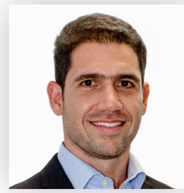
Demystifying Pricing Algorithms Using Artificial Intelligence and Machine Learning

by: Tiago Martin, CPP and Fábio Vakuda, CPP




In this article, the authors explore Artificial Intelligence, Machine Learning and Algorithms, show real examples of applications in the world of Pricing and Revenue Management, and examine the benefits, challenges, and points of caution to consider when using these "new" technologies. Tiago Martin (tmartin@quantiz.com.br) is a Certified Pricing Professional (CPP) and works as Manager Partner at Quantiz Pricing Solutions, a pricing consulting firm in Brazil. He has participated in more than 50 pricing projects in Brazil and Latin America. Fábio Vakuda, CPP (fvakuda@quantiz.com.br) is a Partner Consultant at Quantiz Pricing Solutions. He has experience in the airline Revenue Management industry and has led projects in Brazil in a variety of industries, such as agribusiness, retail, food, auto parts and real estate.

Artificial Intelligence, Machine Learning, and Algorithms. With the advancement of technology and access to more robust information, it is increasingly common to hear these terms in our daily lives. They can often seem complex and difficult to understand, but in reality, they can be applied in a simple way.

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The purpose of this article is to explain these main concepts, show real examples of applications in the world of Pricing and Revenue Management, and to examine the benefits, challenges, and points of caution to consider when using these "new" technologies.

First, what does each term mean?

Algorithm: to put it simply, an algorithm is a process with several questions and options for answers, a kind of decision tree, used to reach a solution (as if they were "if's" in an Excel formula). Algorithms divide all the possibilities of an action into several "paths" or answer options through mathematical programming. The more possibilities or scenarios there are to achieve a certain objective or solution, the more complex this algorithm can be (and the more paths it can have).

The word "algorithm" can be traced back to the Middle Ages, originating from the Persian Al-Khwarizmi, who developed the numerical system we use to this day. More recently, in the 20th century, Alan Turing and Alonzo Church, considered the fathers of computer science, formalized the concept and defined it as "an unambiguous and ordered set of executable steps that define a finite process."

Imagine that you want to decide what you will do in your free time on a Saturday morning. If it were possible to define some possibilities, the algorithm could work like this (see Figure 1):

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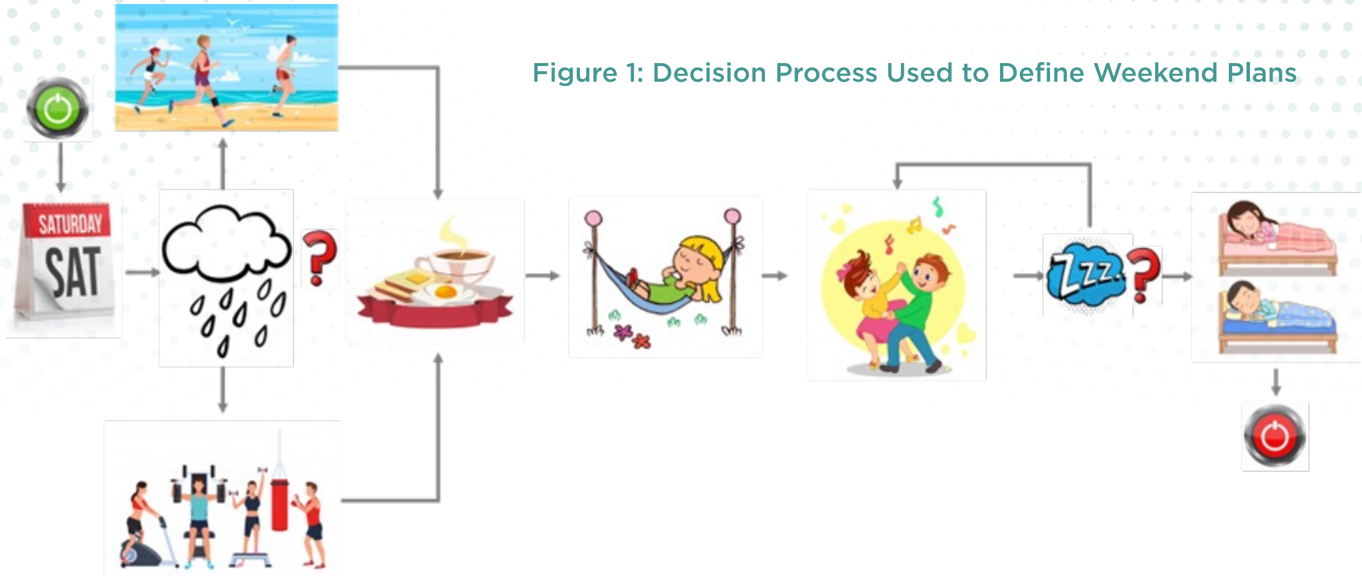

