Demand forecasting model based on product hierarchical classification of fashion brands

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i. Declaration

No portion of the work referred to in this Masters Project has been submitted in support of an application for another degree or qualification of this institution or any other university or other institution of learning.

In the writing of this Masters Project I have received assistance from Dr. Meghna Godya.

I, Hefei Cao, certify that this is an original piece of work. I have acknowledged all sources and citations. No section of this MSc project has been plagiarised.

ii. ACKNOWLEDGEMENTS

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iii. ABSTRACT

Research Context - The study is set in the context of the fast-paced and ever-changing fashion industry environment, whose dynamism and complexity create long-term challenges for demand forecasting. In order to cope with the short product lifecycles, changing demands and sustainable production practices in the fashion industry, there is a growing need for accurate and comprehensive forecasting methods.

Purpose - The aim of this research is to develop hierarchical forecasting models that can be applied to the fashion industry. Through effective forecasting, the challenges posed by the uniqueness of the industry can be addressed in order to reduce consumption, optimise management and increase the market competitiveness of fashion brands.

Design/Methodology/Approach - This study follows a positivist deductive approach using quantitative research methods. The aim of this paper is achieved through data transformation, descriptive statistics, and hierarchical forecasting models for H&M competition data on the Kaggle platform.

Findings - The study found that hierarchical forecasting using a combination of Prophet time series model and random forest model excelled in coping with forecasting in the fashion industry. To some extent, it was realised that as the levels get deeper, the more accurate the prediction will be.

Originality/Value – This study establishes a hierarchical forecasting model for use in the fashion industry, bridging the research gap in this area of the fashion industry. This model is able to effectively capture changes in features as well as trends at different levels, providing multilevel insights into the production and sales strategies of the fashion industry.

Keywords – Demand forecast, Hierarchical forecasting, Fashion retail, Prophet, Random forest

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Chapter One

INTRODUCTION

1. CHAPTER ONE: INTRODUCTION

1.1 Background

Fashion brands operate in a fast-paced, constantly evolving and highly competitive environment. To thrive in this dynamic environment, businesses need to remain agile and responsive to cater to rapidly changing consumer preferences and trends (Ren et al., 2020). In this environment, understanding consumer demand through effective forecasting to launch sound product plans has become one of the key tools for fashion brands (Ren et al., 2020). Especially in the post-epidemic era, to accelerate recovery from losses to capture redistributed market share, fashion brands need to be more precise and sensitive to market and consumer demand (McKinsey, 2021). In this context, accurate and effective demand forecasting is particularly important for companies.

Typically, demand forecasting is the process of predicting future sales by using historical sales data (Kocaoglu et al., 2014) in order for companies to make the right business decisions for the entire process from inventory planning to new product launches and sales. According to Ramos et al. (2022), accurate demand forecasting can improve business profitability and consumer satisfaction by increasing operational efficiency and reducing waste; conversely, inaccurate forecasting will lead to excess or insufficient inventory, which will affect the revenue and competitive position of the brand. In the era of big data, the large amount of sales data and merchandise information generated by the fashion industry has facilitated the development of fashion demand forecasting (Giri et al., 2019). In addition to the constraints considered by traditional forecasting methods, many forecasting methods now incorporate customer information (Choi et al., 2017) and design elements (Giri and Chen, 2022) generated by big data, among others. This allows forecasting to have more application scenarios and adaptability. However, due to rapidly changing consumer tastes, design diversification, long production cycles, fierce competition in pricing, and increasing marketing costs, predicting fashion demand is influenced by many variables that make achieving highly accurate and timely forecasts has always been difficult (Singh et al., 2019). Thus fashion demand forecasting has always been a difficult but rewarding task for the industry.

In addition, the growth of e-commerce has enabled fashion brands to reach more consumers in different regions and expand diverse product lines for them at lower operational costs (Guercini et al., 2018). From a retail perspective, diversified product hierarchies can cater for the different needs of consumers and ensure a broader market for brands (Ruby et al., 2022). However, too many products with ambiguous and confusing categorisation can bring about limitations such as high operational costs, complex inventory and confusing customer purchase intentions (Ruby et al., 2022). Through product hierarchical classification, the products of fashion brands can play a role in satisfying consumer demand, promoting brand differentiation and seizing market share can play a positive role (Jingjing, 2015). Therefore, it is crucial for fashion brands to manage the product hierarchy wisely and purposefully to meet consumer demand.

On the consumer side, with the development of social media and e-commerce, fashion consumers have increasing consumer choices while short delivery times have become a requirement for fashion consumers (Giri and Chen, 2022). Fashion companies anticipating future demand and making effective and quick decisions about retail product categories in advance is one of the priorities to meet current consumer habits (Giri and Chen, 2022). In addition, fashion consumers' concerns about sustainability continue to grow in the wake of the epidemic (Cernasky, 2021). Also social consciousness about material waste and inventory issues in the fashion industry is on the rise. Based on effective demand forecasting, brands are able to develop more detailed production plans to bring production closer to real sales to reduce inventory and additional energy waste. In summary, forecasting sales and demand effectively based on the hierarchical structures of fashion products makes sustainable sense while helping brands to optimise cost and inventory management.

1.2 Rationale

This research project was initially undertaken in an attempt to address the challenge of demand uncertainty faced by fashion brands in a rapidly changing market demand and a highly competitive fashion industry. Demand forecasting based on the hierarchical categorisation of fashion products is able to forecast sales of individual products or groups while also taking into account the overall macro sales, providing brands with multi-level sales guidance.

The fashion industry is a $1.7 trillion industry, but because of overproduction and returns, it is also one of the largest global generators of waste. Fashion retailers need to select the right products from the 150 billion garments produced each year (Vashishtha et al., 2020). a survey by Reichart and Drew (2019) shows that 30% of garments are never sold and more than $400 billion worth of fashion products are wasted each year due to inventory backlogs. Therefore, accurate demand forecasting for fashion merchandise is crucial for fashion retailers.

Despite the wealth of models and research that has been conducted on demand forecasting, accurately predicting demand in the fashion industry has always been a huge challenge. Statistical and forecasting models that currently perform well in other fields struggle to adequately predict demand for fashion products because they rely on historical data, fixed attributes and conventional sales patterns that are not representative of the dynamic nature of the fashion industry (Vashishtha et al., 2020). Traditional forecasting models used to predict product sales and demand tend to be based on historical sales data and product information about the product (Nayak and Padhye, 2018). However, newly launched fashion items generally have different fashion attributes from previous ones, such as patterns, colours, etc., and thus lack historical data (Giri and Chen, 2022). In order to obtain accurate forecasting results, seasonality, short life cycles, trend fluctuations and other factors specific to the fashion industry need to be considered in addition to variable product attributes. Therefore, demand forecasting in the fashion industry is always of research value and relevance.

Current research on hierarchical forecasting in the fashion industry focuses more on the production aspects related to the supply chain and techniques such as classification identification, with little mention of hierarchical forecasting in terms of product and sales.Woubante (2017) emphasises the importance of a well-planned hierarchical structure of the product that can increase customer reliance, build brand image, lead to more consumer engagement, and identify and develop core product and consumers. At the same time, insights gained from demand forecasting can provide a basis for a strategy decision for products of a brand to meet market demand (Ruby et al., 2022), reduce the risk of excess inventory, and improve operational efficiency, profitability, and overall competitiveness of the fashion industry (Liu et al., 2013). Therefore, how to make forecasts to rationally plan different levels of product production as well as sales plays a key role in the development of fashion brands, , and hierarchical forecasting is a powerful tool to deal with it.

The motivation of this study is to review the literature on demand forecasting models and hierarchical forecasting related to the fashion industry, to summarise and analyse the forecasting tools and the important variables included, combine them with the sales characteristics of the fashion industry, in order to develop hierarchical forecasting forecasting models that can be used effectively to forecast the demand for fashion products. By examining forecasting methods specific to the fashion industry, this study will provide companies with new ideas for forecasting sales of fashion products in order to optimise product rationing and inventory planning, make forward-looking product decisions, and respond effectively to rapidly evolving consumer trends.

1.3 Research Aim and Objectives

Research aim:
To develop effective demand forecasting models for fashion brands based on their product hierarchies to guide future sales and improve competitive advantage.

Research Objectives:

- To critically review the existing literature on demand forecasting and hierarchical classification in the fashion industry, taking into account the variables specific to the industry.

- To describe and evaluate, through data visualisation, the complete dataset on Kaggle on H&M product sales used in this study.
- To develop a demand forecasting model based on the dataset to predict future demand through a combination of hierarchical time series and machine learning.
- To test the forecasting model verifying its performance and summarising the impact and implications of hierarchical forecasting models in the fashion industry.

1.4 Research Design

Following the case study design of the quantitative research method, this study utilised a secondary dataset from the Kaggle website, which is a collection of transactional data, as well as customer and product metadata for H&M for the period 2018-2020. This secondary dataset was officially provided by H&M for a featured prediction competition on the Kaggle website. This study will first pre-process this dataset with three datasets involving product segmentation, sales data and consumer information as the primary dataset to support subsequent analysis and modelling. By focusing on a single case, H&M, and gaining insight into real-world issues, events or phenomena (Crowe et al., 2011), single-brand based predictions and analyses will be used to derive impacts and implications that are applicable to most companies in the fashion industry.

1.5 Data Analytics Techniques

Based on the processed H&M sales record dataset, suitable categories will be selected from the product categorisation variables in the dataset as the basis for product hierarchy. Appropriate features will then be selected as inputs to the model based on the hierarchy and appropriate time series forecasting methods will be selected for layer-by-layer forecasting. Then the final hierarchical reconciliation is carried out. Finally, the performance of the model in predicting the sales of fashion products is verified by the appropriate testing indicators. The whole model building and forecasting process will be carried out in R, while the relevant descriptive statistics will be imported into Tableau for visual presentation.

1.6 Outline Structure

Chapter 1: Introduction

This chapter introduces the current situation relating to hierarchical forecasting for products demand in the fashion industry as the background to the study, pointing out the need and potential significance of the research. The aim and objectives of the study are also identified.

Chapter 2: Literature Review

This chapter reviews and summarises existing demand forecasting methods in the fashion industry. On the other hand, it also reviews the theoretical literature on hierarchical forecasting, identifying the models applicable to the fashion industry and the characterising factors that need to be taken into account. It further demonstrates the importance and necessity of demand forecasting as well as product hierarchy for fashion brands and provides a theoretical basis for subsequent forecasting analyses.

Chapter 3: Research design

This chapter presents the research design and research methodology for this study. An initial overview of the secondary data used for the study is provided.

Chapter 4: Dataset

This chapter details the sources of the dataset, presents and introduces the variables relevant to the study in turn, provides an overall overview and visualisation of the dataset through descriptive analysis methods, and analyses its applicability.

Chapter 5: Findings and analysis

This chapter describes the process of hierarchical forecasting model building and forecasting effect testing, as well as the visualisation of related data output.

Chapter 6: Discussion and Conclusion

This chapter summarises the objectives and final results of this study. The significance and implications of this study are clarified. It also highlights the limitations of this research and the way forward.

Chapter Two

LITERATURE REVIEW

2. Chapter Two: LITERATURE REVIEW

The chapter begins by reviewing the qualities of the fashion industry and the characteristics of its product sales and demand, emphasising the importance of conducting forecasts and the challenges faced in forecasting. Secondly, the theories related to product hierarchical classification are reviewed as well as the basic methods of traditional hierarchical forecasting. Finally, the various forecasting methods used in current research are critically discussed to identify ideas for subsequent forecasting.

2.1 Sales forecasts for fashion industry

2.1.1 Characteristics of Fashion Industry

Fashion is a way of expressing oneself through clothing, footwear, lifestyle, dress, make-up, hairstyle and physique in a particular time, place or environment (Kaiser and Green, 2021) with its related business being defined as the fashion industry. As one of the most important manufacturing industries in the world, the fashion industry generates nearly $3 trillion in the economy and accounts for 2% of the worldwide gross product (Akram et al., 2022). But at the same time the fashion industry has always faced excessive waste and sustainability issues. According to McKinsey (2020), the fashion industry accounts for at least 4 % of global greenhouse gas emissions, more than the carbon emissions of the French, German and UK economies combined. In addition according to European Parliament (2023), the European fashion industry uses up to 79 billion cubic metres of water per year, close to one third of the needs of the entire EU economy. However, the cost of this huge consumption is the relatively low full-price sell-through rate of the fashion industry, which averages only 35 % in the first eight weeks (Thomas, 2023). After that, to protect brand uniqueness, unsold products at the end of the season are either sold at huge discounts or destroyed (Reichart and Drew, 2019). Therefore, how to address the overproduction and wastage problems faced by fashion brands to reduce inventory pressure to improve sustainability is always an urgent issue.

Purpose-wise, fashion products generally aim to capture current trends and consumer sentiments, therefore the demand for fashion products is influenced by seasonal trends and the timing of product releases (Chen et al., 2022), such as winter clothes are more likely to be sold in the winter months, and summer clothes are more likely to be sold in the summer months. In addition, fashions are characterised by rapid change and randomness (Ma et al., 2020), which means that fashion products tend to be popular for only a short period of time before they go out of fashion. Therefore, product life cycles tend to be short (Nenni, 2013), even in terms of weeks, and usually focus on 6 to 12 weeks (Sébastien et al., 2003). In this context, in order to meet product timeliness in the competitive fashion market, brands must continuously update their product lines and marketing strategies to meet consumer demand (Giri et al., 2019). The high frequency of updating product lines has led to an inevitable increase in the number of "seasons" for many fashion companies, especially fast fashion brands (Nenni, 2013). For example, fast fashion retailers such as Zara may have nearly 20 product seasons a year.

However, the high frequency of product changes is in contrast to the long delivery and replenishment cycles. Usually, in order to reduce production costs, fashion companies tend to move production and sourcing to low-cost countries or regions (McMaster et al., 2020), and this centralised production model increases the opacity of the supply chain, and it is difficult for each link to obtain the required information in a timely manner, which leads to production delays and prolonged delivery times (Martino et al., 2015).Bruce et al (2004) state that the fashion industry is not a typical Lean or Agile paradigm, but a combination of the two, driven by low margins and high demand volatility. Anticipation and rapid response are essential in order to build and maintain stakeholder partnerships and to strike a balance between production costs, lead times and demand volatility (Bruce et al., 2004).

2.1.2 Importance of Sales Forecasting

Sales forecasting refers to predicting the future demand or sales of a product (Kocaoglu et al., 2014), which is based on the assumption that the factors that have influenced demand in the past will still have an impact on present and future demand (Gharde, 2016). Sales forecasting plays a pivotal role in production scheduling and inventory replenishment decisions, Lawrence et al (2000) stated that inaccuracy in forecasting may expose firms to the risk of excess inventory or lost sales. Therefore, many previous studies have generally identified accuracy as the most important criterion for an implemented forecasting strategy (Mentzer and Cox, 1984; Mahmoud et al., 1988). Accurate sales forecasting can help retailers to better manage inventory, plan purchases, optimise the supply chain and improve customer satisfaction (Liu et al., 2013).

In the fashion industry, forecasting is seen as a service that represents a set of analytical tools that can help fashion brands plan the best decisions for future business activities (Liu et al., 2013). As mentioned earlier, sales forecasting is particularly important for the fashion retail services industry because the demand for fashion products is very volatile and the product life cycle is short. The cycle of a fashion product typically consists of three stages: product development, sales, and finally production and delivery. Each stage takes a relatively long time, as short as 12 weeks and as long as 30 weeks (McKinsey, 2018). Fast fashion brands such as Zara and H&M also rely on a low cost structure based on trend forecasting and shorter lead times (Koren and Shnaiderman, 2023). The competition in the fashion market is thus a competition for market speed (Cachon and Swinney, 2011). In order for design and manufacturing to be able to respond to changes in demand with longer production lead times, the ability to provide predictive sales forecasts is key to product decision making (Koren and Shnaiderman, 2023).

In addition, accurate demand forecasting can reduce inventory costs and sales risk by avoiding too much or too little inventory (Ren et al., 2020). According to McKinsey (2022), although the pandemic is over, the recession caused by a series of unstable factors such as inflation and increased geopolitical tensions continues to threaten the fashion industry. In this context, nearly 37% of fashion executives plan to focus on optimising inventory and cost improvements in 2023, a significantly higher proportion than in previous years (McKinsey, 2022). Therefore, rational and effective predictive analytics will be the focus of more extensive in-depth research into its application in the fashion industry to achieve inventory and cost reduction goals. With the development of technology, AI-driven demand forecasting tools are moving towards this challenge in the fashion industry. Big data and AI technologies are allowing fashion retailers to better utilise data for demand forecasting and inventory planning to improve sales efficiency and profitability (Ren et al., 2020).Standish and Ganapathy (2018) also state in their study that in the best case scenario, utilising sensible forecasting tools enables fashion companies to reduce forecasting by more than 50% of the forecasting error while reducing inventory by 20% to 50 %. Not just for established fast fashion brands, another study by McKinsey (2019) also suggests that the maturation and spread of data analytics technology can facilitate just-in-time production and increase the likelihood of small batch production by enabling faster responses to trends and consumer demand, which can help fashion start-ups to achieve flexible, on-demand production cycles.

2.1.3 Challenges to Sales Forecasting in the Fashion Industry

Despite the strong importance of sales forecasting in the fashion industry in business planning, there are correspondingly always many challenges. Based on the explorations of previous studies, the challenges of conducting sales forecasting in the fashion industry can be categorised as irregular sales patterns (Beheshti-Kashi et al., 2015), high variability in demand (McMaster et al., 2020; Choi et al., 2013) and lack of available historical data (Vashishtha et al., 2020; Giri and Chen, 2022).

2.1.3.1 Irregular sales patterns

The fashion industry will always have irregular patterns in sales data due to seasonal changes in demand and fluctuations caused by external influences such as the supply chain (Beheshti-Kashi et al., 2015). These irregular patterns make it difficult for traditional statistical techniques to produce accurate predictions.Liu et al (2013) have highlighted in their study the strong influence of calendar factor on the sales of apparel products in the fashion retail system. It can be easily observed that sales will rise very quickly and highly during the National Day holiday in China and

Black Friday holiday in the US. As these special dates boost many industries and focus on launching campaigns to attract consumers (Nair et al., 2019), while increasing production puts additional pressure on the supply chain (Chen et al., 2022), resulting in more volatile and unpredictable demand during these time periods. However, on the other hand, the benefits generated during these periods can be significant (Tamilselvi and Rajeswari, 2023). Therefore, it is crucial to accurately predict the demand during special dates and events as an important basis for fashion brands to select products for promotions around special dates (Zhang et al., 2020).

2.1.3.2 High variability

The sales of fashion products are not only affected by internal factors within the industry such as seasonal trendiness, but may also change drastically due to external factors such as consumer preferences and competitor activities, which are difficult to capture by traditional statistical models (Choi et al., 2013).Zhu et al (2019) point out that consumers in different regions and cultures tend to have completely different fashion preferences and their tastes may change over time, making it difficult to accurately interpret and predict customer demand. This changing demand pattern makes the popularity of fashion products more market-determined, which means that only products with high sales volume are defined as "must-have" fashion products (Zhu et al., 2019).

