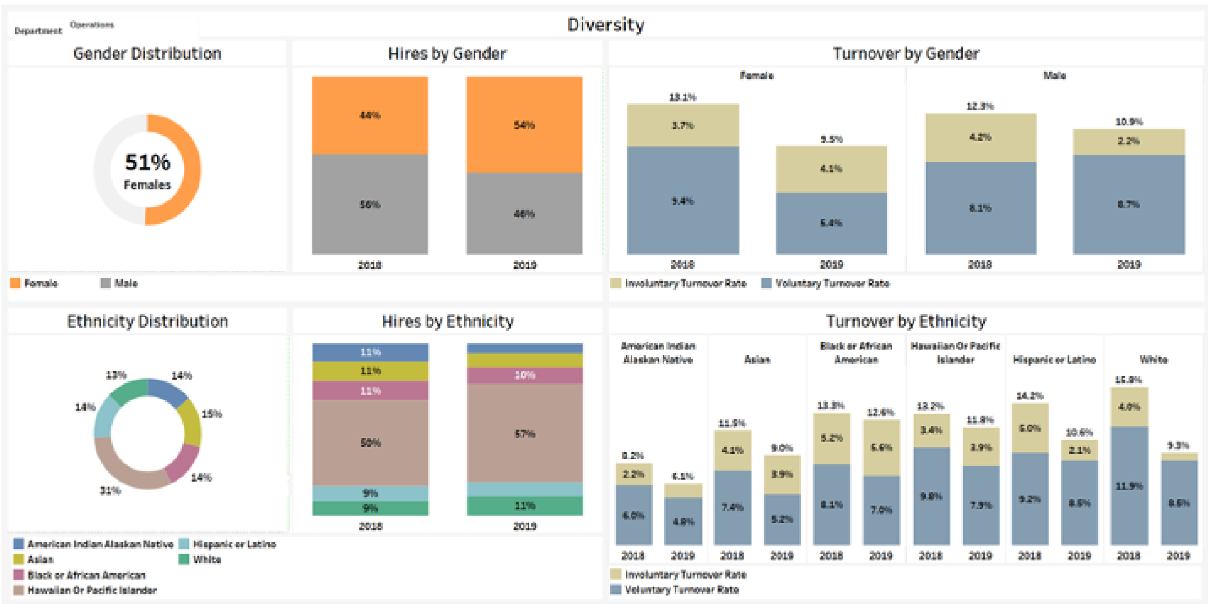
* Are we building an inclusive culture at our organization? i.e. are we open to going with suppliers from all sectors of the society regardless of their race and ethnicity?

* Are we attracting, hiring, and retaining diverse vendors? attracting and retaining diverse suppliers is an important metric that can tell you how diversity-friendly your firm is.

* Do we have equitable compensation practices?

* Are we providing opportunities equitably?

* What are the voluntary and involuntary turnover rates? Voluntary turnover is when an employee chooses to leave an organization by resigning or retiring. Involuntary turnover is when an organization asks an employee to leave.



12 Conclusion

To conclude, this research proposes Time Series Forecasting as a Data Science based candidate solution to the question, "What is the optimal time to take sourcing decisions like negotiating with the vendors?". The proposal is done by taking into account the factors which have the most amount of influence on sourcing decisions and by closely observing contemporary industrial standards. The research then focuses on the technologies used to implement time series forecasting in terms of programming languages, platforms, and algorithms. After that, two case studies were implemented exploring different techniques(plugin-based and Visual ML based) offered by Dataiku to implement forecasting. Then lastly, different perspectives on evaluating forecast results were explored.

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