Automatic Detection of Out-Of-Shelf Products in the Retail Sector Supply Chain

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Abstract: The problem of products missing from the shelf is a major one in the grocery retail sector, as it leads to lost sales and decreased consumer loyalty. Yet, the possibilities for detecting and measuring an out-of-shelf situation are limited, mainly conducted via a physical shelf check. The existence of an automatic method for detecting the products that are not on the shelf based on sales data would thus be valuable, offering an accurate view of the shelf availability both to retailer and the product suppliers. In this paper, an information system is proposed in order to detect (thus measure) products that are not on the shelf. The proposed method is a rule-based information system as iteratively developed by the utilization of Machine Learning techniques. Through the comparison of the proposed method with an existing approach called OOS Index, we draw some results regarding the detection capabilities each method has. Results up to now present that rules related with detection of the out-of-shelf products are characterized by acceptable levels of predictive accuracy and problem support.

1. Introduction

Consumer value and satisfaction are fundamental to building consumer loyalty (to the brand) and shopper loyalty (to the store) and to increase sales and category profitability (Colacchio et al, 2003). A powerful way to create value and satisfaction is to keep shelves fully ranged (Roland Berge, 2002), but out-of-shelf (OOS) is still a frequent phenomenon in the grocery retail sector. Out-of-shelf rates vary wildly among retailers and their outlets depending on a variety of factors, but the majority tends to fall in the range of 5-10 percent. In their analysis, which is a compilation of many global surveys on the extent, causes, and consumer responses to retail out-of-shelf situations in the grocery retail sector, Gruen et al. (2002) estimate an overall average OOS rate of 8.3 percent.

However, in most European countries levels between 10 and 15 percent are not unusual (Roland Berger, 2003). Emmelhainz et al.'s (1991) research results show, for instance, that a stock-out can make a manufacturer lose more than half of his buyers to competitors, whereas retailers face the loss of up to 14% of the buyers of the missing product. This revenue loss (approximates 1.5% of sales) not only stems from lost product sales during the OOS period, but can also extend to later periods or other product categories (Campo et al. 2000).

In this paper, we investigate the possibility of developing a method that detects the OOS products, utilizing AI techniques. In more detail, having available the sales data, ordering info, product assortment of the store etc. we study the development of a rule based system that will automatically discover OOS situations on a daily basis for all the stores of a retail chain. In the following section a detail presentation

The paper is structured as follows. Section 2 provides a brief overview of the Out-Of-Shelf problem as reported by empirical research. Section 3 presents some alternatives methods for the automatic detection of the OOS problem, including the proposed method. In Section 4 a brief comparison is provided between the proposed system and an existing methods, utilizing real data.

2. The Out-Of-Shelf problem

This section describes in brief the problem of Out-Of-Shlef as it had been recognized in the retail sector mainly by empirical investigation. The causes of the problem are included in the daily operation of a typical supply chain and it is amplified by the demand uncertainty for the products. Measuring the intense of the problem is mainly a management consideration, while the physical store audits are not a sufficient tool to cover the need.

2.1 Causes of the Out-Of-Shelf Problem

The term "*out-of-shelf*" (OOS) is used in grocery retailing to describe the situation where a consumer does not find the product he/she wishes to purchase on the shelf of a supermarket during a shopping trip. Despite the extended literature on consumer reactions to out-of-shelf situations, very little has been written on the reasons behind the problem. In the relevant texts that are available (which are fairly sparse and largely empirical), we see a classification of the causes of OOS into two major areas (Gruen et al., 2002; Vuyk, 2003):

- *Retail store replenishment causes*, i.e. the product was not ordered or the ordered quantity was not enough to meet the actual consumer demand. Apart from the ordering parameters this category also implies and the shelving replenishment practices utilized by the store. (e.g. shelf-space allocation, shelf-replenishment frequencies, store personnel capacity etc.)

- *Combined upstream causes*, referring to the product was not delivered due to out-of-stock situations or other problems with the retailer's distribution centre (for centralized deliveries) or the supplier (for direct-store-deliveries). Other upstream causes are the delivery of the wrong product, and the delivery of smaller quantity of products.

