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**As a discipline, predictive analytics has been around for many decades and has been a hot topic in academia for many years. Its application in the field of demand planning, though, is still relatively untapped. Its**[**effective uses in business**](https://demand-planning.com/2019/01/28/10-predictive-business-analytics-examples/)**are more an exception than a rule. Despite the mass of information available to us, and machine learning algorithms that can model the supply chain for insights, companies have barely scratched the surface with data analytics.**

Part of the reason for this may be confusion about traditional demand planning and [predictive analytics](https://ibf.org/knowledge/glossary/predictive-analytics-214). Demand is for “something” and can be for a product or service. It manifests itself as a sale to an end-user, an order, a shipment, inter-plant transfer, distribution requirement, etc. Demand planning is a process and techniques used to create a demand plan.

Broadly speaking, there are two approaches to demand forecasting– one is to obtain information or make assumptions about patterns of past purchases, the other is to obtain information or make assumptions about external factors or the likely purchase behavior of the buyer.

**Predictive Analytics Tells Us Not Only What Will Happen, But Why**

While [predictive analytics](https://ibf.org/knowledge/glossary/predictive-analytics-214) can be utilized to develop a demand plan, more often than not most demand planners still use only demand to forecast demand. [Predictive analytics](https://ibf.org/knowledge/glossary/predictive-analytics-214) does not only forecast the demand itself but uses a systematic computational analysis of data or statistics (analytics) to try to determine *why*. Demand planning only creates an estimate of demand – predictive analytics creates an evaluation of what the future may be “if”.

**Predictive Analytics Interprets A Wide Range Of Factors Affecting Demand**

[Predictive analytics](https://ibf.org/knowledge/glossary/predictive-analytics-214) is the philosophy of extracting information from data sets and using advanced statistical algorithms or even machine learning techniques to identify the likelihood of an unknown future outcome. The goal is to go beyond knowing what has happened to providing a best assessment of why or what drivers will impact something occurring in the future. Predictive analytics takes a more humanistic and sometimes intuitive logical approach. Instead of relying on past historical activities, [predictive analytics](https://ibf.org/knowledge/glossary/predictive-analytics-214) analyzes the influencers, interactions, and activities of the actors (consumers) in demand.

**Traditional Demand Planning asks – what did the item do last year?**

**The new era of Predictive Analytics asks – what does the consumer do when this happens?**

Because of this, it is more than just a forecast of how much we will sell of an item next month but opening up a door into many more insights. This door is not limited to just supply chain either but brings the [predictive analytics](https://ibf.org/knowledge/glossary/predictive-analytics-214) professional into every function and can add value to every business decision.

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**It Allows For Micro Targeting Campaigns**

Applied to business, predictive models are used to analyze current data and historical facts in order to better understand customers, products and partners and to identify potential risks and opportunities for a company. It can be used for micro targeting campaigns to gain strategic advantages or used to determine the color and font on a website that drives the most traffic.  As an online retailer, with [predictive analytics](https://ibf.org/knowledge/glossary/predictive-analytics-214) you can understand how your page ranking, number of comments, ratings, and “winning the buy box” on Amazon impact your sales on any given day.

It translates to consumer loyalty and less churn of customers, and customizing experiences to make a higher probability of sales.

[Predictive analytics](https://ibf.org/knowledge/glossary/predictive-analytics-214) has grown in prominence alongside the emergence of big data systems. As enterprises have amassed larger pools of data, they have created increased data mining opportunities to gain [predictive insights](https://ibf.org/knowledge/glossary/predictive-analytics-214). Heightened development and commercialization of machine learning tools have also helped expand [predictive analytics](https://ibf.org/knowledge/glossary/predictive-analytics-214) capabilities. Because of this and the changing business environment, professionals in our field will continue to migrate to new ways of modeling and planning and start to see cross-over of these predictive models into traditional forecasting and planning as well.

