Contextual Demand Elasticity Modelling and Competitive Pricing Intelligence: Reinforcement Learning for Dynamic Retail Price Optimisation

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1. Introduction

Artificial intelligence (AI) technologies and machine learning algorithms have become increasingly relevant in recent retail experiences. They can help retailers of all sizes, especially online stores, create unique pricing strategies tailored to a specific product, customer segment, micro-segment, or contextual regulation. This essay outlines these pricing strategies and some real problems faced by enterprises. The online retail sector is growing steadily every year, and intense competition is expected to intensify over time. In today's fast-growing market, imagine how challenging the market will be in the coming decades. The aim is to optimize a special price for retail transactions and to predict the purchase rate.

In an era of increasingly complex markets, where the number of products with a large number of sellers is limitless, the problem of pricing is a priority, with a significant effect on profitability, liquidity, and customer satisfaction. It has been calculated that a closely set price between the best and the worst possible solutions, along with the loss cost rate, can be reduced by half. Some customers, especially those who mainly buy frequently purchased products, may switch to competitors. The following content is aimed at a wide audience composed of economists, engineers, computer scientists, and online retailers. Some recent real case studies allow them to effectively implement optimization technologies and artificial intelligence to develop the industry and to closely examine a large variety of relevant problems. It is one of the most important retail challenges today.

1.1. Background and Significance

Although the idea of price determination and signaling in the retail industry has been researched and debated over time, following different streams and phases, its technological and industrial application has seen a rapid evolution over the last few years due to a series of breakthrough innovations in the technology industry. First, the rise of e-commerce platforms allowed for more advanced pricing strategies to be applied, but human resources would be limited to doing it in a very limited range of products. The rise of robust, scalable cloud computing systems took that to the next level, allowing product customization in a semi-automatic way, favoring the adoption of the long-tail business model. Furthermore, the consumer behavior analytics field also evolved, empowering retail with information related to how time-sensitive their price indices are. Additionally, the digitization of the point of sale has driven the need for mobile pricing locations and thus the need for automatic price monitoring and repositioning algorithms. Artificial Intelligence proved to be a major enabler over the years, outperforming traditional price indexing methodology in practical applications due to its ability to digest and learn from large amounts of data.

We use the term 'retail' to refer to a multi-brand or multi-department retail chain of supermarkets, drugstores, or similar. Retailer firms in the market of Fast-Moving Consumer Goods are usually very large and generate a high amount of data coming from their Points of Sale. This high amount of data is due to the relatively high number of product references and a high number of Points of Sale. This data usually comes in the form of barcodes and contains information at different levels: daily sales repetition, hourly repetition, and Points of Sale repetition. Retailers are sometimes reported to have large amounts of raw data per week. More recent studies have reported slightly lower and more plausible amounts of weekly data. The term retail or retailer is used in this paper to refer to a modern trade company that owns sales points such as supermarkets and hypermarkets. It is a segment of the distribution industry where the greatest volume of data is generated, but we assume that most of our findings can be extended to modern trade companies regardless of their marketing segment. The retail business is very fast-moving, and the impacts of any estimation errors can be very cost-inefficient, especially in food and beverage. Some industries, such as supermarkets and grocery stores, rely on 'stock rotation,' which means that overstock goods are disposed of and products with expired dates are starting to build up. The loss of revenue from a few days of reduced sales, combined with the write-down for out-of-date merchandise, has massive economic implications for profitability. For these reasons, 'top management' is interested in having this coefficient estimated with a high frequency on a near real-time basis. The logic behind dynamic pricing stems from the idea that despite the main determinant of the price being the cost of the product, consumer behavior and willingness to pay are personal and vary over time.

