Predicting Product Returns in E-Commerce

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Abstract

Product returns are currently a major complication for online retailers that severely affect overall profits, especially in the apparel sector. In order to minimize the costs associated with product returns, it is not only important for online retailers to understand what drives customers to return purchases, but also to know which product purchases are likely to be returned. In this study, we therefore examine whether an ensemble selection prediction model is able to accurately predict product returns based on customer-, product- and shopping basket characteristic. In addition, we explore the correlation between these particular characteristics and the return probability. Using a large data set containing purchases from a major Dutch online retailer, we demonstrate that our proposed ensemble selection prediction model can predict product return rates at sufficient accuracy to benefit online retailers in their pursuit to minimize product return costs. We also show that our ensemble outperforms a wide selection of state-of-the-art classification algorithms in several ways, where most algorithms of this selection are able to predict product returns effectively as well. Furthermore, we show how return decisions are influenced by customer-, product-, and return shopping basket characteristics. It turns out that important factors influencing the return probability are, amongst others, gender and age, product price and -quality, and the number of different product categories in the basket.

Keywords: *Product returns, e-commerce, online retail, customer-, product and shopping basket characteristics, statistical methods, ensemble selection prediction model, machine learning*

Contents

Introduction

Ever since the beginning of the digital age, engaging in e-commerce has been the path to retail success for many small as well as more substantial retailers. However, selling online does not in itself guarantee success and comes with a host of challenges and costs. The costs of product returns, for example, is a rather considerable expense line that e-commerce retailers have to take into account. It has been estimated that worldwide product returns reduce retailers' profits by 3.8% on average each year (David, 2007). It should therefore not come as a surprise that e-commerce retailers pursue the minimization of product return costs.

In general, there are two strategies online retailers can employ to minimize the costs associated with product returns, namely, what is called 'value creation' and 'cost reduction' (Bijmolt et al., 2017). Value creation in this instance focuses on product value recovery and creating Customer Lifetime Value (CLV), considering an operations- and marketing approach respectively. Cost reduction with an operations approach, on the other hand, concentrates on the optimization of processes to minimize return costs, while cost reduction with a marketing approach focuses on reducing the return rate of customers.

While this may give the impression that e-commerce retailers employing counter measures to reduce the product return costs attempt to achieve return rates of zero by all means, that is not entirely true. That is to say because retailers also realize that customers desire high-quality service, including the possibility to return products. Providing this high-quality service, and thus the possibility to return products, enhances the relationship with customers (Stock et al., 2002) and in that way may increase purchase rates (Wood, 2001); something retailers generally celebrate. Depending on the leniency of a return policy, which may also positively affect the future purchasing behavior of customers, a moderate amount of product returns may even maximize profits (Petersen and Kumar, 2009). In other words, there exists an optimal return rate that balances the costs associated with product returns and the beneficial impact of providing a lenience return policy.

In order to find this optimal return rate and minimize product return costs, it is important for e-commerce retailers to understand what drives the proportion of returns, which customers can be classified as return-prone customers and, most importantly, which products are likely to be returned. Having such information can benefit online retailers in their decision making and action taking in relation to product returns.

For instance, accurate prediction of a customer's likelihood to return a product can help in customer management and determining optimal marketing resource allocation; return-prone customers, for example, can be identified and might be excluded from marketing allocation. Alternatively, correctly predicting product returns can move online retailers to take return-discouraging actions against such customers by, for example, using moral suasion. Knowing that environmental awareness can effectively influence customer behavior (Aguilar and Cai, 2010; D'Souza et al., 2006; Bjørner et al., 2004), an online retailer could remind customers of the environmental impact associated with product returns by using pop-ups.

Hence, for e-commerce retailers to approximate the optimal return rate and minimize the associated costs, accurately predicting the likelihood of product returns is essential. Although all recognize the necessity of this, most find it hard to make such predictions, and consequently, are not able to account for product returns in their return management.

Several methods can be applied in order to predict a certain outcome. Probably the most common prediction method is the logistic regression. However, other classification algorithms such as neural networks, support vector machines or the k Nearest Neighbor have also been demonstrated to be successful across a large variety of problem domains (Fernández-Delgado et al., 2014).

In addition, there exist more advanced techniques that could predict a certain outcome, such as ensemble modeling. The principle of ensemble modeling is to combine multiple predictive models, or so called candidate models, together. Taking multiple predictions of different models into account makes a final prediction generally more accurate and consistent and decreases the bias. Previous studies in other domains have indeed evidenced the efficacy of ensemble modeling (Tsoumakas et al., 2008; Lessmann and Voß, 2010), but more important, ensemble models have also been shown to be effective in predicting product returns (Heilig et al., 2016; Urbanke et al., 2015).

Therefore, the goal of this study is to examine if an ensemble selection prediction model based on customer-, product- and shopping basket specific characteristics yields an efficient prediction of a product return, and in that way potentially provide the online retailers with a useful model that can support their decision making related to product returns. Efficient, in this study, refers to 4 specific model validity aspects, namely, overall performance, calibration, discrimination and practical usefulness, which are explained in full detail later on in this study. Ultimately, this study's aim is to answer the following question:

Is an ensemble selection prediction model based on customer-, product- and shopping basket specific characteristics able to efficiently predict product returns, so that the model is useful to support decision making processing related to product returns?

In order to understand the efficiency of our proposed ensemble selection model, it is important to separately examine the performance of each individual prediction model as well. Therefore, this study will also answer the following two sub-questions:

Is each of the individual prediction able to efficiently predict product returns based on customer-, product- and shopping basket specific characteristics?

Is our proposed ensemble selection model more efficient in predicting product returns, as compared to each individual prediction model?

Moreover, to get more insight in the dynamics behind the predictions, this study also investigates the effect of customer-, product- and shopping basket specific characteristics on product returns by answering the last sub-question:

How are product returns influenced by customer-, product- and shopping basket specific characteristics?

Data of a major Dutch online retailer that sells heterogeneous product categories exclusively through its online store is used to answer the above stated questions.

In order of sequence, this paper discusses the existing literature on product returns in the section *Literature Review*. The sections *Data Description* and *Methodology* then describe the outline of the performed data-analysis in more detail, starting with summary statistics of the dataset, and explain the methods conducted to translate the used data into the models of interest. The section *Results* follows, discussing the results of the models in full detail. Namely, the results of our study suggest that an ensemble selection prediction model based on customer-, product-, and basket level characteristics is able to predict product returns at sufficient accuracy, where we also demonstrate its business value. Ultimately, our study concludes, in section *Conclusion and Discussion*, that although an ensemble may not be the best choice of prediction model to use in practice, under certain circumstances, it could benefit online retailers in reducing product returns and increasing profit margins. In the same section the limitations and suggestions for further research are discussed.

Literature Review

The substantial financial impact of product returns on the profits of online retailers has prompted academic research on product returns. A large number of studies has been done and the existing literature covers a wide variety of theories on this topic; from theories on the antecedents and consequences of product returns to supply chain complexities. Surprisingly, literature related to product return prediction specifically, is scarce.

Therefore, we deem additional research into predicting product returns important. It may not only further benefit online retailers in streamlining their businesses, but may benefit online customers and the broader society as well. For customers, effective product return predictions might indicate whether a particular item has a high probability of fit for them or not, averting unnecessary bad buys and wrongly spent finances. The broader society could also benefit from an accurate prediction model, not only economically, but also ecologically. That is to say because accurately predicting product returns, and, if acted upon, the resulting reduced return rates, need less material used in product packaging. In turn, this reduces the volume of waste sent to landfills, next to many other environmental benefits of a reduced amount of product returns.

Predictive analytics in product returns

Although there is no abundance of literature related to product return prediction, the importance of such studies has been recognized and various statistical methods to address the issue of product returns have been suggested. Toktay (2001), in his book "*Forecasting Product Returns*", for example, describes several time-series forecasting methods to forecast return volumes which are particularly relevant for inventory management and production planning.

Yu and Wang (2008) in their article "*A hybrid mining approach for optimizing returns policies in e-retailing*", on the other hand, propose a hybrid mining approach to analyze return patterns, to classify customers and products with return ratios, as well as to direct suitable return policies and marketing strategies to specific customer and product classes. In other words, their approach

is to divide customers into different segments to which, in turn, different return policies are offered to.

Even though we recognize that the methods proposed by Toktay, and Yu and Wang could have significant impact on retailers' decisions related to product returns, we deem their suggested models only partly relevant to our research. That is to say because the methods proposed by them are not able to assess the likelihood of a product return.

In light of this study's aim to support decision making processes related to product returns by estimating the probability of a product return, literature from Hess and Mayhew (1997), Heilig et al. (2016) and Urbanke et al. (2015) appeared to provide more relevant information for this research.

Hess and Mayhew (1997), in their paper "*Modeling Merchandise Returns in Direct Marketing*", for example, examine product returns in the apparel merchandise category. In more detail, Hess and Mayhew examine the return probability as well as the time between purchase and return, where the main focus is on the latter. On data from a direct marketer of apparel, the authors show that a split adjusted hazard model is better in predicting return times than a regression model.

However, because the interest of our study is the return probability rather than the timing of a product return, it seems inappropriate to adopt the split adjusted hazard model into our analysis. Notwithstanding, as part of their analysis, Hess and Mayhew also comment that the return probability can be estimated by calculating the simple historic return rate of a product, or to use a more powerful approach such as a logistic regression.

In accordance, a logistic regression model in combination with the historic return rates of products to capture the long-term return behavior of products will be included in our own study.

Urbanke et al. (2015), in their study "*Predicting Product Returns in E-Commerce; The Contribution of Mahalanobis Feature Extraction*", on the other hand, introduce a decision support system for the prediction of product returns in the online fashion market, including a new approach for large-scale feature extraction. Such a system can be used by e-retailers as the basis to establish customer-specific return strategies. For the prediction of product returns, Urbanke et al. consider adaptive boosting and compare it to a total of seven other classification algorithms including Classification And Regression Trees (CART), extremely randomized trees, gradient boosting, linear discriminant analysis, logistic regression, random forest and a linear kernel Support Vector Machine (SVM)[1].

Before actually predicting product returns, however, Urbanke et al. reduce the number of independent variables by dimensionality reduction. They explain that the reason for them doing this is that many algorithms do not scale to large data sets, while they work with a data set consisting 5868 features. In order to reduce the number of features, the authors propose a newly defined dimensionality reduction technique which they name Mahalanobis Feature Extraction. This method is compared to other methods including Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). Eventually, the Mahalanobis Feature Extraction creates ten numerical features from the original 5868 features which, in turn, are used to predict product returns.

[1]The algorithms which we adopt in our study are further discussed in the methodology and appendix.

To conclude, using data from a major German online apparel retailer, Urbanke et al. show that a combination of adaptive boosting and Mahalanobis Feature Extraction outperforms all other dimensionality reduction methods as well as the single classifiers in terms of prediction quality.

While the combination of adaptive boosting and the Mahalanobis Feature Extraction was shown to perform well, in our study we do not include dimensionality reduction techniques as the number of features in our data is substantially smaller. Nonetheless, our study will include adaptive boosting for predicting product returns as it thus provides online retailers with opportunities to create dynamic customer-specific return strategies.

A last research found to be particularly relevant to our study into predicting product returns is the study "*Data-Driven Product Return Prediction: A Cloud-Based Ensemble Selection Approach*" by Heilig et al. In their article, Heilig et al. concern a forecast support system that aids e-retailers in reducing product returns. For such a system to be lasting and effective, the authors empathize that the prediction model should fulfill three requirements; first, the model should forecast with high accuracy, second, the model should display high scalability, whereas adaptability of the model is the last important requirement. Accordingly, the authors propose an ensemble selection prediction model consisting of six different classifiers, namely CART, SVM with linear kernel, logistic regression, multilayer perceptron, random forest and adaptive boosting. Using product- and customer specific data from an online apparel retailer, the authors show that the ensemble outperforms all individual classifiers in terms of prediction quality. Acknowledging the effectiveness of an ensemble model to predict product returns, our study into accurately prediction product returns will be based upon an ensemble model as well.

Recognizing the effectiveness of the methods proposed by Hess and Mayhew, Urbanke et al., and Heilig et al., we conclude that each of their studies' contributes a piece to the bigger puzzle of developing a particularly accurate model for predicting product returns. That is to say because Hess and Mayhew advise that using a logistic regression model or the historic return rates of products provides a valuable method of estimating the return probability of a product. Urbanke et al. contribute a method based on adaptive boosting for predicting product returns, which appears to provide online retailers with opportunities to create dynamic customer-specific return strategies. Heilig et al., additionally, demonstrate that an ensemble model outperforms individual classifiers in terms of prediction quality and in that way provides yet another method of predicting product returns.

Variables to complement predictive models of product returns

While others thus have developed product return prediction models before, we believe the accuracy of product return predictions may still be further improved by refining their methods. Our study will therefore build on a combination of the models proposed Hess and Mayhew, Urbanke et al., and Heilig et al. However, it will include additional variables into its prediction model as there exist many more factors that have been proven to have an effect on the return probability, but that were unavailable or not recognized as such by Hess and Mayhew, Urbanke et al., and Heilig et al. These variables are distinguishable in roughly three types of factors, namely 'customer related variables', 'product related variables', and 'shopping basket related variables'.

Customer related variables

One type of customer related variables that influence product return rates, some say, are demographic variables such as consumer age, gender and their residential area (Anderson et al., 2009; Minnema et al., 2016). Yet, whether this is truly so is still a matter of debate, as differences in the actual effects of consumer demographics on product return rates differ per study, and some even found that customer demographics have non-significant effects on product returns (Minnema et al., 2018). However, any prediction model aiming to be as accurate as possible should not exclude any factors that potentially influence product returns, and we therefore deem customer demographics important to our prediction model.

Customer characteristics that surely influence product return rates are related to the experience of the customers with the online retailer (Petersen and Anderson et al., 2009; Minnema et al., 2016). To this extent, Minnema et al. found that customers who made a previous purchase at the online retailer showed lower return probabilities, whereas customers who returned prior to purchase had higher return probabilities.

Moreover, Griffis et al. (2012) developed a measure of the customer's total relationship value, which is the total expenditures that the customer has with the online retailer in a defined amount of time.

Accordingly, our prediction model will also incorporate customer characteristics that capture the experience of a customer with the online retailer.

Product related variables

Besides customer related variables, the decision to return a product is related to the customers' level of expectations of a product's performance. Once a customer decides to purchase a product online and, once delivered, the product does not meet the expectations formed at the moment of purchase, the customer is more likely to be dissatisfied due to expectation disconfirmation, and hence, more likely to return the product.

To this extent, features of a product play an important role as an information source that customers use to form expectations of the performance of a product. For instance, literature has shown not only that customers are more critical towards more expensive products, and hence more likely to return the product (Anderson et al., 2009; Hess and Mayhew, 1997), but also that customers are not as critical towards less expensive products, so that the return rate of products on sale are lower (Petersen and Kumar, 2009). In other words, customers may be sensitive to both the absolute price level as well as percent discount from the regular price. Moreover, when customers have some uncertainty concerning a product's quality, consumers appear to use price and brand name as measures of the product's quality; assuming that a higher product price indicates a higher level of quality (Kirmani and Rao, 2000; Monroe, 1973).

