

Exploring arbitrage opportunities for increased catalogue ROI in a fashion e-tailer

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Abstract

In the highly complex fashion industry, where profitability concerns are relevant, assortment optimization is seen by retailers as a source of competitive advantage. The references to the topic are vast, coming both from the academic research and from across the industry.

In the same line of thought, the present project intends to propose a selective supply model for Farfetch, an online luxury fashion retail platform, so that the Company can benefit from the differences between the markets and thus leverage its financial performance.

The project includes a conceptual development of the topic, specifically the structure of the catalogue management model along with the definition of the business rules to be considered. This is presented in the form of a proof of the concept.

As results, the simulation performed confirms the considerable opportunity for profitability improvements along the season by applying the model. Those improvements derive from a trade-off between the increase in orders' profitability and the risk of sales losses. The benefits are possible to estimate as function of the forecast and the model rules, being the ultimate decision on the Company's hands, tailored to its strategic goals.

As future perspectives, the processes and capabilities to be built for implementation were defined. The starting point should be the development of a solid analytical decision support system. From then on, a pilot project should be carried out, extending progressively the scope of the model until its institutionalization. The model is expected to prove useful within the Company: in a first moment, applicable to 1P; afterwards, having shown its merits in the Marketplace, it can possibly be provided as a service part of Farfetch Platform Solutions.

Resumo

Numa indústria altamente complexa como a da moda, em que os níveis de rentabilidade adquirem uma posição de relevo, a otimização de catálogo é vista entre os retalhistas como uma fonte de vantagem competitiva. São inúmeras as referências ao tema tanto na investigação como na indústria, com provados benefícios, sob um contínuo foco de desenvolvimento.

Na mesma linha, o presente projeto desenvolvido para a Farfetch, plataforma *online* de alta costura, visa propor um modelo de oferta seletiva do catálogo que permita beneficiar das diferenças entre mercados e, assim, alavancar o desempenho financeiro da empresa.

O projeto passa por um desenvolvimento conceptual do tópico, em específico da estrutura do modelo de gestão de catálogo, com a definição do conjunto de regras de negócio a considerar. Ainda, é apresentado sob a forma de prova de conceito.

Como resultados, a análise de simulação confirma a considerável oportunidade de melhoria da rentabilidade, ao longo da *season*, com a aplicação do modelo. Essa melhoria resulta sempre de um compromisso entre o aumento da rentabilidade das encomendas e o risco de perda de vendas. Os benefícios são estimáveis em função do *forecast* e das regras a usar no modelo, cabendo em última instância à empresa decidir de acordo com os seus objetivos estratégicos.

Numa perspetiva futura, os processos e capacidades a construir para implementação são definidos. Deve começar-se pelo desenvolvimento de uma ferramenta analítica sólida de suporte à decisão. Posteriormente, um projeto piloto deve ser realizado, seguido pela extensão do modelo até à sua institucionalização. Espera-se que o modelo seja útil na empresa: num primeiro momento, aplicável a 1P; depois de verificados os resultados positivos no Marketplace, poderá ser vendido como serviço integrante de Farfetch Platform Solutions.

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This is the end of a beautiful and intense chapter of my life that I hold close to my heart.

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“Where I create, there I am true.”

Rainer Maria Rilke

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Acronyms and Symbols

AOV	Average Order Value
APAC	Asia-Pacific
ASP	Average Selling Price
ATV	Actual Transaction Value
Avg.	Average
AW	Autumn-Winter
BAU	Business as usual
CIS	The Commonwealth of Independent States
CO	Carryover
COGS	Cost of Goods Sold
CShip	Customer Shipping
CV	Coefficient of Variation
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
EU	European Union
FP	Full Price
FPS	Farfetch Platform Solutions
FTA	Free Trade Agreement
FX	Foreign Exchange
FxFF	Fulfilment by Farfetch
GBFC	Gender, Brand, Family and Category of items (<i>e.g.</i> , Women x Fendi x Clothing x Dresses)
GFC	Gender, Family and Category of items (<i>e.g.</i> , Women x Clothing x Dresses)
GGP	Group Gross Profit
GGP%GMV	GGP as percentage of GMV – Company’s profitability metric
GMV	Gross Merchandise Value
GTV	Gross Transaction Value
IT	Information Technology
KPI	Key Performance Indicator
LATAM	Latin America
L35	35-days Logic
MAPE	Mean Absolute Percentage Error
MD	Markdown
ME	Middle East
MNL	Multinomial Logit
NGG	New Guards Groups

NYSE	New York Stock Exchange
N/A	Not available
OC	Order Contribution
PT	Price Type
PTG	Period-To-Go
P&L	Profit and Loss
RMSE	Root Mean Square Error
ROI	Return on Investment
ROW	Rest of the World
Sb	Stock at the beginning of the period
Se	Stock at the end of the period
SG	Stadium Goods
ShipS	Shipping Subsidy
SKU	Stock Keeping Unit
SMAPE	Symmetric Mean Absolute Percentage Error
SO	Season Original
SS	Spring-Summer
ST	Season Type
STD	Sales-To-Date
STh	Sell-Through
UK	United Kingdom
US	United States
USD	United States dollar
USP	Unique Selling Proposition
U.A.E	United Arab Emirates
VAT	Value-added Tax
WH	Warehouse
1P	First Party
3P	Third Party
3PL	Third-party Logistics

Definitions

Inbounds/Stock uploads	Stock replenishment events. They generate an increase in stock levels that is not the result of returns: $\text{Inbound} = S_e - S_b + \text{GMV units (Units sold, delivered and not returned)} \quad (0.1)$ There is no stock planning at Farfetch: as the stock is uploaded by Partners, it is the result of their action, and the Company has little visibility beforehand. Three types of stock upload may occur, depending on Partners: one-shot inbounds, phased inbounds or one-shot inbounds with the possibility of replenishment.
LV	LV (“Latest View”) represents the rolling forecast for future months that is monthly updated with the actuals of the past months and with the most recent expectations.
Partner/Merchant	A boutique or brand that sells their inventory through Farfetch’s Platform.
Price Type	Price Type associated to an item, which can be: • Full Price (FP) – No promotion: product at full price • Full Price (FP) – Promotion: product at full price with a promocode discount • Markdown (MD) – No Promotion: product at reduced price • Markdown (MD) – Promotion: product at reduced price with a promocode discount.
Product ID	Product key that has as attributes: Brand, Designer ID, Designer Color, Gender, Family, Category, Season and Material.
Production Centers	Physical location where Farfetch receives the products, photographs and writes the high-quality information that will be available on the website.
Season Type	Season associated to an item. Items have both a season of origin (when they are created in the Platform) and a current season, that can be different from the season of origin. The possible Season Types are: • Spring-Summer (SS) - followed by the year (<i>e.g.</i>, SS21); • Autumn-Winter (AW) - followed by the year; <i>e.g.</i>, AW21); • Carryover (CO) / Continuity - products that transit across seasons: ○ Carryover: Item that transits from its original season to the next season(s); ○ Continuity item: Item without season due date. Items are designated “Season Original” or novel items if they are original from the season at issue. Otherwise, they are “old” (from past seasons).
SKU	Combination of Product ID and size.
Stock Level/Depth	Quantity of inventory carried by Farfetch, to which daily snapshots are made.
Third-party Logistics (3PL)	A provider from another company to which Farfetch outsources operational logistics tasks such as warehousing or delivery.

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1 Introduction

1.1 Farfetch

Founded in 2007 in London by José Neves, Farfetch began as an e-commerce marketplace connecting around 40 boutiques to customers and fashion lovers around the world. It joined the few online fashion businesses pioneering a new model in the market, starting in the 90s with *Net-a-Porter*, *ASOS* and *Vente-Privée*. After them, Farfetch created a new retail model for luxury fashion with very hard-to-replicate network effects on both supply and demand.

A key innovation of Farfetch's business model had to do with its zero-inventory policy. Being a marketplace rather than a store, all the products on offer on Farfetch were owned by a third party (independent boutiques or brands), thus allowing for an extensive selection of items without the hurdles of keeping own inventory. Another differentiating factor was its considerable control over the process, from content creation until the item would reach customers' houses - although still reliant on Partners for some tasks, as items upload or shipping preparation.

Recognized as highly attractive by venture investors, Farfetch raised \$700m across six funding rounds over 8 years. Finally, in 2018 Farfetch went public on the NYSE, with a \$8bn market capitalization on the first day of trading (Felix Capital, 2018).

Today, Farfetch's mission is "to be the global platform for luxury fashion, connecting creators, curators and consumers" (Farfetch). The Farfetch Marketplace connects customers in over 190 countries and territories, with suppliers from more than 50 countries and over 1,300 of the world's most influential brands, boutiques and department stores.

The Group has obtained direct brand ownership of Browns (2015) and Stadium Goods, or SG (2018), that offer luxury products to consumers, and of New Guards Group, or NGG (2019), a platform for the development of global fashion brands like Off-White and Palm Angels. Consequently, Farfetch now holds under its portfolio both first party (1P) and third party (3P) Partners whose items are sold in Farfetch Marketplace. From the total online stock at Farfetch.com, approximately 60% is from 3P Partners.

To Partners, besides access to the Marketplace, there are services that can be provided. Farfetch has launched the Luxury New Retail initiative (2020) that offers a broad range of consumer-facing channels and enterprise level solutions. It includes Farfetch Platform Solutions (FPS), providing e-commerce and technology capabilities to luxury brands and retailers, from the development of the Partner's own website, items production, order processing and delivery; as well as in-store innovations such as the Farfetch Retail suite of technology products; or the warehousing service, Fulfilment by Farfetch (FxFF), in which Farfetch manages Partners' stock in Company warehouses. These services can be provided in combination or separately.

Concerning 1P Partners, all are served by FPS and FxFF services, so Farfetch manages both their Platform and stock (both the online stock at Farfetch.com and at the Partners' websites).

This stock is carried jointly in Farfetch warehouses around the globe: Browns has two warehouses (one in Harlow, UK, and the other in Venray, Netherlands); NGG has two Italian warehouses (Quinto and Villorba); and SG has two American warehouses (New Jersey and LA).

In turn, when it comes to 3P Partners, most (around 87%) have no additional service (simply access to the Marketplace). When subscribing to a service, 89% of the Partners require FPS only. Requiring FPS and FxFF (9%) there is just Thom Browne and JW Anderson; and requiring only FxFF services (2%) there are a few Italian Partners. As result, within the 3P Partners, Farfetch manages the stock of Thom Browne, JW Anderson, and those few Italian Partners on its warehouses, having moved away from the initial zero-inventory policy.

By the end of 2021, the value of goods sold at Farfetch reached \$4.2 billion, up 33% year-over-year, along with the first year of Adjusted EBITDA profitability (Farfetch). Sales from 3P Partners made up 83% of the GTV, whereas 1P accounted for 17% of it (11% from Browns, 3% from NGG and 3% from SG). 1P is expected to keep growing reaching 29% of total GTV share by 2024, as well as 3P Brands, planned to represent 38% of the GTV by 2025, as can be seen in Figure 1.

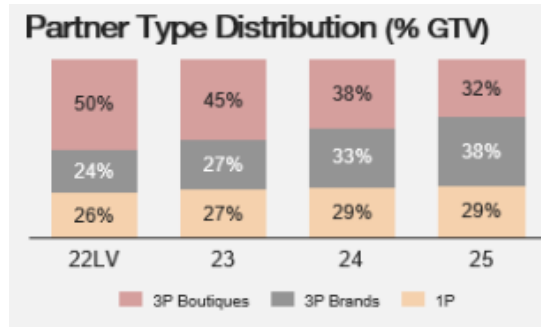


Figure 1 – Projected Partner Type Distribution (%GTV)

1.2 Operations Workflow

A scheme of the Operations workflow is in Appendix A. Overall, the product's lifecycle begins with the Partner, who creates the item on Farfetch Platform and sends it to Farfetch's Production centers for the Website content creation. The Creative Operations Team is then responsible for the content creation steps. After an order is placed by the customer and allocated to a Partner, formal steps of order processing take place, until the order is delivered by third party Logistics (3PL) Partners. In the post-order, customers may want to return the order, and they can contact the Service Support Team during the entire customer journey.

1.3 Operations Department

Farfetch has over 5,000 employees in 14 office locations. The Operations Department manages all the interactions between the platform and the customer, including digital content, processing orders and supporting customers throughout the shopping journey.

The organizational structure of the Operations Department is presented in Figure 2.

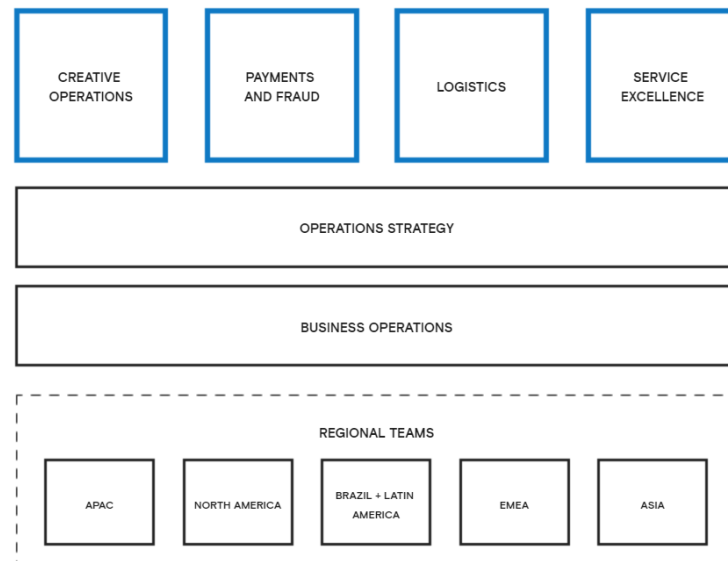


Figure 2 – Operations Department Organizational Structure (*Farfetch Digital Learning, 2022*)

It is split into 4 functional areas to reflect the process workflow at Farfetch: Creative Operations, Payments and Fraud, Logistics and Service Excellence.

There are two cross-functional support areas that are responsible to help all the areas above in different subjects: Operations Strategy, supporting the alignment between long-term strategy, short-term planning and performance management; and Business Operations, helping in finding answers to innovation, transformation or strategic challenges with an independent perspective.

To make sure these services are delivered consistently across the globe, there are regional teams that provide more localized support to the specific needs of each business.

1.4 Department of Marketplace Service Delivery Management

Within the Operations Strategy cross-functional department, the Marketplace Service Delivery Management Team is responsible for managing Farfetch.com towards the achievement of strategic goals. It is a recent team that acts as gatekeeper of Marketplace decisions by planning, guiding and challenging Operations Teams. The project described in this paper was born and developed in the Marketplace Service Delivery Department.

1.5 Project Scope and Goals

The task of finding and maintaining the optimal assortment of products to sell in stores has always been at the core of a retailer's commercial activity. At Amazon, for instance, a lot of this work is taking place, being recognized as important for "a variety of reasons that extend beyond revenue maximization", like long-term customer value (Amazon Science, 2021).

Farfetch is not an exception to the rule. In the past years, it went through exponential growth and that meant it was all hands on deck to make sure it had the items to deliver the ambitious sales targets. Aiming for an attractive assortment, Farfetch offered 355,000 different stock-keeping units (SKUs) from boutiques and brands already in 2018 (Cheng, 2018). Over time, however, profitability has become a strategic priority at par with growth, being one of the main objectives for 2022 to remain profitable and to leverage Marketplace margins. In that

context, several initiatives have been rolled out over time, including this project of Assortment Optimization.

There is the need for a more critical way of thinking about how the catalogue is made available at a local level, considering not just the demand profile of each market but the cost of opportunity of selling (profitability-wise) to market A vs market B. Given the low inventory levels that characterize the Luxury market (where most SKUs have around 5 units), making the best allocation of the stock becomes even more imperative.

The goal of the project is therefore to develop a smart supply model that optimizes where the assortment is sold, to replace the current “everything-selling-everywhere” strategy at Farfetch. This way, the Company is expected to benefit from the most profitable markets where there is demand and to ultimately enjoy bottom-line growth.

The decision should, at each time, attend to other complexities, as the Company’s strategic needs: sales targets to comply with, a catalogue integrity to make sure traffic keeps coming or the appetite for risk, which can vary.

In all, responding to the need for a revised catalogue management strategy at the local level, this project aims at:

- Building the conceptual basis for a decision framework on catalogue management;
- Identifying the specific business rules that need to be considered and their impact; and
- Estimating the economic impact and major benefit drivers at a market level.

The delivery is a decision model structure and business case, materialized by a proof of the concept.

This project falls within the scope of the Marketplace, *i.e.*, Farfetch.com. In a first phase of development, the selective assortment strategy is oriented to 1P, due to the higher control over the stock compared to 3P, and consequent more space for experimentation. And in specific to Browns, as it has a higher stock diversity relative to other 1P Partners, and therefore better replicates the Marketplace Catalogue. It is also the most representative 1P Partner: from the 17% of the GTV coming from 1P, Browns accounted for approximately 70% in 2021.

1.6 Methodology

The project followed the methodology schematized in Figure 3.

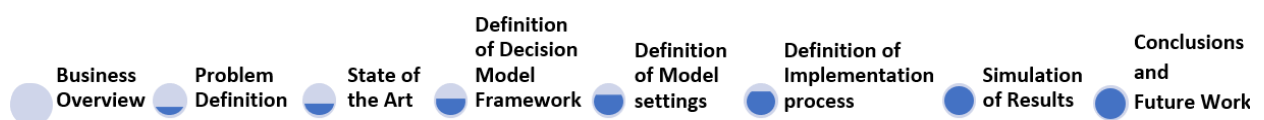


Figure 3 – Project Methodology

It included the main phases:

- Business overview: better understanding of the business and collection of relevant datapoints for further consideration;
- Problem definition: better understanding of the need and brainstorming of ideas – the issue tree built to start approaching the problem is presented in Appendix B;
- State of the art: characterizing the fashion marketplace, researching the benefits from assortment strategies, and gathering inspiration from how it is addressed in the academic literature and industry;

- Conceptual model development:
 - Definition of the decision model framework: how to select items and regions to actively manage as well as other complexities to consider;
 - Definition of the model settings;
 - Definition of the implementation process: guidelines and definition of needed capabilities;
- Simulation of results with historical data;
- Conclusions and future work.

1.7 Dissertation's Structure

The content of the present dissertation is divided into 6 chapters.

Chapter 2 presents a Literature Review of relevant topics used in the project development, mainly related to Assortment Optimization.

Chapter 3 sets the context and provides the complementary information from inside the company that is needed for the development of the project at Farfetch.

Chapter 4 lays out the proposed decision model, focusing on its general framework, settings, and implementation process.

Chapter 5 presents a simulation of results based on historical data.

Lastly, Chapter 6 sums up the key takeaways and lists future work.

2 State of the Art

2.1 Fashion Marketplace

Čiarnienė and Vienažindienė (2014) identify the main characteristics of the modern fashion industry, with a peculiar nature that can be characterized in terms of its volatility, variety, complexity and dynamism. Fashion is defined as the styles of clothing and accessories worn at any given time by groups of people, thus reflecting the changes in aesthetic, economic, political, cultural, and social life, translated by designers into fashion commodities. The fashion system shall encompass both the intrinsic change to fashion, which involves variation for the sake of novelty, as well as external factors like changes in lifestyle or individual trendsetters, who also play a role. As a result, fashion trends combined with the seasonal nature of the industry often mean styles with a short lifecycle, only produced for a few weeks per year. Concerning variety, fashion manufacturers typically produce a mix of style-based and non-style-based products, where the color and size combination within a style tends to create a vast number of end-products. In parallel, as the modern consumer becomes increasingly more demanding and global, the fashion industry thrives by being diverse and flexible enough to gratify any consumer's desire for fashionability.

Regarding e-tailers, Martinez-de-Albeniz et al. (2020) describe Marketplace platforms as Amazon or Farfetch as a convenient meeting point between customers and suppliers that have become an important element of e-commerce. They are considered a particularly interesting sales channel for suppliers that sell seasonal goods under a tight time frame, because of the expanded reach to potential customers that they provide; which exacerbates the seasonal and perishable nature of the inventory. Being these Marketplaces networks between customers and suppliers, the offer of products within the platform - the Catalogue or Assortment – results from Partners' action. It is a critical source of competitive advantage in the highly demanding Luxury Fashion sector.

2.2 Assortment Optimization

2.2.1 Assortment Strategies

Assortment strategies refer to the plans that retailers (both in-store and e-commerce) use to determine the optimal product mix for their daily inventory (CFI, 2022). They are important since customers directly interact with the product mix on display and make purchase decisions based on what they see. Assortment strategies involve the decision on three elements: product width or breadth (how many different categories the retailer carries), product depth (how many SKUs the retailer carries in each category), and how much inventory the retailer stocks of each SKU. Quoting Gürhan Kök et al. (2008), “the breadth vs. depth tradeoff is a fundamental strategic choice faced by all retailers”: some, like department stores, will elect to carry a large number of different categories, following a wide assortment strategy; others,

such as “category killers” like Toys ‘R Us, will specialize in a smaller number of categories but have great depth in each category, thus opting for a deep assortment strategy. A mass-market assortment strategy, in turn, aims to appeal to the mass-market and offer as many products and varieties as possible, catering to a much bigger customer base (used by stores with large physical storage capabilities, such as Walmart and Amazon). Finally, assortment strategies can be localized, and in that case the product mix is tailored to the preferences of the local population and the characteristics of the geographical region, allowing the retailer to cater to different demands and ultimately increase sales.

2.2.2 Selective Assortment Strategy

Roots and Benefits

The task of finding and maintaining the optimal assortment of products to sell in stores has always been at the core of a retailer’s commercial activity (McKinsey & Company, 2019), given that a right assortment leads to “more sales, higher gross margins, leaner operations, and most importantly, more loyal customers”. Several factors put increasing pressure on retailers to get assortment right, like an ever-growing number of SKUs to choose from, limited shelf space, heterogeneous store characteristics and supply chain complexity. Responding to that need, assortment optimization specifies the product mix that maximizes sales or gross margin subject to various constraints, such as a limited budget for purchase of products, limited shelf space for displaying products, and a variety of miscellaneous constraints such as a desire to have at least two vendors for each type of product (Feldman & Topaloglu, 2017).

Across the industry, many retailers are adopting an efficient assortment strategy, which primarily seeks to find the profit maximizing level of variety by eliminating low-selling products, as well as implementing category management, that attempts to maximize profits within a category (Gürhan Kök et al., 2008).

The work of McKinsey & Company (2019) with leading international retail players proved that significant improvement in financial performance and customer experience is possible through assortment optimization.

By knowing the cost to serve each product (SKU end-to-end cost) and its economic performance (financial contribution such as sales), steering customers toward higher-margin products can contribute up to 0.5 of a percentage point in gross margins.

Customer experience can also be enhanced by a selective assortment, more tailored to customer needs. In a context where many retailers have increased product selection in all merchandise categories disproportionately to the shelf space – on average, the number of products in the marketplace increased by 16 % per year between 1985 and 1992 while shelf space expanded only by 1.5 % per year during the same period (Quelch & Kenny, 1994) –, for reasons as heterogeneous customer preferences, variety-seeking consumers and competition between brands, questions have been raised as to whether the rapid growth in variety is excessive (Feldman & Topaloglu, 2017). In addition to management and supply chain complexity, offering too much variety can have the unintended effect of frustrating customers, as the decision becomes harder (CFI, 2022). Even in the e-commerce setting, where there is presumably infinite shelf space, there is the “agony of choice of the endless virtual shelves” (McKinsey & Company, 2019), and therefore it is paramount that retailers manage their assortments in a way that holds customers’ attention. In addition, there is empirical evidence that variety levels have become so excessive that reducing variety does not decrease sales ((Drèze et al., 1994), (Botti et al., 2008), (Boatwright & Nunes, 2001)).

Localization in a Selective Assortment Strategy

As introduced previously, an assortment strategy can integrate location-specific dynamics, thus being defined as a localized assortment strategy: the rationale behind an optimization of the assortment to the specifics of each store location is to cope with local specificities, from heterogeneous store characteristics (as size and format) to different demand patterns or distinct supply chain costs structures (McKinsey & Company, 2019). Vishwanath (2006) advocates that “when it comes to consumer markets, one size no longer fits all” and introduces that smart retailers and consumer goods companies are aware of this and are starting to customize their offerings to local markets.