Revealing the future by getting into the head of the consumers, rather than by analyzing the history of the item can pay enormous dividends. And, with the abundance of real-time consumer data available today, future demand for your organization’s products and services may be more precisely determined using [predictive analytics](https://ibf.org/knowledge/glossary/predictive-analytics-214) rather than relying solely on traditional demand planning processes.

**I’ll be speaking at the**[**Predictive Business Analytics, Forecasting & Planning Conference**](https://ibf.org/events/neworleans2019)**in New Orleans from May 6-18, 2019. It’s a 2-day conference with an optional data science workshop, designed to get you up to speed with basics of predictive analytics, or get you to the cutting edge of the field with the the latest methodologies, tools and best practices.**

# **Predictive analytics for demand forecasting: A deep learning-based decision support system**

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## Abstract

The demand is often forecasted using econometric (regression) or statistical forecasting methods. However, most of these methods lack the ability to model both temporal (linear and nonlinear) and covariates-based variations in a demand series simultaneously. In this context, a novel [forecasting model](https://www.sciencedirect.com/topics/mathematics/forecasting-model) is proposed that combines a state-of-the-art sequence modeling method and a [machine learning](https://www.sciencedirect.com/topics/computer-science/machine-learning) method in an ensemble model. The proposed model can handle both types of variations in demand data, and thus, enhances forecasts’ accuracy. A big sample of 4235 demand series consisting of structured and unstructured data (could be referred to as “big data”) related to packaged food products is used for experimentation. Data contain point-of-sales, promotion, weather, regional economy, internet media, and economic activity index related variables. Some of these variables and their combinations is probably used for the first time in a demand [forecasting model](https://www.sciencedirect.com/topics/mathematics/forecasting-model). The forecasting results are evaluated through multiple error metrics (i.e. mean error, [mean absolute error](https://www.sciencedirect.com/topics/engineering/mean-absolute-error), mean squared error), and it has been observed that proposed method outperformed the benchmarking methods. A demand [sensing algorithm](https://www.sciencedirect.com/topics/engineering/sensing-algorithm) is also proposed to [forecast demand](https://www.sciencedirect.com/topics/engineering/demand-forecast) in real-time.

## Introduction

Demand estimates act as a primary input for effective planning and decision making in any organization. A firm’s marketing, production, distribution, and finance departments use short-to-long term forecasts to support different decisions. Being such a pivotal input to business decision-making, the quality of forecasts is very important.

Demand forecasting needs historical demand data and forecasting methods to forecast the future demand. The first step is to collect relevant data on various factors i.e., product features, promotional activities, calendar events, meteorological and general economic contexts that influence the demand for retail goods [1], [2]. Understanding the impact of these factors on demand provides the needed business intelligence to the retailers for effective sales planning and management. Next, modeling and forecasting of demand data requires suitable forecasting methods/models.

In this paper, authors proposes a big data predictive analytics model capable of handling a large amount of demand data and provide short, medium, and long-term demand forecasts to a retailer. As per the classification of forecasting methods based on data characteristics by Punia et al. [3, p. 4965], the proposed model could be placed in the category of medium to a large dataset with multiple input variables. Thus, machine and deep learning techniques are used for forecasting.

The research on forecasting models started with univariate models with sales series as the input data. These models detect and use the temporal patterns to predict the sales for the future [3]. However, the sales pattern is influenced by multiple factors and forecasts from multivariate models are often better than forecasts from univariate models [4], [5].

In multivariate models, a set of factors, broadly categorized into point-of-sales, promotion, weather, and general economics context variables, have been used as the independent variables in various studies. Geurts and Patrick Kelly [4] highlighted the importance of using point-of-sales and promotion data for sales forecasting. Choi and Li [6] reported that the forecasting models could achieve better performance using autoregressive components of sales variables. Choi [7] reported that market information for pre-seasonal products would lead to better forecasts and recommended the continuous update of forecasts based on available near real-time information. Au et al. [8] used point-of-sales information such as pricing, discounts, and product features to predict the sales in apparel fashion retail; and reported multivariate model are better than univariate models for regular products with low demand uncertainty and weak seasonal trends. Kumar and Patel [9] revealed that performing the clustering based on features leads to better performance of the forecasting methods.

