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Automated Time Series Demand Forecast for Luxury Fashion Online Retail Company

Leonel Murillo Alfaro

Internship report presented as partial requirement for obtaining the Master's degree in Advanced Analytics

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AUTOMATED TIME SERIES DEMAND FORECAST FOR LUXURY FASHION ONLINE RETAIL COMPANY

by

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ABSTRACT

Demand forecasting for a retail company in luxury fashion is a challenging process due to the highly complex and demanding customer profile. As the company keep growing, more and more partners are demanding the expected volume of orders for better operational capacity planning and to justify the return of their investment. This project aims to create an automatic and scalable forecasting process to ensure customer experience and partnership profitability. By studying decomposition time series forecasting taking in consideration the customer behavior, a machine learning process can be applied for parameters tuning depending on customer clusters based on geolocation and marketing events. The proposed process has shown forecast accuracy number up to 90% for non-sale season and 84% for sale season periods, reducing the forecasting time in 88% versus the previous forecast process and increasing the partner coverage from 20% to 100%. Acknowledging that this forecast process is a continuous learning process, the foundation of a robust supply chain planning was created building trust in the organization and adding value to the partners.

KEYWORDS

Decomposition Time Series; Scalable; Marketing; Geolocation; Trend; Error; Seasonality; Cross Validation; Parameter Tuning; Machine Learning; Continuous Improvement; Clustering; Forecast Accuracy; Prophet; Facebook; Open Source; Fashion Industry; Sale Season; Data Visualization; Key Performance Metric; Business Intellengice Platform; Supply Chain Management; Capacity Planning

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LIST OF ABBREVIATIONS AND ACRONYMS

ACRONYM	MEANING
AW	AUTUMN-WINTER
BF	BLACK FRIDAY
BI DW	BUSINESS INTELLIGENCE DATA WAREHOUSE
BO	BOUTIQUE/BRAND ORDER
CS	CUSTOMER SERVICE
CSV	COMMA-SEPARATED VALUES
DD/MM/YYYY	DAY, MONTH AND YEAR FORMAT
DW	DATA WAREHOUSE
EDPL	EUROPEAN DATA PROTECTION LAW REVIEW
ETL	EXTRACT, TRANSFORM AND LOAD
FA	FORECAST ACCURACY
FOL	FACT ORDER LINES
FP	FULL PRICE
FSCT	FORECAST
GMT	GREENWICH MEAN TIME
GMV	GROSS MERCHANDISE VALUE
IPO	INITIAL PUBLIC OFFERING
IT	INFORMATION TECHNOLOGY
KPI	KEY PERFORMANCE INDICATOR
LATAM	LATIN AMERICA
MAPE	MEDIAN AVERAGE PERCENTAGE ERROR
MOM	MONTH OVER MONTH
OLAP	ONLINE ANALYTICAL PROCESSING
PO	PORTAL ORDER
PS	PARTNER SERVICE
R&D	RESEARCH AND DEVELOPMENT
R2	R SQUARE: COEFFICIENT OF DETERMINATION
REV	REVISION
ROW	REST OF THE WORD
SD	SINGLES DAY
SIPOC	SUPPLIER, INPUT, PROCESS, OUTPUT, CUSTOMER
SS	SPRING-SUMMER
VIP	VERY IMPORTANT PEOPLE
WW	WORK WEEK
X10, X20	DISCOUNT PERCENTAGE
YOY	YEAR OVER YEAR
YYYY-MM-DD	YEAR-MONTH-DAY

I. Introduction

Project Introduction

At the company, the Operations Supply Chain Team is in charge of managing the relationship with the partners and brands in which the company operates. Both, the partners and the company, get benefits by improving this relationship in order to maximize the Gross Merchandise Value (GMV). As the company works in the fashion luxury industry, the customer demands excellence in their whole experience. Therefore, the company need to be clear in terms such as: how can a company improve the customer experience? Or: what is the role of the Supply Chain Team, taking in consideration that the end customer won't interact directly with them? Improving the customer experience is a multi-dimensional requirement that include the organization as a whole and the Supply Chain department plays a key role to meet it.

As a retail company, is expected that the Supply Chain Team ensure the supply of inventory levels that will not compromise a bad experience to the customer. By having the right inventory will directly impact the customer satisfaction increasing the retention rate and also reducing operational cost, for example. A good forecast of future orders, will prepare better our partners for the demand, ensure the materials needed (e.g. packaging) and reduce inventory costs (by reducing the over or under stock levels)

In the Fashion industry, having the optimal inventory levels is always a challenge. The historical data (if it is available) is not enough to forecast future trends. In the modern era, the word is connected real time and social media change the customer behavior quick and unexpectedly. Some influencers, opinion-makers and other external factors play here a key role. Fashion trends are extremely sensitive to the social media, creating a difficult process to make purchase projections. Therefore, this forecasting process will require the best technical analysis but also a revision of the results with experts in the industry.

Having a robust forecasting process is key for success of this business. Most of the partners are designers with small to medium companies that don't have the technical capabilities to meet this forecast requirement. Is a company duty to have the best forecasting process, from the data gathering to the monitoring of the results. A good forecast will create a win-win relation between the company and the partners.

The presented project aims to solve this area within the Operation Supply Chain Team with a data science approach using time series methods, in order to improve the performance indicators that measure the relationship company-Partners. This proposal covers the technical part of the forecast of boutique orders, however, it is clear that a judgmental revision from experts in the business will be still needed, creating disturbance in the direct results, but with the intention of increasing the accuracy. Also, the proposal deal with the visualization of the data for better and faster decision making and to provide a closely tracking of the actual demand signals to adjustments if needed. All of this, with the intention that the analyst in charge and the model itself learn from the experience and become better forecaster for the company.

Finally, an Information Technology (IT) solution to automatize as much as possible is covered in the proposal, taking the consideration the risks and limitations that this might have, especially in the diagnostic phase of the time series, where the analyst requires some level of judgment.

Used Software

The project used the following software:

- Microsoft Office 2016
- R x64 3.5.1
- R Studio Version 1.1.456
- Microsoft SQL Sever Management Studio v17.7
- Tableau Desktop 2018.2.0 64bit

Problem Statement

Low forecast accuracy for boutique order in the past, has generated high no stock levels, impacting negatively the customer experience and retention rates driven by incorrect capacity planning during sale and non-sale seasons.

General Objective

Create a robust time series forecast process for boutique and brand orders for the Sale and Non-Sale seasons that meets all the business requirements and ensure acceptable forecast accuracy levels.

Specific Objectives

1. Standardize the forecast performance metrics that the company will use to measure a forecast efficacy.
2. Perform the boutique and brand order forecast with the current (As Is) process during the Non-Sale months (from August and October of 2018) and Autumn-Winter (AW18) 2018 Sale season (that covers November and December of 2018 and January 2019).
3. Measure the performance metrics against actuals for the current (As Is) process, using the agreed metrics proposed in the specific objective number 1.
4. Research about time series forecast done by other companies that could suit the company case.
5. Test and compare new methodologies with the actual performance of the boutique and brand during the months stated in the specific objective number 2.
6. Propose a new forecast methodology based on the research and actual performance metrics.
7. Create a benchmarking process with Finance GMV forecast.
8. Create an IT solution that automatize as much as possible the data gathering, forecast generations and performance metric to facilitate the decision-making process at the time of the judgmental phase.
9. Design a scorecard for live-time forecast tracking monitoring.
10. Propose a realistic yet challenge forecast accuracy target for the business.
11. Create a methodology for quick and efficient What If analysis to measure the possible impact in Orders with a potential marketing change.

Scope and Limitations

The scope of the project covers the boutique and brand forecast at orders level in the required granularity.

The limitations of the project are the following:

- Historical data available: some boutiques and brands could be recently joined the company, therefore there might not be enough historical data to perform a trustful forecast
- Sales and marketing calendar strategies:
    - Boutique Order forecast is aligned to the calendar, however, last minute changes in the strategy will affect the forecast.
    - Brand forecast is also aligned to the calendar, however, brands have the freedom to decide their own calendar that might or not be shared with the company. Therefore, is expected that brand order forecast might suffer a lower forecast accuracy due to this limitation.
    - Since the calendar is released for many other departments that require a very level of detail, in the case of order forecast and for both cases (boutiques and brands) not all levels of granularity of the calendar are included as an input in the forecasting model (e.g. Customer Tier).
- Data privacy: due to the European Data Protection Law Review (EDPL) and Initial public offering (IPO) regulations, some of the data used in this report might be protected or hidden. The actual and forecast data has been protected by multiplying it by a constant. As the results and mainly shown in percentages, this won´t scarify any quality of the report. The company and partners names have been protected as well by naming then as "company" and "boutique n", where n can be 1,2, …, n.

Business Requirements

The order forecast needs to meet the following business requirements:

- Granularity: overall and by boutique (or brand) and by day GMT.
- Boutique and brand to be included in the forecast:
    - Must include all partners of the company.
- The forecasts need to be easily adjustable for last minute changes in the Sale and Marketing calendar.
- The reporting of the forecast need to include all the agreed daily KPI (Key Performance Indicator) and have two approaches:
    - Daily forecast performance: includes the Overall and by boutique (and brand) forecast performance.
    - Weekly forecast performance: aggregated per week KPIs measurements grouped by Store Tier, not by individual boutique/brand levels.
- The selected forecasts, must be stored in a single version of the truth that can be easily shared with other departments.

- The overall forecast process must be as automated as possible without sacrificing accuracy, including the ETL process from the data warehouse, data analytics and data visualization.

Justification: business case and importance

The importance to have a high-quality forecast of boutique and brand orders in Supply Chain department is key for the success of the company and the company's partners. The following list explain the key justification points of the project:

- Partners capacity planning: the partners need an accurate forecast of orders to prepare their human resources to high and low volume seasons. This is key to increase their performance supplying the orders on time and high quality. A low-quality forecast, could create over or under capacity resources, putting in danger the sales expectations for the partner and the company itself.
- Service center capacity planning: the order forecast is used by the company to plan the capacity of the service center department. This department is in charge to answer any query by customers and/or partners. A low-quality forecast could impact their KPIs that measure the speed of answer and solve a problem to their customers. The image of the company could be impacted as well, if there is not enough resources available to satisfy the customer's needs.
- Finance expectations: the partners use the order forecast to calculate their profit at the end of a period. This forecast justifies the partnership with the company, as it creates a overview of the future sales. For each sale, one portion of it, goes to the partner and another to the company. In order to justify the rentability of this partnership, the partners need to ensure enough amount of orders to cover their fixed cost. Therefore, this forecast is highly sensitive to the relationship with the company and the partners.
- Carriers capacity planning: considered as a third-party partner, the carrier is highly important to the success of the order fulfillment. The carrier needs to prepare their capacity to ensure the right delivery of the order to their destination. The carrier uses the order forecast to plan their capacity and justify their rentability.
- Packaging planning: the company is the one paying for the packaging of the orders. Having the right estimation of boxes to pack the order is key in the process. If the amount of orders is right, but not the number of boxes, the whole process would be impacted and the customer will suffer a delay. The Supply Chain department, is the one in charge of ensure this packaging capacity, by analyzing the order forecast.

II. Methodology

Project Methodology and Roadmap

The project will be structured in a theoretical-practical way to ensure success in the results. In general terms, will follow the ongoing process of the scientific method:

- Observation: understand the As Is process and business acumen. Perform the current forecasting processes and deliver them to the customer without affecting the business. Measure current performance with As Is procedure.
- Research and Development (R&D): investigate in the time series-forecasting field, potential solutions that can solve the problem statement.
- Hypothesis: select a potential solution with null hypothesis that will increase the accuracy and meet the business requirements
- Experiment: perform coding in R Studio with potential solutions and test the results.
    - If experiment does not work, go back to experiment by performing the required code improvement and troubleshooting.
- Analyze data and draw conclusions: understand if the experiment had positive results and meets all the business requirements in order to make a final recommendation.
- Project and change management: perform typical project and change management tasks to go live with the solution
- Continuous improvement: ensure ongoing improvements for the future.

Based on the project management task, the following figure show the proposed project Gantt, showing with more details the required actions and approximate timing to have them completed. Since this project is not an independent task from the business as usual, some parallel activities will take place in the experiment phase. This is required since the business can not wait for the solution to be implement (order forecast is a critical activity).

		2018				2019									
	Task	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
1	Work Induction: understand the general business process and overall work environment														
2	Training: receive training and pass down of the As Is process of the forecasting process														
3	Full Price forecast delivery: prepare and deliver Oct order forecast														
4	Sale Season forecast delivery: prepare and deliver AW18 order forecast														
5	R&D: investigate of alternative forecast options that can adjust to the company needs														
6	Reporting and Monitoring: measure the As Is process performance. Create and standard methodology to report and monitoring the results														
7	Data Visualization: create a simple data visualization of the forecast performance with As Is process														
8	R&D: gather the best options available to improve the forecast process with a time series approach														
9	R&D: develop a code in R Studio with the alternative options														
10	R&D: test first results of the alternative options. Ensure business requirement are met.														
11	R&D: select best alternative model. Improve code. Implement cross-training for best parameter selection														
12	R&D: design a complete process including the proposed model with administrative processes														
13	Approval: first presentation to management with the proposal, project roadmap and expectations.														
14	Go Live New Process Revision 0														
15	Parallel models: deliver forecast with As Is process and also run in parallel the alternative model. Compare results.														
16	Training: Prepare a training package-roadmap with new forecast model and process. Deliver training to internal customers if needed.														
17	R&D: design process for monitoring results. Create channels for continuous improvement and gather inputs of the customers.														
18	R&D: improve code by focusing in connectivity with Data Base and Tableau scorecard.														
19	R&D: design a data visualization tool for automatic reporting and fast decision making process.														
20	R&D: improve process by including external inputs into the model (such as stock levels, YoY metrics, etc)														
21	R&D: test the available technological capacity, understanding the amount of forecast per minute that can be performed.														
22	R&D: improve code by focusing in optimization to improve performance. Research about parallel running of loops in R Studio.														
23	Report: formal project report														

Figure 1 Project Gant Roadmap

III. Company History

Founded by J. Neves in 2008, the company is an online luxury fashion marketplace, which connects more than 1200 partners - luxury boutiques, brands and warehouses - to millions of customers all over the world, on a single website. 11 years after its launch, the company has partners in 49 countries, and has clients in more than 190 countries. It has offices in 13 different cities and is growing over 50% every year, having generated a record Gross Merchandise Value (GMV) in 2018 (Halliday, 2019), being since 2017 the first Portuguese company valued more than 1 billion dollars. In October 2018, the firm entered the New York stock exchange and in the same year, revenue rose by 56% and the number of placed orders increased 58%. The company also owns two British renowned boutiques and an American footwear brand.

In 2019 the company already announced the acquisition of JD.com's luxury platform Toplife to enable the gateway to the China market and the partnership with Harrods, to create and manage the department's e-commerce platform (Suen, 2019).

The company's aim is to offer the luxury goods customers a unique, creative, excellence service. The company's business model is what distinguishes it from its competitors and is the one of a marketplace: it does not hold any stock or have its own transportation system. The partners, who, due to their presence on the website, have a visibility and accessibility they would not have otherwise, sell directly from their own stock points to the clients. The client only knows which partner he/she is buying from at the time of delivery, as all the information flow passes through and is managed by the company. In order to guarantee the desired service levels, the company controls the whole process, from content creation through delivery to the client's house to the post-sales customer service. The delivery service is outsourced from third-party logistics partners (3PL), which charge to the company a shipping fee. The price payed by the customers includes the item's price, the company's margin and the shipping fee.

The business model is, however, associated with higher complexity and numerous challenges, such as the risk of stock out, the dependency on the partner's performance, and the complexity of delivery (as there are a great number of possible routes).

The company is organized in the following departments: Global Operations, Product, Communications, Technology, Finance, Strategy and Commercial. The Global Operations Department is responsible for all activities related with daily ecommerce and consists of several teams, as shown in the following figure:

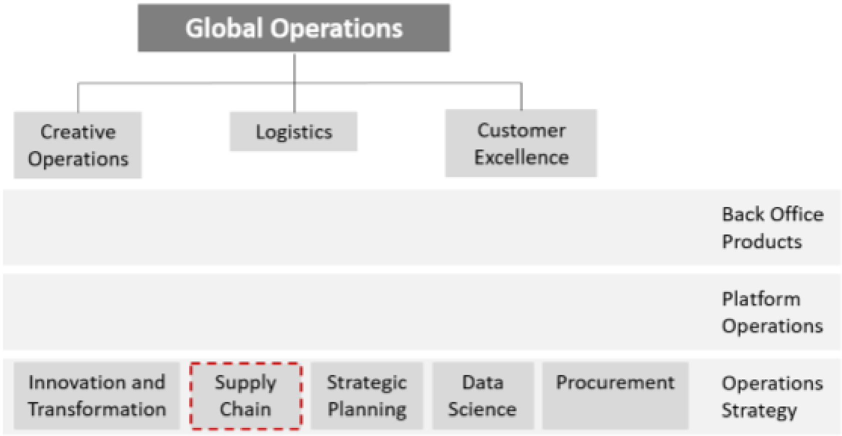


Figure 2 Global Operation Structure

The Creative Operations team is responsible for everything that has to do with the company's content production. It ensures, among others, products' photographing and availability online. The Logistics team manages all order shipment related activities, including products' return processes. The Customer Excellence team is the bridge linking the company to partners and clients, through Customer Service (CS) and Partner Service (PS) teams. CS representatives help customers with their complaints and questions, both pre and post order, and PS supports boutiques and brands on operational issues.

Back Office Products, Platform Operations and Operations Strategy are cross functional teams, which support the other teams and work on the continuous improvement of processes and, ultimately, of customer experience. This project was developed in the Supply Chain team, which is a part of Operations Strategy. The Supply Chain team's responsibility is to ensure the proper order processing flow and to control and monitor partners' performance. All packaging issues are the Supply Chain's responsibility, as well. A core principle of the company is customer-centricity: the focus of the company is to improve customer experience. Objectives, targets and rewards are aligned with this strategy and this is what makes the company a truly data-driven and innovative company. A customer-centric culture is 'unanimously accepted as the driver of future growth and development (BanovicCurguz and Ilisevic, 2018).

IV. Literature Review

General Time Series Forecasting in Fashion Industry

Creating an accurate forecast of any type of data is being researched and developed for a long time in human history. Nowadays, is more crucial than in any other time in history due to the current challenges the industry is facing. Several methods have been released that might or might not suit best of a type of industry, all of them using the common data source: time series, which consists of a set of observations ordered in time, on a given phenomenon (target variable). Usually the measurements are equally spaced, e.g. by year, quarter, month, week, day. The most important property of a time series is that the ordered observations are dependent through time, and the nature of this dependence is of interest. (*Dagum, 2010*). As time is key component in the data source, it adds another layer of complexity versus other common data sources in the predicting machine learning processes.

