Machine Learning Models for Dynamic Product Repricing on the Amazon Marketplace*

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E-commerce has grown hugely and has opened opportunities for retailers big and small to sell their products on online shopping platforms such as the Amazon Marketplace. The Amazon platform hosts thousands of retailers and uses an algorithmic decision process called the BuyBox, to decide which product offer to show first in return to a user query.

Every time the price of a product changes, an auction among all the competing offers for that product takes place, and the BuyBox winner is re-assigned by Amazon. The BuyBox winner typically sells more products and achieves a higher revenue. The price of a product plays a large role, but it is not the only indicator of an offer winning the BuyBox. If we can understand and accurately approximate the BuyBox assignment algorithm, we can advise sellers about how to best customise their offers. We can also employ the same algorithm for dynamic repricing of products, to increase the likelihood of an offer winning the BuyBox, in the context of continuous change in competing offers.

Most existing solutions for predicting the BuyBox and for product repricing are closed commercial solutions. In this study we analyse historical data describing thousands of Amazon BuyBox auctions and build machine learning models that aim to approximate the Amazon algorithm for selecting winners. We also investigate approaches for algorithmic re-pricing based on (1) our BuyBox prediction algorithm and (2) efficient price point search strategies. Our evaluation shows that our learning models can accurately predict the BuyBox winner and can recommend effective repricing strategies.

Additional Key Words and Phrases: Dynamic Repricing, Amazon Marketplace, E-Commerce, BuyBox Prediction, Machine Learning

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1 INTRODUCTION

Nowadays, the rise of e-commerce has opened many opportunities and challenges for merchants to sell their products and re-act their selling immediately. The on-line marketplace such as Amazon, provide many supporting tools to sellers that they can supervise their products at any given point of time. On the one hand, Amazon helps the merchants to adapt their product's price effectively in order to gain their profit. On the other hand, it also increases much pressures to the retailers, who have limited experience with such highly competitive markets and their long-term effects. To deal with that concern, the sellers use dynamic pricing tools to adjust product prices and manage inventories in real-time.

Dynamic pricing is the study of determining optimal selling prices of products or services, in a setting where prices can easily and frequently be adjusted. This applies to vendors selling their products via Internet, or to brick-and-mortar stores that make use of digital price tags. In both cases, digital technology has made it possible to continuously adjust prices to changing circumstances, without any costs or efforts. Dynamic pricing techniques are nowadays widely used in various businesses, and in some cases considered to be an indispensable part of pricing policies. Digital sales environments generally provide firms with an abundance of sales data.

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This data may contain important insights on consumer behavior, in particular on how consumers respond to different selling prices. Exploiting the knowledge contained in the data and applying this to dynamic pricing policies may provide key competitive advantages, and knowledge of how this should be done is of highly practical relevance and theoretical interest. This consideration is a main driver of research on dynamic pricing and learning: the study of optimal dynamic pricing in an uncertain environment where characteristics of consumer behavior can be learned from accumulating sales data.

More recently, research and industry started to combine achievements of price optimization from the research field of operations research with the achievements in data-driven procedures from the field of computer science such as machine learning. This development is basically catching-up with similar approaches already being applied in the field of algorithmic trading or high-frequency trading on stock exchanges. These approaches are far more sophisticated than currently observable approaches on marketplaces such as Amazon, where most merchants thrive to be amongst the cheapest competitors, eventually leading to a typical race to the bottom.

The Amazon Online Marketplace is the largest and fastest growing retailer marketplace, with more than 3 million retailers selling products on this platform []. Amazon constantly ranks the sellers based on different attributes, such as product price, customer satisfaction, amount of transactions completed, etc., and presents the best ranked seller/offer in the BuyBox. Pricing is the the most influential factor short-term to rank at the top, but the other attributes describing the seller and the offer are also important (e.g., shipping time, stock available). Existing repricing solutions use seller-provided rules for updating the product price when a repricing event is triggered (e.g., update price by 1% when a competitor changes the price of a product). These fixed rules are set manually and changed infrequently based on a schedule decided by the seller.

A Machine Learning solution for dynamic repricing can take full advantage of past detailed historical data about competing offers and the outcome of auctions, and should remove the need for slow to update and potentially non-optimal manual-rules. This can result in optimised pricing decisions for the sellers which should rank them top on the sales platform consistently, therefore laying the foundation for increased sales and better competitiveness. Additionally, the insights derived from analysing the historical data and the resulting predictive models should allow sellers to adapt to ever changing market conditions beyond pricing.