In the past decade, researchers discovered several new external indicators to estimate future demand for products. The factors related to weather, economic indicators, internet social media, and sentiments indices are found to be most prominent. Since data on external indicators are not directly available to the retailer and ascertaining the veracity of the external data is challenging too. For these reasons, limited research is available on the use of multiple external factors for demand forecasting.

Osadchiy et al. [10] used financial market information, such as financial index, returns achieved on equity, etc., to better the forecasting performance. Ferreira et al. [5] used the point-of-sales, promotion, and time-based indicators such as day of the week, day of the month, etc., to forecast demand for an online retail company. They reported that the use of additional market and temporal information helped in better accuracy. Papanagnou and Matthews-Amune [11] used the internet social media indicators such as Google index, YouTube index for forecasting the sales of a pharmaceutical drug, and revealed a positive correlation between social media indicators and sales prediction. Verstraete et al. [12] used the weather information to forecast low-margin high-volume products for short-term and long-term forecasts. They inferred that weather indicators significantly influence the sales of low-margin, high-volume products.

With the increase in number of variables, the complexity of the model increases. It requires the management of massive data and complex models to handle, process, and generate a quality forecast. Thus, only a few studies tried to incorporate multiple types of indicators in a single forecasting model. For example, [13] developed a model that included product features, promotion, and economic indicators. However, they also did not include weather information and social media indicators.

This paper addresses the demand forecasting problem by incorporating data on factors related to product features, promotion, weather, regional economy, and internet social media. The data for three years for the 4235 demand time series with independent variables are used for the study. The details of the independent variables and factors are explained in Section 2. To manage the huge data, a big data framework using Apache Spark is designed. This framework is used to process, model, and analyze the data to generate forecasts efficiently. In addition, the relative importance (ranking) of the independent variables are provided to understand the impact of these variables on sales.

The time-series data based demand forecasting methods can be classified into three categories: statistical methods, machine learning methods, and hybrid methods. In time-series methods, the exponential smoothing method, Auto-Regressive Integrated Moving Average (ARIMA), various decomposition models are used for forecasting. Further, the use of some multivariate time-series methods such as ARIMAX has also been used. The details of these methods are available in Hyndman & Athansopoulos [14].

In machine learning methods, artificial neural networks (ANNs) are widely used for demand prediction. Alon et al. [15] used the ANN to predict the aggregate sales in retail stores and reported that ANN could capture the dynamic nonlinear trend and seasonality in the sales data. Au et al. [8] used the evolutionary neural network for sales forecasting in fashion retail and reported improvements in the accuracy of forecasts. Ferreira et al. [5] predicted the sales using the random forest (RF) method based on regression trees and bagging algorithms and reported the advantages of RF over NNs in terms of interpretability and accuracy. The latest addition to the repository of multivariate methods is a deep neural network, and results are encouraging to use of deep learning for the sales forecasting and decision making [16], [17].

In hybrid models, both time-series and regression (or machine learning methods in recent) are used to model the demand patterns. The hybrids of ARIMA-ANN [18], ARIMA-regression [19], ARIMA-SVM [20], and seasonal ARIMA and wavelet transformations [21] were proposed for forecasting. It may be noted that ARIMA is widely used with other methods to develop hybrids. Because sARIMA can efficiently handle and model the linear temporal (level and seasonality) part of the time series, and the remaining nonlinear temporal and regression part is taken care of by method [22].

To further the research on hybrid models, this paper proposes a novel forecasting model, which combines deep learning-based long–short-term-memory (LSTM) networks and random forests (RF) method. LSTM networks are the state-of-the-art techniques to predict the linear and nonlinear sequential data [23], and RF is a machine learning technique to model relationships among sales and independent variables [5]. Both methods are combined using a genetic algorithm into an ensemble model. The forecasts from the proposed model are tested on three error metrics for bias, accuracy, and variance. The results are compared with forecasts from other demand forecasting methods. The proposed method outperformed all other methods on all three metrics. Further, this paper proposes two auxiliary algorithms to generate daily and long-term forecasts. These algorithms use temporal aggregation and temporal disaggregation methods to convert the forecasts from the proposed method to daily and long-term demand forecasts for retailers [14]. The study will significantly contribute to the literature on forecasting and forecasting applications in retail industry.