A question that might be raised by this localized strategy is the optimal level of customization to embrace, *i.e.*, how to strike the balance between a “one size fits all” and “each store is its own” philosophies, which can be a significant source of competitive advantage (Gürhan Kök et al., 2008). To manage this, Vishwanath (2006) suggests an approach of clusters of locations to which assortments are tailored, rather than to individual stores. The approach has been applied in companies like American Eagle, having been first implemented in 1995 by Bain in a grocery store and proven effective in a variety of retailers and consumer goods manufacturers. The rationale behind clustering is to “sort things into groups, or clusters, so that the associations are strong between members of the same cluster and weak between members of different clusters”. The results are manageable, modular operations that capture most of the benefits of customization while also simplifying decisions and protecting economies of scale (keeping most of the efficiencies of standardization).

2.2.3 Assortment Optimization across the Academia and the Industry

There is a multitude of papers in the academic research addressing the topic of assortment optimization. Across the industry, similarly, assortment planning has received high priority from retailers, consultants and software providers, as its impact on sales and gross margin is recognized (Feldman & Topaloglu, 2017).

Academic Research

The academic approach to the assortment planning problem consists of the formulation of an optimization problem to choose the optimal set of products to be carried and the inventory level of each product (Gürhan Kök et al., 2008). For instance, Bebitoğlu et al. (2008) cover multi-location assortment optimization under capacity constraints for an online retailer, where “the problem for the retailer is to determine which products to carry in each of its distribution centers and which products to offer for sale in each region so as to maximize its expected profit (revenue minus the shipping costs)”. Similarly, the work of Gürhan Kök et al. (2007) is about selecting the set of products to be carried in each of the retailer’s stores and setting inventory levels for each product.

In the academic problem-solving process, three demand models are mainly used to model consumer choice: the Multinomial Logit (MNL), Exogenous Demand and Locational Choice models. Besides those state-of-the-art models, also non-parametric choice models have been explored.

A fundamental assumption for many assortment planning models is that of consumer driven substitution, presented with empirical evidence by Gürhan Kök et al. (2008). It considers the substitutability effect between products, that makes decisions for each product in the assortment interdependent and therefore should be modeled: for instance, when customers are willing to substitute within a particular category, then “providing great depth and a high in-stock rate is less critical”, and vice versa. In their work, Fisher & Vaidyanathan (2014) model

each SKU as a set of attributes and apply maximum likelihood estimation to sales history, thereby including possible substitutions when a customer's first choice is not in the assortment, and estimating the demand for any potential SKU (even without past sales).

Regarding the main demand models, according to Gürhan Kök et al. (2008), the Multinomial Logit model is a discrete consumer choice model that assumes that consumers are rational utility maximizers and derives customer choice behavior from first principles. The customer choice behavior in the MNL can be estimated with: panel data (an enormous number of marketing papers estimated the parameters of the MNL model to understand the impact of marketing mix variables on demand); sales transaction data (*i.e.*, the records of the purchasing time and the product choice for each customer who made a purchase); or sales summary data (including the number of customers visiting each store on a given day, sales for each product-store-day, as well as variables that influence demand such as weather, holidays, and marketing variables like price and promotion).

The Exogenous Demand model directly specifies the demand for each product and what an individual does when the demanded product is not available.

The Locational Choice model is also a utility-based model that incorporates differentiation by stores, or “horizontal differentiation”, and where consumer preferences are distributed according to the choice model. For example, Fisher & Vaidyanathan (2014) model the assortment localization problem of choosing assortments that can vary by store, subject to a maximum number of different assortments. When applied to real examples, the recommendations for tires and appearance chemicals produced sales increases of 5.8 % and 3.6 % respectively (significant improvements for the industry). In the same line, Bernstein et al. (2015) present a novel model in a setting with multiple heterogeneous customer segments and show that rationing products to some customer segments may be optimal: based on a real data set from a large fashion retailer, the revenue impact of assortment customization is proved significant.

Alternatively, Non-Parametric Choice models have been used to model consumer choice. Farias et al. (2013), for instance, developed a non-parametric approach to learn the right choice model, using limited data on customer purchase decisions, that when applied to a real data set led to a 20% improvement in prediction accuracy over the mainstream models. They also concluded on the importance of a proper choice model identification in achieving optimal revenues.

The assortment models can have further variations: there are dynamic and competitive assortment models.

Dynamic assortment models consider the situation in which the retailer updates its assortment throughout the season as it updates its demand estimates every period for products in the assortment (Gürhan Kök et al., 2008). For instance, Rusmevichientong et al. (2010) derive structural insights on the optimal assortment for the static case and utilize it to develop an adaptive policy for the dynamic problem, where the algorithm learns demand parameters from past data and chooses the optimal assortment based on that. They find that their algorithm performs well on being applied to sales data from an online retailer.

Finally, competitive assortment models present a duopoly model in which retailers choose prices and variety level in each category and consumers make their store choice between retail stores and a no-purchase alternative based on their utilities from each category (Gürhan Kök et al., 2008).

Industry Approach

Even though the topic of Assortment Optimization is a focus area for both the academia and the industry, there seems to be a huge disconnect between the two groups: their language or

terminology is substantially different and neither group acknowledges the existence of the other. In addition, by 2009 most of the existing theoretical models had not been implemented as part of industry applications (or the predictions empirically tested). Concerning the approach followed, academics “use a more operational and detail-oriented approach”, whereas “industry has taken a more strategic and holistic approach” (Gürhan Kök et al., 2008).

In fact, McKinsey & Company (2019) mentions that for most retailers the process of assortment planning starts at the strategic level. The breadth of product categories and the depth of products offered in each of them is a function of the retailer’s position in the competitive landscape. For example, the retailer might have the strategic objective “to gain a higher share of organic, gluten-free, or regional products”, or to “increase the number of SKUs that are appealing to strategically important customer segments such as millennials, wealthy, or middle-class consumers”.

This way, McKinsey & Company (2019) argues that the decision of whether an SKU is listed or delisted should not be based on financial measures alone, such as total sales or rotation numbers, which only provides a superficial view of the assortment performance. Instead, a multidimensional analysis of the SKU-performance should take place, assessing its economic performance, cost to serve, uniqueness and contribution to strategic objectives. The first three dimensions are already covered by the academic research; the last one, although acknowledged, has had little research focused on incorporating these strategic considerations while optimizing the assortment (Cachon et al., 2005).

To measure the relevance of an SKU to the objectives of the Company, strategic KPIs can be introduced at the SKU level. As a result, the assortment recommended will not necessarily be the most profitable one but will answer at the same time to strategic necessities: “for example, a retailer like Best Buy would carry a rarely demanded product such as a 10 mega-pixel camera, just to maintain consumer perception of Best Buy as offering the latest technologies” (Gürhan Kök et al., 2008).

To capture the uniqueness of an item - equivalent to the academic notion of substitution -, McKinsey & Company (2019) proposes McKinsey’s walk rate metric, that predicts the share of product sales that would transfer to other products in the category when the product is delisted and the share that would “walk away” and be lost sales for the retailer.

The Assortment Optimization Cycle

The continuous/dynamic assortment optimization process is also addressed by the industry. Several factors as the change of seasons, the introduction of new products (Gürhan Kök et al., 2008), evolving customer behavior, as well as the financial, operational, and strategic elements of the fundamental assortment decisions (McKinsey & Company, 2019) make the assortment optimization process endless. Therefore, mastering assortment optimization requires a comprehensive and systematic approach that accounts for these evolving dimensions, in a “continuous and automatic assessment of the listing, de-listing, and optimal allocation of SKUs”. The evolving consumer tastes should, for instance, be captured and incorporated into future predictions, as done by Zara and other high-fashion companies that have employed a learning method of the attributes of the high-selling products (Gürhan Kök et al., 2008): that is, “if a certain color is hot this season, and products with a special fabric are selling relatively well, the prior distribution of the demand for a product with that fabric-color combination can be updated, even if the product was never included in the assortment before”.

Implementation

For the implementation of assortment optimization, IDC Retail Insights (2015) suggests to:

1. Look at the assortment planning assets as the hub of merchandising strategies and tactics that drive revenue, margin, working capital efficiency, and customer value;
2. Evaluate how well or not these assets contribute to financial, operating, and customer satisfaction goals today;
3. Play out what it will take to meet these goals over the next two to five years, especially in terms of pace, scale, value, and risk of the assortment decisions that will be made; and
4. Map the gaps between as-is capabilities and near-term requirements, considering the innovations involved and types of benefits.

To sum up, it is essential to map the gaps between the “as-is” capabilities and the “to-be” scenario that will allow to optimize the supply according to Company needs.

Once those capabilities are in place, McKinsey & Company (2019) suggests a four-to twelve-week pilot to allow the retailer to quantify the value of its assortment lever based on a few select categories and generate actionable insights for immediate implementation. As an alternative to the few categories, the initial assortment developed can be tested across a sample of stores - like happens at many retailers -, to get an early read prior to the actual selling season. The test results are then used to understand trends on winners and losers and gaps in the portfolio so as to redesign the assortment (Gürhan Kök et al., 2008).

After the pilot, McKinsey & Company (2019) suggests a roll-out during three-to six months, where the insights gained are used for the configuration of the analytics tool, then typically applied to all product categories (or all stores), while identifying new assortment opportunities. As the product selection is considered by most retailers as “one among several levers (among promotions, pricing, etc.) that influence sales”, it is critical to integrate assortment planning decisions with the other commercial activities, *i.e.*, to make assortment decisions in conjunction with other key factors that influence sales (Gürhan Kök et al., 2008). To clarify, if for example an apparel retailer is advertising a certain line of clothing heavily, then the variety that needs to be offered is higher than what might have been required without the attention due to advertising. For such reason, this roll-out phase suggested by McKinsey & Company (2019) also includes aligning commercial processes with analytics.

Lastly, to make sure the impact is lasting, the institutionalization phase exists to make sure the analytics tools are tailored to the organization’s needs, through ongoing process checks. In parallel, with continuous analytical skill-building as an analytical foundation within the organization is needed to sustain this analytical process.

After these 3 phases, it is suggested that the Company is “fully equipped to take on the next iterations of the assortment optimization cycle and can begin reaping the benefits of higher margins, lower costs and higher customer satisfaction”.

Predicting Consumer Demand – State of Software Development

A foundational piece of an assortment planning tool is the demand forecast, that predicts customer behavior. The quality of the assortment decision is intimately linked to the forecasting performance, which in turn can be enhanced using powerful technologies as Big Data and advanced analytics (McKinsey & Company, 2019).

The IDC Retail Insights research demonstrates that organizations that introduce new analytics and metrics are much more likely than competitors that introduce one or neither of these

capabilities to achieve better results in the data-driven race to top performance (IDC Retail Insights, 2015). Recognizing the potentialities, more and more global multichannel fashions retailers are using AI and automation to create more targeted assortments (Gadiyar, 2022).

Regarding the assortment planning market landscape, an IDC Retail Insights research into innovations released in 2013, 2014, and 1Q15 from 12 leading assortment planning vendors concludes that a healthy mix of established and emerging vendors is taking advantage of broad emerging information technologies trends to innovate, as retailers need more capable assortment applications to manage complexities for profitable results and customer satisfaction (IDC Retail Insights, 2015). Buying, localization, pricing and promotion, space allocation and visual merchandising, replenishment and allocation decisions, and omni-channel tactics flow from their breadth decisions. Vendors are concentrating their innovations in two areas that account for 48% of innovations: advanced forecasting and analytics (32%) ranked first; and rules, methods, KPIs, and metrics (16%) ranked second - from a set of 10 innovation categories, which makes clear the role of those two dimensions within the model.

To get a more concrete idea of recent trends and innovations in the assortment planning software, Table 1 summarizes the developments from a sample of the 12 leading vendors. Citing IDC Retail Insights (2015), there is “plenty of evidence that strongly suggests the emergence of a “golden era” of commercially available assortment planning software”, where each of these developments can improve assortment planning systems and processes.

Table 1 - Recent Developments of Assortment Planning Vendors (IDC Retail Insights, 2015)

Assortment Planning Vendors	Developments
IBM	- Advanced forecasting and analytics to improve add/drop/keep decisions based on shopper behavior and demand transference analysis constrained by rules limiting the number of changes and protecting products specified by attributes and new products without sales history from deletion. - Optimization can be directed to any weighted combination of user goals of margin, sales, units, and so forth.
JDA	- Innovations in channel (store) and customer clustering to connect merchandise financial planning to width/depth decisions by customer attributes and segments. - Advances in automatic in-season reforecasting can now quickly catch initial sales trending off forecast and later diversions to respond faster.
Logility	- Forecasting and analytics have improved dynamic store clustering and store-level sales forecasts, with style/color/size attributes, to align assortment decisions to supply chain planning, including supplier sourcing as well. - Integration with Logility Voyager Solutions' advanced analytics platform provides advanced alerts, diagnostic analytics, and KPIs for reporting and analysis.
Oracle	- Scenario-based (what-if) assortment creation and swaps capability (to expand, contract, or

	refresh).
Periscope	- Structured analysis of customer shopping behavior and integration of online assortment information from various Web channels product intelligence data analytics.
Predictix	- Early adopter of machine learning-based forecasting for better insight into demand drivers, more granular forecasts, and new SKU Forecasts not based on imperfect model or like-item SKUs.

2.3 Link to the Work Developed

This Literature Review demonstrates that plenty of work has been done so far both academically and industry-wide related to the topic of Assortment Optimization. It keeps on-going, nonetheless, with many future potentialities as it is possible to verify by the state of the software development. This software is not currently available within Farfetch, as for an initial phase the value of the investment is not exactly clear, yet it could make sense in the future.

Generally, this research served as inspiration for the development of the selective assortment model, in terms of the considerations and techniques used: starting with the characterization of the sector, then going deeper into assortment optimization strategies - where benefits are proven -, and then in specific to selective strategies by location, that is the aim (and where clusters of regions will be used).

It should be said that, while typical assortment strategies take an integrated planning decision of which items to source, where to carry and sell them, the challenge in the present case is related just to where to make the existing inventory available – more downstream, closer to the customer. The buying is not covered as the products are uploaded by the Partners in Farfetch Marketplace (no Company control over it), and there is no intention to move stock as the risk would be higher: it would imply movement costs without guarantees of selling to the near regions, whereas by managing the online availability of products decisions can be reversed with no extra costs. As result, no resource restrictions are considered (like limited budget for the purchase of products or limited shelf or warehousing space). Nevertheless, the goal of optimizing supply attending to markets' dynamics and supply chain costs, to leverage profitability, is shared, as well as many other considerations that will be discussed along the next chapters; making it relevant to gather knowledge from that work.

The comparative analysis between the Academia and the Industry allowed us to better position ourselves, and to derive useful insights from each of them: for instance, the model to develop should be dynamic, in a continuous assortment cycle, and the competition dimension could be added in the future. The strategic considerations are considered top-priority and will be included. The model to be developed will not be as theoretical as in the academic case, but rather more practical and strategic, closer to the industry approach; and will list the rules, KPIs and metrics that should be embedded into the tool. The items uniqueness factor, for instance, will not be incorporated into the model due to lack of capacity at the moment, although its relevance is acknowledged. The notes and the links with the Literature will be made along the paper as necessary, and the future work chapter will list what remains to do. Finally, the state of development of the assortment planning tools allows the Company to better place itself in terms of capabilities and to understand its needs, while the implementation guidelines are enlightening for the future process.

3 Problem Description

3.1 The Need for a Revised Catalogue Management Strategy

As introduced in 1.5, there is an opportunity for Farfetch to rethink its way of managing the global catalogue. Having profitability as top priority, in an industry characterized by stock scarcity and with reasonable differences in the profitability of selling to the different markets, an active assortment management that decides where the inventory is made available is key, with a significant potential to grow margins, as explored in 2.2.2. A blatant case that would benefit from this model are certain sneakers from brands like Nike or Yeezy (highly demanded) or drops (limited edition items with low units).

The main goal of this localized assortment optimization model is therefore to make a selective supply allocation that maximizes the profitability delivered by the products. The decision should at the same time encompass strategic considerations as the catalogue integrity, sales targets, appetite for risk at each given moment, as well as other relevant elements to be discussed further.

It should be noted that, at Farfetch, the common assortment strategy (of “everything-selling-everywhere”) is generally the practice, having as exception the blocking rules system. A blocking rule is a restriction that prevents an item, or set of items, from going online for a certain tenant (sales channel), store and delivery country to fulfil business needs from across the organization: from legal constraints to carrier restrictions, brand specific requests, partner requests to, finally, content motives; a legal constraint might have to do with restricted materials/types of items, for instance. These rules, however, exist in very specific cases and are by no means oriented towards a strategic catalogue management.

As starting point, a mathematical formulation of the problem is presented for better comprehension in Appendix C.

In the next subchapters, relevant business information to be considered in the proposed model is presented.

3.2 P&L Structure and Profitability Drivers

As the catalogue management model to be developed is profitability-oriented, it is important to understand the P&L structure, as well as the main drivers of profitability of an order, within Browns (scope of the project).

Firstly, it is important to distinguish between the two types of prices at which a product can be sold: Local Market Price and Geoprice. A Local Market Price can be defined by Partners for their domestic market, that is the price charged in their local offline stores. A Geoprice, in turn, is a price that Brands set by market for their products, *i.e.*, the Website price, in order to have full control over the selling prices.

The way Local Market Price is built is shown in Figure 4.

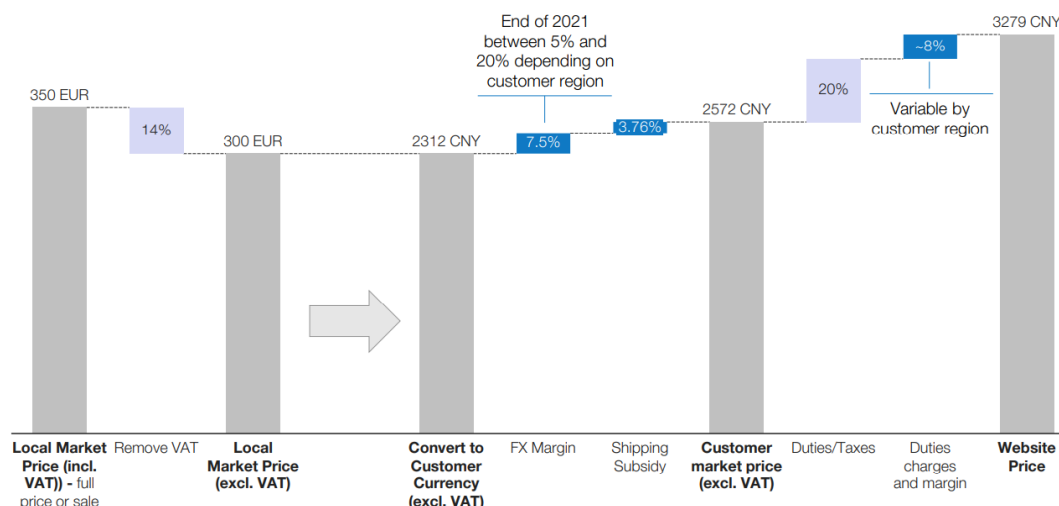


Figure 4 – Build-up of the Website Price for Local Market Price Products

To the Local Market Price (without VAT), the FX Margin (for cross-currency sales), Shipping Subsidy and Customer country Duties/Taxes are added to make up the Website price. The definition of these components can be looked up in Table 2, in the next page.

The Geoprice build-up is shown in Figure 5.

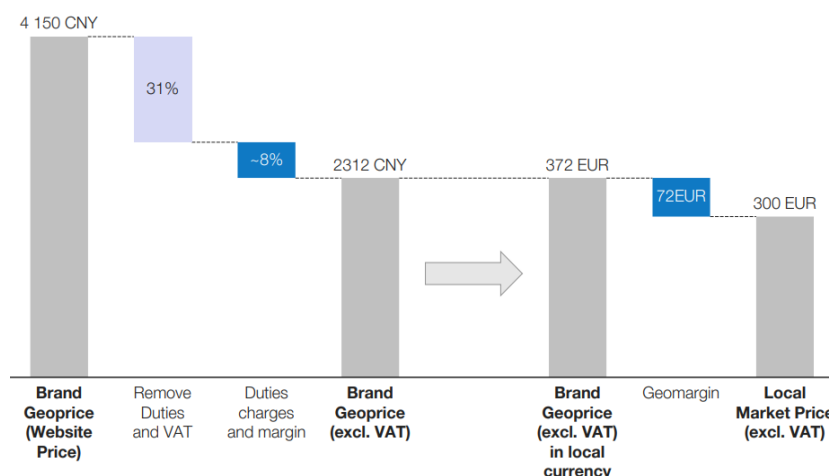


Figure 5 - Build-up of the Website Price for Geoprice Products

For these products, one works backwards from the Geoprice to determine the margin to Farfetch: it is the result of Duties/Taxes and Geomargin (again, the definition of the components is in Table 2).

In both cases, a shipping fee adds to the Website price (CShip) at the end - that is visible to the customer - thus making up the final price.

The P&L structure for Local Market Price items is presented in Figure 6 and for Geoprice items in Figure 7 (a definition of each P&L field is presented in Table 2).