In the present project, the industry of interest for the forecast process is the fashion retail one. This raise even more challenges to the project objectives. The main challenge is the type of data, as it depends of the stock availability. Amazon is a company leader in this type of forecast and is consent of this extra roadblock. In their paper: "Probabilistic Demand Forecasting at Scale" (*Bose, Flunkert, Gasthaus, Januschowski, Lange, Salinas, Schelter, Seeger & Wang, 2017*), the author refers that the demand forecasting problem constitutes in predicting the demand for a group of items at a certain range of days in the future, given demand data for all items up to the present, as well as other input data sources. In a retail context, demand in the past typically refers to customer orders. Note that this is an approximation as demand is partially unobserved: orders for an item are subject to the item's availability. Therefore, forecasting customer order will always have an extra error or assumption inherited in the data accuracy.

Currently, the fashion industry is characterized by a fierce competition that forces companies to constantly change the range of products offered, vastly increasing the number of collections. Traditionally, stylist design collections from six to eight months before the launch, with a high risk due to demand volatility and short life cycle of fashion products (Arrigo, 2010). At the same time, fashion industry demand is so difficult to forecast that companies which want to keep up with the competition have already accepted that products need to be designed, manufactured and delivered based on real-time demand (Christopher, 2004). Several authors agree with the big challenge of forecasting this industry driven by the following summarized characteristics (Christopher, 2004):

- Short life-cycles: the product is often ephemeral, designed to capture the mood of the moment: consequently, the period in which it will be saleable is likely to be very short and seasonal, measured in months or even weeks.
- High volatility: demand for these products is rarely stable or linear. It may be influenced by the vagaries of weather, films, or even by pop stars and footballers.
- Low predictability: because of the volatility of demand it is extremely difficult to forecast with any accuracy even total demand within a period, let alone week-by-week or item-by-item demand.
- High impulse purchasing many buying decisions by consumers for these products are made at the point of purchase. In other words, the shopper when confronted with the product is stimulated to buy it, hence the critical need for "availability".

These facts create that the historical data might not explain easily the future predictions, due to external customer behavior factors. The importance of an accurate demand forecast is vast in several sectors: finance, marketing, operations, supply chain among others. Demand forecast is one of the most important inputs in capacity planning, especially in the fashion retail industry. Poor forecasting effects are stock outs or high inventory, obsolescence, low service level, rush orders, inefficient resource utilization and bullwhip propagating through the upstream supply chain. As such, demand forecasting is a popular research topic and many models for forecasting fashion products have been proposed in the literature over the past few decades (Nenni, Giustiniano & Pirolo, 2013). In general terms, there are two types of forecast methods (Hyndman, 2009):

- Quantitative forecasting can be applied when two conditions are satisfied: numerical information about the past is available and it is reasonable to assume that some aspects of the past patterns will continue. There is a wide range of quantitative forecasting methods, often developed within specific disciplines for specific purposes.
- Qualitative forecasting methods are used when one or both above conditions does not hold. They are also used to adjust quantitative forecasts, taking account of information that was not able to be incorporated into the formal statistical model. These are not purely guesswork—there are well-developed structured approaches to obtaining good judgmental forecasts.

In the presented project, the selected method is a mix between quantitative and quality types of forecast. The base of the forecast follows a quantitative type with a demand in scale forecast with a decomposition – Bayesian approach. However, the is always a space dedicated to the qualitative forecast, in the analytical part of the quantitative results, meaning that judgmental criteria is also key in the forecast accuracy success.

Many literatures explain the methodology needed to perform a time series forecast, however Hyndman (2009) proposes a simple basic steps to perform a forecast of any type, as the following:

- Step 1: Problem definition: often this is most difficult part of forecasting. Defining the problem carefully requires an understanding of how the forecasts will be used, who requires the forecasts, and how the forecasting function fits within the organization requiring the forecasts. A forecaster needs to spend time talking to everyone who will be involved in collecting data, maintaining databases, and using the forecasts for future planning.
- Step 2: Gathering information: there are always at least two kinds of information required: statistical data and the accumulated expertise of the people who collect the data and use the forecasts. Often, a difficulty will be obtaining enough historical data to be able to fit a good statistical model. However, occasionally, very old data will not be so useful due to changes in the system being forecast.
- Step 3: Preliminary (exploratory) analysis: always starting by graphing the data and identify consistent patterns, trend, seasonality important, evidence of the presence of business cycles, outliers in the data that need to be explained by those with expert

knowledge and how strong are the relationships among the variables available for analysis.

- Step 4: Choosing and fitting models: which model to use depends on the availability of historical data, the strength of relationships between the forecast variable and any explanatory variables, and the way the forecasts are to be used. It is common to compare two or three potential models.
- Step 5: Using and evaluating a forecasting model: once a model has been selected and its parameters estimated, the model is to be used to make forecasts. The performance of the model can only be properly evaluated after the data for the forecast period have become available.

From the quantitative point of view, a Bayesian approach to inference from historical data differs from the standard (frequentist) method for inference in its use of a prior distribution to express the uncertainty present before seeing the data, and to allow the uncertainty remaining after seeing the data to be expressed in the form of a posterior distribution (Hastie, Tibshirani & Friedman, 2017). In general, the Bayesian equation is the following:

$$Pr(\theta|Z) = \frac{Pr(Z|\theta) \cdot Pr(\theta)}{\int Pr(Z|\theta) \cdot Pr(\theta) d\theta}$$

Equation 1 Bayesian Equation

Where *Pr(Z|*θ*)* is the sampling model and *Pr(*θ*)* prior distribution for the parameters reflecting the knowledge about θ before the study of the data.

On the other hand, the decomposition approach refers to the capacity of separate the time series into a set of non-observable (latent) components that can be associated to different types of temporal variations. The idea of time series decomposition is very old and was used for the calculation of planetary orbits by seventeenth century astronomers (*Dagum, 2010*). Persons (1919) was the first to state explicitly the assumptions of unobserved components in four basic types of fluctuations (later, other authors will include others):

- A long-term tendency or secular trend.
- Cyclical movements super-imposed upon the long-term trend. These cycles appear to reach their peaks during periods of industrial prosperity and their troughs during periods of depressions, their rise and fall constituting the business-cycle.
- A seasonal movement within each year, the shape of which depends on the nature of the series.
- Residual variations due to changes impacting individual variables or other major events such as wars and national catastrophes affecting a number of variables.

Traditionally, the four variations have been assumed to be mutually independent from one another and specified by means of an additive decomposition model:

$$X_t = T_t + C_t + S_t + I_t$$

Equation 2 Additive decomposition model

$$\mathrm{X_t = T_t * C_t * S_t * I_t}$$

Equation 3 Multiplicative decomposition model

Where *Xt* denotes the observed series, *Tt* the long-term trend, *Ct* the business-cycle, *St* seasonality and *It* the irregulars (also called as the error).

Prophet Model

In the presented project, the solution includes the usage of a Facebook open source code for time series forecasting, called Prophet (Taylor & Letham, 2017), that was developed by Sean J. Taylor with the collaboration of Benjamin Letham. In general terms, the methodology has the following basic characteristics and approached:

- Is considered a forecasting "at scale" methodology: the structure of the code is robust enough to handle different types of forecast data.
- Is a decomposition forecast type: the model uses a decomposition approach in several regressors.
- Analysist-in-the loop approach: the authors consider that the judgmental-human interaction is key in the forecast process, however, the model will create automated forecast but include several visual tools for the analyst to make inspections is the most critical cases.

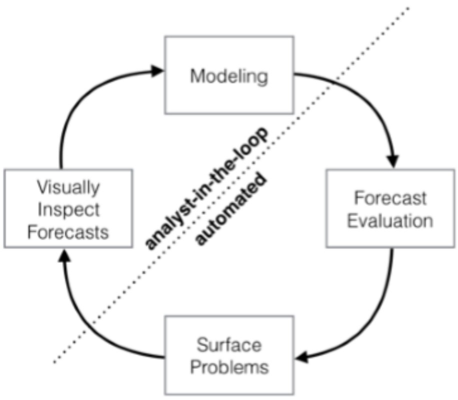


Figure 3 Prophet Analyst-in-the-loop forecast schematic view

- The model is designed for daily data with the capability to adjust it to other time granularity. However, all default values are intended for daily basis data, which fit perfectly to this project's business requirements.

Prophet use a decomposable time series model based on the structural time series model proposed by A.C Harvey and S. Peters in their paper Estimation Procedures for Structural Time Series Models (Harvel & Peters,1990) where "the essence of a structural model is that it is formulated in terms of independent components which have a direct interpretation in terms of quantities of interest. One of the most important models for economic time series is the basic structural model: this consists of a trend, a seasonal and an irregular component:

$$y_{(t)} = g_{(t)} + s_{(t)} + h_t + e_{(t)}$$

Equation 4 Basic Structural Time Series equation

Where, *g(t)* is the trend function which models non-periodic changes in the value of the time series, *s(t)* represents periodic changes and *h(t)* represent the effects of holidays which occur on potentially irregular schedules over one o more days. The error term *e(t)* represent any idiosyncratic changes which are not accommodated by the model (Taylor & Letham, 2017). The following section provides an overview of each of these components (referenced directly for Taylor and Letham paper) adding emphasis in the terms or parameters that were selected for this project:

Prophet: The Trend

The library provides two types of trend: non-linear and liner trends. The main difference from the theoretical point of view is if the demand being forecast can be considered unsaturated or saturated. For saturated demand forecast, non-linear approach is used using a typical logistic growth model. On the other hand, for unsaturated demand forecast, uses a simple linear approach. For the presented project, the overall assumption is that the company is phasing a linear unsaturated growth. The forms for both types are shown in the following equations:

$$g_{(t)} = \frac{C_{(t)}}{1 + exp(-(k + \boldsymbol{a}(t)^{\boldsymbol{T}}\boldsymbol{\delta})\big(t - (\boldsymbol{m} + \boldsymbol{a}(t)^{\boldsymbol{T}}\boldsymbol{\gamma})\big))}$$

Equation 5 Piecewise logistic growth for non-linear trend

$$g_{(t)} = \big(k + \boldsymbol{a}(t)^{\boldsymbol{T}}\boldsymbol{\delta}\big)t + (m + \boldsymbol{a}(t)^{\boldsymbol{T}}\boldsymbol{\gamma})$$

Equation 6 Piecewise linear growth for linear trend

Where:

- *C(t)* refers to the carrying capacity as a function of the time. This is used to tell the model until what value stop growing. It is assumed that this carrying capacity changes is not a constant, therefore a value is required per time unit.
- *k* refers to the base growth rate. However, is known that this rate is not a constant over time, therefore a time effect is included as the following:

- $k + \boldsymbol{a(t)}^t \boldsymbol{\delta}$ refers the growth rate at time *t*, which states as the base rate *k* plus the trend changes in the historical data, defined with a vector $\boldsymbol{\delta}$ containing all the changepoints where the growth rate is allowed to change.
- Whether or not a changepoint is added to the growth rate is specified by the vector $\boldsymbol{a(t)} \in \{0, 1\}$ where a value of 1 is assigned when *t* is higher or equal to the changepoint and 0 otherwise.
- The amount and selection of changepoints can be added by the user as an input vector in the model (vector $\boldsymbol{\delta}$). If not specified, potential changepoints are selected automatically, given a set of candidates putting a sparse prior on $\boldsymbol{\delta} \sim$ Laplace $(0, \tau)$. The parameter τ directly controls the flexibility of the model in altering its rate. For the project, an automatic changepoint is preferred specifying the parameter τ (called "`changepoint.pior.scale`").

- *m* refers to the offset parameter that works to connect the endpoints every time that the rate *k* is adjusted. The adjustment is done using the same $\boldsymbol{a(t)}$ vector plus a new one $\boldsymbol{\gamma}$ defined for an specific changepoint *s* in time *j* as:

$$\boldsymbol{\gamma}_j = \left(s_j - m - \sum_{l<j} \gamma_l\right)\left(1 - \frac{k + \sum_{l<j} \delta_l}{k + \sum_{l\leq j} \delta_l}\right)$$

Equation 7 Adjustment of changepoints

Prophet: The Seasonality

Prophet relay the seasonality effect on Fourier series to provide a flexible model of period effects adjusting the classical decomposition time series from a regression with explanatory variables consisting of a time trend and a set of seasonal dummies into a regression coefficients that changes over time (Harvey & Shephard, 1993). The Fourier analysis or harmonic analysis of a time series is a decomposition of the series into a sum of sinusoidal components, that refers to the coefficients of which are the discrete Fournier transform of the time series (Bloomfield, 2000). Let P be the regular expected period in the time series (e.g. P = 365.25 for yearly data), Prophet approximate the seasonal effect *s(t)* as:

$$S_{(t)} = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right)\right)$$

Equation 8 Seasonal Approximation

The number of terms in the partial sum (the order) is a parameter that determines how quickly the seasonality can change, therefore truncating the series at N applies a low-pass filter to the seasonality, so increasing N allows for fitting season patterns that change more quickly however will increase the risk of overfitting. For fitting the seasonality, it's required the estimation of the 2N parameters as $\beta = [a_1, b_1, \ldots, a_N, b_N]^T$. Prophet creates a generative model where it takes $\beta \sim N\ (0, \sigma^2)$ in order to adjust it to a smoothing prior parameter for the seasonality effect σ (called "`seasonality.pior.scale`") in the following generative equation:

$$S_{(t)} = \sum_{n=1}^{N} \left(cos\left(\frac{2\pi nt}{P}\right) + sin\left(\frac{2\pi nt}{P}\right) \right) \beta$$

Equation 9 Seasonal generative approximation with prior parameter

Prophet: The Holidays

In several types of industries, there are non-periodic events that produce a special behavior in the forecast. This is very common in Fashion Industry and probability is one of the reasons why Prophet was selected for the project. In any kind of decomposition time series forecast, the events can be added as a type of extra regressor, however, the open source capability of Prophet makes it ideal for the project. As Taylor and Letham (2017) mention: "Holidays and events provide large, somewhat predictable shocks to many business time series and often do not follow a periodic pattern, so their effects are not well modeled by a smooth cycle".

The impact of a holiday *i* (from a total list of holidays *L*) with a set of D_i of past and future dates of the holiday, is done through a function that multiplies by 1 if the time t is included in holiday *i* and then each holiday is assigned a parameter k_i which is the corresponding change in the forecast. Therefore, it generates a matrix of regressors like:

$$Z_{(t)} = [\mathbf{1}(\boldsymbol{t} \in \boldsymbol{D_1}), \dots , \mathbf{1}(\boldsymbol{t} \in \boldsymbol{D_L})$$

Equation 10 Matrix of holidays regressors

Then, the final Holiday component *h(t)* will that the form as:

$$h_{(t)} = Z_{(t)}\, \boldsymbol{k}$$

Equation 11 Holidays prophet component

The ***k*** vector works as a prior smoothing parameter such as $k \sim N(0, v^2)$ and it's called `holiday.pior.scale`. The set of dates D_i allows a lower and upper limit, in order to add a window of the effect not a single day.

As a manner of summary, the following table provides a list of the parameters that can be used in the prophet model (some of required and other optional). The definition of each of them is taken from the R documentation for Prophet package (Taylor & Letham, 2018):

Table 1 Prophet parameters summary (with R documentation definition)

Parameter Name	Definition
`growth`	String 'linear' or 'logistic' to specify a linear or logistic trend
`changepoints`	Vector of dates at which to include potential changepoints. If not specified, potential changepoints are selected automatically
`n.changepoints`	Number of potential changepoints to include. Not used if input `changepoints` is supplied. If `changepoints` is not supplied, then n.changepoints potential changepoints are selected uniformly from the first `changepoint.range` proportion of df$ds
`changepoint.range`	Proportion of history in which trend changepoints will be estimated. Defaults to 0.8 for the first 80 `changepoints` is specified
`seasonality.mode`	'additive' (default) or 'multiplicative'.
`seasonality.prior.scale`	Parameter modulating the strength of the seasonality model. Larger values allow the model to fit larger seasonal fluctuations, smaller values dampen the seasonality. Can be specified for individual seasonalities using add_seasonality.
`holidays.prior.scale`	Parameter modulating the strength of the holiday components model, unless overridden in the holidays input
`changepoint.prior.scale`	Parameter modulating the flexibility of the automatic changepoint selection. Large values will allow many changepoints, small values will allow few changepoints

The smoothing the parameters: `holidays.prior.scale` (τ in δ ~ Laplace (0, τ)), `seasonality.prior.scale` (σ in $\beta \sim N(0, \sigma^2)$) and `holidays.prior.scale` ($\nu$ in $k \sim N(0, \nu^2)$) have an incredible functionality to adjust the forecast as needed. Adjusting τ will manage the flexibility of automatic changepoint selection selecting from within a range of more global or locally smooth models. The seasonality and holiday smoothing parameters (σ, ν) allows to tell the model how much of the historical seasonal variation is expected in the future. The regularization is important to avoid under or over fitting the model.

Forecast Accuracy Metrics

There are several metrics to measure the accuracy of the forecast. The choice of the metric is problem specific. The most common metrics are presented in De Gooijer and Hyndman (2006) paper, where the Mean Absolute Percentage Error (MAPE) is the preferred due to the easy interpretability. Using the Actuals as the denominator, based on the rationality pointed by Green and Tashman (2009), the basic MAPE form is the following:

$$MAPE_t = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$$

Equation 12 Basic Mean Absolute Percentage Error

Where A_t is the actual value at time *t*, F_t is the forecast value at time *t* and *n* is the total fitted points. Very straightforward the Forecast Accuracy (FA) metric will be:

$$FA_t = 1 - MAPE_t$$

Equation 13 Forecast Accuracy Metric

A small variation in the MAPE and FA was proposed for the presented project to cover a weekly MAPE and FA metrics in two basic scenarios based on the data segregation:

- **Case 1**: one single FA_w number for all the volume of the company (not segregated per partner) at week *w*.

$$FA_{w,All} = 1 - \frac{\sum_{t=1}^{w} |A_t - F_t|}{\sum_{t=1}^{w} A_t}$$

Equation 14 Forecast Accuracy Metric for All volume

Where:
  - *t* is the day and *w* the week being reported. Weeks start on Sundays and *t* = 1, …,7 (total days of the week *w*).
  - A_t is the actual value at day *t* and F_t is the forecast value at day *t*

- **Case 2**: one single FA_w number that considers the individual partners[1] volume segregation at week *w*.

$$FA_{w,Partners} = 1 - \frac{\sum_{k}^{P} \sum_{t=1}^{w} |A_t - F_t|}{\sum_{k}^{P} \sum_{t=1}^{w} A_t}$$

Equation 15 Forecast Accuracy Metric per partner

[1] All partners that are active in the web portal at the time the forecast is made. Partners are free to decide to be active or not at any time (include their stock or not). Therefore, due to data integrity the sum of the actuals A_t in Case 2 might not be exactly the same as the actuals A_t in Case 1. The actuals in Case 2 will only include the partners that had a forecast versus the actuals in Case 1 where is an aggregated value for all the volume of the company.