The remainder of this paper is organized as follows. The proposed forecasting model for demand planning is presented in Section 2. In Section 3, demand data and its characteristics are discussed. Section 4 contains the data preparation, data analysis, and results. Section 5 analyzes and discusses the results and provides managerial insights for the effective use of the proposed model. Finally, conclusions and future work are described in Section 6.

## Section snippets

## Proposed demand forecasting framework

The proposed demand forecasting framework provides the forecasts for short, medium, and long-term planning horizons. The short-term model can be used for operational decision-making while the medium and long-term model has usage for tactical decisions such as handling products with long lead times in retail. The factors related to point-of-sale, promotion, time, store, and external indicators related to weather, social, and economy are used input data. An overview of the whole methodology is

## Factors influencing the sales

The factors that influence sales can be categorized into point-of-sales, promotion, time, store, weather, and external indicators. The point-of-sales consists of variables related to product specification (category, color, manufacturer, volume, size, etc.) and customer’s transactions (units sold, price, discount, no. of customer visits, etc.). Then, there promotional events and marketing related variables, such as temporary price reduction (TPR), featuring in the display area, etc. These

## Data and summary statistics

The data is taken from a large retailer who operates multiple retail store. The data consists of weekly sales for 55 food items sold through 77 stores and is available for the duration from January 2009 to January 2012. The total sample size adds up to 4235 demand time series with multiple independent variables. The independent variables are divided into five categories: point-of-sales, promotions, store, geographical weather, and other economic indicators. In addition, the sixth category is

## Managerial implications

The proposed demand forecasting framework can be used for effective tactical and operational planning decision by retailers. The accurate and real-time estimates of daily, weekly, and monthly demand will help the retailer to plan the right products mix to procure from the distributors. This will lead to a significant saving of inventory and transportation costs. This will also help in the optimal planning of assortment and assortment promotions at the stores.

The proposed model provides the

## Conclusions

A novel demand forecasting method is developed to generate accurate short, medium, and long term demand forecasts in retail stores. The proposed method combines LSTM networks and random forests into an ensemble model. The principal component analysis is used to reduce dimensionality of the input data. The proposed forecasting method is benchmarked against time-series, machine learning, and hybrid methods. The dataset of 4235 demand series with independent variables is used for analysis. The new

## CRediT authorship contribution statement

**Sushil Punia:** Conceptualization, Methodology, Data curation, Analysis, Writing – Original draft, Writing – reviewing and editing. **Sonali Shankar:** Analysis, Revision, Writing – reviewing and editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

# **Demand Forecasting Methods: Using Machine Learning to See the Future of Sales**

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Reading time: 11 minutes

What is the top pain point for business executives? [Gartner](https://www.gartner.com/en/supply-chain/role/planning-leaders), the world’s largest IT research firm, gives a clear answer: demand volatility. Too many factors — from weather fluctuations to posts by social media influencers  — impact buyers, causing them to frequently change their minds.

Worse still, things reshaping customer intentions happen quite unexpectedly – from a competitor’s shop opening next door to the global lockdown due to the COVID-19 pandemic. Or consider the teenage climate activist Greta Thunberg. Her refusal to fly for environmental reasons kick-started the “flight shame” movement, which caused a five-percent [decrease](https://www.telegraph.co.uk/travel/news/is-swedens-flight-shame-movement-dampening-demand-for-air-travel/) in air passenger numbers in Sweden.

There is no magic wand to predict scenarios like the “Thunberg effect”. But there are technologies to improve the accuracy of demand forecasting. Honestly, it will never be 100 percent precise, yet it can be precise enough to help you achieve your business goals.

