ARTICLE

NEW PRODUCTS FORECASTING

Get out of the blur quicker with Machine Learning !

IRIS by Argon&Co

NEW PRODUCTS INTRODUCTION IS KEY TOPIC IN SUPPLY CHAIN MANAGEMENT

Supply Chain professionals describe the current business environment with four drivers : Volatility, Uncertainty, Complexity and Ambiguity (VUCA). Companies are working constantly on gaining new customers and adapt their products to behavioral changes, not to mention reacting to increasing supply complexity.
In the fashion sector, 70% of products in stores were launched in the last 3 months. In the same way, 25% of the automotive catalog is renewed every year.

Therefore, new products forecasting has become a day-to-day challenge for demand planners who cannot only rely on historical Data to make their predictions.

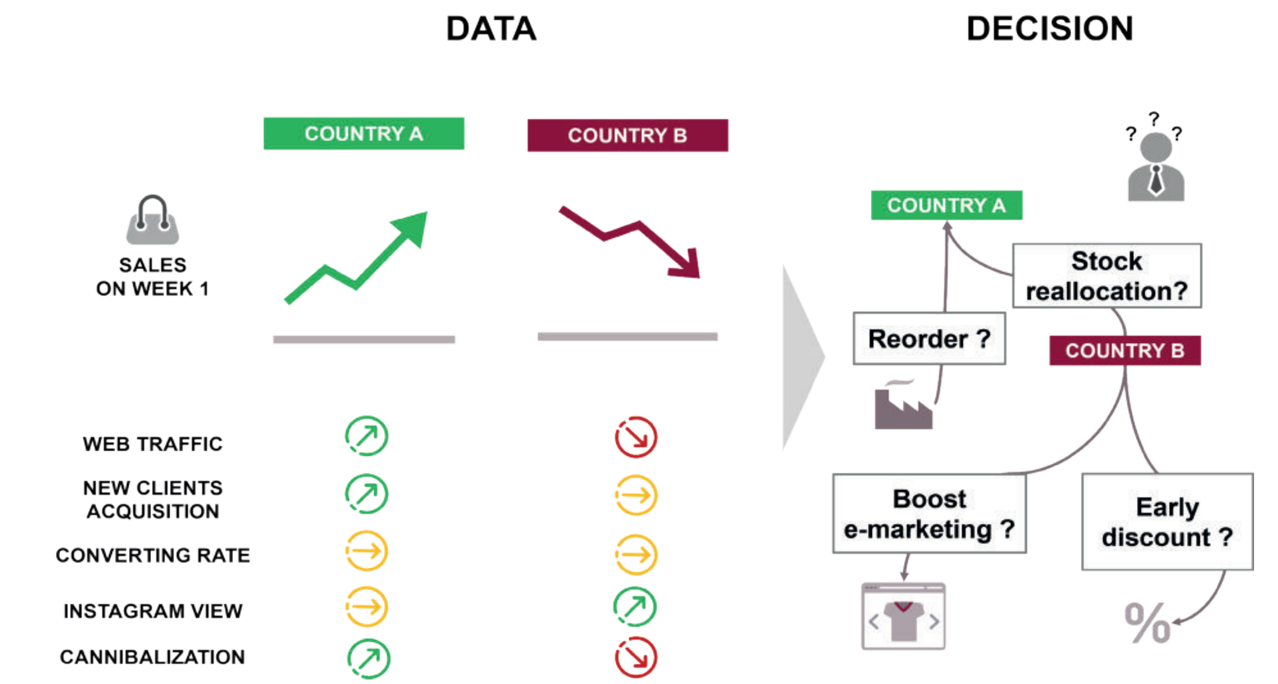
% of the assortment that is renewed every quarter

What is challenging about new products launches?

After each launch, Supply Chain teams, together with Merchandising and Marketing, must closely observe the behaviour of consumers to new products and react accordingly.