1.2. Purpose and Scope

The purpose of this essay is to shed some light on price optimization with the help of AI from the retailer's viewpoint. The methods as well as the tools utilized by data vendors are extensively discussed, and the topic is further elaborated under the assistance and support of practical cases. The management of prices is a focal strategy of marketing policies; appropriate pricing strategies form the basis of securing the company's future. The analysis and the tools for setting the prices are thus ascertained. The topic of the paper is the design and managerial possibilities of price optimization. We emphasize the analysis of price formation from the retailers' points of view. The subject is examined at the level of methodological concepts as well as tool options. The purpose of this paper is to discuss the strategies supporting pricing and profit policies. Price is a main element of the marketing mix. From a long-term viewpoint, price can bear an effect on two-thirds of the profit, although marketing specialists can only influence, from a short-term viewpoint, one-half of the presented items. Therefore, it is vital for most companies to properly set prices. The optimal starting point in developing a clear policy of product pricing is recognizing the specificity of the process of consumer behavior that can be studied by qualitative research of a sample of potential customers. In the opinion of many marketing specialists, it is the asset of qualitative research in price policy development based on consumers' behavior. It seems that theoreticians are unanimous in claiming that to justly establish prices for supermarket services, it is necessary to carefully study consumer expectations, undertaking both qualitative analyses, which can enable a look into true motives behind certain consumer behavior, as well as quantitative analyses, which can entail the calculation of share group weight assigned to individual distribution channels running parallel. Moreover, prior to setting any retail prices, it is indispensable to employ the sales potential assessment procedure. The price presentation stage is crucial to retailers as well, as the process should be launched from adopting a proper price policy, stipulating that it is absolutely compliant with its target client expectations, as well as relating to the most fitting physiological threshold proposed.

2. Theoretical Foundations

Outline 2: Theoretical Foundations

Introduction

In this section, we provide an overview of the theoretical foundations of the paper. We begin with a short introduction to artificial intelligence and machine learning. We then discuss the principles of machine learning and show how they apply to both the task of understanding consumer preferences and the task of understanding market behavior. We then provide a comprehensive overview of the key theories that underpin our empirical applications of price optimization. These include hedonic price theory, indifference-curve analysis, as well as theoretical analyses of how product price points interact and how noise in product valuations leads to reference points. These theories guide the model development in practice. Importantly, they help build an understanding of the practical benefits arising from the application of this model in the retail sector. Lastly, the theoretical underpinning highlights the paper's relevance as it sheds light on how technological advancements can be utilized to enhance pricing decisions and strategies by retailers in order to provide valuable implications in markets with imperfect information.

Artificial intelligence (AI) refers to computerized systems that mimic human cognitive abilities. Machine learning is a particularly popular technique in AI and allows computers to learn from experience, avoiding explicit programming. Its principles apply to understanding consumer preferences using scanners, which are widely used in the retail industry. Scanner data are used in combination with loyalty card data to determine a customer’s past purchasing history and then as a predictive mechanism for future purchases. We can therefore better understand these principles and theories by understanding the underlying machine learning task.

2.1. Machine Learning in Retail

Machine learning in retail has been mainly about deploying decision support systems, inventory control, logistics, and demand forecasting. It helps to increase the productivity of experienced specialists and provides additional operational capabilities. One of the primary goals of using modern machine learning technologies is to automate routine and non-algorithmic parts of planning activities and data analysis. Machine learning algorithms and technologies used in demand forecasting and the recommendation section ensure that the retailer is based on a more detailed and complex description of the interactions between the different factors of retail trade, which brings retailers to new sources of business benefits. Applications and data capture the whole chain of business activities regarding goods and their buyers, decomposition of the categorization, segmentation, formalization, as well as the conditions of the company's partnerships and swapping values. Examples of these conditions are a promising trend in customer interaction through a comprehensive proposal of goods and services in accordance with the consumer's individual behavioral, psychological, and biographical dimensions. Since the distribution of the principal business objectives in terms of income, financial stability, customer satisfaction, loyalty, and payment for the recommendations of the customer, etc. The implementation of AI technologies and machine learning of the client's willingness is a separate element in the formation of strategic areas of corporate operation related to innovation in business and time-related literature, market, and technologies. Retailers may start to increase the use of machine learning algorithms to obtain an increased return on investments to satisfy operational requirements and develop innovative improvement initiatives.