In this article, we will look at the capabilities of advanced forecasting methods and outline their current limitations.

## What is demand forecasting?

**Demand forecasting** is the estimation of a probable future demand for a product or service. The term is often used interchangeably with demand planning and demand sensing, but there’s a difference between the three. Let’s clear it up.

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Watch our video for a quick overview of demand forecasting strategies

### Demand planning  — understanding market needs

**Demand planning** is a broader process that begins with forecasting but is not limited to it. According to the Institute of Business Forecasting and Planning ([IBF](https://demand-planning.com/)), it applies “forecasts and experience to estimate demand for various items at various points in the [supply chain](https://www.altexsoft.com/blog/supply-chain-management-software/).” In addition to making estimations, demand planners take part in inventory optimization, ensure the availability of products needed, and monitor the difference between forecasts and actual sales.

Demand planning serves as the starting point for many other activities, such as warehousing, [shipping](https://www.altexsoft.com/blog/ecommerce-shipping/), [price forecasting](https://www.altexsoft.com/blog/business/price-forecasting-machine-learning-based-approaches-applied-to-electricity-flights-hotels-real-estate-and-stock-pricing/), financial planning, and, especially, supply planning that aims at fulfilling the demand and requires data on the anticipated needs of customers.

### Demand sensing – creating short-term predictions

A relatively new concept in the planning process, **demand sensing** is a forecasting method that employs advanced analytical techniques to capture real-time fluctuations in purchase behavior. The technology can be of great help for companies, operating in fast-changing markets.

Demand sensing solutions extract daily data from [POS systems](https://www.altexsoft.com/blog/pos-hotels/), warehouses, and external sources to detect an increase or decrease in sales by comparison with historical patterns. The system automatically evaluates the significance of each divergence, analyzes influence factors, and offers adjustments to short-term plans.

Adopting demand sensing reportedly reduces near-time forecast errors by 30 to 40 percent. It empowers companies to rapidly address sudden changes in customer needs and facilitates building a data-driven supply chain. Of course, you can’t make all decisions based on this technique alone, as it doesn’t work for mid- or long-term planning. But it may serve as a valuable complement to traditional forecasting methods.

A demand sensing software dashboard, capturing a change in demand in the short term, and showing factors that cause the fluctuation. Source: [E2Open](https://www.e2open.com/intelligent-applications/demand-sensing/)

Here, again, we return to forecasting. Getting as close to reality as possible is the key to improving efficiency across the entire supply chain. How do you reach the uppermost accuracy possible? The answer depends on business type, available resources, and objectives.  Let’s compare the existing options: traditional statistical forecasting and machine learning algorithms.

## Traditional statistical forecasting — good for stable markets, ill-disposed to changes

Traditional statistical methods (TSM) have been here for ages and remain a staple of forecasting processes. The only difference if compared with the previous century is that all calculations are performed automatically, by modern software. For example, you can create [time-series forecasts](https://www.altexsoft.com/blog/business/time-series-analysis-and-forecasting-novel-business-perspectives/) for sales and trends in Excel.

**Data sources.**To predict the future, statistics utilizes data from the past. That’s why statistical forecasting is often called historical. The common recommendation is collecting data on sales for at least two years.

**Why use it.**Traditional forecasting is still the most popular approach to predict sales, and for a reason. As a rule, demand planning solutions based on statistical techniques seamlessly integrate with Excel and existing Enterprise Resource Planning (ERP) systems without requiring additional tech expertise. The most advanced systems can consider seasonality and market trends as well as apply numerous methods to finetune results.

**Things to consider.**An important prerequisite of statistical forecasting accuracy is stability. We assume that history repeats itself: Situations that occurred two or three years ago will reoccur. Which is far from being true. Flawless in an ideal world, statistical methods often fail to foresee illogical alterations in customer preferences or predict when market saturation will occur.