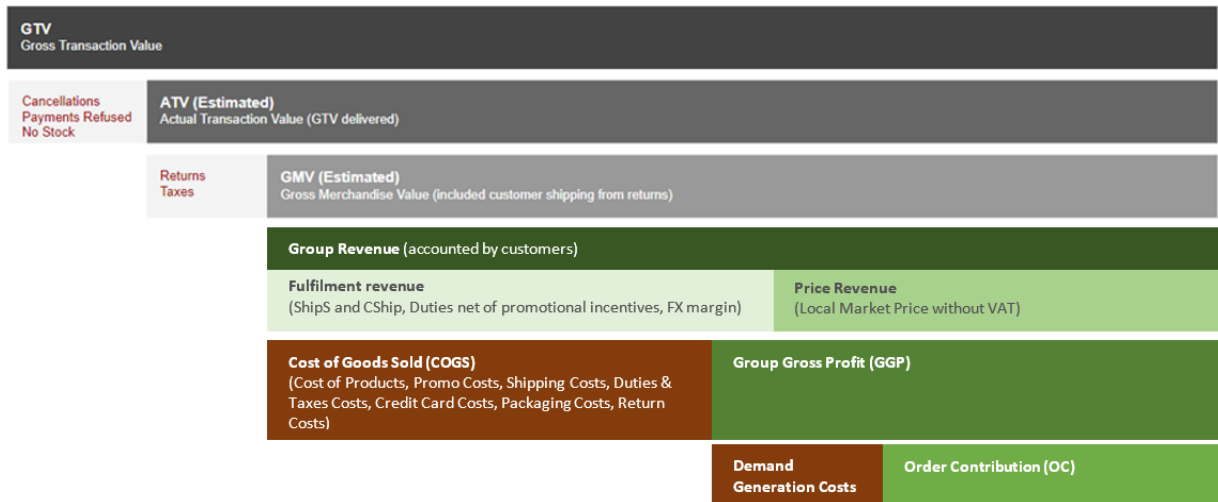


Figure 6 – P&L Structure for Local Market Price Items

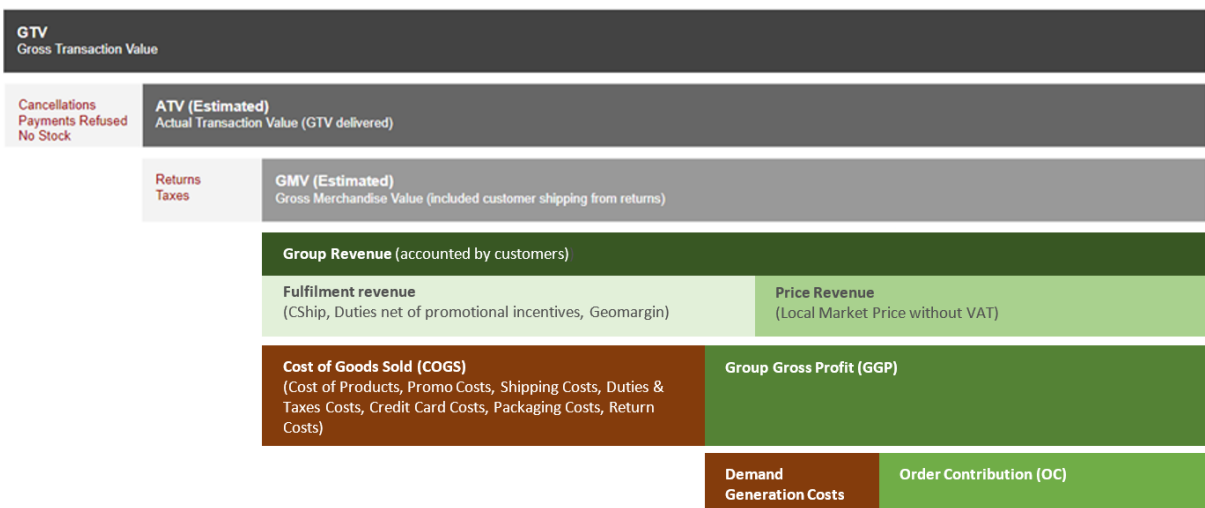


Figure 7 – P&L Structure for Geoprice Items

Table 2 - Description and Impacting Factors of P&L Fields

Field	Definition	Impacting Factors
Gross Transaction Value (GTV)	Gross Item value paid by the Customer	-
- Cancellations	Gross Item value paid by the Customer that is cancelled (by the customer)	-
- Payments Refused	Gross Item value paid by the Customer that is cancelled due to Payment Refused	-
- No Stock	Gross Item value paid by the Customer that is cancelled due to a No-Stock	-
Actual Transaction Value (ATV) (Estimated)¹	GTV net of Cancellations, Payments Refused and No-Stocks	-

¹ Some fields show up as “Estimated” as they are P&L components with predictions (real values still unknown) for orders placed in the last 35 days - L35 days Logic

- Returns	ATV that is returned, excluding Customer Shipping from returns	-
- Taxes	Sales Tax	-
Gross Merchandise Value (GMV) (Estimated)¹ = Group Revenue <i>Comprised by:</i>	ATV net of Returns and Taxes	-
Shipping Subsidy (ShipS) ²	It aims to finance free shipping campaigns as part of sales incentives to final Customers (not visible to the Customer)	Depends on the route and on the AOV; it is applicable if the product is Non Geoprice (Brand decision)
Customer Shipping (CShip)	Value of shipping paid on top of the price by the Customer	Depends on the delivery service chosen by the Customer and on the Customer country (some countries have permanent free shipping)
Duties	Value on the top of the price to finance Duties/Taxes costs	Depend on the Customer country and route (there can be FTAs), on the item and on the AOV
FX margin ²	Extra margin when an exchange rate is applied	Depends on the route and on the AOV; it is applicable if the product is Non Geoprice (Brand decision)
Geomargin ³	The amount of the Pricing difference captured by Farfetch, based on the contract conditions	Depends on the Customer region; it is applicable if the product is Geoprice (Brand decision)
Price Revenue	Local Market price without VAT	Depends on the Customer country
- Cost of Goods Sold (COGS) <i>Comprised by:</i>	Cost of Goods Sold accounted by Farfetch	-
Cost of Products	Browns cost of products	-
Promotion Costs	The discount amount participated by Farfetch	Depend on the Customer country, customer tier and on the AOV
Shipping Costs	Cost of shipping the product (delivery)	Depend on the route (different distances and carriers), on the product characteristics (size and weight) and on the delivery service chosen by the Customer
Duties & Taxes Costs	The consumption tax collected on certain goods entering in some countries	Depend on the Customer country and route (there can be FTAs), on the item and on the AOV
Credit Card Costs	Farfetch Credit Card Payment costs	Depend on the Customer country (Payment Services available) and on the AOV
Packaging Costs	Farfetch Packaging costs	Depend on the product characteristics
Returns Costs	Farfetch costs to ensure the return	Depend on the route, on the product characteristics and on the delivery

² Local Market Price exclusive P&L line³ Geoprice exclusive P&L line

		service chosen by the Customer. Different customer countries have different return rates
Group Gross Profit (GGP)	Group Revenue net of COGS	-
- Demand Generation Costs	Costs of generating demands, as Marketing campaigns, cookies, Google adds, etc.	Depend on the Customer country (type and effectiveness of campaigns, adds, etc.)
Order Contribution (OC)	GGP net of Demand Generation Costs	-

Although similar, the two P&L structures differ in the Fulfilment revenue: the ShipS and FX margin are exclusive to Local Market Prices, whereas the Geomargin is exclusive to Geoprices.

Company-wide, the most used sales metric is the GTV. Concerning profitability, the favored metric is GGP divided by GMV, referred to as GGP%GMV (GGP as percentage of GMV). Although Order Contribution is the ultimate profitability metric (GGP net of Demand Generation Costs), the Demand Generation Costs make the OC value dependent on the type and effectiveness of Marketing campaigns, as those costs are assigned to each order depending on the total volume of orders. Hence, GGP is preferred as it is more representative of what can be logistically controlled. To sum up, for profitability assessment GGP and GGP%GMV will be considered, while for topline GTV is chosen.

Concerning the P&L drivers, it is possible to understand from Table 2 (under the “Impacting Factors” column) that many factors affect the profitability of an order. Overall, they can be:

- Product-related: like the AOV, product type and dimensions, price type;
- Customer country-related: associated with Local Market Prices, Duties and Taxes systems, Delivery and Payment services available, charge of Customer Shipping, Promotions, different Return rates; and
- Route-related: as cross-currencies, Shipping carriers available and distances involved (fuel spend).

In fact, certain product categories at Farfetch (*e.g.*, homeware) have a high share of unprofitable items, and while no route is purely unprofitable, certain routes can exacerbate overall losses.

3.3 Stock, Sales and Profitability Analysis

An analysis to the stock and sales, then to profitability, was performed to better understand operations within Farfetch and to gather business considerations for the proposed model. The analysis was conducted for Browns in the Marketplace in 2021 (including sometimes the last months of 2020 to better capture the trends).

Stock and Sales Analysis

The analysis to the stock and sales is first presented, concerning: their evolution along the season, the relation between stock and sales, and their distribution by Season Type and Price Type; as well as two complementary analyses (the GTV distribution by GBFCs, Brands and Countries, and the sales pattern variation).

During the entire period, there is an approximately constant percentage of stock that is offline (from 25 to 30%). This analysis concerns the online stock, available to the customer, that will be managed by the model.

Seasons (AW and SS) Analysis

To further define the model timeframe, it is important to learn the seasons calendar at Farfetch, and how stock and sales levels vary with it.

The seasons calendar planned by the Commercial Team for 2020 and 2021 is presented in Figure 8.

Year Month	2020												2021											
	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12
SS20 Full Price																								
SS20 Markdown																								
AW20 Full Price																								
AW20 Markdown																								
SS21 Full Price																								
SS21 Markdown																								
AW21 Full Price																								
AW21 Markdown																								

Figure 8 – Farfetch’s Commercial Seasons Calendar

Each season is defined as lasting 9 months, where items start by being sold at full-price (for 6 months) and then enter in discount, or markdown (last 3 months). There are promotional moments along the season, which might be either global or regional.

The Commercial calendar is a projection of the yearly calendar: as the stock is created in the platform by Partners, the actual beginning of the season is when Partners begin the upload of season original products, or change the season name of “old” items from past seasons to the new season (for carryovers).

The graph in Figure 9 represents the stock evolution, together with the units sold, in 2021 for AW and SS items.

Evolution of units online and units sold: AW vs SS

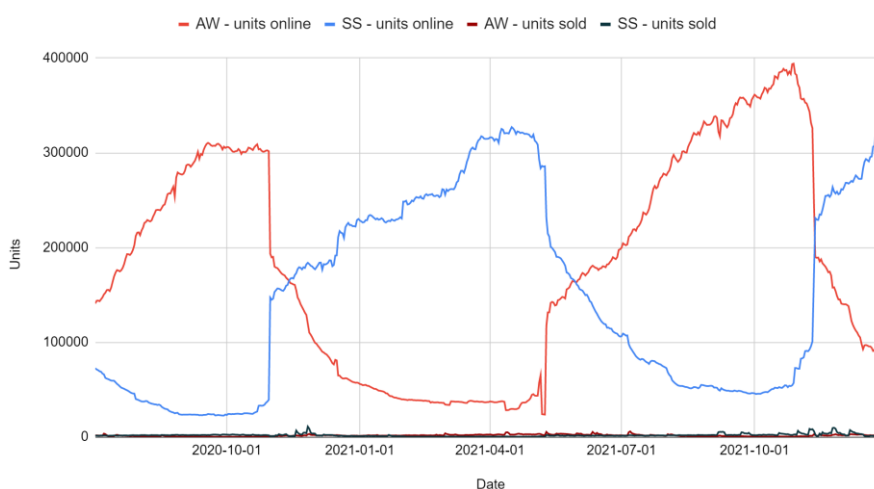


Figure 9 – 2021 Stock Evolution for AW and SS Items (from AW20, SS21, AW21 and SS22)

It is possible to see that SS stock goes up by November (a month after the projected beginning of the season), therefore in practice the SS season starts in November. Similarly, AW stock increases by May - so the AW season starts in May and not April. It is also noticeable that the

moment when SS stock level goes up corresponds to the moment when AW stock starts to decrease, and vice-versa: this coincidence has to do with “old” items being reclassified into the new season.

The same analysis, but now concerning sales, is presented in Figure 10.

Evolution of units sold: AW vs SS

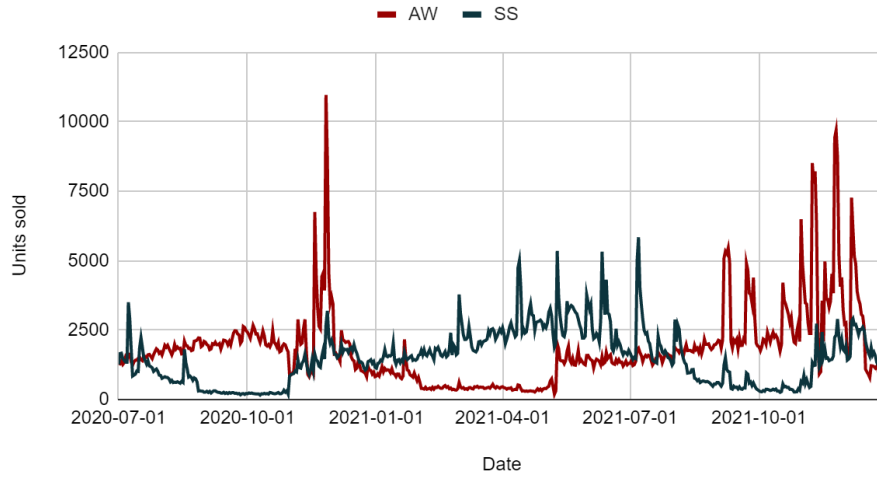


Figure 10 – 2021 Sales Evolution for AW and SS Items (from AW20, SS21, AW21 and SS22)

It is visible that, similarly to stock, SS units sold increase from November until July, then the trend becomes descending until, by the end of September, sales are residual. AW units sold increase from May (again following the stock pattern) until December, then go down to lower values.

This analysis shows the moment from which the model, for each season, should be run: after the stock levels go up (in the case of 2021, May and November).

Finally, while from the Commercial standpoint each season has the duration of 9 months after which the goal is to promote the products of the next season, from the Stock Management perspective each season lasts 3 more months (so, 12 months), as in that final period past stock and sales still exist although in low values. The model could be run until the last “commercial” month, then be lifted to allow for the outlet of the remaining stock.

Relation between Stock and Sales

To compare the offer to the demand, as a premise of the model is to manage items that are scarce, one can assess the relation between stock levels and units sold. Figure 9 shows that daily total stock levels are huge compared to the daily units sold; however, this happens as stock is uploaded to cover the whole season. It is relevant to measure stock rotation along the season, for which an analysis to the sell-through (calculated as in equation 3.1) during SS21 is presented in Figure 11.

$$\text{Sell - Through (STh)} = \frac{\text{Period Sales}}{S_e + \text{Period Sales}} \quad (3.1)$$

where: S_e – stock at the end of the period.

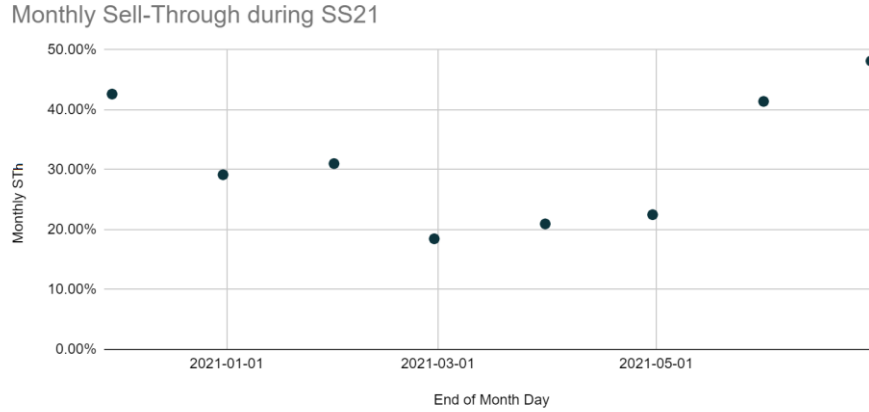


Figure 11 – Monthly Sell-Through in SS21

Figure 11 shows that the monthly sell-through decreases along the season - as inbounds lift stock levels - and then goes up as the stock is consumed. By the end of SS21, 86% of the stock has been sold (close to Farfetch's target of 90%). This value is also high compared to the industry-wide standard for a good sell-through rate (80%) and to the Apparel industry average rate: between 46% and 69%, for the 9 months that make up a season (Decker, 2021).

Figure 12 exhibits the distribution of GBFCs and GTV by tiers of sell-through rates by the end of SS21, where items with a sell-through over 80% represent 83% of the GTV: a very high value of stock rotation.

Percentage of GBFCs and GTV by Sell-Through Tier by the end of SS21

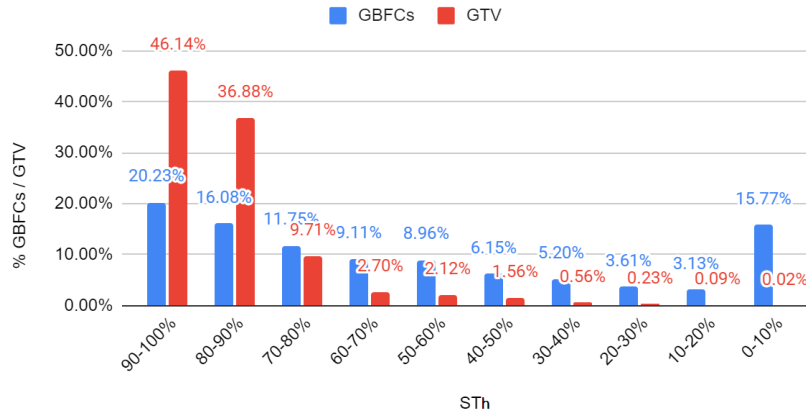


Figure 12 – Distribution of GBFCs and GTV by Sell-Through Tiers by the end of SS21

Figure 13 shows that, whereas the average daily units in stock for a product ID are around 17 times higher than the average daily units sold, at the SKU level this ratio is approximately 6. The average units carried at the SKU level are in fact quite low, further confirming the premise of scarcity.

Avg. units online and sold by ID and SKU

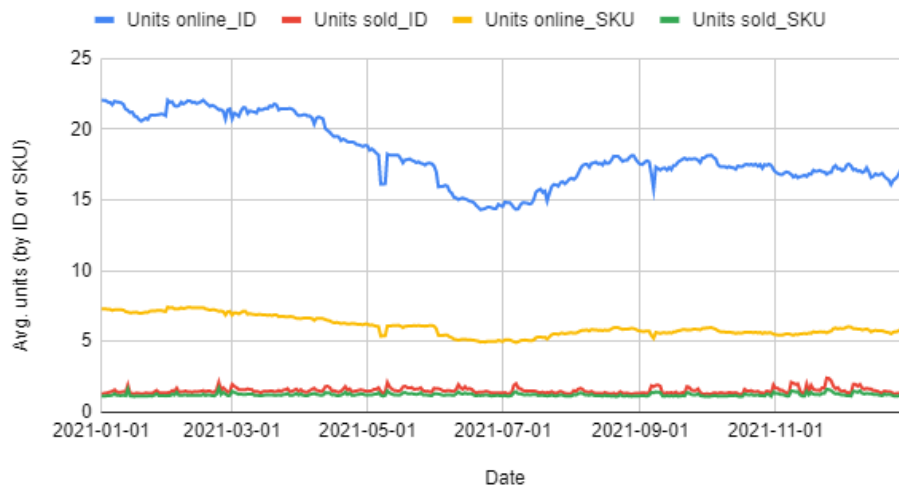


Figure 13 – Average Units Online vs Units Sold by ID and SKU over 2021

An analysis of the stock and sales by Season Type and Price Type is presented next, to comprehend the patterns of each type of items, and to know how to better approach them by the model.

Season Type Analysis

Figure 14 presents the stock evolution in 2021 by Season Type.

Evolution of online stock by ST

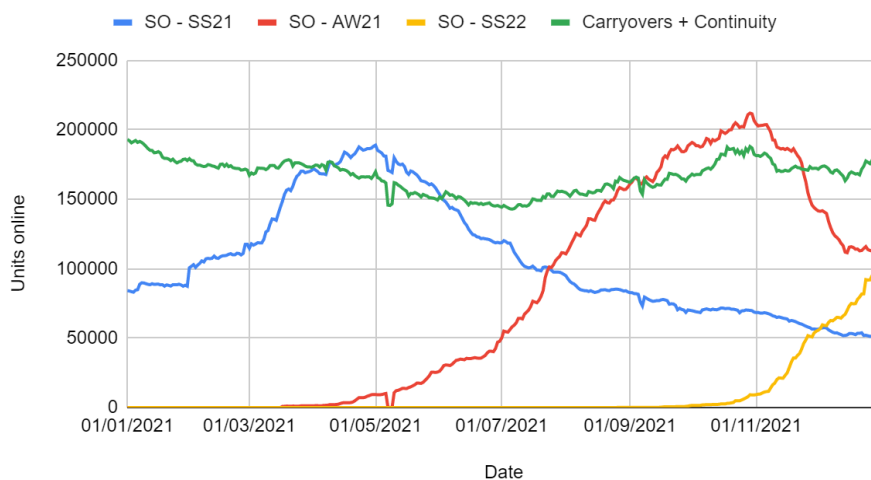


Figure 14 – 2021 Stock Evolution by Season Type over 2021

There are Season Original items from past seasons that are carried into 2021 (Carryovers and Continuity items), showing stable stock levels. Season Original items from the year (SS21, AW21, SS22) grow along the year as they are uploaded, and then go to lower stock levels as they are sold. This suggests that the model could be run right from the beginning of the season for continuity items and carryovers, that should have past sales data (from at least the past 9 months of the previous season), necessary to predict demand; contrary to novel items.

Figure 15 represents the evolution of the share of units sold by Season Type for SS21.

SS21 Percentage of units sold by ST

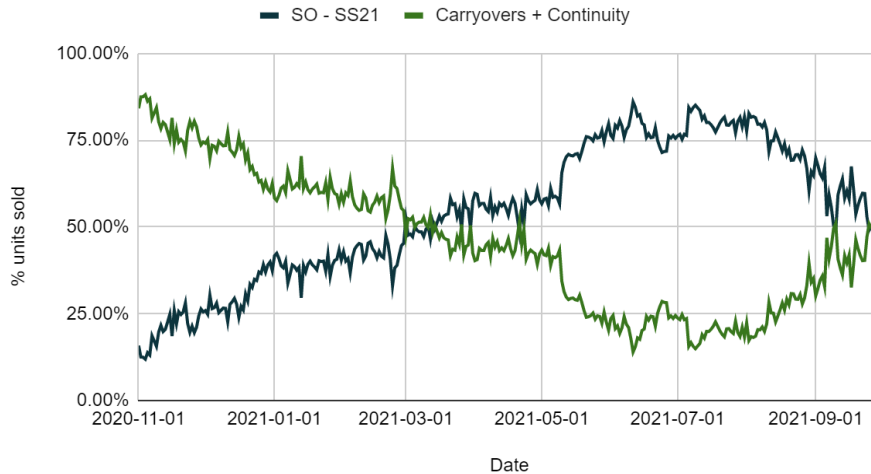


Figure 15 - Percentage of Sales by Season Type over SS21

By November, beginning of SS21, most items sold are original from past seasons (that have transitioned to the most recent season). Afterwards, the share of Continuity items/Carryovers starts to decrease in favor of the novel (Season Original) items, whose sales goes up as new items are uploaded to the collection. This trend leads to the percentage of Season Original sales exceeding that of “old” items by March. This again supports the idea of running first the model for continuity items and carryovers, then to novel items.

In Figure 16, the sales evolution by Season Type shows that sales patterns of Carryover and Continuity items are, just like their stock patterns, reasonably stable. The opposite happens for Season Original items, showing peaks. Therefore, the demand of Carryover and Continuity items should be easier to predict relative to the others (as they seem to not be as affected by trends).

Evolution of units sold by ST

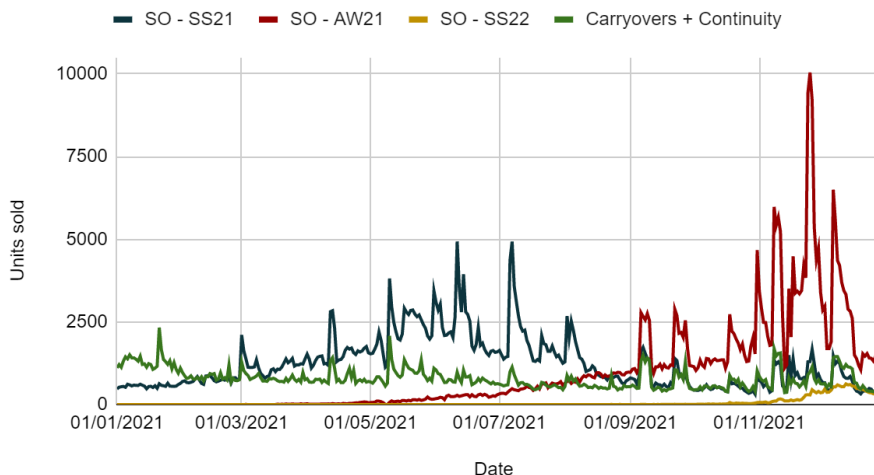


Figure 16 – Sales Evolution by Season Type over 2021

Finally, to get a sense of the value of sales that each type of products represents, the percentage of Total GTV by Season Type in SS21 is analyzed: SO items accounted for 65% of the GTV, while Carryovers and Continuity items for 35%.

Price Type Analysis

Figure 17 exhibits the evolution of orders by Price Type.

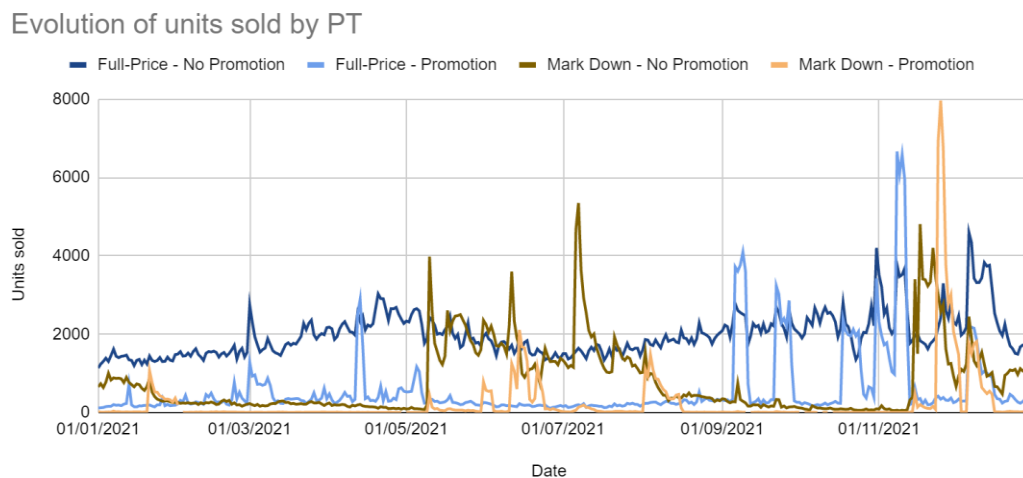


Figure 17 – Sales Evolution by Price Type over 2021

FP–No Promotion items have the most stable demand along the year. The remaining three types, either Mark-Down or Promotion (or both), show peaks in Mark-Down periods (according to the Commercial, from 4/21 to the end of 6/21 and from 10/21 to the end of 12/21, but with a one-month delay in practice) or in Promotional events, respectively. To conclude, the demand is intimately linked to promotions, being another strong effect the festive seasons, with evident peaks during Easter and Christmas. These factors should be considered in the predictions of demand.

