Demand Forecasting Models: Unveiling Business Insights

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Abstract

This document explores key metrics of demand forecasting, challenges of collecting operational data and the types of market response models. Further, it discusses the creation and integration of qualitative models for enhanced demand forecasting and understanding customer behavior. Lastly, it outlines techniques for presenting the forecasted results to leaders, emphasizing on clear visuals and concise explanations for effective demand planning.

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1. Key Metrics in Demand Forecasting

The pillars of demand forecasting involve crucial metrics like: Market share, Net Promoter Score (NPS), Customer Lifetime Value (CLV), ROI (Return on Investment), and the Value of a Like. Each metric offers a unique perspective on business performance and customer engagement.

A. Market share

It's the portion or percentage of the total market that a company or product holds in terms of sales, revenue, or other relevant metrics. Imagine a room full of people all buying smartphones, and Company X sells 30% of all the smartphones in that room. Well, Company X's market share for smartphones in that scenario is 30%. It's a way to measure a company's or product's presence and performance within a specific market (Chase, Jacobs, and Aquilano, 2006).

A survey conducted by Bendle, N. T (2016) in the article "The Metrics That Marketers Muddle", highlights that many managers believe that the primary purpose of a business is to maximize shareholder value. However, some argue that a business should also cater to the interests of non-owner stakeholders like employees and customers. It is emphasized that increasing market share doesn't offer any benefit unless it generates profits. Since market share is a measure of relative success rather than absolute success, pursuing market share objectives can lead companies to engage in unprofitable competitions with competitors. This has, in various industries, resulted in detrimental effects on profits, in the context of price wars.

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B. Net Promoter Score (NPS)

It operates as a satisfaction benchmark for businesses, assessing the likelihood of customers recommending a company's products or services to others. The method involves asking customers simple questions, usually on a scale from 0 to 10: "How likely are you to recommend our product/service to a friend or colleague?" Based on their responses, customers are categorized into three categories:

1. Promoters (score 9-10): Enthusiastic fans who are likely to recommend your business.
2. Passives (score 7-8): Satisfied but not overly excited, may recommend without active promotion.
3. Detractors (score 0-6): Unhappy customers prone to spreading negative feedback.

NPS is calculated by subtracting the percentage of Detractors from the percentage of Promoters. The result can range from -100 to 100, with a higher score indicating better customer satisfaction and loyalty. This method is an effective way for businesses to assess their performance in the eyes of their customers. NPS has found widespread adoption across diverse industries, including telecommunications, banking, and car rental, where it is utilized to monitor and enhance customer service operations (Reichheld, 2003).

C. Customer Lifetime Value (CLV)

It acts as visionary tool for businesses, predicting the total worth of a customer throughout their entirety of association with the company. It's goes beyond the first purchase; encompassing the entire journey. CLV calculates the total revenue a business can expect to earn from a customer throughout their entire engagement. This includes all the purchases they're likely to make, the services they might use, and the loyalty they'll hopefully show. Formula for calculating CLV is:

$$\text{CLV} = \frac{(\text{AveragePurchaseValue} \times \text{PurchaseFrequency} \times \text{CustomerLifespan})}{RetentionRate}$$

- Average Purchase Value: The average amount a customer spends per transaction.
- Purchase Frequency: How often a customer makes a purchase within a given timeframe.
- Customer Lifespan: The average number of years a customer continues to buy from your business.
- Retention Rate (RR): The percentage of customers retained over a specific period.

$$\text{RR} = \frac{\text{Customers at the end of the period} - \text{Customers acquired during the period}}{Customers\ at\ the\ start\ of\ the\ period}$$

Businesses might also customize the above mentioned CLV formula based on their specific needs and industry characteristics as they amass more data and insights into evolving customer behavior over time (Berend Wierenga and Gerrit H. van Bruggen, 2000)

D. The ROI (Return on Investment)

Serving as the scoreboard for your financial endeavors. It's a performance metric, evaluating the profitability and efficiency of an investment. Be it time, money, or resources, ROI describes the returns in relation to the input you put in.

