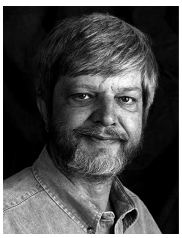
Adopting a dynamic AI price optimisation model to encourage retail customer engagement

Received: 21st November, 2022

Steven Keith Platt
Director of Analytics and Lecturer of Statistics and Applied AI, Quinlan School of Business, USA

Steven Keith Platt's teaching and research are focused on artificial intelligence and statistics. Before joining the Quinlan School of Business in 2021, Steven served as Research Director at the Retail Analytics Council, Northwestern University, where he ran the AI Lab and Retail Robotics Initiative, as well as teaching various AI courses. Steven has consulted with companies including AT&T, Kroger, McDonald's and Microsoft, among many others. In addition to his academic publications, he has published in trade publications including the *ABA Banking Journal*, *American Marketing Association*, *Computing Technology Industry Association*, *Global Retail Management*, *Hospital Information Technology Europe* and *Retail Information Systems News*. He has been quoted in publications including *Bloomberg*, *Business Week*, *Chain Store Age*, *The Chicago Tribune*, *CNN Business, Inc*. magazine, *MIT Technology Review*, *The San Jose Mercury News*, *Time* magazine, *USA Today* and *The Wall Street Journal*. He has also appeared as a guest analyst on the CBS Evening News and Early Show and ABC World News, as well as lectured at conferences around the globe. Steven received his BSBA, JD, and LLM from Boston University.

Quinlan School of Business, Loyola University Chicago
E-mail: splatt1@luc.edu



Martin Paul Block
Professor, Medill School of Journalism, Media and Integrated Marketing Communications, USA

Martin Block is Professor Emeritus, Integrated Marketing Communications, Northwestern University and Executive Director of the Retail Analytics Council. Martin is co-author of *Understanding China's Digital Generation*, *Media Generations: Media Allocation in a Consumer-Controlled Marketplace*, *Retail Communities: Customer Driven Retailing*, *Analyzing Sales Promotion*, *Business-to-Business Market Research* and *Cable Advertising: New Ways to New Business*. He has published in many academic research journals, trade publications and several book chapters. His PhD is from Michigan State University.

Medill School of Journalism, Media and Integrated Marketing Communications, Northwestern University
E-mail: mp-block@northwestern.edu

Abstract Technology innovation, changing consumer preferences and behaviours and competition compel successful enterprises to embrace change. Nowhere are these pressures more acute than in the retail industry and, in particular, for those engaged in the sale of fashion merchandise. As this paper will demonstrate, customer engagement (CE) strategies that leverage artificial intelligence (AI) afford retailers the ability to connect with customers in unique ways. The paper focuses on an AI optimisation model that was built for a fashion retailer. The objective was to build a demand prediction price optimisation model to increase margins realised on the clearance of fashion products. While our discussion will focus on that work, we also present techniques whereby such a model can be employed by CE enthusiasts in their businesses. More specifically, we advance that our model can enhance a company's CE efforts as a method by which it enables a collaborative customer/company value creation system.

KEYWORDS: customer engagement, artificial intelligence, demand prediction, price optimisation, retail management, retail promotion

RETAIL MANAGEMENT

Retail management can broadly be defined as the cumulative collection of activities that add value to the process of selling products and services to consumers. These include, among others, customer-centric activities, merchandising and inventory forecasting and execution, multichannel strategies, automation and information systems, supply chain management, marketing and human resource planning. It can be advanced that for retailers that sell products merchandise management, the process by which a retailer selects products for sale is the most important of these, as the sale of products to consumers underpins these retailers' business.

The type of merchandise a retailer sells can be categorised as either evergreen, seasonal or fashion. Evergreen or basics, such as paint and paper, exhibit continuous demand over an extended time period, thus demand forecasts and pricing for these products tend to be stable. Demand planning for seasonal products, such as candy for Halloween or snow shovels in the winter, present a bit more complexity, but demand estimates and pricing may similarly exhibit a fairly normal distribution. Forecasting the demand for fashion products, such as footwear and apparel, including appropriate inventory levels and pricing structure, on the other hand, is much more complex, as such products may be in demand for a brief period of time. This is complicated by the fact that these products tend to require long purchase lead times if they are manufactured in foreign markets, well before the trend has been firmly established.

Purchase too much of a product and the retailer may need to resort to markdowns. This is a significant problem, as it has been estimated that globally fashion retailers invest more than US$1tr annually in their markdown programmes.[1] In the apparel industry, it is estimated that 50 per cent of merchandise is sold below its list price.[2] Another study finds that '[e]xcessive inventories and widespread markdowns proliferated to the extent that just 60 percent of garments were sold at full price, creating billions of dollars of lost revenues and margin'.[3] In contrast, if a retailer purchases too few items, they will encounter out-of-stocks, resulting in lost sales and disappointed customers. To address this, retailers engage in various forms of product demand planning.