- What are the key performance indicators which could explain why a product is a success in region A and not in region B ? Visibility on Instagram? Web traffic volume? Conversion rate?
- Which quantities should be moved from region B to region A to avoid overstocks in the first and reduce stock-outs in the second?
- Is there any cannibalization between a new product and an old product? Is there any need to re-launch production of the new product as soon as possible?
- What would be the appropriate strategy to reallocate Marketing budget in an effort to improve a deceptive product launch? IRIS by Argon & Co has team up with several luxury brands to address this challenge. The team has mixed industry best practices — processes and agile tools — with rigorous Data-driven approach leveraging AI.

Why existing models are failing?

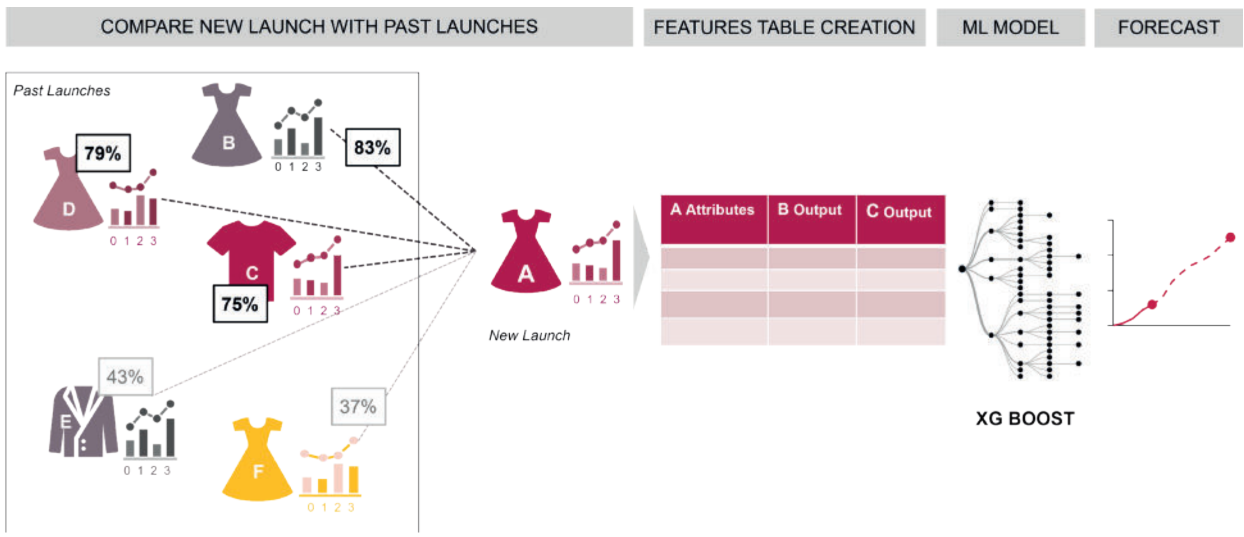


Traditional forecasting softwares use statistical algorithms based on trends and seasonality. There are ineffective for launches because the historical data (previous time periods) is far too limited or even non-existent.

Similarly, mainstream AI forecasting models are found inappropriate for less than 15 data points' time series.

Our experts had to reconsider the problem as a whole and use a completely new approach by trying to capture all types of early warning signals that can influence the sales, hence should drive the forecast in return.