On the other hand, with the development of self-media in recent years, fashion trends are no longer only top-down and dominated by mainstream culture and high-class show venues, but are also increasingly influenced by social media and individual bloggers, resulting in a multitude of unpredictable and unstable viral trends (Kennedy, 2023). These fashion elements are completely random, with little warning of when they will appear, uncontrollable fashion cycles, and even the possibility of two very different viral trends occurring at the same time (Kennedy, 2023). This makes predictions of popular elements and design levels in the fashion industry much more difficult to achieve.

2.1.3.3 Historical data

Generally, sales forecasting requires a large amount of historical data to ensure the accuracy of the forecast. However, the rapid change of products in the fashion industry makes obtaining sufficient historical data a challenge (Chen and Lu, 2021). The short life cycle of fashion products, rapid product iterations, and numerous creative designs mean that the available historical data is extremely limited (Giri and Chen, 2022). In addition, traditional statistical models are more likely to make predictions based on sufficient historical data and the same attributes of the product, but the variability of trends and consumer preferences leads to the possibility that products launched in close proximity to each other or even at the same point in time may have very different or even never-before-existing product characteristics (Vashishtha et al., 2020). Thus forecasting models commonly used in other industries may not be able to accommodate the dynamic attributes of the fashion industry (Vashishtha et al., 2020). In addition to data techniques for forecasting, in terms of trends and consumer preferences, some companies are also using traditional methods based on forecasters collecting influences to skip the need for historical data and go straight to forward-looking forecasts (Ma et al., 2020). These forecasters traverse the globe of art, music and other cultural factors that may influence the fashion industry as well as collecting information on how consumers live, think and behave to summarise predicted trends for the industry as a whole (DuBreuil and Lu, 2020). However, this solution relies heavily on subjective extrapolations by forecasters and provides only vague guidance on specific sales and demand, which can be less reliable and subject to greater variability (Ma et al., 2020).

2.2 Theory and Application of Product Hierarchical Classification

2.2.1 Definition and Significance

Hierarchical classification can be described as a method of summarising the relationships between a set of objects based on the classes of similar objects in a hierarchical nesting, which can be represented by a rooted tree diagram (Gordon, 1987). As shown in the figure 2.1, taking demand as an example, assume that the total demand at the top level is AD, which is subdivided into three Semi-Aggregate Demands (Ds), each of which is a part of AD, and each of the ds further down the hierarchical hierarchy possesses the qualities of the corresponding D, and so on (Fliedner, 2001).

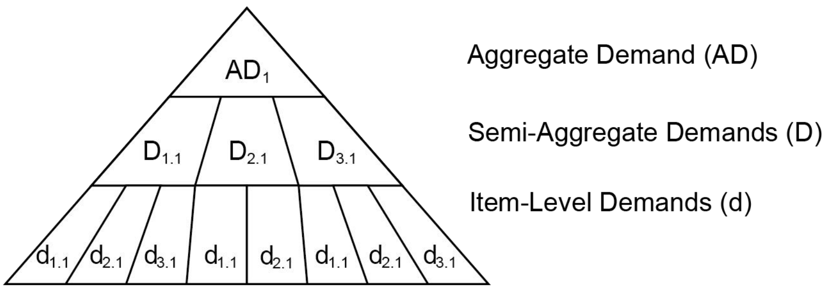

Figure 2. 1 Illustrative hierarchical structure (Fliedner, 2001)

Similarly, on the basis of hierarchical classification, the concept of product hierarchy is to organise a large number of product categories into a hierarchical structure such that each product can be classified into a specific category (Cevahir and Murakami, 2016). As shown in the figure 2.2 is a common illustration of the most basic hierarchical categorisation of fashion products. In the fashion industry, the most basic hierarchical relationship between categories refers to the hierarchy between the inherent attributes of fashion products (Cho et al., 2019), for instance, "trousers" and "skirts" belong to "bottoms", and "tops" and "jackets" belong to "tops". More in-depth, like DeepFashion - a large apparel dataset with comprehensive annotated information - provides detailed hierarchical categorisation through numerous "fine-grained categories" and "attributes" (Liu et al., 2016). Among them, "fine-grained categories" are used to describe clothing categories, while "attributes" are classified into "texture", "fabric texture", "fabric", "shape", "part" and "style", which are used to describe the characteristics of clothing (Liu et al., 2016).

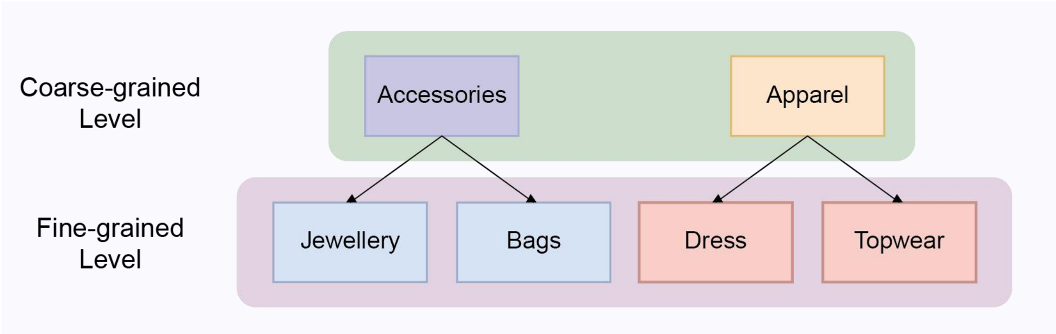

Figure 2. 2 Sample class hierarchy of fashion products(Kolisnik et al., 2021)

Dewsnap and Hart (2004) state that in the fashion industry, through product hierarchical classification, firms can offer the right products for different market niches to increase sales and market share. In addition, hierarchies help to optimise inventory management, reduce costs and risks, and provide clear direction for brand positioning and marketing (Cho et al., 2019). In a survey conducted by McKinsey (2021), it was revealed that more than 50% of fashion executives will revise their product assortment structure in the future and conduct advanced analyses for assortment plans to reduce inventory pressure to ensure revenue. This shows the prevalence and importance of the application of product hierarchy classification in the fashion industry.

2.2.2 Advantages and Challenges of Hierarchical Forecasting

Hierarchical forecasting based on hierarchical classification is a forecasting method based on the entire classified community, where time series data are organised according to a hierarchical classification structure and the relationships between the different levels are used to obtain a more comprehensive picture of the information and the factors influencing it (Spiliotis et al., 2021). fliedner (2001) suggests that hierarchical forecasting, as a centralised forecasting system, can provide decision support to a wide range of departments representing different management levels and product lines, and is able to take into account the forecasting needs of a wide range of large organisations faced with complex businesses or multiple product lines. Therefore, compared with ordinary time series forecasting, hierarchical forecasting can improve forecasting accuracy, reduce forecasting errors, and improve model interpretability by being closer to reality (Zellner and Tobias, 1998).

However, in contrast to its advantages, because stratified forecasting requires the analysis and prediction of comprehensive historical data for the entire project in order to establish the relationship between different levels (Athanasopoulos et al., 2009), it is also strongly affected by the quality of the data, and if the data quality is poor, the accuracy of the stratified forecasting will be compromised, and error transmission will occur with the deepening of the hierarchy and the impact on the results will gradually intensify (Abolghasemi et al., 2019). In addition, stratified prediction requires the selection of an appropriate model to establish the relationship between the different levels. If an inappropriate model is selected, the accuracy of stratified prediction will be affected (Fliedner, 2001). In addition, because stratified forecasting requires the determination of relationships between different levels, it generally requires the operation of multiple time series or forecasting models, and therefore requires a large number of calculations, whose computational complexity will be much higher than that of traditional forecasting methods (Fliedner, 2001).

2.2.3 Technical Approaches to Hierarchical Forecasting

By summarising previous studies, the main hierarchical prediction models include bottom-up (BU), top-down (TD), middle-out (MO) which is in between the previous two, and combination approaches (COM) which is developed on the basis of the previous three.

2.2.3.1 Bottom-up

Bottom-up (BU), namely in time series hierarchical classification, predictions are made only at the lowest and most detailed level of the hierarchy, while predictions for higher levels are aggregated from lower levels without directly using the original aggregated information (Schwarzkopf et al., 1988). Dangerfield and Morris (1992) in their study compared the performance of the BU and TD methods using MAPE as a comparative metric. The results of the study showed that BU predicted family items produced more accurate predictions when there were significant differences in demand between individual items or when the correlation between items was low (Dangerfield and Morris, 1992). Based on this, Kahn (1998) states that the BU method is more suitable for short-term operational decisions such as logistics and production planning. Because the forecasts for each low-level classification are determined individually, the BU strategy has the advantage of being able to better deal with correlations between low-level classifications (Widiarta et al., 2009). At the same time, the BU approach has the significant disadvantage that it is difficult to model each underlying sequence in the presence of large hierarchical structures due to high noise and computational effort (Gross and Sohl, 1990).

2.2.3.2 Top-down

In contrast to the BU approach, top-down (TD) involves developing a forecasting model to predict the topmost level of the hierarchical classification, which is the aggregate, and then allocating the predictions of the aggregate to the individual classifications in the lower level proportionally based on the proportion of the aggregate that each of the lower level hierarchical classifications accounted for in the historical data (Dangerfield and Morris, 1992). Compared to BU, TD typically requires fewer resources and modelling decisions to forecast a single top-level series (Fliedner, 1999) and is more suitable for strategic planning and decision-making such as budgeting (Spiliotis et al., 2021). Widiarta et al (2009) point out that TD forecasting by aggregating lower level categorised time series data into aggregate data can reduce the correlation between lower levels and thus improve forecasting accuracy. However, it also follows that the lower the level, the lower the prediction accuracy (Spiliotis et al., 2021) due to the loss of information that occurs when aggregating lower level data into higher level aggregates.

2.2.3.3 Middle-out

In essence, Middle-out is a combination of BU and TD, where a relatively intermediate level from the entire hierarchical classification is selected to generate predictions, aggregated and summarised towards the higher levels using BU method, and weighted and assigned towards the lower levels using the TD method, attempting to combine the strengths of both in this way (Hyndman et al., 2011). However, accordingly, MO incorporates to some extent the risks faced by both in forecasting.Abolghasemi et al (2019) compared the forecasting ability of MO with that of BU and TD in their study, and the results showed that BU outperformed MO at the lower level, while there was no significant difference at the intermediate level; TD slightly outperformed MO at the top level.Therefore, MO is more suitable for more homogeneous sets of time series , e.g., in the retail domain, since retailers in the middle level and the bottom level generally have similar sales patterns, this homogeneity enables MO to forecast and decompose forecasts more accurately (Abolghasemi et al., 2019).

2.2.3.4 Optimal combination approaches

Pennings and Van Dalen (2017) stated that BU, MO and TD, although they have different forms and advantages and disadvantages, all of them focus on specific aggregation levels to generate predictions, ignoring potentially valuable information in other levels. To cope with this problem, Optimal Combination (OC) approaches have been derived from traditional hierarchical models.OC approaches first make predictions for all levels and combine them with regression models to obtain more accurate predictive information by hierarchically reconciling the predictions from the hierarchical levels (Hyndman et al., 2011). Further, the hierarchical predictions can be weighted and integrated using statistically (Athanasopoulos et al., 2009; Hyndman et al., 2011) or empirically derived weights from professionals in the field. Compared to BU, which uses only lower level sequences, and TD, which uses only the top level, COM takes into account forecasts from all levels of the hierarchy and is able to make forecasts consistent across the levels, which provides more explanatory forecasting information and superior forecasting performance in realistic scenarios such as co-ordinating different departments or planning a product mix (Spiliotis et al. 2021; Hyndman et al., 2011). In addition, OC also has a higher degree of freedom in that any kind of statistical model, machine learning model, or even judgemental prediction model can be used to generate basic predictions and used in coordination with OC (Abolghasemi et al., 2019).

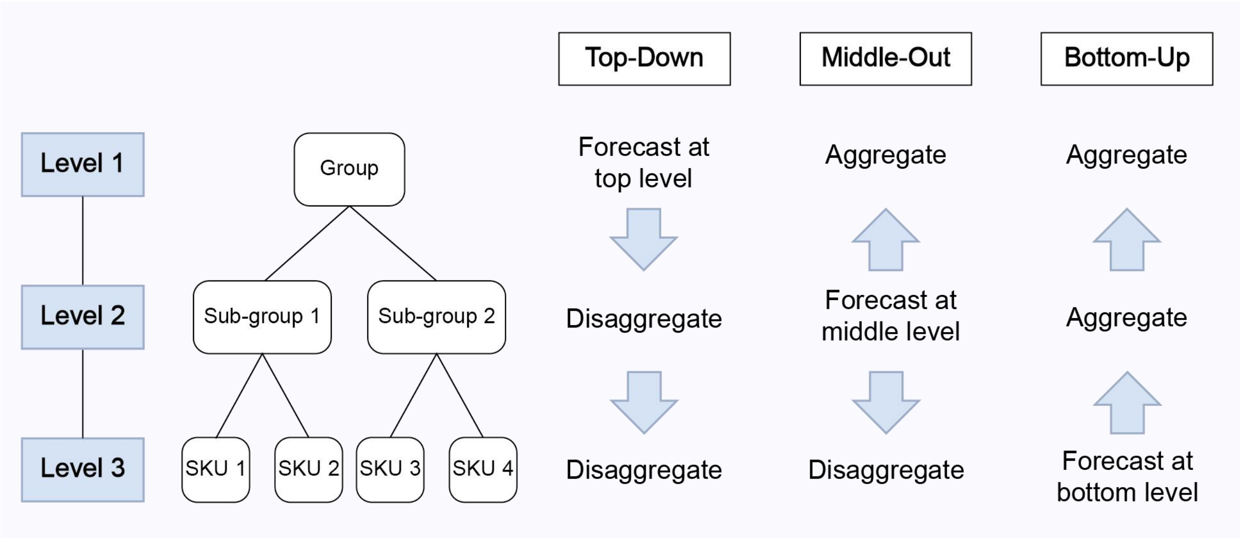

Figure 2. 3 Illustration of the bottom-up, top-down and middle-out approaches (Babai et al., 2022)

2.3 Development of Sales Forecasting Models

2.3.1 Time Series Forecasting Models

Nenni et al (2013) summarised two main product forecasting methods: product feature-based methods and time series-based methods. The product feature-based approach uses product features such as colour, structure, size, and others as forecasting units to reduce demand uncertainty (Nenni et al., 2013). Time-series based methods, on the other hand, use historical data as the basis for forecasting to predict future demand (Nenni et al., 2013). In the fashion industry, sales forecasting is generally categorised into forecasting for product ranges and forecasting for each individual product (Sleiman et al., 2022), where forecasting for product ranges usually involves aggregating sales of products with the same classification or attributes and converting them into a time-series problem for forecasting (Sleiman et al., 2022) . In this direction, models such as autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA) are the most common statistical analysis tools used for sales forecasting (Box, 2013). These methods generally have closed prediction expressions and are therefore simple to implement and less computationally intensive (Liu et al., 2013).

However, a large number of studies (Chen et al., 2022; Ren et al., 2020; Tehrani and Ahrens, 2016; Yelland and Dong, 2013) have mentioned that due to the previously mentioned qualities of irregular patterns and high variability in fashion sales data, traditional statistical methods such as exponential smoothing, regression, ARIMA, and so on, face difficulties in their original form. methods such as exponential smoothing, regression, ARIMA, and others in their original form face the challenge of producing accurate predictions in fashion industry forecasting (Choi et al., 2011).

Prophet, a forecasting method introduced by the core data science team at Facebook Inc (Taylor & Letham, 2018), is a time series forecasting method based on additive modelling in which non-linear trends are adapted to yearly, weekly, and daily seasonality as well as holiday influences (Zunic et al., 2020).Prophet is useful in the case of missing data and changes in trends is robust and generally handles outliers well (Zunic et al., 2020), making the model a good performer in several domains. Current research has shown that Prophet has demonstrated excellent predictive performance in a number of domains including climate (Papacharalampous et al., 2018), healthcare (McCoy et al., 2018), website traffic (Subashini et al., 2019), and to some extent outperforms ARIMA (Satrio et al., 2021) and SARIMA (McCoy et al., 2018). In terms of sales forecasting, in a study by Ensafi et al (2022), the authors used 12 different time series models to forecast against a set of product sales data, and the results showed that the Prophet model, which incorporates the holiday factor, predicts more accurately than most classical models.

In terms of forecasting in the fashion sector, Kaipov and Nedzved (2020) used a Prophet model to forecast a fashion footwear retail data. In their study the holidays feature of Prophet was used to add holidays that are characteristic of the region being forecasted, and monthly seasonality was subjectively adjusted for retailer characteristics. The results showed that the forecasts obtained using Prophet were closer to reality than a variety of other popular forecasting methods (Kaipov and Nedzved, 2020).Ren et al (2020) compared the performance of the traditional ARIMA model with that of Prophet model for fashion trend forecasting, and the results showed that in the long term forecasting, the adjusted parameterised Prophet model significantly outperformed the others, but the unadjusted Prophet model did not significantly outperform the ARIMA model in long-term forecasting. And besides that, Prophet does not have more extensive research and application in the fashion industry.

In summary, the significant advantage of Prophet over other models is its ability to include fluctuations caused by customised seasonality and holidays (Ensafi et al., 2022), making it more suitable for time series with strong seasonal effects based on historical data from multiple seasons (Zunic et al., 2020). This fits well with the main characteristics of the fashion industry and therefore should have more research and practical value.

2.3.2 Machine Learning Forecasting Models

With the development of AI technology and related algorithms, machine learning has been applied more and more frequently to business analysis and sales forecasting (Chen and Lu, 2021; Kharfan et al., 2021; Spiliotis et al., 2020). As a branch of artificial intelligence, machine learning is defined as the process of teaching computers to learn from past data (Das and Behera, 2017). It enables computers to make predictions about future values and events by recognising patterns and relationships in training data (Das and Behera, 2017). Compared to traditional statistical forecasting methods, mechanistic learning has superior accuracy (Ahmed et al., 2010), flexibility and scalability (Das and Behera, 2017).

There are a large number of applications and research cases of neural network (NN) models in machine learning applications related to fashion business forecasting. As a unified approximation, neural network is capable of modelling various time series and non-time series for forecasting (Cybenko, 1989).Mentzer, and Moon (2004) showed that due to its non-linear capability and generality, NN outperforms various classical models in terms of forecasting ability. And both artificial neural network (ANN) and evolutionary neural network (ENN) developed on this basis have been shown to achieve relatively high prediction accuracy in many fields (Alon et al., 2001; Au et al., 2008). Craparotta et al (2019) used siamese neural network (SNN) for sales prediction of new fashion products in their study and demonstrated that the model has the ability to improve prediction accuracy when dealing with heterogeneous data. However, it has also been pointed out that neural network-based prediction models generally require a large amount of historical data and high computing power support (Au et al., 2008; Beheshti-Kashi et al., 2015), and different neural network models are generally only applicable to specific data types or scenarios (Savolainen, 2023), and trying to adapt to the fast changing and uncertain nature of the fashion industry is rapid change and uncertainty is often challenging. In addition, from a business perspective, a balance between simplicity, performance and interpretability should be considered when choosing the best technology (Grilo, 2022), and although neural network-related models have great potential for application, their relative complexity and long time-consuming operations are also a hindrance to their commercial application.