To better characterize the business, analyses to the distribution of GTV by GBFCs, Brands and Countries, and to the sales pattern variation, follow.

Distribution of GTV by GBFCs, Brands and Countries

During 2021, 17% of the 7667 GBFCs represented 80% of the total GTV, while 16% of the 884 Brands represented 80% of the GTV. 16 out of 180 countries (9%) accounted for 80% of the GTV, with United States, China and United Kingdom in the top 3. This indicates that the greatest portion of total sales comes from a small percentage of GBFCs, Brands and regions.

Sales Variation Analysis

The sales pattern variation can be measured by the coefficient of variation (CV): the standard deviation of the demand divided by the mean of the demand. The bigger that value is, the more volatile is the demand pattern. Typically, a stable product has a CV inferior to 30% (Almada-Lobo, 2021).

In Figure 18 it is possible to see the distribution of GBFCs by tiers of coefficient of variation values, as well as the GTV that they represent.

Percentage of GBFCs and GTV by CV Tiers in SS21

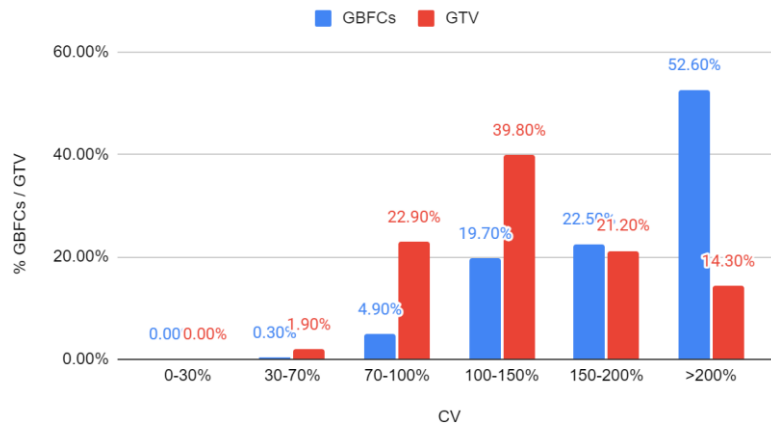


Figure 18 – Distribution of GBFCs and GTV by Coefficient of Variation (CV) Tiers in SS21

The CV values obtained are very high. This has to do with the scarcity of the dataset at the GBFC level (many GBFCs have weeks with zero units sold that result in an exaggerated standard deviation parameter that makes the ratio soar), due to the high level of granularity that a GBFC constitutes. Figure 18 shows that no GBFC has a CV below 30%, while around 100% of the GTV is generated from GBFCs with a CV over 70%. Although the values are exaggerated by the zeros, the industry seems volatile (also evident from Figure 17), which can make the forecasting task harder.

Profitability Analysis

Now, an analysis to the profitability is presented, to understand how its values can be affected by different variables, in specific the Shipping Route and Price Type.

Shipping Route Effect

In Figure 19, the profitability values of serving the different shipping regions from each stock point are presented.

Stock point	Shipping	GGP%
Country	Region	GMV
Netherlands	US	35.0%
	Middle East	32.1%
	Europe	31.4%
	Russia	28.5%
	LATAM	24.7%
	Canada	24.1%
	ROW	23.9%
	UK	22.2%
	APAC	20.2%
	Avg.	26.9%
UK	US	32.8%
	Middle East	30.9%
	LATAM	30.0%
	UK	27.0%
	Russia	23.0%
	ROW	20.2%
	APAC	18.5%
	Europe	14.5%
	Canada	13.4%
	Avg.	23.4%

Figure 19 - Profitability Values of serving different Regions from each of the Stock Points in 2021

It shows that the US and Middle East are the most profitable markets to serve from both origin regions. The remaining, however, are ranked differently in the two cases. So, the route level has impact in the profitability of an order, as introduced in 3.2.

In Table 3, the profitability associated to different order types is represented, showing that international orders are less profitable than intra-EU and domestic orders. This proves, again, that serving different regions from a given stock location generates different margins.

Table 3 - Profitability Values from different Order Types in 2021

Stock point Country	Order Type	GGP%GMV
Netherlands	Domestic	30.4%
	International	26.3%
	Intra-EU	31.1%
United Kingdom	Domestic	27.0%
	International	22.3%

Price Type Effect

In Table 4, follows the profitability values associated to each Price Type.

Table 4 - Profitability Values from different Price Types in 2021

Product Price Type	GGP%GMV
Full Price - No Promotion	32.5%
Full Price - Promotion	21.0%
Markdown - No Promotion	-0.1%
Markdown - Promotion	-13.3%

As expected, FP-No Promotion items lead to the greatest profitability values, and MD-Promotion to the worst; the overall profitability of MD products is even negative. This said, the Price Type of an item is highly impactful to its profitability: it is clearly preferable to sell items at full price, without any promo code, than at markdown, which should be considered by the model (and will be better addressed further). It is also relevant to recall the existence of promotions (both Markdown and Promocodes) at a local level, defined by the Commercial Department, that makes the profitability of an item at a given time vary among the markets, and that should be considered when comparing the regions' profitability values.

Having contextualized the business, it is possible now to develop a model targeted to the Company dynamics, to be addressed in the next section.

4 Proposed Model

To support the aspired localized assortment strategy, a model that optimizes the supply to the different regions at each point in time, in a profitability-oriented manner, was conceptualized. For such output, the model should consider the demand profile and the cost of opportunity of selling to each market, profitability-wise.

Additionally, it should cover other complexities as it needs to be aligned with the strategic goals of Farfetch at each moment. To name a few, there is possibly a catalogue integrity to sustain worldwide, sales targets to comply with in certain markets and a varying risk level that the Company might accept to incur. The devised model should thus encompass the pace, scale, value and risk of the assortment decisions that Farfetch would be making, consistent with its objectives.

The model is to be applied to the Farfetch Marketplace. As explained in 1.5, it is in a first phase oriented to 1P, to Browns in specific.

In the next subchapters, the business model is explored in higher detail. The decision model framework is addressed in 4.1, the model settings in 4.2 and finally, the implementation roadmap in 4.3.

4.1 Decision Model Framework

In Figure 20, an overview of the model framework is presented.

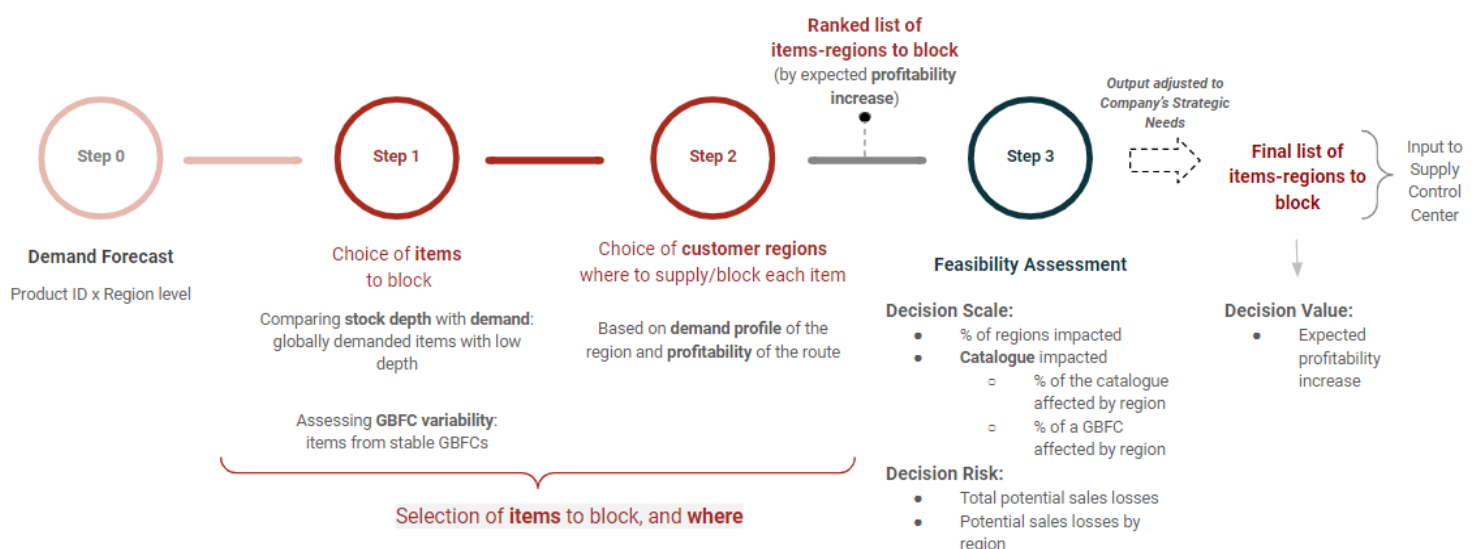


Figure 20 – Decision Model General Framework

In general lines, it comprises the following steps:

- **Step 0:** the model starts with the demand forecast of the products in the different regions, *i.e.*, at the product ID x Region level. The forecast is needed further in the model with that granularity level, that is the level at which the business decision is to be taken.
- **Step 1:** from the universe of products of the season, those that satisfy both the following conditions are considered eligible for the decision model:
 - *having a stock depth lower than its total projected demand:* they are expectedly scarce, meaning that it would be beneficial to block their offer in the least profitable regions; and
 - *belonging to a GBFC, or GFC, with a stable demand pattern:* since the model relies on a granular forecast, the items to be forecasted should have a reasonably stable demand pattern in order to produce a proper forecasting accuracy.
- **Step 2:** having chosen the items to manage, the regions where to supply each product (and reversely, where to cut the offer) should be decided based on the projected demand profile of each region and on the profitability of the respective route. The goal is to favor the supply in the most profitable regions to serve (from the concerned stock point) where there is enough demand for consuming the stock level of the item.

An initial output is hereby produced: a list of items-regions to block, ranked by expected profitability increase that results from selling to the most profitable markets.

- **Step 3:** a feasibility assessment is then performed to the initial list of items-regions to block, testing both the scale and risk of the decision.

The scale has to do with the percentage of items (catalogue) and regions impacted. The risk, in turn, is related to potential sales losses⁴ (in GTV) from the decision to block the supply in some markets. They can be measured both for the Company as a whole or by region.

The values of the scale and risk indicators should be within acceptable values for the Company, in line with the strategic needs of the moment. For example, to protect the integrity of the global catalogue, the Company may define a minimum percentage of each GBFC to be supplied in every region (as 80%).

If the initial output satisfies the imposed restrictions, it becomes the final decision. In case any of the restrictions is not satisfied, the output should be rebuilt and adjusted to those thresholds. The model iterates, by unblocking first the lowest-ranking pairs of ID-regions, in terms of the associated profitability release, until a final list that complies with the specified conditions is produced.

The final decision has an associated value, in addition to the scale and risk, that is the expected profitability increase that comes with it.

Lastly, the final list is passed for implementation to the Supply Control Center Team, that feeds the website Catalogue in the different geographies.

More detail into each step is provided in the next subchapters, from 4.1.1 to 4.1.4.

Concerning the risk incurred by the decision, the settings of the model can have a say in the matter:

⁴ These lost sales might occur if actual demand is below the projected: the model itself does not intend to lose sales, but it can happen as a result of over forecasting

- As the decision is grounded in a demand forecast, the more accurate it is, the better the outcomes. In turn, a more inaccurate forecast means a higher risk.
- The period covered by the forecast (that is the period covered by the decision) is critical to the risk level: a longer forecasting horizon leads to less accurate predictions, thus consequently to higher risk, and the other way around. That said, the frequency of the model (or its pace) is important to control risk.
- Parameter thresholds when selecting the items to manage (in step 1), like the acceptable GBFC demand variability level or the minimum difference between the forecasted demand and the stock depth of items, should have an effect in the risk.
- Risk mitigation rules during the period covered by the decision can be further plugged into the model to help control risk (to be discussed in 4.2.3).

The model settings are discussed further in Chapter 4.2.

An importance dimension of this assortment model is its dynamic, or continuous nature. As suggested by current work in 2.2, this way the retailer can update its assortment throughout the season as it updates its demand estimates for products in the assortment.

4.1.1 Step 0 - Demand Forecast

Forecast Relevance

A demand forecast is needed at the ID x region level. Being the foundation to the model, its performance is critical to the quality of the decisions.

The high granularity required can be prejudicial for the accuracy of the forecast. Nonetheless, it can be controlled by a shorter forecasting time span, *i.e.*, by a shorter decision period. In other words, if the model is run frequently for shorter decision periods, then the forecast accuracy can be improved, possibly counteracting the negative effect from the high granularity level.

The forecast needs to be unconstrained, meaning that the projected sales should not be constrained by stock levels. It is necessary to know the potential of sales in the different regions irrespective of the units in stock both for selecting the items to manage (those with a total projection of demand above their inventory level) and the regions to supply (to select a subset of regions capable of rotating all the stock).

Forecast Options under development

In Farfetch, there are demand forecasting models under development for the Marketplace, by the Data Science Team, aimed at serving various business cases within the organization.

They include a constrained and an unconstrained (by stock levels) version. The specifications of each are detailed in Appendix D. For the present use case, however, they are far from the needed granularity level (ID x Region). An alternative that could be thought of would be an attribute-based forecast, possibly more feasible than a forecast at the ID level and still implementable.

Forecast used for this proof of concept

Due to the unfitness and unavailability of the forecasting models from the Data Science Team, an alternative forecast was used in this project: a tool developed by the Logistics Team, that projects GTV units sold at the Product ID x Region level in an unconstrained way, detailed in

Appendix E. It exists in three development versions: as v2 shows the smallest error, it was the selected for the proof of concept in Chapter 5.

4.1.2 Step 1 - Selection of Items

As mentioned in 4.1, the eligible product IDs for this selective assortment model are those that simultaneously:

- 1) have a total forecasted demand that exceeds the current units in stock; and
- 2) belong to a relatively stable (in sales) GBFC/GFC.

Condition 1)

While the second condition can be eventually dispensable (although worse results are expected without it), the first is central to the model functioning: the regional supply should be blocked only for items that are scarce relative to their total demand, when less open regions still allow to sell the stock in hand. Otherwise, blocking the supply would lead to lost sales compared to the as-is situation, which is not intended.

Figure 21 represents the stock/demand relation. Products that fall within the lower right quadrant, with a global demand for a low stock availability, are the ones to tackle.

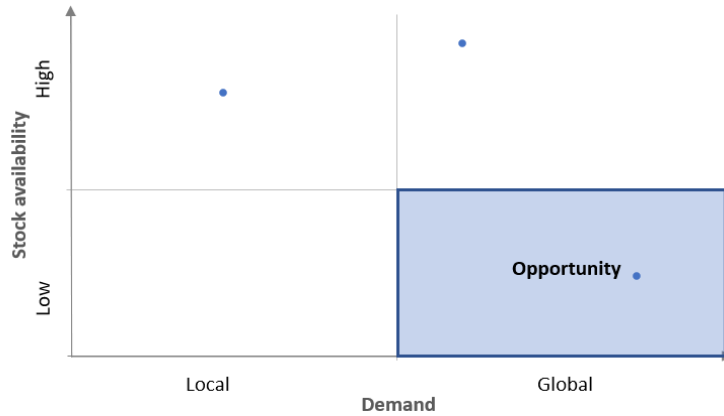


Figure 21 – Stock/Demand Opportunity to grasp by the Model

It is important to say that, attending to the lack of visibility of the stock replenishment moments within Farfetch, the stock values to consider are those of the moment when the model is run. In specific, of the online stock, available for shopping.

The stock/demand condition can be expressed as follows, according to the mathematical definition in Appendix C:

$$\sum_1^R \text{UncDem}_{i,r} > (1 + x\%) * S_i \quad (4.1)$$

$(1 + x\%)$ is the margin defined as the minimum relative difference between the projected demand and the stock level for selecting an item. Increasing values of x should lead to a smaller set of eligible items but to a less risky decision (higher buffer to the risk of losing sales due to over forecasting). The values for x were set as 0% and 15% in this work.

Condition 2)

Table 5 shows how the forecast accuracy changes with the sales pattern of the items.

Table 5 - Products Demand Pattern and associated Forecast Accuracy (Almada-Lobo, 2021)

Product Type	Sales pattern	Forecast Accuracy
X	Constant , with rare or minor fluctuations	High
Y	Stronger fluctuations due to trends or seasonal influences	Medium
Z	Extremely irregular or random	Low

The items to forecast should be preferably the “X” items, or the most stable products.

Figure 22 represents the split of items according to the demand volatility, measured by the coefficient of variation (CV): a relative measure of variability that indicates the size of a standard deviation relative to its mean, expressed in equation 4.2.

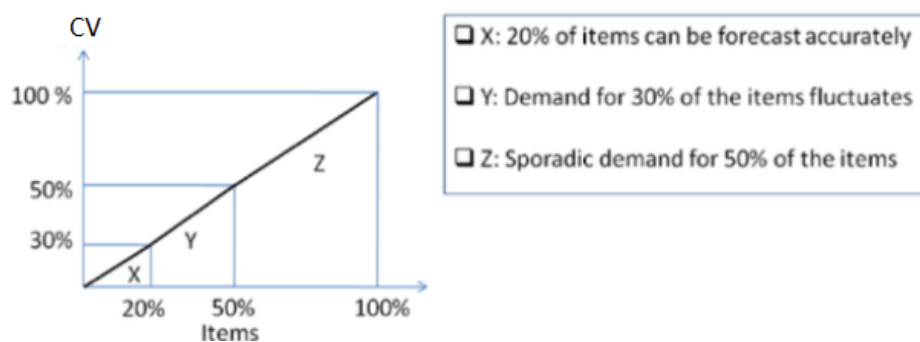


Figure 22 - XYZ Analysis for Selecting which Items to forecast (Almada-Lobo, 2021)

$$CV = \frac{\sigma_{Demand}}{\mu_{Demand}} \quad (4.2)$$

In this logic, the second condition proposed intends to narrow the scope of the model by selecting the most stable items, with inferior CV values, so that an acceptable forecasting accuracy is possible. It is expected that a lower CV threshold will lead to less eligible items but to a less risky decision.

The period suggested for the assessment of sales variability is the homologous season of the previous year. Therefore, it is suggested at the GBFC, instead of the item level, as fashion items are ever changing and consequently many of them have no past data (season original items). If no data exists at the GBFC, the assessment should jump to the GFC level.

In Figure 22, one sees that stable products are considered those with a CV below 30%, that somewhat volatile items (due to trends or seasonal influences) have a CV between 30% and 50%, and that highly volatile items have a CV over 50%. At Farfetch, however, the sales dataset at the GBFC is sparse (with many zero observations for the period in which the item is active) as it is a granular level, what makes the standard deviation wrong and results in a disproportionate CV (as previously described in 3.3). In a context where, by considering the zero observations in the calculation, no GBFC has a CV below 30% and around 100% of the GTV is generated from GBFCs with a CV over 70%, different CV thresholds were proposed:

- 1) 30% - the standard threshold:

$$CV_i < 30\% \quad (4.3)$$

- 2) the aggregate⁵ CV - assuming that the aggregate variation represents the “normal” seasonality of the period:

$$CV_i < Agg.CV (= 78\%) \quad (4.4)$$

- 3) the aggregate CV with an upper margin of 15% - assuming that values around the average pattern are stable:

$$CV_i < (1 + 15\%) * Agg.CV (= 90\%) \quad (4.5)$$

A last method, frequency-based, was also considered. It calculates the percentage of months in which each GBFC/GFC is under control (*i.e.*, has a CV below the aggregate CV), to allow for certain peaks in sales (related to promotional periods) to occur. The condition is expressed as:

$$\#Months \text{ when } (CV_i < Agg.CV) > Y\% * Total \#Months \quad (4.6)$$

Here, a higher value of Y should lead to a smaller universe of items, but expectedly to less risk. In this project, 70% was considered.

Conditions 1) and 2)

From conditions 1) and 2), the proposed combinations of the criteria are in Table 6.

Table 6 - Proposed combinations of Items Eligibility Criteria

Demand/stock relation	Sales variation condition
$\sum_1^R UncDem_{ir} > (1 + 0\%) * S_i$	-
	$CV_i < 30\%$
	$CV_i < Agg.CV (= 78\%)$
	$CV_i < (1 + 15\%) * Agg.CV (= 90\%)$
	$\#Months \text{ when } (CV_i < Agg.CV) > 70\% * Total \#Months$
$\sum_1^R UncDem_{ir} > (1 + 15\%) * S_i$	-
	$CV_i < 30\%$
	$CV_i < Agg.CV (= 78\%)$
	$CV_i < (1 + 15\%) * Agg.CV (= 90\%)$
	$\#Months \text{ when } (CV_i < Agg.CV) > 70\% * Total \#Months$

To sum up, it is expected that the application of the items eligibility conditions with stricter thresholds leads to a smaller set of items, but to less risk. When the two criteria are applied in combination, then the risk of the decision should reduce significantly. The decision for the criteria should attend to the opportunity-risk trade-off: the combination leading to a

⁵ Summing the units sold of all GBFCs, or all GFCs

reasonable impact on the catalogue with a bearable risk level should be selected. These pairs are simulated in Chapter 5.

4.1.3 Step 2 - Selection of Regions

As mentioned in 4.1, the goal of the model is, for the items selected, to favor the supply in the most profitable regions (from the respective stock point) that have enough demand for the stock level of the item.

Profitability

The suggestion is to assess the profitability of selling an item to a region at the route level, considering the origin of the product (stock point country) and the customer region. As seen in 3.2 and 3.3, the route is a relevant profitability driver of an order. It answers to the goal of this model, that is to benefit from the differences in the profitability of serving different regions, as it distinguishes between them. At the same time, it has a granularity level that is not excessive while it is comprehensive enough: an alternative, for example, could be to assess the profitability at a higher granularity level, considering other factors that affect the profitability of an order (*e.g.*, at the level of the route-AOV-PT-Geoprice(Y/N), etc.), but that would bring excessive complexity.

Given that the same product ID can be supplied from different stock points (different countries of origin), the analysis of the profitability at the route level means looking at the combinations of product ID x stock point country x customer region (instead of simply looking at the product ID x customer region level, that would be the case for just one stock point). To avoid the additional complexity that comes with the multiple stock points scenario and still account for its effect, the product ID x customer region level has been maintained by considering the share of stock of the product that is carried in each stock point: the profitability of selling a product to a customer region should be calculated as a weighted average, by the percentage of product carried in each stock point country, of the profitability of the respective route.

The profitability values considered should be from recent data, to capture the latest changes in the revenues and costs (resulting from newly introduced carriers, new fees, etc.). The last 35 days, in which some P&L fields are estimated (by the L35 days Logic), should be excluded. A possible period could be the last 2 months excluding the last 35 days. In addition, since promotions significantly influence profitability (verified in Chapter 3), the profitability values of the regions with promotions plans within the decision period should have a reducing effect on top.

Demand

The demand profile of each region is considered for selecting as many regions as needed (by descending order of profitability) to sell out the existing stock level of each product. The result of the product ID x Region demand forecast, from step 0, is used for this task. Having selected the most profitable regions needed to make up the stock level, the remaining (less profitable ones) should be blocked.

It is relevant to mention that, in the case of forecasting models projecting future sales based exclusively on the units sold to date, there are possible pairs of product ID x Region that will have no projected sales, to which the question of keeping open, or blocking, the supply is posed. There is this notion of “exploration vs exploitation”, addressed by Ulu et al. (2012), that demonstrates “that it might be optimal for the retailer to alternate between exploration

and exploitation, and sometimes offer sub optimal loss producing assortments in a bid to learn valuable information about consumer preferences.” With the same reasoning, it is suggested that the regions without projected demand should remain open, unless the profitability values of those regions are below a given threshold of acceptability. That threshold can be the profitability value of the least profitable region, with projected demand, that is going to be supplied. This approach makes sense as the profitability of those regions (not covered by the forecast) is higher than that of the benchmark (and therefore sales to those regions are preferred), while it allows to collect more data, which is beneficial for the model. Additionally, it acts as a risk buffer for potential sales losses.

An exemplification of the selection of regions where to supply (or to block) the eligible items is presented next, in Figure 23.

