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Machine Learning Applications in Retail Price Optimization: Balancing Profitability with Customer Engagement

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Abstract

There is a growing academic interest in the development of machine learning (ML) models applied to price optimization. Historically, retail prices were set with exogenous reference to competitors, a base price was selected for the promoted product, and a simple markup on cost was applied to all items in a product category. The emergence of e-commerce provided retailers with both opportunity and challenge, as they faced competitive pressures to adjust prices across thousands of products on an hourly basis. Price optimization is now being pursued using methods ranging from simple heuristics to sophisticated, machine-learned price models based on historical sales data. ML models can mine pricing-relevant relationships and patterns from transactional data generated by the ongoing management of price changes. Demand models can then simulate the impact of price adjustments on sales volume, revenue, and profit (or margin). Price models can recommend a price to be applied to the future and/or a scheduled price adjustment to capitalize on the forecasted demand change. Pre-emptive pricing models can be used to profitably pre-empt a new competitor or the next move from an existing competitor.

Demand is affected by many different variables across a variety of time scales. Regular marketing activities are widely adopted by retailers, including regular sales promotions on specific products and regular changes in price tags. In addition, various unexpected exogenous factors, such as extreme weather conditions, holidays, and sports events, may substantially affect demand. Price movements can also affect inventory changes in the subsequent time periods. Retailers could thus benefit from accurately forecasting the impact of these multiple factors/categories on sales demand. Data-driven analytical forecasting methods have gained popularity as they can automatically discover patterns from available data. More complex applications could improve forecasting accuracy by leveraging time-evolution sales data across different stores or product categories, although they remain complicated. Moreover, transparency is lacking in traditional complex ML models, which may lead to perceptions of a "black box" as regards sales forecasts, and hence retail supply-chain executors may lack comprehension of expected demand changes after implemented decisions.

Keywords: Retail; Pricing; Optimal Price; Pricing Strategy; Markdown Price; Machine Learning; Reinforcement Learning; Non-linear Optimization.

1. Introduction

Pricing is one of the most important factors in retail management since it directly affects revenue and profit. With the wide-ranging availability of price and transaction data, machine learning has been applied to the problem of pricing in retail industries. Price optimization refers to finding the optimal price (or prices) for a product that maximizes a firm's objective function, while all related pricing constraints must hold. The optimized result could be a single price or a price schedule. Problems characterized by single prices and multiple sales are called static pricing problems. On the other hand, problems characterized by multiple prices and a single sale are called dynamic pricing problems. Dynamic pricing problems are more complex than static pricing problems since pricing decisions have to be made repeatedly over time.

Pricing optimization problems are affected by three aspects: demand, cost, and pricing constraints. Pricing optimization cannot be separated from the price-demand and price-cost relationships. A firm should understand how demand changes when a price is changed and how costs are modified when the configuration of a product is changed. Both the price-demand and price-cost relationships are complex and can be modeled with machine learning technologies. The pricing constraints profile the pricing settings for a product. It is important to model the pricing constraints since any optimized price that violates the constraints is unacceptable. Pricing constraints take many forms as they vary, depending on the type and usage of a product. Pricing constraints can be fixed or flexible. Pricing constraints can be categorical or continuous. Pricing constraints can also be nonlinear and asymmetric if pricing constraints are not uniformly applied to two competing firms.

Most of the complex pricing problems should be modeled as a constrained optimization problem, and well-established solvers should be used to find the optimal price. One challenge of solvers is that it is difficult to guarantee the optimal price is always valid when the input is updated. Therefore, one important goal of price optimization is to guarantee the optimized price is always valid. One theoretical

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bounds on the range search results for any interior point solver with nonlinear constraints. Systematic investigation of how to improve the compatibility of price optimization is introduced, taking into account solving heuristics and training tags.

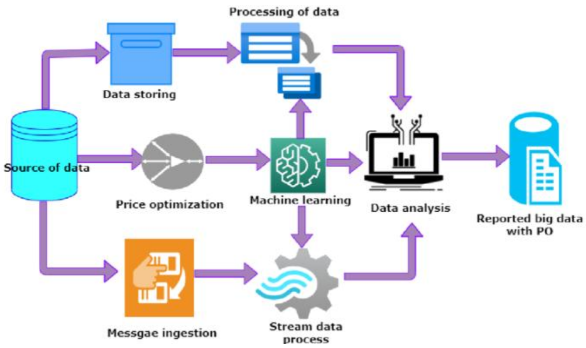

Fig 1: Architecture of machine learning with price optimizing

1.1. Background and Significance

It is a common practice among businesses to monitor their competitors' prices continuously and change their own prices accordingly. Some firms adopt automated computer programs to monitor hourly or daily sales prices and adjust them. These price-monitoring firms often enjoy great sales volume and revenue increase by a quick price adjustment. Likewise, firms offer customers similar or dissimilar products in different price ranges or amounts to dynamic pricing offers. Airlines and hotels frequently set customer-specific prices according to bookings and sleepovers. These are aptly termed ubiquitous dynamic pricing, which has become an indispensable component of revenue management in the modern service industry. The central technique of dynamic pricing is to customize item-specific prices based on observed purchases. The essential goal is to maximize total revenue based on binary purchase feedback.

Traditional dynamic pricing strategies hinge on certain decision processes and learning paradigms, which use behind-the-scenes customer purchasing models. Optimal pricing strategies cannot be formulated if the purchasing pattern is best-governed or private. In stringently competitive online marketplaces, customized pricing interplays with competition pricing. In these settings, there is considerable research interest in training pricing strategies based on observed historical competition pricing and sales in a data-driven manner. However, collected large-volume historical data is often lumped data that does not provide sufficient information with respect to new items of high-dimensional features. Online learning is a means to enhance pricing decisions by continuously fine-tuning pricing strategies based on observed purchase feedback.