As another frequently used machine learning model, the Random Forest model, first introduced by Breiman in 2001, is an integrated approach that combines a large number of decision trees by averaging them to generate a final prediction (Breiman, 2001). The technique is derived from decision trees while overcoming problems such as the high sensitivity of decision trees to small changes in the data, thus improving prediction accuracy (Breiman, 2001).Zhao et al (2020) in their study compared the predictive power of ANN and random forests, and the results showed that although ANNs can identify more complex predictor variables, random forests have higher efficiency and prediction accuracy.Javed Awan et al (2021) used Random Forest for regression prediction of Black Friday sales data and obtained 81% accuracy, which is higher than other single node machine learning.

Random forests also perform relatively well in predictive applications in the fashion industry. grilo (2022), in a study on predicting fashion product order quantities, through flexible parameter optimisation, Random forests were the best performing model when considering the main error metrics. Random forest is also capable of FEATURE importance analysis, as da Silva Alves (2017) in his study used three models, random forest, support vector machine and artificial neural network, to predict the sales of a fashion company, and his results showed that the prediction of the random forest was the closest to the actual sales. The probable reason for its excellent performance is that the random forest model was also used in that study for variable importance analysis, which provided some interpretability of conclusions and guidance for model optimisation (da Silva Alves, 2017). Similarly, Rose and Dolega (2022) used the FEATURE IMPORTANCE function of the Random Forest Model in their study to provide discriminatory power for factors affecting the sales of products.

A study by Jeong et al (2016) demonstrated that random forests outperform multiple linear regression models when the relationship between variables is non-linear or difficult to parameterise. As mentioned earlier, the fact that predictive data in the fashion industry is affected by a variety of complex conditions is one of the main reasons why it is difficult to predict accurately, and the characteristics of random forests can, to some extent, match the characteristics of data in the fashion industry. In addition, Biau (2012) points out that one of the major advantages of random forests over other machine learning models is that they can handle a very large number of input variables without overfitting. Because each tree constructed in a random forest grows independently, and each tree is randomly selected from the full set of features rather than using all of them, this random feature selection reduces the dependence of the model on specific data features, thus reducing the risk of overfitting (Biau, 2012). This property gives Random Forest the ability to fashion industries with diverse and redundant data features and facilitates feature inheritance in the hierarchies in this study.

2.3.3 Machine Learning combined with Hierarchical Structures

According to previous studies (Hyndman et al., 2011; Babai et al., 2022), the main purpose of incorporating machine learning in hierarchical structures is to reconcile the hierarchical levels and prevent the loss of valid information to improve prediction accuracy. Based on the OC proposed by Hyndman et al (2011), there have been many different evolutions in a number of fields (Taieb et al., 2017; Wickramasuriya et al., 2018; Abolghasemi et al., 2019; Spiliotis et al., 2021; (Mircetic et al., 2022;). Among them, Mircetic et al (2022) in their study for a beer company analysed the validity association between several traditional stratified forecasting methods through multiple linear regression, and the results showed better consistency in forecasting with combined OC and BU approaches. However, this study focuses more on the interpretability of the model than on its predictive power (Mircetic et al., 2022), so the accuracy aspect is not confirmed.Abolghasemi et al (2019) in their study on the forecasting of food sales supply used an aggregation approach to predict the total sales volume of the intermediate tier before estimating the upper and lower tiers by a machine learning model proportion of the time series for decomposition. The results show that the method is competitive in terms of accuracy, but the aggregation and disaggregation processes still result in some loss of information. Based on the same dataset as the former, Spiliotis et al (2021) used a nonlinear approach to hierarchical reconciliation. They leveraged the ability of Random Forest and Extreme Gradient Boost (XGBoost) to deal with non-linear relationships on the ARIMA-generated hierarchical control benchmarks, with the advantage of time-series cross-validation as well as hyper-parameter optimisation, which resulted in more accurate and consistent predictions across the different hierarchical levels. However, the applicability of the current model may currently be limited to specific data hierarchies and model complexity implies higher computational resource consumption.

In fashion industry applications, hierarchical structures are more often used in classification and recognition (Cho et al., 2019; Zou et al., 2019;). In terms of sales forecasting, contrary to the previous conformity model, Lenort and Besta (2013) take into account the characteristics of the fashion industry and use a relatively basic TD forecasting method as the basis of a hierarchical forecasting model, which is combined with an ANN, in order to allow forecasts to include both historical data about the sales progress and specific factors that have a significant impact on the quality of the forecasts.) used a new hierarchical forecasting framework utilising TD and BU in their greedy heuristics approach. The approach aims to predict sales for any single stock unit regardless of other products sold in the shop, and total sales are calculated for each item on a daily basis (Li and Lim, 2018). Despite the superior performance compared to the base method, this study builds on the premise that all products are available for purchase at any time, which is not realistic in a sales scenario.

To summarise, in the field of hierarchical forecasting, there are no concrete conclusions to indicate the circumstances under which each method provides higher accuracy is not easy (Babai et al., 2022). It is not the case that the more advanced and complex the model used will result in absolutely excellent modelling results; the industry in which it is used, the computational costs and the differences in dataset characteristics all need to be taken into account.

2.4 Summary

In the fashion industry, which is faced with fluctuating and rapidly changing demand, a hierarchical forecasting approach is not only necessary, but stands out in terms of improving efficiency and accuracy. This chapter first discusses the necessity of sales forecasting in the fashion industry from the perspective of the complexity and variability of sales forecasting in the fashion industry, and presents the issues that need to be addressed in sales forecasting in the fashion industry, namely, the short product lifecycle and variable demand, which increase the difficulty of forecasting; and the uncertainty and diversity of the market, which require a higher degree of flexibility and adaptability in forecasting methods. Section 2 clarifies the significance of hierarchical structure for fashion forecasting by reviewing the literature related to it, and discusses the advantages and disadvantages of several hierarchical forecasting methods. In order to avoid the loss of information due to aggregation or decomposition at the hierarchical level, OC approaches are now being used in major studies. Section 3 outlines the common forecasting methods in current literature and research, among which the outstanding performance of the Prophet time-series model in the face of strongly trending data and the ability of the Random Forest model to deal with non-linear relationships are well suited to the characteristics of the fashion industry, as mentioned in Section 1.Section 3 also discusses the advantages and disadvantages of several hierarchical forecasting methods, such as the Prophet time-series model, the Random Forest model, the Random Forest model, and the Random Forest model, which is a good fit with the characteristics of the fashion industry. In summary, this chapter selects insights as well as modelling approaches that are useful for stratified forecasting in the fashion industry, and prepares the theoretical ground for the subsequent development of forecasting models.

Chapter Three
RESEARCH DESIGN

3. CHAPTER THREE: RESEARCH DESIGN

The main purpose of this chapter is to show the research methodologies used in this study.The first section introduces the research design of this study and explains how the research aims and objectives were achieved. The second part is a discussion for the research methods. The third part ensures the ethical feasibility of the study.

3.1 Research Design

The philosophical position adopted in this study is positivism, as a philosophical position that follows a scientific perspective and asserts that facts must be learnt through observation or sensory experience of the objective environment and external things that each person is in (Saunders et al., 2019). Broadly speaking, any kind of learning that seeks to know through experience-based thinking is positivist (Park et al., 2020). In academic research, positivism favours objective regularities as opposed to interpretivism, which is more often applied to the social sciences (Bryman and Bell, 2022). This can allow this study to conduct replicable predictive model analysis for sales in the fashion industry for further replication and optimisation by subsequent practitioners and researchers.

In order to make the study operational, the research approach used in this study is deductive. In contrast to the inductive approach, which deduces general principles or universal laws from individual cases or particular observations, the deductive approach is a reasoning method that deduces particular conclusions from general principles or premises (Saunders et al, 2019). Deductive methods can support the testing of identified theories and methods proposed by past research cases in the Chapter 2 literature review, and this approach provides a critical discussion of the existing literature and provides the basis for model predictions based on this literature.

3.2 Research Methods

3.2.1 Research Strategy

Quantitative research design is a common approach in positivist philosophy and deductive logic research (Saunders et al, 2019), as is the case in this study. The main difference between quantitative and qualitative research is the nature of the data and how it is processed. Quantitative research is a research methodology based on quantitative data that describes, explains and predicts phenomena through mathematical and statistical analyses ((Saunders et al, 2019)), which is able to meet the requirements of the aim of this study. On the contrary, as a research method based on non-quantitative data, qualitative research tends to emphasise in-depth understanding and interpretation of social phenomena (Fossey et al., 2002). As the main objective of this study is to develop a hierarchical forecasting model and to use publicly available secondary data related to the fashion industry for forecasting and performance testing, this process focuses on modelling and validation over a time horizon in order to find the most effective model for forecasting the demand for fashion brands. Therefore cross-sectional study is more biased towards this study (Olsen and St George, 2004). In contrast, longitudinal studies focus more on observing and measuring the same individuals, groups or variables over time to detect changes and trends (Olsen and St George, 2004). Whilst researchers may look at trends in historical data such as product sales, the main focus is on building and validating models rather than tracking the evolution of variables over time.

3.2.2 Datasets

This study uses a set of publicly available secondary data for modelling and prediction purposes. As data that has already been collated and collected by previous hands, secondary data has a wide range of applications due to its low cost and efficiency (Johnston, 2014) . This study uses a set of publicly available data used for competitions on the Kaggle platform. The data was provided by the fast fashion brand H&M, which contains the purchase records of 1371,980 consumers between 16 September 2018 and 20 September 2020, a total of 105,542 fashion items associated with the purchase records, and the corresponding detailed categorical and descriptive information (Kaggle, 2022). Due to its large amount of data, and the detailed categorisation information that the products possess, it is able to support the purpose of this study to make predictions according to the hierarchical classification of the products.

3.2.3 Data Analysis

After acquiring the data, the data was first checked for completeness, including removing any missing data and outliers that were identified and corrected during the data collection phase. As the Kaggle platform has exhaustive charts of basic information on the number of variables as well as data integrity for the datasets, it can be used as a favourable reference for this step (Kaggle, 2022). The variables that were valuable to the study in several datasets were then aggregated and converted into a new format as a way to make it easier to understand the data and achieve the research objectives (Hair et al., 2015). The main focus of this study is to help create hierarchical product categorisation information as well as time series of individual product sales generated from sales records. Firstly, the selection of appropriate stratification metrics based on the number of products as well as the distribution of category volumes can ensure that stratified forecasts are more meaningful and interpretable (Cho et al., 2019) in order to facilitate the forecasting. Facing the time series, based on the literature review in 2.3.1, it is chosen to use the Facebook Prophet for time series forecasting.Prophet is suitable for data with significant trend changes and has excellent outlier handling (Zunic et al., 2020), which is suitable for the sales characteristics of the fashion industry.The forecasting of Prophet will be carried out using the Box- Ljung test for residual autocorrelation (Burns, 2002). In addition, valuable features will be presented through the feature extraction capability of Prophet, and these features will be incorporated using the Random Forest model to make predictions again. Random forests have an excellent performance in dealing with non-linear relationships (Grilo, 2022), and the linear relationships of the time series captured by Prophet can compensate for the shortcomings of random forests. In summary, the final forecasts were output from the Random Forest model and tested by R-squared with uniform fit metric intervals (Chicco et al., 2021), which facilitates the observation of model performance variations between strata and yields the final performance of the composite model.

3.3 Research Ethics

This research compiles with the "UAL Code of Practice on Research Ethics" (UAL, 2020). As one of the public competitions published on the Kaggle platform, the webpage of the dataset is accessible to anyone. In addition, the competition clearly states in the rules of its page that the data can be used for academic research as well as for any non-commercial purpose (Kaggle, 2022), which supports the present study. Since the purpose of this study was not in line with the theme of the competition, only some of the variables were used through data merging and transformation, but the original information was still maintained without any falsification. The final model training as well as testing was simulated on the dataset provided by Kaggle and is not a real business practice.

Chapter Four

DATASET

4. CHAPTER FOUR: DATASET

This chapter aims to present the selected data and clarify its applicability. Firstly, the chapter describes the data sources and demonstrates their relevance to the research questions. Secondly, the data analysis tools used in this study are summarised. Finally, descriptive statistics and visualisations of the selected dataset were carried out to select key variables relevant to the study.

4.1 About the Dataset

4.1.1 Data Source

Kaggle is a data science competition platform that hosts competitions for business problems, intelligence techniques, and academic seminars, as well as an online community for data scientists and related practitioners, where users are able to find and publish datasets, explore and build models in a web-based data science environment, collaborate with other data scientists and machine learning engineers, and participate in competitions to solve data science challenges (Bojer and Meldgaard, 2021). Among other things, in competitions set in the context of real business problems, the companies involved provide datasets to support the prediction task and usually offer prizes for the best performers (Bojer and Meldgaard, 2021).

The source of the data used in this study is the H&M Group's competition on the Kaggle platform, formerly known as "H&M Personalised Fashion Recommendations". The H&M Group is a fashion brand and business with 53 online marketplaces and approximately 4,850 shops (Kaggle, 2022). With such a large marketplace, effective targeting of product recommendations to consumers is one of the keys to growing the business. Therefore, this competition provided participants with a portion of H&M's product information, consumer information, and consumers' purchase history over time, with the goal of predicting what each consumer would purchase within 7 days of the end of the transaction record (Kaggle, 2022).

4.1.2. Datasets and Variables

H&M Group provided four dataset files and an image folder for this featured prediction competition for Kaggle.As shown in Table 4.1, the datasets include detailed metadata containing products available for consumers to purchase (articles.csv), information metadata about consumers with purchase records (customers.csv), and information metadata about consumers with purchase records (customers.csv). information metadata (customers.csv), a record of each consumer's transactions on each date (transactions_train.csv), images corresponding to each product (images), and a sample contest submission file (sample_submission.csv) (Kaggle. 2022).

Content	Dataset	Features
Product Information	articles.csv	**article_id**: A unique identifier of every article **product_code**: A unique identifier of every product **prod_name**: A unique name of every product **product_type_no**: A unique identifier of every product_type_name **product_type_name**: The type of products **product_group_name**: The group of products **graphical_appearance_no**： A unique identifier of every graphical_appearance_name **graphical_appearance_name**: The graphic designs on products **colour_group_code**: A unique identifier of every colour_group_name **colour_group_name**: The colour on products **perceived_colour_value_id**: A unique identifier of every perceived_colour_value_name **perceived_colour_value_name**: The brightness of product colours **perceived_colour_master_id**: A unique identifier of every perceived_colour_master_name **perceived_colour_master_name**: The broad categories of product colours **department_no**: A unique identifier of every department_name **department_name**: The department of the products **index_group_no**: A unique identifier of every index_group_name **index_group_name**: The board categories of products **index_code**: A unique identifier of every index_name **index_name**: The product classification under index_group **section_no**: A unique identifier of every section_name **section_name**: The section of products **garment_group_no**: A unique identifier of every garment_group_name **garment_group_name**: The garment categories of products **detail_desc**: Detailed description of products

Consumer Information	customers.csv	**customer_id**: A unique identifier of every customer **club_member_status**: Whether the customer is a member **fashion_news_frequency**: The frequency of customer access to fashion news **age**: The age of customer **postal_code**: A unique identifier of postal code on every customer
Transaction history	transactions_train.csv	**t_dat**: The date of transaction **customer_id**: A unique identifier of every customer **article_id**: A unique identifier of every article **price**: The prices of traded products **sales_channel_id**: Sales channels for transaction
Product Images	images (folder)	Product images corresponding to each article_id
Submission Example	sample_submission.csv	A sample submission file in the correct format

Table 4. 1 A summary of the datasets (Kaggle, 2022)

Among the given resources, image is not within the scope of application of this study as it is mainly used in technology assisted recommender systems such as intelligent recognition and is not different from data analysis, in addition sample_submission.csv is only used to standardise the format of submission of the contestants and does not have analytical value. Other than that the three datasets are in the form of long form tables with different categorical and textual variables identified by columns as shown in the table above. Considering that the focus of this study is on product demand forecasting with a hierarchical structure, consumer related personal information is also not considered in this study. Therefore, only the product information dataset (articles.csv) was selected for this study to provide the stratification criteria, as well as the transaction history dataset (transactions_train.csv) to compute the product sales and generate the required time series.

For this purpose, this study firstly arranges the "t_dat" in the transaction history (transactions_train.csv) according to the time and determines the start and end time of the time series. The dataset in the previous study has a weekly granularity (Babai et al., 2022), and considering the seasonal demand of the fashion industry, this study also uses weekly as the granularity of the time series. Next, the weekly sales of each product were inserted into the product information (article.csv) with "article_id" as join key, and the weekly sales of each product were inserted into the product information (article.csv) after the corresponding "article_id". "in the product information (article.csv), and aggregate the total sales of each product after the last column. Finally, due to the equal classification ability, this paper deletes the unique identifier of all classification information in the metadata, and only retains the classification information named by name, so as to complete the preliminary data merging and pre-processing.

4.2 Data Analytics Tools

The main use of R and Tableau Public in this paper is for the analysis of datasets and predictive modelling.R, as a language and environment for statistical computation and graphing (Ihaka and Gentleman, 1996), enables the analysis and prediction of various types of data problems through the enhancement of various packages. And Tableau as a visual analytics platform can facilitate users to explore and present data in a more interactive and intuitive way (Tableau, 2023). Firstly this study will use Tableau to perform descriptive statistics on the variables provided in the data, visualising the variables individually or in association with each other to gain a deeper understanding to guide subsequent analysis and prediction.R, as the main analytical and predictive modelling tool, will be used to perform the time series and random forest model predictions, and to perform the eventual R, as the main analytical and predictive modelling tool, will perform time series and random forest model predictions, as well as final effect testing. The specific predictive analyses will be described in detail in the next chapter. In addition, the preprocessing for generating time series mentioned in the previous section is also carried out in R. In addition, due to the limitation of Tableau on the number of rows of data, the ggplot2 package in R was also used to visualise very few data, which will not be described in detail here.

4.3 Descriptive Statistics and Data Visualization

This part will perform descriptive statistics for the above metadata and create relevant data visualisations using Tableau Public to uncover valuable points in the data.The data will also be merged and appropriate variables will be selected based on the relevant findings and analyses from the process in order to form the dataset used in the final study in preparation for the predictive analyses in the next chapter.

4.3.1 Product information

There are 10 variables in the product information dataset that provide guidance on product categorisation, as shown in figure 4.1. The most categorised variable is department name, which contains 226 categories. The second most numerous, "product type name", has only half the number of groupings as "department name" (n=121). Although there is no further description of these variables in the official information, it can be inferred from the names in the metadata that "product type name" is usually a classification of fashion products in style categories, while "department name" is based on the former. The "product type name" is usually a classification of fashion products in terms of style categories, while the "department name" is a further subdivision based on the former based on the nature and specific characteristics of the products. The "garment group name" seems to be independent of the first two, which is a separate classification after considering the attributes of both, and does not have a subordinate relationship. In contrast, the most macroscopic grouping is the 'index group name', which is based on the most basic apparel audiences and uses, and therefore contains only the five broadest categories, namely 'Ladieswear', 'Menswear', 'Sport', 'Baby/Children' and 'Divided'. Menswear", "Sport", "Baby/Children" and "Divided". In addition to this, there are also three variables related to colour and pattern design (perceived colour master name, perceived colour value name, and graphical appearance name). Although the importance of colour in the fashion industry has been mentioned in many literatures (Tao et al., 2019; Güven. and Şimşir, 2020), colour trends do not only exist in the fashion industry, but it is closely related to other fields of art and design (Doshi, 2023). Moreover, according to the frequency of WGSN colour trend analyses, it can be seen that colour trends in general change on a quarterly or yearly basis and do not have the cyclical or seasonal nature of fashion products. Therefore, this study does not consider colour and pattern factors in product category stratification.