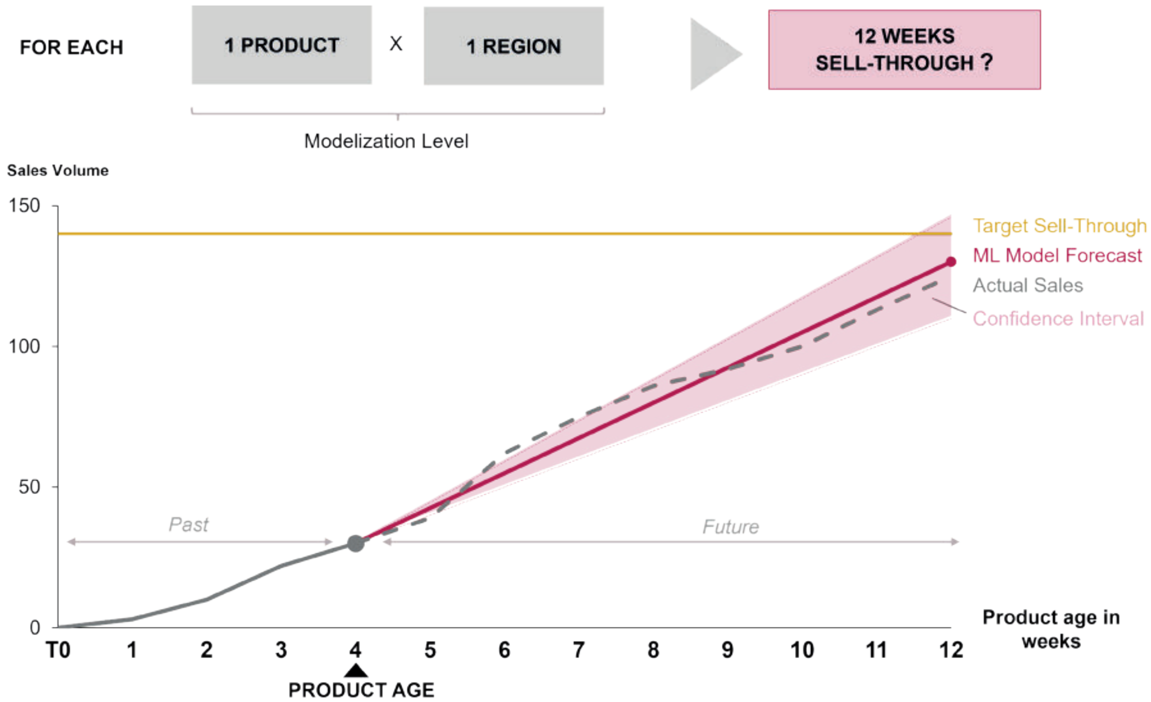
A Machine Learning approach to address new products (re)forecasting



1. Clearly define what business teams need.

After many interviews with Supply, E-commerce, Merchandising and Marketing the team agreed on the required output from the model:

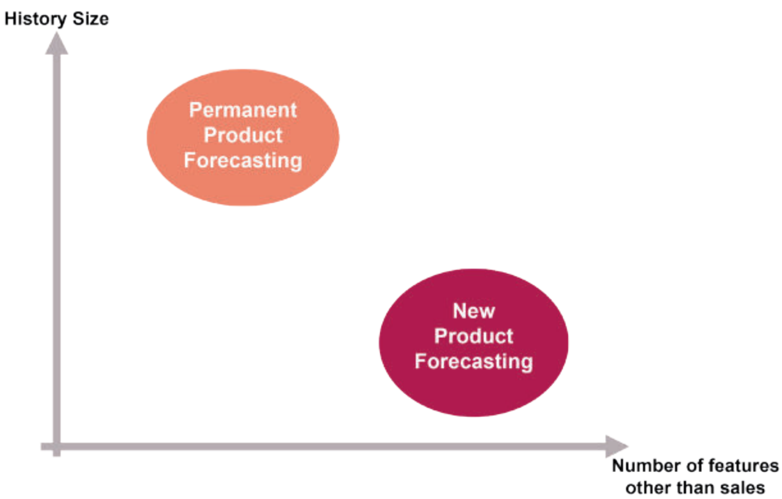
- Forecasting the 3-month Sell-Through
- Modelling at SKU x Region Level
- Updating the forecasts every day



Note : the target sell-through is the initial forecast for the product at the 3 months mark, made and committed by the Teams before product launch