Merchandise demand forecasting for fashion retailers has always been a challenging task because of the uncertainty associated with predicting trends and consumer behaviour. Complicating this further, it has been suggested that the growth in the importance of fashion apparel is more attributable to supply than demand factors, meaning more retailers are competing for the same consumer dollar. And as consumers today have more information at their disposal, ranging from social media influencers to easily accessing which retailer is selling the same/similar product at what price, this has become exponentially more complex.

While a fashion retailer may apply advanced statistical forecasting methods that consider historical sales trends for comparable items and incorporate qualitative data such as fashion trend forecasts and consumer research to solve this problem, these methods have their limitations. As well, many retailers are not even that advanced and will seek to solve this problem by assuming a normal product demand distribution subject to the input of an experienced merchant's intuition. These shortcomings manifest as the fashion product is brought to market and sales either exceed or underperform expectations. The fact that 40–50 per cent of fashion merchandise ends up being discounted points to the need for an artificial intelligence (AI) solution to help address this problem.

As the selling season for a fashion product begins, merchants look at a product's sell-through rate to determine success or failure. If a product is not selling well at a certain point, markdowns (also known as clearance sales) will be applied to move out the merchandise. As with demand forecasting, a particular retailer may employ quantitative models to predict demand at different price points to increase margins. Most often, however, retailers apply their company's culturally established markdown caddice as enhanced by a merchant's intuition, ie the first mark of 15 per cent off, the second mark of 25 per cent off, etc.

In the case of markdowns, applying such a simplistic approach results in lost margin. As we demonstrate here, the application of an AI model that predicts demand at different price points can result in a significant increase in realised margins. This same model can be used to personalise offers, for example, in furtherance of a company's customer engagement strategy by affecting consumption experiences.

CUSTOMER ENGAGEMENT

Customer management strategies have advanced over the years. From an early emphasis on transactions, this later evolved into a focus on customer relationships. The customer engagement (CE) construct takes this to the next level, suggesting that companies should engage with customers 'in all possible ways'[4] to motivate them to undertake various activities in support of a company's marketing activity beyond just transactions. AI and digital technologies provide a range of techniques to fuel this engagement apparatus.

It is not our intent here to present a detailed analysis of the many different interpretations and nuances associated with CE. Rather, we provide a brief overview of the topic with a focus on those aspects of enterprise-initiated CE upon which our AI model can be leveraged to execute.

Conceptually, CE has an 'end goal of persuading desired customer behavior (e.g., positive brand attitudes, purchase intentions, and loyalty)'.[5] Unpacking the CE iterative process slightly, following a purchase, a customer experiences either a positive or negative level of satisfaction. Assuming a positive experience, this happy customer will engage further with the company either directly, by making repeat purchases, and/or indirectly as an advocate of the company. While these activities are consumer-led, they can be instigated by both the customer and the business enterprise.

Enterprise-initiated CE (also referred to as engagement marketing), to which we advance the application of our model, is defined as a 'firm's deliberate effort to motivate, empower, and measure a customer's voluntary contribution to its marketing functions'[6] to increase customer satisfaction, loyalty and company performance.

Whether customer or enterprise-initiated, the behavioural aspects of CE include a focus on purchase behaviour, referral behaviour, influencer behaviour and knowledge behaviour (ie feedback to the company). These customer-initiated activities may include, for example, word-of-mouth activity, blogging, recommendations, referrals, reviews/feedback and customers acting as social brand advocates, all to stimulate customer voluntary contributions to a company's marketing effort. The expected outcome of a CE strategy is increased sales and loyalty. CE is said to be achieved when the customer/company 'relationship is satisfied and [there exists an] emotional bonding'[7] or connection.

CE can be collaborative (company and CE to realise value for both), company-initiated (such as a blog), customer-initiated (which could include reviews) or passive, such as mass media advertising. Aggregated data modelled using AI enables a company, in our case, to create value to enhance customer engagement behaviours by offering personalised proposals that benefit both the customer and the retailer by creating a collaborative value system. Whether personalised offers are delivered online, in an app or by e-mail, the customer benefits from unique access to discounts, while the retailer benefits from selectively managing merchandise inventory, creating value for both. Such a system of creating customer/company interactions is 'likely to affect clients' (e.g., monetary) investments in their service interaction, thus affecting CE'.[8]

AI

The economic and societal impact of AI will be profound. Estimates of the size of the industry vary, but it is undeniable that it is an important and growing technology. Some have gone as far as to suggest that 'AI is poised to revolutionize the world on the scale of the steam engine and electricity'.[9]

The US National Institute of Standards and Technology (NIST) defines AI technologies and systems to 'comprise software and/or hardware that can learn to solve complex problems, make predictions or undertake tasks that require human-like sensing (such as vision, speech, and touch), perception, cognition, planning, learning, communication, or physical action'.[10]

AI in retail is being applied in various areas. This includes, among others, marketing, supply chain optimisation, demand planning, optimal merchandise location, addressing the number of merchandise units to be acquired in a particular size, etc. Our experience with retailers finds that most are focused for now on marketing-related activities, such as recommender systems.