In summary, it was not possible to include all 10 attributes used for categorisation in this study, given the differences and correlations between categories and the complexity of forecasting. Considering the characteristics of fashion products and the hierarchical relationship, "index group name", "product type name" and "department name" are chosen as the stratification. product type name" and "department name" as the basis of hierarchy.

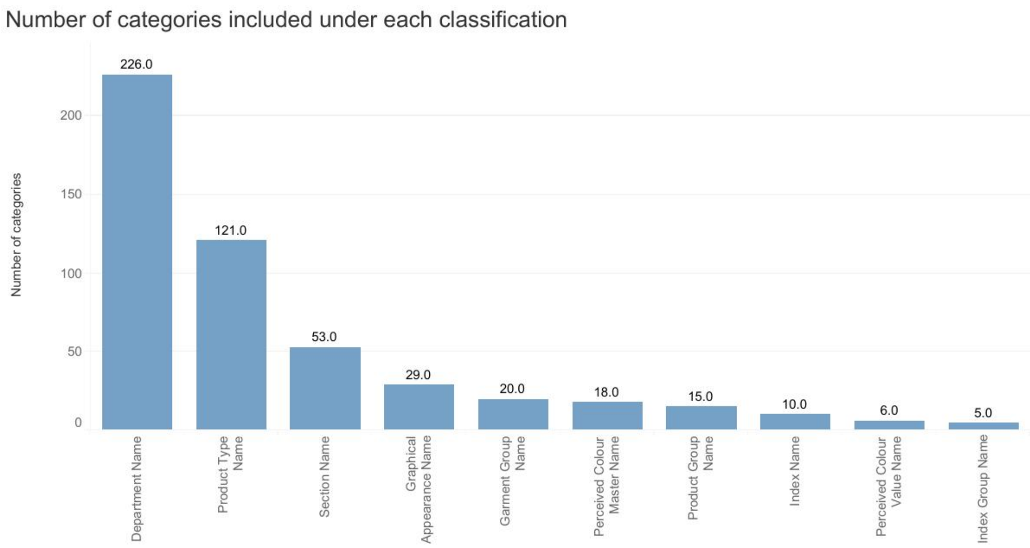

Figure 4. 1 Number of categories included under each classification

The chart below shows the percentage of products in all 5 categories, categorised by "index group name".After the initial data cleaning, "Ladieswear" accounts for the largest number of products in the dataset, 37.22% (n=37172) out of a total of 99,874 products recorded in the dataset.In contrast, its counterpart "Manswear" accounted for only 11.84% (n=11822).Considering that in most cases, women, as the main consumers of fashion, spend almost three times as much as men on clothing (Danziger, 2019), such a product ratio is reasonable. The "Baby/Children" category follows with an almost similar proportion to women's clothing at 34.16% (n=34113).The "Divided" category has a relatively medium level of product volume, with a share of 14.25% (n=14234). According to H&M Group (2007), "Divided", as a product category, represents a young collection that focuses on creative design, with bright colours and avant-garde patterns.Finally, "Sport" is the smallest category with only 2.54% (n=2533).

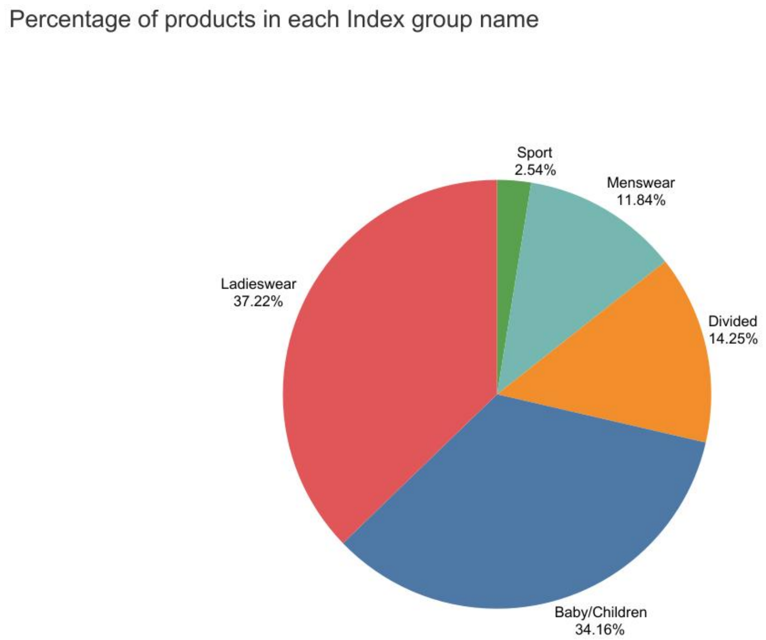

Figure 4. 2 Percentage of products in each index group name

4.3.2 Transaction history

The figure below shows the sales data of 5 categories in the "index group name".In terms of overall trend, all 5 lines are generally consistent, with a continuous upward trend from 2018 Q3 to 2019 Q2.This was followed by a sales trough from 2019 Q3 to 2020 Q2, which was during the height of the COVID-19 outbreak, so fashion sales should have been affected by the embargo and logistics to some extent (Arania et al., 2022).By 2020 Q1 a volatile upturn begins again.Throughout, regular peaks occur at the June, September and November positions respectively.When disaggregated, several categories show a clear order of magnitude difference in sales.It is clear that "Ladieswear" occupies the highest level of sales, followed by "Divided", with sales remaining stable between 50,000 and 100,000.The rest of the three categories tend to be at the same level, with overall sales below 50,000. The "Baby/Children" category showed an overall downward trend until the end of the record to the lowest sales level of the five categories, which is not consistent with its large number of products. It is speculated that this is related to the impact on fertility during the epidemic. As the 5 categories also differed fundamentally in the nature of their products and audiences, there was also a marked difference in sales levels. It would be more reasonable to target forecasts to just one of the categories, so this study will only analyse forecasts for 'Ladieswear', which has the largest sample size.

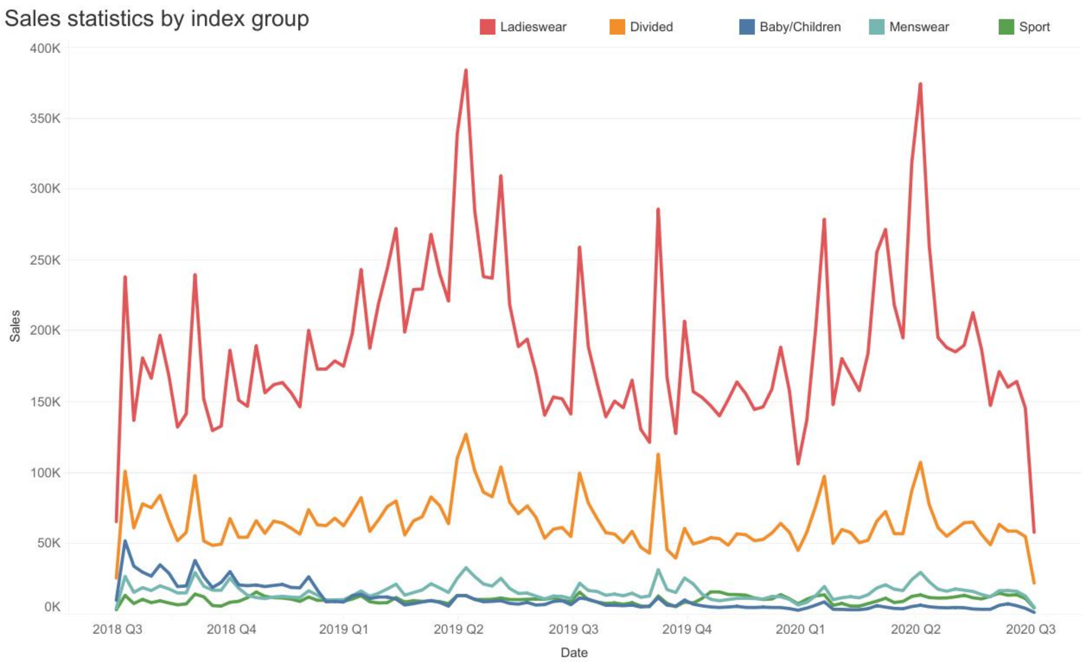

Figure 4. 3 Line chart of sales volume by index group name

After identifying the specific categories for forecasting, further visualisation and analysis of the sales in the selected categories was carried out.Figure 4.4 flags regular peaks in sales, with the most prominent peak occurring at the end of June, and the remaining two asked at the end of September and the end of November respectively. Every year from late June to early July H&M conducts a summer sale in which almost all products participate and are heavily discounted (Davis, 2023), which explains the highest peaks that occur at the end of June every year. The peak at the end of November coincides with Black Friday, so there are also discounts for the brand, leading to a sharp increase in sales. There is no clear trigger for the September peak, but only a few news reports mention H&M clearing out stock at discounted prices during the seasonal change before autumn (Reuters, 2017) as a possible reason. Based on this, in the next chapter of the study, "summer sales" and "Black Friday" can be included in the prophet model as festive factors for prediction.

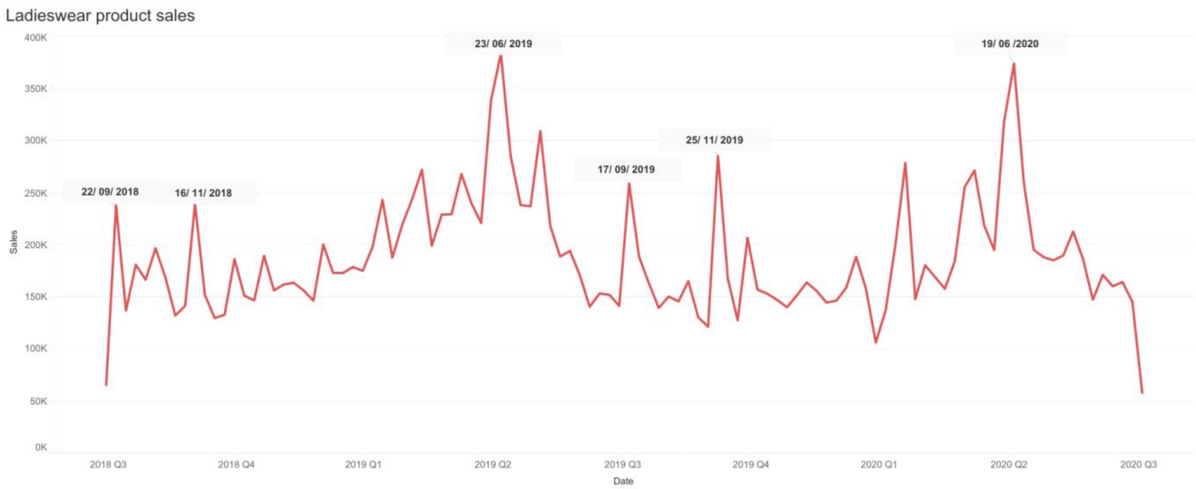

Figure 4. 4 Ladieswear product sales line chart

Based on the filtering of the category "Ladieswear", figure 4.5 shows the number of products of all "product type name" in this category. Overall, there are 90 "product type name" categories in "Ladieswear", with significant differences in the number of products between categories. Among them, "dress" has the highest share of 13.46 % (n=5002). The rest of the major product categories are concentrated between 3% and 8%. 64 categories have a share of less than 1 % (n<372), and 20 categories have a single-digit number of products. In this case, overall sales trends and seasonality can be easily influenced by categories with a higher number of products and thus need to be focused on. The impact of the bottom product categories may tend to be negligible in comparison to the former.

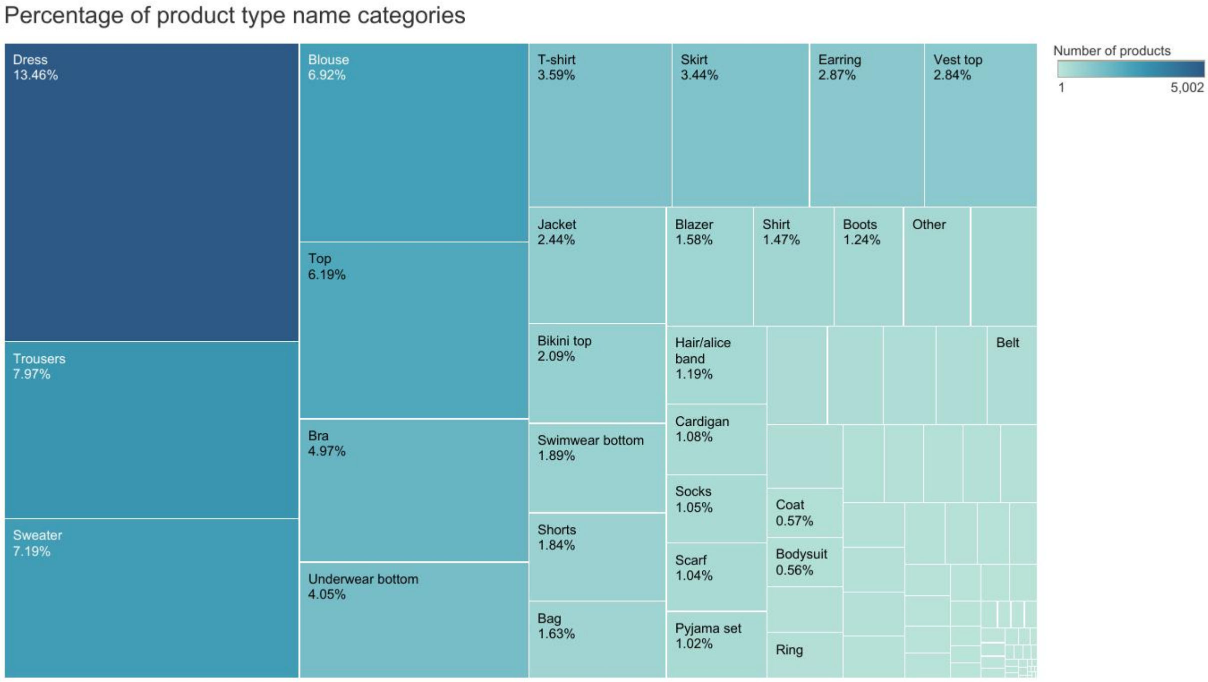

Figure 4. 5 Tree chart of product type name category share

The figure 4.6 shows the sales of the five categories with the highest total sales under the "product type name" category.Combined with the chart above, these five categories coincide with the five categories with the highest number of products, i.e. sales are proportional to the number of products.The top selling category "dress" shows trends and peaks that are largely consistent with "ladieswear"."Trousers", "Blouse" and "Top" are relatively low in sales volume, but the trend is stable, with no significant growth or decline.Sweater, on the other hand, has a significant sales increase in autumn and winter due to its seasonal constraints, and a trough in spring and summer.

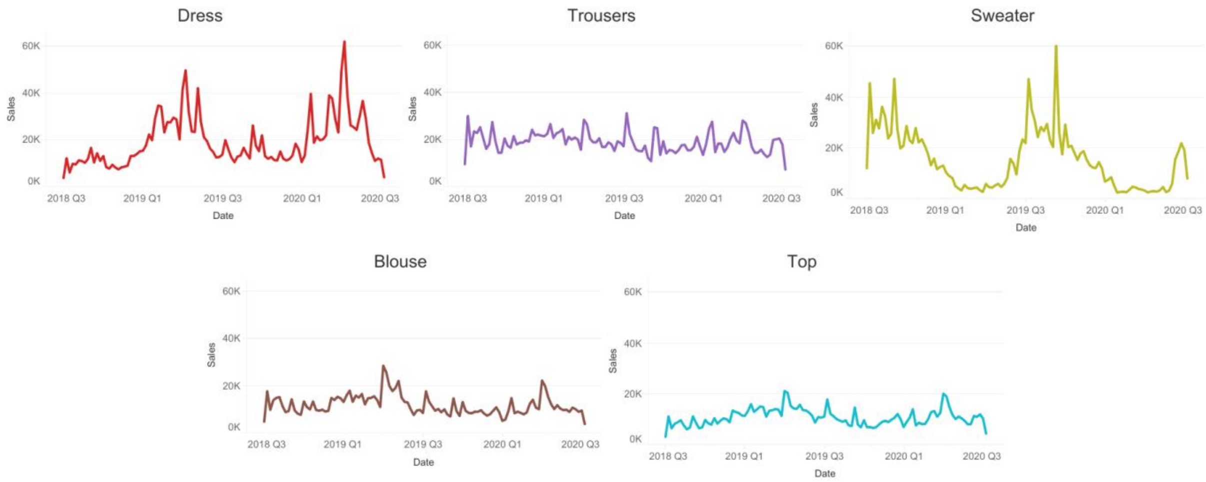

Figure 4. 6 Top 5 highest sales categories in product type name

In the same way, the graph below shows the number of products for all "department name" categories in "Ladieswear". In total, there are 63 "department name" categories in "Ladieswear". Similar to "product type name", there is a clear difference in the number of products in each category. It ranges from a high of 12.09% (n=4494) for "Jersey" to only 1 product for some categories. Figure 4.7 shows that the five categories with the highest sales in 'department name' are also found in the category with the highest number of products, but not in the same order. With 4.91% (n=1825), "swimwear" has the highest total sales, while "Jesery", which has the highest number of sales, has only about 60% of the total sales of “swimwear”. The line graph shows that sales of "swingwear" are also seasonal. As a common summer activewear, it can also be fuelled by H&M's summer sales, which may have contributed to the high sales during the summer period. “Blouse”, “Trouser”, and “Knitwear” are all categorised by "product type name" and have similar sales trends.