Where:

- t is the day and w the week being reported. Weeks start on Sundays and $t = 1, \ldots, 7$ (total days of the week w).
- A_t is the actual value at day t and F_t is the forecast value at day t
- P is the total partners included in the forecast released that meet the condition that $A_t > 0$
- k is an individual partner that meets the condition that $A_t > 0$

V. Diagnosis of the Current Situation

General Concepts

In order to create and analyze an order forecast of the company, some basic concepts are needed to be explained. These terminologies will keep showing up along the presented report.

- As Is process: refers to the current forecast process or the processed followed by the company after the proposed solution is fully implemented.
- Company: refers to the company in which the project is developed, that due to data protection, won't be called by the company official's name.
- Web Portal: online retail web page created by the company, in which a potential customer can explore the products and make a purchase.
- Products or items: refers to an individual product sold in the web portal. Each product or item have their own attributes coming from a boutique or brand.
- Boutique: type of partner of the company, referring to designers or stablished stores all around the world. These boutiques generally have their physical store (s) with their own sales following independent marketing strategies. At the same time, as partners of the company, they have sales done via the company's web portal. These types of sales, follow the company's marketing strategies.
- Brand: type of partner of the company, referring to bigger fashion companies all around the world. These brands generally do not have their own physical store (s) but they have their own retail intermediate partners to sell their products. They have the particularity that they have independence of their marketing strategies (they could follow or not the company's strategies).
- Portal Order: refers to the final purchase done by a customer in the web portal. These portal orders can contain one or more items from a mix of different boutiques or brands. The customer makes the payment based on the total amount of a portal order.
- Boutique/Brand Order: refers a purchase done by a customer organize by a specific boutique or brand. As explained in the Scope and Limitations section, the presented project will cover this type of order to make a forecast process.
- Marketing and Sale Calendar: refers to a day-by-day calendar with the specific sale strategies that the company decide for each type of geo-group and customer tier. The calendar contains sale promotions with the intention of accomplish the company's targets.
- x10/x20: type of sale referring the percentage of discount offered in the web portal for all or specific items. For example, if the discount is 10%, the strategy is called "x10".
- Black Friday (BF): type of sale referring to the typical extra discounts happening in the weekend after the Thanksgiving celebration in United States (US). This sale type, is applied in the entire world (not just US) and usually start on the Thanksgiving's Thursday and finishes in the Tuesday of the week after (includes the Cyber Monday).
- Singles Day (SD): type of sale referring to the extra discounts happening in Asia area celebrating the pride of being single.
- Marketing Geo-groups: included in the Marketing and Sale Calendar, refers to clusters of countries in which the customer is located. Therefore, each Marketing Geo-group has their own marketing strategy.

- Shipping Location: country where the item (s) will be shipped, predefined by the customer. Based on this information, the Marketing Geo-groups are created.
- Store Location: country where the boutique or brand is located at the time that ships an item to the customer's shipping location.
- Sale Season Forecast: type of forecast that include the months of official sales. This type of forecast can be:
    - Spring-Summer (SS) for the months of May, June and July.
    - Autumn-Winter (AW) for the months of November, December and January.
- Full Price Forecast: type of forecast that include the months with no official sales, therefore, the items usually are sold at full price with no discounts. However, this is not a rule: if Sales and Marketing decide it, this time-period can include or not discounts for specific days.
- Customer Tier: refers to cluster (tier) of type of customers. This type is defined at the moment that a customer creates his or her account in the company's web portal and based on the characteristics of the customer. The Marketing and Sale Calendar have a different strategy for each tier. For data protection purposes, the customer tiers will be called Customer Tier 1, Customer Tier 2 and Customer Tier 3.
- Store Tier: depending on the level of importance (sales amount or marketing strategy), the boutiques and brands are classified in store tiers. For boutiques, the classification starts with a letter "T" plus a number (from 0 to 3). For brands, the letter is "B" plus a number (from 0 to 3). The highest level of importance refers to the number 0 and the less to 3.
- Data Warehouse (DW): main data source in which the forecast gathers the historical boutique/brand Orders. The name of the DW used is BI_DW (Business Intelligence Data Warehouse).
- Actuals: refers to the historical data available for a boutique or brand. For the project, usually are actual boutique/brand order in a specific time granularity.

As Is Process

Marketing and Sale Calendar

As explained in the concepts section, the Marketing and Sale Calendar refers to a day-by-day calendar with the specific sale strategies that the company decide for each type of geo-group and customer tier. At this current state, this is manual file done in google sheets and is owned by the Sales team. The following figure show a simulated example of a Marketing and Sale calendar from November, 13th to December, 1st :

Group		13/nov	14/nov	15/nov	16/nov	17/nov	18/nov	19/nov	20/nov	21/nov	22/nov	23/nov	24/nov	25/nov	26/nov	27/nov	28/nov	29/nov	30/nov	01/dez
Group N		C.Tier 1	C. Tier 2	C. Tier 2	C. Tier 2	C. Tier 2	C. Tier 2	C.Tier 3	C.Tier 3	C.Tier 3	C.Tier 3 +Black Friday	C.Tier 3 +Black Friday	C.Tier 3 +Black Friday	C.Tier 3 +Black Friday	C.Tier 3 +Black Friday	C.Tier 3 +Black Friday	C.Tier 3	X20	X20	C.Tier 3
			C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1			C.Tier 1
Group N+1				C.Tier 1	C.Tier 1	C. Tier 2	C. Tier 2	C. Tier 2	C. Tier 2	C. Tier 2	C.Tier 3 +Black Friday	C.Tier 3 +Black Friday	C.Tier 3 +Black Friday	C.Tier 3 +Black Friday	C.Tier 3 +Black Friday	C.Tier 3	C.Tier 3	X20	X20	C.Tier 3
						C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1	C.Tier 1			C.Tier 1

Figure 4 Example of a Marketing and Sales Calendar

In this example, the sale season start in different dates according to the customer tier and the promotions (such as Black Friday and X20) can have different start dates and durations according to the geo group.

The current process to forecast orders in the company only includes a forecast for boutiques Orders (BO), excluding brand orders, and it's done in Microsoft Excel. The BO Forecast have two processes depending on the projected time with different As Is process:

- Full Price Forecast: if the project months exclude the Sale Season months and the items are sold at full price
- Sale Season Forecast: if the projected months includes the Sale Season months and therefore the items are sold with some level of discount according to the sales and marketing strategies.

<u>As Is Full Price Forecast Process</u>

- General Description: the overall BO target of the company is segregated by boutique based on the actual performance of the previous 4 months.
- Scope: Top 50 boutique sorted by historical boutique orders.
- Projected months: February, March, April, August, September and October.
- Timing: delivered the 3rd week of the previous forecast month. For example, the full price forecast of February, is released the 3rd week of January.
- Granularity: weekly by boutique
- SIPOC: the Figure 5 show the SIPOC diagram for the As Is process of the full price months:
    - Suppliers:
        - OLAP Cube
        - Finance
    - Inputs:
        - Historical: actuals total number of boutique orders of the previous 4 months of the forecast month. Granularity: monthly
        - Total list of boutiques (based on the historical data)
        - Historical: actuals total number of boutique orders of the forecast month from previous year. Granularity: daily
        - Finance boutique order target of the forecast month. By default, this value is a value per month for all the company (not segregated per boutique).
    - Detail process:
        I. 4 month performance

- Pull Actuals of the previous 4 months of boutique orders per boutique. Complete an approximation of the last month (since the information is pulled in the 3rd week of the previous forecast month, an approximation is needed to complete the whole month)
- Calculate weight of each boutique per Actual Month (of each of the 4 months)
- Calculate total weight average per boutique. Give extra weight to the Actual last month

II. Finance target split
- For the forecast month, split the Finance target per boutique according to the Average Weight for each boutique calculated in previous step

III. Forecast weekly allocation
- Select the top 50 boutiques according to the actuals total number of boutique orders last 4 months.
- Pull Actuals of the forecast month from previous year per Boutique and approximate the daily shape.
- Calculate the daily volume of the forecast month by boutique and approximate the daily shape based on actuals from previous year (previous step).
- Summarize forecast volume per week of the forecast month per boutique.

- Output
  - Weekly Forecast based on current store performance and last year trends
- Customers:
  - OPS solution, boutiques and carriers

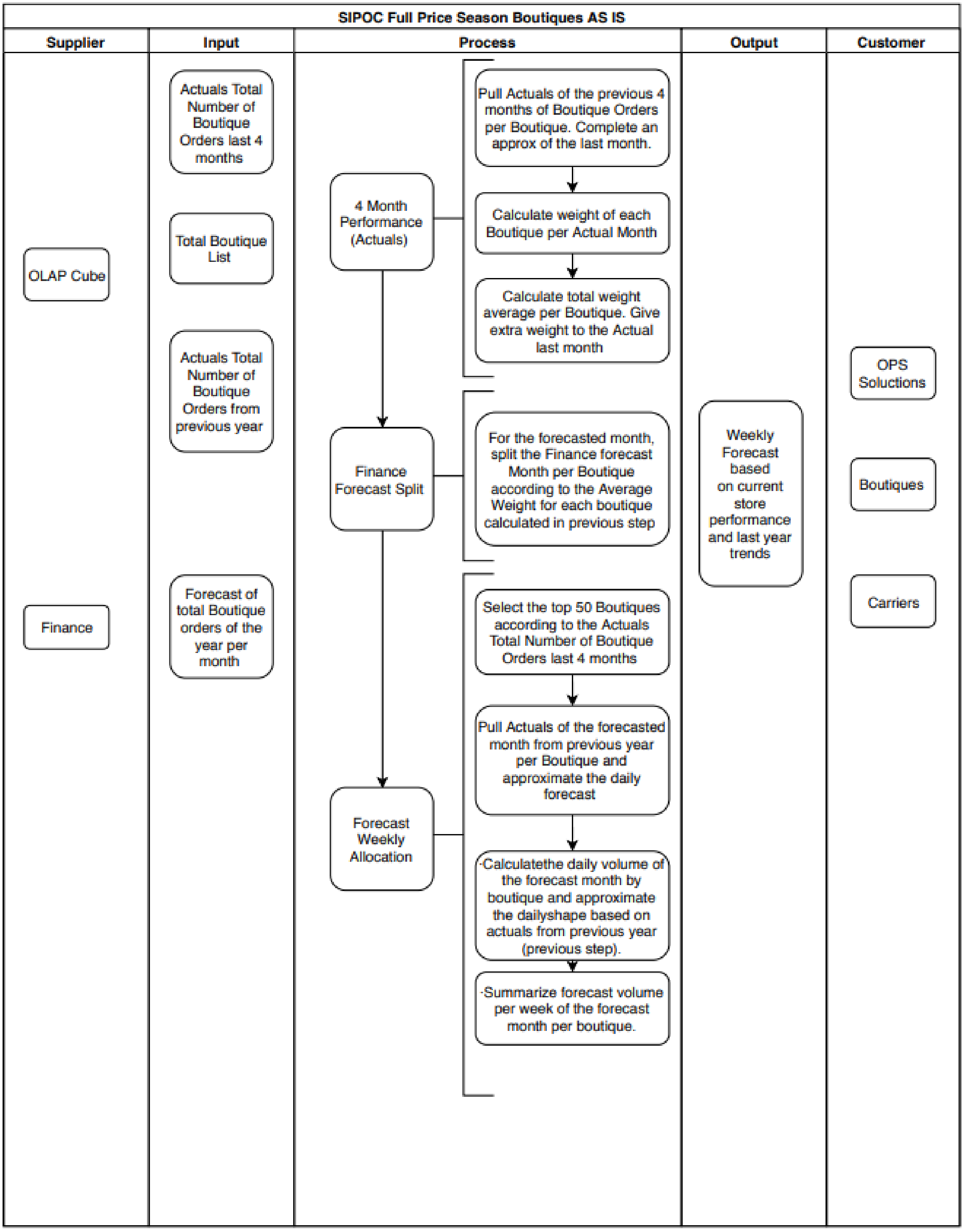


Figure 5 Full Price As Is Process

<u>As Is Sale Season Forecast Process</u>

- General Description: boutique order forecast for the SS or AW sale seasons for the most important boutiques aligned to the marketing and sale strategies.
- Scope: T0 boutiques plus some T1, T2 or T3 previous requested by some customers.

- Projected months: SS months (May, June and July) and AW months (November, December and January)
- Timing: delivered the 2nd week of the previous month from the 1st month of the Sale Season period. For example, the AW forecast, is released the 2nd week of October, as the AW season start on November. This release day have several dependencies (release of some required input data)
- Granularity: daily by boutique
- SIPOC: the Figure 6 show the SIPOC diagram for the As Is process of the sale season months:
    - Suppliers:
        - BI_DW data warehouse
        - Sales and Marketing
    - Inputs:
        - Historical: Total boutique orders from past years (pulled in by a query in Sever Management Studio). Is possible, 3 years of historical.
        - Previous and current marketing and sale calendar. For example, for AW18 forecast, is required the AW18 (current) and AW17 (previous) sale calendars.
        - Previous and current marketing geo-groups.
        - Previous and current customer tier.
    - Detail process:
        I. Actual data preparation
            - Run query to get raw historical data for a specific boutique.
            - Use Excel template to clean up raw data: creates new columns to transform past year data into new data reflecting daily number simulating the current calendar. This is done segregated by customer tiers and geo groups.

        II. Actual number of order: Last year with current geo-groups and previous calendar days.
            - Refresh excel pivot table for number of boutique orders of the sale season months plus one extra month [2] (called "forecast period") from previous year with previous sale calendar per updated geo-groups and customer tier.

        III. Actual number of order: Last year with current geo- groups and current calendar days.
            - Refresh excel pivot table for number of boutique orders of the forecast period from previous year with current sale calendar per updated geo-groups and customer tier.

        IV. Trend growth Calculation (scenario A)
            - Refresh excel pivot table and get the daily number of orders from previous 3 years, grouped by day.
            - Run a Linear Regression with the yearly moving average starting in the 1st sale month available.

[2] This extra month refers to the previous month to the sale season first's month. For example, for AW this previous refers to the sale months (November, December and January) plus the previous one (October). Therefore, the total forecast period will be 4 months. This extra month will be used to assess accuracy of the forecast in following steps.

- Get the linear regression equation and R square. Regress the values at the 1st month day from previous year and the 1st month day of the current year. Get the YoY trend growth from the current sale season start date (calculated by the moving average linear regression) versus the previous sale season start day (given in the historical data).

V. YoY BO Growth Calculation (scenario B)

- Refresh excel pivot table for number of boutique orders of the forecast period from previous 3 year with previous sale calendar per updated geo groups and customer tier.
- Get the YoY growth as the average of months past half-year per updated geo groups and customer tier.

VI. Adjust the actual number of boutique order from previous year of the forecast period with trend (scenario A) and YoY (scenario B) growths

- For each growth, add the impact in the actuals. Get totals per row (daily)

VII. Summary scenarios and assessment

- Summarize in a table the total number of orders for the two scenarios: Trend (A) and YoY (B) growths. Add any other scenario (if available, from external benchmarking).
- Assess forecast scenarios: measure the forecast error (MAPE) of the extra month of the forecast period against actuals for the available. Adjust scenarios as needed and select the best one.

- Output
  - Boutique order forecast trend and YoY growths scenarios.
  - Final recommended boutique order forecast.
- Customers:
  - OPS solution, boutiques and carriers

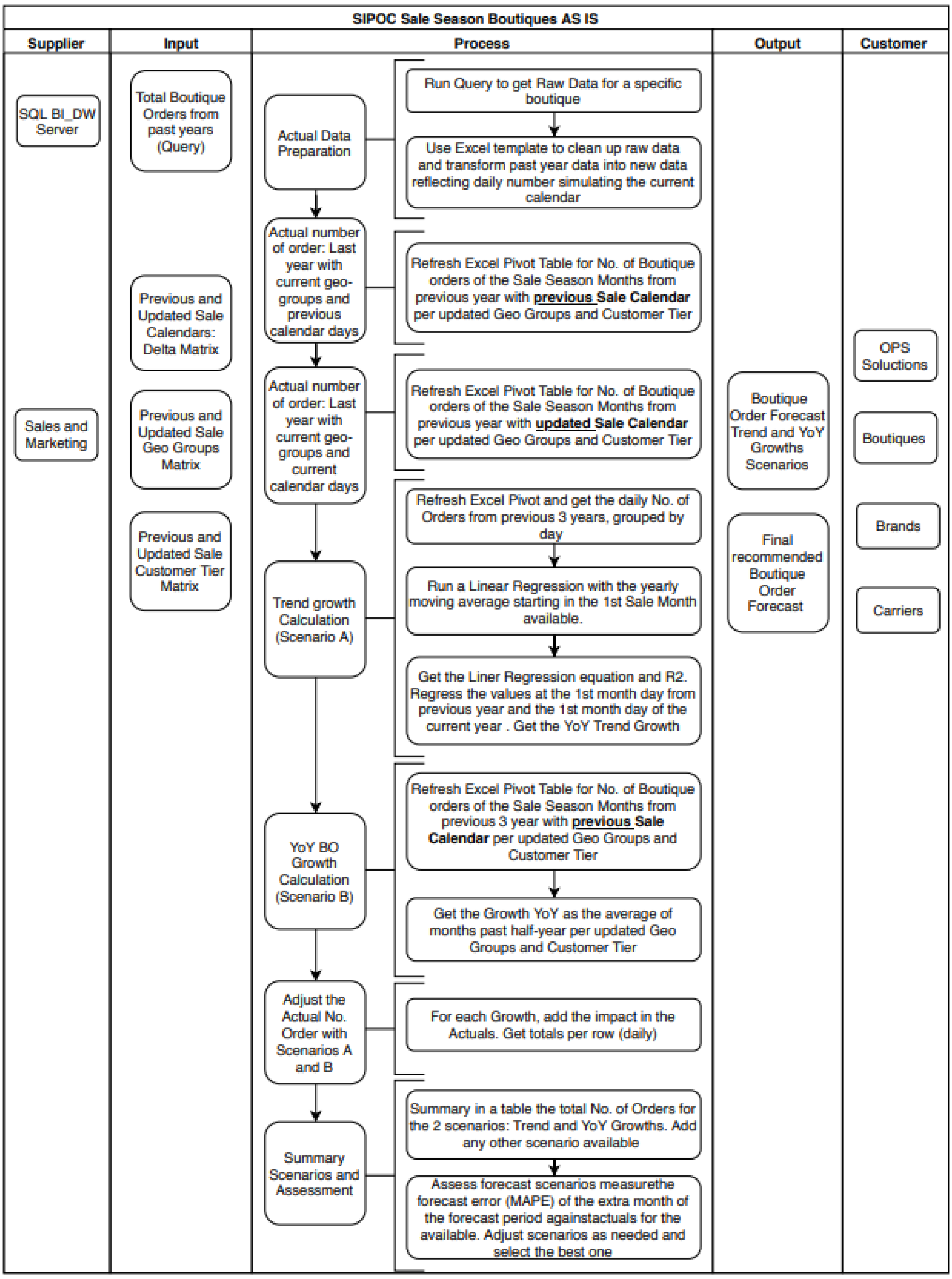


Figure 6 Sale Season As Is Process

As Is Performance

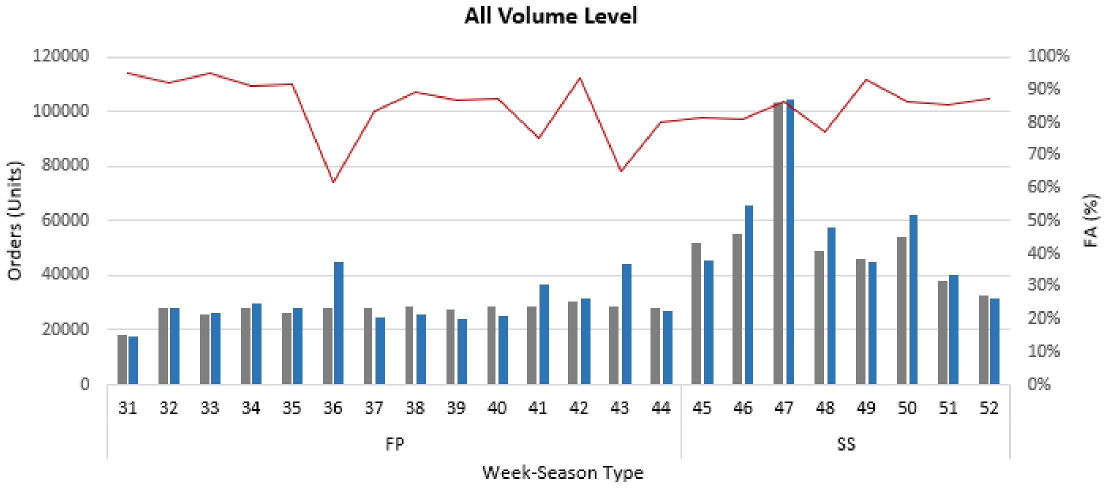
Part of this project is to propose a standard performance measurement process to monitoring and leverage the continuous improvement cycle. Aligned to the literature review chapter IV: Forecast Accuracy Metrics the 2 cases of Forecast Accuracy (FA) were proposed for all volume and segregated by partner (refer to equations number 14 and 15). The data available of the As Is processes include:

- Full price forecast: August, September and October 2018
- Sale season forecast: November and December 2018 (AW18 season)

In order to ensure significance in the conclusions, the way the results are presented and summarized will be as the following:

- Forecast Accuracy (FA) for All Volume: refers to the performance of the forecast for all volume of the company (without partner segregation) using Equation No. 14
- Forecast Accuracy (FA) Per Partner segregation: will be using the Top 3 partners based on the actual boutique orders of the period (highest volume). Normally, these Top 3 boutiques remain the same during the year. Metric will be using the Equation No. 15.

The following figures show the performance of the full price (FP) and sale season (SS) forecast performance for All Volume followed by the Per Partner levels:



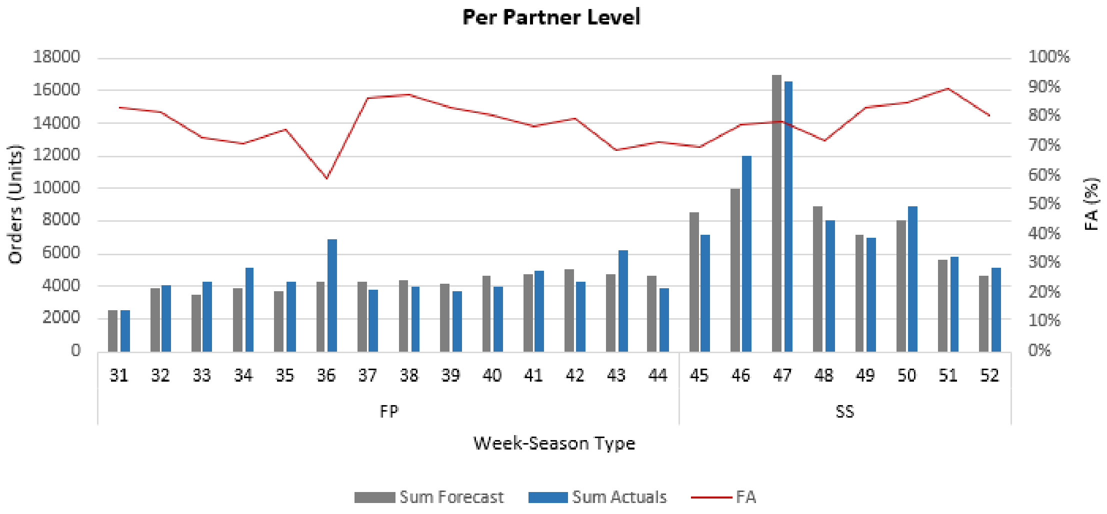


Figure 7 Actual Forecast Accuracy Performance All Volume and Per Partner levels

The detailed performance data can be found in the Annex 1. In order to summarize, a weighted average was calculated (weights based on the actual volume of the week)

Table 2 Weighted Average forecast accuracy full price, Sale Season and Overall for As Is process

All Volume	
FP	83%
SS	84%
Overall	*84%*
Per Partner	
FP	75%
SS	79%
Overall	*77%*

From the summary table, an important trend can be noticed. The forecast accuracy of the full price months is relatively lower than in the sale season. The reason of this difference is due to the limitations of the current process: as explained in the previous section, the full price process is not a real forecast, but a segregation of the finance target orders per boutique based on actuals. For the All volume scenario, in the Figure 7 it can be easily seen 3 main drops in the Forecast Accuracy metrics in the weeks 36, 41 y 43. Similar case happens in the Partner in week 36. The main explanations on the FA for the full price days, is that Sales and Marketing released last minute X20 sale promotions, creating peaks of sales not included in the forecast when it was released. These last-minute promotions are seen very often in the company.

In the case of sale season forecast accuracy, usually the FA is better than the FA in full price. The improvement of the performance is driven by a more statistical process and the capability of re -adjust if needed. During the AW18 sale season, 7 forecasts were released driving by last minute promotion campaign changes or management decisions. The following tables show the 7 revisions, release dates and main business reasons:

Table 3 AW18 forecast releases with adjustments

Revision	Release date	Justification
Rev2	08/10/2018	First release.
Rev3	23/10/2018	Including a X20 during Black Friday weekend.
Rev4	07/11/2018	Adjusting to match the growth of GMV forecast to boutique orders.
Rev5	19/11/2018	Re-forecast it. Updated 3 boutiques based on actual trend.
Rev6	06/12/2018	Including a X20 during one week in December 2018
Rev7	03/01/2019	Including X20 changes during January.
Rev8	12/01/2019	Including X10 in China region during January.

For the All scenario, an overall forecast accuracy of 84% is considered acceptable. The following figure show the Black Friday weekend for the global scenario, where is can be seen that it started with around 10% of MAPE for the first 2 days, however, increased up to 35% for the next days:

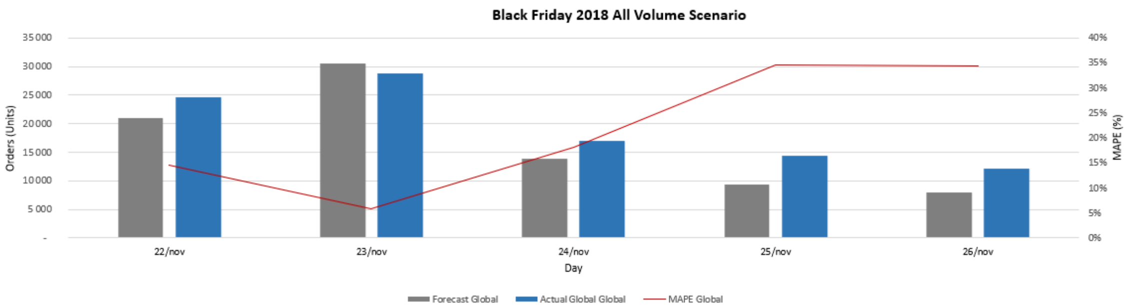


Figure 8 Black Friday weekend MAPE performance All Volume scenario during AW18 sale season

For the top 3 boutiques, the scenario is not as good as the global one. MAPE Simple average for the Back Friday weekend is 21% reaching maximus of 36%:

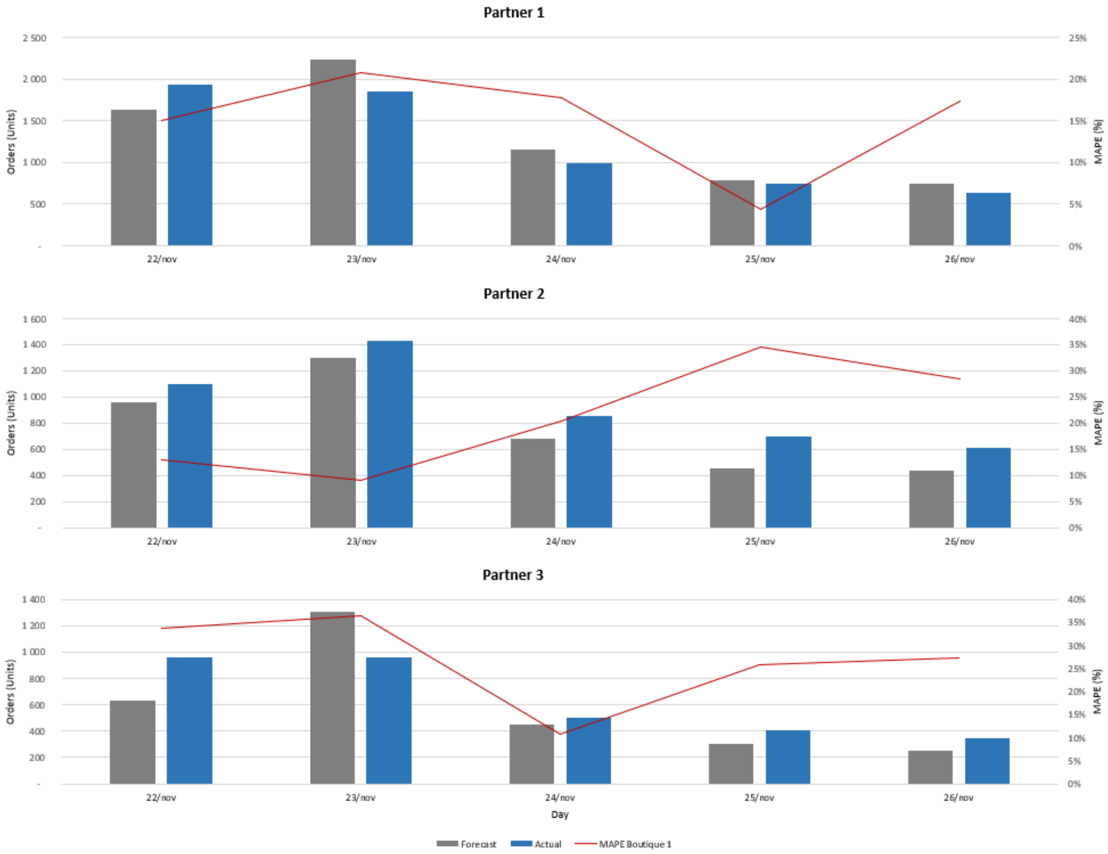


Figure 9 Black Friday weekend performance top 3 boutiques scenario during AW18 sale season

As Is Process Limitations and conclusions

The As Is process present the following limitations that expose the quality of the work:

- Full price process:
  - Is not a real forecast, therefore, the numbers released have no statistical significance. Finance release the targets in boutique orders once per year. This cadence put in danger the usage of this data.
  - Is limited only to Top 50 boutiques and brands. The rest are left out of the release. The volume of actual sales not necessarily implies high importance of a partner in the company.
  - The process is reactive to marketing changes. The release schedule excludes potential promotion changes, creating unwanted MAPE peaks. The process does not allow flexibility to adjust if needed. The daily distribution of the finance target of boutique order based on previous year distribution, put in danger the quality of the forecast, because the promotions from last year doesn't necessary will be re-launched in the current year.
  - Manual process done in excel, implies a risk of human error.
  - The overall forecast accuracy of this process is around 79%

- Sale season process:
    - Is limited only to T0 boutiques that represent around 2% of all the partners. Also, does not include brands. This has caused complains from the excluded partners putting in danger the image of the company.
    - The simple but large manual work done in excel, limits the inclusion more partners and the capacity to perform quick adjustments. Also, increase the risk of human error. Even though, 7 forecasts were released, representing large human working hours to make these adjustments. The amount of time consumed in recreating the excel sheets, limits the time available to high value-added activities, such as the analytic part for better decision making.
    - Poor adjustment to real time marketing campaign changes or to create what if analysis for better decision making.
    - Basic statistical analysis is performed in the process, limited to year over year (YoY) growths and linear regression. The process fails if not enough historical data is available.
    - The process does not include any monitoring sub process nor have any scorecard with standard KPIs and data visualization for the analyst and internal customers of the forecast.
    - The process is considered not robust and reactive to marketing changes.
    - The overall forecast accuracy of this process is around 81%.

Root Cause Analysis

Using a lean manufacturing tool, the root cause analysis will use a Cause and Effect diagram [3] in order to show the complete picture of the possible causes that creates the problem statement. This analysis will help prioritizing the causes and make sure the real cause (called root cause) is being solved in the solutions.

The diagram uses 6 categories to analyze the possible causes. Next, the categories explain followed by the diagram:

- Method: refers to the processes and methodologies used
- Materials: in this case, refers to the input data used in the processes
- Measurement: refers on KPIs used to check the performance of the processes.
- Environment: refers to the work space and cultural organization of the company.
- Manpower: refers to the human resources performing the tasks.
- Tools: in this case, refers to the software and other tools used to perform the processes.

[3] Also called Ishikawa diagram or fishbone diagram, created by Kaoru Ishikawa that show the causes of a specific event.

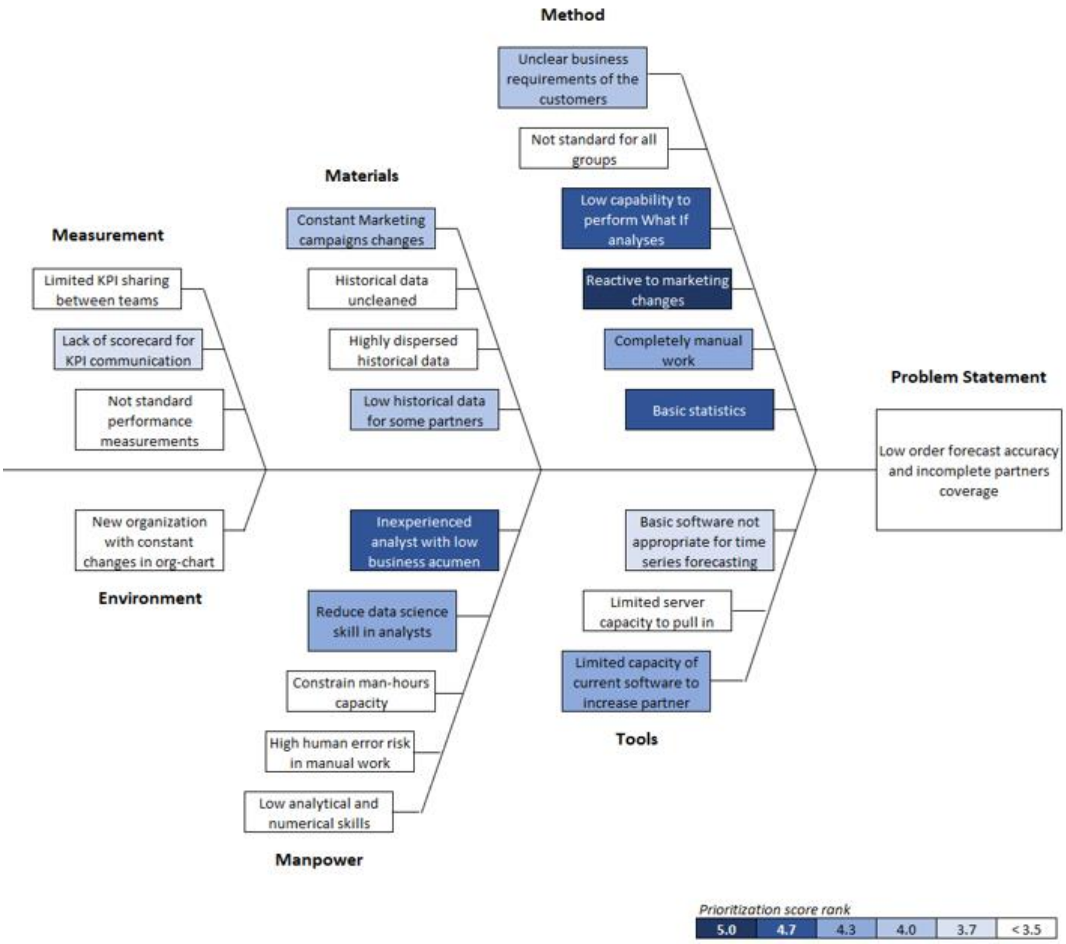


Figure 10 Cause and Effect diagram for the problem statement and prioritization results

As it can be seen in the diagram, the Method category has the most possible root causes of the process, followed by Manpower and Materials. However, in order to get a prioritization on all possible causes, voting was performed in 3 analysis of the department. They were asked to evaluate each listed cause in the Cause and Effect diagram, in a scale from 1 to 5, where 1 mean the least important cause that might be causing the problem statement and 5 the highest. The detailed results of the voting is showed in the Annex 2. The overall results were included by the color coding in the previous figure. It's important to acknowledge that all the listed causes are important, however, in order to prioritize and find root causes, the voting was performed. The causes that had the highest ranking (above the mean, sorted in a descending way) are:

- Reactive to marketing changes
- Low capability to perform What If analyses
- Basic statistics
- Inexperienced analyst with low business acumen
- Completely manual work
- Limited capacity of current software to increase partner coverage
- Reduce data science skill in analysts
- Unclear business requirements of the customers
- Constant Marketing campaigns changes

- Low historical data for some partners
- Basic software not appropriate for time series forecasting
- Lack of scorecard for KPI communication

As a matter of conclusion, the solutions of the problem statement, must ensure that this list is covered in the design of the new process in order to ensure the success of the project.