ROI = (Net Gain from Investment / Cost of Investment) × 100

- Net Gain from Investment: Signifying profit or benefit gained from the investment. It's calculated by subtracting the initial cost of the investment from the total return.
- Cost of Investment: Encompassing the total amount spent on the investment, including any initial costs and ongoing expenses.

For example, if $1,000 is invested in a marketing campaign, yielding $3,000 in sales as a result, the net gain is $2,000 ($3,000-$1,000), resulting in an ROI = 200% (Brealey, Myers, and Allen , 2017).

E. The Value of a Like

Analogous to a thumbs-up or a nod of approval in the online world. It refers to the action of users expressing their positive sentiment or endorsement of content on social media platforms by clicking the "Like" button. The actual monetary value of a single "Like" can be tricky to quantify directly because it depends on various factors, including the context, the platform, and the type of content. However, in a broader sense, the value lies in the engagement and visibility it generates.

For businesses and individuals, a higher count of "Likes" signifies popularity, trust, and a positive brand image. This can contribute to heightened visibility, extended reach, and enhanced credibility on social media platforms. Moreover, a post or page with more "Likes" is more likely to be seen by others, potentially attracting additional followers or customers. From a marketing standpoint, the value of a "Like" is often regarded as an integral facet of broader social media marketing strategies. Establishing a robust online presence and community indirectly contributes to business success. While attaching a direct dollar amount to a single "Like" may be challenging, the cumulative impact of numerous "Likes" translates into tangible benefits for brands and individuals in the digital landscape (Tuten and Solomon, 2017).

2. Operational Data Collection Challenges for Demand Forecasting

The success of demand forecasting hinges on the meticulous collection and analysis of pertinent data for precise predictions. However, the transition from raw data to actionable insights encounters several hurdles. Businesses grapple with the following factors during this process:

Data quality and quantity

The accuracy, completeness, consistency, and timeliness of data constitute data quality, a pivotal factor for model training. Inaccuracies in data can lead to erroneous conclusions.

Lack of accurate historical data

The absence of precise historical data poses a significant challenge, hindering the establishment of reliable forecasting models.

Insufficient collaboration across the supply chain

Effective demand forecasting requires seamless collaboration throughout the supply chain. Inadequate coordination can impede the flow of essential information.

Supply chain dependencies causing last-minute changes

Dependencies within the supply chain can result in unexpected modifications, introducing complexities and uncertainties into the forecasting process.

Ensuring data quality is of paramount importance for model training, as inaccuracies can lead to erroneous predictions. Timeliness is equally critical, as outdated data can steer predictions in the wrong direction. Additionally, selecting an appropriate forecasting method is vital to align the forecast with the unique characteristics of the business and its market, constituting an essential step in the demand forecasting journey (Owczarek, 2023).

3. Using Market Response Models for Demand Forecasting

Market response models estimates future demand. By understanding how the market reacts to changes in pricing, promotions, and other variables, providing businesses with a strategic advantage. Incorporating a market response model into demand forecasting enables businesses to predict consumer behavior more accurately, empowering them to proactively shape business strategies and demand planning based on anticipated market responses. There are two distinct types of demand forecasting methods based on type of data: Quantitative & Qualitative

A. Quantitative Models

For Numerical data types. This is again divided into 2 categories: Time-series and Casual.

Time-Series (or reactive / one-dimensional methods)

Techniques built on the premise that future sales will replicate the pattern(s) of past sales. Various classes of time series methods include (Chase, 2013):

- Naive or random walk
- Moving averaging
- Exponential smoothing
  - Single
  - Holt's and Winters' two-parameter
  - Brown's double
  - Winters' three-parameter
- Decomposition
  - Additive
  - Multiplicative
- ARIMA (AutoRegressive Integrated Moving Average)

The advantages of time series methods include:

- Well-suited for situations requiring demand forecasts for many products.
- Effective for products with a relatively stable sales history.
- Ability to smooth out small random fluctuations.
- Simple to understand and use.

- Easily systematized, requiring minimal data storage.
- Readily available software packages.
- Generally effective for short-term forecasting (one to three periods into the future).