Figure 1: Decision Process Used to Define Weekend Plans

Algorithms can also be utilized considering a company's business rules. For example, in a very simplistic way, a decision to adjust price based exclusively on market share and your main competitor's prices could be drawn as Figure 2 below:

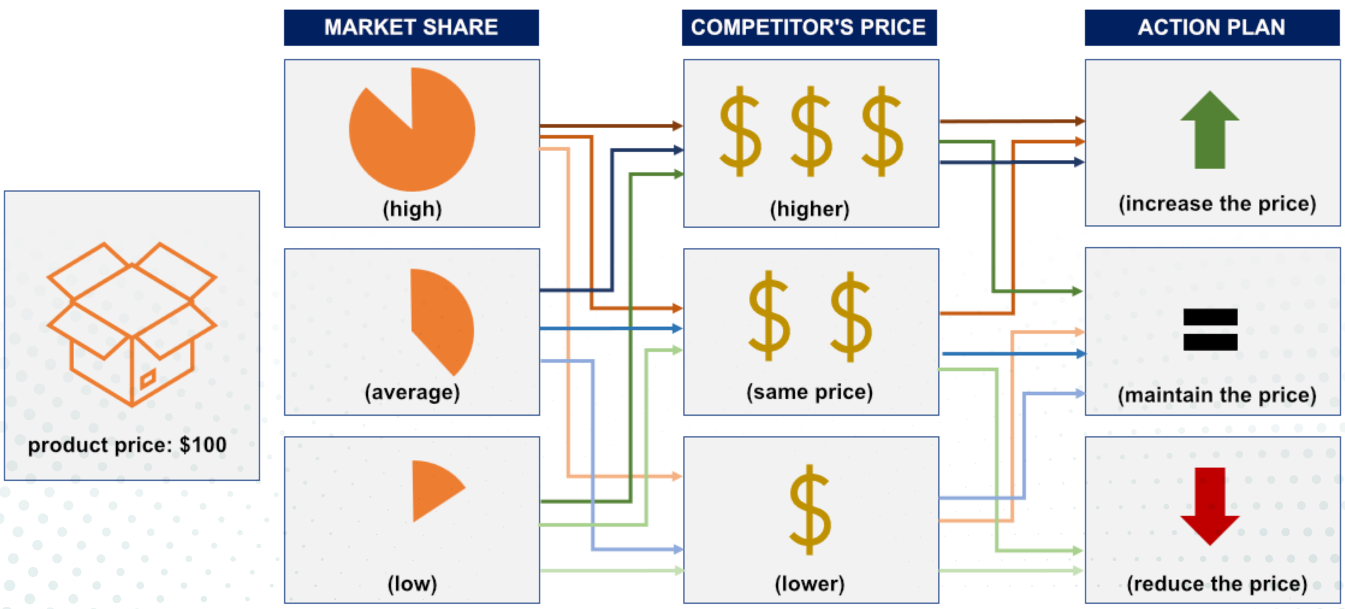

Figure 2: Decision Process According to Business Rules Based on Market Share and Competitor's Price

Artificial Intelligence and Machine Learning: Artificial Intelligence (AI) refers to systems or machines that seek to somehow imitate human intelligence in the decision-making process. Machine Learning (ML) is the transformation of the decision process into something automatic, directing decisions based on the behavior of the data and possibly improving performance as this information accumulates, without human intervention. In this way, it can be said that all ML is AI, but not all AI is ML. Algorithms are contained within both AI and ML.