It has been noted, for example, that '[i]nformation processing systems enabled by artificial intelligence are improving the impact of marketing activities'[11] by enabling customers and organizations to interact. According to a recent McKinsey & Co. survey, 60 per cent of fashion executives plan to implement improved analytics for consumer insights (see Figure 1). The model here extends this into the CE space by affording a collaborative value-creation process by influencing the consumption experience.

AI USE CASE

Our research was conducted in collaboration with a large US retailer of brand-name

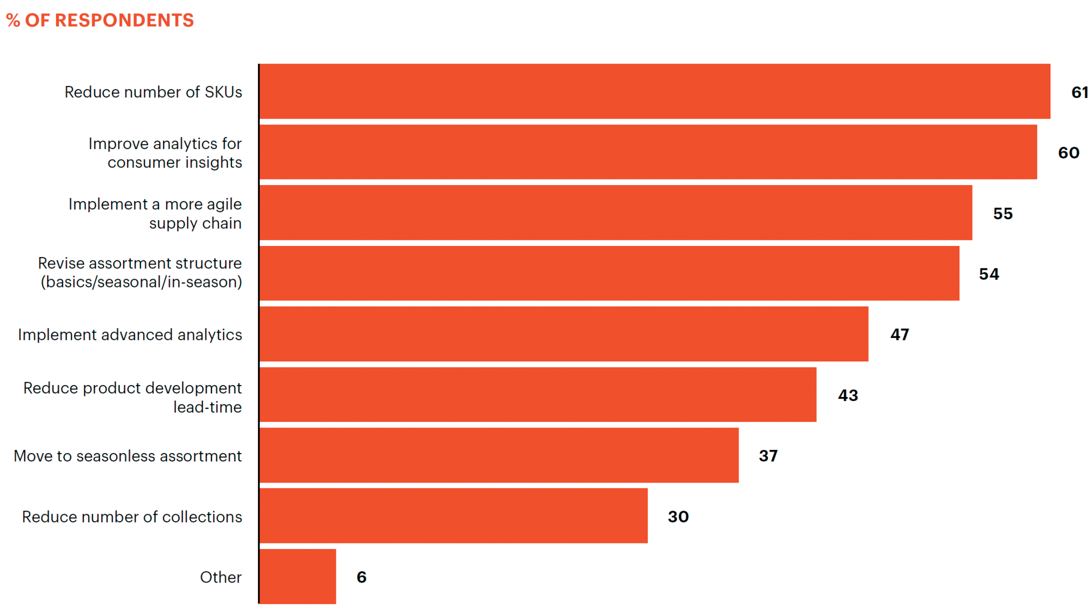


Figure 1: Fashion executives plan to employ several strategies to avoid overstocks in the future
Source: McKinsey & Co.

footwear and fashion-related apparel. As noted, the initial focus was on building a model that recommends the optimal timing (when) and depth (per cent) of markdowns to realise the highest product margin. We illustrate how this model can also be applied to advance a CE strategy in the applications section of this paper that follows.

We advance that an AI model built for price optimisation serves as a good CE application for various reasons, including:

1. Our model advances a method that can be used to influence the consumption experience and thus falls within the CE class, as the model outputs value creation for both parties;
2. Examples of AI models that may fall within the CE space, such as recommender systems are widely used in commercial enterprises, but the specifics of how these are built are not generally within the public domain, ie they are based on proprietary architectures. While a patient search may reveal aspects of the AI architecture, they may not shed light on how the model was built and applied as a CE application;
3. Other examples of AI systems that may lie within the CE space, ie smartphone apps and robotics, may simply not be considered by some to constitute CE;
4. CE did not gain visibility until around 2010. While 12 years may seem like a long time, much of the work in this area is being driven by the academic community. Add to this the complexity of AI generally, and it becomes clear that this is very much an emerging area. In support of this, we note that 'many brands have limited ability and remain unsure how to generate and implement insights from CE data using AI-powered solutions';[12]
5. Finally, note that '[t]he need for longitudinal AI-focused research on CE (e.g., its benefits, costs, efficiency, effectiveness) is also warranted because of its dearth in the extant CE literature'.[13]

Moving back to our research, establishing a product's optimal price at any point in the sales cycle can be a significant challenge. This is further complicated by additional factors encountered by fashion retailers that introduce new products for which there is no sales history. Retailers need to factor in hundreds of parameters including seasonal factors, cross-price elasticity and sales cannibalisation to arrive at the best price at a particular time in a product's life cycle. Deploying AI models that are capable of processing and learning from vast amounts of data can help. Elasticity-based self-learning algorithms can process vast amounts of data, consider as many parameters as necessary and reveal hidden relationships between products in the merchandise portfolio to suggest individual prices which will maximise revenue and sales of the entire portfolio.

On the back end of a product's life cycle, establishing a product's markdown involves both art and science, depending upon the individual retailers' approach. On the art/rules-based side, for example, a retailer may identify markdown candidates when weekly sell-through falls below a certain level, or by the amount of time merchandise remains unsold. Other retailers may use optimisation software, which continually updates price forecasts based on actual sales with a consideration of different price points. In either case, markdowns can have a negative impact on margins. An AI app that is capable of processing a vast amount of data and making accurate demand predictions is ideally situated to address this problem.