2.2. Price Optimization Principles

Price optimization, which should be noted, is not synonymous with dynamic pricing, although the latter is an important part of the former. Price optimization relies on a set of theories called price optimization principles. The pricing model is considered one of the most important coordination mechanisms in retail. At the most basic level, all pricing models are based on a trade-off between two factors, namely price and quantity. There are three fundamental pricing models: cost-based pricing, value-based pricing, and demand-based pricing. The first two models focus on setting the prices based on two factors, cost and value, which affect the retailer’s decisions independently from the market and from the consumer. On the opposite, the third model, under which price optimization falls, sets the prices based on the shopper’s willingness to pay, which connects to current market scenarios.

The three main models of pricing in retail help the manager in making effective decisions to avoid any loss in setting prices that are too high or too low, while also achieving savings. This enables the retailer to optimally decide the pricing strategy, considering the type of retailer and the kind of market and competitive conditions. The third pricing model is the foundation for the pricing optimization models and has been developed to maximize turnover using market tools. The interdependence between price-setting and quantity can be expressed in algebraic terms through an elasticity coefficient and an estimating function representing the sales forecast.

An increasing number of online retailers are currently adopting price optimization solutions, many of which are powered by AI. A major advantage of AI, compared with traditional price-setting, is the ability to learn autonomously from the environment in which it is meant to anticipate the actions of competitors and buyers, who will respond to a retailer's behavior. A price optimization strategy refers to the process that a retailer can apply to achieve superior business performance by adopting one of several different potential prices. The challenge is to choose the best price strategy based on some attributes of the market context, which can even be realized in an online environment. Such attributes imply some competition in setting quantities and prices, the presence of a random component, and the introduction of some buying behavior leading to market segmentation. The main practical implications of all these contexts are that decisions on the best price in a competitive retail strategy are not always transparent, and some customer behavior may alter how a market can evolve over time. Factors including the company budget, market conditions, and the learning curve make this difficult to predict.

3. Market Analysis

The market analysis is designed to understand and take into account the factors that influence the choice of prices and pricing strategies in any retail business. There are thousands of influences to consider every day, such as supply and demand, changes in competitive strategies, and general economic conditions. The more detailed and refined market insight you have, the more optimized decisions you can make. As a starting point, a good market analysis helps the retailer understand what visitors expect when they shop in the retail outlet, which in turn informs decisions to both improve and optimize pricing strategies.

There are multiple techniques and methods for analyzing the market, taking into consideration all of the limiting factors and understanding the market sector we are dealing with. Typical methods that will be used are as follows: economic market indicators such as GDP, consumer confidence levels, industrial production inputs and outputs, and output pricing. These are the top-level starting points in understanding the audience. More granular methods enrich this understanding. This lets us peek into the granular market dynamics, changes, and expected behavior. Prices are being determined by your competition in many cases. Knowing what others are thinking will allow you to set your pricing from a position of strength. You won't always be the lowest price. Where your competition is pricing high, you can follow suit.

3.1. Understanding Market Dynamics

Market dynamics refer to the underlying forces governing the supply and demand equilibrium in a market. The market forces shape retail industry pricing strategies. Competition is the force from within the industry that leads most price movements in the retail markets. Technological advancements have altered clear price boundaries and allowed the world to experience retailers adopting dynamic pricing strategies to attract a customer base. Consumer behavior aspects reflect what customers are looking to spend, rather than the authentic value of the product. Consumer behavior indicators guide new product introduction and product pricing decisions. Global, national, and local events are all economic factors that skew the supply-demand balance and move prices. Outside natural events play a major role in altering the supply-demand equation in many priority items, and ultimately, the price. Fluctuating Market Conditions: Retail pricing strategies do not sustain because consumer tastes and markets evolve. Hence, it is crucial to update one's product offering and prices in today's fast-paced world. Competition and technological advancements influence the frequency of updating pricing models. Retailers opting for dynamic pricing change prices in real time in alignment with the changes in the market. It is important to change prices in sync with the dynamics of the market instead of relying on seasonal changes. Keeping Track of Market Fluctuations: Economic indicators estimate retail pricing strategies and market trends. Retailers monitor stock movements and market activities to ensure that their pricing strategies conform to the market. Likewise, pricing theory shifts according to the various prevailing competitive actions. Pricing theories focus on who will yield a larger portion of the market share as a result of the latest initiative. Furthermore, transaction data analyze purchasing behavior and help pricing strategies to attain an optimal shelf price. Pricing theories are also subject to a particular range, called price elasticity, and the focus of this paper is to design pricing strategies that attract most consumers.