However, time-series methods have their disadvantages, such as:

- Requiring a large amount of historical data.
- Adjusting slowly to changes in sales.
- Necessitating extensive search for smoothing weights (alpha, beta, gamma).
- Typically struggling with long forecast horizons.
- Being sensitive to large fluctuations in current data, leading to forecast errors.

Casual (or proactive / multi-dimensional methods)

The basic premise of causal methods is that future sales of a particular product are closely associated (or related) with changes in some other variable(s). For example, changes in sales can be associated with changes in price, advertising, sales promotions, and merchandising. Therefore, once the nature of that association is quantified, it can be used to forecast sales. The most widely used causal methods are (Chase, 2013):

- Simple regression
- Multiple regression
- ARIMAX (AutoRegressive Integrated Moving Average with eXogenous variables). This is an extension of ARIMA model.
- Unobserved components models

The major advantages of causal methods are:

- Availability in most software packages.
- Coverage in most statistics courses, making them familiar to managers.
- Provision of more accurate short- and medium-term forecasts than time series methods.
- Support for what-if analysis.

However, causal methods come with their set of disadvantages, including

- Forecasting accuracy dependence on a consistent relationship between independent and dependent (or influence) variables.
- An accurate estimate of the independent variable is crucial.
- Many managers view them as black-box techniques.
- More time intensive for development, requiring a strong understanding of statistics.
- Larger data storage requirements and lesser ease of systematization
- Tend to be more expensive to build and maintain.

B. Qualitative Models

For Categorical / Textual data types. Broadly classified into:

- Executive opinion: Opinions from experts, decision makers or customers
- Delphi method
- Sales Force estimates: Individual salespeople making sales estimates.
- Consumer surveys: Pertaining to questions like would you purchase y or x product (Avercast, 2015).

Text and Sentiment Analysis

For applications like language modelling, text classification, question answering and machine translation (Miller, T. W. (2015).

Neural Networks

The most common types of neural networks are as detailed below (IBM, n.d):

Feedforward Neural Networks (FNN). The simplest form of neural network, where data moves straight through layers (input to output). These models are the foundations for computer vision, natural language processing, and other neural networks.

Convolutional Neural Networks (CNN). Specialized for image data, uses convolutional layers. Application: Image and video recognition, object detection.

Recurrent Neural Networks (RNN). Network with loops, retains memory of previous inputs. Application: Natural language processing, speech recognition, time series analysis.

Long Short-Term Memory (LSTM) Networks: Improved RNN with better memory handling. Application: Speech recognition, language modeling, time series prediction.

Gated Recurrent Units (GRU): Simplified RNN variant balancing efficiency and memory. Application: Natural language processing, machine translation.

Transformer Models

These are a powerful class of neural networks / deep learning models commonly used in Natural language processing (NLP) and other applications of generative AI. Transformer models are designed to learn the contextual relationships between words in a sentence or text sequence (DELL Technologies, n.d). Examples of such pre-trained transformer models are:

- OpenAI's GPTs (Generative pretraining transformers),
- Meta's LLaMA (Large Language Model Meta AI),
- Google's BERT (Bidirectional Encoder Representations from Transformers)