Other product information at the moment of purchase, such as review valence, also has an impact on product return decisions. De Langhe et al. (2015) demonstrate that the average review valence can be used as a proxy for average perceived product quality, where higher average valence refers to a higher average perceived product quality. As the return rate for products with higher average valence is lower, it is suggested that higher perceived quality corresponds to a lower return rate (Minnema et al., 2016; Sahoo et al., 2018).

The product category of the purchase is another example of such product related variables that may effect return decisions. That is to say because firms often find product return rates in different product categories to vary dramatically. Product categories like socks or

gloves, for example, have almost no returns, whereas other categories such as shoes or swim wear have return rates of over 25 percent (Petersen and Anderson, 2015).

Because of the demonstrated importance of product related variables on the return probability, these variables should also be included in our prediction model.

Shopping basket related variables

Next to consumer related- and product related variables, do shopping basket variables have an influence on product returns as well. The product return rate may, namely, also depend on the composition of the entire shopping basket. For example, Minnema et al. (2016) demonstrate that the order size shows a positive effect on the return probability. They clarify that the more products are purchased, the more are returned, simply explained by the fact that customers must purchase products in order to return them.

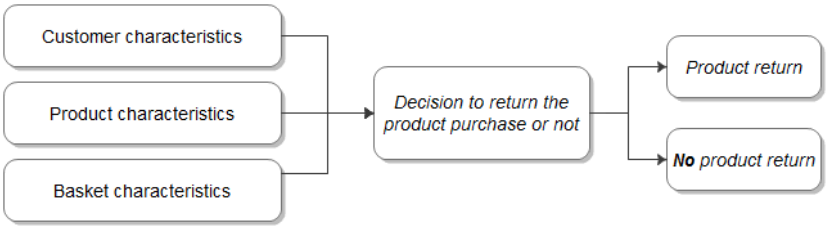
Additionally, complementary and substitute products in a shopping basket play a significant role in the decision to return a product (Anderson et al., 2008). As an example, consider a customer that orders the same pair of shoes in two different sizes as he or she is not sure of what would be the correct fitting size. Logically, only one pair of shoes has the correct fitting size, and it is therefore likely that the other pair of shoes, that does not have the correct fitting size, will be returned. Hence, the customer is using his or her living room as a fitting room. Now consider a costumer whose shopping basket contains multiple similar, but not identical, pairs of shoes; for example, pairs in different brands. Following the same rationale, it is again likely that one or more of these pairs will be returned.

Other basket specific characteristics influencing product returns include the payment method. As an illustration, Petersen and al., (2009) show that products purchased as a gift are less likely to be returned compared to when customers do not purchase the product as a gift.

Because of the proven influence of shopping basket related variables such as the number of shopping items, as well as of complementary and substitute products, and payment method, any accurate product return prediction model will thus have to take into account such variables.

Generally speaking, product returns can thus be considered as a function of customer-, product- and shopping basket specific characteristics, as represented graphically in Figure 1. In our study we should, and will, therefore acknowledge the significant influences of all of the before mentioned features on product returns, in order to take into account the individual differences in the model. In this way, the ensemble selection prediction model may deal with customer heterogeneity and could identify consumption patterns associate with a high (or low) product return rate at sufficient accuracy.

Figure 1: Visualization of product return dynamics



In conclusion, although the existing literature presents product return, -behavior and -prediction in a variety of contexts, it does not incorporate customer-, product- and shopping basket specific characteristics to its full extent. By focusing on the relation between each of these variables and product returns, examining the effects of these variables on the return probability, and to use them to effectively predict product returns, our study will contribute to the existing literature. We aim to provide a more accurate product return prediction model by examining the behavior and prediction of these exact measures all together in combination with product returns – something that has not been done before.

Data Description

Our study uses a database of purchases from a major Dutch online retailer that sells solely through its online store. Although the online retailer sells products in multiple product categories, we gather data on purchases within the fashion industry only. The data that is being used for analysis is cross-sectional taken over the time period from January 2017 until December 2017.

In the past, the return policy of this particular e-commerce retailer encompassed the possibility for customers to return purchased products within 14 days of purchase, and, if a customer indeed wished to return one or multiple items, the retailer offered a pick-up service. However, in November 2017, this policy was changed and the return period of purchased products was extended to 60 days after purchase.

Additionally, the online retailer limited the payment options of particular return-prone customers in September 2017. Knowing that customers who pay after delivery of the ordered products are generally twice as likely to return products in comparison to those who pay in advance (Urbanke et al., 2015), the online retailer now excludes the option to pay after delivery for particular return-prone customers in an attempt to reduce the product return rate. This policy change goes by the name 'Nudge' in our study.

The fact that these changes have been made over the period of our dataset may have an impact on our analysis as different return deadlines, and different payment options may affect customer's return decisions differently (Janakiraman and Ordóñez, 2012; Urbanke et al., 2015). In order to control for policy dissimilarities in our sample, we therefore include a dummy variable that indicates the allowed return deadline at the moment of purchase, and a dummy variable that indicates the customers who comply with the nudge requirements at the moment of purchase.

The variables that are being used in our analysis are differentiated between three levels, namely the customer-, product- and shopping basket level. First, the customer level considers attributes of a particular customer such as a customer's age, gender, and past return rate; indicators that are exactly equal for each observation in the basket. Second, the product level considers indicators such as a product's brand, price, and color; indicators that may be different per product in the shopping basket. Third, the shopping basket level of our model captures features such as the time of purchase, payment method, and the sales channel; indicators that apply to all products in the shopping basket - however taking into account that some basket level characteristics (such as the amount of the exact same item) may differ among products in the shopping basket. An overview and short description of all variables is provided in Table 1.

Table 1: Overview and description of the variables

Variable	Description and measure	# features
Dependent variable		
Return	Variable indicating whether the purchased product is returned	2
Customer level		
Age_group⋆	Variable indicating the age group the customer belongs to	6
Male⋆	Variable indicating whether the customer is male or female	2
Urbanicity⋆	Variable indicating whether the customer lives in an urban area: 1(urban)-5(rural)	5
PastReturnRate$_{Customer}$⋆	The customer's past return rate based on purchases and returns during the last twelve months	1
Total_PastOrders⋆	Number of times the customer placed an order during the last twelve months	1
Total_PastOrderSize	Number of items the customer ordered during the last twelve months	1
Segmentation_info	Variables indicating customer quality- and target segments	53
Relationship_length⋆	Time since first purchase made (in years)	1
Total Relationship Value	Overall value of the customer's relationship to the online retailer	1
Nudge⋆	Variable indicating the customers who have a return rate over 80% given at least 45 purchases during the last twelve months	2
N_Nudge	Number of times the customer belonged to the nudge group	1
Income⋆	Variable indicating the income level of customers	6
OldestChild	Variable indicating the (possible) age of the oldest child of customers	5
Family_Composition⋆	Variable indicating the family composition	5
LifeStage	Variable indicating the customer's current life stage	10
Age_HeadOfHousehold	Variable indicating the age of the head of the household	15
Last_Activity_Days⋆	Number of days since the last purchase and/or return during the last twelve months	1
Product level		
Price⋆	Price of the product once it entered the market (in Euros)	1
Discount$_{permanent}$⋆	Amount of permanent discount on the product (in Euros)	1
Discount$_{temporary}$⋆	Amount of temporary discount on the product (in Euros)	1
Discount_ratio⋆	The product's discount measured in percentages	1
Price_Segment⋆	Variable indicating the price class: *low, middle, high*	3
Quality⋆	Variable indicating the quality class: *low, middle, high*	3
PastReturnRate$_{Product}$⋆	The product's past return rate based on purchases and returns during the last twelve months	1
Category_Main	Variable indicating the main category type of a product: *pants, shoes* or *shirts*	75
Category_Exact	Variable indicating the exact type of a product: e.g. *jeans, sneaker* or *t-shirt*	213
Product_Gender	Variable indicating the gender of the product: *ladies/men, girls/boys* and *unisex*	7
SizeOptions⋆	Number of sizes in which the product can be purchased	1
PlusSize⋆	Variable indicating whether the product is a plus size item	2
Brand	Variable indicating the product's brand	702
Color	Variable indicating the product's color	81
Closure_Type	Variable indicating the product's type of closure: e.g. *zipper, buttons* or *hooks*	36
Season_Indicator⋆	Variable indicating the season for which the product is designed	4
Fit	Variable indicating the fit of a product, e.g. *skinny, slim* or *loose*	9
Fit_warning	Variable indicating warnings concerning the fit of a product: e.g. *smaller* or *larger fit*	3
AVG_Review⋆	Average review value of a product calculated by the reviews' expectation-, price_quality- and overall valence	1
N_Reviews⋆	Number of reviews on the product's website page	1
Outlet⋆	Variable indicating whether the product is showcased or not	2
Size	Variable indicating the product's size	536
Basket level		
Total_Spent_Fashion⋆	Total amount in basket spend on products within the fashion category (in Euros)	1
Total_Spent_Other⋆	Total amount in basket spend on products outside the fashion category (in Euros)	1
Voucher⋆	Amount of discount from a coupon (in Euros)	1
N_Products⋆	Number of products in basket outside the fashion category	1
N_Distinct_Products⋆	Number of distinct products in basket outside the fashion category	1
OrderSize_Fashion⋆	Number of purchased items within the fashion category	1
N_Identical_Products⋆	Number of exactly the same items in the shopping basket	1
N_Diff_Sizes⋆	Number of the same items, but with different sizes in the shopping basket	1
N_Diff_ProductCategory⋆	Number of distinct product categories in the shopping basket	1
N_Diff_Colors⋆	Number of distinct colors from similar type of products in the shopping basket	1
N_Diff_Brands⋆	Number of distinct brands from similar type of products in the shopping basket	1
N_Diff_Sex_Product⋆	Number of distinct product sexes in the shopping basket	1
Daypart⋆	Variable indicating the part of the day: *morning, midday, evening* and *night*	4
Season⋆	Variable indicating the season in which the order is placed	4
PayMethod⋆	Variable indicating the payment method of the order: e.g. *creditcard, ideal or giftcard*	6
Weekend⋆	Variable indicating whether the order is placed in the weekend	2
NoFreeShipping⋆	Variable indicating the orders that are not delivered for free	2
Campaign⋆	Variable indicating whether the online retailer runs a major marketing campaign	6
Holiday⋆	Variable indicating whether the order is placed on a holiday	4
Internet_Information	Variable containing information on total viewed pages, viewed product pages and the spent time on the website measured in seconds.	3
Website_Search⋆	Variable indicating whether the customer searched on the website for a product	2
Browser	Variable indicating the web browser	27
StartChannel⋆	Variable indicating the starting channel of the customer	17
Device⋆	Variables indicating the type of mobile and operation system	21

* Variables indicated with ⋆ are included in model (1) found in the section *Explanatory model*
* Total number of features: 1904

Most of the variables in Table 1 are self-explanatory and do not need to be elaborated on any further. However, in light of the complexity of some, we provide additional explanation for those variables that we see fit.

A variable that we think does require further explanation, is the product's past return rate, for instance. In order to calculate this, we consider historical purchase and return data from twelve months prior to the actual purchase. However, it may be possible that the sample size of the historic product data is small, which could result in an inconsistent and biased calculation of the past return rate. These small sample sizes are usually observed when a product is new on the market or when a product has a small stock. In such cases, the product's past return rate is estimated by taking the average of the past return rates from similar type of products that fall within the same quality- and price segment.

Furthermore, the quality segment of products is determined by the product's price at the moment it entered the market for the reason that, as explained in the literature review of this study, the product's price may capture the product's quality (Kirmani and Rao, 2000; Monroe, 1973). In more detail, for each product type category, the deciles are calculated using the price of the product at the moment it entered the market, and all other introduction prices of products that are on the market at this particular moment. The products that then fall in the first three deciles correspond to a low quality product, whereas high quality products are within the last three deciles. The products that fall between the first- and last three deciles are defined as medium quality products.

The price segments are calculated the way the quality segments of products are determined. However, now the deciles are based on the product's price at the moment of purchase instead of the product's price at the moment of entering the online shop.

Lastly, the total relationship value is calculated in a manner demonstrated before by Griffis et al. (2012). In simple terms, the total relationship value equals the total expenditure of a customer during the last twelve months. For customer i, it is calculated by $\text{TRV}_i = F_i \times N_i \times V_i$, where F_i denotes the customer's order frequency during the last 12 months, N_i the customer's average number of ordered products during the last 12 month, and V_i the customer's average product value during the last 12 months.

In our study we are exclusively interested in estimating returns. Therefore, we exclude other outcomes such as denied-, undelivered- or canceled orders. The sample, after deletion of observations which do not satisfy the requirement stated previously, consist of 16,750,953 purchases from 4,818,306 orders of 1,343,654 unique customers. The data is related to sales of over 150,410 distinct fashion items, which were either returned or kept by the customer. The average return rate over the year 2017 was 52.77 percent.

Customers purchase on average 4 products within an order where the average price of a product is about €37. Furthermore, the average age of the customers in the sample is 42 years, whereas 78 percent of the respondents is female. The majority of the population, that is, 57 percent, are families and respectively, 22 and 25 percent of the respondents has a modal income or an income that is 1.5× higher than the modal income.

More summary statistics are provided in Table 2 below. Because some events rarely occur,

we only present the attribute levels that appear the most.

Table 2: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Return	16,750,953	0.5277	0.4992	0	1
Price	16,750,953	37.13	28.54	1.00	1789.00
Total_OrderSize	4,818,306	3.735	3.602	1	57
Male	1,343,654	0.2210	0.4148	0	1
Age	4,642,509	42.29	11.88	0	118
Income_{Modal}	1,343,654	0.2238	0.4168	0	1
$\text{Income}_{1.5\times Modal}$	1,343,654	0.2587	0.4379	0	1
$\text{Family\_Compostion}_{Families}$	1,343,654	0.5716	0.4948	0	1
$\text{Family\_Compostion}_{Singles}$	1,343,654	0.1731	0.3783	0	1
$\text{Family\_Compostion}_{OlderCouples}$	1,343,654	0.1636	0.3699	0	1
Relationship_length	4,642,509	7.22	4.51	0	21.41
Total_PastOrders	4,818,306	10.60	16.78	0	663
Total_PastOrdersize	4,818,306	40.59	66.33	0	1853
Total_PastReturns	4,818,306	22.734	49.186	0	1390
LastPurchase_Days	4,818,306	49.27	70.57	0	367
LastReturn_Days	4,818,306	46.85	74.53	0	367
Nudge	4,818,306	0.057	0.231	0	1
Total_Spent_Fashion	4,818,306	129.10	140.71	1.00	4149.30
Total_Spent_Other	4,818,306	9.53	43.90	0	4738.19
Website_Search	4,818,306	0.234	0.423	0	1
$\text{StartChannel}_{DirectLoad}$	4,818,306	0.3308	0.4705	0	1
$\text{StartChannel}_{SEA\_Branded}$	4,818,306	0.1917	0.3936	0	1
$\text{StartChannel}_{SEA\_Non\_Branded}$	4,818,306	0.1539	0.3609	0	1
$\text{Device}_{Desktop}$	4,818,306	0.4431	0.4967	0	1
Device_{Mobile}	4,818,306	0.3601	0.4800	0	1
Device_{Tablet}	4,818,306	0.1863	0.3893	0	1

* Note that for all dummy variables, the value of 1 denotes the occurrence is true. The last purchase- and return days have a maximum of 367 which indicates that the customer placed an order more than 365 days ago.