Dynamic pricing should be understandable and explainable rather than a black box making predictions at specific prices. In this respect, it is desirable to learn a pricing model that attributes the pricing decision to a small number of decisive pricing factors to ease the online learned pricing decision interpretation. Automated learning via an algorithm is a well-known research focus in certain fields. A compelling endeavor is to shed light on and assist the understanding of the automated learning and decision making of price-monitoring firms and dynamic merchandise pricing scenarios. It is of great concern to explore how to learn the policy of price-monitoring firms from historical posted prices and sales quantity in converting real-time prices into pricing estimates and accordingly adjust the selling price. This can enhance the customer experience by holding reasonable prices for goods and allow businesses to independently mitigate unfair competition. Furthermore, the opportunity cost of learning pricing policy by historical price monitoring is generally tremendous because of possible unreasonable pricing in price monitoring.

Equ 1: Demand Prediction Model

$$\hat{D}_i = f(P_i, \mathbf{x}_i) + \epsilon_i$$

- $\hat{D}_i$: Predicted demand for product i
- f: ML model (e.g., regression, tree-based, neural net)
- $\mathbf{x}_i$: Features like seasonality, location, customer segment
- ϵ_i: Random error term

2. Understanding Price Optimization

Recently, there has been a growing interest in developing marketing strategies that exploit the uncertainty in the demand model and consumer behavior to maximize expected revenue. Retailers face two main challenges in this regard. The first is a large state space defining the different price schedules allowed for different market segments; the second is the complex structure of demand. Conducting a search over the entire price space is often considered impractical for a time-critical application. A potential alternative is a method that generates random prices to be queried in the price history. However, the underlying assumptions and suitability of price settings for dynamic pricing and demand learning remain largely unexplored. In a retail pricing context, we study the tackle finding near-optimal policy under prices and demand uncertainty.

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Over the years, many myopic and heuristic price-matching or price-testing policies have been proposed to choose the initial price and explore the demand pool history. There has also been research on providing theoretical insights into these models. However, most policies are designed with a fixed horizon in mind, and their performance remains unexplored for a longer time frame. This leads to a heuristic question whether one can learn while doing, i.e., pursuing long-term revenue maximization while still being able to conduct a disciplined/rigorous search for the demand model.

Fig 2: Machine Learning Based Price Optimization

2.1. Definition and Importance Retail pricing optimization is about determining the best ticket or shelf prices for products to maximize returns. Ultimately, retailers want to maximally profit from their customers and price optimization techniques provide a structured way to achieve that goal. However, setting effective prices is not just whale price tags on a selection of products and waiting for customers to buy. Pricing is an ongoing process where prices need to be analyzed, assessed, and amended in a structured way so that effective prices can be set for every product. A good pricing optimization can involve various techniques such as price families, discount process, target customer segments, and price limits. Price families divide products in the portfolio into different segments and the prices for products in the same price family share absolute price differences. Price limits enable an overall price range for products in the same family and risks that some products are priced too low or too high.

Retail pricing optimization is not just a one-off exercise but rather an ongoing process that is constantly assessed off much price deviation there is for a specific product. Manual assessment of that process is time-consuming and requires a lot of insights and analytics into what is effective pricing and when products should change their prices. Some questions include What products need to be re-priced? When do they need to be done? And what should their new price be? The price type selected for a product can also complicate the pricing optimization and the banana example also demonstrates that every price type needs its own set of rules and considerations on how to set effective prices on products. To analyse that inbound product pricing there needs to be products and their price interactions. Pricing models should take into account ongoing scenarios such as historical pricing and changes to be modelled and forecasted in addition to factors affecting price interactions.

Developing pricing models is one of the most data-, time-, and resource-intensive developments to set up and maintain. Pricing is continuously changing in the pricing systems to adapt to input scenarios thus requiring rules to affect it as accurately and effectively as possible. Pricing optimization delivers structured techniques towards pricing and has mechanisms to evaluate and measure previously set pricing. Traditional methods for pricing optimization only allow for a small set of continuous conditions on the price for each product thus making it impossible to apply those traditionally sound techniques for real-time pricing on large lists of products. Although sampling-based techniques are able to deal with a continuous pricing space they cannot ensure efficient and sufficient use of learnings across pricing changes of product families in rapidly changing listings such as utilizing existing pricing models and insights of recently re-priced products.

2.2. Historical Approaches to Pricing Historically, pricing strategies have been implemented through either fixed or heuristic methods. Price ranges can vary over time due to manual calculations, while the high frequency of sales at fixed prices is driven by revenue needs. Due to the demands of dynamic marketing, the cost of changing the price has also increased, necessitating a new perspective on fixed pricing. Manual fixed prices of article streams have been too inflexible in the face of shock demand changes, resulting in stock and revenue loss. Manual seasonal price modification methods cannot respond quickly enough to abrupt demand changes in day-to-day contracts. Thus, new fixed price strategies are needed. They should leverage existing inventory sales and stock information, in combination with future demand forecasts, while taking dynamics into account through time-consistent strategies.

First, as suggested in optimal selling price strategies in basic revenue management, time-discounted Markov decision processes can be used to dynamically determine price paths. Approaches based only on sales history and price records will face the curse of dimensionality produced by price-resource meshes. Manually, the RMS/SSM method significantly reduces the size of search space by allowing price modification instead of price level determination. Specifically, a multi-period rolling horizon price adjustment problem can be solved by a model predictive control approach. However, when re-controlling the queue, it only focuses on the current observation and ignores its price change history.

A modified version of primal-dual bounds is provided for the basic forecast prices of parameterized demand, which efficiently leads to a realization of the parametric-and-curve generation approach for practical-scale stock pricing. Current heuristic methods do not consider greater storage dispersion, high discount rates, and long-range forecasts. Existing price-path optimization approaches widening the problem size of optimal selling price strategies through either price copying or prediction in a model-free manner can be developed efficiently on convex demand f ended over integer prices.