4. Create and Insert Demand Forecast Model

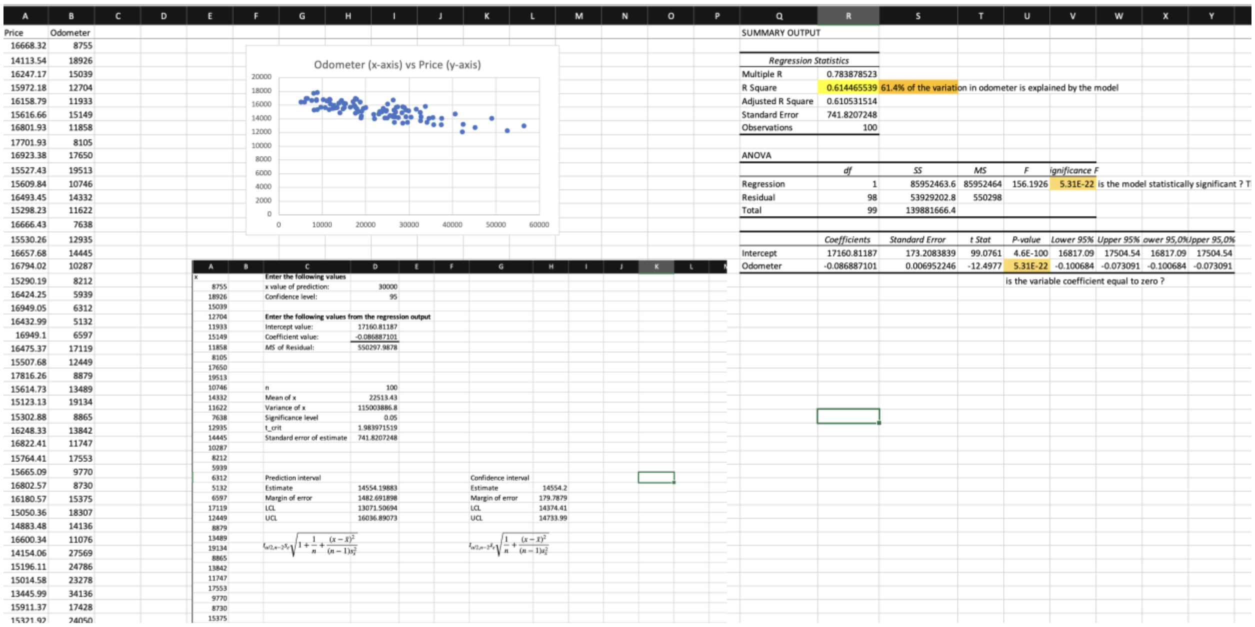
After completing the data cleaning process, conducting initial exploratory analysis on the raw data and selecting the right forecast method, we can proceed to build and train the demand forecast model using tools such as Excel, IBM SPSS, SAS or Google BigQuery for Demand Forecasting.

In this section, we will use car miles & price data and preform regression to derive insights. As an illustration, I developed a linear regression model utilizing the Data Analysis feature in Excel to predict the pricing of used cars based on their odometer values.

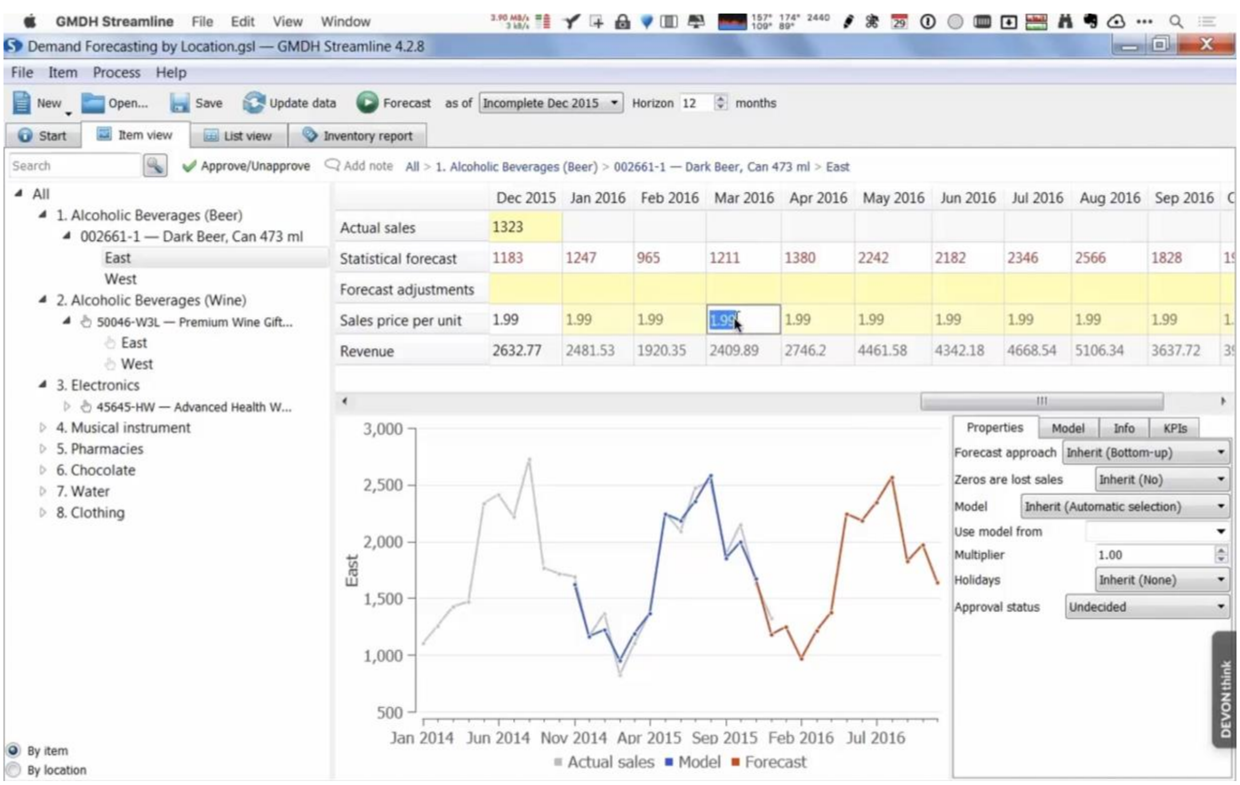
During the preliminary data exploration phase, I identified a negative slope in the scatter plot between price and odometer values. This observation suggests that as the mileage increases, the price of the car tends to decrease. Subsequently, the historical data comprising price and odometer values were input into the linear regression model, which was trained at a 95% confidence level.