As can be seen in Table 2, there seem to be some outliers and missing observations in the data. For example, the variable *Age* has 4,642,509 observations and a range from 0 to 118. This suggest that the true age of a customer is missing, or not observed in some cases. Nonetheless, outliers are not omitted from the data as dealing with such outliers is a practical issue that is rather common for online retailers. As the focus of this study is to provide an accurate- , but also realistic- and practical model as possible, it is especially important that we include such practical issues in our model as well. To explain the effects of the independent variables on product returns, however, both the outliers as well as missing observations are omitted from our study as they may cause inconsistent and biased results.

Methodology

To inspect the data further, we construct multiple models including an explanatory model and multiple predictive models. The first of these, the explanatory model, attends to explain phenomena at a conceptual level. In this sense, the explanatory model is used to provide insights in the dynamics of factors that may influence a consumer's decision to return a product; insights in the influence of customer-, product-, and shopping basket characteristics on a customer's return behavior, for example. The latter, the predictive models, tend to be used to produce expectations of future behavior that are measurable; concrete estimations of the likelihood of a product return. Although there exist diverse statistical methods that are able to both

explain- and predict a certain outcome, in our study, the predictive models are exclusively used to estimate this concrete likelihood of a product return, while the explanatory model provides further insights as to what causes this likelihood estimation. Both types of models can be of particular use in providing online retailers with critical information to base their product return strategies on.

During this study all of the statistical analyses are conducted using R for Windows (R Core Team, 2015).

Explanatory model

To analyze the drivers of product returns binomial logistic regressions are applied as statistical method, since it allows prediction of a binary dependent variable based on the analysis of the independent variables. Recall that in this study the dependent variable of interest is *Return*, which is a dummy variable. Logistic regression seems appropriate as previous studies have applied this technique in examining the influence of various factors on the return probability (Hess and Mayhew, 1997; Minnema et al., 2016).

As stated in the literature review, product returns can be considered as a function of customer-, product-, and shopping basket specific variables. However, other factors, such as situation specific factors like major marketing campaigns or seasonal patterns, may influence return decision as well. In order to control for customer variation, and heterogeneity, we therefore include these situation specific factors as control variables. Accordingly, the probability that customer i returns product j bought at day t can be expressed as,

$$P\big(Return_{ijt} = 1 | \boldsymbol{X}_{ijt}, \epsilon_{ijt}\big) = \frac{1}{1 + e^{-\boldsymbol{X}_{ijt}\boldsymbol{\beta}}}, \quad \text{where} \tag{1}$$

$$\begin{aligned} \boldsymbol{X}_{ijt}\boldsymbol{\beta} =& \boldsymbol{\beta}_1 Customer\_Level_{it} + \boldsymbol{\beta}_2 Product\_Level_{jt} + \boldsymbol{\beta}_3 Basket\_Level_{ijt} \\ &+ \boldsymbol{\beta}_4 Control\_Variables_{ijt} + \beta_0 + \epsilon_{ijt}, \end{aligned}$$

and $Customer\_Level_{it}$ denotes the vector of customer related variables, $Product\_Level_{jt}$ is the vector of product related variables, $Basket\_Level_{ijt}$ is the vector of shopping basket related variables, and $Control\_Variables_{ijt}$ denotes the vector of control related variables. The exact variables contained in these four vectors are given in Table 1 as indicated by a star ($\star$). Then, $\boldsymbol{\beta}_{1-4}$ denote the vector of parameters (i.e., effects) for the different sets of variables, β_0 represent the intercept and ϵ_{ijt} is the unobserved individual error term.

When estimating the model parameters we might encounter 'the p-value problem', namely, due to large-sample issues, relying solely on the p-value and coefficient signs is ill-advised, because p-values approach zero for large samples (Lin et al., 2013). Contrarily, relying on a Confidence Interval (CI) is always safe, because the CI will become narrower as the sample size increases. While the information that CIs convey thus does scale up to large samples, as the range estimate becomes more precise, the information contained in p-values does not. We therefore also calculate 95% CIs for the estimated coefficients.

In our research, we estimate model (1) in steps, in order to examine possible changes in the coefficients. In this way we investigate whether the addition of variables has a large influence on

the significance and altitude of the coefficients.

Moreover, with each step we use the Likelihood Ratio Test (LRT) to test whether the additional variables yield additional explanatory value and are indeed more appropriate to use.

Besides the LRT, the Akaike Information Criterion (AIC) provides a method for assessing the quality of the model through comparison of related models introduced by Akaike (1974). The AIC is based on the deviance, but includes a penalty for overfitting. In other words, the AIC rewards goodness of fit, though intent to prevent including irrelevant variables in the model. So is the Bayesian Information Criteria (BIC), which is similar to the AIC, but with a larger penalty term (Schwarz et al., 1978). Although the AIC and BIC itself are not interpretable, they are useful for comparing models. For more than one similar candidate model (where all of the variables of the simpler model occur in the more complex models), the model which corresponds with the smallest AIC and BIC should be selected.

In the first step, only the demographic customer variables are included, in order to define their effects on the probability of a product return. Note that we explained in the literature review the correlation of these demographic variables to product returns. In the second step we include the product specific variables, to control for product differences in the sample, whereas in the third step we include the shopping basket characteristics as well. At last, we include the control variables to take into account seasonality, marketing campaigns and return policy effects.

Before we interpret the results of our final model we test for multicollinearity using the Variance Inflation Factors (VIF). The VIF provides an index that measures how much the variance of an estimated regression coefficient is increased due to collinearity. The VIF factor for the i^{th} regression coefficient $\hat{\beta}_i$ is calculated by,

$$\text{VIF}_i = \frac{1}{1 - R_i^2},$$

where R_i^2 is the coefficient of determination of the regression in which the i^{th} independent variable is predicted by all the other independent variables. Higher levels of VIF reveal multicollinearity, but Craney and Surles (2002) point out that there is no general cutoff value for the VIF. However, a value of 10 as the maximum level of VIF is common (Kutner et al., 2004).

Finally, to explain how return decisions are influenced by customer-, product-, and shopping basket characteristics, we calculate marginal effects. Marginal effects measure the instantaneous effect that a change in a particular explanatory variable has on the predicted probability of the dependent variable, when all other covariates are kept fixed. Thus, in our context, they can measure how a change in a covariate is related to the return probability. For our final model, the marginal effect of covariate k is given by,

$$\begin{aligned}\text{Marginal Effect } x_k &= \frac{\partial P\big(Return_{ijt} = 1 | \boldsymbol{X}_{ijt}, \epsilon_{ijt}\big)}{\partial x_k} = \frac{e^{\boldsymbol{X}_{ijt}\boldsymbol{\beta}}}{1 + e^{\boldsymbol{X}_{ijt}\boldsymbol{\beta}}} \frac{\partial \boldsymbol{X}_{ijt}\boldsymbol{\beta}}{x_k} \\ &= P\big(Return_{ijt} = 1 | \boldsymbol{X}_{ijt}, \epsilon_{ijt}\big) \times P\big(Return_{ijt} = 0 | \boldsymbol{X}_{ijt}, \epsilon_{ijt}\big) \times \beta_k.\end{aligned}$$

This expression shows that the marginal effect depends not only on β_k, but on the value of all variables in $\boldsymbol{X}_{ijt}$. Hence, in order to calculate the exact impact of covariate k on the return probability, values for $\boldsymbol{X}_{ijt}$ are necessary. To this extent, it is common to set all variables to their

means, which is also known as the Average Marginal Effect (AME). To assess the magnitude of an effect for our explanatory variables, we therefore calculate the AME of each covariate in our final model.

The standard errors of the AMEs are computed using the Delta-Method, but for the fear that the AMEs are not normally distributed, we also calculate bootstrapped standard errors and compare the results.

The data we use to analyze the drivers of product returns consist of 600,000 observations of customer purchases coming from a random subset of the original data.

Predictive models

The success of ensemble modeling relies on the diversity of candidate models (Kuncheva, 2004). In our study we select a total of eight different candidate models that have been shown to be effective prediction models, namely Adaptive Boosting (Adaboost), Extreme Gradient Boosting (EGB), k Nearest Neighbors (KNN), logistic regression (Logit), Multilayer Perceptron (MLP), Naive Bayes (NB), Non-Linear Support Vector Machine (SVM), and the Random Forest (RF) (Partalas et al., 2010; Fernández-Delgado et al., 2014; Urbanke et al., 2015; Heilig et al., 2016). Table 3 provides an overview of all the individual classification models we include in our study, whereas a more detailed description of each prediction model can be found in the appendix.

Table 3: Overview and description of the individual prediction models

Classification Method	Parameter(s)	Setting
Adaptive Boosting model	Number of iterations	$n_{adab} \in (10, 20, 50)$
Extreme Gradient Boosting	Number of iterations	$n_{egb} \in (1, 2, \ldots, 300)$
	Learning Rate	$\lambda_{egb} \in (0.01, 0.05 \ldots, 0.3)$
	Maximum tree depth	$t_{egb} \in (3, 4, \ldots, 10)$
k Nearest Neighbors	Number of Neighbors k	$k \in (1, \ldots, 300)$
Logistic Regression	-	-
Multilayer Perceptron Model	Number of Layers	$l \in (1, 2)$
	Hidden Nodes	$h \in (1, 5, 10, 20, 50, 100)$
	Maximum of iterations	$m_{mlp} = 50$
Naive Bayes	-	-
Support Vector Machine with Non-Linear Kernel	The kernel type	radial: $\exp(-\gamma\lvert\boldsymbol{u} - \boldsymbol{v}\rvert^2)$
Random Forest	Number of trees t	$t_{rf} \in (1, 2, \ldots, 300)$

Prior to generating ensembles, we evaluate the predictive performances of each candidate model for various parameter settings. The exact parameter setting we consider for the algorithms are shown in Table 3. Apart from evaluating different parameter settings, we also test whether including or excluding variables leads to a more efficient prediction of the particular candidate model. On the one hand, in light of prediction quality, some algorithms may be sensitive to including features of low importance, whereas others are merely unaffected by low explaining variables. On the other hand, including a large number of features may considerably increase the computation time of some algorithms, which, from a practical point of view, is undesirable.

After tuning each candidate model we then start to generate ensembles. There are many approaches to construct an ensemble. These include the various ways in which the predictions of the candidate models may be combined. To this extent, the most basic and convenient way is a simple averaging. With averaging, the predictions of each candidate model are equally weighted and the ensemble calculates the average prediction.

A more advanced technique to combine information from multiple predictive models is known as stacking. With stacking, a combiner algorithm is used to put together the output from the candidate models, where in practice, a logistic regression model is often used as the combiner algorithm. Hence, a stacked ensemble trains all of the candidate models using the available data first, then a combiner algorithm is fitted to make a final prediction using all the predictions of the candidate models as inputs. In many instances, stacking outperforms each of the individual classification models due to its smoothing nature and ability to highlight each base model where it performs best and discredit each candidate model where it performs poorly.

In summary, concerning the prediction of product returns, in our analysis we consider a total of eight candidate models when creating ensembles through averaging and stacking, with logistic regression as the combiner algorithm. The total number of unique ensembles (m) one could generate from n individual models is then given by $m = 2 \times \big(2^n - (n+1)\big)$, which exponentially increases as n increases. Hence, our eight candidate models result in 494 unique averaging- and stacking ensembles to consider.

Although our study constructs and evaluates all 494 unique averaging- and stacking ensembles, we ultimately discusses only six out of these, namely, two ensembles (using averaging and stacking) that consider all eight candidate models; two ensembles (using averaging and stacking) corresponding to the best composition of candidate models which have the best average predictive quality based on averaging, and lastly; two ensembles (using averaging and stacking) corresponding to the best composition of candidate models which have the best average predictive quality found by stacked generalization.

Validation measures

To asses the performance of our prediction models, we follow the procedure of model validation given in Vergouwe (2003), which distinguishes several aspects of validity, namely overall performance, calibration, discrimination and practical usefulness. The overall performance captures both calibration and discrimination aspects. To this end, calibration concerns the agreement between observed probabilities and predicted probabilities, and procedures in statistical classification to determine class membership of a given new observation. Discrimination concerns the ability of the prediction model to properly distinguish between subjects with different outcomes. Hence, in our context, discrimination measures how well the model can distinguish between purchases that do return and those that are kept. Finally, the ability of the prediction model to improve the decision making process is captured by the practical usefulness.

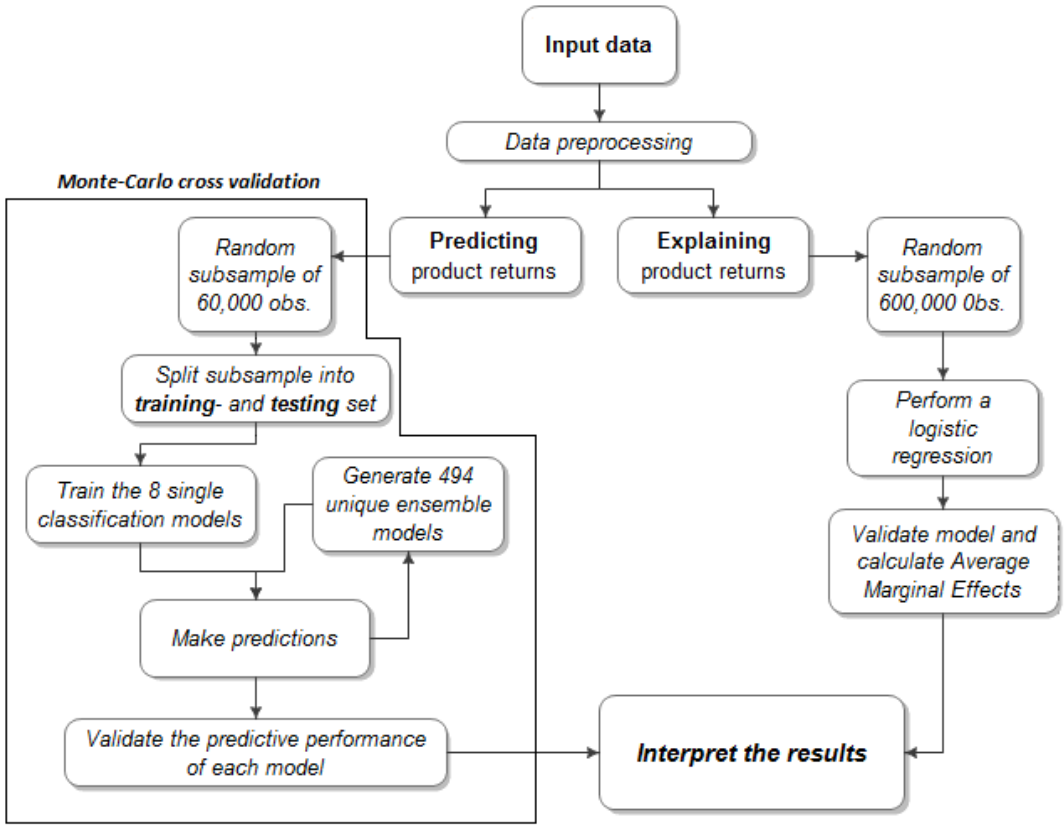
The model validation measures are calculated for all single classifiers, ensemble learners, and the proposed ensembles. In this way the performances of all prediction models incorporated in our study are investigated which enables us to answer our sub-question.