In this work we have access to large amounts of auction data for products sold over the course of 9 months on the Amazon Marketplace. Our aim is to develop machine learning algorithms to predict the BuyBox winner, as well as study dynamic repricing strategies for individual sellers.

Our key contributions are as follows:

- **Data Preparation Techniques:** We present data pre-processing and preparation techniques suitable for product auction data collected from the Amazon Marketplace, with a view to build effective BuyBox prediction algorithms.
- **BuyBox Predictor Algorithm:** We propose a machine learning algorithm that can be trained on historical product auction data from the Amazon Marketplace, and can be used to predict the winner of a new auction on the Amazon Marketplace (i.e., BuyBox winner predictor). Our algorithm is based on a RandomForest classifier that uses carefully engineered features. We also discuss the importance of different features for predicting the BuyBox.
- **Repricer Algorithm:** We implement and evaluate a dynamic repricing algorithm that can take in an auction for a given product and seller, and recommend a repricing strategy to maximise the probability of winning the

next auction for that seller and product. Our algorithm is based on the BuyBox predictor model and on a strategy for selecting candidate price points for recommendation.

- **Evaluation/Deployment:** All our algorithms are tested on research benchmarks and are deployed on commercial platforms. We discuss the results and what we learn from deploying our algorithms.

2 RELATED WORK

3 BACKGROUND

In this section, we first briefly introduce the Amazon Marketplace. Then, we focus on the data features on the markets, that effect to algorithmic repricing, including the offers of 3P merchants, the BuyBox concept, and finally the scaled data, collected from the Amazon Web Services (AWS).

3.1 The Amazon Marketplace

The Amazon Marketplace is one of the most well-known marketing channels for online retailers. It is an e-commerce platform, which enables sellers to sell their products on its cloud markets. Started as a book seller but later Amazon (amazon.com) has expanded to sell varied categories of consumer items as well as its own electronic machinery. The Amazon has separate marketplaces for the United States, Australia, Brazil, Canada, China, France, Germany, India, Italy, Japan, Mexico, Netherlands, Spain, and the United Kingdom.

In 2015, Amazon surpassed Walmart to be the most valuable retailer in the United States [**?**]. In 2017, it becomes one of the top 10 world's largest online marketplace with around 80 million worldwide members (refered to *"Global Powers of Retailing 2017"* report [1]). In the same year, the using Amazon mobile application also reached the peak of 41.50% to become the top most popular mobile shopping app in the United States, this is illustrated by **Fig.1** (refered to www.statista.com [2]).

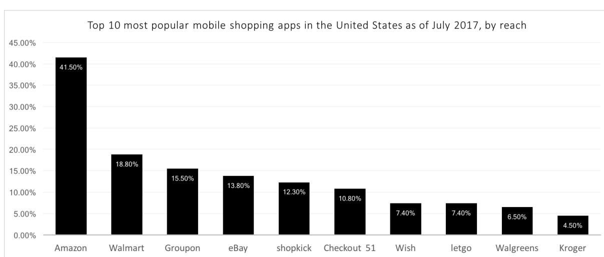


Fig. 1. Top 10 of most popular mobile shopping apps in the United States as of July 2017, by reach.

3.2 The BuyBox

The Amazon BuyBox is definitely the most important element to sellers in Amazon Marketplace. It is the box from the right of the product page which contains the *"Add to Basket"* or *"Add to Cart"* button. **Fig.2**, an example BuyBox, shows that winning the BuyBox is critical for generating sales. The BuyBox contains the price of the product, shipping information, the name of the seller, and a button to purchase the product. When customers click the button, they are

[1]https://www2.deloitte.com/content/dam/Deloitte/global/Documents/consumer-industrial-products/gx-cip-2017-global-powers-of-retailing.pdf
[2]https://www.statista.com/statistics/579505/most-popular-us-shopping-apps-ranked-by-reach/

buying the product from only one merchant who is the BuyBox winner. The winner gets more chance to sell their items by getting the prominent position in product's page , while the other competitors are relegated to the bottom section with a lower priority. Amazon themselves admit that around 82% of purchases are made through the BuyBox [**?**].