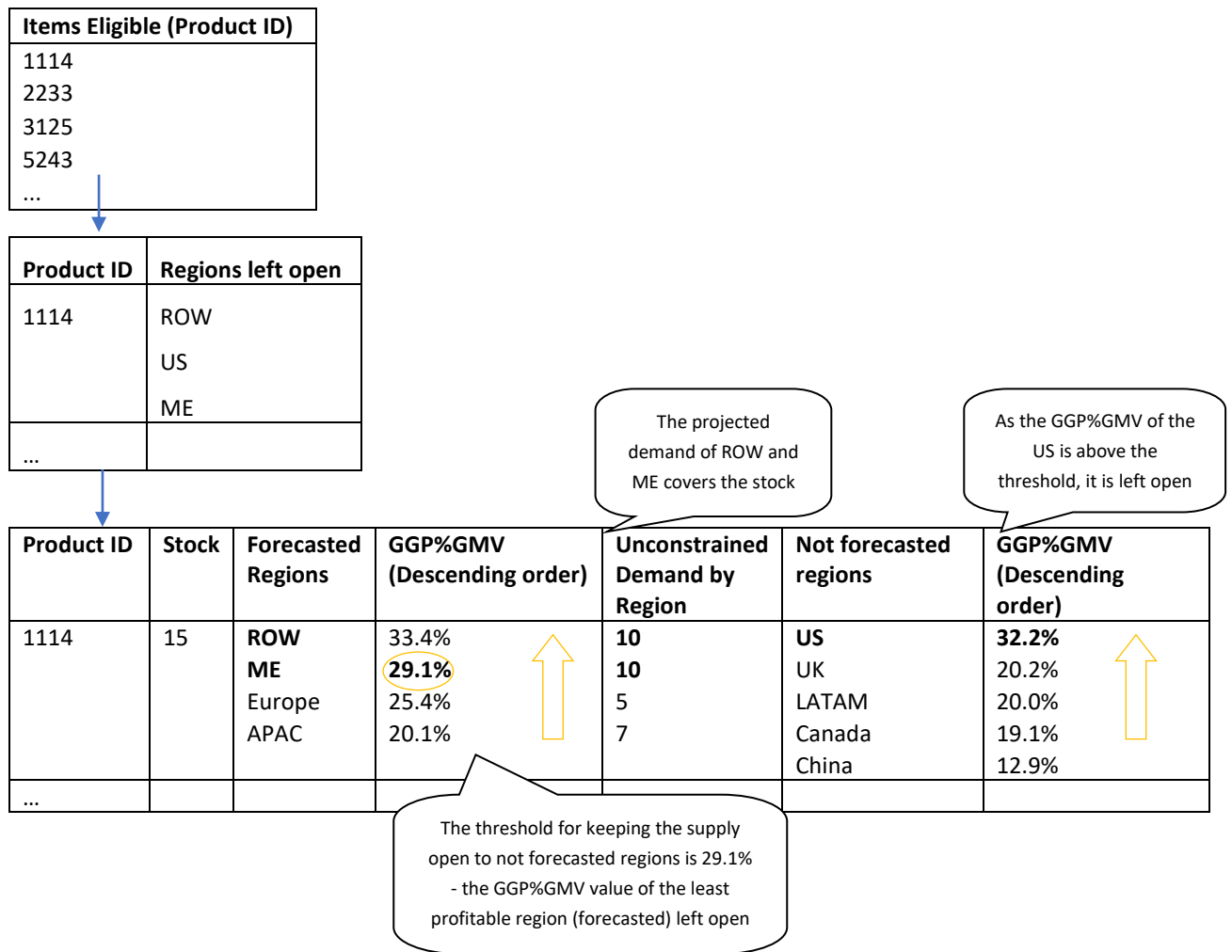


Figure 23 - Example of Regions Selection in practice

Clusters of Regions

As explored in Chapter 2.2.3, a customization-by-clusters strategy where individuals are sorted into groups according to their similarities allows to capture most of the benefits of customization while simplifying decisions and enabling manageable operations. In this case, that approach can be applied to group the countries with similar profitability values, so that a decision can be made in bulk for each region cluster. To decide on a product ID x Country

level would entail great complexity to manage and, besides that, would lead to higher forecast inaccuracy. The clusters of regions proposed for this use case are explored in Appendix F.

4.1.4 Step 3 - Feasibility Assessment

In step 4, the decision is assessed for feasibility, regarding scale and risk, based on the set strategic criteria at the moment.

Concerning scale, the Company might want to protect its catalogue worldwide and guarantee that a minimum percentage of it is standard (in total terms or within each GBFC). Or there might be special considerations: for instance, a new category that the Company is promoting and therefore should remain entirely open; or a minimum percentage of products of a certain AOV tier or style to supply for targeting a specific customer segment; or a minimum percentage of traffic building items to ensure in every or in some specific regions so that traffic keeps coming; among many other possibilities.

The second dimension is the risk that the Company is willing to take at each point in time, related to potential GTV losses, due to the forecast error (of over forecasting). The higher the scale of the decision is, the higher will be the potential GTV losses (for a given forecasting tool), but the opportunity will be inferior as well.

In the definition of the strategic needs, it is essential that a proper alignment with the Commercial Team exists so that the commercial plan is not damaged, but instead fostered, by this selective catalogue. An alignment with the top Strategy of the Company is critical as well: for instance, the Company might want to grow its representativity in a specific region, and so a sales target to comply with in that region would be the case.

As rules for feasibility related to catalogue integrity, in this model it is proposed that every region has:

- 1) 80% of the catalogue available; and
- 2) 80% of each GBFC available.

To these rules, others can be added, depending on the strategic needs of the Company.

After the assessment, if any of the conditions is not met, the output needs to be adjusted to provide an implementable decision. For the regions that fail on validity, some items need to be unblocked. Those items are selected by their order in the output list of IDs x Regions to block: by unblocking first the lowest-ranking pairs of ID-regions, in terms of the associated profitability release, until a final list that complies with the specified conditions is produced. The procedure is illustrated in Figure 24 below.

List of IDs x Regions to block

Product ID	Region block to	Potential sales losses (GTV) ⁶	Weighted (by demand) profitability of regions left open – $GGP\%GMV_{new}$	Expected increase ⁷ profitability (Descending order)
1114	APAC	To be defined	31.3%	$= ((7 \text{ units}^8 * ASP)^9 - GMV \text{ Potential losses}) * GGP\%GMV_{APAC} * \text{Profitability uplift}^{10}$
...	...			
5243	APAC			

If APAC is underrepresented or has an excessive risk of sales losses, the idea is to start by opening the supply to APAC for products from the bottom of the list, until a valid output is achieved

Figure 24 – Example of Output Adjustment for Feasibility in practice

A competition analysis could possibly be added in the future to this feasibility assessment to cross-check the catalogue to what is offered by competitors.

4.2 Decision Model Settings

The settings of the model are now discussed in the present section, in specific the type of approach that can be adopted (pre-season vs in-season), the suggested timeframe for a dynamic model and some risk mitigation rules during each decision period.

4.2.1 Pre-season vs In-season Approach

The decision model can follow a pre-season or in-season approach, when it comes to the timing of the blocking. Their processes can be described as in Figure 25.

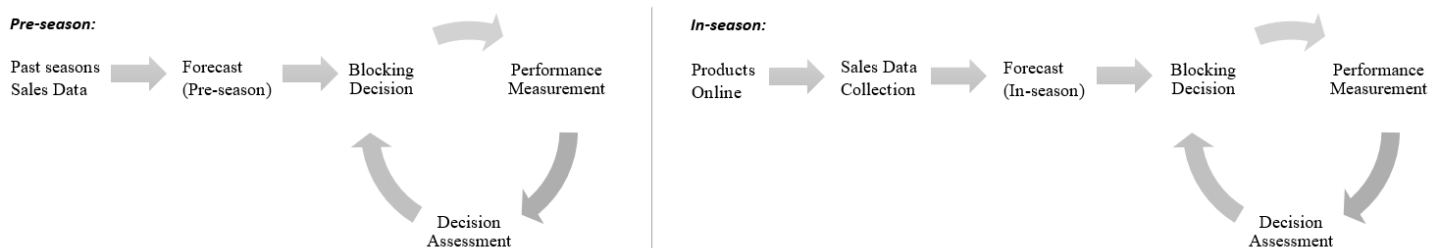


Figure 25 - Process involved in a Pre-season vs In-season Approach

⁶ Potential sales losses due to over forecasting error (when, in practice, sales in the regions left open are inferior to expected); to be addressed in Chapter 5

⁷ By selling the units in more profitable markets (profitability release)

⁸ Demand projected for product ID 1114 in APAC

⁹ GMV

¹⁰ $GGP\%GMV_{new} - GGP\%GMV_{APAC}$

While the pre-season blocks right from the beginning of the season, as there is sales data from past seasons, the in-season approach needs to gather data from the season.

The type of approach depends on the season type of products and on the available forecasting model. A new season always has novel products (season original) and continuity products (continuity/carryovers) - where the former account for approximately 65% of the GTV. For the continuity products/carryovers, there is historical data (from at least the past 9 months) to produce a sales forecast, being thus possible to follow the pre-season method. For the new products, it depends on the forecast: if it is at the ID level but attribute-based, there can be past data that allows to extrapolate to new products; if its granularity level allows for the new items' groups to have past sales (*e.g.*, at the GBFC x Style x Color level), then it is also possible to have a demand forecast for them - in those cases, it should be possible to follow a pre-season approach for some of the novel items. The in-season approach, that acts after a certain time since the beginning of the season, is possible for all types of items (season original or continuity/carryovers).

The proposed approach is a hybrid: to decide rightaway for the items with past data (for which a pre-season forecast is possible) and to decide during the season for the remaining. And for a more sporadic event, drops, it might be interesting to act immediately, even without a demand forecast (*i.e.*, to decide on the markets to supply based on the profitability values only). Then, to measure the performance of the regions kept open and to assess the decision.

Regardless the approach, the model should be dynamic in the sense that the performance of the items should be measured and the decision adjusted as necessary, while accounting for evolving sales patterns and strategic objectives, as well as new items in the catalogue.

4.2.2 Timeframe for a Continuous Assortment Optimization

As mentioned previously, a season has the duration of 9 months. In this work, it is suggested that the model decides for shorter periods within those 9 months because the risk is diminished by increasing the frequency of model: the forecast horizon is shorter, thus entailing less error, and several decision moments along the season allow reforecasting (that incorporates the most recent sales trends) and consequently to make more accurate decisions. Besides that, it allows to decide on new items that have been uploaded in the meantime and to consider new Company needs.

The proposed time span for each decision period (therefore, the forecasted period) is 4 weeks. During each 4-weeks period, risk mitigation procedures can be implemented, to be better detailed in 4.2.3.

Regarding the stock/demand relation for electing items, however, the product's stock level does not need to be compared to the demand projected for the following 4 weeks. Instead, the stock can be compared to the demand over a longer time horizon, expectedly enlarging the scope - possibly at the cost of a higher forecast error (to be assessed in Chapter 5).

In specific, the demand can be considered until the beginning of the markdown season, but never surpassing that moment: this is because, given the profitability differences of selling an item at FP vs at MD (shown in 3.3), it is critical to ensure that the items are sold at FP. In fact, the difference in profitability between FP and MD products is so high (around 30%) that it is preferable to sell items to less profitable markets, but at full price, than to sell them in markdown season to whatever region.

From the beginning of the markdown period, there are still differences in the profitability of selling to the different markets, which makes the model still pertinent. The stock/demand condition from then on should be measured in relation to the period until the end of the season.

When it comes to the timings to run the model, the year 2021 is going to be used for the sake of exemplification. As covered in 3.3, AW starts in May, and SS in November (when online stock and sales start to increase). AW sales go down to lower values by the end of December, whereas SS sales by July; after those months, there are residual sales until around three months after.

Concerning the necessary time of sales data collection for first applying the model, it has to do with how well the forecast predicts with varying amounts of past data (to be simulated in 5).

Attending to the previous considerations, a suggested timeframe for running the decision model in 2021 would be the following, with the moments schematized in Figure 26 (the legend in Figure 27):

- For continuity/carryovers and for some novel items (if the forecast is possible for items without past sales) having enough past data for a proper forecast accuracy, to take a first decision in the beginning of the season (in May and November);
- For novel items (all, if the forecast only projects for items with past sales; or for some, in the reverse case), to take a first decision after collecting X -months data since the beginning of season sales (X months after May and November - X is the number of months allowing for a proper forecast accuracy, to be addressed in Chapter 5);
- Afterwards, retake decisions (assess previous and take new ones) once every month. The last decision moment should be the beginning of June, for SS, and the beginning of December, for AW: after those months, the blocking should be lifted as it is prime concern to sell out the remaining stock (pressured by the inventory perishability of the fashion industry).

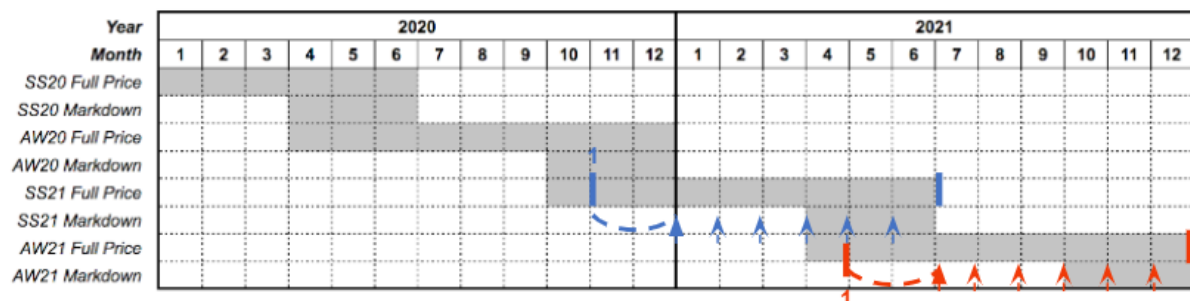


Figure 26 - Suggested Model Timeframe for SS21 and AW21

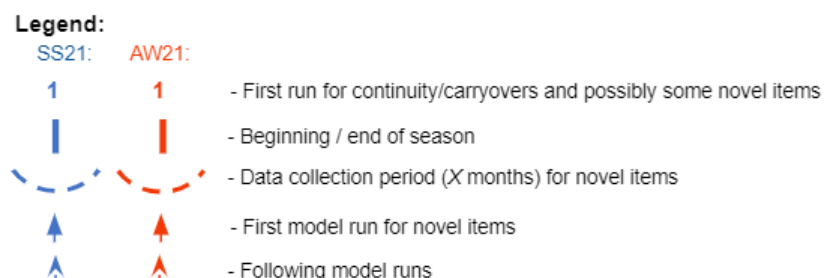


Figure 27 – Legend of symbols in Figure 26

The timeframe here presented is a suggestion, that it is quite flexible and that should be decided upon considering the forecast in-use accuracy and other business considerations, as the promotions period.

4.2.3 Monitoring and Risk Mitigation Rules

Some mechanisms can be plugged into the model to better manage the risk incurred: within each decision period, the performance (in specific, sales) of the items covered by the model should be monitored and, when deemed necessary, the blocking should be lifted. In addition, there are specific situations that can increase the risk of the decision taken, as inbounds, that should be accounted for.

The performance of each item can be monitored by its sell-through, comparing the actual to the forecasted values. A suggestion is to add a checkpoint moment by the middle of the decision period (*i.e.*, after 2 weeks): if the product sell-through is close (within defined thresholds) to the projected, the blocking decision should be kept until the end of the decision period; otherwise, the supply should be reopened to every customer location.

As introduced previously, stock uploads occur along season in an unforeseen manner, possibly during the period covered by a decision, thus likely to make a decision based on past stock levels inadequate. For the items receiving inbounds, the superiority of the projected demand relative to the stock level might no longer verify, and if that is the case the blocking decision becomes risky. Therefore, each time there are substantial inbounds (for example, of over 30% of the previous day stock, to exclude returns) for the items being managed by the model, it is proposed that the blocking rules applied to the respective items are reconsidered, by reevaluating the stock/demand relation. If the eligibility condition is no longer satisfied, the blocking should be removed. The procedure is illustrated in Figure 28 below.

 **Inbound** during period covered by decision

Product ID	S_b	Regions left open	STD sales	$S_{inbound}^{11}$	PTG forecasted sales
1114	15	ROW US ME	8 1 5	18	6 4 3
...					

The PTG forecasted sales are not enough to sell the stock after the inbound. Therefore, the blocking is lifted until the end of the decision period

Figure 28 - Example of the Inbounds Risk Mitigation Rule in practice

Besides these two considerations, it may be a good practice to flag items to which blocking rules are changed often and to reference them as no longer eligible for the model.

Finally, the monitoring task can be eased by categorizing items according to similarity factors, allowing a follow-up by groups of items. The suggested factors are: scarcity relative to demand, selling tendency, level of engagement, trendiness, sales volatility and demand globality; that can be reflected in an overall score. This possible categorization of items, together with the metric that can be used for each factor, is depicted in the matrix in Table 7.

¹¹ Stock level after the inbound

Table 7 - Suggested Items Categorization Matrix to ease the Monitoring task

Is it scarce for the demand? <i>$\frac{\text{Forecasted sales}}{\text{Stock depth}}$</i>	Does it sell? <i>Sell-through</i>	Does it engage? <i>Visits</i>	Is it trendy? <i>Does it belong to a Top GBFC (in GTV)?</i>	Is its demand stable? <i>Coefficient of Variation</i>	Is it globally agreeable? <i>$\frac{\# \text{Demanding Regions}}{\text{Total \# Regions}} > 70\%$</i>	Score
A	A	A	A	A	A	AAAAAA
				...		
D	D	D	D	D	D	DDDDDD

4.3 Implementation Roadmap

Concerning implementation, this chapter explores the process, the need for automation and the integration that is needed inside the Company between departments.

Recalling the implementation guidelines provided in 2.2.3, IDC Retail Insights (2015) suggests using the assortment planning assets to achieve the financial, operating and customer satisfaction goals of the following years, deciding accordingly the pace, scale, value and risk of the assortment decisions that will be taken. In this Chapter 4, ways of integrating and assessing these four dimensions in the decision model have been explored that could be used. For achieving those goals with an assortment planning tool, the Company should map the gaps between the as-is capabilities and near-requirements, related to advanced forecasting and analytics, or to rules, metrics, KPIs, among other innovation needs that might exist.

Applying the guidelines to Farfetch, it is crucial to develop a supporting analytics tool comprised by a demand forecast and by embedded rules, metrics and KPIs that allow for a continuous assortment optimization adjusted to the business. Being the basis of the model, a forecast with good accuracy at the ID x Region, or close to that granularity level, is a needed capability. The decision framework of the tool can be sustained by the work presented in this paper and implement the suggested settings (concerning the timeframe, process of selecting items and regions to manage, feasibility assessment, monitoring and risk mitigation rules).

This supporting analytics tool should therefore respond to the automation need that exists when it comes to selecting the items and regions to manage in the form of a feasible output, as well as for systematically entering in the system the pairs of items-regions to block (from the decision output). In addition, for implementing the continuous cycle with the suggested monitoring mechanisms, the process is only manageable with an automatic tool.

The tool should receive Farfetch's strategic needs as input to produce tailored decisions, that should be aligned with the Company Board. An alignment with the Commercial department is also needed, as it is critical to fine-tune assortment planning decisions with commercial activities that influence sales and profitability, as campaigns and promotions.

After an output is recommended by the tool, a managerial team should validate it prior to implementation. And, at any time, the tool should allow the user to change the blocking rules

applied. The team interacting with the tool is possibly the Product Team, in specific the Supply Control Center Department, managing the catalogue at Farfetch.com. The team should build the needed technical skills to operate the tool effectively.

The suggested process flow for the tool, including the previous considerations, is schematized in Figure 29, and also in Appendix G for better reading.

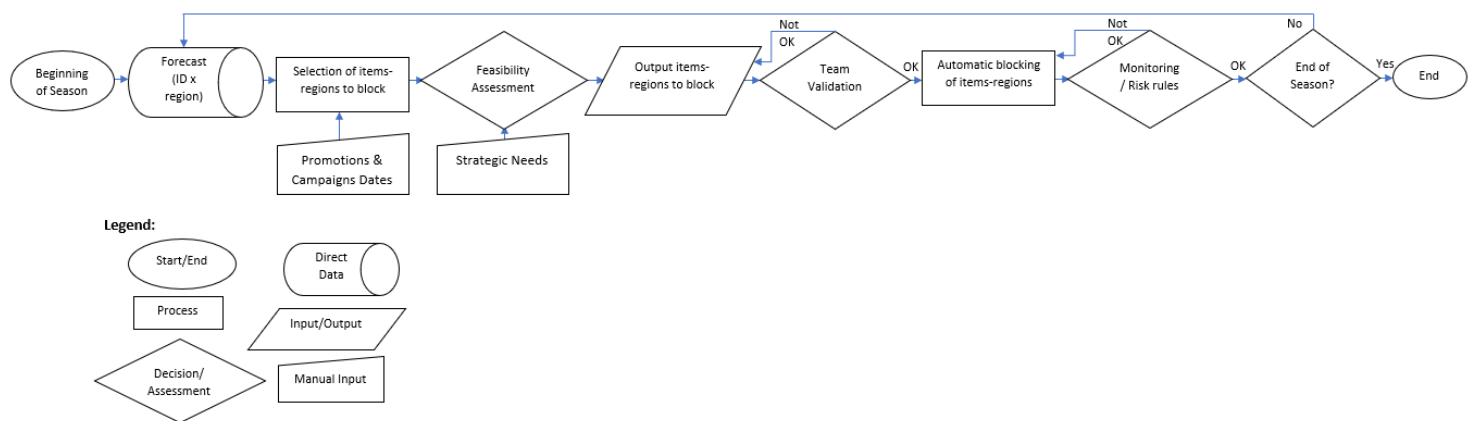


Figure 29 – Analytics Tool Process Diagram

Having a supporting analytics engine, McKinsey & Company (2019) suggests laying a foundation for assortment excellence in three phases (Pilot Project, Rollout and Institutionalization), after which the Company should be equipped to sustain the assortment optimization cycle and achieve financial benefits. Inspired by the former roadmap, the suggested implementation phases for this model are represented in Figure 30 - and the detail of each in the text below.



Figure 30 – Implementation suggested Timeline

The first phase is the Pilot project, from one to three months, aimed at quantifying the value of the retailer's assortment lever based on a few select categories, or a few select stores (by applying the suggested rules for selecting items from the catalogue, a subset is similarly used). It serves to generate actionable business insights for immediate implementation (as mapping commercial processes) and to identify opportunities for improvement. In parallel, Product managers should begin to develop analytical skills by working alongside the IT Team.

The second phase is the Rollout and should span the next three to six months. Insights from phase 1 are used to inform the configuration of the analytics tool, which is then typically applied to all product categories (or stores). A joint work in this phase between the IT team and the Commercial and Product departments fosters the alignment of commercial processes with analytics and the engagement in large-scale skill-building. All assortment opportunities should be systematically evaluated, thus identifying more quick wins.

Finally, Institutionalization makes sure the impact is lasting, ensuring that analytics tools are tailored to the organization's needs through ongoing process checks, while maintaining the analytical skill-building.

5 Results

To prove the concept while estimating the economic impact of the decision model, a simulation of results was performed.

The method used for simulation is presented in 5.1 and the obtained results is in 5.2. Main takeaways are addressed in 5.3.

5.1 Simulation Method

The simulation followed a theoretical method, as testing can be rather inconclusive. By testing, it is impossible to know how the results would have been had the model not been implemented: there is no baseline for comparison purposes. And comparing the results to past periods can be unfair as changes (both in sales and profitability values) can be rooted in plenty of factors external to the model.

Hence, the simulation was set with historical data from SS21 (from 1-11-2020 to 30-06-2021) and it was grounded on the Logistics Team forecasting model, that is a simpler version of a possible future forecast, in specific the v2 (that shows the best accuracy values). Several runs of simulation were performed to replicate the continuous assortment cycle.

The reasoning behind was the estimation of the increase in the profitability metric (GGP%GMV) expected from the application model – *i.e.*, by selling the items in more profitable markets than before –, offset by potential losses in sales volume.

Sales losses are a possibility when there is over forecasting. In this use case, the decision to block the supply in some of regions is based on the projected demand values, so when they fall below the expected there are lost sales. In that sense, the potential sales losses should be expressed by the over forecasting error.

The formula used for the simulation of the new GGP after the application of the decision model was the following:

$$GGP' = GGP\%GMV_{actual} * (1 + x\%) * GMV_{actual} * (1 - error_{overf}) \quad (5.1)$$

where:

GGP' - estimated GGP of the decision period after the application of the model

$GGP\%GMV_{actual}$ – observed profitability metric of the decision period (as-is)

$x\%$ – estimated uplift in the value of the profitability metric after the application of the model

GMV_{actual} – observed GMV of the decision period (as-is)

$error_{overf}$ – over forecasting error, representing the percentage of lost sales.

