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Flexible Pricing based on Strategic Engineering in Retail Sector

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Abstract

The paper proposes utilization of advanced data analytics solutions to support decision makers in retail in their work of identification of best price for sold goods in order to maximize revenue. The authors analyze principal data which required to perform the operation, as well as highlight difficulties related to evaluation and testing of the decision support system.

Keywords: Data Analytics, Simulation, Pricing, Retail, AI, Strategic Engineering

1. Introduction

One of most common yet insufficiently covered operations in retail is price management. Indeed, each new product in assortment will inevitably have assigned to it price; furthermore, once established, it could be subjected to numerous periodic modifications, caused by a series of factors. At the same time, the standard practice to define value visible to the customer, is to rely on experience, on "gut-feeling" of decision maker. Indeed, while there are many influencing factors, discussed in the following, there is no sufficiently reliable way to calculate the "best" price or even a "almost-the-best" price range. Another issue is that widely studied by economists price elasticity of demand is often poorly suitable for real life cases. Indeed, it relies on some assumptions which are poorly applicable in practice. In particular, such analysis starts from assumption that there is a big enough set of sales data related to different prices, free of influence of other factors and subjected to variations caused only by the price itself. In reality, the price of product is not varied widely by retailers just to acquire some statistical data and typically stays somewhere in a kind of safe-zone; at the same time, it is strongly affected by seasonal effects, actions of competitors, advertisement, availability of product etc. Considering this, in case of plotting of sales data in order to construct the curve of price elasticity of demand, it is often possible to observe a set of seemingly stochastically distributed points rather than anything similar to desired inverse S-curve.

Another important consideration is that nowadays it's a common practice to buy goods online, in that case it is especially easy for the customer to compare offers of different sellers. Considering this, it became even more important than ever to provide reasonable price for the products as well as to update it whenever required, keeping track on boundary conditions.

Indeed, definition of price is not only important but also frequent procedure in retail (Hosken et al., 2000; Klenow & Malin, 2010). In any case, it is evident that price revision is very frequent activity. Considering this, the authors propose analysis of quantitative factors affecting the price as well as a model based on machine learning, capable to support decision makers in definition of such fundamental characteristic of a product as its sales price. Furthermore, once fully operational, the system could support also regular update of prices, based on actions of competitors, variations of acquisition price etc. In facts the authors plan to adopt an integrated approach by Simulation and AI & Data Analytics in closed loop with big Data as suggested by Strategic Engineering.

2. Factors affecting selection of sales price

In order to be able to find the best price for a product it is essential to define first the target function for optimization. In case of retailers, the goal is to maximize profit, hence, to find a price such as difference between sales price and acquisition cost, multiplied by number of sold product, is maximum; in other words, to ensure that quantity of sold goods multiplied by margin is as big as possible. At the next step, it is necessary to identify which factors should be taken in consideration in order to achieve the goal (Bruzzone et al., 2021). Hereafter is present the analysis of principal pricing-affecting factors considered in this project:

- Acquisition price. Its value is fundamental, as the profit depends on difference between it and sales price. In most of situations, the acquisition price sets the lower border for the sales price, while proximity to this value could be desirable only on special occasions, e.g. in promotion to show economic advantages respect to competitors or to clean old stocks of products. This consideration is even more important considering that in some legislations, going below acquisition price is subjected to strict regulations in order to avoid fraud.
- Actions of competitors. Based on pricing approach of specific retailer, e.g. to position itself as cheaper alternative, price and promotions used by the competitors could limit range in which price of product could be set. Often this information could be obtained automatically from relative online shops, but in some cases a manual processing could be required. Identification of competitor(s) must be done by the retailer wishing optimize its pricing.
- Price awareness and availability of alternatives. The clients typically do not know or remember exact prices of products seen in different occasions. However, specific well-known brands could be exceptions, hence, such products should be priced more carefully than others. In some cases, clients could easily switch to alternative products, e.g. bottled water, toilet paper, while some advertised articles normally could not be replaced, e.g. some types of sugar drinks in which company name has more influence than the product itself; in the last case, the clients typically demonstrate also better price awareness. Hence, these specific products will create perception of convenience of specific sales point respect other ones and must be addressed accordingly. In this case as well as in previous one, the factors are mostly subjective and require manual analysis and estimations by Subject-Matter Experts (SME).
- Price format. Psychologically, consumers prefer to see specific formats of prices. e.g. 9,99$. Indeed, in some cases it could be easier to sell a good at 9,99$ than, for instance, at 9,88$, just because the first price looks more psychologically attractive (Larson, 2007).
- Seasonal effects. Some products are strongly related to certain holidays or events, while others demonstrate significant variation in sales in different seasons (Bottani et al., 2013). Hence, aggressiveness of pricing should vary based on this property of products, e.g. chocolate is mostly consumed is cold season, and its sales would not grow much during summer regardless actions of retailer. This correlation could be extracted from sales data of past years.