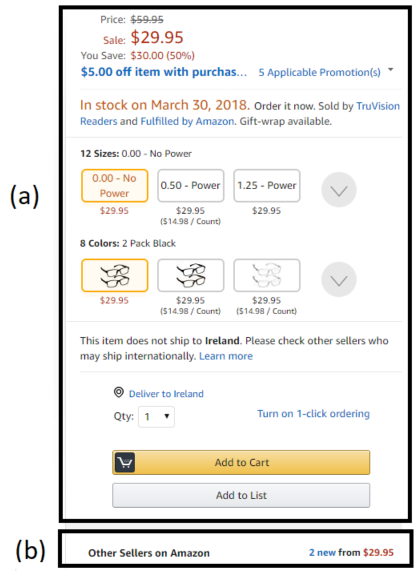


Fig. 2. In the Amazon's product page, the products of the BuyBox winner can be highlight effectively in the BuyBox (a), while the other competitors get lower positions (b).

However, multiple sellers can offer the same product in Amazon Marketplace. If more than one eligible seller offers a product, they may compete for the BuyBox position. **Fig.3** is an example of one product's auction provided by many competitors with different information, prices, deliveries, and conditions. Every time one seller changes the price of a their product, the BuyBox winner is re-assigned by Amazon.

Amazon has a convoluted algorithm to determine which seller gets the prime location on the BuyBox. Understanding the BuyBox algorithm is essential, because it may help sellers choose better pricing strategies for their next auctions. Amazon has a notation about the features which are used by the BuyBox algorithm [**?**], but it is uncertain whether the feature list is complete, or what the important weights of the features are. Because winning the BuyBox is so critical for making sales on Amazon, sellers may use dynamic pricing strategies that give them an advantage to be chosen by the BuyBox algorithm.

3.3 Amazon Web Service (AWS)

Amazon offers an array of tools to help sellers manage product selling. The most knowing of these tools is the Amazon Marketplace Web Service (MWS). Amazon Web Services (AWS) is a bundled remote computing service that provides cloud computing infrastructure over the Internet with storage, bandwidth and customized support for application programming interfaces (API).

From AWS, users has a capability to control their product updates for specified products from the Amazon cloud service. They are able to acknowledge their current state in the price-battle competed to their competitors. They can

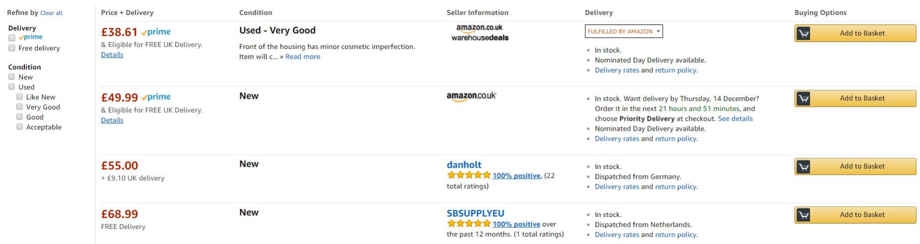


Fig. 3. An example of the offers for one product item on Amazon with many different competitors.

know who is the buy box winner, how many offers are provided by their competitors ... They also can execute several tasks through the provided functions such as listing products, managing inventory, and changing prices.

The data from AWS can be pulled using the XML format, and then it can be parsed and stored into comma-separated value (CSV) file. Each row in the CSV file is a single data record or observation of one seller in the product's competition. Each column in the CSV contains a attribute of offers.

For example, **Fig.4** illustrates small vision of one CSV file which has four sellers, each in its own row. This observation contains 21 attributes, and some of them are very important such as *IsBuyBoxWinner, ListingPrice, ShippingPrice, ShippingTime_maxHours, ShippingTime_minHours, IsFulfilledByAmazon*, ... In order to reduce the space, the description of features are skipped here. However, they can be briefly found in **Chapter 4.2**.

IsBuyBoxWinner	MarketplaceId	ConditionNotes	IsFeaturedMerchant	IsFulfilledByAmazon	ListingPrice	ShippingPrice	ShippingTime_maxHours	ShippingTime_minHours	ShippingTime_availtype	ShipsDomestically	SellerFeedbackRating	SellerFeedbackCount
1	FRANCE	0	1	1	11.94	0	0	0	NOW	1	92	38
-1	FRANCE	0	1	0	27.72	2.08	72	48	NOW	1	100	1
-1	FRANCE	0	0	0	5.99	7.99	48	24	NOW	1	67	3
-1	FRANCE	1	0	0	9.99	6.99	48	24	NOW	1	100	1
-1	FRANCE	0	1	1	16.98	0	0	0	NOW	1	93	14
-1	FRANCE	0	1	0	6.64	0	48	24	NOW	1	90	231
1	FRANCE	0	1	1	15.98	0	0	0	NOW	1	94	47

Fig. 4. An example of Amazon's data with 7 samples.