The OOS covers the cases where the product exists in the store (so it is not out-of-stock), but it is not placed in the right position on the shelf where the consumer can find it (it is, for example, in the store's back-room or delivery facilities). However, the term *"stock-out"* (or *"out-of-stock"*) is used in the pertinent literature to describe both the situations where the product does not exist in the store or in the warehouse and the situations where the product is not on the shelf (so it is a "shelf out-of-stock"). In general a Stock Out certainty implies an OOS situation, while the opposite is not always stands. An OOS occurs more frequently than a Stock Out and it is rather difficult to capture it. On the one hand the Stock Out problem has been investigated in the area of Inventory Management for over thirty years and several models has been presented. On the other hand, the OOS problem is mainly discussed in the marketing literature from the consumer reaction perspective (Campo et al. 2000).

In brief various variables had been identified to affect product availability on the shelf. For example Anupindi et al (1998) argues that Sales Velocity determines product availability. According to Clark and Lee (2000) product availability is an issue of Inventory Levels. A more qualitative perspective is provided by various researches (Yang, 2001; Desmet et al, 1998; Corstjens and Corstjens, 1999) who examined product availability as an issue of the shelf layout.

2.2 Complexity of the Out-Of-Shelf problem: Measurement considerations

The recognition of OOS as a major problem in the retail sector has been based on the measurement of the phenomenon. All the available studies have been based on physical store audits, where a researcher visits the retail outlet and reports the status of the product or the status of the shelf. From the empirical point of view, availability (and consequently the OOS rate) might be determined in two different ways:

1. Measurement of ***product availability*** by determine whether a product is (or not) on the shelf.
2. Measurement of ***shelf availability*** through the identification of how many items are on the shelf divided by how many items could exist on the shelf when it is fully replenished.

The first (and most popular) method examines if the product is on the shelf regardless of the number of available units. Thus every product is characterized by a binary state (e.g. EXISTS or OOS). By summarizing the frequency of OOS observations, we get the OOS rate.

The shelf availability measurement method is slightly different since it assumes that a specific shelf space is allocated to a single product and the idea is to estimate the load of this shelf space. Thus, the result of this measurement method is a continuous variable (shelf availability) ranging from full OOS (shelf availability = 0%) to a full shelf (shelf availability = 100%).

Due to the nature of retail store operations (e.g. the concurrent execution of shelf replenishment by the store personnel and the consumers' shopping) the product/shelf availability might change during the day. In order to overcome such an issue, it is possible to measure product/shelf availability more than once during the working hours of the store (e.g. measure product/shelf availability in the morning and again during the evening). Although repeated measurements could provide a more accurate insight of the product/shelf availability levels, the measurement frequency is subject to cost constraints.

In practice the measurement of OOS is sometimes an ambiguous task since it involves many contextual factors. Indicative factors are:

- **Shelf-layout related factors:** Consider that a product is on the shelf but is not visible to the consumer (e.g. at the top of the shelf) or the product is in the store but at a different position than what the consumer expected (e.g. at a promotional stand). This means that the consumer would assume that the product is not available. However, the researcher would strive to report correctly the status of the product on the shelf.

- **Human related factors**: This refers to the fact that behavior of the store manager and the rest of the store personnel changing, when conducting a shelf availability study in the store. Usually, the store manager interacts with the researcher and the products marked as OOS in the store. As a response to this, the store managers takes care that the missing products are ordered and replenished as soon as possible. Moreover the store personnel increase their commitment and replenish the shelf more frequently. In other words, when conducting store audits the reported results tend to present a more effective picture of shelf/product availability than on the normal days.
- **Cost related factors:** Due to budget constraints most of the product/shelf availability studies monitor a sample product list for a limited number of stores in a specific time window. Thus the study dose not addresses the dynamic changing states of the shelf for various product categories, but only provides a snapshot of what was the situation when the researcher visited the store.

The above factors give an indication of the various obstacles that exist in acquiring accurate and timely information regarding the intension of the OOS problem. Thus, it is a crucial requirement for the retail sector to have a single and uniform method that estimates product availability without having to conduct physical store audits, what we describe in the following as call automatic detection approaches (or methods).