The outcomes from the regression model are presented in the attached Excel sheet. Particularly noteworthy is the R-Square (coefficient of determination) value, which, when multiplied by 100, provides the percentage of variation in the Price (dependent variable). A higher R-squared value signifies a better alignment of the model with the data.

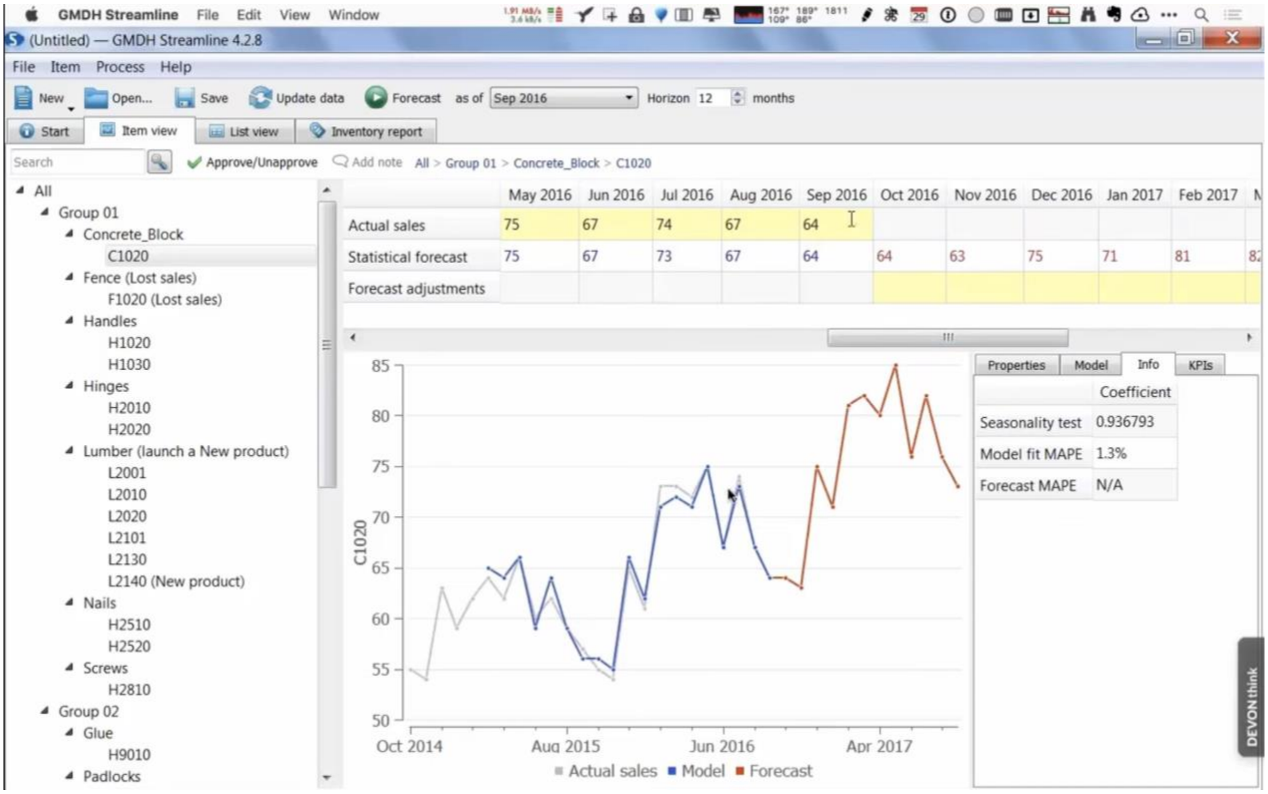
The model output facilitates the estimation of used car prices. For instance, in the accompanying Excel sheet, the forecasted price of a used car with 30,000 miles on the odometer is approximately $14,500.