3. Role of Machine Learning in Retail

As retail has predictable repetitive patterns, demand forecasting plays an important role in the supply chain. Accurate forecasting ensures correct stock levels, allowing to maintain customer satisfaction while minimizing costs. Despite its importance, it has been a long standing difficult task, especially in the fast moving consumer goods (FMCG) domain where there is a huge number of products. These products are characterized by low demand volume, being sold at low margins. Consequently, any error has an important impact on stock outs or excess inventory with consequent missed sales or waste. In this context, forecasting is particularly difficult, as the best performing models are the more complex and time consuming ones. Making forecasting complex only where the benefit justifies the cost, is the right approach to increase accuracy and speed, and it is therefore the objective of this work.

Different years have different prices, and the banking crisis can reduce sales greatly. In promotions, the forecasting methods greatly differ among the retailers. One approach can be multi-item forecasting with promotion features using sophisticated Machine Learning Algorithms. New product forecasting is a tough but interesting problem. This approach can integrate various kinds of information, including promotion, competition, environment, product information and so on, and meets success in different business cases. These problems are non-iid and multi-scale, posing huge challenges for adoption of standard methods. Demand forecasting is a crucial task for retailers, which has far-reaching consequences on management of the supply chain. Good forecasts promote optimal ordering, efficient storage and utilization of transportation channels, competitive market pricing, and an ability to leverage revenue management techniques like markdowns and promotions. An accurate estimate of the incoming demands allows the retailer to ensure the satisfaction of demand while minimizing storage costs and transportation costs. The decision of ordering usually depends on the forecast of demand, stock available and cost of storage per item.

Fig 3: Machine learning in retail

3.1. Overview of Machine Learning Techniques

This section provides an overview of the supervised machine learning techniques applied to pricing decision-making requests. Topics include an introduction to supervised machine learning tasks and techniques, detailed descriptions of supervised ML methods including tree-based ensemble methods and neural networks, hyper-parameter optimization techniques, and a brief discussion of machine learning interpretability. Supervised machine learning (ML) techniques can create predictive models using rich information on customers and products for pricing analytics. Pricing analytics tasks include estimating demand models for customer sensitivity to prices, item pricing models to determine either optimal price points or price ranges, and predicting returns on pricing events. Given a dataset with rich data for the historical variables and pricing decisions, a central task is to use supervised ML to build models for long-term, effective pricing.

Supervised ML is a statistical learning paradigm used to develop models to predict an outcome variable Y with one or more covariates X. There are two main classes of supervised learning methods. In parametric models, the functional relationship between Y and X is completely captured by a relatively small number of parameters. Linear regression is a classic example. Flexibility of the model is limited by the number of the parameters. Given Y in the response space, nonparametric models fit the observed data as closely as possible without prespecified restrictions on the functional form of Y and X. Given Y in the response space, the complexity of the fit increases as more data are revealed. Hence, strong extrapolation or smoothness assumptions must be made (i.e. there are typically few covariates).

3.2. Data Sources and Their Relevance

The focus of the investigation is on price optimization as one of the competitive priorities in retail, as it is believed that an organization's pricing strategy should be aligned with its

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target market for achieving superior business performance. A comprehensive review of the literature reveals an emergent, growing, but nascent body of knowledge related to retail pricing strategies. Substantial knowledge gaps exist regarding the use of big data analytics, particularly data sources and analytic techniques, in retail price optimization. Against this backdrop, a qualitative study was undertaken with pricing executives in large retailers to shed light on the research topic. It was found that retailers are placing increasing focus on retail price optimization lately due to the advent of big data, but they are disequilibrated in their pursuit of it. Furthermore, it was revealed that external market data and customer data constitute key data sources for retail price optimization.

Substantial academic literature related to pricing strategy has received attention from marketing scholars. Pricing strategy consists of price alignment and price optimization. Pricing alignment refers to the alignment of a retailer's pricing strategy with its positioning in a target market. Price optimization entails the use of analytic methods to optimize retail price for maximizing trade margin and market share. Price optimization can be regarded as one tumbling stone in the dynamic pursuit of retail competitive advantage because it is able to optimize pricing for maximizing trade margin, thereby sustainably achieving a superior business performance. Pricing optimization is an analytical process that calculates the optimum prices for products or services considering numerous variables. It involves raising money through the right combinations of prices and sales strategies while taking into account consumer purchasing behaviour and other internal and external factors. It is important for business administration because a poor pricing strategy can cost a company more than it earns.

Equ 2: Customer Engagement Score (CES)

$$CES_i = g(P_i, \mathrm{CX}_i, \mathrm{Promo}_i, \ldots)$$

- g: Engagement model (could be classification or regression)
- CX_i: Customer experience data
- Promo_i: Promotion variables

4. Customer Behavior Analysis

Pricing plays a significant role in any business operation and it can directly affect firm revenues and profitability. Retail price optimization is a key activity that firms need to perform regularly. Several firms have simple and traditional processes for calculating optimal prices using a combination of cost and competitors prices. As the product categories become large and complex, retailers need automated price optimization systems. Such a system takes historical transactional data and determines the effect of price on the sales and profit margin performance of each product. By predicting sales and profitability under alternative price scenarios, the optimizer recommends the price that achieves the projection of a predefined objective. Data, applicable algorithms, and model features are important aspects of the price optimizer design.

Pricing analysis is a primary area of research in marketing. Early work typically specified a price-performance relationship either as a main effect or as a moderator. Later research extended this effort toward understanding the effects of prices on spillover and cross-category sales. Pricing decisions oftentimes involve situations that cannot be treated independently. Consequently, optimizing across multiple interdependent pricing decisions is the need of the hour. Such a need has given rise to a family of research on dynamic pricing. Many of these models are formulated using Markov processes. However, analytic solution techniques are generally only available for relatively small-state space problems, whereas simulation methods are required for larger problems.