Our retailer falls into the art/rules-based approach and sought a more advanced method to establish product markdowns. In general, the retailer's buyer and planner make product markdown suggestions which are then submitted to management for approval. Factors considered in making these suggestions include desired product sell-through per schedule (looking at the historical and projected rate of sales), end-of-season sales and time of year (ie 4th of July), among other things, to determine a good selling product (defer markdowns) versus a poor one (advance markdowns).

Figure 2 illustrates the markdown approach of our retailer. The percentage markdown taken is indicated by the green dotted line. So, for example, at week 25, a 20.04 per cent discount on a product was taken to address a falloff in the sell-through rate (indicated on the Y-axis). Thereafter, from that period to week 75, we observe that sales at first improved, but as they started to slow, another 20.04 per cent discount was taken, which again improved sales.

The retailer supplied transactional data from May 2017 to October 2019 representing 30 continuous months and about 1,500,000 records. Additional data included inventory data by week (units, cost, value), product data (style, colour, vendor, department and class), store data (store number) and calendar data (fiscal year, week). Time-related data, sales (transactions) and inventory were aggregated by week.

Developing a markdown optimisation model begins with an understanding of how the current markdown approach affects sales and margins. This requires establishing baseline metrics or key performance indicators (KPIs) against which to measure the AI markdown model's performance. The model then needs a product demand prediction function that suggests the optimal timing (when) and depth (per cent) of markdowns to realise the highest margin.

Among the KPIs we created are sell-through rate (cumulative sales/[cumulative sales + inventory units]), markdown (difference between manufacturer's

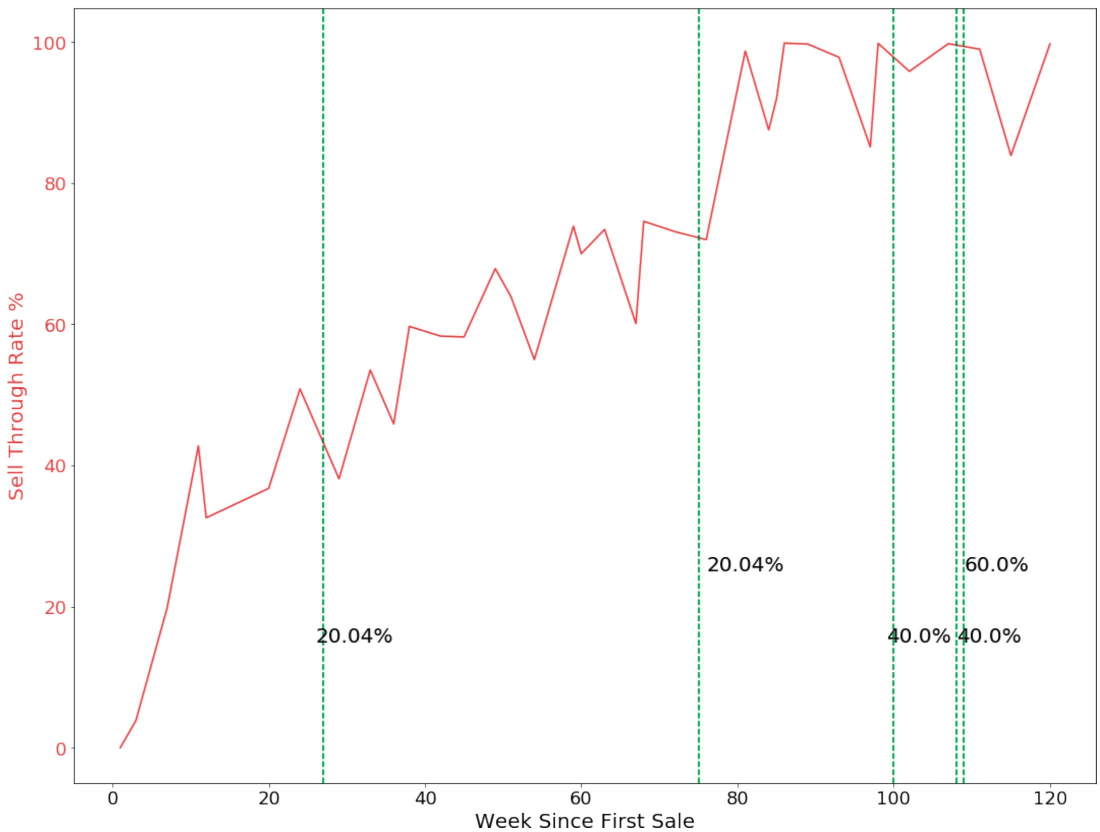


Figure 2: Markdown impact on sell-through rate

suggested retail price [MSRP] and current selling price [>3 per cent]), elasticity (%∆demand/%∆price) and margin (product sales -product cost)/product sales). All the KPIs are calculated at the item level for each stock-keeping unit (SKU).

Working with retail operational data also requires making assumptions to proceed with the analysis. Issues such as store openings and closures during the time frame, returned items, items remaining in the inventory file that is discontinued, items that have very low unit sales and missing data all require attention as part of the data processing pipeline.