Additionally, a screenshot of a custom-built tool exemplifying streamlined demand forecasting and inventory planning is featured below. In this tool, as demonstrated by the author (Serating, 2016), forecasts for beer sales are conducted.



In an another example, the author (Serating, 2016) introduces modifications to certain variables, such as launching a new product at a different time of the year than initially planned and implementing promotions. These changes trigger real-time updates in the forecasts, showcasing the tool's dynamic adaptability to alterations in input variables.

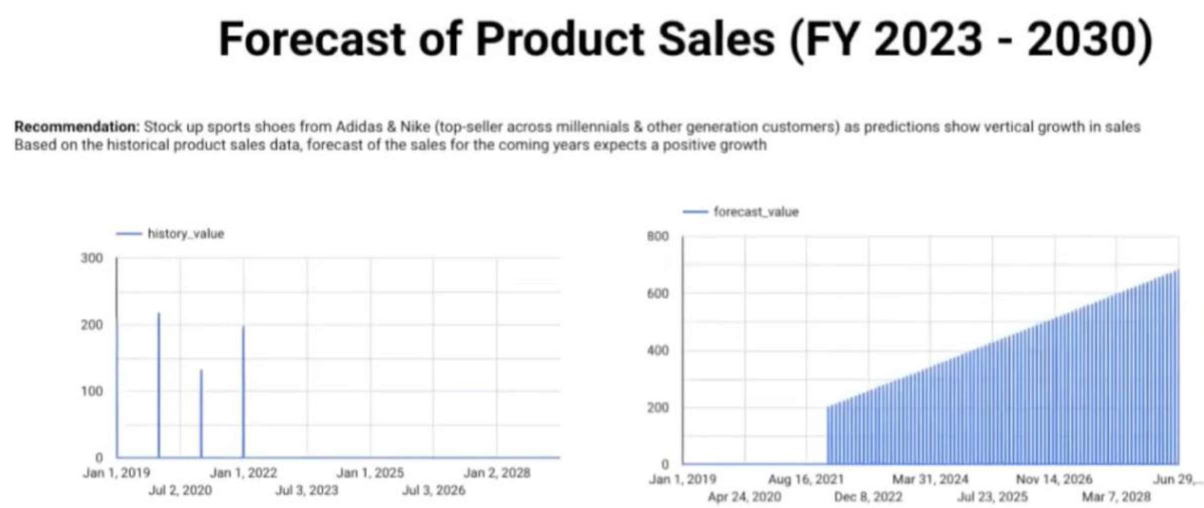


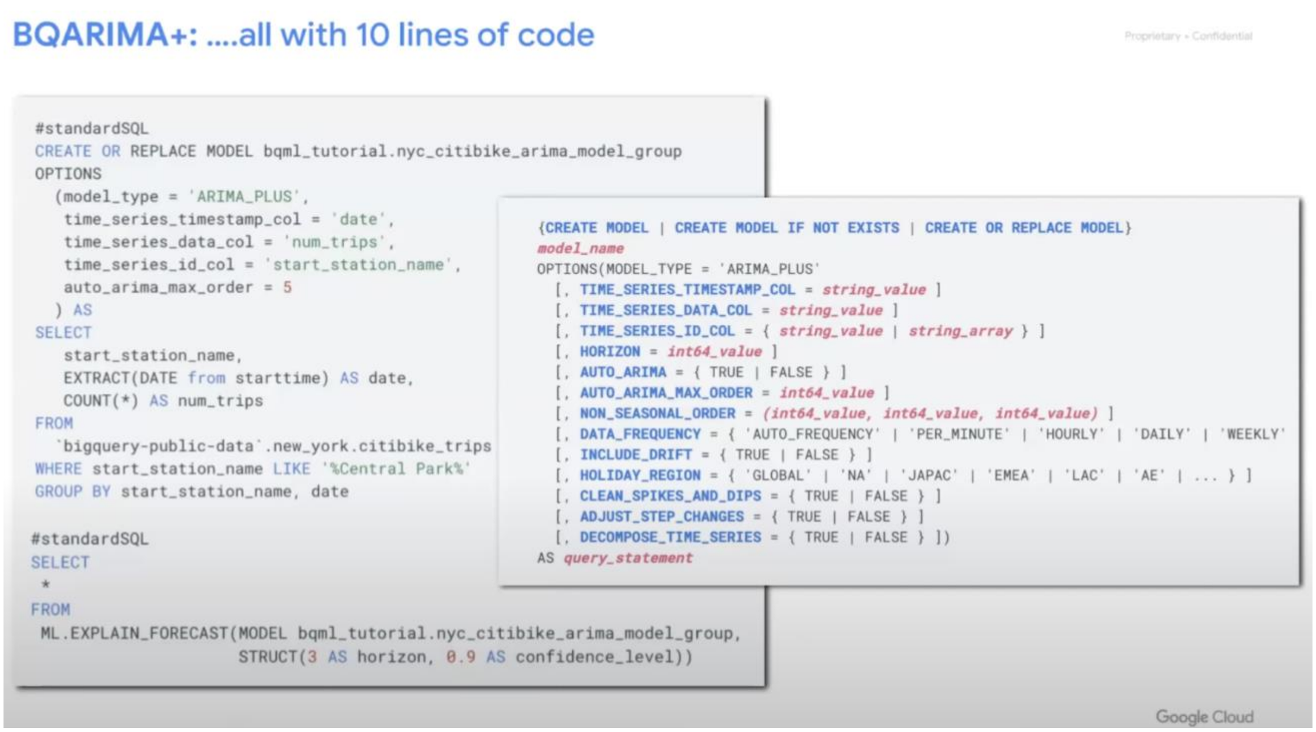
5. Communicate the Forecasted Results to Leadership

The outcomes of the demand forecasting process are typically conveyed to business stakeholders in a readily comprehensible language, incorporating key business value metrics.

For example, the product sales forecast presented in the below screenshot is an example of time-series model. The initial analysis of historical shoe sales data spanning from 2019 to 2022 is presented in the report. After the initial examination of data at hand, a suitable ARIMA time-series prediction model is selected, and model is constructed on Google BigQuery (BQ) Datawarehouse to forecast future shoe sales. The model forecast results are plotted in a line chart utilizing the Google LookerStudio reporting tool. After evaluating the results, business value of anticipated 20% growth in product sales over the next two years is observed. Hence, it is recommended in the below report to the business / leadership team to replenish the inventory of sports shoes, particularly those from Adidas and Nike, with a specified quantity (e.g., 5k)

The below comprehensive report can be easily shared with the leadership team through a collaboratively editable report URL link, fostering dynamic engagement and input into the report. Additionally, the report can be exported to formats such as Excel or PDF, facilitating further in-depth analysis. Moreover, various other business intelligence tools like PowerBI and Cognos provide sophisticated interactive visual diagrams. These tools serve as effective mediums to communicate the forecasted results and recommendations to the leadership team, ensuring a seamless exchange of insights and strategic decision-making.





(Timoteo, 2021)

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