Fig 4: Customer Behavior Prediction

4.1. Understanding Customer Preferences

Understanding consumer behavior over longer time periods is typically accomplished with Customer Lifetime Value (CLV) models. In particular, because estimating CLV requires predicting future purchases based on limited purchase history, and because consumer preferences vary with time and change dynamically, this task is often considered challenging. Furthermore, the vast majority of past CLV models in academic literature are pre-big-data-era capabilities that predict loyalty purchasing behavior for a retailer's entire product categories, based on purchase behavior of limited time periods. Most CLV models utilized in academia focus on the prediction of future purchases, customer purchase frequency, or average transaction value, with little to no focus on estimation across other dimensions, such as behavior across product categories. Inherent in the modeling of customer purchase behavior, there are many assumptions competitors specifically, all CLV models in the literature assume—perhaps in different forms—that customer purchase behavior, i.e., how much a customer purchases and how frequently she purchases, is defined by only two dimensions: frequency and average transaction value, which neglects rich details contained in purchase history and states. Traditionally, most CLV models assume that, once a customer becomes inactive, no further purchases will be made from that customer; therefore, customer loyalty is determined over a time horizon and this time horizon is typically chosen arbitrarily with solely consideration on data availability. In the big data era, as the impact of a customer's earlier behavioral data may far go beyond the design of most fixed time window features, it also makes sense to utilize the entire "past" history of customer purchase behavior, the potentially huge number of CLV estimation. To understand CLV and its dimensions more deeply and accurately, and to model the customer purchase behavior in a more sophisticated manner, sophisticated approaches are needed, such as Current State + Future State approaches, Hidden Markov Models (HMMs), or deep-learning based sequence models. These models leverage customer features, product features, potential state variables, etc. and consider the effect of marketing activities on the customer behavioral state and subsequent purchase behavior.

4.2. Impact of Pricing on Customer Engagement

Pricing is one of the important marketing mix components from which retailers can build a competitive advantage. Retail price planning determines a price level at which each selling item is offered in a store, store layout and shelf-space-allocation decisions of selling items to be showcased. Retail price planning directly affects many decisions that eventually determine a retailer's profit and customer engagement. Hence, pricing is a crucial decision area in retailing, and effective price planning can help a retailer win over competitors and sustain business. Pricing decisions encompass a multitude of elements and can be made at different hierarchical levels. Retail price optimization can be done at the store-level, chain-level, and SKU-level, which represents the hierarchy of decision variable sizes. Price change-promotion (temporary price reductions) and roll back-are two common events that directly change retail prices. Retail price optimization also includes strategies on mix promotions, the number of promotion items, and the largest discount level for the promotional items to be featured. Pricing optimization can be done in a long-term planning horizon that spans weeks to months, in the short run from days to weeks, or in a very short term from hours to days.

Every new price for each SKU can be a price change candidate based on historical data. Price roll-back events could also adjust the prices of a larger number of SKUs when new prices are introduced after, sometimes, a short marketing test. For retailers that can update prices within the same day, a rich set of pricing candidates can become extremely large, calling for effective approximation methods. Finding a 'Good-Enough' set of price paths on each candidate that has no price in the short-run or affects its own sales is one strand of research. Once this candidate list is generated, most of the existing optimization frameworks take it as given and design some heuristics to pick a number of candidates to be priced. This reduction step can be very critical because computational effort will be entirely wasted if the wrong options are chosen. A specific case of concurrent pricing learning is designed by which the retailer, who prices a single product, carefully selects prices at which the demand may be queried. The proposed algorithm will eventually learn the right price while making little revenue loss during the learning process.

5. Machine Learning Models for Price Optimization

A multitude of approaches have been proposed to improve pricing systems, making them more automated and effective. Some solutions are based purely on heuristics, explicitly considering the problem's nature. Two main types of heuristics were noted: a breadth-first search procedure, which accepts all but the highest histogram bin, and a depth-first search procedure, which, following the rejected bin, accepts a certain number of the lower bins before rejection. Several constraints further reduce the range of possible investment segments, focusing instead on the key pricing policy. Both approaches were able to develop pricing strategies on par with those currently adopted by systems managers. However, these strategies might often be of a heuristic nature. Automatic pricing can also be based on machine learning techniques. A pricing model can be built using an ML model on historical data for the forecast horizon. With access to predicted item sales, the correct price can be decided using any algorithm that solves the optimization between revenues, competition, or stock levels. Some of the models explored include regression models estimating the relationship between pricing and sales, process-based models that simulate the behavior of different agents in decisions, and Bayesian inference models focusing on integrating historical decisions with sales. The focus was then placed on one model among these machine learning systems: the quantile regression forest. This algorithm estimates to a greater or lesser extent the uncertainty range of sales depending on the customer's reservation price. The combination of revenue optimization and forecasting is studied, proposing a closure by means of a procedure to approximate probability distributions.

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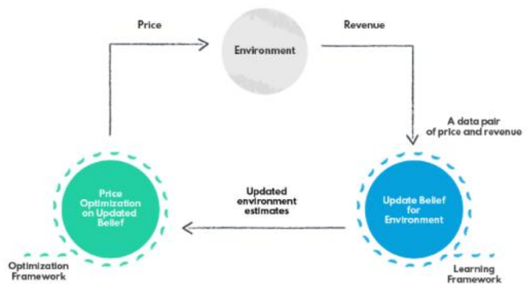

Fig 5: Pricing Optimization? Machine Learning

5.1. Regression Analysis As the first and the most widely applied machine learning algorithms in retail price optimization, regression analysis encapsulates a broad family of methods, with multivariate regression and time-series modeling among the most remarkable. Regression analysis rests upon the choice of a dependent variable (or target) and a single estimate variable (feature). The former captures price optimization objectives, while the latter summarizes price data in a flexible way, including price level, price promotion, price shape, and price cut. Regression analysis characterizes functional relationships between target and feature variables, usually in the form of polynomial basis functions, indicator variables, and log transformations. It can be used both in static dimension and dynamic extent. Static multivariate regression is often used in the context of weekly observations, with multivariate price features, e.g., price history. The fitted function provides price estimation with prior demand volume and demand model parameters. Static functional regression provides price estimation with prior price-data distribution, which is modeled in its non-parametric form. Dynamic time-series modeling fits the relationship between a dependent variable and current/past realized target values, implementing various lagged target variables.