Attending to the previous formula 5.1, the GGP increase is defined as:

$$\begin{aligned}
 GGP_{increase} &= GGP' - GGP_{actual} = (GGP\%GMV)' * GMV' - GGP\%GMV_{actual} * GMV_{actual} = \\
 &= GGP\%GMV_{actual} * (1 + x\%) * GMV_{actual} * (1 - error_{overf}) - GGP\%GMV_{actual} * GMV_{actual} = \\
 &= GGP\%GMV_{actual} * GMV_{actual} * ((1 + x\%) * (1 - error_{overf}) - 1)
 \end{aligned} \tag{5.2}$$

where:

GGP_{actual} - observed GGP of the decision period (as-is)

GMV' - estimated GMV of the decision period after the application of the model.

From formula 5.2, there is a GGP increase (i.e., the difference in GGP is positive) if:

$$\begin{aligned}
 (1 + x\%) * (1 - error_{overf}) - 1 &> 0 \\
 \Leftrightarrow x\% - error_{overf} - x\% * error_{overf} &> 0 \\
 \Leftrightarrow x\% * (1 - error_{overf}) &> error_{overf} \\
 \Leftrightarrow x\% &> \frac{error_{overf}}{1 - error_{overf}}
 \end{aligned} \tag{5.3}$$

Equation 5.3 presents the relation that needs to exist between the uplift of the profitability value and the over forecasting error for an increase in GGP to be generated.

In addition, it should be added that, for the calculation of the forecasting accuracy, the projected sales have been adjusted (i.e., constrained) by the stock level, considering that it is not possible to sell more units than those carried. A consequence of that adjustment is a situation where many IDs have a perfect forecast merely due to the item being out of stock (as stock is null, no sales are possible). The accuracy of the forecast would benefit from that case, in an unrealistic and not rigorous manner. For such reason and since considering items out-of-stock would only add unnecessary complexity to the process (there is no interest in managing stock-outs), the analysis excludes product IDs with zero stock.

The error of the forecast is assessed at the product ID x Region level, the level at which the business decision is made. The error metrics chosen for assessing the forecast accuracy were weighted RMSE and weighted SMAPE. A higher detail and support in the chosen metrics are presented in Appendix H.

Estimation of $x\%$ and $error_{overf}$

Profitability uplift ($x\%$):

The increase in $GGP\%GMV$ was estimated based on the differences between the values of the profitability metric in the different markets, in Table 8.

Table 8 - Matrix of values of GGP%GMV Increase, for SS21, between pairs of Shipping Regions

GGP%GMV difference	China	Canada	LATAM	APAC	UK	Europe	ME	US	ROW
China	-	-	-	-	-	-	-	-	-
Canada	6.19%	-	-	-	-	-	-	-	-
LATAM	7.11%	0.92%	-	-	-	-	-	-	-
APAC	7.23%	1.04%	0.12%	-	-	-	-	-	-
UK	7.29%	1.10%	0.18%	0.06%	-	-	-	-	-
Europe	12.49%	6.30%	5.38%	5.26%	5.20%	-	-	-	-
ME	16.20%	10.01%	9.09%	8.97%	8.91%	3.71%	-	-	-
US	19.29%	13.10%	12.18%	12.06%	12.00%	6.80%	3.09%	-	-
ROW	20.52%	14.33%	13.41%	13.29%	13.23%	8.03%	4.32%	1.23%	-

Considering the positive differences in the profitability values summarized in Table 8, three scenarios were drawn up:

- Best case scenario: increase in the profitability metric of 20.52% (highest value of profitability increase between each two regions);
- Average case scenario: increase in the profitability metric of 8.05% (average value of profitability increase across all the combinations of two regions);
- Worst case scenario: increase in the profitability metric of 0.06% (lowest value of profitability increase between each two regions).

Percentage of lost sales ($error_{overf}$):

To express the percentage of lost sales, the over forecasting error metric should be a relative metric (to then multiply by the sales value, the GMV) and should be weighted by the contribution of each observation to total sales (as instances contributing more to the total sales volume have a higher impact in the total lost sales).

Considering the needed specifications, the weighted sMAPE was calculated for the items with actual sales in the decision period where there is over forecasting. It is important to highlight here that, if under 30%, sMAPE can be interpreted in the same way as MAPE. In addition, that the error weight considered was the percentage of sales units that each over forecasting observation represents to the total of cases (with both right, under and over forecasting cases), as in the same way the GMV value of the GGP simulation expression (equation 5.1) concerns all the cases.

This over forecasting error was derived from the forecasting model used.

5.2 Simulation Results

At this stage, results were simulated resorting to historical data from SS21 and following the method described in 5.1, using the Logistics Team forecast (v2).

Seven runs were performed to simulate the monthly runs of the model along the season, listed in Table 9. Since SS21 in practice only starts in November (see Figure 9), that is the period

considered to start the collection of historical data. And that is why there are 7 runs (and not eight).

Table 9 - Historical and Decision Periods of the Simulated Model Runs

Model run #	Historical period	Projection/decision period
1 st	1/11/20 – 30/11/20	1/12/20 – 31/12/20
2 nd	1/11/20 – 31/12/20	1/1/21 – 31/1/21
3 rd	1/11/20 – 31/01/21	1/2/21 – 28/2/21
4 th	1/11/20 – 28/2/21	1/3/21 – 31/3/21
5 th	1/11/20 – 31/3/21	1/4/21 – 30/4/21
6 th	1/11/20 – 30/4/21	1/5/21 – 31/5/21
7 th	1/11/20 – 31/5/21	1/6/21 – 30/6/21

The first run starts with one month of historical data, to which a month adds in each next iteration. The inclusion of different periods of history allows to assess how the forecasting error evolves along the season, and thus to decide when to start the model. A first analysis of the average results is presented, then individual runs are discussed by the end of the chapter.

Table 10 provides detail on the eligibility pairs of conditions, referenced along the chapter. Pair 1 only serves as baseline (for the model it is essential the application of the demand/stock condition), so the simulated results exclude pair 1.

Table 10 - Detail on each pair of Criteria for selecting Items

Pair	Sales variation condition	Demand/stock condition
1	-	-
2	-	$\sum_{i=1}^R UncDem_{ir} > (1 + 0\%) * S_i$
3	-	$\sum_{i=1}^R UncDem_{ir} > (1 + 15\%) * S_i$
4	$CV_i < (1 + 15\%) * Agg.CV (= 90\%)$	$\sum_{i=1}^R UncDem_{ir} > (1 + 0\%) * S_i$
5	$CV_i < (1 + 15\%) * Agg.CV (= 90\%)$	$\sum_{i=1}^R UncDem_{ir} > (1 + 15\%) * S_i$
6	$CV_i < Agg.CV (= 78\%)$	$\sum_{i=1}^R UncDem_{ir} > (1 + 0\%) * S_i$
7	$CV_i < Agg.CV (= 78\%)$	$\sum_{i=1}^R UncDem_{ir} > (1 + 15\%) * S_i$
8	$CV_i < 30\%$	$\sum_{i=1}^R UncDem_{ir} > (1 + 0\%) * S_i$
9	$CV_i < 30\%$	$\sum_{i=1}^R UncDem_{ir} > (1 + 15\%) * S_i$

10	<i>#Months when $(CV_i < \text{Agg. CV}) > 70\% * \text{Total \#Months}$</i>	$\sum_{i=1}^R \text{UncDem}_{ir} > (1 + 0\%) * S_i$
11	<i>#Months when $(CV_i < \text{Agg. CV}) > 70\% * \text{Total \#Months}$</i>	$\sum_{i=1}^R \text{UncDem}_{ir} > (1 + 15\%) * S_i$

Concerning the items eligibility criterion of stock/demand, it was first considered as covering the days until the markdown period, by the rationale mentioned in 4.2.2. To simplify, that is going to be referred to as “Markdown stock/demand relation”. For comparison purposes, the simulation was then reperformed with the stock/demand criterion covering just one month. It is expected that the “Markdown stock/demand relation” generates a broader set of eligible items (bigger scope of the model) when compared to the 1-month relation, possibly at the cost of the forecast accuracy.

Average results

Markdown Stock/Demand Relation

Table 11 and Table 12 present the average results obtained for the seven runs by the “Markdown stock/demand relation”.

Table 11 - Catalogue/Regions Impacted from each pair of Criteria in the Historical and Decision Period and associated Forecasting Error – Markdown Stock/Demand Relation

Eligibility criteria	Historical period					Decision period				
	Avg. catalogue impact					Avg. catalogue impact		Avg. forecasting error		
Pairs	%IDs	% regions affected	max. % catalogue blocked regionally	%GTV	GGP%GMV	%GTV	GGP%GMV	wRMSE	wSMAPE	wSMAPE_over f
1	75% ¹²	100%	80%	71%	33%	75%	33%	60.6	122%	-
2	30%	100%	39%	36%	34%	31%	36%	42.6	113%	19%
3	28%	100%	37%	34%	34%	29%	36%	44.2	113%	18%
4	8%	100%	11%	8%	36%	7%	38%	14.2	100%	8%
5	8%	100%	11%	8%	36%	7%	38%	14.5	99%	8%
6	4%	100%	6%	4%	37%	3%	39%	7.4	93%	5%
7	4%	100%	5%	3%	37%	3%	39%	7.5	93%	5%
8	0%	0%	0%	0%	-	0%	-	-	-	-
9	0%	0%	0%	0%	-	0%	-	-	-	-
10	1%	100%	1%	1%	31%	1%	33%	13.1	102%	11%
11	1%	100%	1%	1%	30%	1%	33%	13.1	101%	12%

¹² Value is different from 100% as stock-outs are excluded from the model

In Table 11, the average impact on the catalogue from each pair of items eligibility criteria in the historical period is represented by indicators as: the percentage of items managed in volume (%IDs) and in top line (%GTV); as well as regional indicators, as the share of regions affected, and the maximum share of catalogue blocked by region. The actual catalogue impacted in the decision period is presented as well, together with the forecasting error. The percentage of GTV affected by each pair is generally lower in the decision period compared to the historical period, what might be linked to the introduction of new products, different stock levels or changing demand patterns.

Regarding the error metrics presented, the first two concern all the observations, to perceive the forecasting error evolution. The third, $wSMAPE_{overf}$, concerns only the over forecasted observations, and it is the error metric to be included in the GGP simulation expression (equation 5.1). It is possible to observe how inferior the $wSMAPE_{overf}$ values are in comparison with $wSMAPE$ values. This has to do with the way how the weight is calculated. As explained in 5.1, the weight given to each over forecasting case in $wSMAPE_{overf}$ is in relation to the total of cases (with both right, under and over forecasting cases). As result, unlike for $wSMAPE$, the sum of the weights of the considered instances will not make up 100%, and therefore the error will be smaller. The over forecasting weighted $sMAPE$ in all the runs was under 30%, which means it can be interpreted like $MAPE$, validating its use in the simulation.

The values in Table 11 (from pairs 1 to 9) confirm the previous expectations: the catalogue affected goes down as one applies the eligibility criteria with higher severity of the threshold value, and even more as the two conditions are applied in combination. The forecasting accuracy, in turn, gets better. The threshold of 30% for the CV (pairs 8 and 9) produces an empty subset of items (no item belongs to a GBFC / GFC with a CV inferior to 30%). The frequency-based criterion of variability (pairs 10 and 11) generates a slightly bigger set of items than the “CV < 30%”, but smaller than the “CV < 78%”. Its forecasting error is at the same time bigger than that of the pairs 4 to 7, so the outcomes are definitely worse. In all, as previously noted in chapter 4.1.2, there is a risk-opportunity trade-off as one applies the different pairs of criteria. A good compromise between the two seems to exist for combinations 4 to 7.

The simulation results from the application of the GGP increase expression (equation 5.2) are shown in Table 12, in relation to the period GGP and to the GGP managed (eligible by the model). The three scenarios are depicted in decreasing order of conservatism (for values of the profitability ratio increase of 0.06%, 8.05% and 20.52%) for each pair of eligibility criteria.

Table 12 - Simulation Results in the Decision Period from each pair of Criteria for the Worst, Average and Best-case Scenarios – Markdown Stock/Demand Relation

Eligibility criteria	Simulation – Average results						
	Potential losses (% Period GMV)	Worst case		Avg. Case		Best case	
		GGP%GMV increase: 0.06%		GGP%GMV increase: 8.05%		GGP%GMV increase: 20.52%	
		Only errors below 0.0599% yield GGP increase		Only errors below 7.45% yields GGP increase		Only errors below 17.03% yield GGP increase	
Pairs		Period GGP Increase (%)	Managed GGP Increase (%)	Period GGP Increase (%)	Managed GGP Increase (%)	Period GGP Increase (%)	Managed GGP Increase (%)
2	4.7%	-5.1%	-19.1%	-3.4%	-12.6%	-0.7%	-2.5%
3	4.2%	-4.6%	-17.5%	-2.9%	-11.0%	-0.4%	-0.7%
4	0.4%	-0.5%	-7.8%	-0.1%	-0.5%	0.7%	11.0%
5	0.4%	-0.5%	-7.6%	-0.1%	-0.2%	0.6%	11.3%

6	0.2%	-0.2%	-5.4%	0.1%	2.1%	0.4%	13.9%
7	0.1%	-0.2%	-5.1%	0.1%	2.5%	0.4%	14.4%
8	-	-	-	-	-	-	-
9	-	-	-	-	-	-	-
10	0.1%	-0.1%	-11.3%	0.0%	-4.2%	0.0%	6.8%
11	0.1%	-0.1%	-11.5%	0.0%	-4.4%	0.0%	6.6%

The relation in equation 5.3 that should be verified between the profitability uplift and the over forecasting error for a GGP increase to occur produces different risk thresholds for each of the three scenarios, presented in Table 12. Expectedly, a bigger uplift in profitability (as for the best-case scenario) leads more easily to an increase in the GGP, without requiring such a low over forecasting error, and vice versa.

Since no over forecasting error is below 0.06% for any eligibility pair, there are always losses in the GGP for the worst-case. The least negative pairs relative to the period GGP are 10 and 11 (smallest universe of items impacted, thus lowest GMV losses).

For all the three scenarios, the best percentual increase in managed GGP occurs for pairs 6 and 7, in specific 7, since it holds the lowest value of over forecasting error.

The average-case scenario already presents some increases in the GGP. Pairs 6 and 7 lead to positive results.

For the best-case scenario, all the pairs in which the sales variability criterion is applied in combination with the stock/demand one show positive results. The highest period GGP increase is obtained by pairs 4 and 5, where a wider universe of items pays off.

The average case should most probably be the considered scenario for drawing conclusions, with a moderate level of conservatism. Overall, the model allows for increases in the GGP value of the period covered by the decision. This increase is higher as the uplift in the profitability ratio increases and the over forecasting error decreases, with the compromise of the affected catalogue. Eligibility pairs 6 and 7 seem to be the ones leading to the best outcomes: they are the best in the average situation and perform comparatively well in the worst and best cases. The values of the period GGP increase are seemingly not very high. It is important to recognize, however, that they are the result of a considerable GGP uplift (between 2% and 14%) applying, in turn, to just approximately 3% of the period GTV.

1-month stock/demand relation

If, instead, the stock/demand condition would have considered just the 1-month period, the scope would have been significantly limited. Whereas the GTV affected is limited by the stock/demand condition on approximately 44% in the Markdown case, it goes down by 61% in this case, as shown in Table 22 from Appendix I. And the accuracy, contrary to what was questioned, does not benefit from this option.

The simulation results obtained by this 1-month relation are in

Table 23 from Appendix I, showing worse values. Concluding on the two options, the model produces better improvements in profitability when considering the longer time horizon (until the markdown season) instead of the one-month period.

Individual results

Results of each individual run for the markdown stock/demand relation are in Appendix J.

In Table 24, the average catalogue impacted and the forecasting error are presented. Individually, there are no significant differences in the accuracy values obtained for the first runs relative to the others (although the first have fewer past data). Since stock is uploaded along the season, new items appear at any time, which can be a justification for the accuracy values not to improve with time. Concerning the percentage of eligible items by the application of the stock/demand relation, the %GTV decreases the closer it gets to the markdown season (as there is less time for the demand to sell out the stock) or to the end of the season, for the runs in the MD period.

The simulation results are presented in Table 25. It is beneficial to include the first months, where a higher percentage of the GTV is impacted and no additional risk (in over forecasting) is incurred, resulting in overall bigger increases in profitability values. Hence, running the model from the end of the first month onwards seems beneficial.

It is relevant to add that the company may opt for a given rule for selecting the items at each point in time according to its willingness to risk: for instance, by the beginning of the season the company may find it more acceptable to risk, as there is still a long time until the end of season, and the other way around.

Simulation with a higher forecasting accuracy

To get a sense of how the results could be improved with a more accurate forecast, the simulation was reperformed assuming an improvement of 60% of the over forecasting error compared to the Logistics forecast. Results from this study are shown in Appendix K.

The values get better for all the cases. However, even with a significantly better forecast accuracy, the uplift in profitability is not enough to compensate for the expected sales losses in the worst-case scenario. In the average and best cases, the increases in managed GGP range now from 6% to 18% (for pairs 6 and 7), but the best values of period GGP increase are obtained by pairs 4 and 5 in the average case, and by pairs 2 and 3 in the best case – less strict criteria than in the real scenario. The values of GGP increase are now more impacting.

5.3 Simulation Takeaways

In conclusion, it has been proven how key an accurate forecast is for the model to generate good results. If the universe of items needs to be severely restricted for producing more reliable projections (and thus limit the risk), then the increase in profitability might be residual. A forecasting tool that allows for a good accuracy to be produced without excessively restricting the affected catalogue should leverage relevant improvements in profitability. Finally, the rules for managing catalogue should be aligned with the strategic objectives and appetite for risk at each moment.

Methods for controlling the risk within each decision period, as detailed in 4.2.3, are aimed at correcting badly performing decisions, acting as a risk buffer. They were not materialized in this simulation of results, but expectedly have a positive contribution to the overall performance of the model.

Lastly, this simulation was conducted for all items from the catalogue that would satisfy the eligibility conditions, where no continuity items have been directly selected (but rather indirectly by the variability condition). There is still a window of opportunity for applying the model right in the beginning of the season (November, for SS21) for continuity items, that represent 75%-85% of items sold in that first month of the season.

6 Conclusions and Future Work

6.1 Conclusions

In a complex industry where the costs to serve can be high – and are becoming generally higher over time due to increasing delivery costs -, and the inventory is limited, protecting the Company margins by adopting a more selective assortment strategy is seen, more than ever, as a source of competitive advantage. There are location-specific dynamics that affect the cost-effectiveness of selling the same item to different regions, and if the Company can act more actively on its catalogue in order to account for those differences, the outcomes are likely to be positive.

As said along the work, the decision of blocking supply has an intrinsic risk of not selling the items in the regions that were left open, contrary to the expectations (associated to an over forecasting error). The bigger the universe of items affected (or the opportunity), the bigger the risk as well (of absolute GTV losses). Other strategic considerations should affect the decision to be taken, as a minimum representativity of the catalogue to sustain in specific (or all) regions, customer segments, brands, among others. A proper alignment with the Commercial Team should not be neglected, since knowing the exact promotion dates (that drive profitability and sales) is critical for a good performance of the model.

The idea of a continuous assortment optimization cycle, that incorporates the most recent items in catalogue, demand patterns and performance of the items, is feasible with an automatic analytical tool, likely to embed metrics and KPIs, a forecast that can be rerun along the season and other risk mitigation rules. The suggested approach can be followed: to act right in the beginning of the season for continuity items and in events as drops, and in-season for season original items. Also, the timings and the pace of the model have to do with the forecast used and with the acceptable level of risk for the Company; it is flexible and can always be adjusted to the situation. Lastly, this tool should be managed by a Product Team with the needed technical skills to do the best use of it and to validate the recommendations prior to implementation.

The simulation performed was intended to estimate the economic impact of the model, thus proving its relevance. The main takeaways of it are that profitability increases are achievable with this model, running along the season, for a subset of eligible items filtered by their superiority of projected demand relative to stock level (a must-have condition) and by their sales variability. The results can be improved with a more accurate forecast - with inferior over forecasting error – that leads to a smaller percentage of sales losses while producing the best results for less strict eligibility pairs: therefore, impacting a larger share of the catalogue. The consequence is higher values of GGP increase relative to the as-is situation. Although the simulation was theoretical and so, could not replicate the suggested functioning of the model in completeness, in specific the monitoring dimension, it is expected that its inclusion only helps to control risk and enhances the model.

It is never too much to stress the foundational role of the forecast for the use case: it feeds the decision, and the lost sales are intimately linked to its quality. It is needed with a significant granularity level, but the short time periods suggested to be covered by the decision should allow to balance the negative effect of the former. Other components could be added to it, to increase its feasibility, as an attribute-based logic. Then, the specific rules to embed in the model, for selecting items and monitoring the decision, should be finetuned according to the forecast in place.

The project presented in this document has been highly conceptual, aimed at maturing important business considerations for the execution of a selective assortment optimization strategy, in the form of rules, metrics and general settings of a possible decision model, as well as needed capabilities and required integrations within the organization. In all, it was intended to build a decision model framework while proving the concept's value. The more practical part of implementation is now future work, to be addressed in 6.2.

As final note, it should be said that, from a bulk of other initiatives with profitability concerns, this project challenges the *status quo* of catalogue management at Farfetch, rather passive and undifferentiated, and proposes a more financially conscious strategy. It can be a source of competitive advantage, that is already being practiced by other retailers, and that could generally benefit the Company. Its potential is even more obvious for cases where the offer is so limited (relative to demand) that only gains could come from the decision – as for drops and some highly demanded items. To sum up, the project raises a pertinent topic and a new way of looking at the assortment, that is the beginning of a path to pursue, adjusted to the needs of the Company.

6.2 Future Work

To deploy this model, a three-stages roadmap can be followed: consisting of a pilot project, then a roll-out and lastly institutionalization. To be able to initiate it, there are capabilities needed by the Company in the short-term.

Short-term:

A solid analytical tool, comprised of a good performing forecast at the needed level of granularity and of the framework proposed, is the first thing to build.

Concerning the forecast, as suggested along the document, it should be plugged with the promotions dates, it could include both real sales data and daily visits, it should cover the interdependency of products in the catalogue (*i.e.*, substitution effect) and it could adopt the attribute-based logic to produce a forecast close to the ID x region level that even allows for projections for newly introduced items. It is key for a good performance of this model.

When it comes to the decision model framework, it can follow the proposed structure. Adding to that, the feasibility assessment step should include an important dimension in the future - items' role in the overall catalogue:

Items' role in the overall catalogue

Besides the addressed strategic considerations (as sales targets in specific regions or appetite for risk), when deciding on the items to include in each regional assortment the Company should attend to the role items play in the overall catalogue, that can be of different types as presented in Table 13.

Table 13 - Types of Contributions of the Items to the Catalogue

Area of impact	Specific role	Description
Financial	Sales volume/top line builders	Items with high selling rotation, critical for line targets for growth
	Margin/bottom line builders	High margin items, critical for bottom line targets
Customer engagement	Website traffic builders	Critical items to bring in traffic because of appeal, novelty or brand, or an entry door for good customers
Platform and brand image	Credibility boosters	Items relevant to the brand positioning and message. For instance, they can legitimize Farfetch's claim as a luxury store
	Choice creators	Unique items important for creating variety and thus supporting the USP of the catalogue

These roles can be measured as follows: financial role is straightforward and can be based on past sales data; website traffic building can be derived from visits; concerning platform and brand image contributions, those are way harder to measure (and more subjective) - a way to systematically quantify them should be devised. A possible way to incorporate each of these roles in the decision model is by introducing strategic KPIs at the SKU level, each related to one of the dimensions, to be considered in the production of an output aligned with the specifications (*e.g.*, a minimum level of the website traffic that is desirable). In all, this add-on should be further studied, as it is an important element in a catalogue decision.

Once the tool is ready for use, with a minimum level of maturity that can then be better calibrated along the implementation process, the Company can start the pilot.

Medium-Term:

The medium-term has to do with the live trial of the tool, from pilot to institutionalization, for the 1P Partners. The test should be progressive, starting by items with less risk (in the pilot) and expanding as convenient (in the rollout and institutionalization phases), possibly following the sequence: drops, continuity items, season original items from quite stable GBFCs. In all these phases, it is critical to better synchronize the tool - in terms of rules, metrics, and model settings as timings - with the business dynamics and to ensure that the Organization develops the needed skills to interact with the system.