A statistical forecasting software dashboard. Source: [Streamline](https://gmdhsoftware.com/demand-planning-software)

**Best fit.** All in all, automated statistical forecasting offers a satisfying level of accuracy for:

* mid- to long-term planning,
* well-established products, that enjoy stable demand, and
* predicting total demand rather than sales of separate stock-keeping units (SKUs).

Does it make business sense to invest in more sophisticated technologies? We’ll try to clear things up in the next section.

## Machine learning for demand planning — advanced accuracy at the price of added complexity

Increased computer power on the one hand and increased demand volatility on the other created prerequisites for wider use of [machine learning](https://www.altexsoft.com/whitepapers/machine-learning-bridging-between-business-and-data-science/) (ML) to design predictions. Say, demand sensing that we mentioned above solely relies on ML techniques to generate short-term predictions in response to diverse market changes. ML also drives [**predictive analytics**](https://www.altexsoft.com/blog/analytics-maturity-model/#predictive-analytics) beyond just estimating demand. It combines historical and current data to generate insights in trends and custom behavior under certain conditions.

**Data sources.**Built upon statistical models, machine learning utilizes additional internal and external sources of information to make more accurate, data-driven predictions. ML engines can work with both [structured and unstructured data](https://www.altexsoft.com/blog/structured-unstructured-data/) including

* past financial and sales reports (historical data),
* marketing polls,
* macroeconomic indicators,
* social media signals (retweets, shares, spikes in followers),
* weather forecasts,
* news about local events,
* competitors activity, and more.

Data sources for demand forecasting with machine learning. Source: [IBF](https://demand-planning.com/2019/08/26/forecasting-data-types/) (Institute of Business Forecasting and Planning ).

**Why use it.**Machine learning applies complex mathematical algorithms to automatically recognize patterns, capture demand signals, and spot complicated relationships in large datasets. Apart from analyzing huge volumes of information, smart systems continuously retrain models, adapting them to changing conditions thus addressing volatility. These capabilities enable ML-based software to produce more accurate and reliable forecasts in complex scenarios.

What does more accurate really mean? Companies that added machine learning to their existing systems report an increase of[5 to 15 percent](https://www.toolsgroup.com/blog/improving-demand-forecasting-and-planning-with-machine-learning/) in forecast reliability (up to 85 and even 95 percent). In addition to this, your team gets rid of time-consuming manual adjustments and recalibrations.

**Things to consider.**To take advantage of the machine learning solution, you need sufficient processing power and really large batches of [high-quality data](https://www.altexsoft.com/blog/data-quality-management-and-tools/). Otherwise, the system won’t be able to learn and generate valuable predictions.

Also, bear in mind the additional complexity in terms of software maintenance and result interpretation. While ML mechanisms come to conclusions without human intervention, it’s up to a live tech expert to determine what features should be fed to the model, which of them have the largest impact on the output, and why the model generates a certain prediction. Check our detailed article about [roles in a data science team](https://www.altexsoft.com/blog/datascience/how-to-structure-data-science-team-key-models-and-roles/) to get a picture of which specialists have to be involved.

**Best fit.**The list of situations in which machine learning definitely works better than traditional statistics includes:

* short- to mid-term planning,
* volatile demand patterns,
* fast changing environment, and
* new product launches.

Comparison between traditional and machine learning approaches to demand forecasting.

As you can see, employing machine learning comes with some tradeoffs. Depending on the planning horizon, data availability, and task complexity, you can use a combination of different statistical and ML solutions.

Whichever methods you choose, you’ll need specialized software that can help you with your predictions.

## Demand forecasting software: how to choose

Today, there are a lot of solutions on the market that can support your demand planning activities. They have different capabilities, and the choice depends on your business needs. Here are several things you should consider if you’re thinking of acquiring an off-the-shelf tool.

### Functionality

Obviously, the first thing you have to look at is whether it fits your business requirements. Depending on your industry and business model, you might need

* short-term or long-term predictions (or both);
* demand forecasting for new products;
* multitiered planning for different regions, channels, and product groups;
* price elasticity estimation;
* multidimensional modeling and comparisons of what-if scenarios (for promotions, price changes, market fluctuations, display variations, assortment changes, etc.);
* accounting for halo effects and product cannibalization (when demand fluctuations of one product impact complementary or competitive items);
* granular dashboards and reports, and so on.