Preparing and linking the data files yielded a reduced merchandise product portfolio to analyse from an initial 2,500 based on style and color to a more usable file of 1,100. Products were then divided into two groups: continuing products that exhibit sales throughout the 30 months and new products that were not sold before (that is, have no sales history).

There are three main components to this model: clustering, classifying and predicting. Clustering was required to classify all products sold, classifying was necessary to assign new products to a cluster and a demand prediction function to account for sales of continuing and new product sales at different prices.

K-means clustering: Classifying all products sold

A K-means cluster analysis allows the products to be grouped (clustered) which makes it practical to estimate product demand by cluster, rather than by thousands of individual products. In this phase, the number of k clusters was ascertained by the elbow method, which resulted in three clusters (see Figure 3). The reasoning behind clustering is to assign a categorical variable to each item that will facilitate prediction models to give more accurate predictions on new items. Using all the training data, the variables (features) that were used are week number, price for that week, average cost, quantity sold that week and sell-through rate that week. The three product clusters were then classified as expensive, lower price and moderate price (see Figure 4).

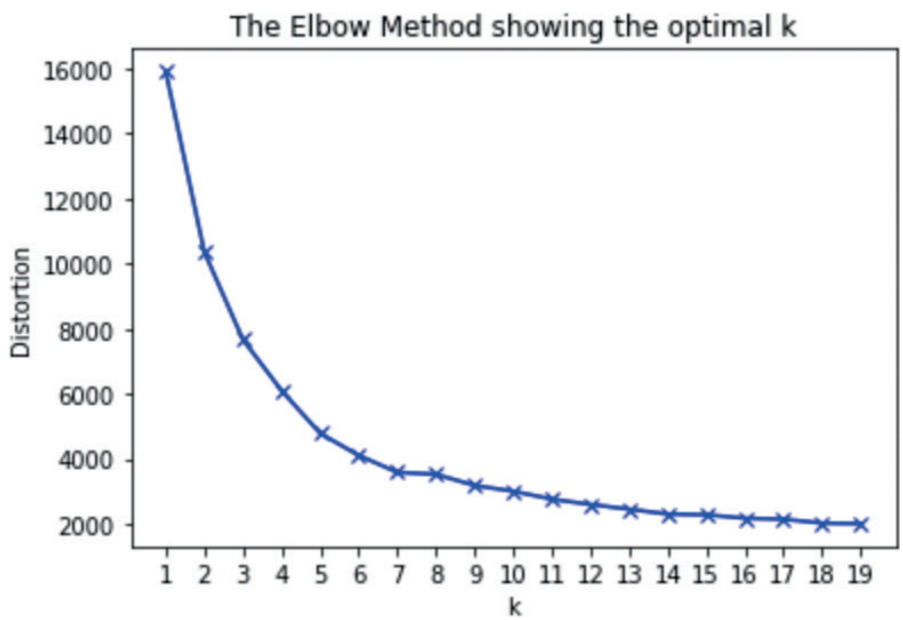


Figure 3: K clusters

	Cluster_0 Expensive	Cluster_1 Lower price	Cluster_2 Moderate price
# data points	297 (1.5%)	17,026 (89.8%)	1,634 (8.61%)
Average MSRP	$119.55	$81.34	$102.57
Average weekly product sell through rate	42%	74%	51%
Average price elasticity	2.42	1.08	3.66

Figure 4: Cluster classification

Support vector machine (SVM): Classifying new products

New products cannot be assigned to a cluster from the K-means analysis because new products do not have historical transactions. SVM was therefore used to assign cluster numbers to new products. The variables used to classify new product clusters were style, colour, year, week, class, vendor, MSRP and cost. This essentially is using the continuing product clusters to classify new products to assign to because we do not have prior training data.

Prediction: Random forest — the markdown model

A random forest algorithm was used for demand prediction of both continuing and new products, as they tend to perform well with categorical data. A 20 per cent holdout sample was retained to compare train versus test results. A separate analysis was performed for both continuing and new products, for all products. Figure 5 summarises the continuing and new product performance of the algorithm by looking at its ability to correctly predict demand for all continuing and new products.

It is not surprising that our model performs better on continuing products than new products, as we lack historical data for new products. The R-squared, which explains the variation in the predicted outcome from our actual inputs, provides a measure of how well the observed outcomes are replicated by the model. The closer to 1.00 the R-squared, the better the prediction. The mean absolute error is an evaluation metric that measures the prediction errors versus the observed values. A lower mean absolute error is best.

	New Products	Continuing Products
Models used	RF, K-Means,SVM	RF, K-Means
# features	11	15
Important features	Kcluster, Cost, Week, MSRP	Kcluster, Week since first sale, Cost
Mean Absolute Error	30.72	13.94
R-squared	0.46	0.63

Figure 5: Model performance on continuing and new products

Figure 6 illustrates the model's ability to predict demand for a group of continuing products. The Y-axis shows the unit demand while the X-axis is the demand over time. The blue predicated line tracks the orange true value, or ground truth, fairly closely.