VI. Problem Solution

Solution design

Based on the root cause analysis, business requirements and scope of the project, the proposed solution include a series of steps to produce an outcome in the most automatic way possible using R as the official analytical software, Microsoft SQL Server Management Studio as the connection with the data source, Microsoft Excel for reporting and post-analytical software and finally Tableau for data visualization (dashboard for forecast accuracy tracking). The following figure show the high-level structure from the software perspective:

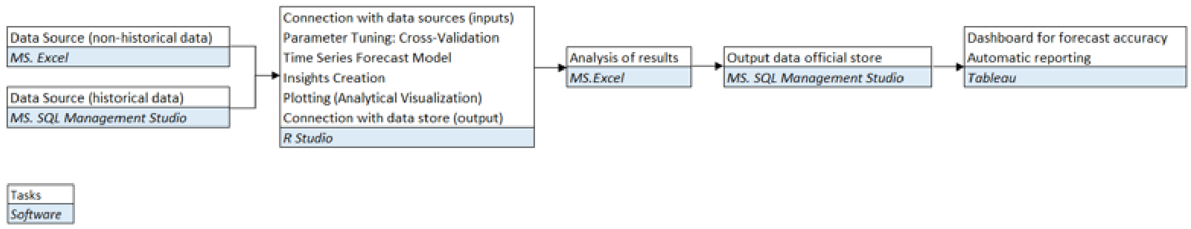


Figure 11 Solution software structure design

The software structure of the solution has no extra cost implication to the company, as all licenses are already used by the company, and in the case of R and R Studio are open source software.

After analyzing the possible time series algorithms, the proposed one is Prophet Model (Taylor & Letham, 2017) given the following benefits aligned to the project proposals:

- Time granularity: Prophet model is designed for daily time series data and outcome forecast. As Per the business requirements, the forecast should be delivered at daily time granularity, making Prophet a right fit to it.
- Easy for interpretation: results of the forecast are easy to interpret for non-data science audience
- Good to treat missing values: in order to meet the coverage requirement (total partners in the forecast) at the required moment, Prophet allows a good automatization for cleaning the data of missing values, creating easy and rapid forecast scenarios.
- Fits very good to the marketing events: part of the Prophet model equation is the effect of "holidays" creating an optimal fit for the marketing events of the company. This effect is easy to include in the model, embracing the speed and accuracy.
- Data visualization: the Prophet library in R produces several plots options that make easy to interpret and make analyzes to support a better decision making process.
- Parameter tuning: even if Prophet offers the capability to use default parameter in the model, it has the option to adjust the several "prior scale" parameters that controls the learning effect of the historical data in terms of the trend, seasonality and holidays. This capability is good to improve the forecast accuracy.
- Parallel running: Prophet fits perfect to the parallel running of loops in R Studio, creating much faster results. This is key to meet the coverage (number of partners) requirement.

The design of the solution has an administrative overall process (called Step 0) and 6 technical steps process (some optional and other required) to ensure the business requirement are met and the root cause of the problem statement covered. The high-level steps are shown in the next figure, followed by sections explaining with detail each step:

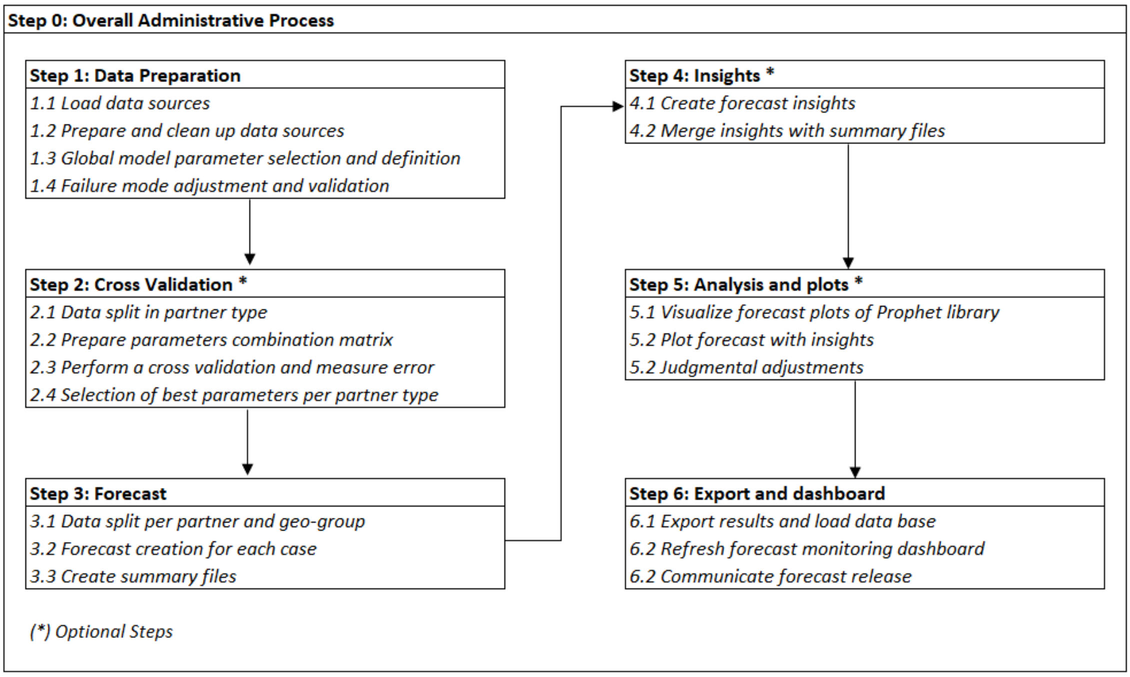


Figure 12 Overview of the Solution steps

Step 0: Overall Administrative Process

The overall administrative procedure is designed to attack the problem statement with a robust and trustful process as the following:

- Owner: Supply Chain Analytics.
- Forecast release cadence: weekly releases every Thursday end of day.
- Forecast timeframe: 7 weeks ahead starting the week after the release. Every new release will include one extra week at the end of the horizon and will refresh the forecast of the weeks that are shared in the previous release. The following figure show the logic graphically:

Release Week t	Forecast week t+1	Forecast week t+2	Forecast week t+3	Forecast week t+4	Forecast week t+5	Forecast week t+6	Forecast week t+7		
	Release Week t	Forecast week t+1	Forecast week t+2	Forecast week t+3	Forecast week t+4	Forecast week t+5	Forecast week t+6	Forecast week t+7	
		Release Week t [...]	Forecast week t+1	Forecast week t+2	Forecast week t+3	Forecast week t+4	Forecast week t+5	Forecast week t+6	Forecast week t+7

Figure 13 Solution forecast release schema

- Forecast graduality:
  - Time unit: day

    - Locations: partners and all company volume
- Forecast coverage: all partners (boutiques and brands, approximate this represent 1200 partners) that has at least 7 weeks of historical data plus the overall "all" company volume.
- Forecast release formats: excel sheet and loaded in BI_DW.
- Communication method: e-mail with a pre-defined distribution list.
- Forecast accuracy and monitoring results dashboard[4]: the forecast accuracy will include two measures depending of the locations: all volume forecast accuracy and overall partners forecast accuracy.

The proposed overall administrative process is intended to be able to capture all marketing events in a proactive way, increasing the accuracy and creating trust of the partners and internal customers of the forecast by having the proposed cadence release and partner coverage. Also, will create one single source of truth of the order forecast data by centralizing the ownership, data release channel and standard formatting.

The following sections of this chapter will explain more the "how" of the solution from a more technical point of view and show the preliminary results of the solution, making a benchmarking against other methodologies (using the current As Is method and ARIMA) with the intention of showing the suitability and trust in the proposed solution. Finally, a proposed dashboard for monitoring the results will be explained in the last section, in order to track and share the results.

<u>Step 1: Data Preparation</u>

The data preparation phase is intended to ensure all necessary information and data is ready and clean to continue to the following phases. As usual, the data needs to be cleaned and structured for data quality purposes. In this phase, the raw data is transformed and merged with other data sources. The step by step diagram is shown in the next figure followed by the detail description of the steps:

[4] Details of the data included the outcome of the forecast are explained in the following section of the present chapter: Forecast Release Table.

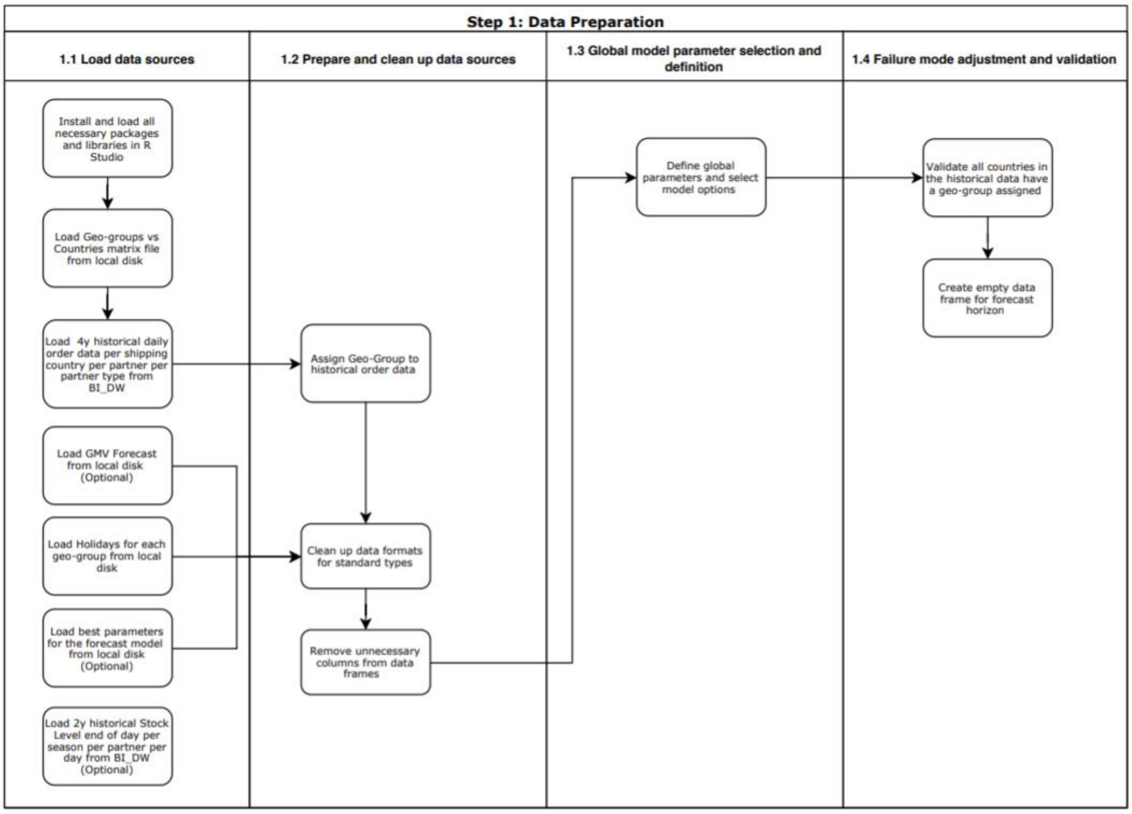


Figure 14 Step 1: Data Preparation flow

Sub Step 1.1: Load data sources

- Objective: load R libraries and raw data from data sources: R packages and BI_DW and excel documents.
- Tasks:
    1. Install and load all necessary packages and libraries in R Studio. The required packages and libraries are listed in the Annex 3. This loading is required to ensure no failure will happen during the rest of the model.
    2. Load Geo-groups vs Countries matrix file from local disk (excel document): previously prepared, this excel document is loaded as a CSV into the R Studio code and contains all the countries of the customers that the company has. Each country has a geo-group classification. This classification is defined by Sales and Marketing team. The rationality is that each geo-group will have a different marketing strategies (events). Therefore, the forecast needs to be personalized by geo-group. The following is a high-level description of the geo-groups:

        - Group 1a: LATAM area.
        - Group 1b: North America area except Mexico.
        - Group 2a: Asia area except Japan and Singapore.
        - Group 2b: Japan and Singapore.
        - Group 3: ROW (rest of the word)
        - Group 4a: United Kingdom
        - Group 4: Spain

- Group 5: Italy and Belgium.
- Group 6: France
- Group 7: Russia

3. Load 4 years of historical daily orders data per shipping country per partner and partner type from BI_DW. Historical data will include the day, order, partner name and partner type (boutique or brand). General rule is 4 years of historical data; however, this will depend on the time that the partner has been with the company (could be less for more recently joined partners).
4. Load GMV Forecast from local disk (optional) as an excel CSV document. This information is released by Finance once per month and contains the forecast of the GMV for all the company (not per partner) per day. Usually only include 1 month ahead from the release date. This information is optional, as is not an input to make the order forecast but is used as an insight information for benchmarking purposes (explained with more details in the Step 4: Insights)
5. Load Holidays for each geo-group from local disk as an excel CSV document. This information are all the marketing events in the past and future (if known) for each individual geo-group according to the Sales and Marketing campaign calendar. Holidays is the terminology used following the Prophet library however, in this case, more than a holiday, it is a marketing promotion, such as X20, Black Friday weekend or a VIP customer tier sale season. The document includes the name of the Holiday, date and geo-group.
6. Load best parameters for the forecast model from local disk (optional) as an excel CSV document. This information refers to the parameters (called "best parameters") that Prophet model will use to make the forecast. This is optional, as the user can run Prophet model with the default parameters. To obtain these best parameters, the Step 2 (Cross Validation) need to be performed first (explained with more detail in the Step 2)
7. Load 2 years historical Stock Level end of day per season per partner per day from BI_DW (optional). This information comes from a query and is not a required information to run the Prophet model (same case as the GMV Forecast). This information is only used as extra insight data used in the Step 4 (Insights).

Sub Step 1.2: Prepare and clean data sources

- Objective: Do a general cleanup of the data, remove unnecessary information and generate structure in the data.
- Tasks:
  1. Assign Geo-Group to historical order data: this is done through a join function, where the order historical data is merged with the geo-groups CSV file loaded in the previous steps. The join is done by the shipping country. The outcome will be the historical data including the geo-group depending on the shipping country (that refers where the customer is)
  2. Clean up data formats for standard data types (for example, Date type as DD/MM/YYYY)

3. Remove unnecessary columns from data frames

Sub Step 1.3: Global model parameter selection and definition

- Objective: user needs to select some options to run the model based on the objectives of the outcome.
- Tasks:
    1. Define global parameters and select model options. This section is user-based, meaning that the user needs to input in the model some information required to run it. The options selected will answer the following questions:
        - Forecast horizon (integer): how many days does the user want to forecast? Always the time unit is days.
        - Insights (Binary: True-False): does the user want to include insights (Step 4) in the forecast or not? This decision implies around of 30% more of computer performance and time to run the model, but the benefit is to have more information to support a better decision making process.
        - All Company (Binary: True-False): does the user want to run the model for all the company volume (one single forecast for all the partners as a whole) or does the user want to run the model for each individual partner?
        - Export (Binary: True-False): does the use want to export a CSV document with the output forecast into the local device?
        - Text options to be printed in the outcome file:
            - Scenario Name
            - Scenario Revision
            - Release Week

Sub Step 1.4: Failure mode adjustment and validation

- Objective: provide a general check that no information is missing to run the model without errors.
- Tasks:
    1. Validate all countries in the historical data have a geo-group assigned. In case a new country is included in the historical data, this validation will make a check that all countries have a geo-group defined. If a country is found without a geo-group, will print a message of warning.
    2. Create empty data frame for forecast horizon. This is a data frame with zero values in all the forecast horizon. This will ensure that the model won't crush in case no historical data is available for a specific partner and geo-group.

Step 2: Cross Validation

The Cross-Validation phase is intended to maximize the forecast accuracy by splitting the historical data in training (70%) and test (30%) data set, then train different models (each model with a possible combination of Prophet parameters). Finally measure the performance of each model with the test data set, in order to select the model with the lowest error. The step is optional as the user can decide to use the default Prophet parameters. The benefit is implying a better model and better accuracy; however, this Step takes a long period of time to run due to the heavy performance driven by the amount of training models and validation. The user can perform this Cross-Validation in two ways:

- Cross-Validation for each partner type: boutique, brand and all company volume. This option takes approximate 18 hours to finish. This partner type generalization is the most used option as it provides reasonable results and the required time to run it is manageable.
- Cross-Validation for each individual partner: This option takes approximate 6 hours to finish on single partner. This option might be useful for the highest volume partners that highly impact the overall company forecast accuracy levels.

Even with the long performance time this step takes, the benefit is worth it. Also, the results aren't highly sensitive to short amount of times. This mean, that the user can run this step once per month and reuse the best parameters for all the weekly forecast releases. The final outcome will be a data frame exported as a CSV document with the best parameters of the Prophet model per partner type (or individual partner) per geo-group. The parameters and values to be tested are the following:

- `n.changepoints`: 20, 25 (default), 30
- `holidays.prior.scale`: 5, 10 (default), 15
- `seasonality.prior.scale`: 5, 10 (default), 15
- `Seasonality mode`: "additive" (default), "multiplicative"

The step by step diagram is shown in the next figure followed by the detail description of the steps:

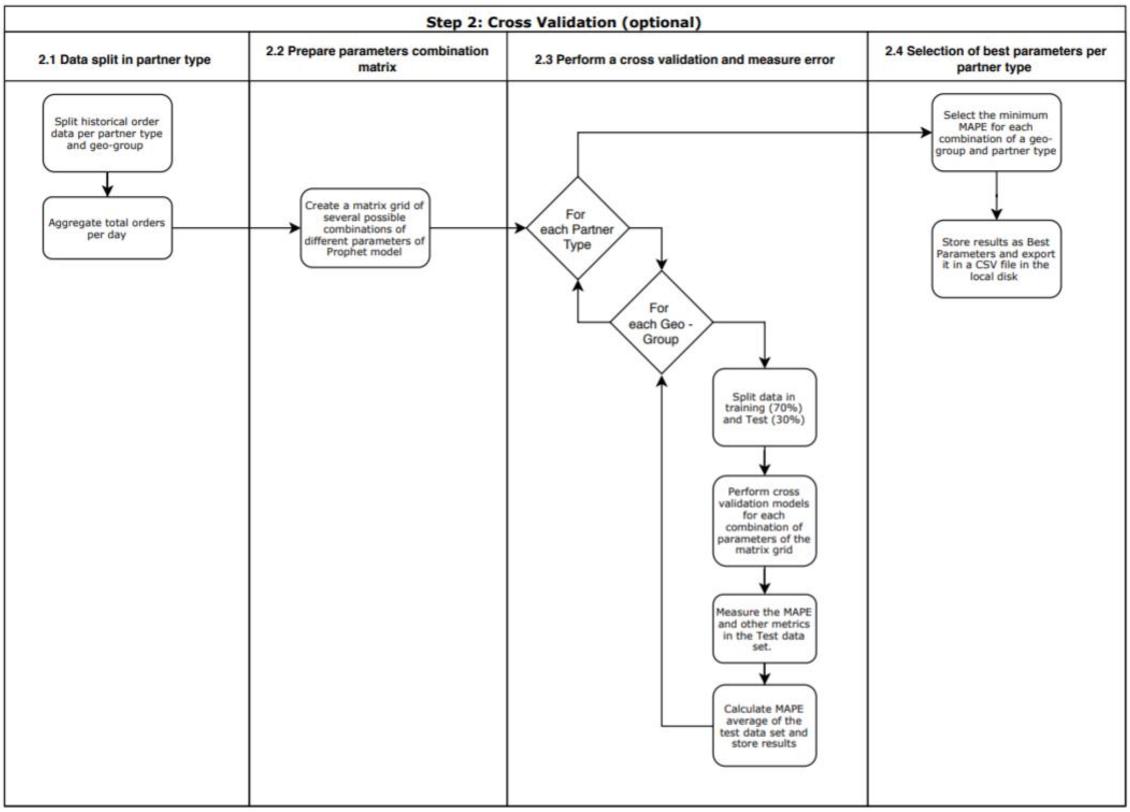


Figure 15 Step 2: Cross Validation

Sub Step 2.1 Data split in partner type

- Objective: prepare the data by splitting and aggregating it according to the desired output
- Tasks:
    1. Split historical order data per partner type and geo-group
    2. Aggregate total orders per day

Sub Step 2.2 Prepare parameters combination matrix

- Objective: create all the possible combinations of Prophet parameters. Each of these combinations will be a model to be trained and validated.
- Tasks:
    1. Create a matrix grid of several possible combinations of different parameters of Prophet model

Sub Step 2.3 Perform a cross validation and measure error

- Objective: perform the cross validation to measure the error in all possible combinations.