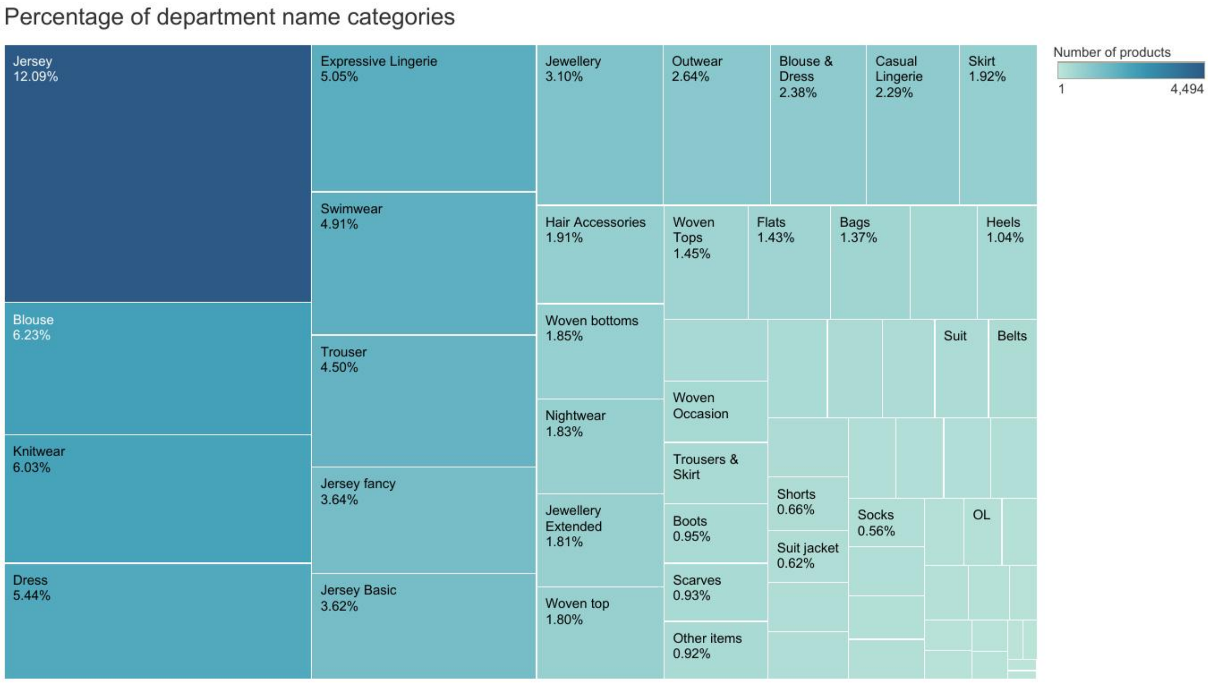

Figure 4. 7 Tree chart of department name category share

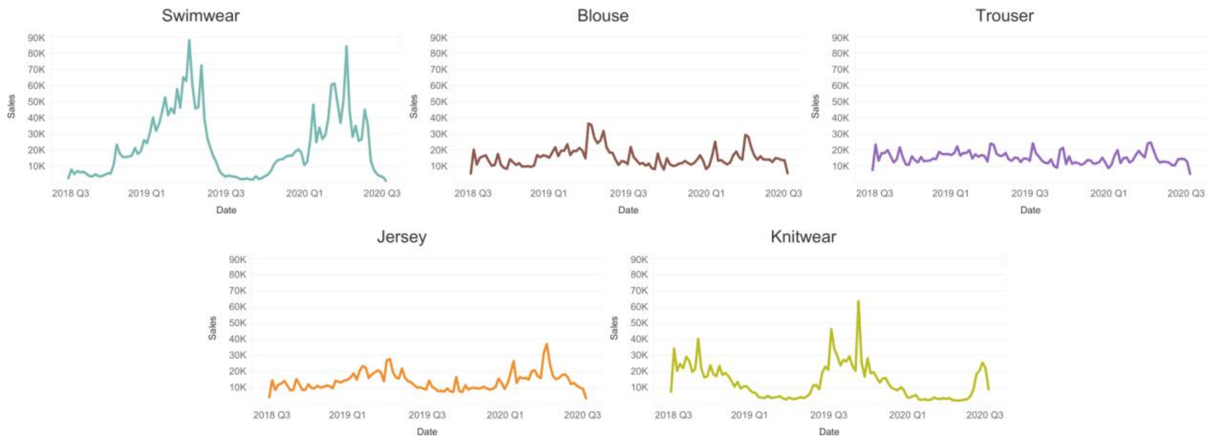

Figure 4. 8 Top 5 highest sales categories in department name

The transaction history also includes a "price" variable that records the transaction price of the product.As a popular fast fashion brand, H&M products are relatively inexpensive and affordable.The following figure shows the price range, it can be seen that most of the products are concentrated in a very low price range. As a popular fast fashion brand, H&M products are relatively inexpensive and affordable, and Figure 4.9 shows the price range, which shows that most of the products are concentrated in the very low price range.

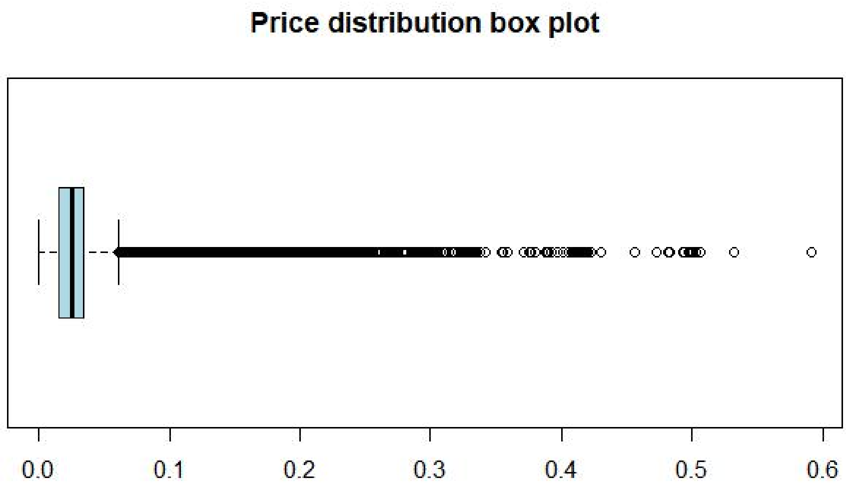

Figure 4. 9 Product price range box chart

4.4 Summary

Through the preprocessing of metadata and descriptive statistics, this chapter provides the basis and insights for the subsequent predictive modeling. Firstly, the multiple product classification information contained in the metadata is used to identify the key stratification bases used in the subsequent hierarchical time series, which are "ladieswear" as the top level, middle level according to the "product type name", and bottom level according to the "department name". Meanwhile, the visualization of the sales trend reveals that some products have obvious seasonal trends, and in addition, the sales peaks caused by H&M's summer sale and Black Friday are also worth paying more attention to in the subsequent forecasts. Based on the above findings, a complete dataset was generated for subsequent use, with the variables shown in Table 4.2.

Dataset	Content	Features
ladieswear.csv	Product Information	**article_id**: A unique identifier of every article
	Basis for the hierarchy	**index_group_name**: The board categories of products, "ladieswear" in this study **product_type_name**: The type of products **department_name**: The department of the products
	A record of sales in weeks, with the variable name being the date of the first day of the week	**2018/09/23** until **2020/09/13**

Table 4. 2 Summary of dataset used in the study

Chapter Five

FINDINGS AND ANALYSIS

5. FINDINGS AND ANALYSIS

Based on the final dataset and the main variables of interest identified in the previous chapter, Chapter 5 will focus on predictive model building based on a combination of the prophet time series and random forest model with associated tests. Finally, forecasting sales for the next year (52 weeks).

5.1. Feature engineering

5.1.1 Volume of products on sale

According to the exploratory analysis in the previous chapter, the number of types of products is to some extent proportional to the sales volume, so the number of products on sale can be taken as one of the characteristics. Although there is no specific record of the number of products on sale, but from the known information to carry out the corresponding rough deduction, the specific method is as follows: first of all, record each "ladieswear.csv" in the 'article_id' in the sale of time sequence from the left on the first non-zero data, recorded as the sales start time. Similarly, record the first non-zero data from the right, recorded as the end of the sales time, so as to generate each product in the sales time period. A new on sale time series is then generated by counting how many products are in their on sale time period in each time period.

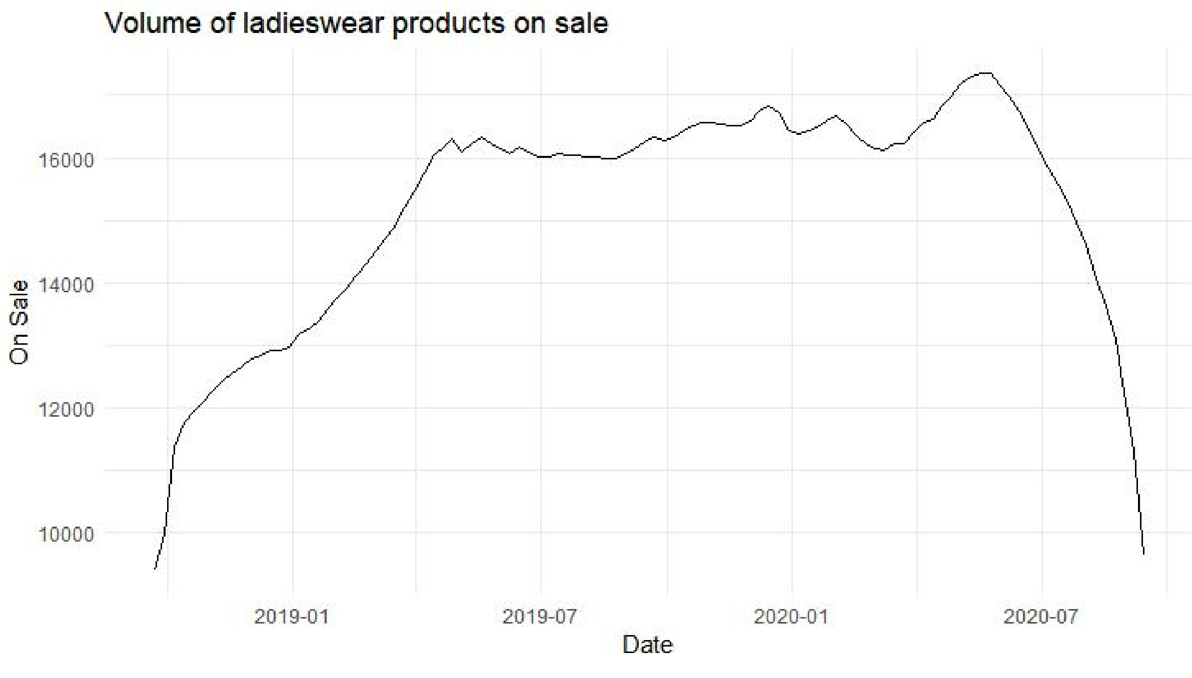

Figure 5. 1 Line chart of the number of products on sale at ladieswear

On this basis, time series forecasting was performed for the number of on sale using the prophet model to complement the data length for subsequent random forest models. Based on the visualised line graphs, the number of on sale products did not show significant seasonality, and only YEARLY seasonality was turned on for prediction given the time series length. The model was then tested using Prophet's "cross_validation" function. This function compares predicted values to actual values by selecting cut-off points in the history and fitting the model using data prior to each cut-off point (Prophet, 2023a). The target variable is close to zero, resulting in metrics such as MAPE and MDAPE not being accurately calculated leading to the phenomenon of some metrics being zero in the early prediction cycle. According to Table 5.1, the prediction model performs well at the beginning, but as the prediction period increases, both MSE and RMSE gradually increase, which indicates that the model's prediction error also increases in a longer time horizon. This is a common phenomenon in forecasting models as the uncertainty increases as the forecasting horizon increases.

Horizon	MSE	RMSE	MAE	SMAPE	Coverage
14	0	0	0	NA	1
21	1.49382716	1.222222222	0.135802469	NA	0.987654321
28	33.89052288	5.82155674	0.791394336	NA	0.972948439
35	81.56027596	9.031072802	1.627814089	NA	0.958242556
42	114.5	10.70046728	2.320261438	NA	0.943536674
49	130.3905229	11.41886697	2.796840959	NA	0.928830792
56	145.9591503	12.08135548	3.275054466	NA	0.914124909
63	154.5047204	12.42999278	3.624546115	NA	0.899419027
70	156.0915033	12.49365852	3.750544662	NA	0.884713145
77	156.966594	12.52863097	3.863471314	NA	0.870007262
84	157.1299927	12.53515029	3.89469862	NA	0.85530138

Table 5. 1 Cross validation test results of ladieswear products on sales volume forecasts

Similarly, data on the number of products being sold and related predictions were created for "product type name" and "department name". Based on the "ladieswear" data, the corresponding product categories were extracted, and the same prediction method was used to traverse each category to complete the feature creation. Since the method is the same, we will not repeat it here because it is a repetitive operation.

5.1.2 Holidays and special events

The 'Modeling Holidays and Special Events' function in Prophet models holidays or other recurring events by creating a data frame for them (Prophet, 2023b). This dataset contains columns for both the holiday name and the corresponding date, and the past that can be traced back from the historical data needs to be included to predict the future that can be traced back from the projections (Prophet, 2023b). Based on this methodology and the observation in the previous table of events that cause significant sales spikes, the discount event "Summer sales", which starts in the last week of June, and the traditional shopping holiday “Black Friday”, which is held on the last

Friday of November, are included in the model. Considering that the time series are recorded on a weekly basis, this study also uses the "upper_window" parameter in the model to expand the special times to the week of the corresponding date and the following week to ensure that the impact of the special dates is covered as completely as possible.

5.2. Prophet time series forecasting

This part will use the prophet model for the initial forecasting of sales for each stratum, the purpose of which is to extract information such as trends and seasonality from it as inputs to the subsequent random forests in order to enhance the comprehensiveness of the final forecasts.

5.2.1 Prophet forecasting for top level

As mentioned earlier, the Facebook Prophet model is suitable for time series with strong seasonal effects and multi-seasonal historical data from which annual, weekly and daily seasonality as well as holiday effects can be captured (Zunic et al., 2020). Therefore, this study chose to use the prophet model for time series forecasting in order to extract relevant and valuable information.

The Prophet model was created based on the overall sales data of "ladieswear", and the forecasts were completed by passing in holiday information through the holidays parameter created in 5.1.2. Figure 5.2 shows the sales forecasts for the coming year. Observation shows that the line graph shows an overall slow downward trend. The forecast intervals (red lines) essentially mimic the trend of the last two years as well as the peaks, with two prominent peaks matching the inclusion of ”Summer Sales“ and “Black Friday” in the model, indicating to some extent that the feature engineering based on “holidays and special events” has had a positive impact, and that the model has been able to capture important cyclical sales patterns, but there are a number of other peaks triggered by potential events or factors that are not fully and effectively identified.

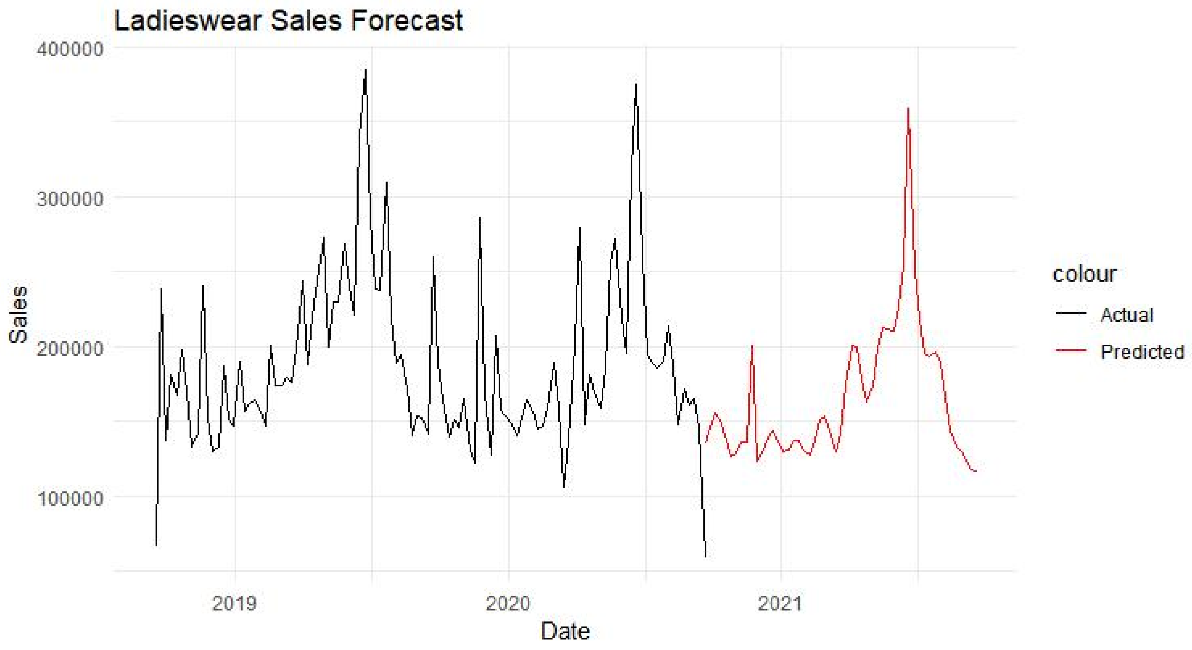

Figure 5. 2 Ladieswear sales forecast line chart using prophet

5.2.2 Residuals test

In this study, the main purpose of initial forecasting using prophet is to generate relevant influences to use as inputs for subsequent random forests, so model testing is more focused on whether as much trend and seasonal information as possible will be captured than on forecasting accuracy. Hence residuals are used as the test. The remainder of the model fit of a time series model is defined as the "residual", which is the difference between the observed value and the corresponding fitted value (Cox et al., 1984). Thus performing a reference test can be effective in identifying the unexplained part of the time series.Figure 5.3 shows the residuals of the sales forecasts performed by prophet. The residuals appear to be randomly distributed around the zero line, indicating to some extent that the model is not systematically over- or under-estimating the forecasts. According to the figure, the range of residuals is centred around the range of about -50000 to 50000, which is acceptable considering the million level of sales and the purpose of prophet's forecasts. In addition, there is no clear trend or seasonal pattern visible in the graph, which means that the model may have captured these components fairly effectively.

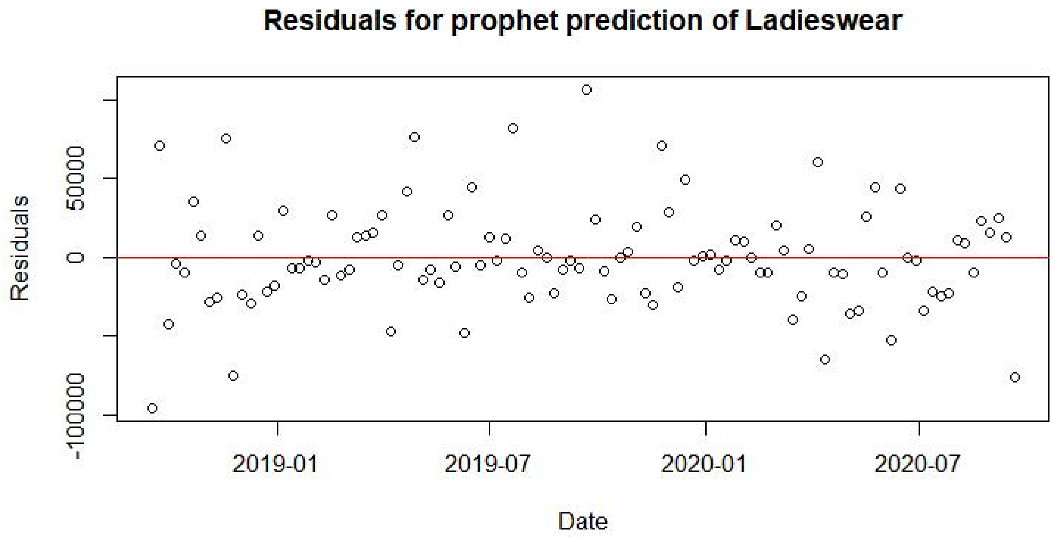

Figure 5. 3 Residuals for prophet prediction of Ladieswear

Further, the Box-Ljung test was conducted on the model residuals, which is a statistical test used to check for autocorrelation in the residuals of a time series model, whether the residuals are randomly distributed and have no autocorrelation structure (Burns, 2002). The test is based on the null hypothesis that "the residual series are not autocorrelated for a given number of lags" (Burns, 2002). Typically, if the p-value is less than a predetermined level of significance (0.05), the null hypothesis is rejected, indicating that there is autocorrelation in the residuals and that there is room for model improvement. If the p-value is greater than 0.05, the null hypothesis is usually accepted that the residual series is white noise. According to the test results shown in Table 5.2, the p-value is 0.1255, which is greater than 0.05, therefore no evidence of autocorrelation is found in the residuals and can be recognised as an indication that the model has a good fit.