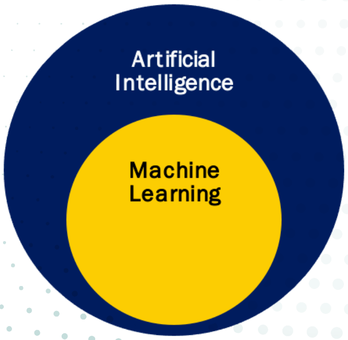

Figure 3: Machine Learning vs. Artificial Intelligence

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Within Pricing and Revenue Management, these concepts can be the set of rules used to define the price of products and services according to established criteria, optimizing, automating, and improving pricing based on the company's strategy, behavior history, and business rules.

To use AI, ML, and Algorithms in the pricing journey, it is necessary to know the company's exact goals. For example, consider that a company's objective is to automate the entire price adjustment process to capture more value and increase the company's margin. For this, it is important to ensure that the company's strategy is clear. This includes understanding the key issues of both the company and its products: (1) the role of each product category (destination, routine, convenience, or occasional), (2) the company's goal (profitability, increased market share, etc.), (3) the regions that call for direct distribution with a higher margin, and (4) the regions where it would be acceptable to have a lower margin and conduct indirect sales via a distributor. Finally, (5) understanding the product attributes that the customer values and their purchase behavior (loyal customer, price-buyer, value-seeker, or convenience buyer), among other strategic business definitions.

Identifying which criteria should be taken into account when discussing pricing decisions will

Figure 4: Pricing Definitions for Creating Algorithms

direct how prices can be changed and which profitability direction is sought. Combining this with product sales curve analysis (items with higher turnover vs. long-tail items) is a way to achieve the price that meets the objective sought in each category and each product. There are several other criteria possibilities, and they are different for each industry. With that said, it is necessary to define which criteria can be higher or lower price drivers.

The business rules that guide your company's price management should also be taken into account. That is, under what circumstances should the price be readjusted? What are the triggers for reviewing product prices? Inventory? Increase/decrease sales of a particular product? Competitors' prices? Market share gain/loss? In addition, it is necessary to understand how dynamic the company's segment is, as this will reflect on the possible frequency of product price changes. Does the market allow prices to be changed several times a day, as in many e-commerce businesses? Or, as in many more traditional industries, does the market tend to change prices only a few times during the year? The world is currently going through a period of generalized inflation and, as a result, companies have increased the frequency of price adjustments. But in addition to the adjustment for inflation (passing over costs), how often is the price adjusted? It is essential that this information is reflected in the price change logic.

Case Study: Pricing and Revenue Management Project

In recent years, we have been developing Pricing and Revenue Management projects that use this logic to improve and provide more agility in the management of companies' prices. To make it more tangible, let's use an example of an auto parts company that sells to the final consumer in physical stores and

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mainly to auto repair shops. This company has over 200,000 products and serves more than 100,000 customers in hundreds of stores across the country. In this scenario, price management work is extremely intense and challenging, as it can leave a lot of money on the table if monetization opportunities are not taken advantage of or sales are lost due to non-strategic prices.

Figure 5: Automobile Parts

To begin designing the algorithm, we divided the price positioning criteria into three pillars: Product, Customer, and Region.