For other factors, such as positioning of products on the shelves and availability, it could be impossible to obtain reliable enough data, even if it could be pretty important; for instance, it could define if a specific product was sold less due to ineffective pricing or because it was out of stock. In general, these factors could be omitted if the sales data is present for big-enough set of sales points for long enough period of time. All these factors do not consider some instant effects, such as surge in sales of umbrellas during unexpectedly rainy day, e.g. in summer. Similarly, it is practically impossible to foresee some previously-unseen and unknown factors due to lack of relative statistics, e.g. grow of sales of face masks due to legal obligation to use them and consecutive shortages were observed at the beginning of 2020 (Kampf et al., 2020).

The price could also be affected by regulations, e.g. in case a government sets temporarily a price cap for specific essential product. However, such conditions are quite rare and difficult to foresee as they are typically applied in case of some kind of emergency. Similarly, product could be subjected to temporary variation of VAT (Value Added Tax) or of excise, e.g. in order to ensure accessibility of some sorts of essential goods. Obviously the list of factors affecting sales is much bigger, however, listing all of them is out of scope of this paper; for simplicity, such factors are omitted in this analysis.

The proposed factors could be used to evaluate elasticity of demand and other useful metrics at different scales, in order to improve precision of calculations as well as to improve generalization capabilities of the system, e.g. to price better completely new product with no available past sales information:

- Single product identified by EAN (European Article Number), e.g. single format of pasta by specific manufacturer.
- Group of similar products, e.g. packs of pasta of same weight and manufacturer with different formats.
- Lower groups, e.g. all pasta.
- Upper groups, e.g. nutrition products of similar nature.
- Category, e.g. all non-fresh/frozen food.

Obviously, based on requirements and categorization of products done by specific retailer, the grouping of similar articles could be done in different ways, even if the idea would remain mostly the same.

For instance, another approach could be clustering of products based on market basket data (Holy et al., 2017); this approach requires more data and in some cases could be poorly applicable in some cases.

3. State of the art

A quantitative theoretical approach to pricing-related problems is known since 19th century, when such economists and mathematicians as Cournot (1838) first applied mathematical apparatus to evaluation of macro-economic performance; though, most noticeable and practically applicable advances are related to middle of 20th century (Den Boer, 2015). It is necessary to note that even technological giants of that time such as General Motors did not manage to achieve a reliable estimation of elasticity of demand for their products (Horner et al., 1939); among other factors, one of main difficulties of that period was data acquisition. Hence, only with digitalization it became possible in practice to perform actual analysis of data and to quantify impact of different factors in revenue. Considering this, in past decades, the pricing was mostly done manually by experts, while some theoretical models and software could be used mostly to narrow down the range of uncertainty. Nowadays, it is possible to observe growing number of solutions, often based on Machine Learning (ML), Genetic Algorithms (GA) and other techniques of Artificial Intelligence (AI), capable to support decision makers in this process. Indeed, with advances in these fields as well as with availability of detailed and complete sales information it became possible to perform various types of analysis and use different techniques to address the problem (Bruzzone et al., 2019; Kephart et al., 2000). Considering availability of systems with capabilities similar to that one required by the authors, it is necessary to highlight the idea of improvement of already developed by the authors solution in order to benefit from already available in it data fusion and forecasting capabilities.

4. Proposed solution

In the past, the authors developed a solution to support companies in strategies related to promotional sales that integrated AI and Simulation with Data Analytics based on Strategic Engineering paradigm (Bruzzone et al., 2020, 2021). Considering that that system is currently in service and has access to all required data banks, it is proposed its extension in order to include pricing module, hence, to benefit from already available data extraction and fusion modules present in the main software. The system analyses available data in order to weight such factors as acquisition price of specific product, main competitors' price (if available), check if product is in the top-list of advertised goods, determine variation of its sales in different seasons and based on sales prices, check for the same kind of dependencies for similar products (e.g. other types of coffee or of pasta). Once these and other key factors are quantified, the model estimates price range which is expected to lead to maximization of profit for this given article. Obviously, based on available data and acceptable tolerance the price range could have pretty different extensions. For example, for products with numerous data points a practically valid range could be of 10% of normally used price, while for other products it could be of tens percent. Important consideration which must be highlighted is that as for requirements of the client, the system is not expected to replace decision maker nor to introduce automatic pricing, but rather to be used in man-in-the-loop approach, providing suggestions to relative authorized personnel, which could choose to use its suggestions or not. At the same time, the system does not address any kind of promotional sales or special offers (e.g. 1+1) as they are covered by the previously developed solution; it is focused on regular sales instead.