2. Collect a wide range of Data sources and aggregate it through a robust Data pipeline.

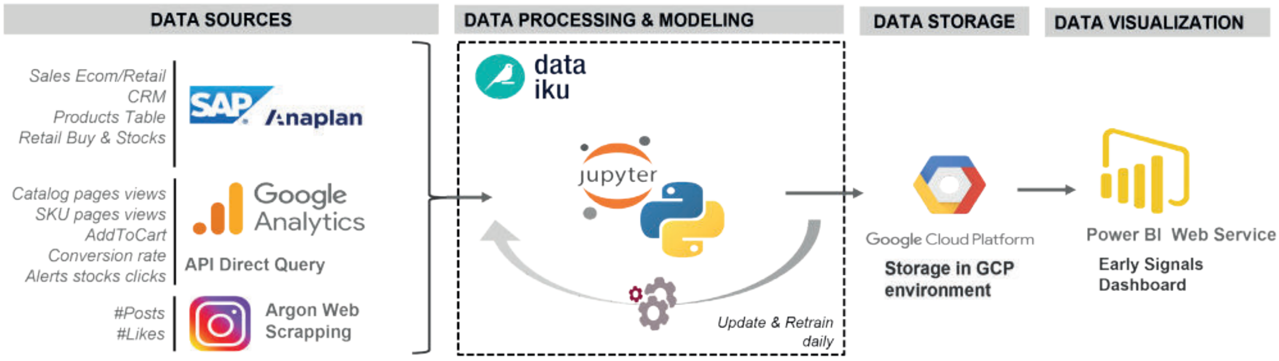
To counterbalance the fact that the size of the history is very small, IRIS by Argon & Co tried to aggregate a maximum of additional Data, to give more context to the model



Our experts built a pipeline on Dataiku that was able to provide all the following Data sources daily:

- Actual sales volumes by distribution channel (stores / department stores / retailers / e-commerce)
- CRM Data of the first customers (age, nationality, new or existing?)
- Traffic Data on product web pages (click-through rates, conversion rates, acquisition channels)
- Number of Instagram posts containing the product family name, number of likes and reposts generated
- Retail Buy and Stocks Data
- Product attributes (materials, colors, prices) and product images
- Store attributes (geographic location, average sales volume)

Scenario 1 - Early Signals use case architecture.



The pipeline that allowed us to source and process all the Data from various sources

3. Define a Launch Similarity Score.

The team defined the Launch Similarity Score between two products as the weighted distance between their main attributes.

Let $X(w)$, $Y(w)$ be two products states vectors after w weeks from their respective launch date.

$$X = \begin{pmatrix} x_1(w) \\ x_2(w) \\ x_3(w) \\ \\ \dots \\ \\ \\ \\ x_n(w) \end{pmatrix} = \begin{pmatrix} IsCategoryH \\ IsSummerCollection \\ IsGroupA \\ \dots \\ Sales[0,w[\\ MarketingBudget[0,w[\\ WebTraffic[0,w[\\ ConvertingRate[0,w[\\ InstagramLikes[0,w[\end{pmatrix}$$

Then, they defined the Launch Similarity Score as follows:

$$ComparisonScore(X,Y,w) = \alpha.|X(w) - Y(w)|$$

$$\alpha = (Weight_{x_1} \quad \dots \quad Weight_{x_i} \quad \dots \quad Weight_{x_n})$$

Different options were found to best estimate weights according to our problem:

1. Choose it arbitrarily with business teams, their experience can tell us which attributes is most important for products similarity calculation.

2. Optimize these parameters within an embedded grid search.

4. Construct the output vector.

Knowing (w) weeks of sales, our experts wanted to predict the 3-month Sell-Through. So, it was accorded to build 1 model for each product age w in weeks (w in [1,6]).

Conversely to traditional forecasting models where the output is generally the absolute value of sales, the team rebased the Data with the first days' sales. In other words, our experts trained the model not to answer the question "how much units will I sell, in absolute ? " but "Will I sell more or less on average in the coming weeks than in the past few weeks ? ".

5. Construct the features table.

For each product X, it was necessary to build the feature table with:

- All the Data concerning product X characteristics (attributes, first sales, web traffic, etc.)
- Data concerning other previously launched products that are similar to product X (using the Similarity score previously defined). As these products are older, it was possible to feed the model with all the information concerning their complete launch profile, and in particular their output (= target) value

6. Use the power of the XGBoost Algorithm.

XGBoost was tuned to hyperparameters with cross-validation on the train set and then used it to fit the Data and predict on the test set.