3.4 Competition Auction

From mentioned above, the AWS helps users control their selling, including updating prices for their products. Whenever one seller changes or updates their offer for one item, AWS keeps a new record for that update with fully information for the lowest 20 prices offered of that product item (or less, if there are fewer than 20 offers). Since one auction happens, then one new XML is created from AWS.

4 BUYBOX PREDICTION

This section provides a machine learning algorithm which can take as input any dataset describing the offers made by sellers for a set of products, for a specific market (e.g., US, UK, France) or across markets. It then trains a machine learning model that, when presented with an auction, it can predict the offer that will win the auction (BuyBox). The algorithm also outputs a ranked list of the feature importance discovered from the training data. For example, the algorithm can discover data-specific feature importance for each input dataset. This means that the algorithm can be targeted to the data of a single seller or a specific product, and it delivers a list of feature importance for that custom data. So besides predicting the auction winner, the algorithm can be used to advise sellers on how best to update their offer profiles to increase their chance of winning the BuyBox.

4.1 Business Understanding

Amazon hosts thousands of sellers on their marketplace. They use an algorithmic decision process to decide the winner of every auction. An auction as mentioned above is a set of merchants that compete to sell a product. Amazon selects a winner for the auction, and place that seller's product into the BuyBox. The BuyBox winner typically sells more products, and ideally achieves a higher profit margin. This means that the winner is highly competed by many retailers in auction.

Motivated by that, our target is clearly declared as: can we use historical data about auctions and knowledge about the winners and losers, to learn the rules by which Amazon decides the winners? If we can approximate AmazonâĂŹs algorithm, we can advise sellers about the best strategy to use for winning the BuyBox. For example, we can recommend a new price for the product, or give advice about shipping time and user feedback profile to improve the offer and increase the chance of winning the BuyBox.

4.2 Data Understanding

As mentioned above, every changing for a seller's offer detail in product page provides an auction, in AWS cloud. It includes aggregated information about the 20 lowest prices offered for a product (or less, if there are less than 20 sellers). Each auction is represented as a XML, the total size of raw-data folder, which is a cross-market database, is about 100.000 files.

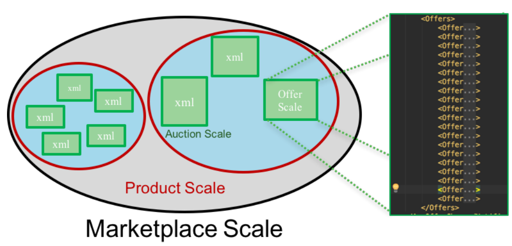


Fig. 5. The scales of data in one Marketplace.

Illustrating from **Fig.5**,which is the scaling scheme of data in one market, there are four basic layer for the Amazon data:

1. **Marketplace layer**: The Amazon has many marketplaces for the United States, Australia, Brazil, Canada, China, France, Germany, India, Italy, Japan, Mexico, Netherlands, Spain, and the United Kingdom. One marketplace is an separated environment with its own characteristics. e.g. in India market, there is one seller who wins almost product's competing, while in U.S. market, the auction is normally with two or three competitors.

2. **Product layer**: From the market place, sellers can sell many products. It could be very different in price, shipping time, conditional note for two different products. The category list of product can be found in the Amazon Web Service.

3. **Auction layer**: In product's layer, the auction can be recorded when sellers update their product's offers. For example, one seller changes their shipping time from 0 hour to 24 hours, the new auction is saved as one XML file.

4. **Offers layer**: There are many sellers give their offer for a product in marketplace. However, only the 20 lowest price offers are saved in XML when an auction is happened.

4.3 Data Preparation

4.3.1 Raw Data: To facilitate the analysis, we model the BuyBox as a prediction problem. Specifically, for a product offered by n sellers, each of which is characterized by a feature vector, our goal is to predict which seller will be chosen to get in the Buy Box.