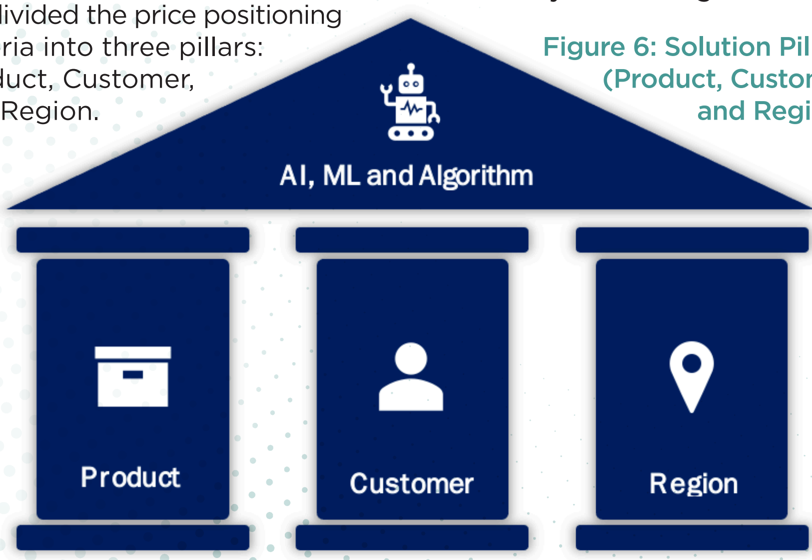

Figure 6: Solution Pillars (Product, Customer and Region)

Strategic Adjustments: Product

For the Product pillar, purchase frequency, product value, and price sensitivity (elasticity) were considered. Frequency: the products with the highest purchase frequency and quantity sold were more commoditized products with a higher level of competition, so pricing was more aggressive in these cases, and vice versa.

Product Price: Products with a very high or very low unit price also had higher or lower margins, respectively. The idea behind this attribute is that the more expensive products are, the more research the customer will conduct, so these products have to be competitively priced. On the other hand, very cheap products sold for pennies, when raised by a few cents, do not significantly impact the customer's decision, so these products were priced with a higher margin.

Elasticity: The products were divided into some elasticity levels (between more elastic and less elastic) according to the result of the log-log regression between price and volume for each product: products with lower price sensitivity lead to higher margins.

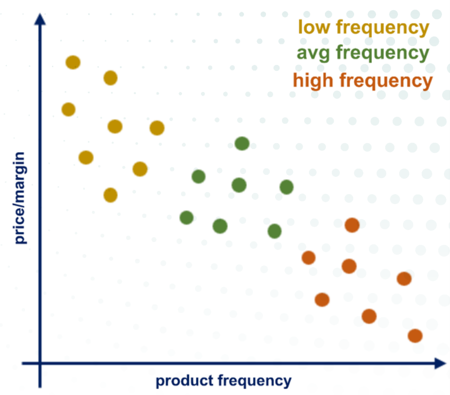

Figure 7: Frequency of Product vs. Price/Margin Used

Note that a Supervised Machine Learning "tool" was used in the pricing algorithm to find the elasticity value. (The elasticity topic deserves a separate article discussing elasticity calculation methods, regression, treatment of outliers, etc., but we will leave that for another time.)

Strategic Adjustments: Customer

For this pillar, both the channel and the customers' purchase profiles were considered.

- **Channel:** distinct positioning for the final consumer and other professional channels, such as distributors, resellers, etc.
- **Purchase Profile:** customer segments/clusters were created according to their purchase frequency and average ticket. For example, customers who buy more products, have a higher average ticket, and have a higher frequency of sales can be considered loyal customers and get different discounts. On the other hand, customers who buy few items and purchase infrequently can be considered opportunists—they probably only buy when they can't find the product in another competitor, and for those, we charge a higher price.

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Figure 8 shows an illustrative example of a 2-criteria behavior-based customer segmentation analysis using the K-means clustering method: Unsupervised Machine Learning. (Note: The clustering topic also deserves an article just on the subject. There are several methods such as K-means itself, Agglomerative Hierarchical Clustering, Fuzzy C-means, etc. Each method has advantages and disadvantages, and it is up to the team to evaluate which method best fits the clustering objective.)