X-squared	df	p-value
2.3474	1	0.1255

Table 5. 2 Box-Ljung test for prophet prediction of Ladieswear

5.2.3 Generate time series features

The forecasts produced by the Prophet model generate a variety of factors that can be used as references for subsequent studies, from which holidays, trends, yearly seasonality, and additive terms were selected for subsequent forecasts in this study. Holidays, one of the main strengths of the Prophet model, helps the model to identify the effects of special events that are outside of seasonality and trends. Additive terms is the sum of the various seasonality and holiday effects added to the model. It combines the effects of all components within the model and can provide Random Forest with a benchmark for forecasting based on historical data.

The trend component represents long-term changes in the data excluding seasonal fluctuations (Kirchgässner et al., 2012). In sales data, trends can reveal potential growth or decline, which is crucial for predicting long-term future sales performance. Random forests, on the other hand, predict outputs by means of multiple decision trees, which are usually based on non-linear relationships in the data (Breiman, 2001). Although Random Forest is able to handle non-linear patterns, it may not capture linear trends in the data as naturally as models designed specifically for time series. As seen in FIGURE 5.4 the sales data has a significant downward trend, so using the trend as a feature input helps the Random Forest model to identify and adjust for this long term trend.

The annual seasonality component captures cyclical changes in the data at different times of the year (Kirchgässner et al., 2012). This periodicity may be associated with specific holidays, seasonal changes, or other cyclical events. As shown in FIGURE 5.4, the sales data exhibit significant annual seasonality, which is a factor that needs to be fully taken into account in forecasting. Random forests themselves, on the other hand, do not automatically take into account the cyclical or seasonal structure of the data (Goehry et al., 2021). This means that unless information about seasonality is explicitly provided to the model, the model may not recognise seasonal patterns. Therefore, adding this feature can help the random forest model predict seasonal peaks and troughs more accurately.

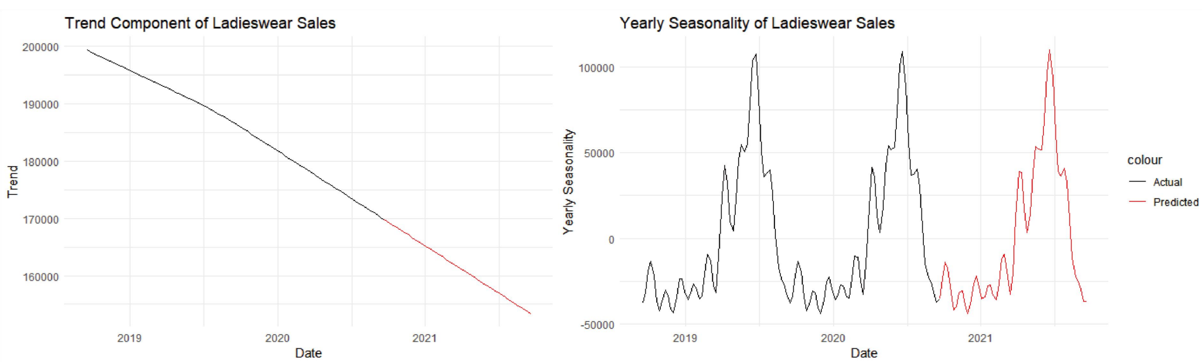

Figure 5. 4 Line charts of trend and yearly seasonality for ladieswear sales

5.2.4 Prophet forecasting for middle level and bottom level

The prediction process for middle level and bottom level using the prophet model is almost identical to that for top level, i.e., the same prediction intervals are set and the same holidays parameters are incorporated for prediction, so the process will not be repeated here. By performing the Box-Ljung test on all models, it can be seen that the distribution of residuals for more than half of the product categories meets the null hypothesis (p-value > 0.05), while the non-compliance is mainly concentrated in the categories with a low total volume or number of products. The likely reason for this is that these products are too highly influenced by their own attributes and do not match the overall trend, making it impossible for an unadjusted forecasting model to capture all of their information well.

Figure 5.5 and figure 5.6 show the predicted sales of the five highest selling product types and the trend of the decomposition. It can be seen that the forecasts for all the categories basically follow their original trends and seasonality, and the seasonal rows for "sweater", which has a significantly different sales pattern, are also accurately captured and forecasted accordingly. In addition, it can be seen that "Dress" is trending upwards, while the category as a whole and other categories in its class are trending downwards. Trends and seasonality such as these are also recorded in the same way in R by creating a loop through all the predictive models for subsequent predictions.

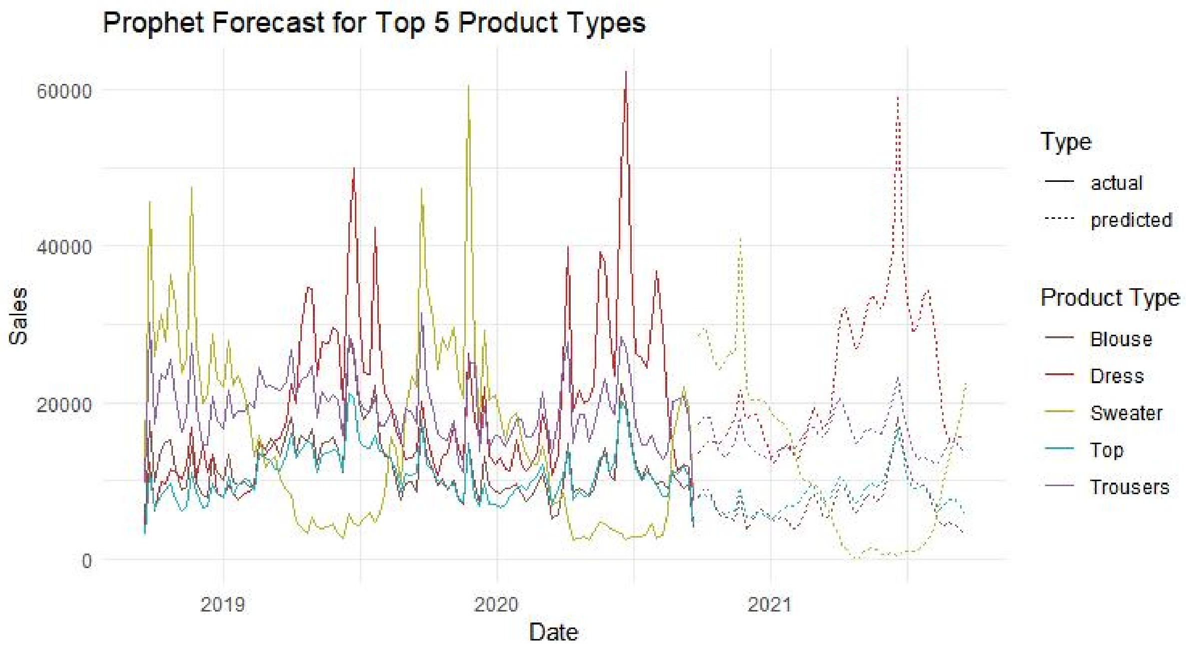

Figure 5. 5 Top 5 product types sales forecast line chart using prophet

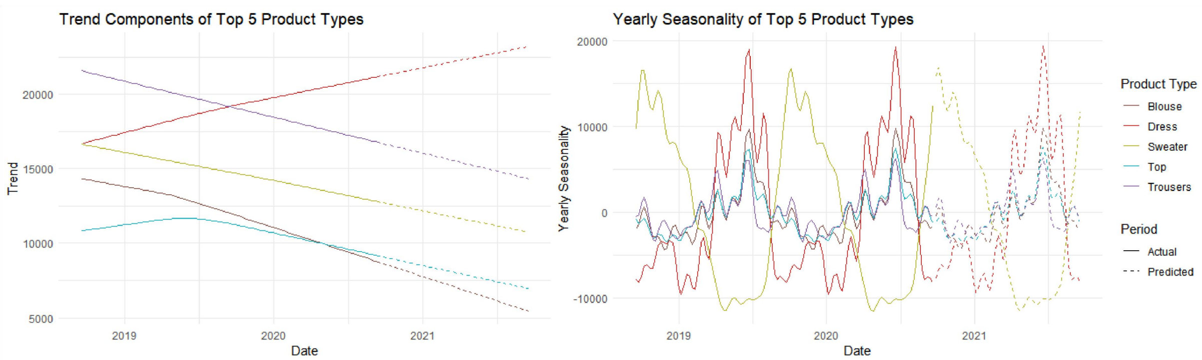

Figure 5. 6 Line charts of trend and yearly seasonality for top 5 product types

For bottom level, since “product_type_name” contains 90 categories and “department_name” contains 63 categories, if all the hierarchical categories are fully expanded, 5670 model branches will be generated. Due to the repetitive nature of the operation and the large amount of computation involved, this study only expands the model for the “Dress” with the highest sales in “product_type_name” at level 3, and as an example for level 3, the predicted sales with trend and seasonality are shown in figure 5.7 and figure 5.8.

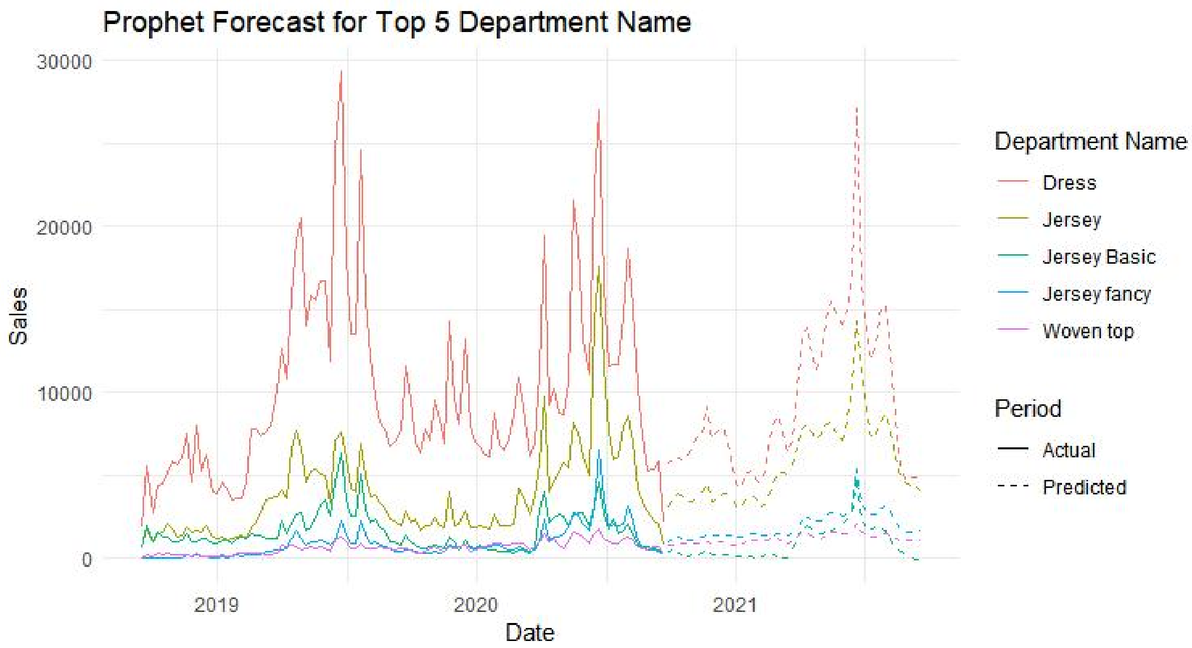

Figure 5. 7 Top 5 departments sales forecast line chart using prophet

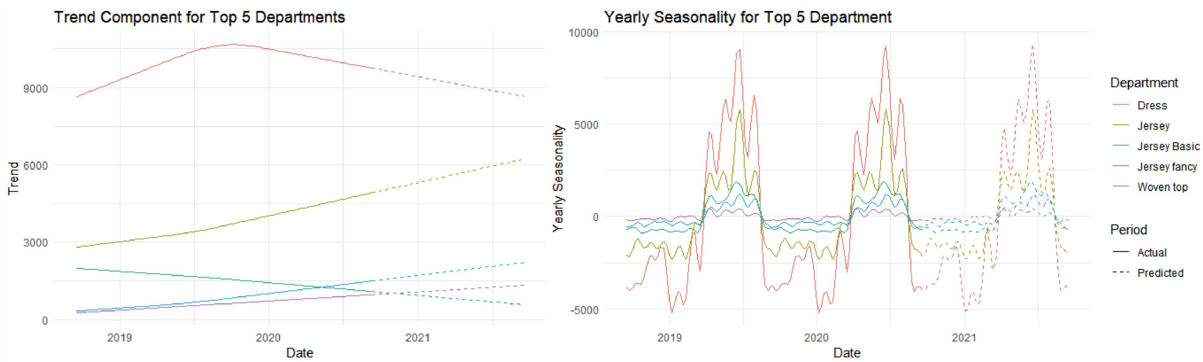

Figure 5. 8 Line charts of trend and yearly seasonality for top 5 departments

Combining the three visualisations of yearly seasonality reveals a polarisation of trends as the tiers are progressively decomposed. That is, categories with significant volatility become more volatile, while categories that tend to level off see their trends slow down further with the decomposition of the hierarchy. The reason for this is that at higher levels, where sales data from individual product types or departments are aggregated, this aggregation tends to even out the volatility, for example, the peaks in sales generated by the “dress” category and the troughs in “sweater” are at the same time period and may cancel each other out. However, when drilling down to individual product types or departments, only a single piece of data is observed for that category, demonstrating a more realistic and specific trend volatility. Similarly, in terms of trend, the overall trend shows a decline, but with stratification top down, it is possible to more clearly identify which categories are causing the decline and which ones are consistently growing. On the other hand for categories with inherently lower sales and volume, it is also important to consider whether there is an effect of statistical randomness. Because sample sizes are typically reduced at lower tiers, smaller sample sizes allow each observation to have a greater impact on the overall picture, and therefore individual outliers or short-term fluctuations may also cause significant trend fluctuations.

5.3 Random forest forecasting

In 5.1 and 5.2 all feature extraction has been done. In this section random forest will be used as the main prediction model for independent prediction of each hierarchical structure. Firstly, the random forest prediction is performed for the top level, and then the prediction results and related variables are used as the feature inputs for the middle level, and similarly, the related prediction results of the upper two levels are used as the feature inputs for the bottom level, so as to form a progressive prediction model.

5.3.1 Top level forecast

In the operation of R, this study uses "ranger" as the main model building tool. The goal of the RANdom forest GEneRator (Ranger) is to implement the random forest model in a fast way with reduced computation (Demir and SAHİN, 2023). For this purpose, Ranger can utilise multiple processors in parallel to build trees faster (Tiyasha et al., 2021). Also, its optimised search algorithm is able to find the best segmentation point for each feature quickly, with shorter computation time and reduced risk of overfitting compared to other ways of building random forests (Demir and SAHİN, 2023). In addition, "trainControl" and "expand.grid" functions in the caret package were used to set and optimise the hyperparameter of the random forest. Firstly, the cross-validation method was set up using "trainControl", and through iterative debugging, the number of cross-validations was specified (n = 3), which means that the data will be divided into three parts for cross-validation. This ensures the generalisation ability of the model through multiple resampling methods (Kuhn, 2008). The search space for the hyperparameters was then defined using "expand.grid". Specifically, this includes the "mtry" parameter for random forests, i.e., the number of variables considered when splitting the tree, the splitting rule "splitrule" (set to "variance"), and the minimum number of samples from the tree nodes “min.node.size”. These settings allow the model to be trained with different combinations of parameters randomly chosen within a given parameter range. In this way, the model is able to automatically figure out the best parameter configuration as a way to better tune and optimise its performance, thus improving the accuracy and robustness of the predictions (Kuhn, 2008).

In terms of feature inputs, "yearly" is not included as one of the variables in the prediction of the top level, considering that the fluctuations in yearly seasonality observed in 5.2.4 are cancelled out with the aggregation of the levels. In addition, the number of products on sale generated in 5.1.1 will be included as one of the features in the random forest model. Since "on sale" is relatively independent of the other variables, in order to consider the correlation between the features, the “additive terms” with relatively comprehensive sales data information will be combined with it to generate additional interaction features to be included in the model. To sum up, sales volume was used as the dependent variable, and the previously mentioned features such as the number of products on sale, trend, holidays, additive terms, and the interaction between on sale and additive terms were used as the dependent variables for prediction. The following figure shows the visualisation of the prediction results of the Random Forest.

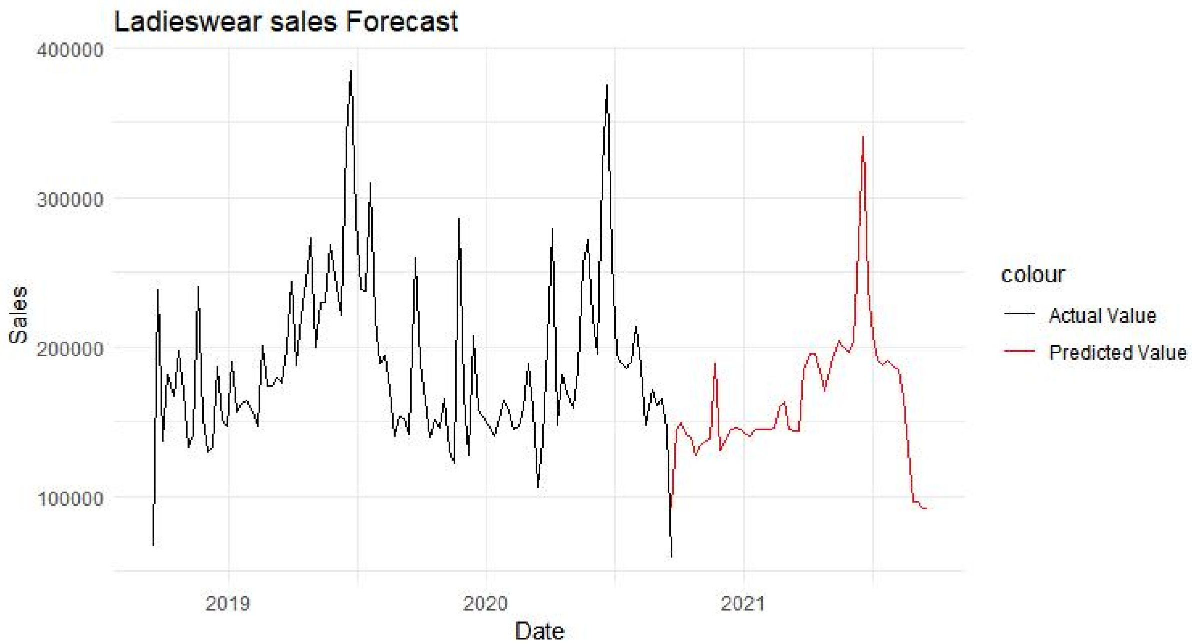

Figure 5. 9 Ladieswear sales forecast line chart using random forest

Figure 5.10 shows the distribution of residuals from the Random Forest predictions. The overall distribution pattern is similar to prophet's initial prediction in that it is distributed around a baseline of 0 with no apparent regularity. However, in order of magnitude the range narrows from 50,000 to -50,000 to 20,000 to -20,000 compared to prophet's prediction. This change can be partly justified by the fact that the random forest model incorporating the features captured by Prophet has a higher prediction accuracy.