Long-term:

In the long-term, this assortment optimization program could be sold as a catalogue management service within FPS, for 3P Partners, after the proof of concept and real results have proven solid in the Marketplace. With FPS Partners, there is the needed visibility in terms of stock and orders being processed (therefore, to sales and profitability values to the different markets).

Institutionalizing this strategy for 3P Partners not subscribing to FPS in the Marketplace could be done as well, however there would need to be some kind of financial incentive to the Partners that should be revised in the contracts.

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APPENDIX A: Farfetch Operations Workflow

When it all starts and how products come to life at the FARFETCH Platform

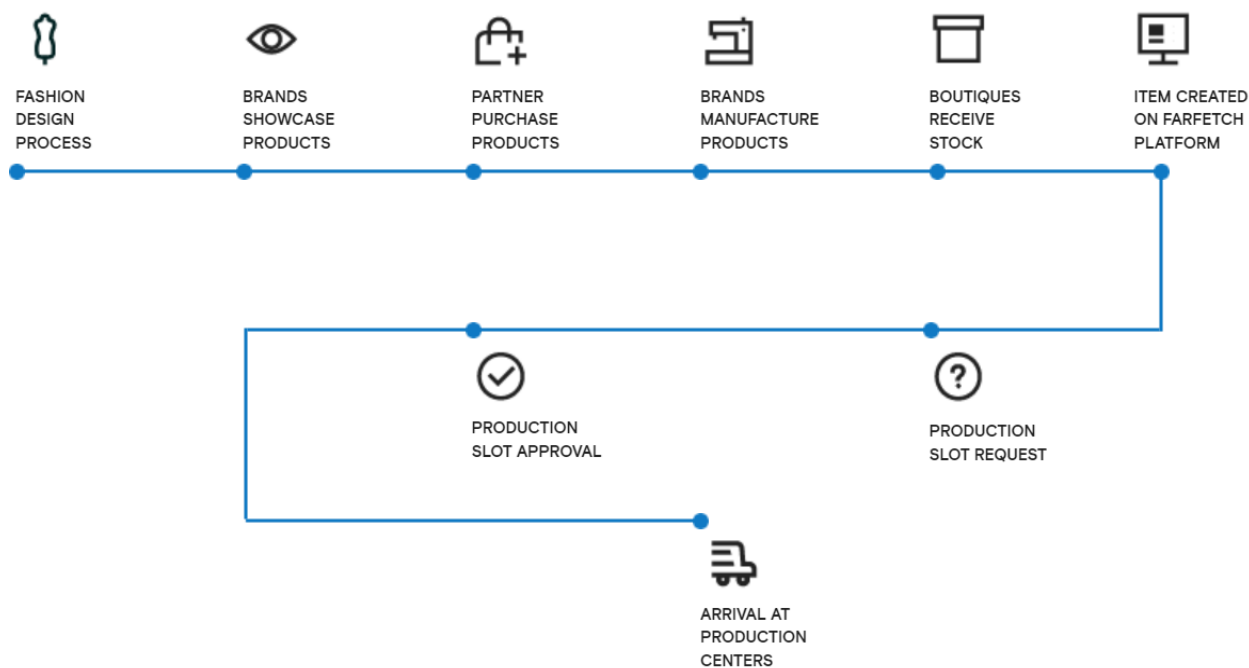




Figure 31 – Farfetch Operations Workflow (Farfetch Digital Learning, 2022)

APPENDIX B: Issue Tree for Brainstorming the Catalogue Management Model

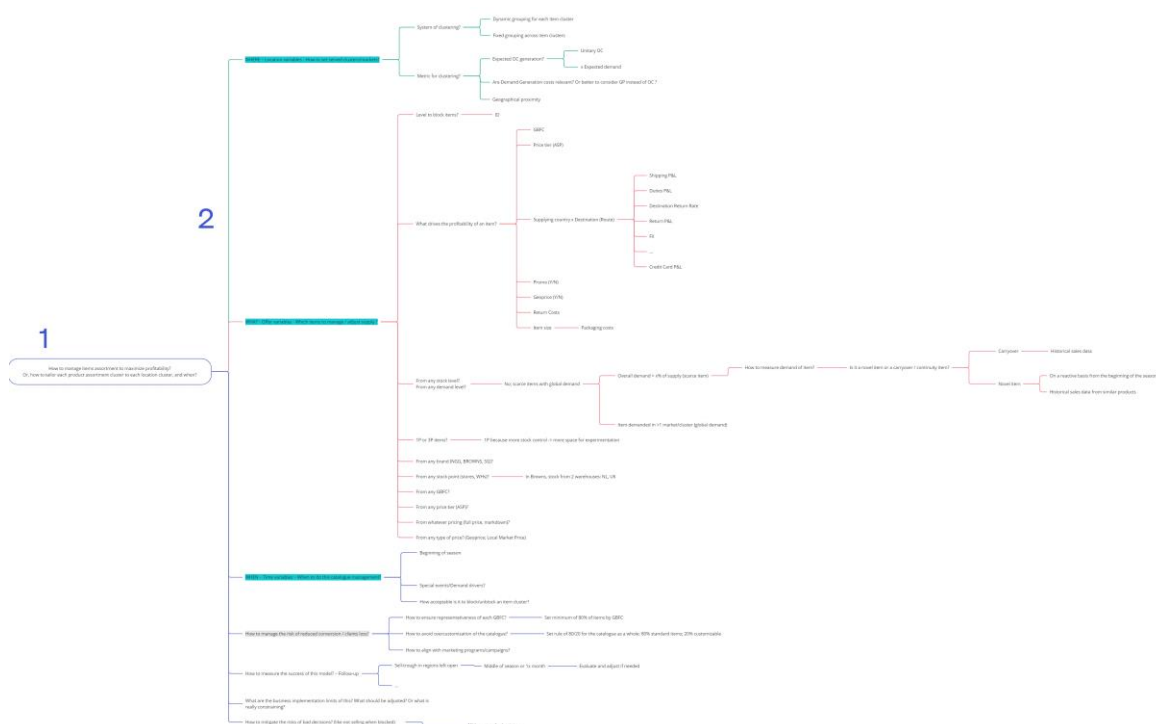


Figure 32 – Issue Tree built while brainstorming the Catalogue Management Model

A zoom-in to each component in the tree is provided next for better reading:

1

How to manage items assortment to maximize profitability?
Or, how to tailor each product assortment cluster to each location cluster, and when?

Figure 33 – Issue Tree: Main Question the Model answers to

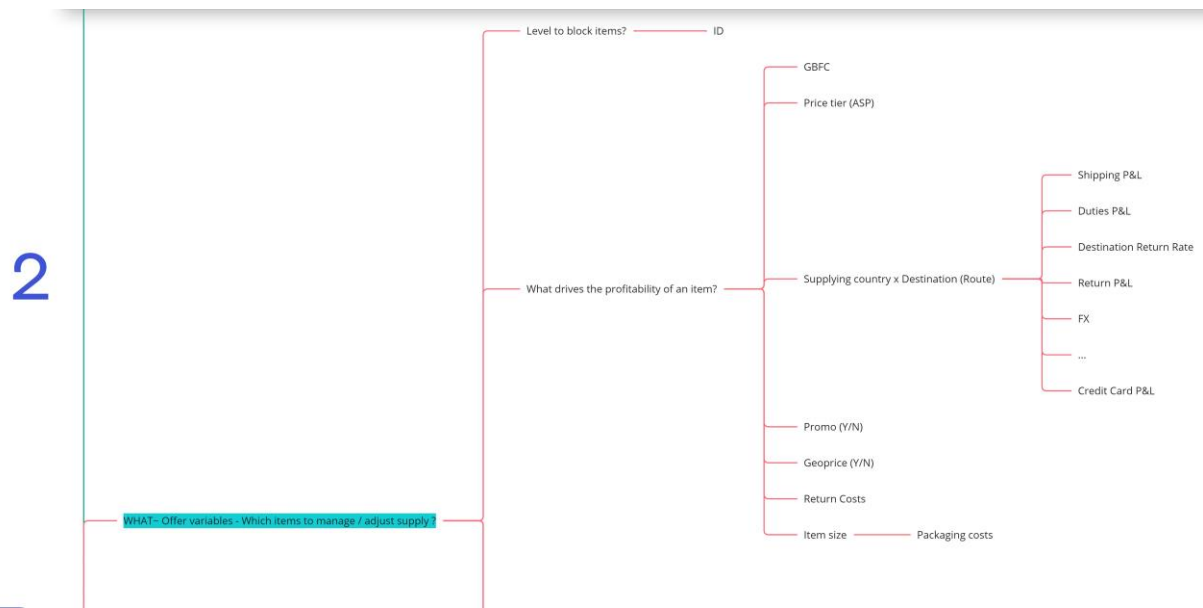


Figure 34 – Issue Tree: Selection of the Items to manage with the Model (Part I)



Figure 35 - Issue Tree: Selection of the Items to manage with the Model (Part II)

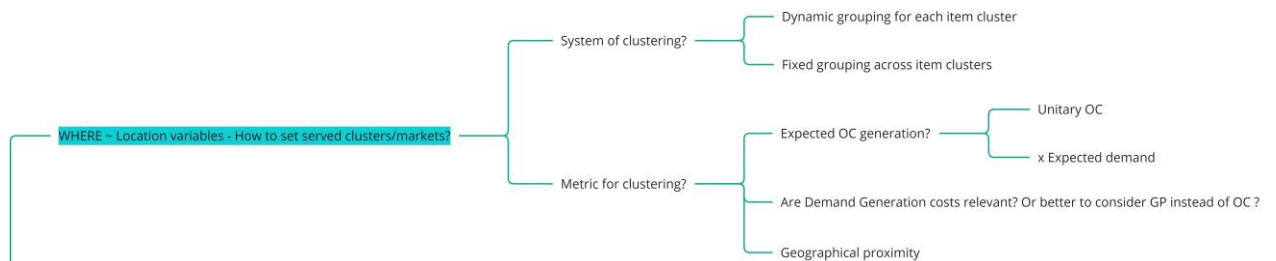


Figure 36 - Issue Tree: Selection of the Regions to manage with the Model

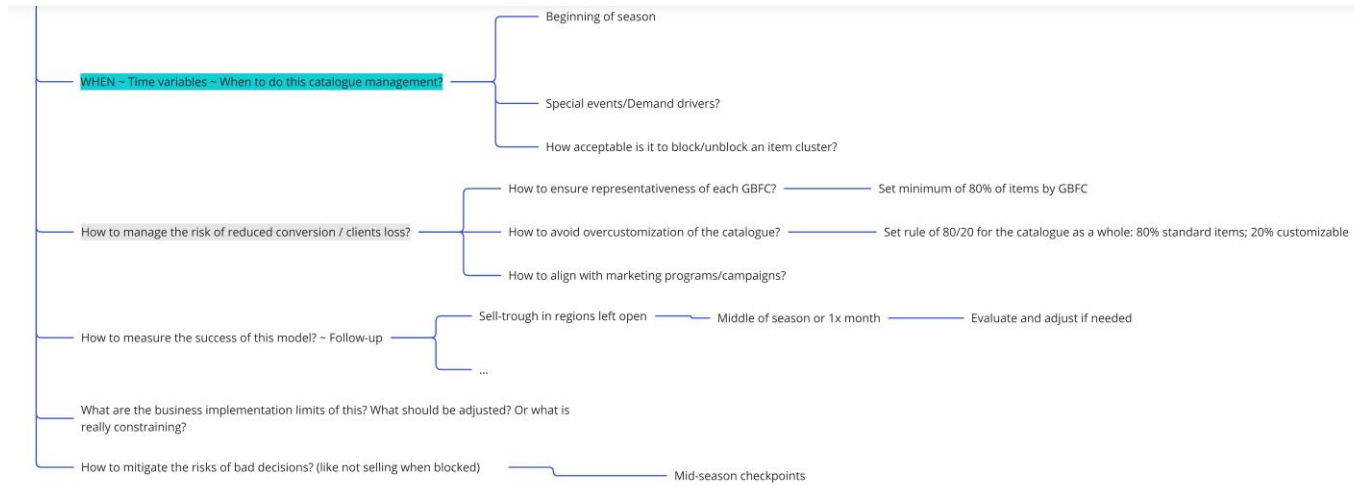


Figure 37 - Issue Tree: Definition of when to run the Model, as well other considerations (Risk Management, Monitoring, and Implementation)

APPENDIX C: Mathematical Definition of the Problem

This is a problem of deciding the optimal combination of products-regions to supply that maximizes overall profitability, in a scenario with multiple stock points.

It is important to mention that the substitution effect, *i.e.*, the share of demand that would transfer to an alternative product if the product demanded was not available, is not encompassed by this formulation, for the sake of simplicity.

The parameters are defined in Table 14, and the decision variable in Table 15, followed by the objective function and restrictions.

Table 14 – Parameters Definition

Parameter	Definition
$GBFC_x$	GBFC carried by the retailer, $GBFC_x \in \{1, \dots, GBFC_x\}$
p	Product ID carried by the retailer, $p \in \{1, \dots, P\} \subset \{1, \dots, GBFC_x\}$
i	Product ID eligible by the model, $i \in \{1, \dots, I\} \subset \{1, \dots, P\}$
r	Shipping (customer) region, $r \in \{1, \dots, R\}$
s	Stock point, $s \in \{1, \dots, S\}$
S_{is}	Stock level of product i in stock point s
P_{sr}	Profitability of serving route s - r (as GGP%GMV)
P_{ir}^{13}	Profitability of serving product i to region r (as GGP%GMV)
ASP_i	Average Selling Price (ASP) of product i
$UncDem_{ir}$	Forecasted (unconstrained) demand, in units, of product i in region r
$CDem_{ir}$	Forecasted (constrained by decision and by stock levels) demand, in units, of product i in region r
Sh_{ir}	Share of stock of product i consumed by region r
CV_i	Demand coefficient of variation of product i 's GBFC (or GFC)

¹³ The profitability value of each pair product-region is a weighted average of the profitability of each route (stock point-shipping region) by the percentage of stock in each stock point

Regarding the set of product IDs eligible by the model, i is a given product ID p for which:

$$\sum_{r=1}^R UncDem_{ir} > (1 + X\%) * \sum_{s=1}^S S_{is} \quad (C. 1)$$

$$CV_i < Y\% \quad (C. 2)$$

C.1 and C.2 are the items eligibility conditions: items with a forecasted demand exceeding in $X\%$ their stock level, and with a moderately stable demand pattern, should be managed by the model. These conditions to select items are further explored in Chapter 4.

Table 15 – Variables Definition

Variable	Definition
X_{ir}	Binary of supply of product i to region r , $\in [0,1]$

where:

$$Sh_{ir} = \frac{X_{ir} * UncDem_{ir}}{\sum_{r=1}^R X_{ir} * UncDem_{ir}}, \forall i, \forall r \quad (C. 3)$$

$$CDem_{ir} = Sh_{ir} * \sum_{s=1}^S S_{is}, \forall i, \forall r \quad (C. 4)$$

$$P_{ir} = \sum_{s=1}^S \frac{S_{is}}{\sum_{s=1}^S S_{is}} * P_{sr}, \forall i, \forall r \quad (C. 5)$$

Objective function:

$$\begin{aligned} & Max. \sum_{i=1}^I \sum_{r=1}^R CDem_{ir} * P_{ir} * ASP_i \\ & = Max. \sum_{i=1}^I \sum_{r=1}^R Sh_{ir} * \sum_{s=1}^S S_{is} * P_{ir} * ASP_i \\ & = Max. \sum_{i=1}^I \sum_{r=1}^R \frac{X_{ir} * UncDem_{ir}}{\sum_{r=1}^R X_{ir} * UncDem_{ir}} * \sum_{s=1}^S S_{is} * P_{ir} * ASP_i \end{aligned} \quad (C. 6)$$

s.t.

- GBFC (proxy of catalogue) representativity to ensure in every region:

$$\frac{\sum_{i \in GBFC_x}^I (1 - X_{ir})}{\sum_{i \in GBFC_x}^I 1} \leq 20\%, \forall GBFC_x, \forall r \quad (C. 7)$$

The restriction presented has to do with a catalogue integrity to maintain globally, that could be expressed by a minimum percentage of each GBFC to offer in every location (80% is the suggested value). This condition is further explored in Chapter 4.

The solving of this problem will follow a more practical method compared to a pure optimization problem, to be addressed in Chapter 4. Still, the formulation helps define the problem in terms of the variables involved, restrictions and objective function.

APPENDIX D: Data Science Forecast Specifications

Table 16 and Table 17 summarize the demand forecasting versions under development by the Data Science Team: the constrained and unconstrained scenarios respectively.

Table 16 - Specifications for the Unconstrained Forecasting Model

Frequency	Monthly (18 months)
Aggregation/Granularity	GBFC (filtered by Season Type & Price Type)
Output	Gross Units + GTV USD
Season Type	SS, AW, CO aggregated
Price Type	FP Only
Region	N/A

Table 17 - Specifications for the Constrained (BAU) Forecasting Model

Frequency	Monthly (18 months)
Aggregation/Granularity	GBFC x Season Type x Price Type x Region
Output	Gross Units + GTV USD
Season Type	SS, AW, CO
Price Type	FP, MD
Region	Europe, North America, China Region, APAC (Excl. China Region), CIS, LATAM, Middle East, ROW

Predictions are made for GBFCs with at least one unit sold or one unit of stock online in the previous 12 months. The monthly update of the two versions is valid for the aimed use case, allowing the decision to be reassessed once a month for the most recent demand patterns. The forecasting time horizon also fits, as it covers the decision period (within a season, the decision period should be inferior to 9 months).

However, no forecast is being developed with the needed granularity level (close to the ID x Region). Firstly, the region is essential to have, which it is not covered by the unconstrained version. The unconstrained version is at the GBFC, too high level for the objective (it is not an option to block an entire GBFC). The BAU provides a more granular forecast, at the GBFC x ST x PT x Region (*e.g.*, Women x Fendi x Clothing x Dresses x AW x FP x LATAM). However, it is still a quite high level for the purpose.

If the Product ID x Region level is not feasible at all (for accuracy reasons), at least an intermediary level of aggregation between that and the GBFC x ST x PT x Region would be desirable. It could include, for example, product attributes such as the style, color, fabric, etc.

An alternative attribute-based forecasting approach to the previous (at the GBFC x ST x PT x Style x Color x Fabric x Region) would be at the product ID level while modeling each ID as a set of attributes. For instance, as explored in 2.2.3, some high-fashion companies, as Zara, predict at the SKU level for assortment purposes by a learning method of the attributes of the high-selling products, in order to extend their demand distribution to other products with the same attributes (even if they are new to the assortment).

To sum up, an attribute-based forecast, whether by the first or second alternatives, could be considered: it would be possibly more feasible than a forecast at the ID level (without the attributes dimension) and would be implementable in the current use case.

APPENDIX E: Logistics Forecast Specifications

The method used by Logistics calculates period-to-go (PTG) sales by a linear projection of season-to-date sales (STD), adjusted by the sales curve of the previous year through an uplift effect. Therefore, it is the result of the following expression:

$$PTG\ Sales = STD\ Sales * \frac{PTG\ days}{STD\ days} * Uplift \quad (E.1)$$

The STD days considered, for each pair product ID x Region, are the minimum value between the STD days and the days online of the ID in that region.

The forecasted units are not limited by the momentary stock levels, therefore the forecast is unconstrained, as needed.

It is straightforward and does not consider important effects as the substitution between items. In addition, it only generates projections of sales for the pairs Product ID x Region with past sales (as a result of E.1), being purely reactive.

There are three development versions of the forecast, that vary in the uplift factor. They are summarized in Table 18, regarding the calculation and input data used for each factor.

Table 18 - Logistics Forecasting Model Versions

Version	Field	PTG Linear Sales	Uplift	PTG Sales
v1	Calculation	$STD\ Sales * \frac{PTG\ days}{STD\ days}$	-	$PTG\ Linear\ Sales$
	Input Data	Units sold at Product ID x Region level	-	-
v2	Calculation	$STD\ Sales * \frac{PTG\ days}{STD\ days}$	$\frac{Past\ year\ PTG\ Sales\ Proportion\ (\%)}{Past\ year\ STD\ Sales\ Proportion\ (\%)}$	$PTG\ Linear\ Sales * Uplift$
	Input Data	Units sold at Product ID x Region level	GBFC; GFC if GBFC inexistent	-
v3	Calculation	$STD\ Sales * \frac{PTG\ days}{STD\ days}$	$\frac{Past\ year\ PTG\ Avg\ Daily\ Sales}{Past\ year\ STD\ Avg\ Daily\ Sales}$	$PTG\ Linear\ Sales * Uplift$
	Input Data	Units sold at Product ID x Region level	GBFC; GFC if GBFC inexistent	-

V1 simply makes a linear projection of sales. It can be seen as the Naïve case, the baseline for accuracy comparison, where the prediction is that sales will be the same as before, simply adding the adjustment for the days considered.

V2 and v3 already include the uplift factor: from v2 to v3, the uplift calculation changed to focus on PTG performance.

APPENDIX F: Clusters of Regions

Starting from a Company defined regions clustering system (in Table 19) mainly based on geographical proximity, it is critical for this application to evaluate if there are outliers, profitability-wise, within each cluster. If that is the case and if the country concerned has a considerable share of Farfetch total sales, it is proposed to change the country to another group that better represents it.

Table 19 – Company Regions System

Region	# Countries
APAC	14
Canada	1
Europe	35
LATAM	14
ROW	171
Russia	1
UK	1
US	1

The assessment of the Company regions system is presented hereby. For the 15 countries accounting for 82% of the total GTV, a comparative analysis of the countries' GGP%GMV in relation to their regions' GGP%GMV (expressed by the relative difference) was conducted. The results are presented in Table 20, where the countries are ranked by descending order of contribution to the Group GTV.

Table 20¹⁴ - Relative difference of the GGP%GMV of the Top 15 Countries to their Region

Shipping Country	Region	Relative difference from Region's GGP%GMV
United States	US	0%
China	APAC	-27%
United Kingdom	UK	0%
Hong Kong	APAC	6%
Mexico	LATAM	-1%

¹⁴ Data is from 11/21 to 5/22, to show the most recent indicators. Russia and Ukraine were removed from the assessment, as they are markets no longer served by Farfetch

Korea, Republic of	APAC	-1%
Australia	APAC	7%
Germany	Europe	-10%
Italy	Europe	-11%
Japan	APAC	23%
Saudi Arabia	Middle East	-15%
France	Europe	2%
U.A.E.	Middle East	1%
Canada	Canada	0%
Switzerland	Europe	31%

Differences, in absolute values, above 20% are considered significant, which happens for: China (27% below APAC value), Japan (23% over APAC value) and Switzerland (31% over Europe value). These values flag a possible need to remove the countries from the respective region. To confirm the need, a comparison of the GGP%GMV of the regions with and without the country concerned, and similarly of the country if in the “mother” region vs independently, is presented next, for each of the three flagged cases.

Firstly, it was performed to the China case, in Figure 38.

	GGP%GMV		GGP%GMV
APAC with China	17.7%	China in APAC	17.7%
APAC without China	20.1%	China independent	12.9%
Difference	2.5%	Difference	-4.8%
Relative Difference	14%	Relative Difference	-27%

Figure 38 – GGP%GMV of APAC As-Is vs without China, and of China in APAC vs independently

It is possible to verify that the profitability value of APAC without China goes up by 14% relative to its prior value. In turn, China’s profitability value when considered in isolation goes down in 27% relative to the prior value. That is a significant difference, hence it makes sense to consider China separately from APAC.

Having validated the decision to separate China from APAC, it is necessary to reassess if Japan still shows significant differences relative to the “new” APAC, without China. The same analysis was therefore performed to the Japan case, in relation to APAC without China, and the results are shown in Figure 39.

	GGP%GMV		GGP%GMV
APAC without China	20.1%	China in APAC	20.1%
APAC without China and Japan	19.9%	China independent	21.7%
Difference	-0.3%	Difference	1.6%
Relative Difference	-1%	Relative Difference	8%

Figure 39 - GGP%GMV of APAC As-Is (without China) vs without Japan, and of Japan in APAC (without China) vs independently

APAC without China and Japan shows a profitability value in 1% lower to that of APAC without China. And Japan, if considered as an independent region, would have an uplift of 8% compared to the previous value. As the differences now, having removed China, are inferior to the 20% threshold of significance, Japan should remain part of APAC.