First step is to parse the XML raw data files into a single CSV dataset that can be use for further data analysis. We do this by parsing every single XML file, and turning each tag in the XML file, into a row of the CSV file. This row describes the features of an offer and the target feature is the **IsBuyBoxWinner** (which is 1 if the offer in BuyBox, -1 otherwise). All the offers under the tag **<Offers>** become rows in the CSV file. Since each XML file has up to 20 offers, this means that for each auction we generate up to 20 rows in the CSV file. Each Offer tag becomes a row in the CSV file, and each tag or subtag, becomes a column name. We give details below for the number of rows and columns generated by parsing over 100k XML files.

The feature vector is described into four categories as follows :

1. Prices: The price's features are related to the price of products, which customers have to pay for buying a product. They are the *ListingPrice* and *ShippingPrice*. In addition, the new feature *LanddedPrice* = *ListingPrice* + *ShippingPrice* is also calculated.

2.Shipping Time Informations: These are the shipping details for one seller's product, including the *ShippingTime_minHours*, *ShippingTime_maxHours* for delivery.

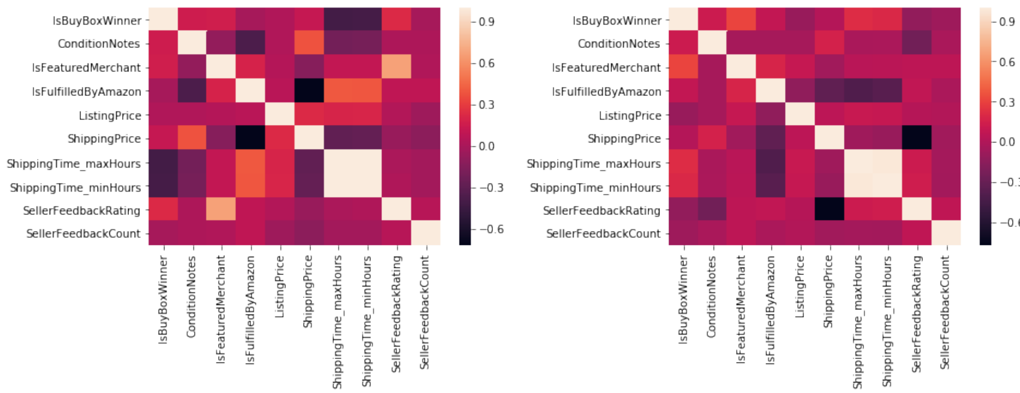
3. Seller Feedback Information: These features describe the detail of seller's feedback, including feedback's counts (*SellerFeedbackCounts*) and feedback's rating (*SellerFeedbackRating*).

4. Retailers' Details: These features are the basic detail of sellers when they have a cooperate to Amazon. These features denote whether the seller is fulfilled by Amazon (*IsFulfiledByAmazon*) or by merchant (*IsFeaturedMerchant*). The last feature is the product's condition notes *ConditionNotes* from sellers to their buyers.

4.3.2 Data Analysis: After parsing data into CSV format, the features are analyzed to help us having a clear understanding. Our first concern is about whether we can use data from cross-market to learn model. By observation **Fig.6**, it clearly shows that we should not train model with cross-market data. The correlations between features of two markets are really different, e.g. the possibility to be in BuyBox is higher if we have smaller shipping times in U.S. market, while it is not a really strong concerned effect in U.K. market. Hence, the separated treatment for each marketplace is necessarily provided.

In addition, we create some new features to enrich the information of an auction. These features are described as follows:

1. Difference to Minimum Price in Auction: (*DifftoMinLandedPriceCompetition*)This is the difference from current LandedPrice to the minimum landed price in that auction.



(a) The U.S. *"amazon.com"* market

(b) The U.K. *"amazon.co.uk"* market

Fig. 6. The correlation between features in (a) U.S. market and (b) U.K. market.

2. Difference to the Minimum Price of Product: (*DifftoMinLandedPriceProduct*) This is the difference from current LandedPrice to the minimum landed price, grouped by product.

3. Difference to the Amazon Seller's Price: (*DifftoAmzLandedPriceCompetition*) We capture who is the Amazon Seller in the auction. Then, we calculate the difference from current LandedPrice to the Amazon Price. If there is not Amazon Seller in the auction, we use the difference to minimum price in the auction instead.