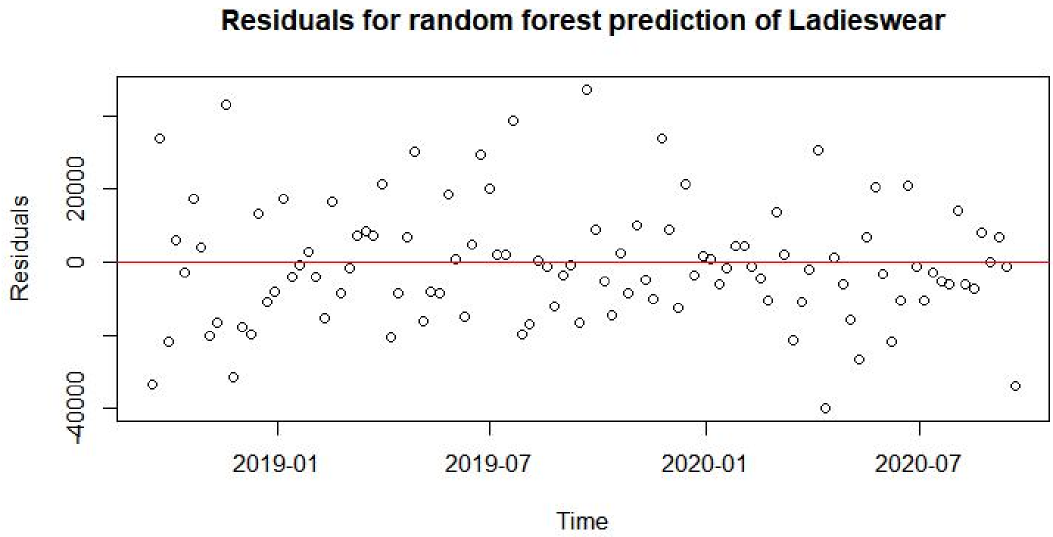

Figure 5. 10 Residuals for prophet prediction of Ladieswear

For model testing, this study used mean absolute error (MAE), root mean squared error (RMSE), and R-square as test metrics. MAE can be considered as the mean of the absolute value of the difference between the predicted and actual values, while RMSE is the square root of the mean of the squared error. The smaller the two values, the smaller the prediction error of the model and the higher the accuracy of the model (Willmott and Matsuura, 2005). R-squared represents the proportion of the variance of the dependent variable explained by the model to the total variance (Chicco et al., 2021), and its value ranges from 0 to 1. The closer it is to 0, the more portion of the model model is unable to explain, and conversely the closer it is to 1, the more portion of the variance of the dependent variable is explained by the model (Chicco et al., 2021). Due to its fixed range of values, it can be used as a medium for comparison of models between tiers in this study. Table 5.3 shows the results of the prediction detection for the TOP level. The MAE and RMSE are acceptable compared to the sales level which is basically around 200,000, and in particular, the R-squared value of 0.87 indicates that the model is able to explain about 87% of the variability in the sales data and has a relatively good fit.

MAE	RMSE	R-squared
15091.91	19805.32	0.87

Table 5. 3 Tests for random forest prediction of Ladieswear

In order to explore feature importance, this study still calculated the importance of individual input features using Ranger. The two main methods used by Ranger to calculate feature importance are based on Gini impurity and permutation importance (Wright and Ziegler, 2015). Gini impurity is a measure of the quality of the split point. A higher Gini impurity means that the node contains more mixed data categories, while a lower impurity indicates that the node is more pure, i.e., contains more uniform data categories (Nembrini et al., 2018). In addition, the importance calculated by the ranger is affected by the size of the original data values, so in order to facilitate visual comparisons between different levels, for each category of feature importance, a percentage was calculated for each category, normalised by the value of the most important one of them as the denominator. In the output results, as shown in Table 5.4, the "Importance" of each feature indicates the average reduction of Gini impurity of the feature in the whole forest; the higher the value, the more important the feature is in reducing the prediction error of the model. It can be seen that the interaction features of number of products sold and yearly seasonality have the highest importance, followed by yearly seasonality with almost equal importance. The remaining two features also have some importance, but the difference is larger than the first two. The importance of "holidays" is minimal, probably because its effect corresponds to only two data points in each yearly cycle, and even though it is objectively important for identifying idiosyncrasies, its importance for the overall picture is neglected.

Feature	Importance
on_sale_additive_interaction	1.00
additive_terms	0.80
on_sale	0.31
trend	0.23
holidays	0.02

Table 5. 4 Feature importance of ladieswear sales by random forest

5.3.2 Middle level forecast

Middle level predictions use essentially the same methodology as top level, which is a random forest model based on hyperparameter tuning and feature engineering. The difference is that the forecasts for the top level are entered as new variables in this level of forecasting. Since there is a significant order of magnitude difference between the overall sales volume at the top level and the sales volume of each category in the middle level, the z-score transformation is applied to the top level forecasts in order to allow the forecasts to effectively incorporate information from the upper level without compromising the accuracy of the forecasts. Z-score is a data normalisation technique that uses mean and standard deviation to transform the range of data between 0 and 1 for comparison and analysis (Patro and Sahu, 2015). This enables the upper sales data layer to retain its original trending information without the disparity in data size affecting the forecast. Based on the above approach, this layer incorporates the interactive features of trend, yearly seaeonality, holidays, on sale, additive_terms, on sale and additive terms as well as z-scored upper layer forecasts, totalling seven features, and adjusted the hyperparameter according to the number, completing the prediction for the middle level. As in figure 5.11, the trend of the predicted interval is basically the same as the actual interval, but there are many peaks and valleys missing, and the overall fold is smoother. However, at the two special time points marked by the "holidays" parameter, there are corresponding peaks in several folds, which can show that the Random Forest model effectively learns the characteristics of the prophet's output.

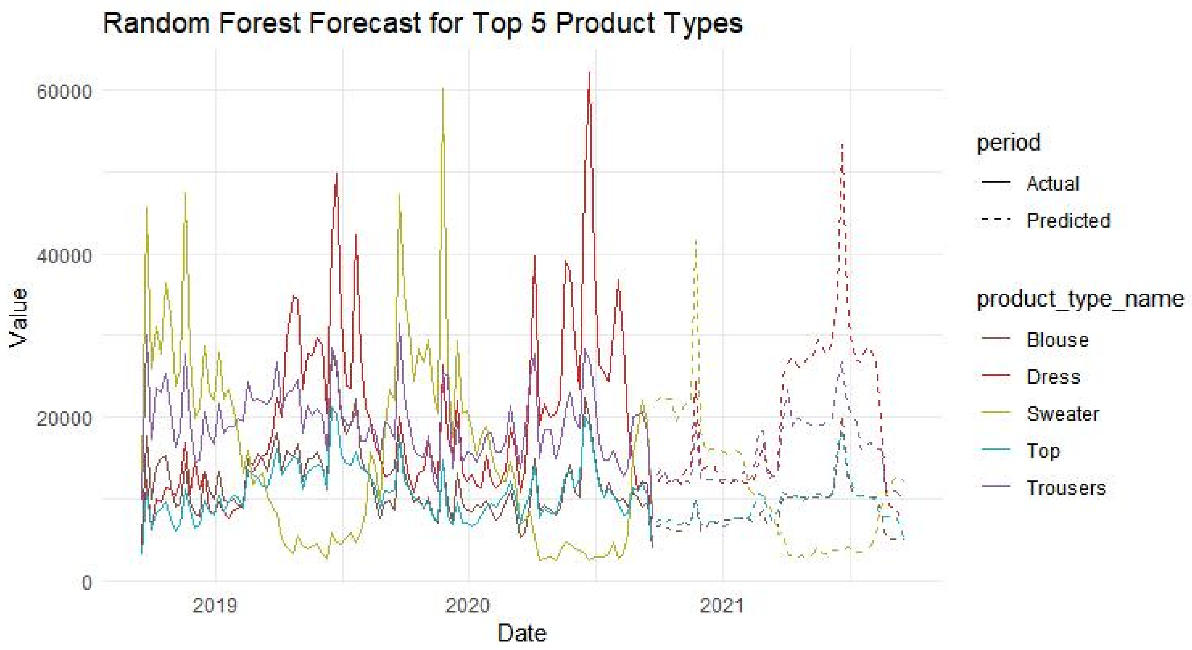

Figure 5. 11 Top 5 product types sales forecast line chart using random forest

Next, the same test was performed for the middle level predictions as for the top level.Table 5.5 shows the results for the five most sold categories, all of which have r-squared values higher than the top level of 0.87. Based on the overall results, it can be seen that the r-squared of all product types is higher than 0.6, with an average value of 0.93, which is an improvement compared to the top level of 0.87. The lower r-squared parts are mainly concentrated in the categories with relatively low sales volume, the reason for their low fit may be that their low sales volume leads to a relatively large impact of individual sales points, which do not exist in the overall trend or seasonality, and are not captured by features, which improves the random error of the prediction. Considering that the categories themselves are not of high importance, a minimum of 0.6 is somewhat acceptable from a business needs perspective.

Product type name	MAE	RMSE	R-squared
Blouse	549.89	760.85	0.97
Dress	1045.72	1504.11	0.98
Sweater	895.79	1594.90	0.98
Top	475.29	633.84	0.96
Trousers	761.66	1051.49	0.94

Table 5. 5 Tests for random forest prediction of top 5 product types

Similarly, in the analysis of feature importance there are differences due to sales volume, and Tabel 5.6 shows the feature importance of the five categories with the highest sales volume. It can be seen that the product types for which "sales-zscore" is considered as the most important feature have basically a high level of sales. This may be due to the fact that high volume product types are likely to make up a larger proportion of the dataset, meaning that their sales data have a greater impact on the overall trend. The model may tend to focus more on these more data-rich and representative product types. According to the full test, the most important feature in the forecasts for the majority of product types is "on_sale_additive_interaction", with 51 categories, which is consistent with the upper level performance. In addition, although the importance is generally low, it shows a strong positive correlation with sales, probably for reasons similar to those of "sales-zscore".

Features	Blouse	Dress	Sweater	Top	Trousers
trend	0.17	0.11	0.03	0.14	0.33
yearly	0.06	0.46	0.50	0.13	0.25
holidays	0.00	0.02	0.00	0.00	0.01
on_sale	0.06	0.15	0.04	0.08	0.20
on_sale_ additive_ interaction	0.11	0.77	1.00	0.10	0.23
additive_ terms	0.04	0.88	0.45	0.10	0.27
sales_zscore	1.00	1.00	0.47	1.00	1.00

Table 5. 6 Feature importance of top 5 product types by random forest

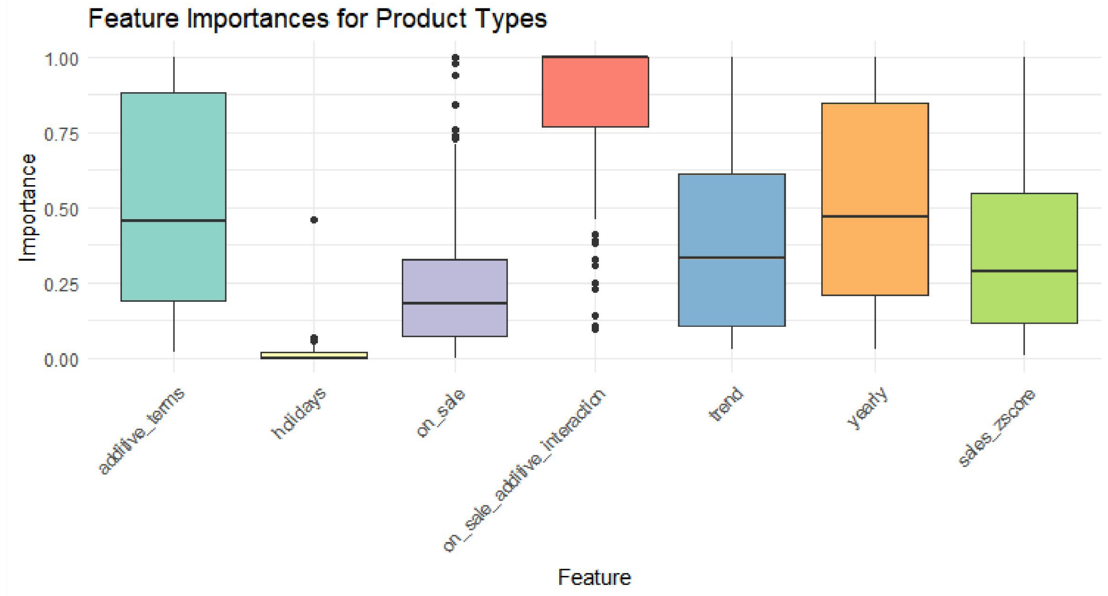

Figure 5. 12 Box plot of product types feature importance

5.3.3 Bottom level forecast

As with the first two levels, the prediction at the bottom level is based on the same methodology, i.e. using the same Random Forest model with an additional z-scored middle level prediction and the consequent adjustment of the hyperparameters.As mentioned earlier, due to the large number of categories, a full expansion of the bottom level would result in thousands of models with the same methodology, and therefore only the bottom level prediction for the "Dress" product type is used as an example in this study.As can be seen in figure 5.13, similar to the upper level, the prediction intervals are accurate in terms of trend but less volatile.

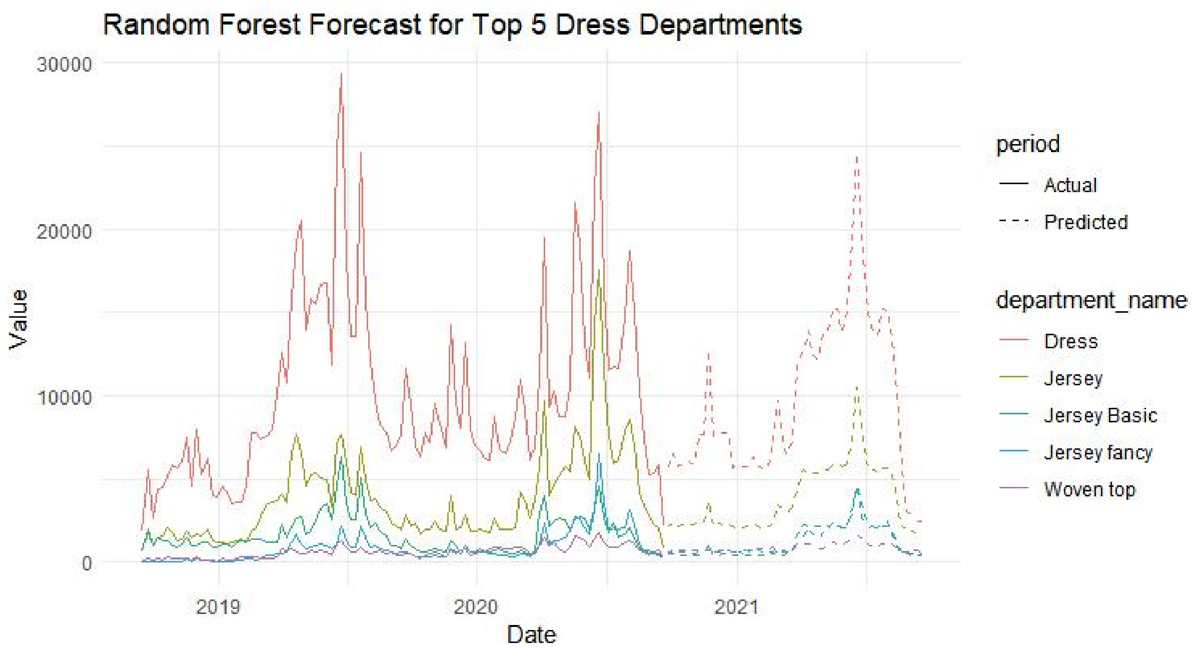

Figure 5. 13 Top 5 dress departments sales forecast line chart using random forest

The results of this layer are similar to those of the upper layer, with r-squared higher than 0.6 for all categories, and the mean value is 0.87, which also maintains a high degree of fit. In addition, table 5.7 shows that the five categories with the highest sales all have very high fit, with r-squared above 0.95, or even close to 1, which is nearly the same model level as the corresponding upper level "dress" category.

Department name	MAE	RMSE	R-squared
Dress	448.71	680.24	0.99
Jersey	341.49	550.9	0.96
Jersey Basic	147.83	233.92	0.96
Jersey fancy	71.40	169.35	0.97
Woven top	35.58	45.76	0.98

Table 5. 7 Tests for random forest prediction of top 5 dress departments

In terms of feature importance, the bottom level is no longer as clearly signalled as the upper two levels.In the five highest volume departments, the volume features in the MIDDLE level all possess relatively high importance. And according to the importance intervals shown in FIGURE 5.14, the intervals at this level start to show a polarisation trend compared to the top level. Compared to the middle level, the top level's sales characteristics have a lower priority in terms of importance. It can be seen that the decomposed and refined trends at the middle level are more helpful to the neighbouring lower levels in improving forecast accuracy than the overall trendiness of sales. In addition, combining figure 5.12 and table 5.8, it can be seen that "on_sale_additive_interaction" is consistently the most important feature for the largest number of categories.As an interaction feature that includes most of the Prophet-generated information as well as relatively independent on-sale data, it is able to cover to some extent most of the key information that is important for forecasting, and can therefore be applied to some extent to most product groupings.

