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Machine Learning and Genetic Algorithms to Improve Strategic Retail Management

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Abstract

The paper presents a case study related to a combination of artificial and natural intelligence in order to find the most effective sales strategy in retail. In particular, it proposes a solution which benefits from the combination of machine learning, genetic algorithms and simulation with a man in the loop approach to allow the decision maker to check additional proposals and to impose different constraints. The comparison of different techniques and their evaluation in terms of usability is presented.

Keywords: Machine Learning, Retail, Simulation, Strategic Management, AI

1. Introduction

The utilization of Artificial Intelligence (AI) and Machine Learning (ML) in particular is a fast growing framework which finds its application in numerous fields (Bruzzone et al., 2019a). Indeed, while the framework of interest in the past was mostly covered by high-end and high performing hardware solutions, nowadays there is a growing interest in adoption of more diffused and low-cost systems, such as home personal computers and microcontrollers (Sakr et al., 2020). At the same time, number and quality of supporting software and libraries is constantly growing (Géron, 2019). Obviously, the most critical aspects in utilization of ML are availability, completeness and quality of data to be used in training. In fact, in order to create operative ML solutions requires significant amounts of data, even if in some cases relatively small datasets could be sufficient. Nevertheless, thanks to ML, nowadays data is considered to be one of most precious resources (Dean 2014).

Considering this aspect, the authors focused their attention on the application of these advances to the field of retail as extension of previous works on this subject (Bruzzone et al., 2020). Indeed, during this phase of the research the partner companies are interested to investigate the potential of the proposed solution: the main goal is the development of an intelligent solution able to support decision makers operating in retail in order to improve sales, while providing tight coupling between machine and user. Therefore, while during the initial phase of the development the attention was mostly focused to create a fully automated solution, meanwhile, the combination of generated forecasts and suggestions with boundary conditions tuned by the expert/man in the loop became the main goal.

Another difference is that at this step of the research the usability requirements imposed tight constraints on available computational time, hence, metaheuristic algorithms are used to identify best solution within the available time frame (Bruzzone et al., 2002).

2. State of the Art

Forecasting of sales and consequently of demand and load on the logistic network was used for many years. For instance, the oldest and most simple way to do so is in calculating of the average demand and apply basic algorithms; obviously, this approach has numerous limitations, such as a total lack of seasonal effects, but it could still give an insight on expectations of the market while having very little requirements on available data. With higher quality of information and quantity of data, it could be possible to extract more accurate and useful metrics and to consider influence not only of past demand, but of seasonal effects, advertisement and marketing plans, foreseen expansion of sales network and release of new products, actions of competitors, environmental effects and even popularity and perception of certain products and services (Bruzzone et al., 2013). Nowadays it is easy to observe a growing trend in application of Artificial Intelligence in general as well as of machine learning, in particular for the situation analysis based on historical data and boundary conditions, in order to extract valuable information (Bruzzone et al., 2009). Indeed, even the data handling infrastructures are adopting to the needs of the market. For instance, constantly growing solutions are related to data acquisition and IoT, databases, analysis solutions and DataViz (Harrison, 2015; Kim et al., 2016); furthermore, in search for competitiveness companies are looking carefully also on various emerging solutions (Bruzzone et al., 2019b).

3. Proposed Solution

In this project the authors are focusing their attention on development of a decision support instrument to be used for optimization of sales and management/optimisation of promotions on different product groups along future weeks. Nowadays, this activity is often done manually which requires a significant level of experience and knowledge of the market its trends, plus an intensive workload. However, by using machine learning, it could be possible to analyze every entry related to sales in the past years and to build automatically a reliable forecast model capable to identify different trends of interest such as seasonality, weather, long term trends (e.g. preference of biological and nature-friendly products)as anadvertisement strategy, while potentially also identifying correlations previously unnoticed by the experts.