How promotion influences demand. Source: [Relex](https://www.relexsolutions.com/resources/4-keys-to-better-retail-promotion-forecasting-and-replenishment/)

### Compatibility with your business tools

It’s crucial to connect your internal systems (like ERP or sales management software) to a demand forecasting solution to enable data sharing, collecting complete historic information, and building demand trends. Besides, smooth integrations with your [inventory management system](https://www.altexsoft.com/blog/inventory-management-software/) or [warehouse management system](https://www.altexsoft.com/blog/warehouse-management-systems/) (WMS) will allow you to streamline procurement and capacity management.

Many vendors of demand forecasting software offer out-of-the-box integrations with the most popular ERP providers, Excel, and other business tools, so check if the chosen provider can assist you with system connections. If not, you’ll have to engage IT specialists to build internal integrations.

### Tech support and training

Logically connected to the previous recommendation, make sure the software provider offers all the necessary support during and after implementation. Such tools aren’t something you download and just start using – they need a lot of data for analysis that has to be imported properly. Also, remember that you’ll have to conduct sufficient training for your staff.

### Data sources and external factors

Depending on your industry, you might need to consider external factors to increase the accuracy of your predictions, e.g., weather, macroeconomic trends, and others. Contact your provider to find out which data sources they use.

Typically, the more data you have, the more impacting factors would be considered, and the more accurate your forecasts will be. But building such complex, custom analytical infrastructure requires investment and engagement of [ML engineers](https://www.altexsoft.com/blog/machine-learning-engineer/), [data scientists](https://www.altexsoft.com/blog/data-scientist-vs-data-engineer/), and other specialists. However, it pays off. Let’s talk about some real-world examples of successful ML-based demand forecasting.

## When machine learning works best for demand planning: successful use cases

Highly variable environment, dozens of factors driving buying behaviors, many types of data involved — all these often make demand planning too complex to be successfully performed with simple tools. So, big companies choose to invest in smart technologies to optimize their inventory management.

### Nestlé implements demand-driven forecasting

Nestlé used to create 80 percent of their forecasts with human intervention. But they wanted to better understand their customer motives. SAS forecasting and analytics technology allowed them to sense and analyze demand signals associated with sales promotions, price, advertising, in-store merchandising, and economic factors.

Charles Chase, an Industry consultant, [reports](https://supplychaindigital.com/logistics/how-demand-driven-forecasting-paid-nestle), “Today, 80 percent of Nestlé’s forecasts are driven right out of the solution with no human judgment at all. …Every one percent improvement in forecast accuracy translated into a two percent reduction in inventory safety stock. They were eventually able to take out anywhere between 14- 20 percent of their inventory safety stock, reduce it and still meet consumer demand with this improved forecasting capability. If you have US $100 million in inventory that’s a US $20 million reduction.”

### PUMA adopts an integrated approach to inventory management

PUMA experienced losses and had a gap between supply and demand due to disconnected business systems and fragmented tools. After [implementing](https://www.board.com/en/case-study/integrated-business-planning-puma#gref) a comprehensive solution with data management, forecasting, and simulation capabilities, they managed to fix and standardize their planning and analytics processes. As a result, they streamlined procurement, mitigated shortages and residual stock, and gained fuller visibility into both external market conditions and internal operations.

### UK hospitals reduce waste from blood overstocks with ML

The significant complexity of supply chain, short-term demand spikes, and the high cost of errors (with human lives at stake) prompted the Blood and Transport department of the UK’s National Health System (NHS) to transfer from spreadsheets and manual databases to ML-fueled planning system with enhanced predictive capabilities. It allowed hospitals to reduce waste from blood overstocks by [30 percent](https://www.toolsgroup.com/success-stories/nhs/?_ga=2.27875388.101788408.1543232035-138887441.1543232035) without any drop in service quality and enabled rapid responding to potential shortages. “If there’s no yogurt on the supermarket shelf — well, that’s unfortunate. If there’s no blood in the hospital, the consequences are very different,” an NHS executive explained as the reason to invest heavily in the advanced solution.