- Tasks (for each partner type and geo-group):
  1. Split data in training (70%) and Test (30%)
  2. Perform cross validation models for each combination of parameters of the matrix grid
  3. Measure the MAPE and other metrics in the Test data set.
  4. Calculate MAPE average of the test data set and store results

Sub Step 2.4 Selection of best parameters per partner type

- Objective: select the best parameters based on the minimum MAPE model.
- Tasks:
  1. Select the minimum MAPE for each combination of a geo-group and partner type
  2. Store results as Best Parameters and export it in a CVS file in the local disk

<u>Step 3: Forecast</u>

This is the core step of the process where the forecast is generated for the horizon pre-defined by the user. The forecast can include or not insights and can use the best parameters to maximize the accuracy. As explained before, each partner's historical data will be segregated by geo-group and a forecast will be create for each group. Then, merging them into one single partner forecast. The rationality is that the forecast is highly sensitive to the marketing campaign events (called "Holidays" in the Prophet model). The marketing events are different per region (Singles Day promotion, for example, only happen in China Region), therefore, in order to increase the accuracy, each partner will have 10 different forecasts (one per for each geo-group). This will make the performance running time 10 times longer than if one single forecast is created per partner, however, the accuracy will be degraded. The step by step diagram is shown in the next figure followed by the detail description of the steps:

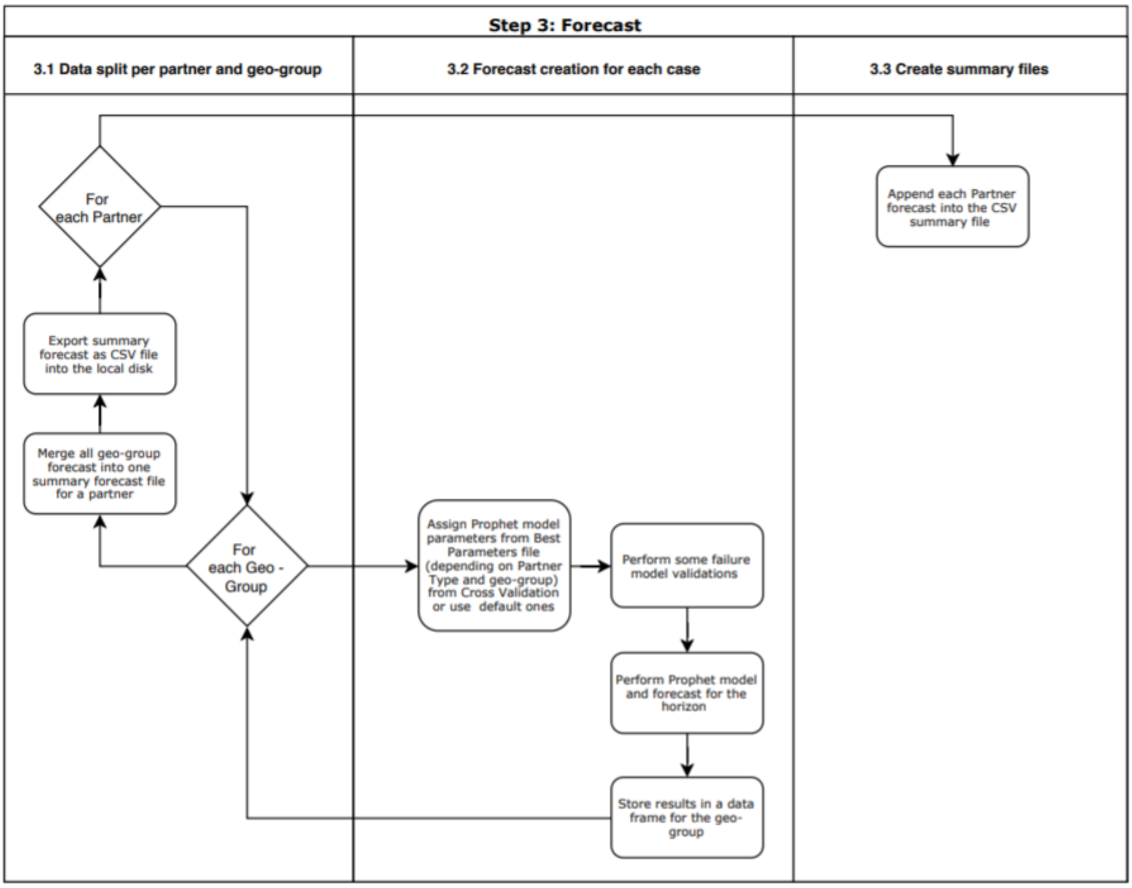


Figure 16 Step 3: Forecast

Sub Step 3.1 Data split per partner and geo-group

- Objective: prepare the data by splitting it by partner (if this option was selected. If all company volume is selected, then the data won't be segregated per partner) and then by geo-group.
- Tasks:
    1. Through 2 nested loops, the historical data will be segregated first by partner and then by geo-group

Sub Step 3.2 Forecast creation for each case

- Objective: create the forecast for the pre-defined horizon.
- Tasks:
    1. Assign Prophet model parameters from Best Parameters file (depending on Partner Type and geo-group) from Cross Validation or use default ones.
    2. Perform some failure model validations, such in case there is no historical data, then the empty data frame will be assigned to that specific geo-group and partner.
    3. Perform Prophet model and forecast for the horizon.

4. Store results in a data frame for the geo-group
5. Merge all geo-group forecast into one summary forecast file for a partner

Sub Step 3.3 Create summary files

- Objective: merge all forecast of each individual partner into one single data frame.
- Tasks:
    1. Append each Partner forecast into the CSV summary file. Export it into the local device if user selected in the global model parameters.

Step 4: Insights

The insights phase is an optional process that produce extra information in the forecast output, in order to support the analytical process (following step) for a better decision-making process. As mentioned before in the sub step 1.3, the user can enable or disable this feature as a global parameter in the model. Including the insight will produce a slower performance time but will create more information. Depending on the user objective, this feature will be used or not. The step by step diagram is shown in the next figure followed by the detail description of the steps and insights:

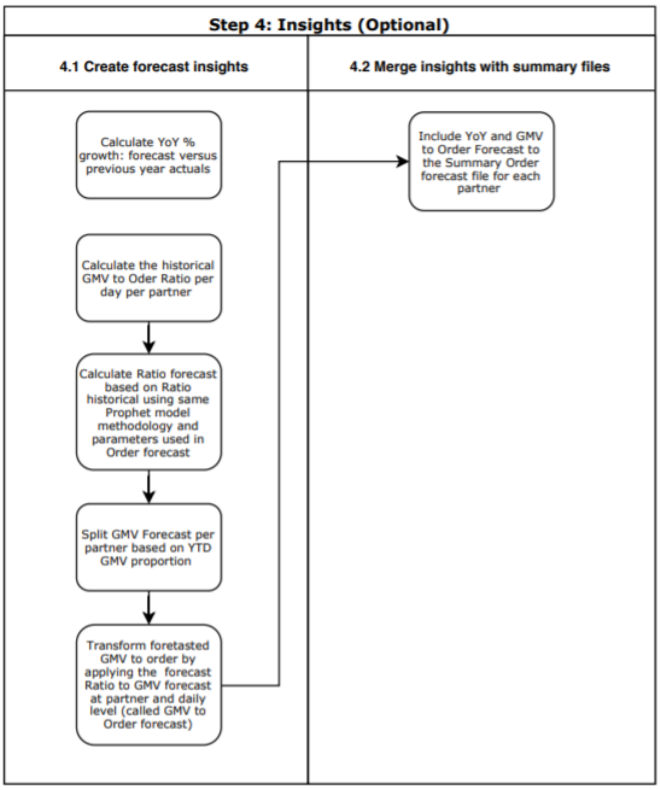


Figure 17 Step 4: Insights

Sub Step 4.1 Create forecast insights

- Objective: produce 2 insights (YoY change and GMV to order forecast) to the normal forecast to support the analytics phase.
- Tasks:
    1. Produce the Year over Year (YoY) change: produce the relative percentage of change from a forecasted day versus the previous year same day actual value. For example, an insight YoY value of 30% in November, 3rd of 2019 means that there is a growth of 30% from the historical value in November, 3rd of 2018 and the forecasted value calculated by the model. This information, help understand the general change of a forecast.
    2. Produce the GMV to order forecast transformation (value, lower value and upper value): the basic idea is to convert the GMV finance daily forecast (GMV is measure in currency USD units) into an order forecast based on a forecasted ratio GMV-order. This insight is where the majority of the performance requirement of the insight option take place. As mentioned before, the GMV forecast is provided by finance once per month in a daily granularity but is not segregated by partner, only a whole GMV number for all the company value. The rationality of this insight is to produce an alternative order forecast from the main one produced in Step 3 and be able to compare it if needed. The general logic to create this insight is the following:
        - Calculate the GMV portion per partner based on the YTD (Year to Date) historical GMV value.
        - Estimate the GMV forecast per partner based on the portion calculated in the previous step.
        - Calculate the historical GMV-order ratio per day and per partner in the previous 4 years. This will be the historical data of the forecast model.
        - Estimate the GMV-order forecasted ratio value using the same Prophet model algorithm explained in the Step 3.
        - Covert the finance GMV forecast into order per day using the forecasted ratio.

Sub Step 4.2 Merge insights with summary files

- Objective: merge insights created into the summary forecast data frame.
- Tasks:
    1. Include YoY and GMV to order forecast to the summary order forecast file for each partner

Step 5: Analysis and plots

The intention of this solution design is to provide a forecast in the most automatic and accurate way to meet the company needs. However, as in any forecast process, the judgmental phase of the analysist is highly important. This is based on the expertise of the analysist in the industry. To help on this process, the insight option is available in the previous Step, but also, some visuals can be printed to help on this phase. This step is also optional, as it not a requirement to run the Prophet model. The step by step diagram is shown in the next figure followed by the detail description of the type of plots:

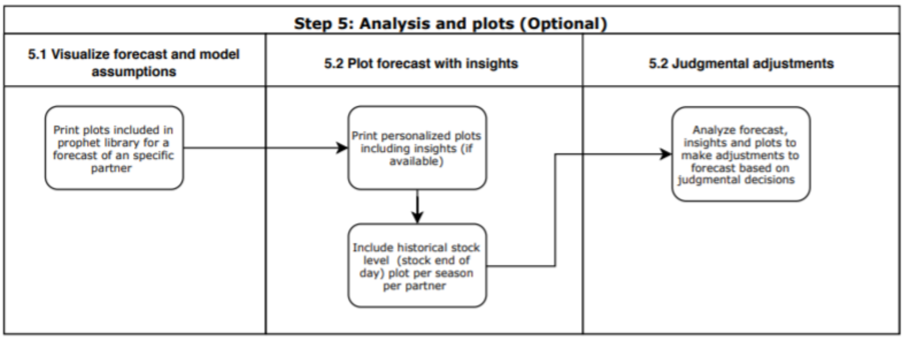


Figure 18 Step 5: Analysis and plots

Sub Step 5.1 Visualize forecast and model assumptions

- Objective: merge insights created into the summary forecast data frame.
- Tasks:
    1. Print plots included in prophet library for a forecast of a specific partner. The most used plots are:
        - Historical and forecast scatter-line plot: show the historical data by black points and the model forecast by a blue line. The following figure show an example:

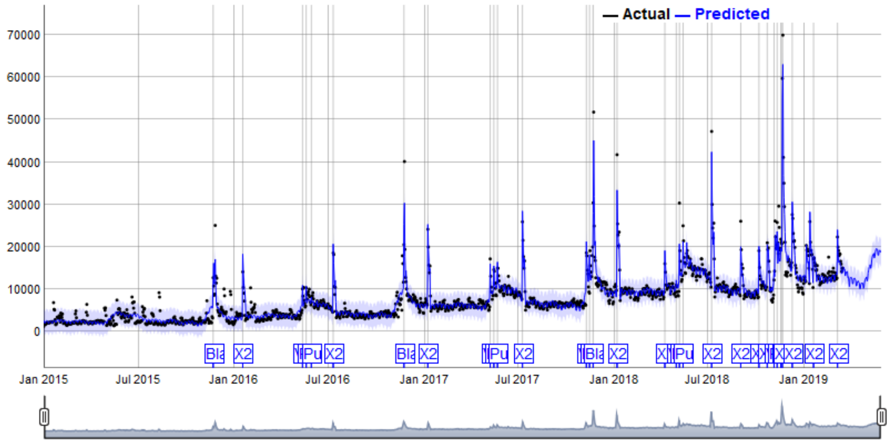


Figure 19 Example Prophet historical and forecast scatter-line plot

- Forecast components: show the impact of the different components of the forecast (trend, seasonality, holidays). The following figure show an example:

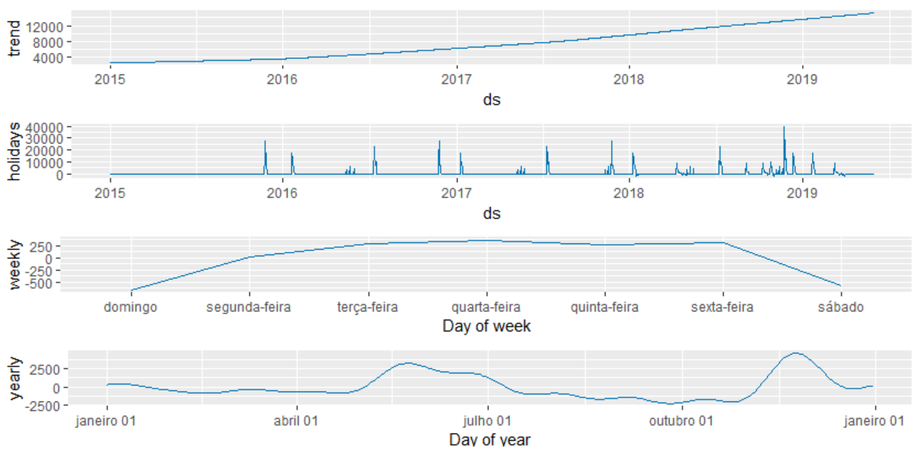


Figure 20 Example Prophet forecast components plot

Sub Step 5.2 Plot forecast with insights

- Objective: produce personalized plots with extra insights for better forecast analysis.
- Tasks:
    1. Include historical stock level (stock end of day) plot per season per partner (area plot): this plot shows the stock level (in units) per seasons, with the intention to understand the possible impact of the stock levels in the forecast.

2. Include the historical percentage of discounted stock plot per day (line plot): this plot shows the portion (%) of the stock that was had any type of discount in the historical data. For example, a value of 20% in this plot, means that for the selected partner in that specific day, 20% of all their stock had any type of discount.
3. Include the average discount rate plot (line plot) per day: this plot provides a weighted average of the discount percentage that certain partner that in all of the items per day. For example, a value of 20% in this plot, means that for the selected partner in that specific day, from the stock of items that had any type of discount, in average, the discount was 20% of the normal selling price.
4. Include the overall discount metric per day: this plot shows is the multiplication of the previous 2 metrics (historical percentage of discounted stock times the average discount rate). This metric will provide a combination of the previous 2 metrics to get an overall impact of the discounts: in stock levels and discount value. The following figure show an example:

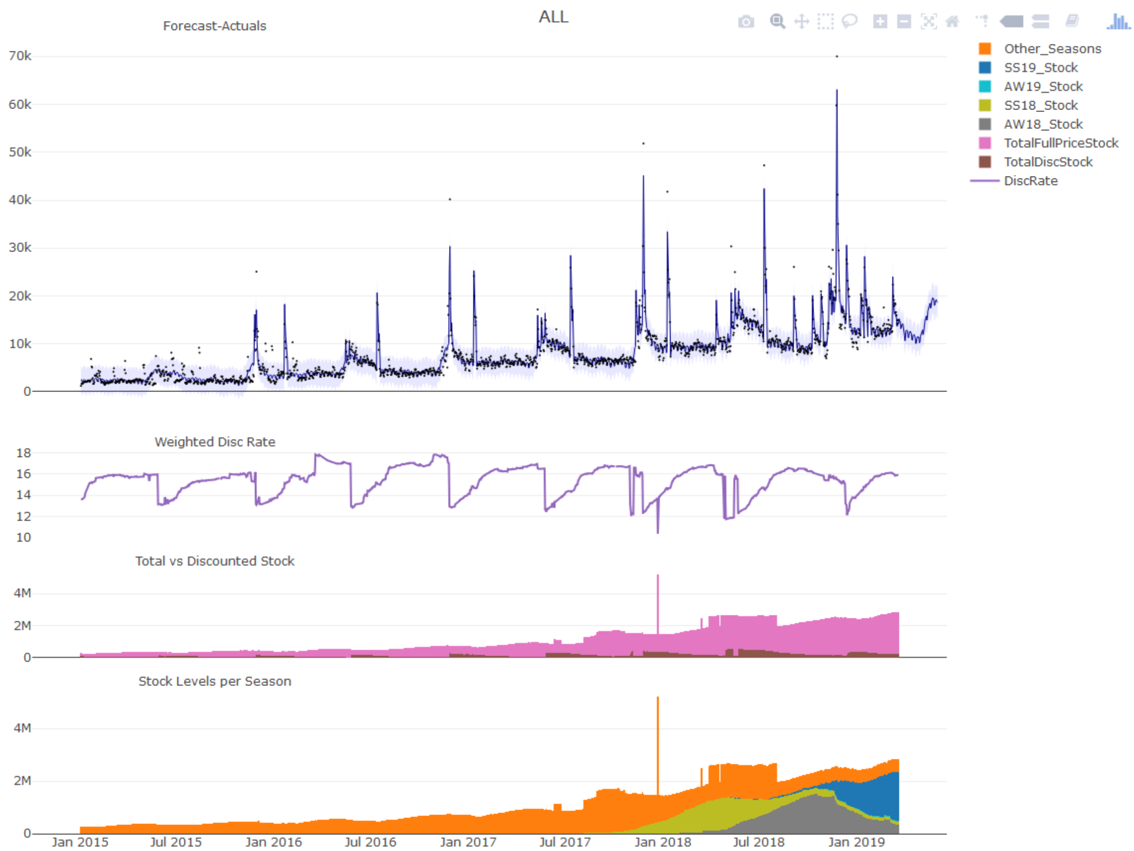


Figure 21 Example personalized plots with extra insights

Sub Step 5.2 Judgmental adjustments

- Objective: use analyst experience and knowledge (supported by the insights) for a revision of the forecast and adjust it if needed.
- Tasks:
    1. Analyze forecast, insights and plots to adjust forecast based on judgmental decisions.