3. Approaches for the automatic detection of the OOS

A first approach for the automatic detection of the OOS is the use of ***Radio-Frequency Identification*** (RFID) technology. Using item-level RFID tags and several readers throughout the store it would be possible to track and locate every single item, thus determining product availability. However this enabling technology is not fully functional yet at this level and it is expected that it will take several more years before item-level tagging is widely adopted by the industry.

A second approach has been proposed by ECR Europe and is referred as the ***OOS Index*** (or European OOS Index - EOI) (Hausruckinger, 2006). Taking into account only fast moving items with low sales volatility, the OOS Index monitors on a daily basis the sales of the corresponding products; if for a given day such product sells zero items (or lower than a predefined ceiling) then it is consider to be OOS. The problem that the OOS Index has is that it is relevant for only a very limited number of products, normally less than 5% of a typical assortment.

A third proposition, which is further explained in the next section, suggests the automatic detection of OOS products based on a ***Rule-Based System***. The system takes into account information that is currently available in any retail information system (e.g. POS data, orders, product assortment etc) and according to some rules, it detects products missing from the shelf. The rules are drawn from previous known OOS examples, collected from physical store audits, and are extracted through several Machine Learning algorithms (part of Artificial Intelligence).

3.1 The rule-based information system

The proposed rule-based information system had been developed for a large size retail chain in Greece. This retail chain has more than 160 retail stores, uses new technologies to support the operational level and in general, is engaged with many ECR initiatives. The request was to conduct research and develop an information system missing from the shelf based on information currently existing in the retail information system. The project started in the beginning of 2004 and several alternative approaches were examined. After many experimentations, we concluded that a rule based system is the most appropriate class of information system to cover such a requirement.

The system that resulted from this research consists of three main modules. These are:

- *Data Consistency Module*: This is the module that communicates with the existing retail information system and gathers the required data on a daily basis. The module incorporates heuristic methods and integrity checks to remove noise from the data.
- *Attribute Measurement Module*: This modules implements all the required processes in order to calculate the attributes for every product (e.g. average sales, days to sell etc).
- *Inference Module*: The last module hosts the OSS detection rules and applies them to all the products in order to identify the OOS ones.

Figure 1 gives an overview of the detection system ISOS (Information System Out of Shelf).