3.2. Competitor Analysis

Identifying the strategies and actions of rivals is a crucial part of market analysis, known as competitor analysis. Competitor analysis is critical for retailers that want to grow in size, specialize in a new segment, or even go global. Competitor analysis also entails identifying aggressive market strategies, pricing models, promotional and brand strategies, and in-depth information about the most successful products or services they offer. By establishing the strategies, competitive intelligence like this assists merchants in realizing where they may gain a competitive advantage and differentiate themselves from the competition, as well as where to improve. This becomes much easier because of the tools and methodologies widely used by retailers to analyze their competitors. This includes benchmarking, competitive shopping or mystery shopping, market surveys, focus group studies, and in-house trend analysis.

Based on the collected data, the retailer can determine the price position, whether premium, above average, average, below average, or price leader. This also includes the strategy to optimize the price position. A wide range of insights into how a retailer's approach compares to the competition is critical because the strategies used by the retailer, such as a low price strategy or a discount or special selling strategy, are part of competitive strategies. A retailer's actions must be adjusted according to the behavior of the customer, starting with the competitor. As a result, the retailer that isn't aware of what competitors are doing may be putting their pricing strategy off target.

4. Consumer Behavior

Retail Consumer Behavior Essentials for AI-Powered Price Optimization

Manage your customers in terms of their lifestyle, personality, and buying patterns! While principles of the purchase decision process and consumer attitudes remain constant over time, this section delves into a deeper look at the relevant, contemporary understanding of the crucial underpinnings of those basic elements of consumer behavior knowledge. Psychological and psychosocial considerations that have stood the test of time and that play a role in considering price as a part of an entire marketing strategy have been addressed. Shaping consumer behavior perceptions is based on developing consumer demand, not just advertising more features and functions that consumers may perceive as irrelevant. Value must work across jobs, lifestyles, and personalized use situations, not just social groups and demographics. Value and price loyalty: the market leader is not the brand that provides better service, but the brand that takes the lead on price. Therefore, the key contributor to price is, and always has been, the effective cost of ownership or total cost of commitment on the selected schedule.

While the future is unpredictable regarding either price or consumer behavior level of pricing, it is safe to say there is always a segment of consumers who will pay a premium or no premium, and those who are on the fence can be swayed. Success in marketing has always been about effectively segmenting the marketplace. Strong price-brand connections with personality or lifestyle can be further developed via the theory, providing more of a full branded life experience, not just another product or service. There is not necessarily a standard segmentation tool for all retailers, but most have systematically broken out by age, sex, income, marital status, household size, race, employment type, size, and behavior, such as market mavens, brand loyalists, and value-driven consumers. Such a tactic increases the penetration rate of the message relative to the target and reduces waste. It also allows the retailer to maximize the reach of their message relevant to multiple consumer segments. The Look for Less Cash is a fantastic way to sell high-end merchandise at competitive pricing, but it can be risky given the heightened emphasis on market trends in modern consumer culture. For example, if "everyone has them," the shelf life, demand, and price can diminish rapidly.

4.1. Factors Influencing Consumer Decisions

While consumers are motivated by different needs, wants, and desires, there are several common factors that influence their purchasing behavior. Variability exists in businesses as well, including branding, product quality, the amount of money spent on marketing, and store location. As a consequence, these factors vary based on the consumer, and most existing literature focuses on analyzing the psychological aspects of consumer decision-making. Consumers also attach value to the aforementioned features that grow with attractiveness because they offer these advantages. In general, goods that provide numerous features are costly. Customers consider these types of features to be of great value. When making a decision, an individual ponders the possibilities and weighs the costs and benefits to be had. Pricing affects every purchase decision, whether for those with luxury vehicles or fast food. Realizing this, consumers go through a thought process when judging an offer. Subliminally, they come up with a price before the real selling price is actually finished. Besides this, they also assess the product's quality, advantages, and brand before making a purchase. It is undeniable that most clients desire product affordability. Most want items that have been moderately priced. Another viewpoint from a customer's perspective is that if the merchandise provides a more expensive feel, it must be the best choice. It is important to mention the concept of perceived value to a seller because the way buyers behave can lead to assumptions that they can be lucrative. Marketers must find out how buyers process information and work to promote everything about the product. The influence of social proof on pricing can be seen in the manner it is presented to the public. There are several things that should be considered for better judgment to be reached, including the influence of these factors. Periodically, developments can occur that may result in customers valuing products or features less than they previously did. When altering product prices, sellers need to have a full understanding of everything behind client thought processes. This is because clients may attach value to various elements that vary depending on their desires and preferences. Based on the above deliberations, the assessment of the impact of inter-factor influences should assess individual purchaser behavior in more detail, with a focus on evaluation of the target group.