Furthermore, in order to assess how the results of the statistical analysis generalize to an independent data set, we apply the model validation technique named Monte Carlo cross-validation. Specifically, a random subsample of 60,000 observations is taken from our original data set, where this subsample, in turn, is randomly split into a training set and a testing set. Randomly splitting the data into the training and testing set ensures that performance estimates are issued on completely independent data. The training set is used to fit the model, whereas the testing set is assessed to model validation.

The procedure of sampling and partitioning the data set is repeated n times, where n is preferably large. Collecting all the outcomes may provide understanding in the dispersion and distribution of the validation measures and allows us to create for example confidence intervals. In our analysis we set $n = 200$.

An overview of the methodology of this study is presented in Figure 2.

Figure 2: Overview of the methodology of this study



Overall performance

Regarding the overall performance of our prediction models, the predictive accuracy and the Area Under the ROC-curve (AUC) are used as validation measures.

The predictive accuracy could be used as a statistical measure of how many observations in the testing set are correctly classified. It is calculated from predicted probabilities, where in our case the predicted probability denotes the probability of a purchased product being fitted with a return; mathematically denoted by $P(Return_{ijt} = 1|\boldsymbol{X}_{ijt})$, where $\boldsymbol{X}_{ijt}$ contains the independent variables. However, in order to practically assign the corresponding class to the predicted probability of each purchased product, a decision boundary is needed.

For instance, by setting the decision boundary equal to the traditional default of 0.5, we conclude that the dummy variable $Return_{ijt} = 1$ if $P(Return_{ijt} = 1|\boldsymbol{X}_{ijt}) > 0.5$ and otherwise $Return_{ijt} = 0$. This threshold is of great importance, because it ultimately decides the predicted class of observations and could therefore have a dramatic impact on the model's quality in terms of predictive accuracy.

There exist numerous possibilities to determine the optimal threshold value (Liu et al., 2005; Freeman and Moisen, 2008). These include subjective approaches such as taking a fixed value like the traditional default of 0.5, or a threshold that meets a given management requirement. More objective approaches are based on the dataset where the threshold is set to, for example, the mean probability of occurrence of the dependent variable. Objective approaches typically select the threshold that maximizes the agreement between observed and predicted classes. To this extent, one could determine the optimal cut-off point using the Receiver Operating Characteristic curve (ROC-curve).

The ROC graph provides a method of evaluating the performance of prediction models. It is created by plotting the true positive rate (sensitivity) against the false positive rate (1-specificity) for a threshold value which varies from 0 to 1. At the diagonal, the true positive rate equals the false positive rate which implies that the model makes random predictions. Ideal models realize a high true positive rate, whereas the false positive rate remains small. The ROC-curve of a well-defined model thus rises steeply close to the origin and flattens at a value near the maximum of 1. On the contrary, the ROC-curve of a poor model lies adjacent to the diagonal, because at the diagonal the true positive rate equals the false positive rate which implies, as previously mentioned, that the model makes random predictions.

Since the upper left corner of the ROC plot can be considered as the 'perfect' model, the threshold which minimizes the distance between the ROC-curve and this 'perfect' point is appropriate to use as an optimal cut-off point. In truth, it is shown that selecting the threshold based on the shortest distance to the top-left corner in ROC plot is indeed a good method to find the optimal cut-off (Liu et al., 2005; Freeman and Moisen, 2008; Kumar and Indrayan, 2011).

In our analysis we therefore use this method to provide us with the threshold which is used to classify the predicted probabilities into a class. Comparison of the predicted classes and the observed classes then yields the predictive accuracy for the model, calculated by taking the mean of correctly predicted observations.

In some instances, however, the results of the predictive accuracy must be approached with caution, as the predictive accuracy could only reflect the underlying class distribution. In other words, a disproportionately high number of members from one class could result in a classifier that is biased to this class. For example, suppose that 80% of the fashion products are returned, then a constant prediction of a product return is bound to be correct 80% of the time, although this predictive accuracy is truly non-informative and useless. This problem is known as the accuracy paradox, but as Table 2 reveals a mean return rate of 52.77%, the accuracy paradox does not appear to be a problem in our case.

In light of the ROC-curve, it follows that the area under the ROC-curve (AUC) is a well-defined measure for overall model performance, in particular for discrimination ability (Steyerberg et al., 2010). From this perspective, ideal models have an AUC approximating 1, while random models have an AUC of 0.5.

Calibration and discrimination

Accurate prediction models discriminate between those with and those without the outcome. Ideally, for a prediction model to excellently distinguish between observations with different outcomes, the predicted probabilities approximate 1 for the respondents with the outcome, whereas the predicted probabilities are close to 0 for those without the outcome. To this extent, a wide spread in the distribution of the predicted probabilities (away from the average probability) is evidence in favor for a good discriminating model.

To visualize the discriminative ability of our prediction models we therefore create histograms that plot the distribution of the predicted probabilities, conditional on the observed outcome.

The interpretation of this histogram is as follows: on the basis of the testing set, for a given predicted probability value on the x-axis, one can find the total number of times this particular predicted probability value is observed, conditional on the true observed class, against the y-axis. Perfect discriminating models show no overlap in the predicted probability values of each observed class, whereas the predicted probability values of classes completely overlap for a random models. Roughly, the less overlap the graph shows, the better the model is able to discriminate between the classes, and the more accurate the model is able to predict product returns.

Well calibrated prediction models are probabilistic models for which the output can be directly interpreted as a confidence level. A well calibrated prediction model, for example, should classify the samples such that among the samples to which it gave a predicted probability value close to 0.8 for belonging to a particular class, approximately 80% actually belong to that class. Hence, the histograms that help to visualize the discriminative ability of our prediction models, can also help to provide additional insights in the calibration. Especially, biases in the predicted probabilities may be observed.

Practical usefulness

As mentioned before, an accurate prediction of a customer's likelihood to return a product could constitute a contribution to many online retailers' overall profit margins. That is to say because it is essential to account for product returns when calculating CLV (Minnema et al., 2018), but product return predictions could also facilitate online retailers with a number of return preventive actions, such as the aforementioned moral suasion. Other examples of preventive actions are to offer a coupon conditioned by the fact that the product is not returned to customers who display a high risk of returning, or more invasive, to charge a risk premium through increasing the product price.

Recognizing that product returns are inherently part of online retailers' business model, systems for prediction and prevention of product returns should only focus on extreme cases. In our case, the extreme cases are defined as the purchases that are expected to be most likely to be returned.

In order to evaluate the impact that our prediction models could have on the online retailer's profits, we are then particularly interested in two aspects. First, how many out of all the purchases we expect to be returned, are actually returned, and second, how many out of all the purchases that are actually returned, were identified as a product return by our prediction models. These aspects are also known as precision and recall, and are calculated by,

$$Precision = \frac{TP}{TP + FP} \quad \text{and} \quad Recall = \frac{TP}{TP + FN}, \tag{2}$$

where TP denotes the true positives, FP the false positives, and FN the false negatives.

As last validation measures we therefore calculate precision and recall, while focusing solely on product purchases with a very high return probability. It is important to keep in mind, however, that there is a trade-off between these measures. That is to say because expecting more product returns will increase the precision, but will reduce the recall.

Results

Explaining product returns

Binominal logistic regression models are performed for the dependent variable *Return* to inspect the data for the drivers of product returns. The logistic regression models where the variables are added stepwise are given in Table A.2, presented in the appendix.

This table reveals that, all in all, the coefficients of the independent variables do not vary significantly for any of the models, although, with some exceptions. For instance, one can observe that the coefficient of Age_{25to34} becomes significant once the product level variables are included, and then reverses in the third column as we include shopping basket characteristics, while the results for all other age groups are roughly constant over the steps. Note that the reference level of the age groups are customers under the age of 24. This suggest that, especially between this group of customers and customers aged between 25 and 34, the return behavior significantly varies, when adjusting for product- and shopping basket characteristics.

Another example of a varying coefficient concerns the variable $Discount_{temporary}$, which becomes insignificant once the shopping basket variables are included. This implies that $Discount_{temporary}$ and the shopping basket variables explain the same effect on the return probability, which results the coefficient of $Discount_{temporary}$ to become insignificant.

Generally, the reason of possible changes in the coefficients is that the addition of variables in a model likely changes the bivariate relationship between a independent variable, the other independent variables and the dependent variable. This provides an explanation of sign reversals or varying significancy of coefficients one may observe in Table A.2.

As described in the methodology, several measures are taken in order to evaluate the final model. In each step, LRT tests are performed followed by comparison of both AIC and BIC. Table A.1 in the appendix reports the exact results of the LRT, whereas the AIC and BIC can be found in Table A.2. Certainly, the LRTs indicate that the inclusion of extra variables (e.g., product- and basket characteristics) yield more explanatory value for all models. The AIC and BIC support this finding by showing that the AIC and BIC are the lowest for the final model. This also suggest that for the prediction of product returns it is desirable to use customer-, product-, and basket characteristics. At last, multicollinearity does not appear to be a concern in our analysis as none of the variables in the stepwise models show a VIF which exceeds the threshold of 10.

Table 4 shows our final model that is used to analyze the drivers of returns, where the average marginal effects of the logistic regression from our final model is provided. The average marginal effects can be interpreted as follows: for a change in one of the independent variables, the corresponding estimated coefficient represents the average change in the probability to return a product within the fashion category, ceteris paribus.

Additionally, we present the CIs associated with the average marginal effects, which are based on standard errors computed by the delta-method[2]. Recall that we determine the CIs because we were likely to be misguided by p-values due to the large sample size. However, the results do not support our suspicion of the p-value problem. That is to say because not all independent variables are highly significant (while believing that not each effect of the covariates on the return probability is truly zero), indicating that the sample size is not large enough to let all p-values approach to zero.

[2]Bootstrapped standard errors (1000 samples) gave similar results.

Table 4: Logistic Regression results

	Dependent variable: Return		
	Average Marginal Effects (AME)	95% CI Lower	95% CI Upper
Customer level			
Male	-0.016^{***} (0.002)	−0.020	−0.013
Urbanicity_2	0.003^{*} (0.002)	−0.001	0.007
Urbanicity_3	0.008^{***} (0.002)	0.004	0.012
Urbanicity_4	0.006^{***} (0.002)	0.002	0.010
Urbanicity_5	0.006^{***} (0.002)	0.002	0.011
$\text{Family\_Compostion}_{YoungCouples}$	0.0002 (0.003)	−0.006	0.006
$\text{Family\_Compostion}_{Families}$	0.004^{**} (0.002)	0.001	0.008
$\text{Family\_Compostion}_{OlderCoupes}$	0.002 (0.002)	−0.002	0.007
$\text{Family\_Compostion}_{Other}$	0.027^{**} (0.011)	0.006	0.047
Age_{25to34}	-0.007^{**} (0.003)	−0.013	−0.001
Age_{35to44}	-0.026^{***} (0.003)	−0.032	−0.020
Age_{45to54}	-0.029^{***} (0.003)	−0.035	−0.023
Age_{55to64}	-0.017^{***} (0.004)	−0.024	−0.010
Age_{65plus}	0.0003 (0.005)	−0.009	0.009
$\text{Income}_{Minimum}$	0.011^{***} (0.003)	0.005	0.017
$\text{Income}_{BelowModal}$	0.015^{***} (0.003)	0.010	0.020
Income_{Modal}	0.015^{***} (0.002)	0.012	0.019
$\text{Income}_{1.5\times Modal}$	0.014^{***} (0.002)	0.010	0.017
$\text{Income}_{2\times Modal}$	0.010^{***} (0.002)	0.006	0.013
Nudge	0.116^{***} (0.005)	0.108	0.125
LastPurchase_Days	0.0003^{***} (0.00001)	0.0003	0.0003
LastReturn_Days	-0.0001^{***} (0.00001)	−0.0001	−0.0001
Total_PastOrders	0.001^{***} (0.0001)	0.001	0.001
Relationship_length	-0.001^{***} (0.0002)	−0.002	−0.001
Total_RelationShip_Value	0.000^{***} (0.000)	0.000	0.000
AVG_Total_Spent	-0.0002^{***} (0.00002)	−0.0003	−0.0002
$\text{PastReturnRate}_{Customer}$	0.340^{***} (0.003)	0.334	0.345
Product level			
Price	0.001^{***} (0.00003)	0.001	0.001
$\text{Price\_segment}_{Middle}$	−0.0003 (0.002)	−0.004	0.004
$\text{Price\_segment}_{High}$	0.001 (0.003)	−0.004	0.007
Quality_{Middle}	-0.010^{***} (0.002)	−0.014	−0.007
Quality_{High}	-0.022^{***} (0.003)	−0.026	−0.017
$\text{Discount}_{permanent}$	−0.00001 (0.0001)	−0.0002	0.0002
$\text{Discount}_{temporary}$	0.00002 (0.001)	−0.001	0.001
Discount_ratio	-0.055^{***} (0.006)	−0.066	−0.043
DiscountMultipleProducts	-0.035^{***} (0.005)	−0.044	−0.025
Outlet	0.013^{***} (0.002)	0.008	0.018
$\text{PastReturnRate}_{Product}$	0.473^{***} (0.003)	0.466	0.479
AVG_Review	-0.0001^{*} (0.00004)	−0.0002	0.00000
N_Reviews	-0.0005^{***} (0.0002)	−0.001	−0.0002
SizeOptions	0.0003^{***} (0.0001)	0.0001	0.001
PlusSize	0.003 (0.002)	−0.001	0.007
$\text{Season\_Indicator}_{Winter}$	-0.023^{***} (0.003)	−0.028	−0.018
$\text{Season\_Indicator}_{All}$	-0.028^{***} (0.002)	−0.032	−0.024
$\text{Season\_Indicator}_{Zomer}$	-0.048^{***} (0.003)	−0.054	−0.043
$\text{Season\_Indicator}_{Tussen}$	−0.004 (0.004)	−0.011	0.004
Basket level			
NoFreeShipping	-0.089^{***} (0.008)	−0.104	−0.074
Ordersize_Fashion	−0.001 (0.001)	−0.002	0.0004
Total_Spent_Fashion	0.0002^{***} (0.00001)	0.0002	0.0002
N_Products_Other	0.001 (0.002)	−0.002	0.005
N_Products_Sport	0.007^{***} (0.002)	0.003	0.011
N_Distinct_Products_Other	-0.009^{***} (0.003)	−0.015	−0.003
N_Distinct_Products_Sport	-0.010^{***} (0.003)	−0.016	−0.003
Total_Spent_Other	−0.00002 (0.00002)	−0.0001	0.00002
Total_Spent_Sport	0.0001^{**} (0.00004)	0.00001	0.0002
PayMethod_{Giro}	0.034^{***} (0.002)	0.030	0.037
PayMethod_{iDeal}	-0.061^{***} (0.002)	−0.066	−0.056
$\text{PayMethod}_{Creaditcard}$	−0.007 (0.005)	−0.016	0.003
Voucher	-0.015^{***} (0.003)	−0.021	−0.009
Giftcard	-0.091^{***} (0.023)	−0.136	−0.046
N_Identical_Products	-0.065^{***} (0.003)	−0.070	−0.059
N_Diff_Sizes	0.118^{***} (0.001)	0.115	0.121
N_Diff_Colors	-0.017^{***} (0.001)	−0.019	−0.016
N_Identical_ProductCategory	0.031^{***} (0.001)	0.030	0.032
N_Diff_ProductCategory	-0.002^{***} (0.001)	−0.003	−0.001
N_Diff_Brands	0.004^{***} (0.0004)	0.003	0.004
N_Diff_Sex_Product	0.001 (0.001)	−0.001	0.003
Website_Search	−0.001 (0.001)	−0.004	0.001
Daypart_{Midday}	−0.002 (0.002)	−0.005	0.001
$\text{Daypart}_{Evening}$	0.008^{***} (0.002)	0.005	0.011
Daypart_{Night}	0.009^{**} (0.004)	0.002	0.016
Mobile_{Phone}	0.004^{***} (0.001)	0.001	0.007
Mobile_{Tablet}	0.001 (0.002)	−0.002	0.004
$\text{StartChannel}_{DirectLoad}$	-0.009^{***} (0.001)	−0.012	−0.006
$\text{StartChannel}_{SEA\_Branded}$	-0.005^{***} (0.002)	−0.008	−0.002
$\text{StartChannel}_{SEA\_NonBranded}$	0.009^{***} (0.002)	0.005	0.013
Control variables			
Campaign	-0.009^{***} (0.002)	−0.012	−0.005
Campaign_WeekBefore	-0.009^{***} (0.002)	−0.013	−0.006
Campaign_WeekAfter	0.001 (0.002)	−0.002	0.005
Holiday	−0.001 (0.002)	−0.005	0.003
Holiday_WeekBefore	−0.003 (0.004)	−0.012	0.005
Policy	-0.019^{***} (0.002)	−0.022	−0.015
Weekend	0.006^{***} (0.001)	0.003	0.008
Season_{winter}	-0.009^{***} (0.002)	−0.014	−0.005
Season_{spring}	-0.011^{***} (0.002)	−0.016	−0.007
Season_{summer}	−0.001 (0.002)	−0.005	0.002
Constant	-0.4924^{***} (0.0056)	−0.5031	−0.4811
Observations	600,000	600,000	600,000