Finally, the same analysis was performed to Switzerland, in Figure 40.

	GGP%GMV		GGP%GMV
Europe with Switzerland	25.4%	Switzerland in Europe	25.4%
Europe without Switzerland	24.9%	Switzerland independent	33.2%
Difference	-0.5%	Difference	7.8%
Relative Difference	-2%	Relative Difference	31%

Figure 40 - GGP%GMV of Europe As-Is vs without Switzerland, and of Switzerland in Europe vs independently

Removing Switzerland from Europe leads to a residual relative 2% decrease to Europe's profitability. And while 31% is a significant difference between Switzerland's profitability relative to its region's value, Switzerland's share for total GTV is just 1.3%, not very significant (it is the lowest ranking of the 15 countries; US, for instance, accounts for 20%). For that reason, it is proposed that Switzerland remains part of the Europe region.

To conclude, the regions list defined by Farfetch is maintained except for China, that deserves an independent region, for the present use case.

APPENDIX G: Analytics Tool Process Diagram

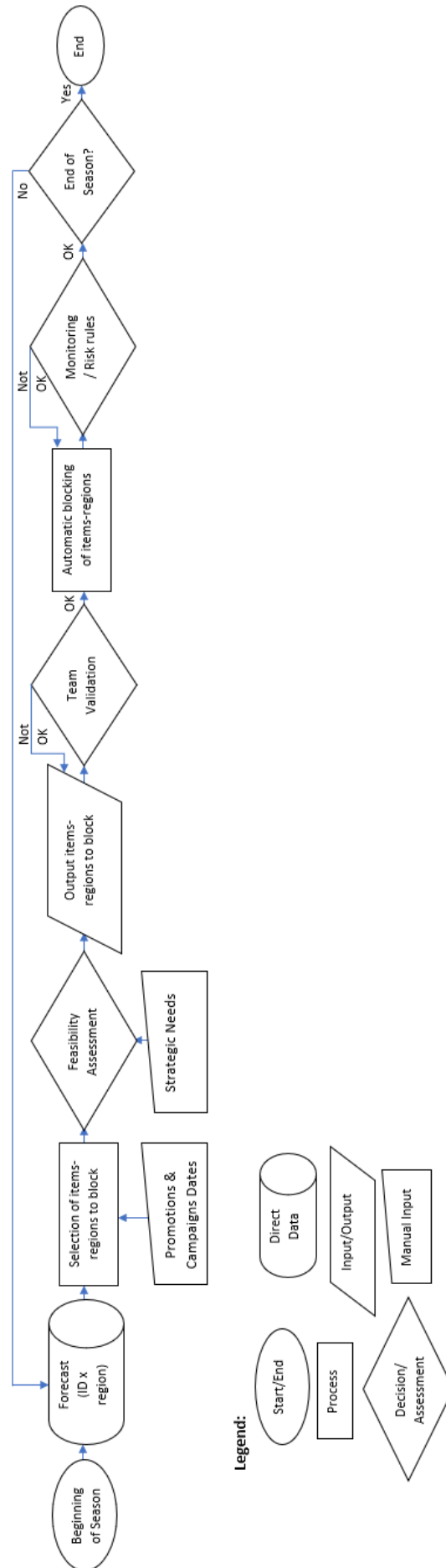


Figure 41 – Analytics Tool Process Diagram

APPENDIX H: Forecasting Metrics Tutorial

Goal

This appendix illustrates some of the difficulties in finding a single metric to guide the efforts in forecasting demand at a product ID level, following the guidelines of the Data Science Team at Farfetch (Farfetch Data Science (2021); Sarra (2022)).

What is a metric?

A metric tries to distill the performance of a prediction model into a single number. Ideally this number will get smaller if the model produces more accurate predictions. Some of the relevant properties of the metrics are the following:

Interpretability

MAPE (Mean Absolute Percentage Error) is a very interpretable metric:

$$MAPE = \frac{1}{n} \sum \frac{|y_{true} - y_{pred}|}{y_{true}} \quad (H. 1)$$

It essentially sums up the errors and normalizes them with respect to the observed true value, then averages it across all observations. MAPE tells us how many percentage points the predictions are off on average with regard to the actual observed value.

RMSE (Root Mean Square Error), on the other hand, is much harder to interpret:

$$RMSE = \sqrt{\frac{1}{n} \sum (y_{true} - y_{pred})^2} \quad (H. 2)$$

Clearly RMSE will still get bigger when the predictions and actuals are further apart from one another (and smaller vice-versa) but there is no direct interpretation of the resulting number - a MAPE of 10 is easy to explain: on average the predictions are off by 10%; RMSE lacks such an easy interpretation.

Robustness to zero

Often times time series can have zeros in the actuals. Looking at the formula for MAPE, it is a problem (metric undefined due to division by zero). Therefore, MAPE has no robustness to zero values, and even a single zero observation in a time series will make the metric undefined. RMSE on the other hand does not even contain a fraction and thus does not suffer from this problem.

Scale (in-)variability

A limitation of RMSE, contrary to MAPE, is its scale variability: as in the former there is no normalizing factor, the actual scale of the time series is a contributing factor to the scale of the error. This mean it is difficult to use RMSE as a metric to compare time series on vastly different scales.

Symmetric with respect to over- and under forecasting

A curious property of MAPE is that it does not punish over- and under forecasting the same, which is not an issue with RMSE.

Example:

Table 21 – Example of MAPE Assymetry

Time Series	Period	y_{true}	y_{pred}	$y_{true} - y_{pred}$
1	2020-01	10	20	-10
1	2020-02	20	10	10

$MAPE(\text{Time Series} = 1) = (|-10|/10 + 10/20) / 2 = (1 + 0.5) / 2 = 0.75 = 75\%$

Here, the error in absolute terms is the same for both observations (=10) but they contribute unequal amounts to the final MAPE number (1 vs 0.5). Specifically, the over forecasting period contributes twice as much to the overall MAPE as the under forecasting one.

This can be problematic since by looking only at MAPE the picked model would always be one that under forecasts, rather than over forecasts (even if all the individual errors are the same, just with different signs).

Robustness to outliers

Finally, RMSE is very sensitive to outliers (due to the square in the RMSE formula), whereas MAPE is much less sensitive.

What about SMAPE?

sMAPE (symmetric mean absolute percentage error) is another metric which tries to solve some of MAPE's problems:

$$sMAPE = \frac{2}{n} \sum \frac{|y_{true} - y_{pred}|}{|y_{true}| + |y_{pred}|} \quad (H. 3)$$

It is quite similar to MAPE, with some important differences. First off, not only y_{true} is in the denominator but rather the sum of y_{true} and y_{pred} . This means that for the metric to be undefined both y_{true} and y_{pred} have to be zero. And, if that is the case, one can easily insert $sMAPE = 0$ since if both prediction and actual are 0 it only makes sense to say it was a perfect forecast (*i.e.*, 0 error).

In essence sMAPE is interpretable just like MAPE if it is $\sim < 30\%$ and becomes less so the closer it gets to 200%. It is still much more interpretable than RMSE and solves the issue of zeros in actual observations that MAPE has, thus serving as the north star metric for the Company.

Why is finding a metric hard specifically for product ID forecasting?

The dataset at the GBFC, and even more pronounced at the ID level, contains a lot of zero observations due to the high granularity of the forecast, and so it is not possible to use the otherwise easily interpretable MAPE.

And since the observations cover a wide range of values (the smallest time series have less than a couple or no units at all while larger ones contain thousands of units per observation), it is not possible to easily use a scale variable metric as RMSE.

Considering the previous, the Data Science team has settled on sMAPE and RMSE. While neither of these metrics captures the whole picture, together they do a decent job. It is noteworthy that there is no guarantee that these two metrics actually move in the same direction on any given model iteration: it could for example very well be that the outlier sensitivity of RMSE makes it go up while sMAPE (which is less sensitive to outliers) goes down. Ideally, it would be desirable to see both metrics go down to promote a new model to be the best.

It is important to add that the contribution of each observation to the overall metric is weighted with respect to the observation's volume of sales. This tries to give more weight to the error of observations with higher sales, considering that a loss on a huge sale will have more impact in the overall sales loss. The forecasting error metrics of reference are therefore **weighted sMAPE** and **weighted RMSE**.

APPENDIX I: Simulation Average Results for the 1-month Stock/Demand Relation

Table 22 - Catalogue Impacted from each pair of Criteria and associated Forecasting Error in the Decision Period – 1-Month Stock/Demand Relation

Eligibility criteria	Decision period				
	Avg. catalogue impact		Avg. forecasting error		
Pairs	%GTV	GGP%GMV	wRMSE	wSMAPE	wSMAPE_over f
1	75%	33%	60.6	122%	-
2	14%	34%	44.9	101%	22%
3	13%	34%	46.8	100%	21%
4	3%	35%	14.2	98%	9%
5	3%	39%	14.6	97%	8%
6	1%	40%	7.5	92%	6%
7	1%	40%	7.6	92%	4%
8	0%	-	-	-	-
9	0%	-	-	-	-
10	0%	33%	10.1	101%	13%
11	0%	33%	7.8	93%	13%

Table 23 - Simulation Results in the Decision Period from each pair of Criteria for the Worst, Average and Best-case Scenarios – 1-Month Stock/Demand Relation

Eligibility criteria	Simulation – Average results						
	Potential losses (% Period GMV)	Worst case		Avg. Case		Best case	
		GGP%GMV increase: 0.06%		GGP%GMV increase: 8.05%		GGP%GMV increase: 20.52%	
		Only errors below 0.0599% yield GGP increase		Only errors below 7.45% yield GGP increase		Only errors below 17.03% yield GGP increase	
Pairs		Period GGP Increase (%)	Managed GGP Increase (%)	Period GGP Increase (%)	Managed GGP Increase (%)	Period GGP Increase (%)	Managed GGP Increase (%)
2	3.3%	-3.2%	-20.9%	-2.3%	-15.0%	-0.9%	-5.8%
3	3.0%	-2.9%	-20.1%	-2.1%	-14.2%	-0.7%	-5.0%
4	0.3%	-0.3%	-8.8%	0.0%	-1.4%	0.3%	10.0%
5	0.2%	-0.2%	-7.0%	0.0%	-0.3%	0.3%	10.2%
6	0.1%	-0.1%	-5.0%	0.0%	1.9%	0.2%	12.6%
7	0.1%	-0.1%	-3.8%	0.0%	3.1%	0.2%	13.9%
8	-	-	-	-	-	-	-
9	-	-	-	-	-	-	-
10	0.0%	0.0%	-10.6%	0.0%	-4.9%	0.0%	4.0%
11	0.0%	0.0%	-10.3%	0.0%	-4.8%	0.0%	4.0%

APPENDIX J: Simulation Individual Runs for the Markdown Stock/Demand Relation

Table 24 - Catalogue Impacted from each pair of Criteria and associated Forecasting Error, for each Individual Run – Markdown Stock/Demand Relation

Model run #	Eligibility criteria	Historical period	Decision period				
		Catalogue impacted	Catalogue impacted		Forecasting error		
	Pairs	%GTV	%GTV	GGP%GMV	wRMSE	wSMAPE	wSMAPE_over f
1 st (FP season)	1	77%	59%	38%	58.9	139%	-
	2	72%	50%	38%	61.8	138%	17%
	3	71%	49%	38%	62.3	138%	17%
	4	17%	12%	38%	12.8	136%	10%
	5	17%	12%	38%	12.8	136%	10%
	6	7%	5%	40%	7.4	135%	6%
	7	7%	5%	40%	7.5	135%	6%
	8	0%	0%	-	-	-	-
	9	0%	0%	-	-	-	-
	10	2%	1%	35%	46.4	149%	10%
	11	2%	1%	35%	46.5	150%	10%
2 nd (FP season)	1	73%	96% ¹⁵	39%	36.6	81%	-
	2	66%	80% ¹⁵	39%	29.0	78%	23%
	3	64%	79% ¹⁵	39%	29.3	78%	23%
	4	15%	20% ¹⁵	40%	7.5	77%	9%
	5	15%	19% ¹⁵	40%	7.5	77%	9%
	6	7%	10% ¹⁵	41%	6.6	68%	7%
	7	7%	10% ¹⁵	42%	6.7	69%	7%
	8	0%	0%	-	-	-	-
	9	0%	0%	-	-	-	-
	10	2%	2% ¹⁵	37%	4.3	80%	10%
	11	2%	1% ¹⁵	38%	4.4	81%	10%
3 rd (FP season)	1	74%	74%	34%	97.0	89%	-
	2	37%	24%	34%	29.8	78%	23%
	3	34%	21%	34%	31.6	76%	24%
	4	8%	5%	37%	6.6	75%	7%
	5	7%	4%	36%	6.3	73%	7%

¹⁵ Values are higher than those of the 1st run because the sales in the decision period of the 1st run (December) are mostly of AW items, what changes from January (2nd run) onwards

	6	4%	2%	38%	7.1	73%	6%
	7	3%	2%	38%	6.3	72%	6%
	8	0%	0%	-	-	-	-
	9	0%	0%	-	-	-	-
	10	1%	0%	28%	3.2	85%	9%
	11	1%	0%	27%	3.2	86%	10%
4 th (FP season)	1	70%	67%	32%	42.5	98%	-
	2	24%	18%	33%	32.4	146%	15%
	3	22%	16%	33%	34.4	147%	14%
	4	5%	4%	37%	5.9	80%	6%
	5	5%	3%	36%	6.1	79%	5%
	6	2%	2%	37%	5.7	78%	4%
	7	2%	2%	37%	6.0	79%	3%
	8	0%	0%	-	-	-	-
	9	0%	0%	-	-	-	-
	10	0%	0%	26%	19.1	85%	8%
	11	0%	0%	24%	20.3	84%	9%
5 th (FP season)	1	69%	75%	31%	94.2	130%	-
	2	16%	10%	31%	83.3	118%	23%
	3	15%	9%	31%	86.9	118%	21%
	4	3%	2%	34%	38.1	111%	12%
	5	3%	2%	33%	39.1	110%	11%
	6	2%	1%	36%	8.3	105%	8%
	7	1%	1%	36%	8.3	105%	6%
	8	0%	0%	-	-	-	-
	9	0%	0%	-	-	-	-
	10	0%	0%	33%	5.6	92%	18%
	11	0%	0%	33%	5.8	85%	17%
6 th (MD ¹⁶ season)	1	65%	81%	31%	29.3	144%	-
	2	20%	25%	34%	18.3	106%	11%
	3	18%	22%	34%	19.0	107%	5%
	4	5%	7%	34%	12.5	100%	4%
	5	5%	6%	34%	13.2	98%	4%
	6	2%	3%	34%	9.2	76%	3%
	7	2%	2%	34%	9.9	75%	4%
	8	0%	0%	-	-	-	-
	9	0%	0%	-	-	-	-
	10	0%	1%	32%	6.5	105%	11%
	11	0%	1%	32%	6.5	104%	11%
7 th (MD season)	1	70%	74%	29%	65.8	170%	-
	2	16%	9%	28%	43.7	125%	22%
	3	15%	8%	28%	46.1	123%	20%
	4	3%	2%	31%	15.8	123%	8%
	5	3%	2%	32%	16.3	121%	7%

¹⁶ Given that the season start month is November (and not October as in the Commercial Calendar), the MD season is considered to start also one month after, covering May and June

6	1%	1%	32%	7.7	117%	5%
7	1%	1%	32%	7.7	116%	4%
8	0%	0%	-	-	-	-
9	0%	0%	-	-	-	-
10	0%	0%	23%	6.3	117%	14%
11	0%	0%	22%	4.8	114%	14%

Table 25 - Simulation Results in the Decision Period from each pair of Criteria for the Worst, Average and Best-case Scenarios, for each Individual Run – Markdown Stock/Demand Relation

Model run #	Eligibility criteria	Simulation – Average results						
		Potential losses (% Period GMV)	Worst case		Avg. Case		Best case	
			GGP%GMV increase: 0.06%		GGP%GMV increase: 8.05%		GGP%GMV increase: 20.52%	
			Only errors below 0.0599% yield GGP increase		Only errors below 7.45% yields GGP increase		Only errors below 17.03% yield GGP increase	
	Pairs		Period GGP Increase (%)	Managed GGP Increase (%)	Period GGP Increase (%)	Managed GGP Increase (%)	Period GGP Increase (%)	Managed GGP Increase (%)
1 st (FP season)	2	8.6%	-8.6%	-17.2%	-5.3%	-10.6%	-0.1%	-0.3%
	3	8.3%	-8.3%	-16.9%	-5.0%	-10.3%	0.0%	0.1%
	4	1.2%	-1.2%	-9.9%	-0.3%	-2.7%	1.0%	8.6%
	5	1.2%	-1.2%	-9.9%	-0.3%	-2.7%	1.0%	8.5%
	6	0.3%	-0.3%	-5.6%	0.1%	2.0%	0.8%	13.8%
	7	0.3%	-0.3%	-5.6%	0.1%	2.0%	0.8%	13.8%
	8	-	-	-	-	-	-	-
	9	-	-	-	-	-	-	-
	10	0.1%	-0.1%	-9.8%	0.0%	-2.6%	0.1%	8.7%
	11	0.1%	-0.1%	-9.6%	0.0%	-2.4%	0.1%	8.8%
2 nd (FP season)	2	18.1%	-18.0%	-22.6%	-13.1%	-16.4%	-5.4%	-6.7%
	3	18.0%	-17.9%	-22.9%	-13.1%	-16.8%	-5.6%	-7.2%
	4	1.8%	-1.8%	-9.2%	-0.4%	-2.0%	1.8%	9.3%
	5	1.8%	-1.8%	-9.3%	-0.4%	-2.0%	1.8%	9.3%
	6	0.7%	-0.7%	-6.8%	0.1%	0.6%	1.3%	12.3%
	7	0.7%	-0.7%	-6.8%	0.1%	0.7%	1.3%	12.3%
	8	-	-	-	-	-	-	-
	9	-	-	-	-	-	-	-
	10	0.1%	-0.1%	-9.9%	0.0%	-2.7%	0.1%	8.6%
	11	0.1%	-0.1%	-9.9%	0.0%	-2.7%	0.1%	8.5%
3 rd (FP season)	2	5.4%	-5.4%	-23.1%	-4.0%	-16.9%	-1.7%	-7.4%
	3	4.8%	-4.7%	-23.5%	-3.5%	-17.4%	-1.6%	-7.9%
	4	0.3%	-0.3%	-6.5%	0.0%	1.0%	0.6%	12.6%
	5	0.3%	-0.3%	-6.8%	0.0%	0.7%	0.5%	12.3%
	6	0.1%	-0.2%	-6.0%	0.0%	1.5%	0.3%	13.3%
	7	0.1%	-0.1%	-6.0%	0.0%	1.5%	0.3%	13.2%
	8	-	-	-	-	-	-	-
	9	-	-	-	-	-	-	-
	10	0.0%	0.0%	-9.0%	0.0%	-1.7%	0.0%	9.6%

Exploring arbitrage opportunities for increased catalogue ROI in a fashion e-tailer

	11	0.0%	0.0%	-9.9%	0.0%	-2.7%	0.0%	8.5%
4 th (FP season)	2	1.9%	-1.9%	-14.6%	-1.0%	-7.8%	0.4%	2.9%
	3	1.5%	-1.6%	-13.7%	-0.8%	-6.8%	0.5%	4.0%
	4	0.1%	-0.2%	-5.5%	0.1%	2.0%	0.4%	13.8%
	5	0.1%	-0.1%	-5.4%	0.1%	2.2%	0.4%	14.0%
	6	0.0%	-0.1%	-3.5%	0.1%	4.2%	0.2%	16.2%
	7	0.0%	0.0%	-3.4%	0.1%	4.3%	0.2%	16.4%
	8	-	-	-	-	-	-	-
	9	-	-	-	-	-	-	-
	10	0.0%	0.0%	-8.2%	0.0%	-0.9%	0.0%	10.6%
	11	0.0%	0.0%	-9.1%	0.0%	-1.8%	0.0%	9.5%
5 th (FP season)	2	2.3%	-2.2%	-23.3%	-1.6%	-17.2%	-0.7%	-7.7%
	3	1.8%	-1.8%	-20.9%	-1.2%	-14.5%	-0.4%	-4.7%
	4	0.2%	-0.3%	-12.0%	-0.1%	-4.9%	0.1%	6.0%
	5	0.2%	-0.2%	-10.6%	-0.1%	-3.5%	0.2%	7.7%
	6	0.1%	-0.1%	-7.8%	0.0%	-0.4%	0.1%	11.1%
	7	0.0%	-0.1%	-6.4%	0.0%	1.1%	0.1%	12.8%
	8	-	-	-	-	-	-	-
	9	-	-	-	-	-	-	-
	10	0.0%	0.0%	-17.8%	0.0%	-11.3%	0.0%	-1.0%
	11	0.0%	0.0%	-17.3%	0.0%	-10.7%	0.0%	-0.4%
6 th (MD season)	2	1.8%	-2.0%	-11.0%	-0.7%	-3.9%	1.3%	7.2%
	3	0.7%	-0.7%	-4.7%	0.5%	2.9%	2.3%	14.8%
	4	0.2%	-0.2%	-3.7%	0.2%	4.0%	0.8%	16.0%
	5	0.2%	-0.2%	-4.2%	0.1%	3.4%	0.6%	15.4%
	6	0.1%	-0.1%	-3.2%	0.1%	4.5%	0.3%	16.6%
	7	0.0%	-0.1%	-3.5%	0.1%	4.2%	0.3%	16.2%
	8	-	-	-	-	-	-	-
	9	-	-	-	-	-	-	-
	10	0.0%	-0.1%	-11.1%	0.0%	-4.0%	0.0%	7.1%
	11	0.0%	-0.1%	-11.0%	0.0%	-3.9%	0.0%	7.2%
7 th (MD season)	2	2.0%	-1.9%	-21.7%	-1.4%	-15.4%	-0.5%	-5.7%
	3	1.6%	-1.6%	-20.2%	-1.1%	-13.9%	-0.3%	-3.9%
	4	0.0%	-0.1%	-8.0%	0.0%	-0.6%	0.2%	10.9%
	5	0.0%	-0.1%	-6.8%	0.0%	0.6%	0.2%	12.2%
	6	0.1%	0.0%	-5.2%	0.0%	2.4%	0.1%	14.2%
	7	0.1%	0.0%	-3.9%	0.0%	3.8%	0.1%	15.8%
	8	-	-	-	-	-	-	-
	9	-	-	-	-	-	-	-
	10	0.0%	0.0%	-13.6%	0.0%	-6.7%	0.0%	4.1%
	11	0.0%	0.0%	-13.6%	0.0%	-6.7%	0.0%	4.0%

APPENDIX K: Simulation with a Higher Forecasting Accuracy

Table 26 - Simulation Results in the Decision Period from each pair of Criteria for the Worst, Average and Best-case Scenarios, by an Improvement of Forecast Accuracy – Markdown Stock/Demand Relation

Eligibility criteria	Simulation with forecast improvement – Average results							
	If over f. error decreases 60%	Potential losses (% Period GMV)	Worst case		Avg. Case		Best case	
			GGP%GMV increase: 0.06%		GGP%GMV increase: 8.05%		GGP%GMV increase: 20.52%	
			Only errors below 0.0599% yield GGP increase		Only errors below 7.45% yield GGP increase		Only errors below 17.03% yield GGP increase	
Pairs	Hypot. wSMAPE over f		Period GGP Increase (%)	Managed GGP Increase (%)	Period GGP Increase (%)	Managed GGP Increase (%)	Period GGP Increase (%)	Managed GGP Increase (%)
2	8%	1.9%	-1.9%	-7.6%	-0.1%	-0.2%	2.8%	11.3%
3	7%	1.6%	-1.6%	-7.0%	0.1%	0.4%	2.8%	12.0%
4	3%	0.2%	-0.2%	-3.1%	0.3%	4.6%	1.0%	16.7%
5	3%	0.2%	-0.2%	-3.0%	0.3%	4.8%	1.0%	16.8%
6	2%	0.1%	-0.1%	-2.1%	0.2%	5.7%	0.5%	17.9%
7	2%	0.1%	-0.1%	-2.0%	0.2%	5.8%	0.5%	18.1%
8	-	-	-	-	-	-	-	-
9	-	-	-	-	-	-	-	-
10	5%	0.0%	0.0%	-4.5%	0.0%	3.1%	0.1%	15.0%
11	5%	0.0%	0.0%	-4.6%	0.0%	3.1%	0.1%	14.9%