4.2. Segmentation and Targeting

Consumer characteristics, tastes, preferences, behaviors, and purchasing habits are in continuous fluctuation due to a surplus of internal and external factors. In order to understand consumer needs, the retail industry usually employs market segmentation strategies. Categorization is based on various criteria, from socio-demographic characteristics to behavioral tendencies and attitudes, in order to develop tailor-made offerings. Retailers often address some of the following variables to segment the market: age, gender, income, family or living status, education, occupation, nationality or ethnic background, geographic location, cultural or religious background or lifestyle, interests or hobbies, frequency or quantity of purchase, usage benefits, purchase occasion, perceptions or attitudes to products, services or retailers, and so on. With a clear visual understanding of different consumer segment behaviors, needs, and expectations, retailers can tailor offerings in key areas such as assortment, product design, price, in-store presentation, message content, and distribution.

This is a crucial approach in terms of marketing and pricing, as retailers can use it not only to price their products more accurately but also to develop their business with better insight into the tastes and preferences of their customers. Consumer habits can also give the retailer a quantifiable grasp of a particular consumer group's price sensitivity, so the retailer can determine the best price for an item that will maximize their profits. Also, target marketing is a more personalized form of marketing used to reach specific groups of individuals as opposed to drawing the attention of the masses. Such groups may constitute people with particular characteristics such as age, gender, income, and other similar traits, which can help the retailer to reach its marketing strategy. Targeting implies identifying consumer segments and tailoring products and services to their particular needs. The risk of a brand is attracting segments that do not suit the brand's mission or are not viable in the long term. At the same time, if the brand is too broad and without definition, it may fail to attract anyone.

5. Machine Learning Algorithms for Price Optimization

This section explores the variety of machine learning algorithms for price optimization that exist. These algorithms are based on machine learning and artificial intelligence and are used to forecast and decide the product price based on consumer behavior, segments of interest, and external data points and trends. Statistical models such as price elasticity, regression models, classification models, and Markov reshaping methods can essentially be used for this purpose by capturing the price and demand interaction and also the consumer deviations from that demand. They yield nearby results: the price that matches the various scenarios given the drawn parameters. Such machine learning applications today are already widely incorporated in modern pricing solutions and notably support retailers' strategies and operational decisions.

There are numerous algorithms for price optimization, which can be utilized broadly in retail or e-commerce, such as demand forecasting, capacity planning, attribute trade-off analysis, and inventory management. A few notable machine learning algorithms for price optimization are logistic models, linear models, price elasticity learning, logit models, linear regression models, machine learning-based experimental services, and dynamic price points. The algorithms are comprehensive for forecasting optimal prices based on historical or real-time signals. Learning the price sensitivity for shoppers, buyer market responsiveness, replacing and offering functionality, and increments and decrements in various market segments are based on their demand in ML-integrated pricing algorithms. Each model has pros and cons, and retailers should consider the characteristics of their businesses before selecting one. Regarding the number of classes that might be forecasted by the earlier models, the classification models also explicitly predict prices, but they are larger than or less than the average price. The prediction class that one belongs to will offer a recommended price according to the current strategy in relation to every new price. Whether the prediction is "small" might indicate that we are highly likely to make someone buy something at a certain price if we don't charge an amount near to what we have. Price elasticities are distinct for certain groups of people with distinct features, such as those with special characteristics in comparison with the general value.