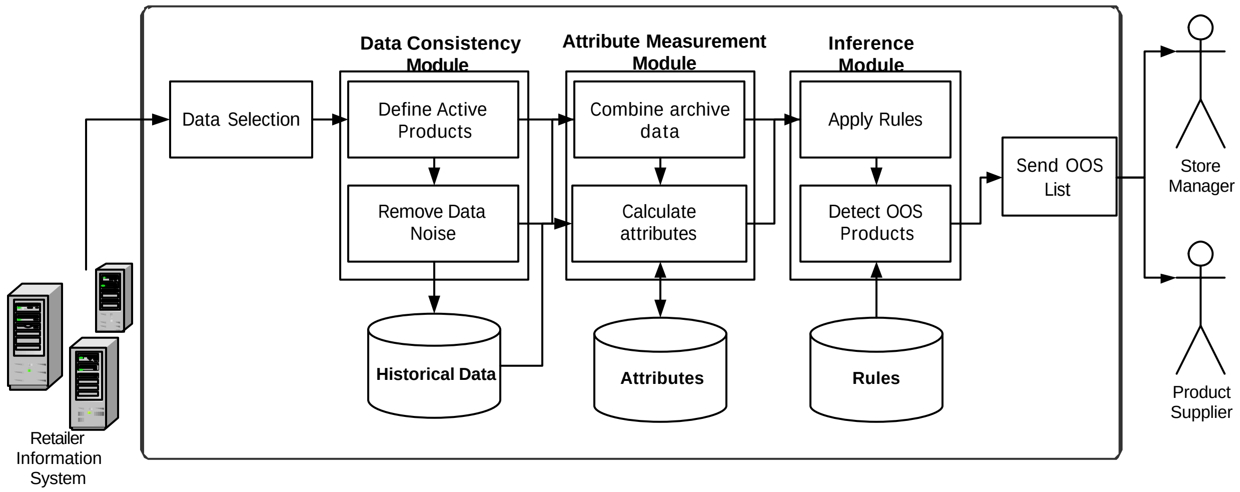


Figure 1 The Architecture of ISOS

At the end of the day the ISOS system retrieves the available data from the retailer information system. These include: Sales (POS) data, orders / deliveries, product assortment per store etc. The system handles every product at SKU (Store Keeping Unit) level. For every product several attributes are calculated and updated daily (e.g. sales average, sales averages per day, days without selling an item). Then the OOS-detection rules (having the form "IF ….. THEN") are applied. If the attributes of a product fire a rule, then the system classifies it as OOS.

Thus the most critical part of the system is the development of the appropriate rules. For this task, two are the main options

a) Use expert opinion to build a rule-set
b) Let the machine decide

The OOS Index is an example of a rule developed based on expert opinion and has the following form in general: "IF (*a product is fast-moving*) AND (*has low sales volatility*) AND (*POS sales = 0 for today*) THEN the product is OOS".

The other option (machine) necessitates the existence of several learning examples (both OOS and EXISTS) from the real world. Feeding these examples into appropriate classification algorithms, it is possible to extract several rules based on similar patterns that OOS examples have. These rules are then used to predict the status of product availability for new and unknown examples. This approach is called Heuristic Classification and is a well-known method in the area of Intelligent Information Systems and used widely in fraud-detection systems, anti-spamming software etc.

4. Exploring the detection capabilities and comparison with the OOS Index

The rule based system was initially developed (ISOS ver.1) and after several tests was further extended with new rules and attributes resulting into a new system (ISOS ver. 2). The next table summarizes the characteristics of these two different versions of ISOS.

System Version	**Number of rules**		**Attributes Supported**	**History of data used**
	Before Validation	After Validation		
ISOS ver. 1	127	35	19	6-Month
ISOS ver. 2	154	58	22	6-Month and 14-Month

Table 1Different Versions of the ISOS system

The backbone of the ISOS system is the inference engine as composed by the rules. The ISOS ver.1 initially had 127 different rules and after the validation procedure we kept only 35 in order to fine-tune the detection effectiveness of the system. These 35 rules were embedded in the next version of the ISOS together with new rules added. The ISOS ver. 2 was initially designed with 154 different rules and after the validation we have chosen 58 rules.

Each version was compared to the detection capabilities of OOS Index based on results of physical store audits. At the beginning of the day we activated both ISOS and OOS Index to create OOS product lists, which had all the OOS cases according to the detection rules. We then moved to

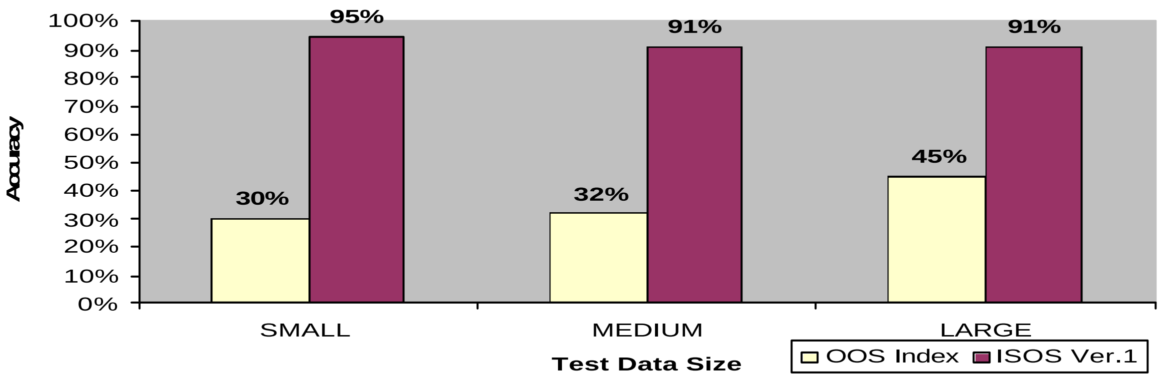
the stores and checked whether these predictions were right or wrong. The result of such a process was the creation of one data set with 1800 examples of OOS products. By adding many EXISTS examples (15.000) we created the “Small” Test Set (in total 17.000). Through the incorporation of data analysis techniques we had the opportunity to expand the “Small” test set and create two additional test sets, namely “Medium” and “Large”. These are the basis for comparing the two detection approaches. The comparison of the detection approaches was based on two complementary criteria (or measures) : (a) accuracy and
(b) support as explained below