Figure 7 demonstrates the model's markdown suggestions for this same group of continuing products. The Y-axis shows the percentage markdown, while the X-axis indicates the suggested week to take the markdown. The blue predicated line is the model's suggestion, while the orange line is the retailer's actual markdown taken. This illustrates that the retailer took higher markdowns around week 24 than suggested.

Finally, we demonstrate the results that could have been realised by the retailer if they had followed the model's recommendations on the timing and percentage markdown on this group of continuing products. Figure 8 illustrates the predicted product sell-through rate (orange) versus the actual sell-through rate for these continuing products (blue) with the introduction of the model's markdown suggestions. The result was that the predicted gross margin realised would have been 50 per cent if the retailer followed the model's recommendations versus the 41 per cent that the retailer realised while achieving a similar sell-through rate. The crucial point here is that the retailer could have achieved a 9 per cent margin pickup with the same sell-through rate achieved over the 35-week sales period.

APPLICATIONS

We begin with a discussion of the model's retail operating applications, and then discuss how it can be extended in support of an organisation's CE efforts.

Operating applications

Test demand for new products — in a bid to match a product with preference, retailers can leverage this model to gauge

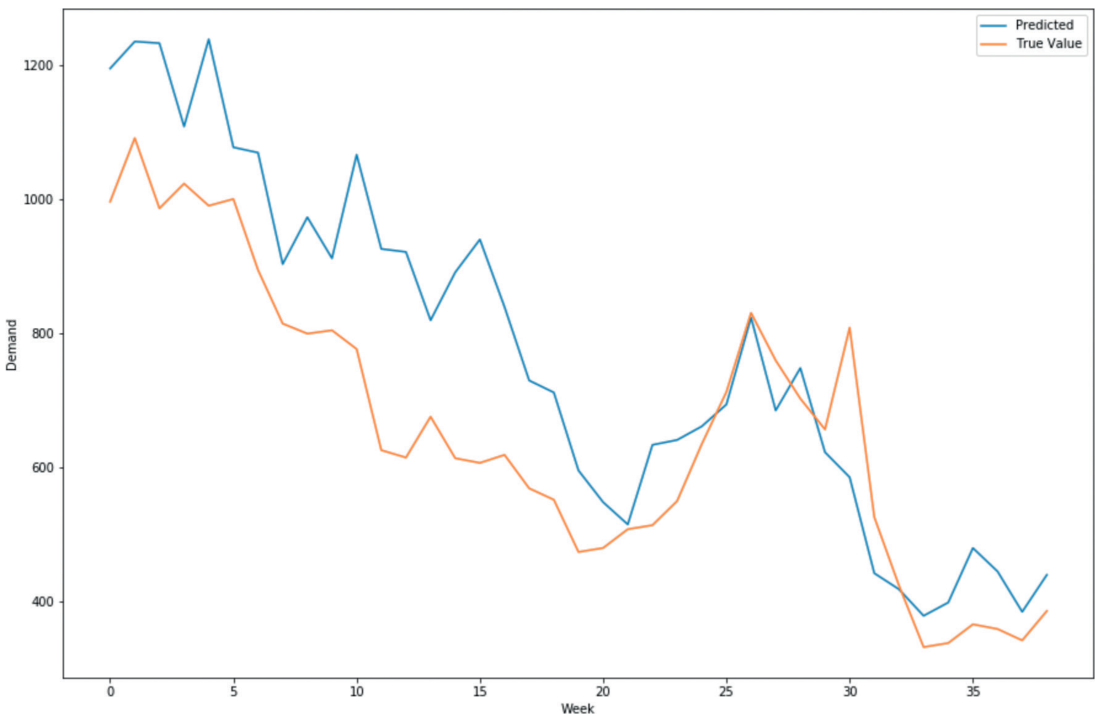


Figure 6: Demand prediction for continuing product sales

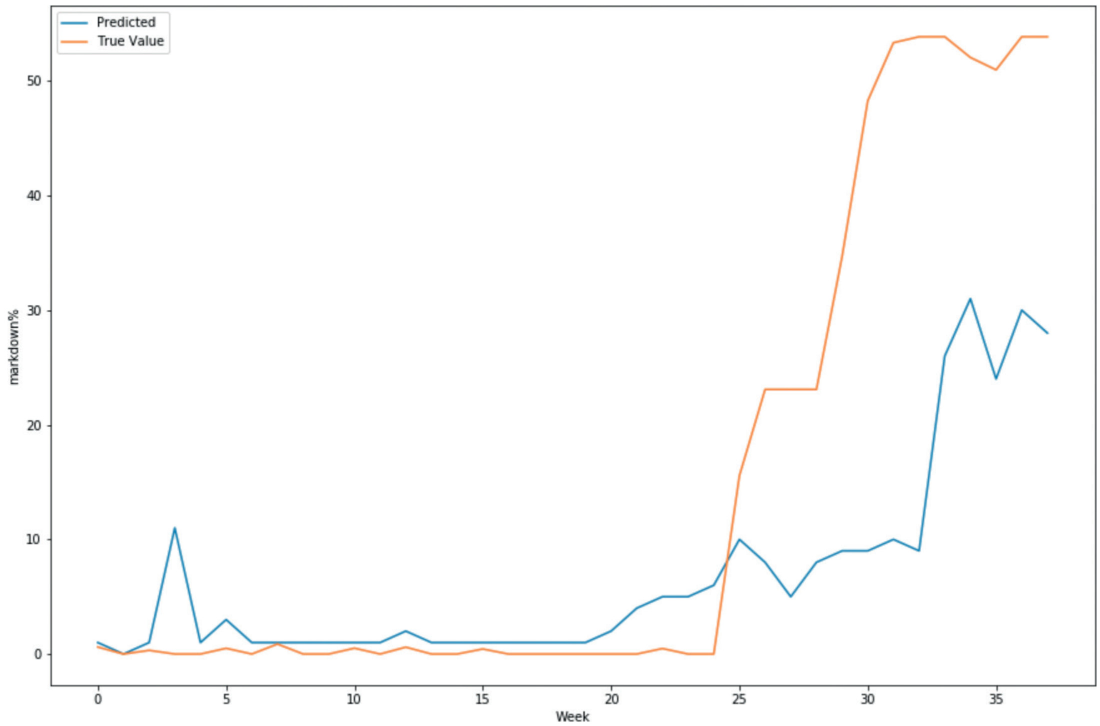


Figure 7: Markdown suggestions for continuing products

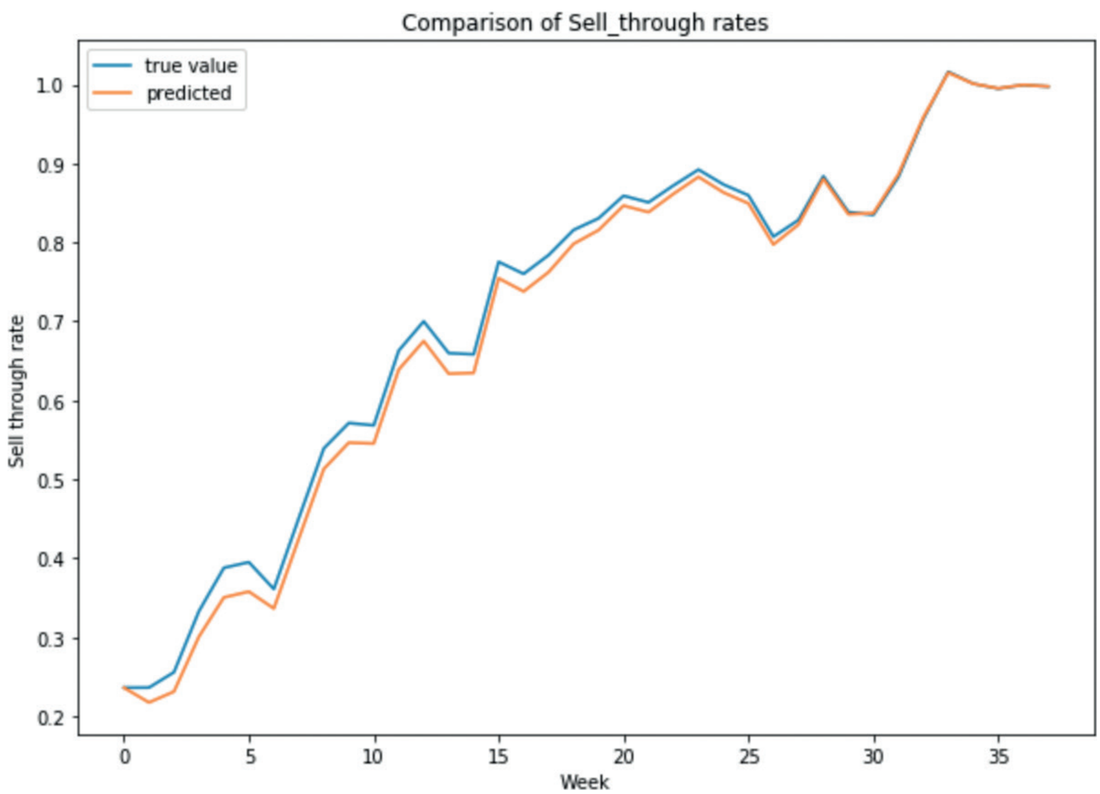


Figure 8: Comparison of continuing product actual and predicted sell-through rates

consumer sentiment prior to a new product acquisition to enable better decision making by merchandisers. This model affords an opportunity, via clustering and classification algorithms, to predict new product demand. Products not previously offered are clustered and classified along with related products, and demand at various price points can be predicted.

Adjust inventory purchase levels of evergreen and seasonal products — while ascertaining demand for evergreen and seasonal products is not as volatile as for new products, demand for these products can change over time. This can be affected by weather conditions, new competition and positive/negative social media, among many other things. A well-constructed model with concise features can improve demand predictions for these products, resulting in reduced carrying costs if demand is predicted to decrease, or increased revenue if demand is unexpectedly predicted to increase.