[I] Significance levels are indicated with: *p<0.1; **p<0.05; ***p<0.01

[II] Standard errors of the Average Marginal Effects are given in parentheses (Delta-method)

[III] Dummy reference levels: Urbanisatie_1, $\text{Family\_Comp}_{Singles}$, $Age_{under24}$, $\text{Income}_{2.5\times Modal}$, $\text{Price\_segment}_{Low}$, Quality_{Low}, $\text{Season\_Indicator}_{None}$, PayMethod_{Other}, $\text{Daypart}_{Morning}$, $\text{Mobile}_{Desktop}$, $\text{StartingChannel}_{Other}$, Season_{autumn}

Customer characteristics

The logistic regression results on the dependent variable *Return* in Table 4 show several significant effects of customer demographics on the return probability. The results present, for example, a negative effect of *Male* (AME *Male* =-0.016) on the probability of a product return at the 1% significant level. Hence, granted that a customer is a man, the probability of a product return decreases by 1.6% on average, ceteris paribus. More informative is the 95% CI which exposes that being a male customer decreases the probability of a return on average between 1.3% and 2%, with 95% confidence. Regarding the living area of a customer, the customers who live in more rural areas have a higher average return probability in comparison to the customers who live in urban areas. Both these findings support the study of Minnema et al. (2016).

Other customer demographics, however, exert also significant effects on the return probability. For example, the return probability of the customers who fall in the age groups between 24 years and 65 years decreases, on average, by at least 0.1% and at most 3.5%, as compared to the under 24 year old customers, with 95% confidence. Moreover, families and other life stage customers showed higher return probabilities compared to the customers who are single. The results furthermore showed that customers who fall within a lower income group are more likely to return a product, as to customers who have an income at least 2.5 times higher than a modal income. Depending on the particular income group the customer belongs to, the average increase in the return probability lies between 0.5% and 2%, with 95% confidence.

Results related to the customer experience show that the customers who have a multi-year relationship with the online retailer (*Relationship_length*), have lower return probabilities. A possible explanation of a lower return probability as the relationship length increases, could be that customers become more familiar with the products the retailer offers over time, reducing the level of uncertainty that comes with a purchase, and thereby reducing the return rate. However, those who have placed multiple orders over the last twelve months (*Total_PastOrders*), have higher return probabilities. Customers who have on average a higher total relationship value (*Total_Relationship_Value*) have a significantly higher return probability, but customers who spent on average more per purchase (*AVG_Total_Spent*) have a lower return probability. Another finding is that customers who meet the 'Nudge' requirements (*Nudge*) are on average at least 10.8% more likely to return a product, with 95% confidence.

Finally, the average marginal effect corresponding to the historic return rate of customers report the largest impact on the return probability compared to all other marginal effects on the customer level. With 95% confidence, each 1% increase in the customer's past return rate increases, on average, the likelihood of a product return between 33.4% and 34.5%, ceteris paribus.

Product characteristics

Explaining the product characteristics that impact the return probability, the product's price takes on a positive significant effect (AME *Price* = 0.001) on the likelihood of a return. Each 1 euro increase in the product's price increases the likelihood of a return on average by 0.1%, ceteris paribus. Discounted products (*Discount_ratio*), on the contrary, have a lower on average return probability. Specifically, each additional percentage in the discount rate decreases the probability of a return on average between 4.3% and 6.6%, with 95% confidence.
Products belonging to the middle- or high perceived quality segment groups ($Quality_{Middle}$, $Quality_{High}$) decrease the on average return probability at most by 1.4% and 2.6% as compared to the lowest quality segment, respectively, with 95% confidence. These findings are consistent with the literature discussed in the literature review of this study. Fur-

thermore, showcasing (*Outlet*) a product increases the likelihood of a return. A possible explanation for the positive impact of showcasing a product may be that showcasing leads to impulse buying (Akram et al., 2017), whereas impulse buying increases the return probability.

With regard to product information at the moment of purchase, which has an impact on return decisions (Minnema et al., 2016), products online specified as relating to a particular season (*Season_Indicator*) have on average a lower return probability. In addition, the number of reviews (*N_Reviews*) decreases the likelihood of a return. In line with the study of Minnema et al. (2016), the results of our analysis suggest a negative correlation between the average review valence (*AVG_Review*) and the return probability. However, this result needs to be approached with caution as it is only significant at the 10% level, and consequently, the 95% CI of the AME of *AVG_review* cannot exclude zero.

Moreover, the results suggest that the total number of available sizes of a product (*SizeOptions*) positively affect the return probability. This means that if products can be purchased in many different sizes, the chance the purchase is returned increases. This positive effect on the return probability could be related to fit uncertainty. Customers may experience more difficulties when choosing the right size when there are many size options to pick from, resulting in more returns.

Finally, historic return information ($PastReturnRate_{Product}$) has a large influence on the return probability. Each additional percent in the past return rate of a product increases on average the return probability by at least 46.6%, ceteris paribus.

Shopping basket characteristics

Concerning the shopping basket variables, the higher the total amount of euros spent in the fashion- and sports categories (*Total_Spent_Fashion* and *Total_Spent_Sport*, respectively) the higher the return probability, whereas the results suggest the opposite for purchases outside the fashion- and sports categories (*Total_Spent_Other*). The likelihood of a return also increases as more sports products are purchased (*N_Products_Sports*).

Factors related to the composition of the shopping basket also seem to be important drivers of return decisions. For example, each additional purchase of the exact same product (*N_Identical_Products*) decreases the likelihood of a return on average between 5.9% and 7%, with 95% confidence. Moreover, the more different product colors for products within the same category (*N_Diff_Colors*), the more the return probability decreases, where the same holds true for purchases in different product categories (*N_Diff_ProductCategory*).

More purchases in the same product category (*N_Identical_ProductCategory*) or a greater number of different product brands in the shopping basket (*N_Diff_Brands*), on the contrary, increase the return probability. Furthermore, *N_Diff_Sizes* has an AME equal to 0.118, significant at the 1% level. This means that for each additional purchase of the same product, but with a different size, the probability of a return increases by 11.8% on average, ceteris paribus.

With respect to the payment method of the order, paying by Giro ($PayMethod_{Giro}$) increases the return probability of products between 3.0% and 3.7%, whereas paying by iDeal ($PayMethod_{iDeal}$) decreases the return probability of products between 5.6% and 6.6%, with 95% confidence. When a giftcard or voucher is redeemed, the return probability decreases

between 4.6% and 13.6%, and, 0.9% and 2.1%, respectively, with 95% confidence.

The results further show that the part of the day the order is placed also influences the return probability. In particular, when compared to the morning, purchases made in the evening (*Daypart_evening*) or night (*Daypart_night*) are more likely to be returned. Customers who place orders with their mobile phone ($Mobile_{Phone}$) have, on average, an higher return probability, as compared to those who place orders on their desktop. Finally, the starting channel of the customer significantly affects the return probability. Customers who visit the e-retailers shop directly in their browser ($StartChannel_{DirectLoad}$), or via an online advertisement on the e-retailers name ($StartChannel_{SEA\_Branded}$) are less likely to return a product, whereas customers who visit the shop through product advertisements ($StartChannel_{SEA\_NonBranded}$) are more likely to return, as compared to all other starting channels to visit the online retailer's shop.

Control variables

The most interesting result of the control variables comes from the variable *Policy*. The results show that extending the return deadline from 14 to 60 days has a negatively, significant effect on the return probability at the 1% level. Customers who made a purchase during the extended return deadline policy, are between 1.5% and 2.2% less likely to return, with 95% confidence. This result is in line with the study of Janakiraman et al. (2016) who showed that longer deadlines reduces the return probability.

Furthermore, the likelihood of a product return decreases as there is a campaign (*Campaign*), where, surprisingly, the same holds true the week before a campaign (*Campaign_WeekBefore*). A possible explanation might be, on the one hand, under the assumption that customers know that the e-commerce retailer has a major campaign the upcoming week, purchases made by customers the week before the campaign may be more conscious, and hence, are less likely to be returned. On the other hand, assuming that customers had no information about the upcoming campaign at the moment of purchase, the negative effect of the week before a campaign on the return probability may in reality be the opposite. That is to say because if a customer purchased a product and would find out, a week later, that there is a campaign and the exact same product is now discounted, this customer could contact the online retailer to demand a refund. Knowing that the customer would otherwise freely return the product, resulting in extra costs, the online retailer gives a refund, which ensures that the product is not returned, and hence, decreases the return rate.

To conclude, purchases made over the weekend (*Weekend*) are more likely to be returned, whereas the return probability decreases for purchases in the winter ($Season_{winter}$) and spring ($Season_{spring}$), when compared to purchases made in autumn.

Predicting product returns

Besides examining the dynamics of customer-, product- and shopping basket characteristics on product returns, the goal of this study is to create a practical and efficient prediction model based on these characteristics.

Prior to the creation of the ensembles, we evaluate the predictive quality of each classification algorithm for different parameter settings and independent variables. The appendix, in the section *Individual algorithms*, provide a detailed discussion of the way in which we evaluate each individual prediction model, and also presents the final setting of the eight candidate models.

In order to determine the best ensemble, and to evaluate all final single classifiers, ensemble learners and other proposed ensembles, Monte Carlo cross-validation is conducted, where we consider $n = 200$ iterations.

Separately, for each ensemble combining method, we explore which composition of candidate models is best suitable to predict product returns. Concerning averaging, out of all 247 unique combinations of candidate models, the ensemble which combines AdaB, EGB, SVM and RF offers the highest mean predictive accuracy and AUC. As this combination of candidate models is based on averaging as the combining method, we refer to this set of candidate models as Best Averaging (BA). In a similar way, the AdaB, EGB, MLP, NB, SVM and RF shows the highest average predictive quality with stacking as the combining method, where we refer to this candidate model set as Best Stacking (BS). Furthermore, we refer to the full set of candidate models, that is, all eight candidate models, as ALL.

We apply the ensemble combining methods averaging and stacking for each above-mentioned set of candidate models, where the results are presented in Table 5, given below.

Table 5: Average predictive accuracy and AUC for the six final ensembles

	Ensemble		
	Averaging	Stacking	Candidate model set
Accuracy	0.7152	0.72176	ALL
	0.7209	0.7210	BA
	0.7161	**0.72178**	BS
AUC	0.7855	0.7912	ALL
	0.7906	0.7907	BA
	0.7862	**0.7915**	BS

[I] *The average predictive accuracy and AUC of 200 Monte-Carlo iterations, where the training set consists of 80% of the random sample*
[II] *Candidate model set: ALL denotes all eight candidate models, BA covers AdaB, EGB, SVM, RF, and BS represents AdaB, EGB, MLP, NB, SVM, RF*

Table 5 reveals that stacking with candidate model set BS achieve superior predictive quality, in terms of both accuracy and AUC, when compared to the other ensembles. The difference in predictive quality between the ensembles, however, is rather small. Especially between the stack-

ing ensemble with candidate model set BS, the other stacking ensembles, and the averaging ensemble with candidate model set BA. We therefore test whether the outperformance between the ensembles is statistically significant, by means of Welch's Two Sample t-test. The results from this test can be found in Table 6.

Table 6: Statistical significance (p-value) of outperformances between our final ensembles

	Averaging			Stacking		
	All	*BA*	*BS*	*All*	*BA*	*BS*
Averaging						
ALL	1	0	0.056	0	0	0
BA	0	1	0	0.222	0.856	0.158
BS	0.056	0	1	0	0	0
Stacking						
ALL	0	0.222	0	1	0.154	0.841
BA	0	0.856	0	0.154	1	0.106
BS	0	0.158	0	0.841	0.106	1

[I] *Welch's Two Sample t-test in order to test equality of means*

From Table 6, it now follows that stacking constantly outperform averaging with compositions ALL and BS, statistically significant at the 1% level. While this may be true, this does not hold true for averaging the candidate model set BA. Unsurprisingly, Table 6 shows that averaging with candidate model set BA is the best performing averaging ensemble, and from this point on, we will refer to it as such. Although the results also show that there is no significant difference between the stacking ensembles, we accept stacking with candidate model set BS as the best performing stacking ensemble, because it has shown before to achieve the highest average predictive accuracy and AUC.

With regard to our proposed ensemble models, from this point on, our study only focuses on the best performing averaging ensemble and the best performing stacking ensemble.

Overall performance

In order to provide the full picture that is needed to examine the efficacy of ensemble modeling, we compare the best averaging- and stacking ensemble to the predictive quality of all single classifiers and other ensemble learners. Accordingly, the average predictive accuracy and the AUC for each candidate model, the best performing averaging ensemble, and the best performing stacking ensemble are shown in Table 7.