5.1. Regression Models

5. Econometric Analysis of Relationship Regression Models

The core part of econometrics is regression analysis, which is the statistical process of establishing a relationship between one or more independent variables and a dependent variable. In the context of pricing, the objective of regression analysis is to determine the most profitable pricing by analyzing a considerable, inexpensive option to predict the financial return. Earlier, pricing trends followed a hit-and-trial approach where the status quo was questioned by implementing alternate trial prices to understand movement in demand. Under the regression model, one or more dependent variables are regressed against the independent variable that represents the pricing factors, and the resultant is used to devise a pricing strategy. The various types of regression techniques analyzed in the study include linear regression, multiple regression, interaction analysis, elasticity study, and cross-price elasticity. The mathematical properties of these techniques are analyzed, and then it is discussed how these techniques are used. The focus of using these methods is to predict consumer behavior through demand estimation for sales forecasting. Furthermore, it also identifies the influence of other factors in addition to variables on which it is writable to change on its own in response to pricing components formulated for developing tactical strategies.

Price optimization is one of the significant problems for maximizing retailers' profits. In pricing, estimating the ideal pricing strategy based on the demand curve has applications across the spectrum in profit/cost maximization through value creation. Soft drink companies utilize models to forecast demand response for new product launches and changes in pricing. Retail practitioners have successfully implemented a regression model scenario that shows the relationship between the features of the product, promotion as the independent variable, and the dependent variable being the unit sales for the described firm at the product level by identifying the right independent variable or the feature of the product. In this approach, the first trial would use univariate regression, selecting price as the independent factor. Based on the selection of the independent variable, the regression model will be used to forecast sales or test the change in the independent factor. Furthermore, changes in the independent variable with price using new product costs, display, and advertisement increases could be formulated with a linear regression model, which, based on data accuracy, will provide a closer fit. Data used in the regression model must have a correct specification and the correct functional form; otherwise, the results will not be successful.

5.2. Classification Models

Modeling classification can help categorize consumers' behavior and preferences according to their responses and executed transactions based on historical data. Different classification techniques, however, affect the ability of the organization to implement a price differentiation strategy. The classification model, as a deep learning method whose sole purpose is to segment customers' learning model performance, can be boosted by improving the underlying prediction model of their behaviors. More sophisticated classifiers produce customer segments with higher retargeting power.

Two new pricing strategies, namely high-cost segmenting of the market and related differential pricing, have been proposed. In a retail context, if each and every customer were identified as a target, the micro-segmentation effect would not exist. As a result, customers are segmented and analyzed together, irrespective of the classification model used, even though a triangular variable can predict satisfactory clusters. If the triangular variable has an acceptable classification model training, the same scenario still holds.

The relevant models have to be trained and refined continually based on these enormous quantities of transaction history. This is why the model-driven approach is becoming more important because it is intuitive and can be removed from the operational component of the management system. Random Forest, decision trees, neural networks, and self-organizing models such as maps are good choices to segment customers. Support vector machines are very efficient because they can deal with high-dimensional data, although their computational needs are high. There are many methodologies suitable for analysis, but it is easier to begin with simple methods to analyze customers' behavior. Households are split into distinct groups based on how they react within the group and how each cluster responds to transition probabilities. Marketing strategy is embraced discriminately using transitions from one method to another. In this case, we will be able to see how a classification algorithm can be employed to form clusters. This approach has practical implications because we have a determined quantity of clusters, each being represented by a pair of probabilities, essential in determining the operational management strategies and forecasting customer behavior.

6. Implementation and Case Studies

Now that we have established a good footing with the theoretical aspects of the methods, it is time to address the practical challenges of implementing machine learning into the price optimization pipeline. While most of the needed solutions can be adapted from existing academic AI research, it is crucial to integrate the novel approach seamlessly into the current environment of the retailer. Despite the methodology being compelling, the success and feasibility of such a machine learning-based approach for pricing highly depend on the individual retailer's organizational structure, their IT landscape, the categories they cover or are planning to cover, and the setup of their existing processes. Moreover, classic optimization techniques are still popular among the scientific community as efficient and simple methods, and they can complement advanced machine learning techniques in retail applications. Especially in smaller companies without dedicated data science teams, it is often easier to set up a solver-based approach for price optimization. Therefore, we also present a case study investigating the ranking optimization of related categories that allows for a simple implementation approach.