In particular, the entire process is the combination of the following macro steps:

1. Extraction of data related to past sales and offers, as well as its check and fusion.

2. Training of ML algorithm for the prediction of sales based on data from step 1.

3. Setting of boundary conditions by the user.

4. Proposal of the most suitable marketing plan.

5. Repeat of steps 3. and 4. until the user decides to keep the result.

This sequence of operations guarantees a significant advantage due to the possibility to combine strengths of Artificial and Natural Intelligence. Indeed, while AI is good in search for optimal solutions within the given boundary conditions, it is the user who defines them and who can further refine the proposals made by the machine. Furthermore, proper architecture and the choice of parameters of the system would allow to the end user to rapidly update constraints and to have fast feedback on possible results. The following figure illustrates the logical flow of the application.

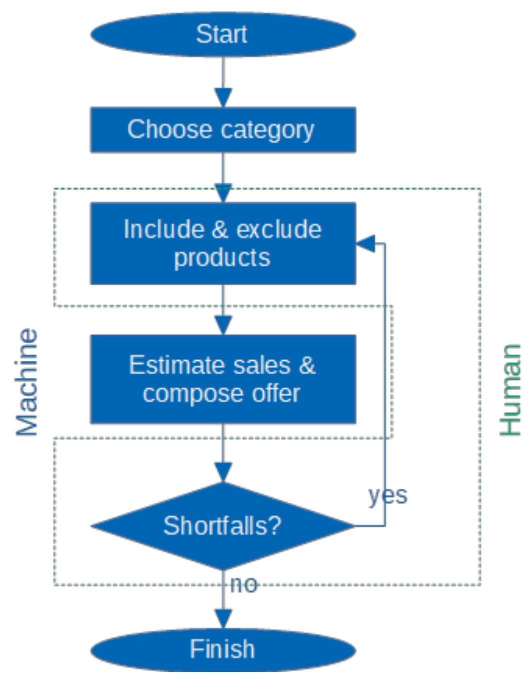

Figure 1. Workflow

Following the figure shows how the users are enabled to force a product to be in the promotion in certain week or to exclude it.

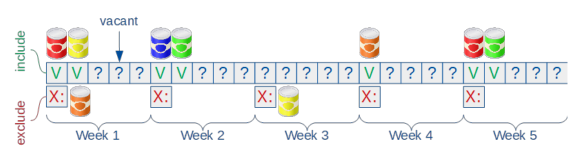

Figure 2. Blocking and forcing products by the user

In this study different methods of optimization utilized to identify the most promising solution have been evaluated in terms of efficiency. Indeed, the presence of the man in the loop and a consequent necessity to be able to perform dynamically the testing on various boundary conditions highlights the necessity of being able to generate automatically several proposals in an iterative as well as interactive way, instead of just finding the best solution starting from some fixed constraints.

This happens, for instance, when the user wishes to evaluate the performance of a completely different product with respect to a future promotion or to exclude some specific category of goods from the solution. Hence, it is necessary not only to find a well performing solution combining a mix of product groups to be promoted, but also to finalize the decision among many possible alternatives in short time to include it within the commercial-logistics processes. In addition from the point of view of usability, extended computational time would not be suitable for the truly interactive process.

4. Optimization & Experimentation

In order to create an effective man-in-the-loop solution, it is decided to conduct an experimentation in order to identify the most fitting optimization model in terms of suitability for the chosen approach.

Considering this aspect, different optimization algorithms were implemented:

- Genetic algorithm (GA)
- Adaptive stochastic optimization
- Intensive Search

In this case, the intensive search corresponds to a systematically check within the input ranges, increasing the resolution by a successive process in order to investigate the most promising area; this approach was used as reference algorithm for the estimation of required time and maximum possible value of the target function; indeed, if used in exhaustive mode, this approach is capable to find most performing solutions with a predefined resolution.In this way it is possible to check how solutions obtained by other algorithms come close to the optimal value as well as how fast they converge. In other words, it shows how faster and how much precise other solutions are. Considering that first two algorithms are metaheuristic and formal identification of their computational complexity is impractical for the estimation or for the comparison of their efficiency, experimentation on a real dataset of size comparable to the production-ready one was conducted. The goal was to identify 40 most suitable products from the pool of 2000, considering that each product has several adjustable variables and that 40 available positions are not equal in terms of sales performance, while the target function depends on exact position. Furthermore, there were imposed compatibility constraints on similar products, which should not be used in the same week promotion. The next figure illustrates the algorithm for identification of similar products. The software was implemented in Python, using proprietary Libraries of SIM4Future, while the machine learning part is done using Tensorflow library (Géron, 2019).