Step 6: Export and dashboard

Once the final forecast was been selected by the analyst, the next and final step will be to upload it in the official data base to support the right storage and communication of this information. This will ensure that the forecast will have one and only one single source of truth in the organization, in a standard and structured format (detail on this data structure are explained in the next section: Forecast Release Table). Then, a data visualization is required to track the day to day forecast behavior against the actual performance by tracking the forecast accuracy metric. This will be done through a simple yet complete dashboard, where the information flow automatically from the data base to the dashboard using Tableau software. The step by step diagram is shown in the next figure followed by the detail description of the type of plots:

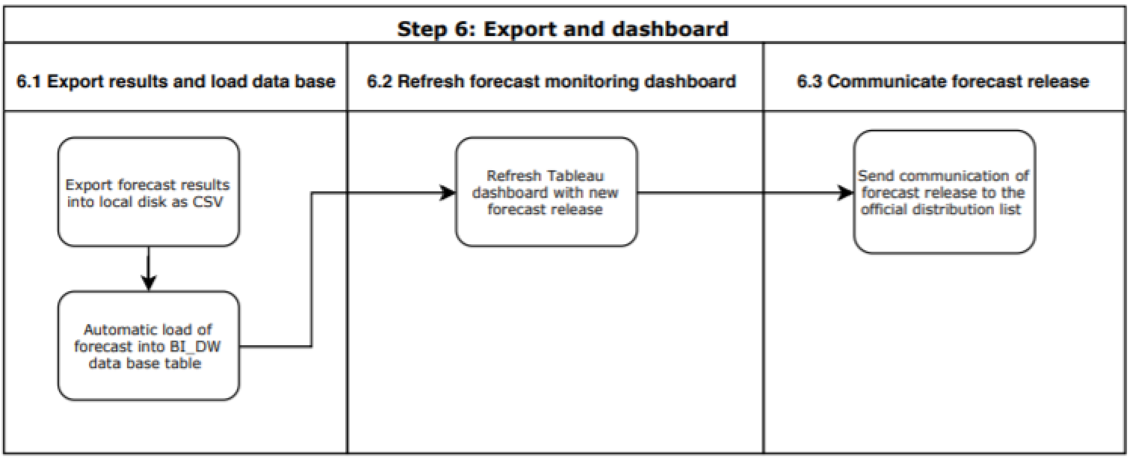


Figure 22 Step 6: Export and dashboard

Sub Step 6.1 Export results and load data base

- Objective: export official forecast result in the required formats for the proper communication.
- Tasks:

1. Export forecast results into local disk as CSV forecast. This format is required as some customers of the information does not use SQL Server to query information.
2. Automatic load of forecast into BI_DW data base table. This is key for data standardization and support the dashboard.

Sub Step 6.2 Refresh forecast monitoring dashboard

- Objective: provide a dashboard with forecast accuracy with automatic refresh cadence. The details of the dashboard are explained in a following section of this chapter: Forecast Accuracy and dashboard reporting.
- Tasks:
    1. Refresh Tableau dashboard with new forecast release through automatic linkage between Tableau and BI_DW. Updates must be done in a daily basis.

Sub Step 6.3 Communicate forecast release

- Objective: proper communicate the release of a new forecast to a pre-selected distribution list (internal customers).
- Tasks:
    1. Send communication of forecast release to the official distribution list using electronic mail as the channel. The communication includes the following sections:
        - Forecast release week (called as Scenario Name)
        - Highlights of the forecast: This section is optional, depending on the analyst judgment to make a remark of any special situation, for example, the inclusion of a new marketing event.
        - Forecast terms and assumption

The following figure show an example of a normal forecast release communication e-mail:

Hi,

Find attached the **WW25'19_FSCT** daily forecast release per Partner Location and "All" Farfetch for the 7 week ahead. Forecast is loaded in BI_DW table: `[BI_ANALYTICS].[dbo].[SCA_Order_Forecast]`.

Forecast assumption and terms:

- The forecast is an order projection of our partners (boutique and brands) at the day entering in the system, simulating based on their past behavior. This estimation is based on a combination of: a non-periodic unsaturated changes in the value of the times series (*trend*), a periodic changes (*seasonality*), a *holidays* effect (unusual disrupt behaviors, such as X20 or Black Friday) and an *error* (assumed normally distributed):
  - The holidays effect refers to the official sales Global Campaigns contained in this official communication link. Brands and Boutiques are considered within the same calendar of events.
  - As any forecast, the error term represents any idiosyncratic changes which are not accommodated in the model.
  - Due to data quality, partners with less historical data than 6 months are using as forecast the historical average with the pre-defined daily distribution.
  - Forecast is sensitive to offline days in the platform.
- If the forecast is communicated to our partners, is highly important for them to acknowledge that this is the best approximation possible we have at the time it's released, keeping in mind the pressure in the *error* term driven by the high granularity level (daily forecast by partner location) and industry field.
- The actual error of the forecast will be measured in a weekly basis and communicated as Forecast Accuracy in the Operations KPI reports. Public forecast accuracy dashboard in this link. Scenario comparisons dashboard in this link.

Thanks

Leonel M
OPS - Supply Chain Analytics

Figure 23 Example of a standard forecast release commutation e-mail

Forecast Release Table

To ensure the structure of the data, a standard table and data type is part of the solution. This is key for the data integrity specially with the linkage with the forecast dashboard. The table include 9 different fields and are explained in the following table:

Table 4 Forecast Release Table fields

Column Name	Data Type	Description
Season	Character (225)	Code showing the season and year with two capital letter (season, SS for Spring Summer, AW for Autumn-Winter and FP for full price months) and two numbers (last two digits of the year). For example: SS19 refers to Spring Summer 2019 season
Scenario Name	Character (225)	Code showing the release week with two capital letter (week acronym) and two numbers (week number). For example: WW07 refers to the seven work week forecast release
Scenario Revision	Character (225)	Code showing the revision of the forecast with three capital letters ("Revision" acronym) and number of the revision. For example: Rev1 refers to the revision number one of the forecast for a specific week release. Ideally should be only one revision per week.
Partner Location	Character (225)	Partner location name used in the official data source from BI_DW.
Date	Date	Date of the forecast order formatted as YYYY-MM-DD
Forecast Value	Integer	Partner location unique identifier coming from the official data source from BI_DW.
StoreKey	Integer	Upper range of the forecast number for the 80% of uncertainty interval
Active Row Date	Date	Date of the forecast release making this day the active forecast. The format is the same as the forecast date.
Exclusive Row Date	Date	Date when the forecast become "expired" due to a new forecast was released. The format is the same as the forecast date. Will be NULL for the most updated forecast release.

Forecast Accuracy and dashboard reporting

The success of the forecast dashboard is to ensure the quality and integrity of the data. The company uses Tableau as the official data visualization software for dashboard creation. Is important to mention that the dashboard is designed for the internal customers. Is not intended for the forecast analyst. Therefore, the dashboard is simple and easy to understand for any audience. The following figures show the Tableau data source join table design:

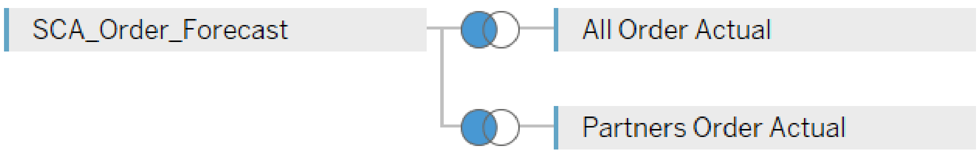


Figure 24 Tableau join tables design for forecast dashboard

Basically, Tableau will connect to only two tables in BI_DW merged by “Date” and “StoreKey” fields as the unique identifiers.

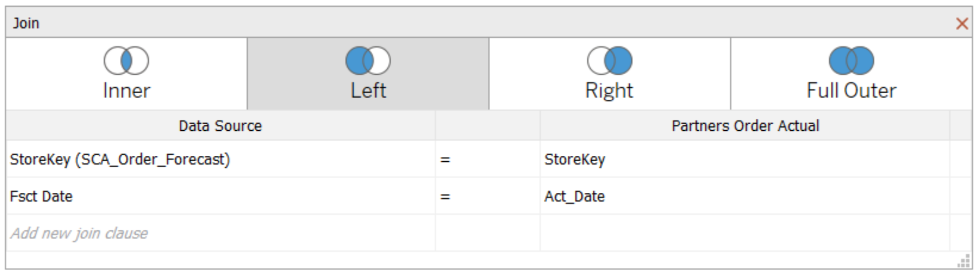


Figure 25 Example final forecast dashboard

The data sources are Fact Order Lines (FOL: for actuals) and Order Forecast (for the forecast values). The first one (FOL), have two types sections based on the granularity (different queries to pull in the information): one for each individual partner and another for All volume of the company. This structure will pull and merge the information to create the proposed dashboard. The following figure show an example of it:

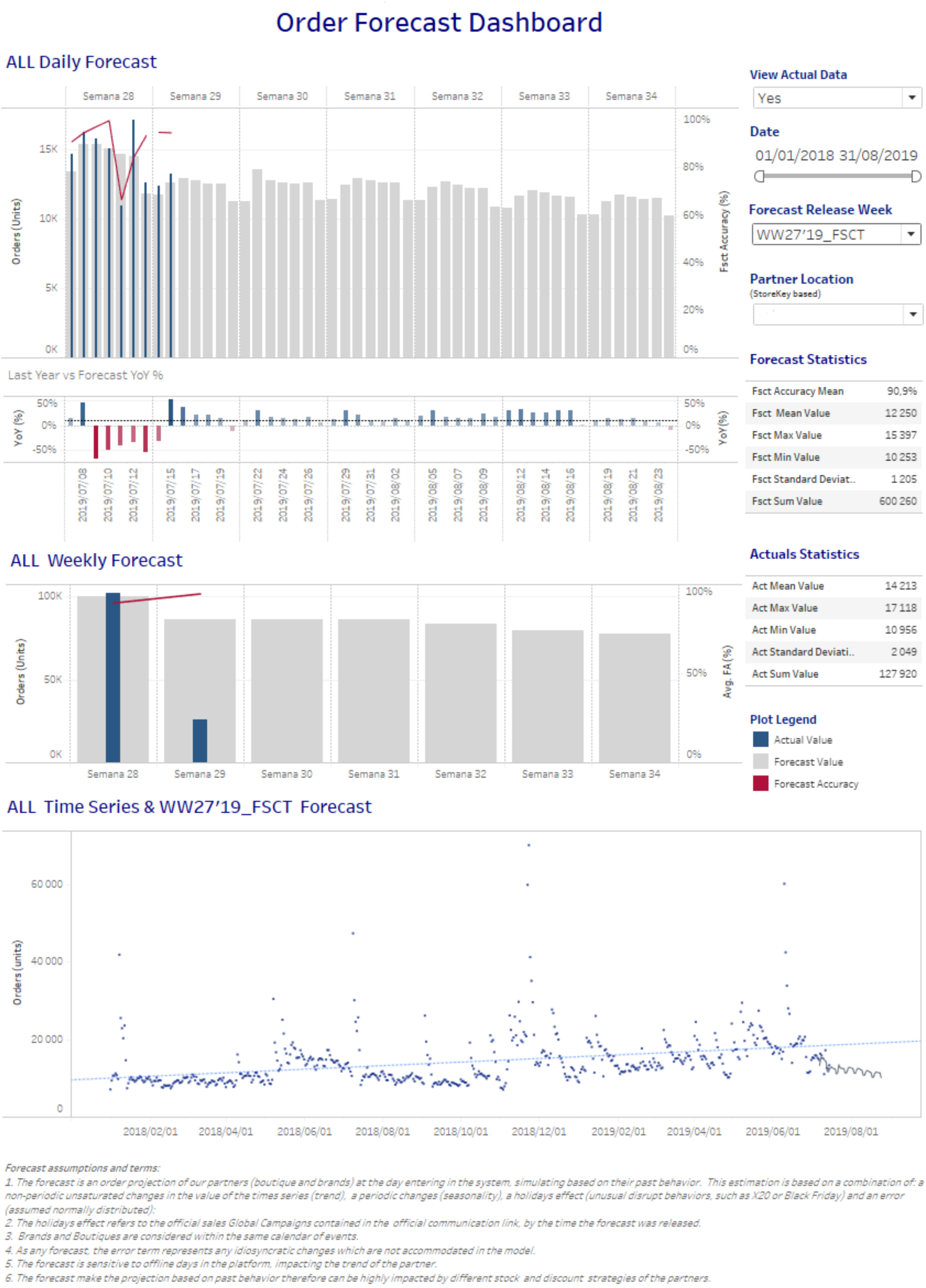


Figure 26 Example final forecast dashboard (data protected)

The sections shown in the dashboard are:

1. Date slider: user can select the time frame required. Date units are the same as the forecast: days.

2. View Actual Data: user can select weather or not to see the actual data and forecast accuracy metric.
3. Scenario Name: user can select the scenario name, which refers to the forecast release week.
4. Partner Location: user can select the All volume or by partner location.
5. Basic Statistics: show a basic descriptive (simple average, maximum and minimum values, standard deviation) and the forecast accuracy and MAPE simple averages of the time frame selected in the date slider.
6. Daily Forecast, Actual and Forecast Accuracy percentage: bar and line plot showing the forecast and actual values (bars) and forecast accuracy (line).
7. Last Year Actual versus Forecast: provide Year over Year change percentage of the forecast to the actual value from that exact day the previous year.
8. Weekly aggregated Forecast & Actual values and the simple daily average of the: bar and line plot showing the sum of the forecast and actual values (bars) and forecast accuracy (line) as the simple average of the daily forecast accuracy values within the time frame selected in the date slider.
9. Time Series with the actual data (scatter point plot) from one year of historical plus the forecast selected (line plot)
10. Forecast assumptions and terms: general explanation of the model and the most important assumptions.

The dashboard's administrator is the forecast data analyst in charge of creating the forecast. The dashboard is updated every day at 00:00 hours and is shared as a link for public access within the company. The link is included in the forecast communication e-mail. Also, the dashboard has the capability to send automatic screenshots to a pre-defined distribution list. This can be easily done by the administration under previous request.

VII. Results and Discussion

The new process was implemented since January 4th with the Top 50 partners. Then, the number of boutiques keep increasing until reach a 100% of coverage by end of March 2019. The data available for the 2 processes (As Is and new) are well represented and include the 2 types of periods (Full Price and Sale Season). The As Is process include data from week 31 until week 52 of 2018. The new process was implemented from week 6 to week 26 of 2019 (by the time this documented was written):

Table 5 Weeks available for Forecast Accuracy Comparisons

	As Is																						New																				
	Full Price (FP)														Sale Season (SS)								Full Price (FP)												Sale Season (SS)								
Week	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26

The forecast accuracy numbers where calculated using the Equations No. 14 and No. 15 for the All Volume and Per Partner, as explained in the Chapter IV (Literature Review). The regular proposed process includes 100% of the partners for the Per Partner Forecast Accuracy metric. For this case, the Per Partner metric includes only the Top 3 partners for data consistency between the As Is and new processes. The detailed calculations can be found in Annex 1

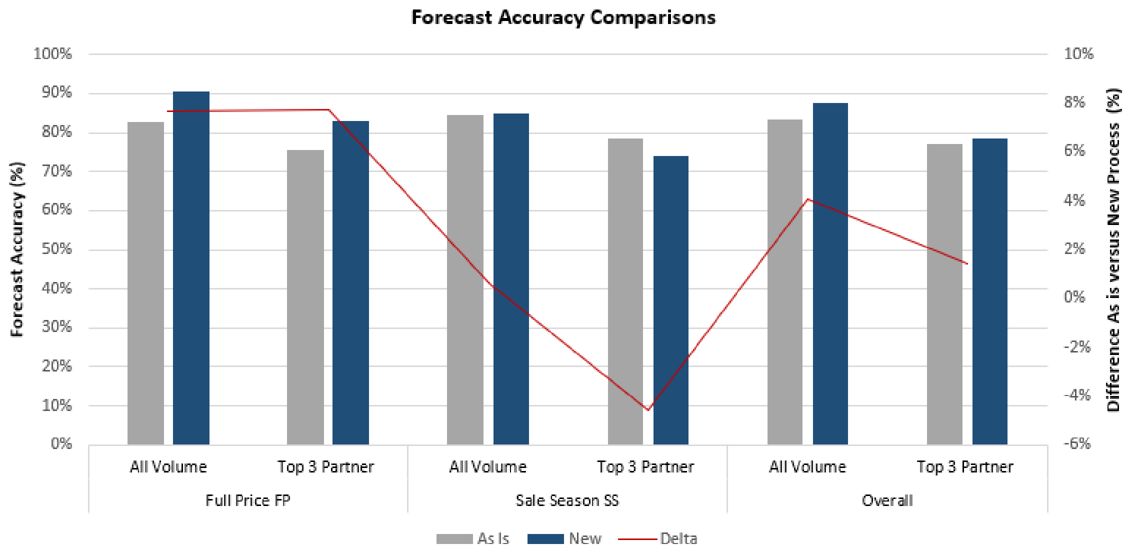


Figure 27 Forecast Accuracy Comparisons As Is process with new (Prophet)

The figure show that Prophet model is has the best performance in all the cases except the Top 3 Partners, however, this in reasonable as the AW18 Sale Season (using the As Is process) was less complicated than SS19 (using Prophet). The amount and types of holidays used in SS19 has being new types, creating difficulties in the regression. Some remarks about this preliminary results and comparisons are:

- In general, Prophet is performing in average 3% better than the As Is process, especially against the Full Price months, where is performing up to 8% better.
- Considering the amount of manual work of the current process, Prophet can perform higher number of partners in less amount of time with better accuracy. The proposed solution estimates an order forecast automatically in 1.83 minutes per partner versus approximate 15 minutes in previous model (88% of time reduction).
- This time reduction allows to have more flexibility (quick What If analysis and adjustments), quality (assign more time to high value-added analytical activities) and coverage (our target to cover 100% of the partners).
- The geo-group forecast approach of the solution, allows fitting the marketing events in a personalized way. The Holidays effect in the forecast, solves the problem that Auto Arima has, which is, create smart peaks in the future based on trained events from the past (like an X20 or Private Sale). The following figure, show how the proposed solution adjust better to the actual volume in the peak days when a marking event was modeled as a Holiday input:

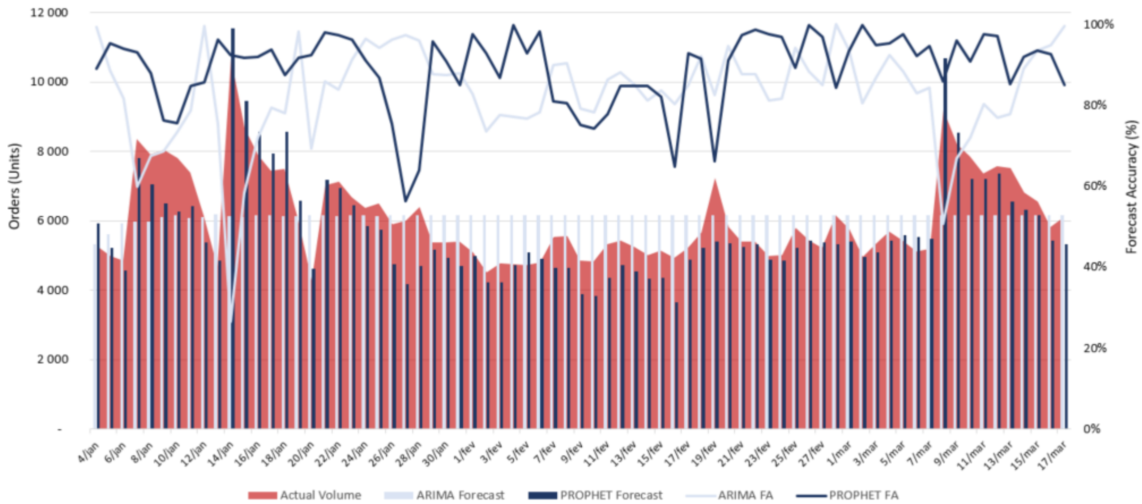


Figure 28 Daily Forecast Accuracy Prophet and Auto Arima

The proposed solution clearly states that the role of the analyst is key for the success of the process. The preliminary results, for sure, can be improved as the analysist growth the business knowledge in the industry. The Step 5 (Analysis and plots) has the intention to review the outcome of the model and adjust if needed with extra insights (such stock and discount levels). As the coverage will be 100% of the partners (as per the business requirements), is obviously that making a revision for all the partners won't be possible for one single analyst, therefore, is suggested to implement a strategy of prioritization.

