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Decision trees for supervised multi-criteria inventory classification

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Abstract

A multi-criteria inventory classification (MCIC) approach based on supervised classifiers (i.e. decision trees and random forests) is proposed, whose training is performed on a sample of items that has been previously classified by exhaustively simulating a predefined inventory control system. The goal is to classify automatically the whole set of items, in line with the fourth industrial revolution challenges of increased integration of ICT into production management. A case study referring to intermittent demand patterns has been used for validating our proposal, and a comparison with a recent unsupervised MCIC approach has shown promising results.

Keywords: multi-criteria inventory classification; decision trees; machine learning; inventory control; intermittent demand

1. Introduction and research background

Forecasting, inventory control and MCIC represent strictly interrelated fields of research. When dealing with a huge amount of items, firms are often interested in grouping them with the aim of simplifying their management. Each class is thus managed by means either of the same inventory control system or the same forecasting technique. With regards to classification approaches oriented to the inventory control, inventory managers often associate the

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same target cycle service level (i.e. the probability of not incurring in a stock-out during a replenishment cycle) to the items belonging to the same cluster for the safety stock calculation or the same target fill rate (the percentage of demand not satisfied) or the same type of re-order policy (e.g. continuous or periodic review systems). However, current methodologies produce classification models based on criteria and threshold values that may not be adequate for the predefined set of re-order policies or cycle service levels associated with the obtained classes. This limitation has been recently underlined by [1]. In general, three ABC classes of ordered importance are defined and then inventory control policies are attached to them. These policies are negotiated with (or imposed by) the suppliers (e.g. deliveries can be done only on Fridays) and are often fixed before the classification of the items. Actually, the best service-cost assignment of items to one of the classes can be obtained by means of an exhaustive simulation search of the best policy at single item level. However, an exhaustive search is highly onerous, especially when the number of items is high. Therefore, companies prefer to use predefined criteria for the classification without running an exhaustive classification search. Historically, items are classified into three classes, ABC, according to a single criterion, which is often the usage value. The assignment is typically based on an arbitrary percentage, for example class A receives 20% of the items with the highest usage value, class B receives the next 30% and class C the remaining 50%. [2] recognised that multiple-criteria would give more precision in the definition of classes by augmenting the item characterisation. Therefore, several multi-criteria methods have been proposed for enriching the inventory classification: AHP and its extensions [3, 4, 5, 6, 7, 8]; TOPSIS [9]; the weighted linear optimisation [10, 11, 12, 13, 14, 15, 16, 17]; fuzzy logic [18]; and case-based reasoning [19, 20]. Artificial intelligence-based methods are applied as well to learn and replicate classical ABC classifications [21] or actual decision of inventory managers [22]. These last methods assume that a classification has already been produced in some way and considered correct. Once the classes have been established, a unique inventory control method (e.g. type of policy, cycle service level, fill rate and etc) is selected for all items of the same class [23]. However, there is no certitude that the criteria used for the classification are appropriate to guarantee the best performance of the inventory method. Indeed, it has been empirically shown that MCIC methods based on the annual dollar usage and the unit cost criteria have a low cost-service performance [1]. Moreover, it may be argued that different MCIC methods reach different classifications [24] when applied to the same dataset, and this trivially proves that these methods are not robust. [24] introduced new procedures for reaching the consensus among different MCIC approaches, but the relationship of the criteria with the inventory system is not even explored, and the class cardinalities are again pre-defined. [25] provided the first contribution devoted to constructing a criterion aimed to minimise the inventory cost. The calculation of this criterion is based on the probability that there is no stock out during the lead time. [26] derived another criterion which incorporates the cost of stock out. In both cases, the items are ranked and the classification is done arbitrarily with the first 20% assigned to group A, 30% to group B and 50% to group C.

As already underlined, selecting the optimal item classification and the best policy for each class can be done by an exhaustive search, but it is highly time-consuming for thousands of items. Meta-heuristics [27, 28, 29] or exact methods [30] have been proposed to solve this combinatorial problem through simplified assumptions without recurring to the exhaustive solution, but the classification still remains opaque.

In this paper, the classification rules will be generated through supervised classifiers well-established into machine learning field by starting from the exhaustive solution on a subset of items, on which the classifiers are trained. This approach bridges the gap between the theories of MCIC and inventory control when the exhaustive classification is impractical on the whole set of items, and a set of re-order policies is already defined and unchangeable. In particular, decision trees and random forests are compared as effective tools for overcoming the main concerns of MCIC, which are: i) the need for a set of predefined criteria that are not robustly linked with the inventory control system; ii) the predefined cardinalities of the generated classes defined a priori without any justification.

Among the machine learning techniques available for classification purposes, decision trees and random forests have been selected for theoretical simplicity and readability of the results. The connection between input features and obtained results in other methods, such as neural networks and non-linear SVM, is harder to analyse. Examining a decision tree it is possible to rank the splits and obtain a visual representation of what features are the most impacting in the classification process. Said features can be monitored by the management with the controlling unwanted shifts towards categories more expensive to manage. For the intermittent spare parts related to new