Regarding the platform for operating the system, a virtual machine was created with resources similar to that one expected to be available atthe end users. The target system has access to 2 virtual cores, 8GB of RAM and Nvidia CUDA-enabled GPU for speeding up the computations. Consequently, it was measured that the reference brute-force search was capable to check all possible combinations on this data set in approximately 30 minutes on the user workstation, while GA achieved comparable value of target function in 10 minutes. Finally, the adaptive stochastic algorithm was capable to find it in less than 5 minutes. In all scenarios, significant part of time, approximately 3 minutes, was required for data preprocessing and pre-calculations that could be reduced by caching among executions. Regardless specific hardware and implementation details, the possibility was confirmed to guarantee sufficiently smooth user experience, devoid from excessive waiting times.

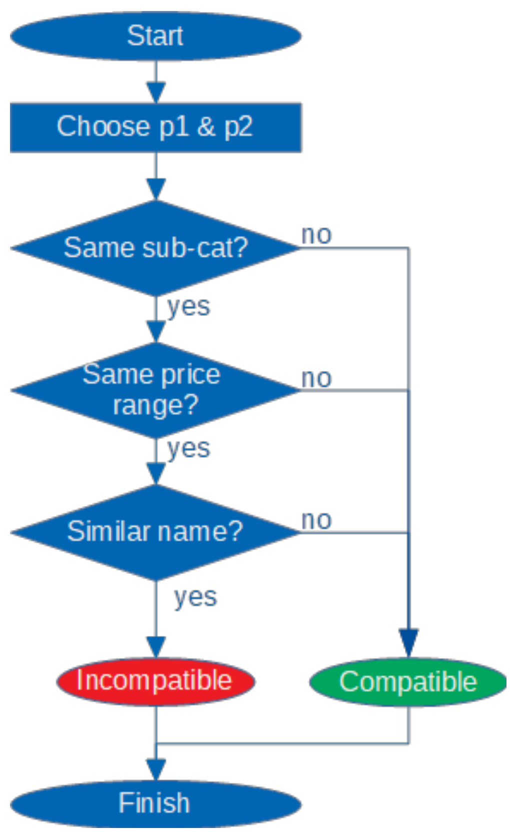

Figure 3. Identification of similar products

The approach of reduction of computational time, even with sacrifice of precision, seems to be very efficient according to the experts at the end user level. Indeed, while the idea of finding the "best" solution seems to be very attractive, in practice the end users are more interested in the possibility to have multiple "good" proposals, being able to modify them, impose new boundary conditions and perform next round of optimization. In other words, they more interested in flexibility rather to the “one” solution.

5. Conclusions

Quantity and quality of data produced by digitized activities, such as retail, constantly grows, as well as the utilization of Machine Learning. However, even if in some cases AI could play role of the decision maker, the real-world experience shows that for various critical tasks the human in the loop approach is fundamental. Considering this, the proper integration of these techniques seems to require additional attention.Indeed, some of solutions which are expected to function as decision support tools, demonstrate improvable efficiency in terms of usability. For instance, such solutions could dedicate too much time for search of the "best" solution instead of providing actual decision maker with "good" yet rapid ideas. Indeed, in this work the authors propose a system in which the user and AI combine their strengths in order to find better solution for optimization of sales While the system is still in its late development phase, the overall results seem to be very promising and overall efficiency and functionality are at high level.

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