Table 7: Average accuracy and AUC for all single classifiers, ensemble learners, and the best performing averaging- and stacking ensembles

	Ensemble		*Single classifiers*							
	Averaging	Stacking	AdaB	EGB	kNN	Logit	MLP	NB	SVM	RF
Accuracy	0.721	**0.722**	0.715	0.718	0.697	0.712	0.714	0.681	0.714	0.717
AUC	0.791	**0.792**	0.784	0.788	0.761	0.778	0.781	0.730	0.776	0.785

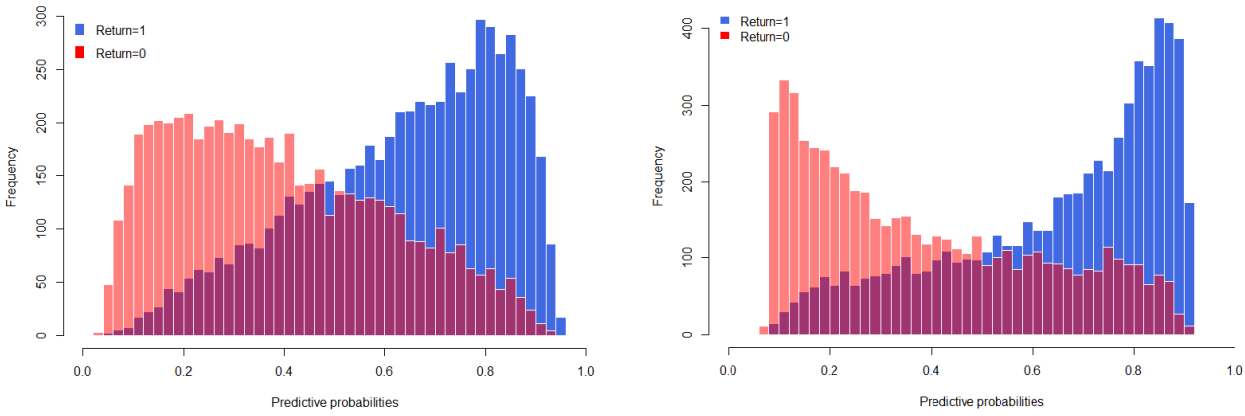
[I] *The average predictive accuracy and AUC of 200 Monte-Carlo iterations, where the training set consists of 80% of the random sample*

Given any classifier, we find that the best performing stacking ensemble realizes the highest predictive quality, as measured both in terms of predictive accuracy and AUC. While we thereby provide evidence in favor of the ensemble's ability to accurately predict product returns, this does not necessarily imply that the ensemble model is also suitable to benefit online retailers in practice. In light of more practical aspects, we therefore turn to the calibration, discrimination and usefulness of the prediction models.

Calibration and discrimination

Regarding calibration and discrimination of the prediction models, we plot the calculated predicted probabilities for each observed class (i.e., return versus non-return), from a randomly selected iteration of the Monte Carlo cross-validation. However, we only do this after we check if the dispersion of the predicted probabilities of each observed class is somewhat constant across the iterations in the Monte Carlo cross-validation. Because the predicted probabilities are indeed moderately constant across the iterations, we select a random iteration and present the histogram of the predicted probabilities from the best performing averaging- and stacking ensembles conditionally on the true observed class, in Figure 3. Recall that a better discriminating model will show less overlap between those with and those without the outcome (i.e., $Return = 1$ and $Return = 0$, respectively).

Figure 3: Histogram of the predicted probabilities corresponding to the observed class *Return* using the averaging and stacking ensemble



(a) *Best averaging ensemble*

(b) *Best stacking ensemble*

As one can see in Figure 3, both ensembles display significant overlap in the predicted probabilities for each true class. The histogram shapes of the ensembles, however, significantly differ. The histogram's shape of the averaging ensemble seems to be bimodal, whereas the histogram of stacking appears to be more U-shaped. Hence, stacking tends to push the predictive probabilities more to extremes, as compared to averaging. In other words, the stacking ensemble assigns lower predictive probability values to non-returns, and higher predictive probability values to returns, as compared to the averaging ensemble - suggesting it is better able to discriminate amongst the classes. This result is as expected, since, by definition, the averaging ensemble averages predicted

probabilities of the candidate models, whereas the stacking ensemble attempts to correct for outliers in the predicted probabilities of each candidate model.

However, both ensemble combining methods appear to return biased probabilities, namely, the histograms show peaks around 0.1 and 0.9 predicted probability, while predicted probabilities close to 0 or 1 are either very rare or not even observed. A possible explanation of the difficulty the ensembles have in making predictions close to 0 and 1 could be that, variance in the underlying candidate models tend to move predictions, that should be approximating 0 or 1, away from these values. This bias caused by variance, in turn, tend to be one-sided close to 0 and 1, because predictions are restricted to the interval [0,1]. As an example, for an ensemble to calculate a predicted probability of 0, every single candidate model has to calculate a predicted probability of 0. In this case, noise in the candidate models that the ensemble combines, results in predicted values larger than 0, and hence, moves the predicted probability of the ensemble away from 0.

To provide more insight in the dynamics of the candidate models within the ensembles, we present visualizations of the predictive probabilities of the eight candidate models in Figure A.4, given in the appendix. These figures also give more understanding in the calibration and discriminative ability of each candidate model. They show, for example, the diversity between the candidate models in these aspects. But, more importantly, for most candidate models, they also show that predicted probabilities close to 0 or 1 are either very rare or not observed - suggesting that most candidate models return biased probabilities. In fact, the logistic regression appears to be the only candidate model that is properly calibrated. This provides an additional explanation why the predicted probabilities of the best performing ensembles are hardly ever close to 0 or 1.

Hence, we find evidence, although limited, that most candidate models and ensembles are not well calibrated. They may be over- or underconfident when predicting a low or high probability, suggesting that the predicted probability of an outcome does not reflect the real world probability of that outcome. Consequently, a prediction model might predict that a particular product purchase has a 80% probability of being returned, when in reality, the true probability of the product being returned equals 90%.

Practical usefulness

As mentioned before, systems for prediction and prevention of product returns should focus on extreme cases. On the basis of the testing set, we define the extreme cases by the 10%- and 15% thresholds, such that for these thresholds, the purchases that are expected to be most likely to result in a return, are evaluated. The results are reported in Table 8.

Some classification algorithms, however, including the support vector machine, do not provide a probabilistic interpretation. Therefore we transform the output of the SVM first, before we interpret the results, where we follow a procedure that uses a logistic regression to map the SVM output to probabilities, proposed by Platt et al. (1999).

Table 8: Average precision, recall and percentage of observations (Obs.), in extreme cases, for all single classifiers, ensemble learners, and the best performing averaging- and stacking ensembles.

	Ensemble		*Candidate model*							
Threshold	Averaging	Stacking	AdaB	EGB	kNN	Logit	MLP	NB	SVM	RF
at 10%										
Precision	0.857	0.936	**0.940**	0.925	0.901	0.894	0.776	0.750	0.875	0.915
Recall	0.001	0.014	0.013	0.043	0.035	0.090	0.073	**0.505**	0.006	0.021
Obs.	0.001	0.008	0.007	0.025	0.020	0.053	0.044	**0.355**	0.004	0.012
at 15%										
Precision	**0.916**	0.886	0.911	0.891	0.875	0.875	0.862	0.731	0.847	0.896
Recall	0.059	0.168	0.070	0.144	0.109	0.163	0.220	**0.580**	0.060	0.076
Obs.	0.034	0.100	0.041	0.085	0.066	0.098	0.136	**0.419**	0.037	0.045

[I] *Average precision, recall and observation percentage based on 200 Monte-Carlo iterations, where the training set consists of 80% of the random sample.*
[II] *10%-threshold:* $Return = 1$ *if* $P(Return = 1|\boldsymbol{X}) > 0.90$*, and*
15%-threshold: $Return = 1$ *if* $P(Return = 1|\boldsymbol{X}) > 0.85$

Concerning the extreme cases, Table 8 shows mixed results. For the 10%-threshold, AdaB achieves the highest average precision, even though it does not achieve the highest recall and it does not include a large percentage of the observations in the testing set. At the 15%-threshold, however, the best averaging ensemble reports superior precision over all other prediction models.

Although the stacking thus may not be the best choice of model to generate predictions that are accurate enough, regarding a system of prediction and prevention of product returns, we can demonstrate the business value of it using the precision, recall and percentage of observations, as calculated in Table 8. Suppose we were to construct a system of prediction and intervention based on the best stacking ensemble. With a threshold of 15%, the system would intervene for 10% of all purchase intentions, where 88.6% of all these interventions would be justified. Assuming a perfectly effective intervention strategy, the system then would be able to reduce the number of product returns by up to 16.8%. Considering that the online retailer sells over ten millions of products every year, and every product return incurs costs of several euros, realizing such a system could easily reduce annual costs by a six-digit figure.

Conclusion and Discussion

The main ambition of this study was to create an ensemble selection prediction model that is able to accurately predict a product return, and can thereby benefit online retailers to support decision making related to product returns. Using random samples from a large dataset related to apparel product returns in e-commerce, we created 8 classification models and 494 associated ensembles. We applied several measures in order to examine model validity aspects; overall performance, calibration, discrimination and practical usefulness.

Theoretical conclusions

Our analysis demonstrated that the stacking ensemble which combines AdaB, EGB, MLP, NB, SVM and RF together, is able to outperform any of the classification algorithms that we considered, in terms of predictive accuracy and AUC. In particular, the ensemble model predicted product returns with average accuracy of 72.2%, which is 0.6% more accurate than the next best single classification model; EGB. Furthermore, we showed that the ensemble model is able to appropriately discriminate among purchases that do return and those that do not, despite some evidence that the ensemble is not perfectly calibrated. Overall, the ensemble model was shown to effectively identify consumption patterns associated with a high- or low rate of product returns.

Hence, corresponding to the first part of our main research question, "*is an ensemble selection prediction model based on customer-, product- and shopping basket specific characteristics able to efficiently predict product returns?*", we conclude that it is, indeed, able to efficiently predict product returns.

In addition, our analysis showed that several of the single classifiers that we considered in our study were also able to generate accurate predictions. Namely, each of the single classifiers, with the exception of KNN and NB, were able to predict product returns with an average accuracy of at least 71% and at most 71.8%. Corresponding to our first sub-question, "*Is each of the individual prediction models able to efficiently predict product returns based on customer-, product- and shopping basket specific characteristics?*", we therefore conclude that AdaB, EGB, MLP, Logit, SVM and RF are all efficient in predicting product returns. Corresponding to our second sub-question, "*Is our proposed ensemble selection model more efficient in predicting product returns, as compared to each individual prediction model?*", we conclude that our proposed ensemble is, indeed, more efficient in predicting product returns as compared to each individual prediction model.

Next to analyzing the efficacy of the diverse prediction models, our study demonstrated that return decisions are influenced by customer-, product- and basket related characteristics. In answer to our last sub-question, "*How are product returns influenced by customer-, product- and shopping basket specific characteristics?*", we conclude that, amongst others, gender and age, product price and -quality, and the number of different product categories have a substantial impact on the likelihood of a product return. Additionally, the analysis demonstrated that several control variables, such as return deadlines as well as seasonality, also have an influence on return decisions.

Practical implications

As the stacking ensemble achieved the highest predictive accuracy, the stacking ensemble turned out to be especially useful to account for product returns when computing CLV. Moreover, our analysis demonstrated the business value of the ensemble when used in a system of prediction and prevention of product returns, that focuses only on purchases with a very high return probability. To this end, the ensemble could constitute a meaningful contribution to online retailers' overall profit margins, even with a conservative intervention strategy. Whether and to what extent a system of prediction and intervention should be implemented is, however, essentially a business decision considering the fact that our stacking ensemble did not achieve the highest precision compared to some other classifiers.

Hence, corresponding to the second part of our main research question, "*Is the ensemble model useful to support decision making processing related to product returns?*", we conclude that it, indeed, can have practical usefulness.

Our study thus provided an accurate product prediction return model, establishing, that several single classifier models compose good alternatives to it. Besides, it clearly showed that any model aiming to efficiently predict product returns should take into account customer-, product- and basket related variables. This knowledge is especially beneficial to online retailers in their decision making and action taking in relation to product returns. It may ultimately prompt online retailers to compose innovative return strategies in order to approach the, by them desired, optimal return rate and minimize associated return costs. We do note though, that, as the ensemble model and most single classifiers are not perfectly calibrated, a pure probabilistic interpretation needs to approached with care.

Limitations

We do have to note, however, that the explanatory model resulting from our study has its limitations and therefore would be most useful to particular online retailers specifically. First, that is to say because the study solely focused on fashion products and did not take into account other product types, such as electronica or furniture. Second, our study did not distinguish between different fashion categories, whereas there appear to be significant differences in overall return probabilities across product categories.

Our model does also not exclude features that only become available after purchase, such as the payment method, and therefore cannot be used to predict the return probability before a transaction takes place. For online retailers that would like to focus on identifying the consumption patterns with a very high return rate before the transaction takes place, a model that excludes these features would be more useful. However, excluding these features from the model negatively influences the accuracy of the product return predictions, and we therefore chose not to do so.

Recommendations

We recommend several routes to overcome these limitations and for further research. First, it is recommended that future research on the explanatory model is extended to other merchandise types. Second, it is recommended that further research is being done on the exact differences in overall return probabilities across fashion product categories. Third, it is recommended that further research into a model that excludes features that only become available after purchase is being done. Additionally, more in depth research into further increasing the accuracy of the ensemble model by including additional candidate models, and generating ensembles using other strategies, such as the directed hill-climbing strategy (Caruana et al., 2004) and bagging strategy (Breiman, 1996), is recommended.

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Appendix

Individual algorithms

Adaptive Boosting

The AdaBoost algorithm, introduced by Freund and Schapire (1997), is a type of ensemble learning method where multiple learners are employed to build a stronger learning algorithm. AdaBoost works by choosing a base algorithm (e.g., decision trees) and iteratively improving it by accounting for the incorrectly classified examples in the training set. This ensemble technique is also known as boosting.

To put it briefly, the AdaBoost algorithm starts by predicting the original data set with the first learner, where each observation has an equal weight. After the first learner is then trained, the predictions are evaluated, and a higher weight is given to those data points that have been predicted incorrectly. The next learner would focus thereby more on the misclassified observations. Hence, while taking into account the higher weighted observations that are created in the first step, the AdaBoost algorithm continues to predict with the second learner. Similar to the first step, the second learner is evaluated and weights for incorrect predictions are determined, where the next learner will account for these particular new weights while making the predictions. Being an iterative process, these steps continue until a limit is reached in the number of models to train (i.e., maximum iterations), or at a certain benchmark for predictive accuracy. Hence, Adaboost generates a sequence of learners, each focusing on the previous one's errors.

In our study, we consider the so called 'AdaBoost.M1' algorithm. That is, the AdaBoost algorithm with decision trees as the base algorithm. In order to find the 'optimal' number of iterations (or the number of decision trees to use) for which AdaBoost runs, we compare the predictive accuracy, AUC and computation time of three different settings, namely $n_{adab} \in (10, 20, 50)$.

Ultimately, using the same set of variables as the optimal explanatory model given in equation 1, we deem setting the number of iterations equal to $n_{adab} = 50$ as appropriate to use. That is to say because with this number of iterations, the AdaBoost algorithm achieves the highest predictive accuracy and AUC, while the computation time is still reasonable (approximately 25 minutes).

Extreme Gradient Boosting

Extreme gradient boosting is a classification method based on the principles of gradient boosting. Analogous to adaptive boosting, gradient boosting is a type of ensemble learning method where multiple weak learners are converted into a single stronger learner. Although adaptive- and gradient boosing algorithms follow the same fundamental theory, they substantially differ on how they build the weak learners during the iterative process. In ther words, these algorithms consider alternative ways to empathize difficult instances.

In particular, instead of focusing on weighting wrongly predicted instances, as is done in adaptive boosting, gradient boosting focuses on the difference between the observed- and

predicted value of the dependent variable, or so called residuals. In brief, gradient boosting determines, in each iteration, the residuals and, in turn, fits another weak learner to these residuals. The contribution of the weak learner to the strong learner is then determined using a gradient descent optimization process, where the calculated contribution is the one minimizing the overall error of the strong learner.