Increase margins for slow-moving items — as previously noted, this model enables merchants to make better pricing decisions based on a product's predicted selling rate, with a time constraint, at various prices, resulting in the ability to maximise revenue.

Reduce out-of-stocks — improved demand predictions can avoid out-ot-stocks, disappointed customers and lost revenue opportunities.

CE applications

Our model can be used in support of various CE activities. The model itself is easy to run via the created graphical user interface (GUI), which enables a manager to import various files, select whether a new or continuing product is being tested, and select a time frame that will then produce a demand forecast and markdown suggestions for new products and continuing products at an individual product level.

CE activities include the following:

- *Personalisation*: Our model affords retailers an opportunity to personalise product promotions and predict the related cost-benefit at a specific time. Unlike across-the-board promotions offered to all customers, the enterprise can fine-tune the amount and timing of discounts to select customers and predict the impact on demand and margins. These exclusive offers to select customers will not only encourage loyalty but can also engage positive feelings toward the company. The offers can be executed by e-mail, on an app or on the web to loyal customers;
- *Customer referrals*: Similarly, select discounts (with an understanding of the economic costs) can be extended to customers through incentivised referrals. Unlike an open incentive (ie refer a friend and get US$10 off), we envision this as related to specific product referrals. Advantages to the company include a positive customer engagement experience and the fact that such an uptake can result in the retailer disposing of merchandise that it is trying to move off the shelves;
- *Continuous performance improvement*: The model itself can continually learn from customer personalisation and referral activity to better identify which customers value what, to predict customer behaviour to these different engagement opportunities to further increase CE;
- *Active customer engagement in design as a new feature input*: Analytics and AI will also gain traction in the product development process as more data becomes available to brands and designers become more skilled at using data. For example, footwear and apparel brand Wolverine plans to optimise assortments with digital consumer testing based on predictive analytics, where the voice of the customer feedback is combined with AI. Due to the model's continuous performance feedback, this can aid in the design/selection of merchandise to be sold by the retailer.

CONCLUSION

AI-enabled customer engagement technology is forecast to rapidly grow in the future. While this may be true, there is an absence of published research demonstrating how such models are constructed and applied. Our model, for example, illustrates a method by which retailers can increase customer interactions that create value for both the customer and the company, whereby the customer's desire to bond or identify with the company is increased.

In summary, business performance can be improved in many ways by implanting AI solutions. In a retail environment inventory management, distribution, merchandising and marketing are several areas where efficiency and profitability can be enhanced by taking a data-driven, mathematical approach to improve performance, rather than relying on traditional approaches.

References

1. Seara, J., Biscarini, L., Bianchi, F., Todescan, S., Callerstan, J. A. and Dodero, L. (March 2020), 'The advanced analytics behind fashion company markdown', p. 1, BCG, available at https://www.bcg.com/publications/2020/advanced-analytics-fashion-company-markdowns (accessed 21st November, 2022).
2. Hardman, D., Harper, S. and Notaney, A. (2007) 'Keeping inventory-and profits-off the discount rack: Merchandise strategies to improve apparel margins', Silo Tips, available at https://silo.tips/download/keeping-inventory-and-profits-off-the-discount-rack/ (accessed 21st November, 2022).
3. McKinsey & Co. (2020), 'The State of Fashion 2021', p. 59, available at https://www.mckinsey.com/~/media/McKinsey/Industries/Retail/Our%20Insights/State%20of%20fashion/2021/The-State-of-Fashion-2021-vF.pdf (accessed 21st November, 2022).
4. Pansari, A. and Kumar, V. (2017), 'Customer engagement: The construct, antecedents, and consequences', *Journal of the Academy of Marketing Science*, Vol. 45, p. 294.
5. Lim, W. M., Rasul, T., Kumar, S. and Ala, M. (February 2022), 'Past, present, and future of customer engagement', *Journal of Business Research*, Vol. 140, p. 439.
6. Harmeling, C. M., Moffett, J. W., Arnold, M. J. and Carlson, B. D. (December 2016), 'Toward a theory of customer engagement marketing', *Journal of the Academy of Marketing Science*, Vol. 45, p. 312.
7. Pansari and Kumar, ref. 4 above, p. 295.
8. Hollebeek, L. D., Sprott, D. E. and Brady, M. K. (January 2021), 'Rise of the machines? Customer engagement in automated service interactions', *Journal of Service Research,* Vol. 24, No. 1, p. 2.
9. US Patent and Trademark Office, Office of the Chief Economist (October 2020), 'Inventing AI: Tracing the diffusion of artificial intelligence with U.S. patents', available at https://www.uspto.gov/sites/default/files/documents/OCE-DH-AI.pdf (accessed January 11th, 2023).
10. *Ibid*.
11. Perez-Vega, R., Kaartemo, V., Lages, C. R., Borghei Razavi, N. and Mannisto, J. (May 2021), 'Reshaping the contexts of online customer engagement behavior via artificial intelligence: A conceptual framework', *Journal of Business Research*, Vol. 129, p. 902.
12. Lim *et al.*, ref. 5 above, p. 452.
13. Lim *et al.*, ref. 5 above, p. 452.