For the recommended target, is necessary more level of detail on the actual performance. As explained in this chapter, the forecast process includes a forecast release each week for 7 weeks ahead. Each forecast released in called "scenario". The following figures show the forecast accuracy for All Volume and Per Partner (Top 3) using the Equations No. 14 and 15 for each scenario in each forecasted week. The light blue frame refers to Full Price weeks and the dark black Sale Season weeks (in this case: Spring Summer 2019):

Forecast Release	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Average
WW05'19_FSCT	89%	83%	74%	81%	73%	63%	71%	76%
WW06'19_FSCT	83%	74%	81%	73%	63%	71%	70%	73%
WW07'19_FSCT	91%	94%	81%	76%	88%	87%	71%	84%
WW08'19_FSCT	94%	93%	92%	96%	86%	71%	91%	89%
WW09'19_FSCT	93%	94%	97%	93%	72%	92%	82%	89%
WW10'19_FSCT	93%	94%	95%	66%	81%	71%	85%	84%
WW11'19_FSCT	96%	93%	73%	93%	80%	82%	75%	84%
WW12'19_FSCT	95%	73%	93%	80%	82%	78%	80%	83%
WW13'19_FSCT	88%	95%	79%	82%	71%	80%	92%	84%
WW14'19_FSCT	94%	81%	87%	75%	84%	94%	91%	87%
WW15'19_FSCT	81%	88%	75%	86%	93%	90%	91%	86%
WW16'19_FSCT	87%	71%	91%	89%	92%	84%	94%	87%
WW17'19_FSCT	73%	90%	94%	92%	83%	88%	57%	82%
WW18'19_FSCT	84%	95%	89%	90%	90%	56%	91%	85%
WW19'19_FSCT	94%	92%	84%	81%	60%	89%	83%	83%
WW20'19_FSCT	92%	81%	77%	62%	87%	80%		80%
WW21'19_FSCT	88%	78%	62%	86%	79%			79%
WW22'19_FSCT	81%	86%	76%	81%				81%
WW23'19_FSCT	86%	80%	83%					83%
WW24'19_FSCT	78%	83%						81%
WW25'19_FSCT	84%							84%
Overall Average	**88%**	**86%**	**83%**	**82%**	**80%**	**80%**	**82%**	
FP Average	**90%**	**87%**	**85%**	**82%**	**78%**	**77%**	**78%**	
SS Average	**84%**	**84%**	**81%**	**82%**	**82%**	**82%**	**84%**	

Figure 29 Weekly performance of the proposed process (Prophet) for All volume (Global)

Forecast Release	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Average
WW05'19_FSCT	85%	85%	81%	84%	68%	66%	71%	77%
WW06'19_FSCT	86%	80%	82%	66%	66%	68%	63%	73%
WW07'19_FSCT	86%	79%	67%	75%	72%	65%	65%	73%
WW08'19_FSCT	84%	75%	79%	73%	65%	67%	61%	72%
WW09'19_FSCT	77%	77%	72%	67%	66%	71%	68%	71%
WW10'19_FSCT	83%	77%	67%	64%	72%	60%	67%	70%
WW11'19_FSCT	87%	80%	72%	77%	71%	70%	54%	73%
WW12'19_FSCT	87%	73%	77%	71%	70%	54%	59%	70%
WW13'19_FSCT	83%	85%	79%	74%	58%	72%	88%	77%
WW14'19_FSCT	83%	78%	78%	54%	73%	85%	76%	75%
WW15'19_FSCT	81%	78%	53%	76%	84%	74%	68%	73%
WW16'19_FSCT	78%	56%	85%	61%	57%	37%	67%	63%
WW17'19_FSCT	57%	85%	76%	67%	48%	65%	66%	66%
WW18'19_FSCT	87%	74%	73%	59%	74%	65%	74%	72%
WW19'19_FSCT	68%	69%	55%	62%	68%	60%	47%	61%
WW20'19_FSCT	86%	71%	72%	67%	65%	54%		69%
WW21'19_FSCT	82%	75%	67%	65%	56%			69%
WW22'19_FSCT	79%	75%	55%	57%				67%
WW23'19_FSCT	72%	64%	61%					66%
WW24'19_FSCT	64%	62%						63%
WW25'19_FSCT	70%							70%
Overall Average	**79%**	**75%**	**71%**	**68%**	**67%**	**65%**	**66%**	
FP Average	**83%**	**79%**	**76%**	**72%**	**69%**	**67%**	**66%**	
SS Average	**74%**	**70%**	**66%**	**63%**	**65%**	**63%**	**67%**	

Figure 30 Weekly performance of the proposed process (Prophet) for Per Partner (Top 3)

As expected, the Forecast Accuracy is higher in the first weeks and decreases across the horizon. Also, in both cases the majority of the forecasted weeks, the Full Price weeks perform better than the Sale Season. As expected, the Sale Season weeks will always be harder to forecast, due to the higher complexity in the holidays (marketing events) as the market keep being more a more competitive. A small poll was done to understand from the point of view of the partners and other customers, how many weeks in advance do they need to know the order forecast in order to be prepared on time to fulfill the expected demand? The answer was around 2 to 3 weeks. Based on this feedback, the preliminary performance results and the continuous improvement efforts of this model, a suggested bold but realistic target of forecast accuracy would be around 90% for All company volume and 70% for individual partners, using the 4th week of each forecast release.

VIII. Conclusions

- Time series decomposition approach of the solution allows an easy way of interpretation of the forecast recommendation. Using Prophet methodology adjusted with the geo-group forecast approach of the solution, allows fitting the marketing events in a personalized way, increasing the probability of have a better forecast accuracy.
- The End to End design of the solution deals with the data extraction, transformation, analysis, forecasting, loading, distribution and visualization in an automatic way, creating a robust and reliable process.
- The solution is a complete Business Intelligence platform: is connected with the official data warehouse, ensuring the data integrity and security. Also, creates an automatic Tableau dashboard with the visualization of the forecast and the actuals (including the forecast accuracy metric).
- The performance of the proposed solution shows an average of 3% better accuracy than the As Is process, especially against the Full Price months, where is performing up to 8% better. As the model and knowledge from the analysis keeps evolving towards the luxury fashion industry, the accuracy will keep increasing.
- The new process increases the partner coverage up to 100% having the capability to create a forecast recommendation for all the partners (more than 1000) in short amount of time. The proposed solution estimates an order forecast automatically in 1.83 minutes per partner versus approximate 15 minutes in previous model (88% of time reduction).
- Obviously, this automatic End to End solution does not eliminate the analytical part of the data scientist, but in fact, reinforces it. Allows to release time from the non-value activities to focus in the high value-added ones (for example: tuning parameters, deciding to use the lower or upper case based on stock levels, etc).
- Finally, using open source libraries and free high analytical software (R Studio) the proposed solution doesn’t add any financial implication to the business.

IX. Limitations and Recommendations for Future Works

- The business needs to reinforce the communication of the forecast, in order to create trust. This process is considered as “new” for the majority of the partners, is recommended to work in the distribution and usage of the forecast. In order to maximize the benefits, the business need to ensure that the partners are using this information for their capacity planning.
- The officialization and communication of marketing events from the Sales and Marketing department is still consider slow. Even though the solution fits to the marketing events per geo-groups, is still a customer of this information. Is recommended to create awareness of the importance to release as fast as possible any new or change marketing event.
- In order to improve the accuracy, some modifications in the proposed model can be performed and tested. Is important to acknowledge that the model can always be improved. Some of the recommended exploration are:
  - Perform a cross validation by partner, not by partner type (brand or boutique). The model doing a generalization of the best parameters by partner type to each individual partner. This generalization can work fine for the high-volume partner but might be impacting negativity the rest of partners. Therefore, is recommended to explore the best way to treat this low volume partners.
  - Test a rolling window cross validation approach (Svetunkov, 2019): the model is selecting the best parameters based on a simple cross validation technique, but time series data might not be the best for a simple cross validation data partition. Is recommended to explore a modification with the rolling window approach.
  - Fit the model to solve the Brands calendar limitation: as explained in the current situation, Brands can follow their own calendar of events and have the freedom to participate or not in a marking event of the company. The next level of the forecast model should be to adjust as much as possible to these cases.

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XI. Annexes

Annex 1: Forecast accuracy calculations

All Volume (coded: data protected)

		Week	Sum Forecast	Sum Actuals	Sum of Abs (Forecast Bias)	MAPE	FA	H.Weight	H.Weight Per Type
As Is	FP	31	18316	17426	890	5%	95%	2%	4%
		32	28246	28360	2164	8%	92%	3%	7%
		33	25653	26625	1326	5%	95%	3%	6%
		34	28055	29765	2564	9%	91%	3%	7%
		35	26585	28082	2401	9%	91%	3%	7%
		36	27895	44789	17142	38%	62%	5%	11%
		37	28314	24329	3985	16%	84%	3%	6%
		38	28545	25807	2754	11%	89%	3%	6%
		39	27308	24116	3192	13%	87%	3%	6%
		40	28562	25320	3242	13%	87%	3%	6%
		41	28930	36596	9082	25%	75%	4%	9%
		42	30534	31290	1962	6%	94%	4%	8%
		43	28765	44218	15453	35%	65%	5%	11%
		44	28040	26842	5384	20%	80%	3%	6%
	SS	45	51763	45649	8442	18%	82%	5%	10%
		46	55378	65560	12462	19%	81%	7%	14%
		47	103580	104385	14355	14%	86%	12%	23%
		48	49203	57478	13119	23%	77%	7%	12%
		49	45743	44862	3087	7%	93%	5%	10%
		50	54087	62359	8562	14%	86%	7%	14%
		51	38125	40511	5972	15%	85%	5%	9%
		52	32632	31814	4104	13%	87%	4%	7%
New	FP	6	32147	35025	3777	11%	89%	3%	7%
		7	29831	35921	6091	17%	83%	3%	7%
		8	36314	39746	3432	9%	91%	4%	8%
		9	36599	38361	2114	6%	94%	4%	8%
		10	46361	44167	3239	7%	93%	4%	9%
		11	46225	49581	3356	7%	93%	5%	10%
		12	43762	42390	1875	4%	96%	4%	8%
		13	41484	42783	2299	5%	95%	4%	8%
		14	59076	53040	6109	12%	88%	5%	10%
		15	43364	41067	2408	6%	94%	4%	8%
		16	39312	47467	9049	19%	81%	5%	9%
		17	36687	36158	4840	13%	87%	3%	7%
	SS	18	48096	47718	12990	27%	73%	5%	9%
		19	51184	60752	9568	16%	84%	6%	11%
		20	64451	61228	3546	6%	94%	6%	12%
		21	64362	63533	5400	8%	92%	6%	12%
		22	60355	54035	6524	12%	88%	5%	10%
		23	58026	48743	9283	19%	81%	5%	9%
		24	95326	92946	12968	14%	86%	9%	18%
		25	63524	52957	11497	22%	78%	5%	10%
		26	49829	48033	7677	16%	84%	5%	9%

Per Partner (coded: data protected)

		Week	Sum Forecast	Sum Actuals	Sum of Abs (Forecast Bias)	MAPE	FA	H.Weight	H.Weight Per Type
As Is	FP	31	2505	2495	418	17%	83%	2%	4%
		32	3861	4079	756	19%	81%	3%	7%
		33	3507	4299	1160	27%	73%	3%	7%
		34	3836	5183	1507	29%	71%	4%	8%
		35	3699	4231	1040	25%	75%	3%	7%
		36	4250	6920	2828	41%	59%	5%	11%
		37	4310	3829	525	14%	86%	3%	6%
		38	4348	3934	502	13%	87%	3%	6%
		39	4156	3674	612	17%	83%	3%	6%
		40	4662	3949	761	19%	81%	3%	6%
		41	4768	4914	1150	23%	77%	4%	8%
		42	5036	4227	877	21%	79%	3%	7%
		43	4745	6166	1935	31%	69%	5%	10%
		44	4657	3858	1113	29%	71%	3%	6%
	SS	45	8524	7215	2205	31%	69%	5%	10%
		46	9980	12024	2718	23%	77%	9%	17%
		47	16989	16589	3556	21%	79%	12%	23%
		48	8962	8025	2263	28%	72%	6%	11%
		49	7164	7024	1198	17%	83%	5%	10%
		50	8057	8953	1368	15%	85%	7%	12%
		51	5645	5851	594	10%	90%	4%	8%
		52	4683	5092	999	20%	80%	4%	7%
New	FP	6	5563	5770	879	15%	85%	4%	7%
		7	5117	5923	842	14%	86%	4%	7%
		8	6019	6433	927	14%	86%	4%	8%
		9	6490	6416	1019	16%	84%	4%	8%
		10	7511	7652	1744	23%	77%	5%	10%
		11	7328	7762	1319	17%	83%	5%	10%
		12	7423	6679	883	13%	87%	4%	8%
		13	6380	6710	887	13%	87%	4%	8%
		14	9206	8204	1422	17%	83%	5%	10%
		15	7184	6283	1061	17%	83%	4%	8%
		16	6903	7266	1398	19%	81%	4%	9%
		17	5497	5296	1152	22%	78%	3%	7%
	SS	18	8866	8855	3832	43%	57%	5%	11%
		19	10761	11388	1463	13%	87%	7%	14%
		20	12786	10215	3319	32%	68%	6%	13%
		21	10024	9067	1235	14%	86%	6%	11%
		22	8866	7595	1405	18%	82%	5%	9%
		23	8655	7285	1540	21%	79%	4%	9%
		24	15453	12893	3626	28%	72%	8%	16%
		25	10051	7383	2668	36%	64%	5%	9%
		26	8201	6943	2086	30%	70%	4%	9%

Annex 2: Root cause prioritization matrix (voting)

Cause	College 1	College 2	College 3	Average
Reactive to marketing changes	5	5	5	5,0
Low capability to perform What If analyses	4	5	5	4,7
Basic statistics	5	4	5	4,7
Inexperienced analyst with low business acumen	4	5	5	4,7
Completely manual work	4	4	5	4,3
Limited capacity of current software to increase partner coverage	5	4	4	4,3
Reduce data science skill in analysts	4	4	5	4,3
Unclear business requirements of the customers	4	3	5	4,0
Constant Marketing campaigns changes	3	5	4	4,0
Low historical data for some partners	4	5	3	4,0
Basic software not appropriate for time series forecasting	3	4	4	3,7
Lack of scorecard for KPI communication	3	3	5	3,7
Not standard performance measurements	4	3	3	3,3
Low analytical and numerical skills	2	3	4	3,0
New organization with constant changes in org-chart	3	2	4	3,0
Not standard for all groups	2	3	2	2,3
Highly dispersed historical data	3	2	2	2,3
High human error risk in manual work	2	1	4	2,3
Limited server capacity to pull in data	1	2	3	2,0
Historical data uncleaned	2	1	2	1,7
Constrain man-hours capacity	1	1	2	1,3
Limited KPI sharing between teams	2	1	1	1,3

Annex 3: Required R Packages and libraries

```
install.packages("textshape")
install.packages("prophet")
install.packages("gcookbook")
install.packages("RODBCDBI")
install.packages("ggplot2")
install.packages("ggplot")
install.packages("tidyverse")
install.packages("xlsx")
install.packages("rio")
install.packages("foreach")
install.packages("parallel")
install.packages("doSNOW")
install.packages("forecast")
install.packages("expss")
install.packages("splus2R")
install.packages("dplyr")
install.packages("plotly")
install.packages("reshape")
install.packages("plotly.js")
install.packages("devtools")
install.packages("pracma")
install.packages("glue")
install.packages("DBI")
install.packages("odbc")
install.packages("smooth")
install.packages("Mcomp")
install.packages("base")
install.packages("rpanel")
install.packages("IDPmisc")
```

```
install.packages("stats")
install.packages("distr")
install.packages("tidyquant")
install.packages("epitools")


library(dplyr)
library(lubridate)
library(forecast)
library(textshape)
library(prophet)
library(plyr)
library(gcookbook)
library(xts)
library(DBI)
library(RODBCDBI)
library(ggplot2)
library(tidyverse)
library(lubridate)
library(xlsx)
library(data.table)
library(rio)
library(textshape)
library(expss)
library(splus2R)
library(data.table)
library(doSNOW)
library(foreach)
library(parallel)
library(tcltk)
library(plotly)
```

```
library(reshape2)
library(devtools)
library(pracma)
library(glue)
library(DBI)
library(odbc)
library(smooth)
library(Mcomp)
library(base)
library(rpanel)
library(IDPmisc)
library(stats)
library(distr)
library(tidyquant)
library(epitools)
```