Essentially, gradient boosting calculates the gradient of the loss function with respect to the prediction and this way generates an extra 'helper prediction' to enhance the prediction and push the weak prediction closer and closer to the true outcome. Therefore, gradient boosting is prone to over-fitting the data.

Finally, extreme gradient boosting is an advanced implementation of the gradient boosting algorithm with regularization in order to avoid overfitting. The extreme gradient boosting algorithm uses multiple parameters, where, in turn, parameter tuning is necessary in order to improve the predictive quality.

To this extent, using the same set of variables as the optimal explanatory model given in equation 1, we apply a grid search. The principle of grid search is, essentially, to use cross-validation in order to evaluate a set of models, which differ from each other in their parameter values, lying on a grid.

Ultimately, we find that the parameter set with the best performance is given by: number of iterations $n_{egb} = 14$, Learning Rate $\lambda_{egb} = 0.3$ and Maximum tree depth $t_{egb} = 6$. The set of independent variables that we use to train extreme gradient boosting is the same set of variables as the optimal explanatory model given in equation 1.

k Nearest Neighbors

The k Nearest Neighbor (KNN) algorithm is a non-parametric classification method that predicts a particular class based on the k closest points to an observation. The KNN algorithm then simply determines the predicted class by a majority vote of these closest points. For instance, if $k = 1$, the predicted class equals the same class of the single nearest neighbor. Consequently, the choice of the parameter k is very crucial in this algorithm, where the best choice of k depends upon the data.

The presence of noisy and irrelevant features, or feature scales that are not consistent with their importance, severely affects the performance of KNN. Therefore, scaling the features may improve classification. In our study, we normalize the data using the Min-Max normalization given by,

$$z_i = \frac{x_i - \min(\boldsymbol{x})}{\max(\boldsymbol{x}) - \min(\boldsymbol{x})}, \tag{3}$$

where $\boldsymbol{x} = (x_1, \ldots, x_n)$ and z_i is the i^{th} normalized data from n observations.

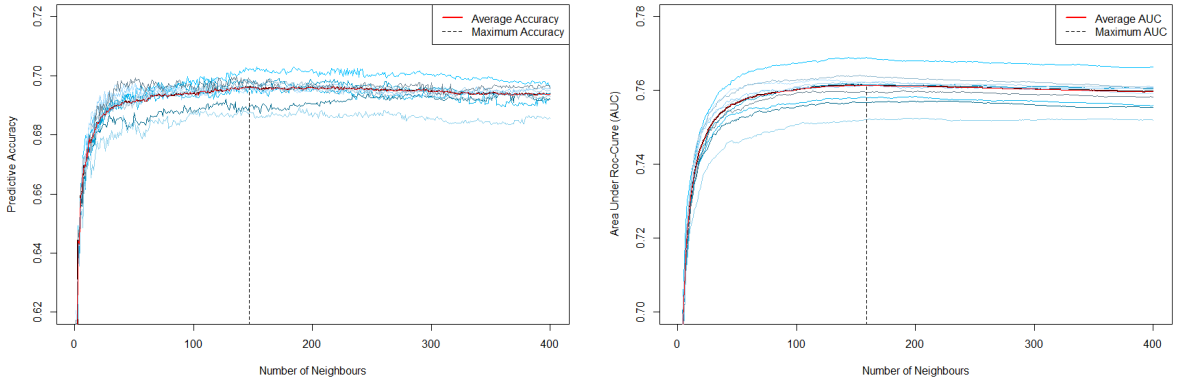
Eventually, the variables we include in KNN are *Ordersize_Fashion*, *Price*, *Discount_ratio*, $Discount_{permanent}$, $Discount_{temporary}$, *Voucher*, *NoFreeShipping*, $PastReturnRate_{Product}$, $PastReturnRate_{Customer}$ and an interaction term calculated as

$$\text{ReturnRates} = \text{PastReturnRate}_{Product} \times \text{PastReturnRate}_{Customer}.$$

As mentioned before, the best choice of k depends upon the data, we therefore apply cross-validation for different values of $k \in (1, 2, 3, \ldots, 400)$ and examine the predictive quality of KNN in terms of both the predictive accuracy and AUC. The results are presented in Figure A.1, given below.

Concerning the predictive accuracy, Figure A.1a shows that, on average, setting $k \approx 150$ is optimal. The AUC supports this results as can be seen in Figure A.1b. Consequently, we select $k = 150$ as the final number of neighbours.

Figure A.1: Plot of predictive accuracy and Area Under the Roc-Curve (AUC) for different number of neighbours k



(a) *Predictive Accuracy* (b) *AUC*

Logistic Regression

Logistic Regression is a statistical method which is used to estimate the probability of an event occurring. Logistic Regression is applied when the dependent variable is binary, where either the event happens (1) or the event does not happen (0). We construct the predictive model based on the optimal explanatory model for the dependent variable *Return* as given in equation (1).

Multilayer Perceptron

A multilayer perceptron (MLP) is a feedforward artificial neural network which can be used, amongst other applications, for classification problems. The MLP consists of multiple layers of nodes, namely the input layers, hidden layers and output layers. An illustration of such a structure is shown in figure (A.2).

The input layer consist of neurons that accept the input values, which represents the input data (variables). Hidden layers are in between the input and output layer and consist of (logistic) functions that map the input to the output of a node. Finally, in the output layer the results from the hidden layers are converted to an actual outcome. In the case of classification, The number of nodes in the output layer corresponds to the number of classes of the dependent variable.

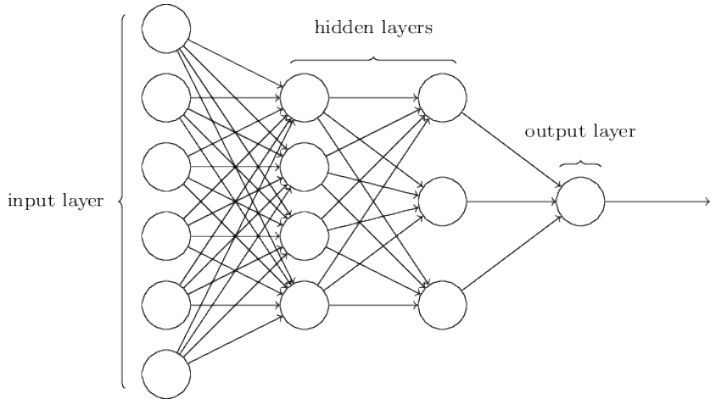


Figure A.2: An example of a Multilayer Perceptron architecture

In order to secure the ability of the MLP to generalize, the number of hidden nodes has to be kept as low as possible. For a large excess of nodes, the MLP becomes a memory bank which can recall the training set to perfection, but does not perform well on samples that outside the training set.

We consider a maximum of two hidden layers, because they can represent an arbitrary decision boundary to arbitrary accuracy with rational activation functions and can approximate any smooth mapping to any accuracy.

Moreover, neural networks require the input to be scaled in a consistent way, where we will again use Min-Max normalization as given in equation (3).

Using grid search, with parameter setting as given in Table 3, we find that the number of layers equal to $l = 2$, with the hidden nodes in each layer $h = 5$ and a maximum of iterations $m_{mlp} = 50$ yield the best results, for the same set of variables as the optimal explanatory model given in equation 1.

Naive Bayes

The Naive Bayes (NB) algorithm is a classification method that predict classes based on Bayes' theorem of probability with an assumption of independence among predictors. In other words, the Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature.

In more detail, Bayes theorem provides a way of calculating posterior probability $P(c|x)$ from $P(c)$, $P(x)$ and $P(x|c)$, namely,

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)}, \text{ where} \tag{4}$$

$P(c|x)$ denotes the posterior probability of class c given predictor x,

$P(c)$ denotes the prior probability of the class c,

$P(x|c)$ denotes the likelihood which is the probability of the predictor given the class,

$P(x)$ denotes the prior probability of the predictor x.

When a class of a categorical predictor is not observed in the data used to train the Naive Bayes model, we have that $P(x) = 0$. However, if one does observe this class when making a prediction, it turns out that the Naive Bayes model is unable to make a prediction (as can be seen from equation (4)). This problem is also known as the Zero-Frequency problem.

In order to solve this, one can use smoothing techniques. Basically, employing smoothing shifts some of the probability from the observed classes to the unseen classes. One of the simplest smoothing techniques is the so called Laplace estimation, which is also included in this study.

The major advantage of the Naive Bayes model is that it is straightforward and useful for very large data sets. It performs especially well when the assumption of independence holds. In real life, however, it rarely occurs that a set of predictors is completely independent.

Because of this assumption, we do not include many variables for the NB. Especially, we will use the same set of variables as considered by the KNN.

Support Vector Machine

A Support Vector Machine (SVM) is a supervised machine learning algorithm that is commonly used in classification problems. The basic principle of SVMs is to find a hyperplane that best divides the dataset into classes. One can think of a hyperplane as a line that (linearly) separates and thereby classifies a set of data.

However, most classification tasks are not that simple, and often more complex structures are needed in order to make an optimal separation. It usually happens that the classes to discriminate in the data are not linearly separable in a particular dimensional space. For this reason, SVMs can map the data into higher dimensions by using a kernel function. The use of kernel function allows much more complex discrimination between sets which are not convex at all in the original space. For a set of independent variables $\boldsymbol{X}_i$, there are number of kernels that can be used in SVMs. These kernel functions include linear, polynomial, radial basis function (RBF), and sigmoid:

$$K(\boldsymbol{X}_i, \boldsymbol{X}_j) = \begin{cases} X_i X_j & \text{Linear} \\ (\gamma X_i X_j + C)^d & \text{Polynomial} \\ exp(-\gamma |X_i - X_j|^2) & \text{RBF} \\ tanh(\gamma X_i X_j + C) & \text{sigmoid,} \end{cases} \tag{5}$$

where γ denotes the inverse of the standard deviation of the RBF kernel ($\gamma > 0$), and C is the capacity constant ($C \geq 0$). Note that the larger the C, the more the error is penalized, and large values for γ leads to high bias and low variance models, and vice-versa.

Because SVMs are extended versions of linear classifiers, where classes may not be linearly separable, SVMs yield usually accurate predictions. Nevertheless, due to the fact that the computation times can be high, it is not well suited to larger datasets.

In the end, we will use the same set of variables as the optimal explanatory model given in equation 1, and select the RBF kernel function and $\gamma = 1/(\text{dimension}(dataset))$.

Random Forest

A random forest is an ensemble learning method which can be used for classification. Specifically, random forests apply the ensemble technique known as bootstrap aggregating (bagging) to decision trees. Besides bagging, the random forest selects a random subset of the features at each split to train the tree. This combination of bagging and selecting a random subset of features is also known as feature bagging.

Shortly summarized, random forests average multiple decision trees that are trained on different parts of a data set. Random forests generally reduce overfitting and high variance which mostly provides an improved accuracy. That is to say because separate decision trees are prone to overfitting their training sets. Individually they have a low bias, but usually a high variance.

Because of the design of the random forest it is a suitable classification method for large data sets that consist of many features. In fact, reducing the number of features (of low importance) does not negatively affect the performance of the random forest in term of accuracy. Here, the number of decision trees does has an impact on the efficiency of a random forest. Incorporating more decision trees in a random forest would usually result in gains in accuracy. Nonetheless, using a large number of trees could greatly increase the computation time while it may hardly increase the accuracy. For this purpose, we plot the predictive accuracy against the number of trees used, where we use all variables contained in the data set to train the random forest.

Figure A.3: The Mean Squared Error for different number of trees

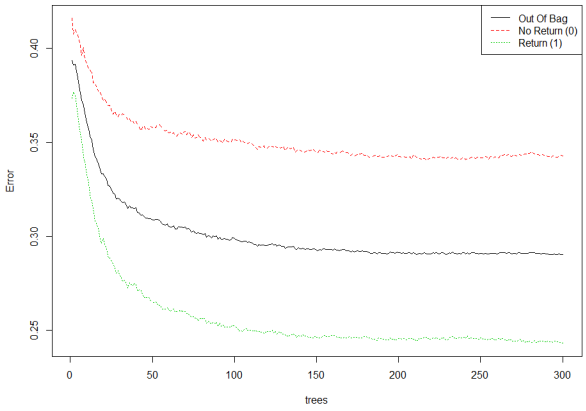


Figure A.3 above helps in deciding the number of trees to include in the model. The number of trees used in the model can be found on the x-axis, whereas the y-axis presents values for the error of the model. It follows that between a number of trees between 0 and 50, the error of the model remains quite high, but decreases significantly. The error term keeps decreasing for a number of trees up to 150, however, seems to flatten out after this number of trees. There exist, of course, a point where each additional tree only adds further time and computational power, but does not improve overall model performance.

In the end, for our final model we set the number of trees equal to $t_{rf} = 150$.

All logistic regression results

In Table A.2 we demonstrate the build up of our model explaining product returns (dependent variable: *Return*).

In the first step, we only include the customer characteristics, that is,

$$P\big(Return_{ijt} = 1 | \boldsymbol{X}_{ijt}, \epsilon_{ijt}\big) = \frac{1}{1 + e^{-\boldsymbol{X}_{ijt}\boldsymbol{\beta}}}, \quad \text{where} \tag{6}$$

$$\boldsymbol{X}_{ijt}\boldsymbol{\beta} = \boldsymbol{\beta}_1 Customer\_Level_{it} + \beta_0 + \epsilon_{ijt},$$

In the second step we also take the product level variables into account while estimating the probability of a product return. Namely, we now have

$$\boldsymbol{X}_{ijt}\boldsymbol{\beta} = \boldsymbol{\beta}_1 Customer\_Level_{it} + \boldsymbol{\beta}_2 Product\_Level_{jt} + \beta_0 + \epsilon_{ijt}.$$

In the third step we include the shopping basket characteristics,

$$\boldsymbol{X}_{ijt}\boldsymbol{\beta} = \boldsymbol{\beta}_1 Customer\_Level_{it} + \boldsymbol{\beta}_2 Product\_Level_{jt} + \boldsymbol{\beta}_3 Basket\_Level_{ijt} + \beta_0 + \epsilon_{ijt}.$$

The last step includes the control variables, and we end up with our final model as given in equation (1).

The corresponding Likelihood Ratio Tests between each step are given in Table A.1.