Features	Dress	Jersey	Jersey Basic	Jersey fancy	Woven top
trend	0.01	0.53	0.17	0.07	0.45
yearly	0.01	1.00	0.60	0.12	0.11
holidays	0.00	0.31	0.03	0.02	0.00
on_sale	0.02	0.67	0.07	0.15	1.00
on_sale_ additive_ interaction	0.01	0.99	1.00	1.00	0.78

additive_ terms	0.01	0.95	0.67	0.13	0.13
sales_ zscore_l1	0.05	0.83	0.62	0.03	0.07
sales_ zscore_l2	1.00	0.98	0.48	0.36	0.36

Table 5. 8 Feature importance of top 5 dress department by random forest

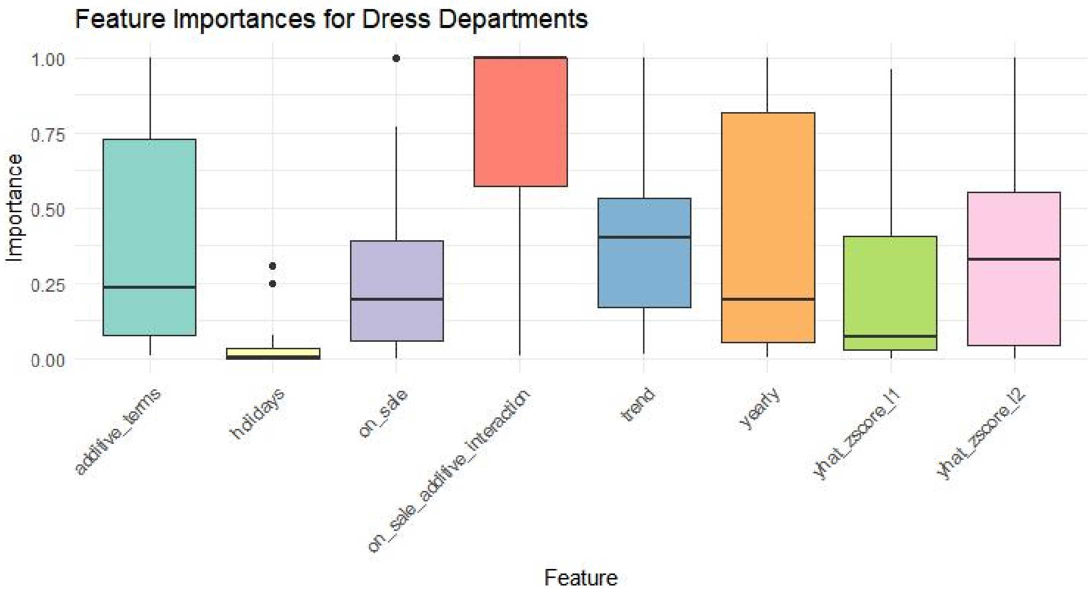

Figure 5. 14 Box plot of dress department feature importance

5.4 Summary

In this chapter, H&M's ladieswear category has been subjected to Hierarchical forecasting by combining Prophet time series forecasting and Random Forest model. In this case, the Prophet model, which excels in capturing seasonality and trends in sales data, is used with the help of which the phase variables are generated as the features of the Random Forest. whereas the Random Forest model, which has the ability to deal with more complex non-linear relationships, is used to complete the final forecast. In the descending process of the layers, the forecasts of the upper layers are used as new inputs to the lower layers through normalisation, which is used to convey the overall characteristics of the sales volume and improve the forecasting ability. In addition, this study also analyses the importance of features in each tier to provide reference and summarise changes in feature selection between tiers. In particular, the interaction features generated using the number of products on sale and the additive terms generated by prophet maintained a high level of importance between the tiers, emphasising the importance of considering the on-sale status of products and seasonal variations when making sales forecasts. Finally, in terms of testing, this study used the Box-Ljung test for residual testing of prophet time series forecasts, mainly in order to check the completeness of information in prophet forecasts in order to generate features. While the Random Forest model mainly used R-squared as a test criterion to check the goodness of fit, and explored whether the hierarchical forecasting achieved the effect of progressive enhancement of forecasting ability with the help of its normalisation feature. The results show that as the levels top to down, the fit of the model steadily improves while maintaining a high level. In summary, although the model has some limitations in terms of capturing details such as peaks and troughs, it is generally able to forecast with good accuracy at all levels, and can better capture the complexity and volatility of sales data in the fashion industry.

Chapter Six

DISCUSSION & CONCLUSIONS

6. CHAPTER SIX: DISCUSSION & CONCLUSIONS

As the final chapter, this chapter aims to summarise all the key findings and elaborate on the significance of the study for the fashion industry. By summarising the challenges of forecasting in the fashion industry highlighted in the literature and the performance of existing forecasting models in the fashion industry, this chapter further discusses the practical implications of Prophet combined with Random Forest for forecasting models in the fashion industry. In addition, this study also summarises some trends and characteristics from the research process that change during the hierarchical forecasting process, which can be used for subsequent related model applications in the fashion industry. Finally, this chapter analyses the limitations of this study and suggests possible areas for future work.

6.1. Discussion on Research Findings

Almost all literature dealing with fashion forecasting mentions the many difficulties of demand forecasting in the fashion industry, such as irregular patterns and high variability in demand (Beheshti-Kashi et al. 2015; Choi et al. 2013; Giri and Chen, 2022), as well as unstable and strongly seasonal demand due to the short product life cycle (Nenni 2013; Chen et al. 2022). However, the development of appropriate forecasting models seems to have been lagging behind compared to the ever-changing fashion industry. It is widely recognised in the literature that many traditional statistical forecasting methods in their original form of a single forecasting approach often struggle to cope with the large amount of complex information and identify the dynamic characteristics of demand for sales forecasts in the fashion industry (Chen et al., 2022; Ren et al., 2020; Tehrani and Ahrens, 2016; Yelland and Dong , 2013). In particular, the accuracy and flexibility of these models are limited when dealing with seasonal fluctuations and the impact of special events in fashion product sales. The Prophet model, on the other hand, as an additive model-based time series forecasting method, has shown superior forecasting performance to ARIMA and SARIMA in several areas (Taylor & Letham 2018; Satrio et al. 2021; McCoy et al. 2018). Past research cases have demonstrated Prophet's robustness to missing data and trend changes, as well as its ability to handle outliers, but little has been said about its strengths for special data features and trend capture. Considering the previously mentioned predictive features of the fashion industry makes it an ideal choice for handling fashion sales data in this study.

On the other hand, machine learning models, especially random forests, have been shown to have significant advantages in dealing with complex datasets (Breiman 2001; Zhao et al. 2020).In sales forecasting in the fashion industry, because Random Forest models are able to deal with non-linear and non-parametric variable relationships (Jeong et al 2016; Biau 2012), this is particularly effective when confronted with the redundant predictive influences in the fashion industry. This study combines this ability to handle complex and large numbers of input variables with the Prophet model's ability to capture seasonality and trends. As a composite model capable of accurately handling multiple complex variables, this approach not only outperforms traditional models in terms of forecasting accuracy, but also provides a solution to the specific data characteristics and fast-changing market environment in the fashion industry.

In terms of the application of hierarchical forecasting, the complexity of the product structure and the difficulty of allocating resources in the fashion industry have been highlighted in much of the literature, though (Woubante, 2017; Vashishtha et al., 2020; Ruby et al., 2022). These difficulties can be solved to some extent by creating a hierarchy of products for forecasting, but few studies have conducted hierarchical forecasting in the fashion industry. Previous studies have pointed out its importance in the fashion industry (Spiliotis et al., 2021; Fliedner 2001). Some of the relevant past studies have used hierarchical Bayesian models for hierarchical forecasting (Yelland and Dong 2013; Guigourès et al., 2018), but due to the nature of their models, the focus tends to be on the probability distribution of the data and the consistency of the hierarchy. The forecasting method used in this paper is able to effectively integrate diversified features such as the number of products on sale, holidays, and special events through feature engineering. The processing power of such integrated features may outperform traditional hierarchical Bayesian models. The hierarchical time series used by Lenort and Besta (2013) uses a top-down approach to forecasting the fashion industry based on the segmentation of historical proportions. The authors argue that the top-down approach better incorporates seasonal factors into the forecasting model and is applicable to the data characteristics of the fashion industry.Lenort and Besta (2013) integrated the seasonal factors into the forecasting system by using the proration procedure, which only focuses on the hierarchical structure and overall trend of the sales data and may have limited ability to deal with detailed features. In addition, numerous studies have argued that traditional hierarchical models often result in the loss of important information due to the aggregation or decomposition of hierarchies (Hyndman et al., 2011; Pennings and Van Dalen, 2017). To address this issue, the first adjustment to the way it incorporates impact factors is the use of Prophet to generate impact factors. This method is able to generate more diverse and comprehensive influencing factors at once than the former, which fits the complex and changing characteristics of the fashion industry, and has higher flexibility and adaptability. Afterwards, an optimal combination method based on independent prediction at each level is used, but following a top-down structure for feature transfer. The combination model avoids the problem of information loss by extracting the features of each levels and the normalised transfer of the prediction results of the upper levels to make independent predictions for all levels in a top-down process. The final prediction results also prove that the model maintains a high prediction level by independently predicting each level and feature transfer in top-down form.

6.2. Managerial Implications

Based on greater flexibility and adaptability, the model in this study has the ability to forecast demand in a rapidly changing and highly seasonal market such as the fashion industry. By improving forecast accuracy, fashion retailers can manage their inventory more effectively and reduce the risk of excess or shortages, which is essential for controlling costs and maximising profits (Reichart and Drew, 2019). At a broader strategic planning level, demand forecasting can help fashion brands better understand market trends and thus make more insightful decisions (Ren et al., 2020). At the merchandise level, accurate demand forecasting can also help retailers better understand consumer needs and optimise product recommendation strategies to increase customer satisfaction and improve customer loyalty, thereby enhancing brand value (Ren et al., 2020). As for new product development and market positioning, accurate forecasting can guide companies to launch the right product at the right time, avoid the risk of market mismatch, and achieve brand differentiation and competitive advantage (Liu et al., 2013). Previous studies have built targeted prediction models for different levels of demand separately. In contrast, the model in this study is able to take into account the different needs of the top and bottom layers simultaneously in its prediction by virtue of its generalisability in terms of features and its hierarchical structure characteristics.

Insights gained from demand forecasting can inform brands' strategic product decisions, align products with market demand (Ruby et al., 2022), reduce the risk of overstocking, and improve operational efficiency, profitability and the overall competitiveness of the fashion industry (Liu et al., 2013).It is estimated that 30% of all apparel production, will be destroyed or become inventory due to overproduction (Samuel, 2023).Whereas, it is possible to reduce the inventory of fashion brands by 20 to 50 per cent through accurate sales and demand based forecasting (Standish and Ganapathy, 2018).The model developed in this study allows for effective forecasting to optimise inventory levels and provide production recommendations by considering product and demand characteristics from multiple levels and perspectives.Further, by categorising and using hierarchical information in a rational hierarchical manner, to some extent, it is also the basis for fashion brands to achieve on-demand production (McKinsey, 2019).For example, by using hierarchical forecasting models to filter products with the same fabric properties in a complex hierarchy, analyse their correlations for demand forecasting and work together for coordinated sourcing and production.Through on-demand production, inventories and frequent production are reduced, which helps to reduce transport costs and mitigate the adverse environmental impacts of the supply chain, with some sustainability implications.

In addition, the forecasting process analyses feature importance, revealing the polarisation of trends and seasons at the hierarchical level, which guides the prioritisation of factors that brands need to consider when designing and selling at different levels.For example, top-level forecasts for the broad category and for the enterprise as a whole can support the overall volume and variety of products to be produced.The bottom level of segmentation, on the other hand, is more focused on detailed market trend analysis and product-specific sales forecasts, and is better suited to scenarios that require accurate forecasting and in-depth market analyses.

6.3. Final Conclusions

6.3.1. Research Aim Attainment

The initial aim of this research is to develop an effective demand forecasting model based on the product hierarchy of fashion brands to guide future sales. In order to achieve this objective, four relevant research objectives are listed in Section 1.5.Following the guidance of the objectives, the research firstly reviews the existing literature on demand forecasting and hierarchical classification, whilst highlighting the factors that need to be specifically considered for fashion forecasting based on the unique features of the fashion industry. Subsequently, the second objective is completed in Chapter 4 through descriptive statistics and data visualisation, which prepares the data for subsequent forecasting. The third objective was completed in Chapter 5, where stratified forecasts were made and the results analysed using the Prophet time series model and the Random Forest model. For the last objective, the forecasting effect of the established model and its implications for the fashion industry are presented in 6.1 and 6.2 of this chapter. Based on this, the research aim of this study has been achieved considering the positive forecasting effect of the model and its practical value.

6.3.2. Originality and Contribution

This study combines the Prophet time series model with the Random Forest model for hierarchical forecasting based on the inherent classification of fashion products. According to the reviewed literature and related researches, Prophet, as a newer model that has performed well in other fields, has the ability to identify features that match the highly seasonal and trending nature of the fashion industry, however, there are few cases of its application in the fashion industry. Similarly, there are only a few cases of hierarchical structure in the fashion industry, and the few cases focus on cluster analysis and recognition systems. Faced with the large number of products and redundant categorisations in the fashion industry, a hierarchical forecasting approach is able to provide multiple levels of forecasting simultaneously, offering more comprehensive insights to guide brand production and sales. Therefore, the model developed in this study bridges this part of the application gap to some extent.

6.3.3. Limitations and Further Research

Despite the positive performance of the model forecasts, there are inevitably some limitations to the research.

In terms of the dataset, the main reason for using the H&M competition dataset from Kaggle in this study is that it contains a large number of products with specific classification attributes, which is one of the bases for stratification and prediction. However, from the initial visualisation of the figure 4.3, it can be seen that the data has a distinctly unnatural rise and fall at the beginning and end of the time series. The possible reason for this is due to the initialisation process and the ending process at the time of data collection. In this regard, a better approach would have been to intercept a portion of the middle section of the time series for research purposes. However, considering that the length of the time series is only 106 weeks, this practice is subjectively ignored in this study in order to retain two complete annual cycles. In addition, due to the content limitations of the dataset, a more comprehensive hierarchical reconciliation in terms of the number of forecasts at each level was not performed in this paper. In practical applications in the fashion industry, one possible direction is to further reconcile the product forecasts at each level by linear programming with more comprehensive information such as budget, cost, and inventory, setting the corresponding constraints to provide guidance to the product planning of the brand.

On the other hand, according to the find of feature importance, the more down the level, the more it can show the special influence of specific fashion items or styles on its sales, so the diversity and individuality of its features are more obvious compared with that of the upper level. So perhaps bottom-up, a hierarchical forecasting structure that aggregates these personalities, might be more suitable for fashion industry forecasting. However, since only 3 layers of stratification are involved in this paper, this type of relationship is not deeply explored and needs to be further proved by future research. In addition, the test results for features importance can be further incorporated into the hierarchical optimisation, e.g., the corresponding weighting operation in the lower prediction layers according to the importance in order to give full play to the capabilities of the features. In addition, since the data source is from H&M, as a fast fashion brand with a clear positioning, its sales characteristics and consumer groups will also carry significant features, such as a concentrated low price range, extreme sales volatility, and extreme sensitivity to promotional activities. Therefore, if the model is applied to other fashion brands in the future, some of the features may not be fully used. This needs to be defined by future researchers according to the actual situation.

Overall, these limitations can provide opportunities for further research and provide ideas and directions for related research and applications.

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Appendix One – Learning Agreement

Title of Project	Demand forecasting model based on product hierarchical classification of fashion brands			
Name/s of collaborators if applicable	NA			
Supervisor	Meghna Godya			
Aim of the project:	To develop effective demand forecasting models for fashion brands based on their product hierarchies to guide future sales and improve competitive advantage.			
Objectives (Maximum 5)	● To critically review the existing literature on demand forecasting and hierarchical classification in the fashion industry, taking into account the variables specific to the industry. ● To describe and evaluate, through data visualisation, the complete dataset on Kaggle on H&M product sales used in this study. ● To develop a demand forecasting model based on the dataset to predict future demand through a combination of hierarchical time series and machine learning. To test the forecasting model verifying its performance and summarising the impact and implications of hierarchical forecasting models in the fashion industry.			
Agreed outcomes	An Individual Theory-Based Traditional Dissertation (17,000 words)			
Formats	Chapter 1: Introduction (2500-3000) Chapter 2: Literature Review (4000-5000) Chapter 3: Research Design (1500-2500) Chapter 4: Dataset (1500-2500) Chapter 5: Finding and Analysis (3000-4000) Chapter 6: Discussion and Conclusions (3000-4000)			
Agreed contact points/ Tutorial dates	June 08	July 13	July 20	
Project Timeline				

Ethics Form Attached (as needed)	No	**Risk Assessment Attached (if needed)**	No
Learning Outcomes		**How you will evidence attainment of the outcome (max 200 words per outcome)**	

1. Execute research informed self-directed project, demonstrating an advanced level of analytical (i.e., forecasting or machine learning) and evaluative skills (Process, Enquiry, Knowledge) 2. Apply your critical understanding of contemporary relevant theory and practice in your subject area (Enquiry, Knowledge)	● The aim of this study is to build a hierarchically structured forecasting model based on known product categorisation information using data from a competition on Kaggle about H&M Personalized Fashion Recommendations. The study will combine quantitative and qualitative research methods to ensure in-depth examination and evaluation of the findings. ● The study will refer to reliable literature to ensure the validity of the research work. ● In terms of analysis and modelling, appropriate methods from previous studies will be summarised and improved for data analysis, while the results will be presented visually through graphs and charts. ● This study is quantitative in nature and adopts a positivist worldview that can be found through research and described through measurable attributes independent of the observer and his/her instrument. ● The study will follow research guidelines to ensure compliance.
3. Demonstrate effective communication of your project, context, and research design (Communication)	● The literature review section outlines the relevant theories, summarises the strengths and weaknesses against the existing models, and presents convincing arguments and justifications for the analysis section. ● The analysis section uses a combination of time series and machine learning approaches to model building in order to obtain more accurate predictions. ● Conclusion and discussion session to evaluate the project, summarise the significance and likely impact of the research

	and describe any gaps in the research.
4. Evaluate the execution of your Masters' project against relevant academic and professional standards (Process, Realisation) *5.*	• Forecasting in the fashion industry has always been difficult but rewarding because of the complexity of factors such as seasonality, unstable ground cycles and external fashion trends. Combining the analytical results of time-series forecasting with the correlations between the layers of a hierarchical structure through machine learning enables the model to take into account a variety of features in order to generate forecasts. This can provide new ideas for the application of composite models in the fashion industry.

Signed Tutor: Date: November 16th, 2023

Signed Student: *Hefei Cao* Date ………July 28 2023……………

Students should submit any written work for review by their supervisor **three working days** prior to a tutorial, in order to give the supervisor sufficient time to consider your work and respond to any issues. Students should **normally** expect a response to an email by your supervisor within five working days. It is your responsibility to find out when your supervisor will be on leave or out of the country

Appendix Two – Digital Consent Form

Consent form to allow a Master's Project to be stored in the library

I hereby give my consent for my dissertation / report to be stored in the library. *

Please note:

- Master's Project will be kept on the open shelves and are accessible to all library users i.e. students, staff, alumni and visitors.
- Master's Project are clearly labelled informing other library users that they should not be photocopied, scanned or photographed.
- Master's Project given to the library in digital form will be printed; the original digital copy will not be stored by the library.
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- If your report contains any confidential commercial information, please ensure you seek permission from the company concerned for this to be lodged in the library. Written consent from companies may be forwarded onto the library separately.

Name:	Hefei Cao
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Course and level:	MSc. Fashion Analytics and Forecasting; Level 7
Title of Master's Project:	
Signature:	Hefei Cao
Date:	26/09/2023

Consent form to allow a copy of your Master's Project to be used as an exemplar

I hereby give my consent for my Master's Project to be used as an exemplar for other students.

Please note:

- Master's Project will have any reflective statement/self-evaluation removed.
- Other students will not be allowed to print, copy or distribute your work.

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Signature:	Hefei Cao
Date:	26/09/2023