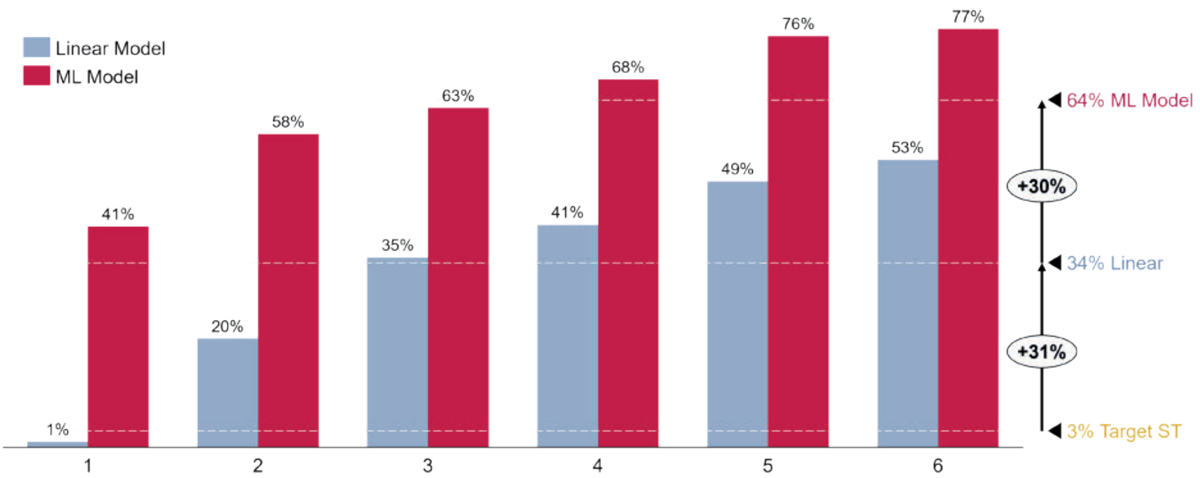
Results and business case

To evaluate the performance of our model our experts used the common forecast metric Forecast Accuracy = 1 — WAPE, with A being Actuals and F Forecasts

$$WAPE = \frac{\sum_{t=1}^{n} |A_t - F_t|}{\sum_{t=1}^{n} |A_t|}$$

Here are the results obtained compared to a simple linear model (i.e extending first sales linearly). The x-axis is the number of weeks after the launch.

It appears that the Machine Learning Model largely outperforms Linear Model and company's target sell-through, especially for the very first weeks of launch (1,2,3).



As a summary, IRIS by Argon & Co has also calculated that this improvement of Forecast Accuracy can increase company's turnover by 7% thanks to stocks re-balancing and early reorders. This does not include benefits in storage and obsolescence costs from avoiding overstocks situations.

IRIS BY ARGON & CO

IRIS by Argon & Co is an integrated team of operations experts, data scientists and data engineers within Argon & Co that specialise in data analytics for operations.

We use data analytics, AI, IoT and digital technology to design and build clear solutions, and provide a new level of efficiency and profitability for clients. Our people apply a combination of operations experience, data expertise and broad business knowledge to improve operational performance. We deliver robust, transparent and practical data-driven insights and solutions to generate real change.

We are based in Paris, and work collaboratively with the Argon & Co global offices.

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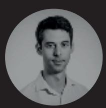

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Guilhem delivered Supply Chain transformation projects for several years before joining the IRIS by Argon & Co team as a Data Project Manager. He leads the design, build,deployment, and execution phases of datadriven use cases for Supply Chain and Logistics(Business Intelligence, Machine Learning models, Enterprise Data Platforms).

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Cyprien joined IRIS by Argon & Co as a Data Scientist 3 years ago. He builds Data and AI-powered solutions to support operational performance and efficiency. He has worked in different sectors, mainly demand forecasting, Supply Chain optimization and Manufacturing excellence.