Accuracy describes how many times the system correctly identifies OOS products. High accuracy (>80%) means that the system makes the right prediction in most of the cases (i.e. detects an OOS product) and dose not misclassify as OOS a product existing on the shelf. Thus it is required that the detection scheme has as high an accuracy value as possible. An accuracy of 100% means that the detection scheme always makes the right judgment in detecting OOS products. The next figure presents the accuracy for OOS Index versus ISOS Ver.1

between OOS Index and ISOS

It is easy to observe that the accuracy of the OOS Index is much lower than that of ISOS Ver.1. We examined the accuracy for three different test data sets (small, medium and large size). In all the cases the accuracy of OOS Index was below 50%, which meant that half of the products OOS Index detected (proposed) were really OOS cases (so the rest were just wrong predictions). The ISOS Ver.1 system seemed to perform much better with more than 90% accuracy. Note that the accuracy of the ISOS Ver.1 has been calculated after the validation phase and was based on the 35 effective rules.

Another important aspect of assessing the detection capabilities relates to the scope of the solution. This is translated into measuring how many OOS products the system detects from all the existing OOS cases, and we call this measure support (or coverage). For example, if during a day there are 100 OOS products and the system identifies only 40, then the support measure is defined as 40%. Profoundly we desire to have high support from the detection system in order to ensure that all the OOS products are captured.



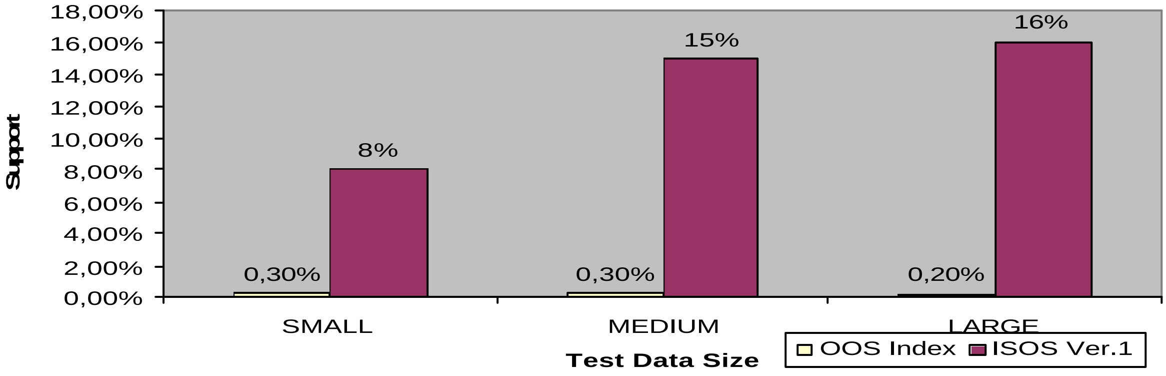


Figure 2 Comparison of Accuracy and Support

Profoundly we desire to have high support from the detection system in order to ensure that all the OOS products are captured. However, figure 1 compares OOS Index and ISOS Ver.1 based on the support measure. We see from the figure that the OOS Index has very limited scope. Specifically the test data sets contained between 1.800 and 3.000 different OOS examples and the OOS Index could detect less than 60 of them. Thus, the support measure for the OOS Index comparatively very low.

The main problem with OOS Index is the inability to cover most of the OOS cases. Indeed from our experimental data we found that the most frequent cases of OOS are not happening in the fast moving items, but in the area of slow moving products. Usually the store manager dose not forgets to order milk, sugar or coffee because of the routine. In addition usually the stores are keeping safety stocks for these items in order to minimize ordering cost. We argue that the main problem of OOS is on the slow moving items. Targeting the OOS cases for high selling items has the drawback to lose the most frequent OOS products, which belongs in the group of slow moving items. Additionally the fast moving items are visible in the store because they are holding big space, so if one product is not shelf then the employees could easily detect it. Thus if the detection system works daily the information about the OOS for a fast moving items might be worthless, since it is already known at the store level. Fast moving items are important from a sales perspective and we argue that the automatic detection should be conducted in an hour basis only for this class of products.