4. Difference to the Ideal Point in Auction: (*IdealPointCompetition*) The ideal point is the combination between the best (i.e., minimum) LandedPrice and the best (i.e., minimum) ShippingTime_maxHours, across all offers, in each auction. This feature captures the difference from this ideal point, for each offer in the auction.

In order to check the model's improvement capability for the new features, we add those features one after another and compare them with the F1-scores by using Random Forest Classifier. **Fig.7** illustrates that the prediction becomes better when adding the extra information. This upgrading also points that the new features can enrich the Amazon data and help to build a better hypothesis.

4.4 Machine Learning Model for Predicting BuyBox Winner

In here, we introduce the model construction with BuyBox Predictor. The goal of this algorithm is to predict the probability to win buy box. From parsed data, we use the Random Forest classifier to build the R.F. tree, which has information of who is winner and who can never win. The **Fig.8** shows the flowchart of BuyBox prediction algorithm.

4.5 Experiment for Predicting BuyBox Winner

5 REPRICER ALGORITHM

5.1 Problem Understading

One of the main inputs influencing who becomes the auction winner is the price offered by a seller for the product being auctioned. Product prices change dynamically on the Amazon platform, depending on the real-time competition for selling that product (i.e., the competing offers) and manual repricing rules decided by the seller. We aim to automate

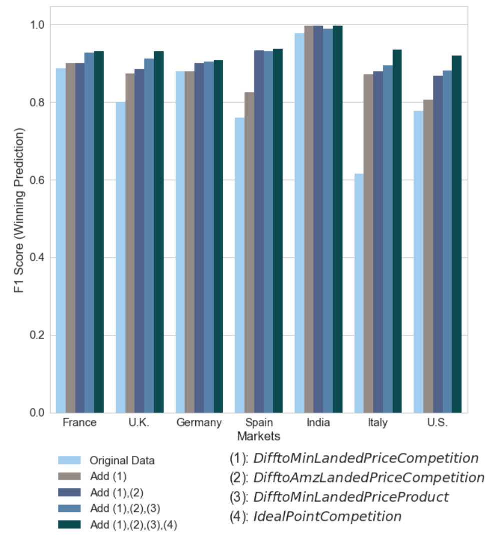


Fig. 7. A comparison of F1-score when predicting winner BuyBox for 7 marketplaces. The scores are provided by Random Forest classifier.

Fig. 8. The flowchart of BuyBox model for winner prediction using feature importance to rank and select best features.

the repricing strategy to adapt to observed changes in auction behaviour. The repricing strategy helps to maximise the probability of winning the next auction for the given seller/customer and product.

The problem to be solved is: can we use our BuyBox predictor algorithm to dynamically recommend a product price to a given seller (i.e., a dynamic repricing strategy), for a given auction?

This section provides a dynamic repricing tool that uses BuyBox prediction model in Section 4. The repricing algorithm takes in data describing an auction for a given product and a given seller on the Amazon Marketplace, the BuyBox predictor model trained to predict the winner of any auction (a BuyBox winner predictor algorithm) and the data used to train that model. As output, it produces a few candidate price points for the given customer in the auction, ranks the price candidates and selects the top ranked price as a new price recommendation for that customer.

5.2 Spliting the Price's Bins

The first problem we have to solve is how to generate the recommended candidate prices.

Markets (Sample size)	Class	R.Forest		L.Regression		3-NN		AdaBoost		SVM-RBF		XGBoost	
		mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
France (475,612)	-1	1.000	0.000	0.990	0.000	0.990	0.000	0.990	0.000	0.990	0.000	0.990	0.000
	1	0.960	0.004	0.800	0.000	0.860	0.015	0.870	0.005	0.830	0.011	0.900	0.000
UK (86)	-1	0.980	0.019	0.935	0.013	0.950	0.011	0.905	0.011	0.915	0.031	0.980	0.012
	1	0.970	0.022	0.915	0.019	0.940	0.011	0.880	0.014	0.895	0.045	0.970	0.018
Germany (113)	-1	0.930	0.023	0.940	0.014	0.945	0.024	0.940	0.012	0.930	0.016	0.940	0.012
	1	0.895	0.027	0.910	0.021	0.915	0.031	0.915	0.017	0.905	0.020	0.905	0.017
Spain (150)	-1	0.955	0.028	0.840	0.004	0.925	0.041	0.795	0.021	0.825	0.020	0.960	0.023
	1	0.925	0.037	0.735	0.024	0.890	0.054	0.665	0.025	0.715	0.050	0.935	0.040
India (36)	-1	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
	1	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
Italy (12,506)	-1	0.990	0.000	0.960	0.005	0.970	0.005	0.980	0.000	0.970	0.000	0.990	0.004
	1	0.960	0.007	0.830	0.018	0.850	0.013	0.890	0.004	0.850	0.005	0.930	0.007
US (3,200)	-1	0.950	0.005	0.940	0.007	0.940	0.005	0.940	0.004	0.940	0.005	0.950	0.007
	1	0.910	0.010	0.880	0.009	0.890	0.008	0.885	0.007	0.885	0.010	0.900	0.011