With regard to retail price optimization, regression analysis has long been applied in demand modeling, elasticity estimation, and control price approximation. It aims to uncover the function of capturing price-demand interactions. Among the regression analysis works, a great body of research tackles demand modeling. Three empirical studies either rigorously scrutinize dense functional approximation of the relationship between price and demand or plausibly explains how unmissed variables or structure is treated. A reduced attention has been paid on price-explaining price change, while such modeling using price- and event-based features helps identify key promotional variables, providing foundational conditions for budget allocation on particular events. Flat price and promotion are used as exogenous variables with dense functional approximations in determining price strategies.

5.2. Classification Techniques
Classification techniques play a major role in machine learning applications, so they are selected as the main domain of machine learning technique. The simplest form of supervised ML is classification, consisting of an input (attribute) and a binary target (class label). For classification tasks, ML analyzes learned functions, which output the probability of an instance belonging to a class. The classification of retail products is essential for business decision making. One common approach is to classify the products based on their quantitative and qualitative characteristics. However, that practice is often outsourced to external companies or done by in-house experts, resulting in high costs. It is possible to automate this process using various methods, but this is not pleasant, as these methods focus solely on product characteristics and neglect the fact that product classification is a subjective process. To address that problem, one purely data-driven approach for clustering the retail products is proposed. The approach is based solely on customer behavior and has the potential to be generalized across industries. It uses market basket data, clusters products into sets where the similar behavior appeared from the customers, and avoids an essential multi-class classification task in the form of an optimization problem involving binary variables. The problem is formulated as a payoff matrix where pairs of products are assigned weights. The weights are then found using genetic algorithms while optimizing the fitness function involving similarity measurement. Using real datasets from a drugstore in the Czech Republic context, the proposed method is illustrated through case studies. These case studies demonstrate the behavior and scaling of the model as well as its generalizability across different industries or types of shops. The output of the algorithm is pairs of products that are more or less alike based on customer behavior, naturally leading to conclusions similar to other product clustering methods. In terms of retail companies decision making, the product-set approach is more broadly applicable as it does not require product characteristics.

5.3. Clustering Methods The categorization of retail products is essential for the business decision-making process. It is a common practice to classify products based on their quantitative and qualitative characteristics. However, the most valuable product categorization for a retailer is based on customer behaviour. These categories can reveal commonly purchased items which show how products compete in the market in comparison to their characteristics. The joint and separate marketing of competing products can effectively depend on the categorization of products into behaviourally similar groups. Our clustering of products is based exclusively on customer behaviour.

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In an extensive product portfolio, products are often categorized into several subcategories. This categorization is not easy, computationally extensive, and time-consuming. Given that product categorizations can affect business decisions including pricing, promotions, shelf placement, etc., it is worth considering the automatic clustering of products. We propose a method for clustering retail products using market basket data. We assume basket purchases of related products as the proxy for their similarity. Our model is formulated as an optimization problem. The objective is to partition existing products into clusters which maximize the similarity of products within each cluster and minimize the similarity of products from different clusters. To solve this NP-hard optimization problem, a Genetic Algorithm is employed.

The application using real data from a Czech drugstore company shows that our method leads to similar results in comparison with the classification by experts. On the contrary, the existing clustering methods based on the product characteristics yield quasi-identical clusters for varying products. The number of clusters is a parameter of our algorithm. If the number of desired clusters is known, the proposed method returns that number of clusters. If not, the algorithm supplies the ordered list of clusters together with the detailed inter-cluster comparison. Finding the right categories is crucial for sales promotions planning.

Equ 3: Price Elasticity of Demand (PED)

$$\mathrm{PED}_i = \frac{\partial D_i}{\partial P_i} \cdot \frac{P_i}{D_i}$$

- If PED < -1: demand is elastic (lower prices → more sales)
- If PED > -1: demand is inelastic (sales less sensitive to price)

6. Conclusion

This study described a method for predicting the effects of price changes in a store. The method follows the steps of cleaning data, transforming data, fitting a model, simulating a price change under uncertainty, and calculating economic values. Thanks to the possible price changes historically available from the database, this simulator is able to suggest the price changes for many items in a store. Due to the advent of dynamic pricing, a more advanced planning system combining the suggested prices with an inventory management model should be developed. This modeling approach may be extended to include price-sensitive products, where price changes affect consumption as well as purchase patterns. In addition, it may be possible to derive name-brand equivalent prices based on the retailers' own sales data, in assisted price comparison scenarios or in flavors approximation problems. More tailored predictions could also be sought, based on the ability to infer which predictive metrics account for the differences in purchase patterns between two distinct periods.

While the case studies have demonstrated that the proposed method can give meaningful economic values and sound predictions in practice, there are few untested assumptions and limitations that have yet to be addressed. First, further work should be conducted to evaluate how well this QMDP method performs in predicting effects of complicated products. Second, this study has assumed that prices of other items remain constant when gauging the effects of a change. In reality, retailers usually want to adjust prices of several products simultaneously. In addition, simple forms of pricing trajectory have been assumed at the simulation stage. However, prices may rise or fall until a price point is reached in practice, and such a changing path could be better modeled using local search techniques. Lastly, this approach cannot account for cross-selling effects given the assumption of independence in prediction. These cross-selling effects could be addressed by adding heuristic estimates or by deriving joint probabilities from available data.