Looking closely at Figure 8, based on these two chosen criteria, there are four specific purchase behaviors, which can be perceived by the four clusters created by K-means (A: low frequency, low average ticket, B: high frequency, low average ticket, C: low frequency, high average ticket, D: high frequency, high average ticket). The next step is to assess whether it makes sense to have different strategies and prices for each cluster.

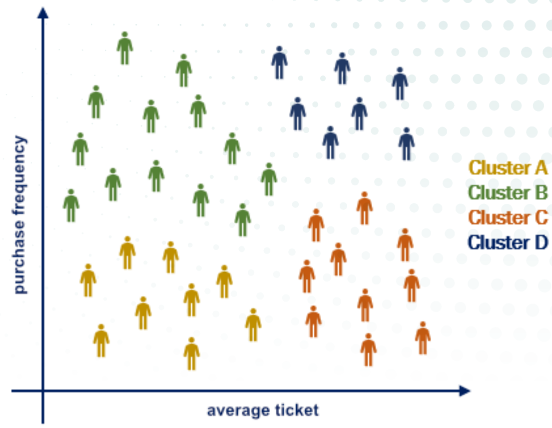

Figure 8: Customer Clustering

Strategic Adjustments: Region

Countries with continental dimensions often have very different scenarios according to the region where the client is located due to regional competition, taxation differences, logistical complexity, and even cultural differences. Therefore, customer location was also a factor considered in the pricing algorithm. In this project, the location factor was mainly a reflection of competition around each region. The regions were classified by different levels of competitiveness and the distance from the customer vs. the main competitor (the further away the competitor was and the closer the customer was, the higher the Pricing Power would be since delivery agility is an important factor in customers' purchase decisions).

Tactical Adjustments

All these factors built the basis for pricing. There is also the possibility for price adjustments based on the time of sale (time of year), high or low product stock, and discount policy within the scope of the commercial team (different discounts depending on the quantity and mix sold).

	PILLAR	ATTRIBUTES	SOLUTION
STRATEGIC	product	▪ attribute A ▪ attribute B	▪ algorithm ▪ machine learning
STRATEGIC	customer	▪ attribute C ▪ attribute D	▪ algorithm ▪ machine learning
STRATEGIC	region	▪ attribute E ▪ attribute F	▪ algorithm ▪ machine learning
TACTICAL	other adjustments	▪ attribute G ▪ attribute H	▪ algorithm ▪ machine learning

Figure 9: Macro View of the Solution

In this real case demonstration, we transformed activities and decisions that were already made in a non-standardized way into a process based on structured algorithms, Artificial Intelligence, and Machine Learning. As a result, the quality of decisions was maintained as planned without relying on manual interventions, which greatly reduces the possibility of human error. In addition, this allows the team to focus most of their time on discussing business strategy and direction instead of operational activities.

Final considerations

With the evolution of technology, increased availability of information, and increasing competition, the faster we identify opportunities for improved decision-making and business adjustments, the greater the chance of success, margin capture, and market competitiveness.

Dynamic businesses with many products, a large volume of negotiations, and several

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possibilities for price adjustments cannot be dependent on manual operations for price management. They risk failing to capture market value and, consequently, leaving money on the table.

In structures that involve more systematization and greater automation, manual intervention is purely strategic, not operational, assessing whether it makes sense to make the adjustments signaled by algorithms and artificial intelligence. In other words, we simplify the numerous combinations between product, client, and region without disregarding the appropriate strategy for each negotiation. Consequently, there is greater capture of business value. For example, the case presented in this article allows the pricing team to manage prices with more than 20,000 possible combinations and scenarios (multiplication of all pillar possibilities) in an organized and dynamic way. All attributes become levers for the pricing team, which now has greater control over the definition of the prices, in addition to enabling a more assertive identification with structured KPIs for each pillar and attribute.

The combination of the algorithm presented with Machine Learning techniques (case examples: regressions for the calculation of elasticity and k-means for clustering customers) accompanied by structured review processes guarantees the sustainability and perpetuity of the pricing structure and constant evolution of the model.