Table 1. The comparison between 6 classification algorithms for BuyBox prediction through 7 markets.

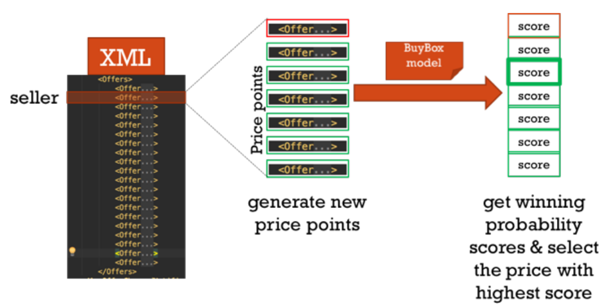


Fig. 9. The flowchart of repricing strategy for one specific seller.

5.3 Finding Recommendation Score

5.4 Proposed Algorithm for Repricer

We provide here the repricing strategy to generate the predictive move of repricing. Our concentration is on the probability of what point of price we can get into buy box with the highest chance we can do. The strategy is defined into three steps:

1) First step is the getting and splitting. We get the point of our customer, who want to make a repricing. After receive the customer's price, we generate many bins of price, which we would like to test the probability.

2) Second step is the applying model and generating prediction score. On this step, we apply the Random Forest model, which is learned in BuyBox Predictor. Then we calculate the final scores of all price's points.

3) Final step is selecting. The top 10 largest scores, which has the highest probability to occupy the buy box, is provided as recommended price points.

5.5 Experiment for Repricing

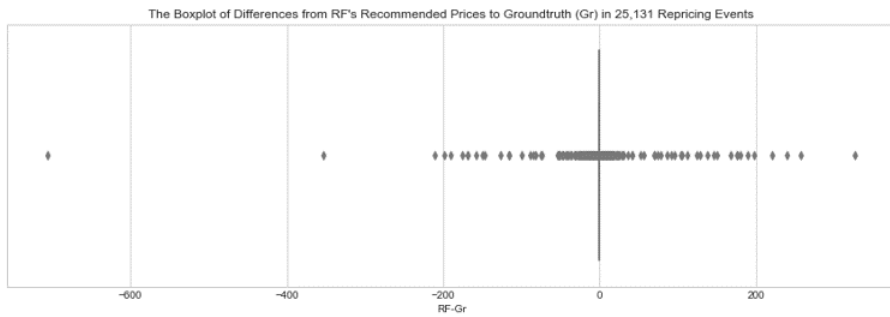


Fig. 10. The Box plot of Prediction for Winning Cases.

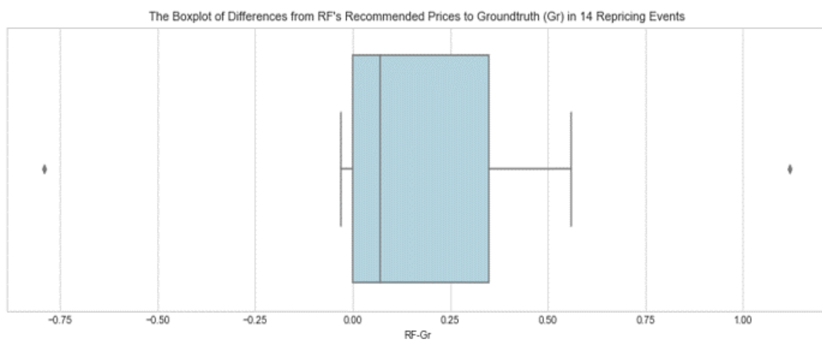


Fig. 11. The Box plot of Prediction for Losing Cases.

6 CONCLUSION