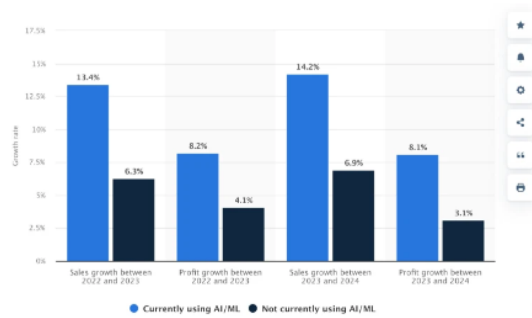

Fig : Machine Learning in Retail

6.1. Emerging Trends

Due to the unparalleled availability of information and advanced technology, users are increasingly being overwhelmed by the vastness and diversity of digital knowledge. They frequently find it difficult to locate the finest fit for their unique qualities or requirements. As a result, online firms are striving to compete through creating tailored assistance, such as recommendation systems that help reduce the search costs of ultraVariety. However, how to express suitability in a suitable manner for conveying interpreted and personalized content is a major challenge.

The non-valuation segment of the recommendation process remains largely unexplored. The current study looks at a customizable photo recommendation encounter and presents a novel structure that combines pattern and style recommendations. This system aims at retrieval methods in social tagging research and stylistic modeling with explicit model weight tuning so that tagging is placed on a separate layer that helps to group photos and tune their consumability and attribute parameters to refine their appeal atmosphere. The system was experimentally tested in two distinct settings. Clearer recommendation targets and more efficient computations were achieved via an evaluation function modeling.

Pricing and promotion decisions are critical to inventory and revenue management in hospitality and retailing industries. In online service industries for digital products, a pricing decision must respond to customer requests in real-time. Cloud technology has made it possible to develop high-frequency web servers with a large service capacity and wide range of digital products. However, competition is often fierce and price wars are common. Bayesian price promotion approaches implement multi-armed bandit concepts to deal with revenue estimation and pricing promotion in real-time with machine learning. Practical implementations have been established by understanding the market logic, including selling rules, resort possibilities, and on-line price selection. The Bayesian price promotion approach thus serves as an effective pricing tool for digital products with parametric modeling.

7. References

[1] Polineni, T. N. S., Ganti, V. K. A. T., Maguluri, K. K., & Rani, P. S. (2024). AI-Driven Analysis of Lifestyle Patterns for Early Detection of Metabolic Disorders. Journal of Computational Analysis and Applications, 33(8).

[2] Sondinti, K., & Reddy, L. (2024). Financial Optimization in the Automotive Industry: Leveraging Cloud-Driven Big Data and AI for Cost Reduction and Revenue Growth. Financial Optimization in the Automotive Industry: Leveraging Cloud-Driven Big Data and AI for Cost Reduction and Revenue Growth (December 17, 2024)

[3] Sambasiva Rao Suura. (2024). Integrating Generative AI into Non-Invasive Genetic Testing: Enhancing Early Detection and Risk Assessment. Utilitas Mathematica, 121, 510–522. Retrieved from https://utilitasmathematica.com/index.php/Index/article/view/2046

[4] Venkata Narasareddy Annapareddy. (2024). Harnessing AI Neural Networks and Generative AI for Optimized Solar Energy Production and Residential Battery Storage Management. Utilitas Mathematica, 121, 501–509.Retrievedhttps://utilitasmathematica.com/index.php/Index/article/view/2045

[5] Harish Kumar Sriram. (2024). Leveraging AI and Machine Learning for Enhancing Secure Payment Processing: A Study on Generative AI Applications in Real-Time Fraud Detection and Prevention. Utilitas Mathematica, 121, 535–546. Retrieved from https://utilitasmathematica.com/index.php/Index/article/view/2048

[6] Karthik Chava. (2024). Harnessing Generative AI for Transformative Innovations in Healthcare Logistics: A Neural Network Framework for Intelligent Sample Management. Utilitas Mathematica, 121, 547–558. Retrieved from https://utilitasmathematica.com/index.php/Index/article/view/2049

[7] Komaragiri, V. B. Harnessing AI Neural Networks and Generative AI for the Evolution of Digital Inclusion: Transformative Approaches to Bridging the Global Connectivity Divide

[8] Chaitran Chakilam. (2024). Revolutionizing Genetic Therapy Delivery: A Comprehensive Study on AI Neural Networks for Predictive Patient Support Systems in Rare Disease Management. Utilitas Mathematica, 121, 569–579. Retrieved from https://utilitasmathematica.com/index.php/Index/article/view/2051

[9] Murali Malempati. (2024). Generative AI-Driven Innovation in Digital Identity Verification: Leveraging Neural Networks for Next-Generation Financial Security. Utilitas Mathematica, 121, 580–592. Retrieved from https://utilitasmathematica.com/index.php/Index/article/view/2052

[20] Challa, K. (2024). Artificial Intelligence and Generative Neural Systems: Creating Smarter Customer Support Models for Digital Financial Services. Journal of Computational Analysis & Applications, 33(8).

[21] Nuka, S. T. (2024). Exploring AI and Generative AI in Healthcare Reimbursement Policies: Challenges, Ethical Considerations, and Future Innovations. International Journal of Medical Toxicology and Legal Medicine, 27(5), 574-584.

[22] Burugulla, J. K. R. (2024). The Future of Digital Financial Security: Integrating AI, Cloud, and Big Data for Fraud Prevention and Real Time Transaction Monitoring in Payment Systems. MSW Management Journal, 34(2), 711-730.

[23] Intelligent Supply Chain Optimization: AI Driven Data Synchronization and Decision Making for Modern Logistics. (2024). MSW Management Journal, 34(2), 804-817.