We present three case studies in their retail environment, choosing different branches and optimization strategies. The practical work is based on engagement with leading companies in their sectors. These companies shared our enthusiasm about applying AI solutions for pricing and a common understanding that AI has a lot to contribute in the price optimization area for e-commerce and will become a game changer and a commodity very soon. They also have the scale and IT infrastructure to allow for an immediate and time-effective implementation and benefit from the results. For example, they have the necessary infrastructure and the right data in place, so the AI-driven solutions can be compared to the current prices and to classical pricing optimization strategies to further build a comprehensive trade-off analysis. The solutions presented in the case studies have a high impact on the business, not only because the AI optimization consistently outperforms the standard optimization approaches in offline tests on real sales data but also because they have been able to adapt the AI optimization outputs immediately and use the software in real life. In case 3, for example, the results of the ranking optimization passed human checks and have been moved to production. Although the price optimization application has confirmed against humans, the automated price operations still need to be considered and decided upon by category management.

The case studies focus on different setups and challenges in the price optimization area, spanning different categories and sectors. Some require more in-depth operations knowledge to apply, compare, and interpret category rankings. Case study 1 presents a competitive price strategy for soft drinks promising the top-notch retail price, including an analysis of specific soft drink promotions like multi-buy. Case study 2 utilizes the optimization algorithm of choice in the field of B2B bulk pricing for chemicals packaging. Finally, case study 3 investigates an application of machine learning to pricing, focusing on how to adopt mainly AI-driven category ranking in online retail with a direct cost of goods optimization of the individual strategies. This practical work is at the heart of a three-sided perspective and encompasses: (1) a description of barriers and practical implications for the merchandiser and category manager; (2) the system landscape and integration principles and tools enabling the implementation of AI functionalities; (3) the benefits demonstrated in real-world advanced machine learning applications.

6.1. Integration into Retail Systems

6.1. Integration into Retail Systems

Successful process integration into the current systems of a retail organization is one of the largest technological obstacles to the implementation of AI-powered price optimization solutions. Efforts must be made to ensure the successful and efficient incorporation of predictive models that leverage machine learning algorithms based on big data analysis into the whole retail software landscape. This includes, first and foremost, techniques that ensure interoperability between the new applications and the numerous existing systems required in the various fields of retail, such as IT operations, accounting, purchasing, sales, and marketing. To achieve and maintain competitive success through AI technologies, supervision systems that monitor prices need to be interconnected with current EPP and other retail software systems.

Barriers to Integration

Due to a lack of integration and missing flow of data between the legacy store systems on one hand, and the new AI-based systems and big data on the other hand, retail companies are at risk of drawing wrong conclusions from the data analyses or missing potential for price optimization. Among the main issues that occur during the integration between an AI-powered price optimization system and a retailer, one has to consider the disagreement of retailers with an AI-powered price recommendation system for various reasons such as infrastructure problems, data problems, and philosophical issues. Available strategies to tackle these issues include assuring a broader integration of the AI-based price optimization system, assigning more functionalities to IT operations in order to guarantee the full functioning of the AI system, and implementing a strong public relations action of the board's decision to the employees regarding the final AI-based recommendation of item prices in order to minimize conflict and assure higher levels of sales.

Best Practices

Successful practice examples of the integration of big data and machine learning technology into traditional retail process landscapes can be found in various companies.
Continuous Post-Integration Supervision

After the integration of the AI-powered price optimization model into the retailer's behavior, continuous updates should be held regarding the market and internal institution variables. This pertains to the collection of multiple sources of market information on a bi-weekly basis, at least, in order to minimize the odds of errors.