On behalf ISOS Ver. 1 captured more OOS products, but we still consider the performance low. According to the calculations the ISOS Ver. 1 was able to detect approximately 15% of the OOS products occurring daily in a store. This means that the remaining 85% are not able detectable, so we started thinking approaches to increase the support of the solution. This efforts lead to the ISOS Ver.2.

The improvements were concentrated mainly in the detection capabilities. These was achieved by the followings activities

- Adopt new rules.
- Design new attributes and remove redundant.
- Better handling of information quality issues.
- Increase history data from 6-month to 14-month

A crucial issue during the development of ISOS Ver.2 had been the selection of the appropriate data. On the one had few mechanisms to remove noise incorporated while on the other hand we decide to increase the time horizon of data (POS, Ordering Info) with the expectation that the larger set of data used, the better measurement is achieved for the attributes and consequently a more accurate inference engine will be build. This decision push the development of two different instances of the same system: (a) ISOS Ver.2 (6-month) and (b) ISOS Ver.2 (14-Month).

The next table summarizes all four detection mechanisms that had been examined and provide the .

Detection Mechanism	*ISOS Ver.1*	*OOS Index*	*ISOS Ver.2. (6-month)*	*ISOS Ver.2. (14-month)*
Accuracy	95%	32%	92%	94%
Support	15%	0.3%	27%	18%

Table 2 Overview of detection capabilities for all the mechanisms presented

ISOS as a detection approach seems to achieve high levels of accuracy, which means that the system correctly predicts OOS products. However all the detection mechanisms could not cover all the different OOS cases occurring in the store, thus the low levels of support measure are observed. ISOS system is build upon iterative procedure and we have strong indications that with large scale trials the system might cover more than 35% of the OOS products in the store with small error (or high accuracy).

Last but not least had been the development of ISOS system for another retail chain in Greece. We conducted almost identical physical audits, we analyzed data with the same procedure but we got different rules and results. The observed differences are subject to the practices and the management style of the stores. In more detail the one retail chain utilizes a modern ordering Web based system, while the other supports the stores from a semi-automatic ordering system resulting to different Out-of-Shelf rates. In addition we noted differences in the ordering policy of the stores, in the communication between headquarters and the store, the collaboration with suppliers and the employee's culture between the retail chains. Although these factors placed in the macro level of the firms, they affect store operations and in particular store replenishment and shelf replenishment processes. Consequently we suggest that the rules deployed in the context of a retail chain might not be transferable in general to another retail chain.

5. Conclusions

Analytical approaches like Inventory Control or Demand Forecasting could be the basis for development solutions for the detection of OOS products. However some important assumptions could not be met in the retail environment (e.g. the information sources of inventory are not accurate, the sales of a product could not fit a statistical distribution), thus a convenient and flexible approach could be delivered from a heuristic approach.

Heuristic approach resulting to a rule based system could not guarantee an optimal solution and it requires continuous development of the detection system. The initialization of such effort is crucial because few decisions had to been made (e.g. which are the appropriate methods of classification, which are the most relevant attributes, how to increase quality of the available data etc). While new versions of the detection system launch, new more effective solutions are created. The challenge is to reach a solution with an appropriate trade off between accuracy and support. From our experiments we found that with accuracy greater than 90% the system is able to detect about 27% of the OOS cases occurring daily in the store.

Taking into account the OOS cases where the detection occurs before the expected next sale, we are able to calculate the economic impact of the system. In more detail taking into account the how many cases are detected, how many of them are detected timely and the assuming that the consumer response to a stock out is about 9%, it is possible to estimate that the retail chain would increase sales by 0.37%. Note that this is the lowest and most conservative estimate because we didn't take into account long term benefits occurred by consumer loyalty.

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