[24] Pamisetty, V. (2024). AI Powered Decision Support Systems in Government Financial Management: Transforming Policy Implementation and Fiscal Responsibility. Journal of Computational Analysis & Applications, 33(8).

[21] Revolutionizing Automotive Manufacturing with AI-Driven Data Engineering: Enhancing Production Efficiency through Advanced Data Analytics and Cloud Integration . (2024). MSW Management Journal, 34(2), 900-923.

[22] Leveraging Deep Learning, Neural Networks, and Data Engineering for Intelligent Mortgage Loan Validation: A Data-Driven Approach to Automating Borrower Income, Employment, and Asset Verification. (2024). MSW Management Journal, 34(2), 924-945.

[23] Lahari Pandiri, Subrahmanyasarma Chitta. (2024). Machine Learning-Powered Actuarial Science: Revolutionizing Underwriting and Policy Pricing for Enhanced Predictive Analytics in Life and Health Insurance . South Eastern European Journal of Public Health, 3396–3417. https://doi.org/10.70135/seejph.vi.5903

[24] Mahesh Recharla, (2024). The Role of Agentic AI in Next-Generation Drug Discovery and Automated Pharmacovigilance for Rare and Neurological Diseases. Frontiers in Health Informatics, Vol. 13(8), 4999-5014

[25] Botlagunta Preethish Nandan. (2024). Revolutionizing Semiconductor Chip Design through Generative AI and Reinforcement Learning: A Novel Approach to Mask Patterning and Resolution Enhancement. International Journal of Medical Toxicology and Legal Medicine, 27(5), 759–772. https://doi.org/10.47059/ijmtlm/V27I5/096

[26] Challa, S. R., Challa, K., Lakkarasu, P., Sriram, H. K., & Adusupalli, B. (2024). Strategic Financial Growth: Strengthening Investment Management, Secure Transactions, and Risk Protection in the Digital Era. Journal of Artificial Intelligence and Big Data Disciplines, 1(1), 97-108.

[27] Intelligent Technologies for Modern Financial Ecosystems: Transforming Housing Finance, Risk Management, and Advisory Services Through Advanced Analytics and Secure Cloud Solutions. (2024). MSW Management Journal, 34(2), 953-971.

[28] Pallav Kumar Kaulwar,. (2024). Agentic Tax Intelligence: Designing Autonomous AI Advisors for Real-Time Tax Consulting and Compliance. Journal of Computational Analysis and Applications (JoCAAA), 33(08), 2757–2775. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/2224

[29] AI-Powered Revenue Management and Monetization: A Data Engineering Framework for Scalable Billing Systems in the Digital Economy . (2024). MSW Management Journal, 34(2), 776-787.

[30] Paleti, S., Pamisetty, V., Challa, K., Burugulla, J. K. R., & Dodda, A. (2024). Innovative Intelligence Solutions for Secure Financial Management: Optimizing Regulatory Compliance, Transaction Security, and Digital Payment Frameworks Through Advanced Computational Models. Journal of Artificial Intelligence and Big Data Disciplines, 1(1), 125-136.

[31] Singireddy, J. (2024). Deep Learning Architectures for Automated Fraud Detection in Payroll and Financial Management Services: Towards Safer Small Business Transactions. Journal of Artificial Intelligence and Big Data Disciplines, 1(1), 75-85.

[32] Sneha Singireddy. (2024). Leveraging Artificial Intelligence and Agentic AI Models for Personalized Risk Assessment and Policy Customization in the Modern Insurance Industry: A Case Study on Customer-Centric Service Innovations . Journal of Computational Analysis and Applications (JoCAAA), 33(08), 2532–2545. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/2163

[33] Challa, S. R. (2024). Behavioral Finance in Financial Advisory Services: Analyzing Investor DecisionMaking and Risk Management in Wealth Accumulation. Available at SSRN 5135949.

[34] Maguluri, K. K., Ganti, V. K. A. T., & Subhash, T. N. (2024). Advancing Patient Privacy in the Era of Artificial Intelligence: A Deep Learning Approach to Ensuring Compliance with HIPAA and Addressing Ethical Challenges in Healthcare Data Security. International Journal of Medical Toxicology & Legal Medicine, 27(5).

[35] Danda, R. R., Nampalli, R. C. R., Sondinti, L. R. K., Vankayalapati, R. K., Syed, S., Maguluri, K. K., & Yasmeen, Z. (2024). Harnessing Big Data and AI in Cloud-Powered Financial Decision-Making for Automotive and Healthcare Industries: A Comparative Analysis of Risk Management and Profit Optimization.

[36] Suura, S. R. (2024). Generative AI Frameworks for Precision Carrier Screening: Transforming Genetic Testing in Reproductive Health. Frontiers in Health Informa, 4050-4069.

[37] Annapareddy, V. N., & Sudha Rani, P. (2024). AI and ML Applications in RealTime Energy Monitoring and Optimization for Residential Solar Power Systems. Available at SSRN 5116062

[38] Kannan, S., & Seenu, A. (2024). Advancing Sustainability Goals with AI Neural Networks: A Study on Machine Learning Integration for Resource Optimization and Environmental Impact

[39] Chava, K., & Saradhi, K. S. (2024). Emerging Applications of Generative AI and Deep Neural Networks in Modern Pharmaceutical Supply Chains: A Focus on Automated Insights and Decision-Making

[40] Komaragiri, V. B. (2024). Generative AI-Powered Service Operating Systems: A Comprehensive Study of Neural Network Applications for Intelligent Data Management and Service Optimization. Journal of Computational Analysis & Applications, 33(8).

[41] Chakilam, C., & Seenu, D. A. (2024). Transformative Applications of AI and ML in Personalized Treatment Pathways: Enhancing Rare Disease Support Through Advanced Neural Networks. Frontiers in Health Informa, 4032-4049..