## How to approach demand forecasting?

If you want to implement any kind of demand forecasting solution to enhance your supply chain and planning operations, there are several important considerations.

### Buy or build?

As we said, the answer depends on your needs and resources.

**Use a demand forecasting module**. The easiest (not the cheapest) thing to do is get comprehensive business software such as ERP or WMS that already has an in-built demand forecasting module and manage all your business operations from a single system.

Pros and cons: you don’t need to build internal integrations, but the functionality might be limited and hard to customize.

**Buy a separate tool**. If you’re big enough to track and forecast demand, but still not ready for a full-blown ERP, get a specialized solution that fits your needs.

Pros and cons: It’s cheaper and you’re more flexible with choosing the functionality, but you’ll have to build bespoke integrations.

**Build a custom system**. If you have unique business needs and want to have a system tailored for them, it will require custom development.

Pros and cons: Maximum customization and accuracy, but takes a lot of time and investment.

### Test the waters with ML

While adoption of machine learning tools can somewhat narrow the gap between anticipation and reality, it doesn’t mean that every company should immediately jump to complex intelligent technology. You can start with small enhancements to your existing system that will address those problems that are difficult to solve by traditional methods. For example, use a machine learning module to make data-driven changes in planning for the short term and leave long-term forecasting to old-school statistics.

### Remember about cost-effectiveness

Sometimes it turns out that dealing with forecast errors (such as excessive stock) is cheaper than fine-tuning your ML models to obtain maximum accuracy. Don’t get carried away with perfectionism; better calculate the ROI and think if further investment is worth it.

Besides, sometimes forecasts are erroneous because of random or completely unpredictable factors, so any efforts to increase prediction accuracy are pointless.

Who could’ve predicted those notorious toilet paper shortages? Source: [USA Today](https://www.usatoday.com/story/money/2020/04/08/coronavirus-shortage-where-has-all-the-toilet-paper-gone/2964143001/)

### Integrations and testing are key to success

Some 20 years ago, the retail giant Nike invested $400 million in their supply chain software and demand planning system. However, instead of having the right inventory to fulfill customer demand, they ended up [losing $100 million](https://www.cio.com/article/264637/enterprise-resource-planning-nike-rebounds-how-nike-recovered-from-its-supply-chain-disaster.html) because the predictions were wrong. It happened because the system wasn’t tested sufficiently. It turned out that it had some bugs and wasn’t properly integrated with data sources.

The lesson learned: Build seamless integrations to establish smooth data exchange and give sufficient attention to your testing activities to make sure your system functions properly and forecasting results are reliable.

### Short-term forecasts are typically more accurate

It’s simply easier to predict what happens in a day or two than trying to imagine what life will be like in a year. Starting from simple factors like weather and ending with ever-changing customer preferences and other unstable market and macroeconomic conditions, the shorter the time frame the more accurate the prediction is likely to be.

### Human brains still matter

Forecasting demand is a challenging task, and it still has much room for improvement. Upland, the U.S. provider of business management software, [claims](https://uplandsoftware.com/altify/resources/blog/sales-forecast-accuracy-the-results-are-in-and-its-not-pretty/) that sales forecasts are less than 75% accurate and calculates that the US economy spends around $50 billion on predictions that are pretty much worthless. Sounds scary, doesn’t it?

However smart your forecasting solution is, the key decisions still rest with human capital. You need industry specialists to define which factors should be considered in your predictive models. Human logic is still required to evaluate the relevance of outcomes produced by digital brains and to make final conclusions based on common sense and deep domain expertise.

That’s why even ML-powered demand planning systems often include a collaborative platform that allows for engaging different specialists in a forecasting process. Only by taking the best of what both artificial and human intelligence offer can you see and plan a better future for your business.