5. Results

The model is currently in testing phase and already provided some promising suggestions for pricing strategies. One of main difficulties in this project is related to evaluation of results and to assessment of the proposed technological solution. Indeed, in order to quantify impact of suggested prices, in case of their acceptance by decision maker, it would require to acquire at least several weeks of data from different stores, in order to ensure that stochastic factors influencing sales are outnumbered by more reliable data. At the same time, the client must take risk to test the proposals in live conditions, with uncertainty if it would lead to expected improvement of revenue or not. Utilization of the proposed solution for pricing could be especially effective if combined with other advanced support tools based on data analytics, machine learning and simulation. Indeed, this kind of solutions would allow drastic improvement in efficiency of supply chain and retail management (Bruzzone et al., 2022; Braglia & Frosolini, 2014; Fancello et al., 2017). Another important factor is related to utilization of prediction models, which would allow not only to find proper price but to make assumptions on its possible variations in the future (Bruzzone et al., 2013). Efficiency analysis should be not limited to revenue generated by specific product but rather supported by different types of metrics, with the exact list of performance indicators depending on available data. For example, it could be required to check variations of overall revenue and turnover, as well for similar impact on single categories and sub-categories of products. Similarly, average value of receipts, especially containing suggested by the algorithm price products, would be of particular interest for the stakeholders.

6. Conclusions

Pricing is essential activity for retailers. Indeed, proper price could lead to maximization of profit for given products as well as the overall one, while its poor choice could lead to loss of money and clients. Considering this, the authors propose to extend previously developed and deployed software in order to address new problem taking advantage of already available information. It is expected that the effectiveness of software will be improved by integration of additional datasets as well as based on feedback provided by decision makers. Currently the software is in testing phase and it was already demonstrated capability to identify and quantify all mentioned factors from available datasets in order to find relation between price and profit.

References

Bottani, E., Ferretti, G., Montanari, R., Vignali, G., Longo, F., & Bruzzone, A. G. (2013). Design of supply networks with optimized safety stock levels. International Journal of Engineering, Science and Technology, 5(2), 93-109.

Braglia, M. & Frosolini, M. (2014). An integrated approach to implement project management information systems within the extended enterprise. International Journal of Project Management, 32(1), 18-29.

Bruzzone, A. G., Longo, F., Nicoletti, L., Chiurco, A. & Bartolucci, C. (2013). Multiple forecasting algorithms for demand forecasting in the fashion industry. In 2013 8th EUROSIM congress on modelling and simulation (pp. 421-426). IEEE.

Bruzzone A., Massei, M., Sinelshchikov, K., Fabbrini, G., Gotelli, M. & Molinari., A (2019). Machine learning to support industrial digitalization and business transformation. In proceedings of 31st European Modeling and Simulation Symposium, EMSS 2019, pp. 390-393.

Bruzzone, A. G., Sinelshchikov, K., Massei, M. & Schmidt, W. (2020). Artificial Intelligence to Support Retail Sales Optimization. In proceedings of 32nd European Modeling & Simulation Symposium.

Bruzzone, A. G., Massei, M., Sinelshchikov, K. & Schmidt, W. (2021). Machine Learning and Genetic Algorithms to Improve Strategic Retail Management. Proceedings of the 20th International Conference on Modeling & Applied Simulation (MAS 2021), pp. 186-189.

Bruzzone, A. G., Massei, M. & Frosolini, M. (2022). Redesign of Supply Chain in Fashion Industry based on Strategic Engineering. Procedia Computer Science, 200, 1913-1918.

Cournot, A. A. (1838). Researches into the Mathematical Principles of the Theory of Wealth. Translated in 1897 by N.T. Bacon, with a bibliography of Mathematical Economics by Irving Fisher. The Macmillan Company, New York, 1838.

Den Boer, A. V. (2015). Dynamic pricing and learning: historical origins, current research, and new directions. Surveys in operations research and management science, 20(1), 1-18.

Fancello, G., Paddeu, D. & Fadda, P. (2017). Investigating last food mile deliveries: A case study approach to identify needs of food delivery demand. Research in transportation economics, 65, 56-66.

Holý, V., Sokol, O., & Černý, M. (2017). Clustering retail products based on customer behaviour. Applied Soft Computing, 60, 752-762.

Hosken, D., Matsa, D. & Reiffen, D. A. (2000). How do retailers adjust prices?: Evidence from store-level data. Federal Trade Commission.

Horner, S. L., Roos, C. F., von Szeliski, V., Court, A. T., & DuBrul, S. M. (1939) The Dynamics of Automobile Demand. General Motors Corporation, New York.

Kampf, G., Scheithauer, S., Lemmen, S., Saliou, P. & Suchomel, M. (2020). COVID-19-associated shortage of alcohol-based hand rubs, face masks, medical gloves, and gowns: proposal for a risk-adapted approach to ensure patient and healthcare worker safety. Journal of Hospital Infection, 105(3), 424-427.

Kephart, J. O., Hanson, J. E. & Greenwald, A. R. (2000). Dynamic pricing by software agents. Computer Networks, 32(6), 731-752.

Klenow, P. J. & Malin, B. A. (2010). Microeconomic evidence on price-setting. In Handbook of monetary economics (Vol. 3, pp. 231-284). Elsevier.

Larson, R. B. (2007). Pricing Principles from Psychology for Agricultural Organizations with Market Power. Presented at American Agricultural Economics Association Annual Meeting, Portland, OR, July 29-August 1, 2007.