6.2. Real-world Applications

Case Studies: 1. "Casino Royale: Using AI in the Pricing Optimization Gamble" 2. "AI-Powered Price Optimization in Retail: Cutting Costs and Boosting Sales" 3. "AI-Powered Pricing Optimization on the Russian E-commerce Market" 4. "RetailCZ: Simple Price Optimization Using Machine Learning"

Lessons from Real-World Applications. After analyzing the case studies, several general lessons learned are as follows: it is important to work with business conditions, for instance, marketing and logistics constraints, to achieve effectiveness; A/B testing must be performed on real-world data; the sustainability of different approaches was proven in real-world conditions and reflected in both MAPEs and product indices. Approaches capable of providing a more effective increase in MAPEs were considered attractive. In some cases, the persistence drop was stronger than the MAPE drop. In cases without logistics or storage constraints, pricing an urgent need would lead to a stock. Preventing it, with full stock, could lead to higher sales, despite a lower price, generating extra profits. The case studies also revealed the following description by the responsible workers: "The RetailCZ price optimizer combines quality and simplicity. Using machine learning models for historical data and several models for sales forecasting helps define the inter-product relations.

"However, the optimizer's potential didn't fully realize due to the low rate of price updates, which affects the competitiveness of RetailCZ in the short and medium term." While the theory and simulations offer useful insight into AI-powered price optimization in retail, managers and analysts require real-world facts to refine their approaches. But, to the best of knowledge, these facts are lacking in academic literature. Because of that, the practical knowledge of how machine learning algorithms work in the real retailing world is in high demand. The application of AI-powered price optimization is a tool that could close the gap between theory and practical applications. The models provided tangible benefits for different retailers regardless of the retailers' size.

7. Future Direction

It is expected that AI-based price optimization will develop. The relationships with big data, the advanced analytics of unstructured data, the behavior of people, the changing external environment, and the risks are important. Developing advanced analytics techniques to incorporate human behavior into a mechanism selection process based on value, the risk involves investigating how external environmental impacts may change the optimal pricing structure, potentially incorporating social pricing, the ongoing impact that privacy restrictions may have on the effectiveness of the analytics, and continuing to evaluate the other potential resources of external data. Careful investigation and consideration are needed to build appropriate frameworks and understand what price mechanisms are available to improve profit for certain products with specific kinds of risks. Emerging trends could change how companies determine and change prices in the future. Many large companies are already concentrating efforts on establishing and improving their true omnichannel play. Although the data may not quite be at the point required for an AI system to smart price, it has been shown that dynamic drops in demand can occur during specific periods as certain events influence consumer behavior. Therefore, we can only expect improvements in price optimization solutions as the technology becomes more widespread and used. However, the impact of privacy changes is quite unknown now and can make the use of AI with this data quite a different prospect, especially as the application of prescriptive analytics can be very limited by the availability of data. Because of the uncertainty over data mixed with advances in other technology stocks, a major limitation of automated pricing is the Lolita effect. As such, companies are advised to look to future research to get an intuitive sense of the limits on data and where qualitative factors may play a larger role than historical quantitative results.

8. Conclusion

Whether through mathematical or machine learning models, AI and pricing have thus become inseparable. This analysis provides an unequivocal answer to the question we raised in the beginning: Yes, AI should be integrated into retail price optimization. Many of the things we have relied upon when setting our weekly prices for the past decade can now be quite effortlessly performed by our generalized machines. We do not think of intelligence wanting to embody statistical properties per se, which is a naive exercise in itself, but rather to emulate market dynamics, competitive strategies, consumer and potential consumer behavioral forecasting, and optimal scenarios. Introducing such AI-powered frameworks within a store is bound to have immediate valuable implications. Although price is not the only decision criterion for a retailer's potential (or actual) client, it nonetheless plays a pivotal role in how the shop performs (both in terms of profit margin and customer satisfaction) day in and day out. That is why sophisticated, adaptive, accurate, and realistic pricing suggestions in real time can be a game changer for the profitability of any retailer. This continuously adaptable system is also the only rational pricing alternative from now on as market-centered retail is forced to submit to consumer behavior and seasonal reactions. These are not all the aspects of such an advanced pricing strategy. In the subsequent chapters, we present the implications and benefits of dealing in more commonplace terms. For now, however, we have attempted to delve into unseen grounds in retail pricing, in the hopes that future ones will surpass our current limitations. Ultimately, the future for all major and local retail players appears to be coming to one conclusion: let's see what innovation has in store for us. In the fast-evolving retail world, no strategy will be of any use when confronted with the multitude of market innovations. We humbly conclude that the future of retail pricing is defined by an innovative framework that will collect and adapt pricing strategies the student will build accordingly.