[43] Malempati, M. (2024). Leveraging cloud computing architectures to enhance scalability and security in modern financial services and payment infrastructure. European Advanced Journal for Science & Engineering (EAJSE)-p-ISSN 3050-9696 en e-ISSN 3050-970X, 1(1).

[44] Nuka, S. T. (2024). The Future of AI Enabled Medical Device Engineering: Integrating Predictive Analytics, Regulatory Automation, and Intelligent Manufacturing. MSW Management Journal, 34(2), 731-748.

[55] Singireddy, S., Adusupalli, B., Pamisetty, A., Mashetty, S., & Kaulwar, P. K. (2024). Redefining Financial Risk Strategies: The Integration of Smart Automation, Secure Access Systems, and Predictive Intelligence in Insurance, Lending, and Asset Management. Journal of Artificial Intelligence and Big Data Disciplines, 1(1), 109-124.

[46] Kalisetty, S., & Lakkarasu, P. (2024). Deep Learning Frameworks for Multi-Modal Data Fusion in Retail Supply Chains: Enhancing Forecast Accuracy and Agility. Journal of Artificial Intelligence and Big Data Disciplines, 1(1), 137-148.

[47] Venkata Krishna Azith Teja Ganti ,Kiran Kumar Maguluri ,Dr. P.R. Sudha Rani (2024). Neural Network Applications in Understanding Neurodegenerative Disease Progression. Frontiers in HealthInformatics, 13 (8) 471-485

[48] Venkatasubramanian, K., Yasmeen, Z., Reddy Kothapalli Sondinti, L., Valiki, S., Tejpal, S., & Paulraj, K. (2024). Unified Deep Learning Framework Integrating CNNs and Vision Transformers for Efficient and Scalable Solutions. Available at SSRN 5077827.

[49] Sambasiva Rao Suura. (2024). Artificial Intelligence and Machine Learning in Genomic Medicine: Redefining the Future of Precision Diagnostics. South Eastern European Journal of Public Health, 955–973. https://doi.org/10.70135/seejph.vi.4602

[50] Satyasree, K. P. N. V., & Kothpalli Sondinti, L. R. (2024). Mitigating Financial Fraud and Cybercrime in Financial Services with Security Protocols and Risk Management Strategies. Computer Fraud and Security, 2024(11).

[51] Suura, S. R. (2024). The role of neural networks in predicting genetic risks and enhancing preventive health strategies. European Advanced Journal for Emerging Technologies (EAJET)-p-ISSN 3050-9734 en e-ISSN 3050-9742, 1(1).

[52] A comparative study of identity theft protection frameworks enhanced by machine learning algorithms. (2024). MSW Management Journal, 34(2), 1080-1101.

[53] Komaragiri, V. B. (2024). Data-Driven Approaches to Battery Health Monitoring in Electric Vehicles Using Machine Learning. International Journal of Scientific Research and Management (IJSRM), 12(01), 1018-1037.

[54] Reddy, J. K. (2024). Leveraging Generative AI for Hyper Personalized Rewards and Benefits Programs: Analyzing Consumer Behavior in Financial Loyalty Systems. J. Electrical Systems, 20(11s), 3647-3657.

[55] Singireddy, S., Adusupalli, B., Pamisetty, A., Mashetty, S., & Kaulwar, P. K. (2024). Redefining Financial Risk Strategies: The Integration of Smart Automation, Secure Access Systems, and Predictive Intelligence in Insurance, Lending, and Asset Management. Journal of Artificial Intelligence and Big Data Disciplines, 1(1), 109-124.

[56] Kalisetty, S., Pandugula, C., Sondinti, L. R. K., Mallesham, G., & Rani, P. S. (2024). AI-Driven Fraud Detection Systems: Enhancing Security in Card-Based Transactions Using Real-Time Analytics. Journal of Electrical Systems, 20, 1452-1464.

[54] Suura, S. R. (2024). Agentic artificial intelligence systems for dynamic health management and real-time genomic data analysis. European Journal of Analytics and Artificial Intelligence (EJAAI) p-ISSN 3050-9556 en e-ISSN 3050-9564, 1(1).

[55] Komaragiri, V. B., Edward, A., & Surabhi, S. N. R. D. Enhancing Ethernet Log Interpretation And Visualization

[57] Challa, K. (2024). Neural Networks in Inclusive Financial Systems: Generative AI for Bridging the Gap Between Technology and Socioeconomic Equity. MSW Management Journal, 34(2), 749-763.

[58] Moore, C., & Routhu, K. (2023). Leveraging Machine Learning Techniques for Predictive Analysis in Merger and Acquisition (M&A). Available at SSRN 5103189.

[59] Moore, C. (2023). AI-powered big data and ERP systems for autonomous detection of cybersecurity vulnerabilities. Nanotechnology Perceptions, 19, 46-64.

[60] Chinta, P. C. R., Katnapally, N., Ja, K., Bodepudi, V., Babu, S., & Boppana, M. S. (2022). Exploring the role of neural networks in big data-driven ERP systems for proactive cybersecurity management. Kurdish Studies.

[61] Katnapally, N., Chinta, P. C. R., Routhu, K. K., Velaga, V., Bodepudi, V., & Karaka, L. M. (2021). Leveraging Big Data Analytics and Machine Learning Techniques for Sentiment

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 34 Issue 2, July-Dec 2024, Pages: 1132-1144

Analysis of Amazon Product Reviews in Business Insights. American Journal of Computing and Engineering, 4(2), 35-51.

[62] Maka, S. R. (2023). Understanding the Fundamentals of Digital Transformation in Financial Services: Drivers and Strategic Insights. Available at SSRN 5116707.

[63] Krishna Madhav, J., Varun, B., Niharika, K., Srinivasa Rao, M., & Laxmana Murthy, K. (2023). Optimising Sales Forecasts in ERP Systems Using Machine Learning and Predictive Analytics. J Contemp Edu Theo Artific Intel: JCETAI-104.

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