Table A.1: Likelihood Ratio Tests for stepwise models with dependent variable *Return*

	Model I	Model II	Model III	Full Model
Model I	1	$2.2e^{-16***}$		
Model II		1	$2.2e^{-16***}$	
Model III			1	$2.2e^{-16***}$
Full Model				1

[I] Corresponding significance levels are indicated with: *p<0.1; **p<0.05; ***p<0.01

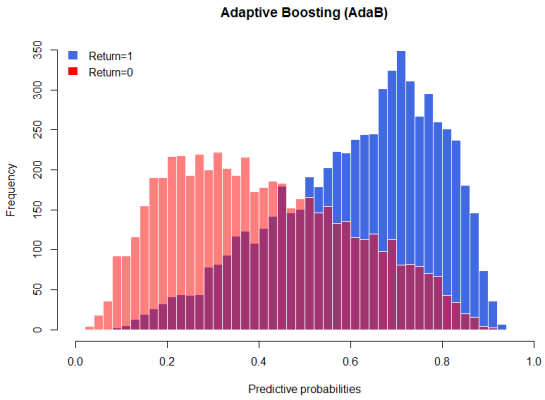
[II] Likelihood Ratio Tests corresponding to columns (1) to (4) in Table A.2

Table A.2: All logistic regression results

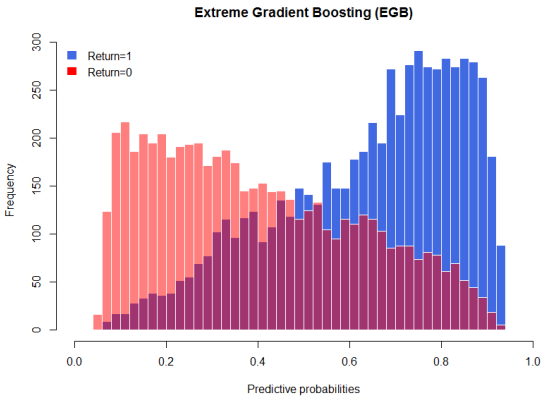
	Dependent variable: Return			
	Model I (1)	Model II (2)	Model III (3)	Full Model (4)
Customer level				
Male	−0.211*** (0.008)	−0.096*** (0.009)	−0.087*** (0.009)	−0.086*** (0.009)
Urbanicity_2	0.033*** (0.009)	0.050*** (0.010)	0.015 (0.010)	0.015 (0.010)
Urbanicity_3	0.056*** (0.009)	0.092*** (0.010)	0.032*** (0.010)	0.033*** (0.010)
Urbanicity_4	0.053*** (0.011)	0.097*** (0.011)	0.033*** (0.012)	0.033*** (0.012)
Urbanicity_5	0.058*** (0.010)	0.087*** (0.010)	0.043*** (0.011)	0.043*** (0.011)
$\text{Family\_Compostion}_{YoungCouples}$	0.030** (0.015)	0.026* (0.015)	0.007 (0.015)	0.007 (0.015)
$\text{Family\_Compostion}_{Families}$	0.027*** (0.008)	0.058*** (0.009)	0.029*** (0.009)	0.029*** (0.009)
$\text{Family\_Compostion}_{OlderCoupes}$	0.020* (0.011)	0.025** (0.011)	0.016 (0.011)	0.016 (0.011)
$\text{Family\_Compostion}_{Other}$	0.180*** (0.051)	0.174*** (0.053)	0.149*** (0.054)	0.150*** (0.054)
Age_{25to34}	−0.003 (0.015)	0.060*** (0.015)	−0.030* (0.016)	−0.031** (0.016)
Age_{35to44}	−0.110*** (0.015)	−0.033** (0.015)	−0.116*** (0.016)	−0.118*** (0.016)
Age_{45to54}	−0.106*** (0.015)	−0.091*** (0.016)	−0.131*** (0.016)	−0.133*** (0.016)
Age_{55to64}	−0.066*** (0.017)	−0.080*** (0.018)	−0.069*** (0.018)	−0.070*** (0.018)
Age_{65plus}	−0.057*** (0.022)	−0.038* (0.023)	0.018 (0.023)	0.017 (0.023)
$\text{Income}_{Minimum}$	−0.023 (0.015)	−0.009 (0.015)	0.044*** (0.016)	0.045*** (0.016)
$\text{Income}_{BelowModal}$	0.007 (0.013)	0.017 (0.013)	0.064*** (0.014)	0.064*** (0.014)
Income_{Modal}	0.034*** (0.009)	0.043*** (0.009)	0.067*** (0.009)	0.067*** (0.009)
$\text{Income}_{1.5\times Modal}$	0.051*** (0.008)	0.056*** (0.009)	0.062*** (0.009)	0.062*** (0.009)
$\text{Income}_{2\times Modal}$	0.047*** (0.009)	0.051*** (0.009)	0.045*** (0.009)	0.044*** (0.009)
Nudge	0.813*** (0.012)	0.799*** (0.013)	0.691*** (0.013)	0.689*** (0.013)
LastPurchase_Days	0.002*** (0.00004)	0.002*** (0.00004)	0.001*** (0.00004)	0.001*** (0.00004)
LastReturn_Days	−0.001*** (0.00004)	−0.001*** (0.00004)	−0.001*** (0.00004)	−0.001*** (0.00004)
Total_PastOrders	−0.004*** (0.0003)	−0.003*** (0.0003)	0.004*** (0.0003)	0.004*** (0.0003)
Relationship_length	0.002*** (0.001)	0.003*** (0.001)	−0.007*** (0.001)	−0.006*** (0.001)
Total_RelationShip_Value	0.00004*** (0.00000)	0.00004*** (0.00000)	−0.00000*** (0.00000)	−0.00001*** (0.00000)
AVG_Total_Spent	−0.001*** (0.0001)	−0.001*** (0.0001)	−0.001*** (0.0001)	−0.001*** (0.0001)
$\text{PastReturnRate}_{Customer}$	2.091*** (0.014)	2.041*** (0.014)	1.579*** (0.015)	1.579*** (0.015)
Product level				
Price		0.004*** (0.0001)	0.005*** (0.0001)	0.005*** (0.0001)
$\text{Price\_segment}_{Middle}$		0.008 (0.010)	0.002 (0.010)	0.0005 (0.010)
$\text{Price\_segment}_{High}$		0.017 (0.014)	0.007 (0.014)	0.007 (0.014)
Quality_{Middle}		−0.017** (0.008)	−0.049*** (0.009)	−0.049*** (0.009)
Quality_{High}		−0.054*** (0.013)	−0.104*** (0.013)	−0.105*** (0.013)
$\text{Discount}_{permanent}$		−0.00003 (0.0005)	−0.0001 (0.0005)	−0.00003 (0.0005)
$\text{Discount}_{temporary}$		0.007** (0.003)	0.001 (0.004)	0.001 (0.004)
Discount_ratio		−0.455*** (0.029)	−0.293*** (0.030)	−0.293*** (0.030)
DiscountMultipleProducts		−0.204*** (0.025)	−0.175*** (0.025)	−0.173*** (0.025)
Outlet		0.051*** (0.012)	0.064*** (0.012)	0.065*** (0.013)
$\text{PastReturnRate}_{Product}$		2.660*** (0.018)	2.431*** (0.018)	2.436*** (0.018)
AVG_Review		−0.001*** (0.0002)	−0.0004* (0.0002)	−0.0004* (0.0002)
N_Reviews		−0.004*** (0.001)	−0.002*** (0.001)	−0.003*** (0.001)
SizeOptions		0.005*** (0.001)	0.002*** (0.001)	0.002*** (0.001)
PlusSize		0.027*** (0.010)	0.019* (0.010)	0.020** (0.010)
$\text{Season\_Indicator}_{Winter}$		−0.152*** (0.013)	−0.114*** (0.013)	−0.119*** (0.013)
$\text{Season\_Indicator}_{All}$		−0.158*** (0.011)	−0.140*** (0.011)	−0.143*** (0.011)
$\text{Season\_Indicator}_{Zomer}$		−0.223*** (0.014)	−0.249*** (0.014)	−0.246*** (0.014)
$\text{Season\_Indicator}_{Tussen}$		−0.070*** (0.020)	−0.019 (0.020)	−0.022 (0.020)
Basket level				
NoFreeShipping			−0.455*** (0.040)	−0.454*** (0.040)
Ordersize_Fashion			−0.004 (0.003)	−0.004 (0.003)
Total_Spent_Fashion			0.001*** (0.00003)	0.001*** (0.00003)
N_Products_Other			0.004 (0.010)	0.004 (0.010)
N_Products_Sport			0.030*** (0.011)	0.031*** (0.011)
N_Distinct_Products_Other			−0.041*** (0.015)	−0.040*** (0.015)
N_Distinct_Products_Sport			−0.039** (0.016)	−0.040** (0.016)
Total_Spent_Other			−0.0001 (0.0001)	−0.0001 (0.0001)
Total_Spent_Sport			0.0005** (0.0002)	0.0004** (0.0002)
PayMethod_{Giro}			0.166*** (0.010)	0.168*** (0.010)
PayMethod_{iDeal}			−0.324*** (0.013)	−0.321*** (0.013)
$\text{PayMethod}_{Creaditcard}$			−0.040 (0.025)	−0.037 (0.025)
Voucher			−0.076*** (0.017)	−0.077*** (0.017)
Giftcard			−0.462*** (0.117)	−0.465*** (0.117)
N_Identical_Products			−0.332*** (0.015)	−0.331*** (0.015)
N_Diff_Sizes			0.598*** (0.008)	0.599*** (0.008)
N_Diff_Colors			−0.089*** (0.004)	−0.089*** (0.004)
N_Identical_ProductCategory			0.157*** (0.003)	0.158*** (0.003)
N_Diff_ProductCategory			0.018*** (0.002)	0.019*** (0.002)
N_Diff_Brands			−0.011*** (0.003)	−0.012*** (0.003)
N_Diff_Sex_Product			0.013** (0.006)	0.014** (0.006)
Website_Search			−0.008 (0.007)	−0.008 (0.007)
Daypart_{Midday}			−0.009 (0.009)	−0.010 (0.009)
$\text{Daypart}_{Evening}$			0.039*** (0.008)	0.039*** (0.008)
Daypart_{Night}			0.044** (0.019)	0.044** (0.019)
Mobile_{Phone}			0.014* (0.007)	0.018** (0.007)
Mobile_{Tablet}			0.005 (0.008)	0.005 (0.008)
$\text{StartChannel}_{DirectLoad}$			−0.070*** (0.008)	−0.068*** (0.008)
$\text{StartChannel}_{SEA\_Branded}$			−0.048*** (0.009)	−0.049*** (0.009)
$\text{StartChannel}_{SEA\_NonBranded}$			0.020* (0.011)	0.020* (0.011)
Control variables				
Campaign				−0.043*** (0.008)
Campaign_WeekBefore				−0.047*** (0.010)
Campaign_WeekAfter				0.003 (0.010)
Holiday				−0.003 (0.010)
Holiday_WeekBefore				−0.011 (0.022)
Policy				−0.073*** (0.009)
Weekend				0.030*** (0.007)
Season_{winter}				−0.065*** (0.011)
Season_{spring}				−0.083*** (0.012)
Season_{summer}				−0.048*** (0.009)
Constant	−0.961*** (0.018)	−2.546*** (0.023)	−2.545*** (0.028)	−2.457*** (0.030)
Observations	600,000	600,000	600,000	600,000
Log Likelihood	−373,414	−354,177	−341,310	−341,242
Akaike Inf. Crit.	746,883	708,448	682,776	682,661
Bayesian Inf. Crit.	747,898	709,810	683,757	683,655

Note: Standard errors in parenthesis *p<0.1; **p<0.05; ***p<0.01

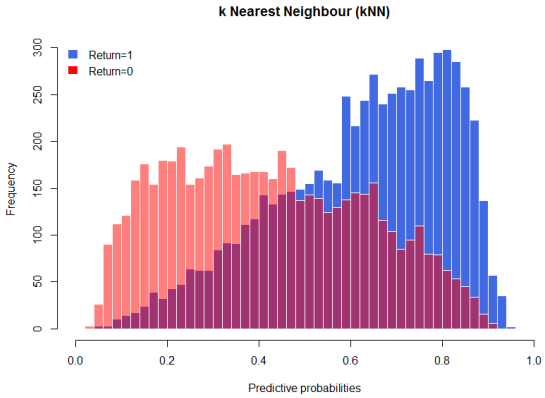
Figure A.4: Histograms of the predicted probabilities associated with the true observed class of *Return*



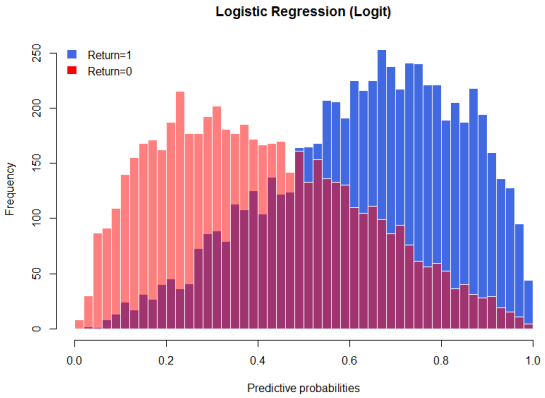
(a) *Adaptive Boosting*



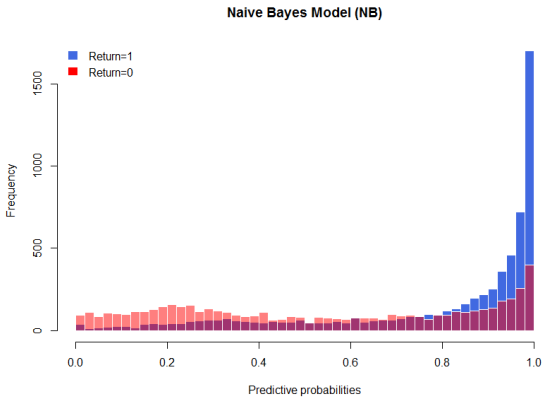
(b) *Extreme Gradient Boosting*



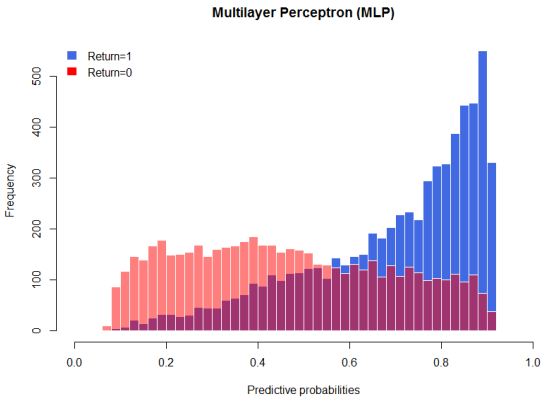
(c) *k Nearest Neighbours*



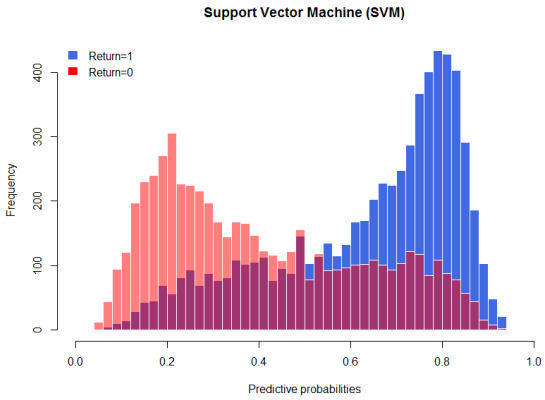
(d) *Logistic Regression*



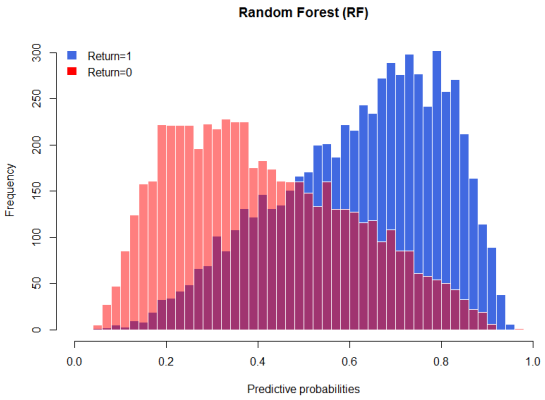
(e) *Naive Bayes*



(f) *Multilayer Perceptron*



(g) *Support Vector Machine*



(h) *Random Forest*