

# A Data Mining Framework for Optimal Product Selection in Retail Supermarket Data: The Generalized PROFSET Model

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## Abstract

In recent years, data mining researchers have developed efficient association rule algorithms for retail market basket analysis. Still, retailers often complain about how to adopt association rules to optimize concrete retail marketing-mix decisions. It is in this context that, in a previous paper, the authors have introduced a product selection model called PROFSET.<sup>1</sup> This model selects the most interesting products from a product assortment based on their cross-selling potential given some retailer defined constraints. However this model suffered from an important deficiency: it could not deal effectively with supermarket data, and no provisions were taken to include retail category management principles. Therefore, in this paper, the authors present an important generalization of the existing model in order to make it suitable for supermarket data as well, and to enable retailers to add category restrictions to the model. Experiments on real world data obtained from a Belgian supermarket chain produce very promising results and demonstrate the effectiveness of the generalized PROFSET model.

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<sup>1</sup>PROFSET stands for PROFitability per SET because the optimization model is based on the calculation of the profitability per frequent set in order to determine the cross-selling potential between products.

# 1 Introduction

Since almost all mid to large size retailers today possess electronic sales transaction systems, retailers realize that competitive advantage will no longer be achieved by the mere use of these systems for purposes of inventory management or facilitating customer check-out. In contrast, competitive advantage will be gained by those retailers who are able to extract the knowledge hidden in the data, generated by those systems, and use it to optimize their marketing decision making. In this context, knowledge about how customers are using the retail store is of critical importance and distinctive competencies will be built by those retailers who best succeed in extracting actionable knowledge from these data. Association rule mining [2] can help retailers to efficiently extract this knowledge from large retail databases. We assume some familiarity with the basic notions of association rule mining.

In recent years, a lot of effort in the area of retail market basket analysis has been invested in the development of techniques to increase the interestingness of association rules. Currently, in essence three different research tracks to study the interestingness of association rules can be distinguished.

First, a number of objective measures of interestingness have been developed in order to filter out non-interesting association rules based on a number of statistical properties of the rules, such as support and confidence [2], interest [14], intensity of implication [7], J-measure [15], and correlation [12]. Other measures are based on the syntactical properties of the rules [11], or they are used to discover the least-redundant set of rules [4]. Second, it was recognized that domain knowledge may also play an important role in determining the interestingness of association rules. Therefore, a number of subjective measures of interestingness have been put forward, such as unexpectedness [13], actionability [1] and rule templates [10]. Finally, the most recent stream of research advocates the evaluation of the interestingness of associations in the light of the micro-economic framework of the retailer [9]. More specifically, a pattern in the data is considered interesting only to the extent in which it can be used in the decision-making process of the enterprise to increase its utility.

It is in this latter stream of research that the authors have previously developed a model for product selection called PROFSET [3], that takes into account both quantitative and qualitative elements of retail domain knowledge in order to determine the set of products that yields maximum cross-selling profits. The key idea of the model is that products should not be

selected based on their individual profitability, but rather on the *total* profitability that they generate, including profits from cross-selling. However, in its previous form, one major drawback of the model was its inability to deal with supermarket data (i.e., large baskets). To overcome this limitation, in this paper we will propose an important generalization of the existing PROFSET model that will effectively deal with large baskets. Furthermore, we generalize the model to include category management principles specified by the retailer in order to make the output of the model even more realistic.

The remainder of the paper is organized as follows. In Section 2 we will focus on the limitations of the previous PROFSET model for product selection. In Section 3, we will introduce the generalized PROFSET model. Section 4 will be devoted to the empirical implementation of the model and its results on real-world supermarket data. Finally, Section 5 will be reserved for conclusions and further research.

## 2 The PROFSET Model

The key idea of the PROFSET model is that when evaluating the business value of a product, one should not only look at the individual profits generated by that product (the naïve approach), but one must also take into account the profits due to cross-selling effects with other products in the assortment. Therefore, to evaluate product profitability, it is essential to look at frequent sets rather than at individual product items since the former represent frequently co-occurring product combinations in the market baskets of the customer. As was also stressed by Cabena et al. [5], one disadvantage of associations discovery is that there is no provision for taking into account the business value of an association. The PROFSET model was a first attempt to solve this problem. Indeed, in terms of the associations discovered, the sale of an expensive bottle of wine with oysters accounts for as much as the sale of a carton of milk with cereal. This example illustrates that, when evaluating the interestingness of associations, the micro-economic framework of the retailer should be incorporated. PROFSET was developed to maximize cross-selling opportunities by evaluating the profit margin generated per frequent set of products, rather than per product. In the next Section we will discuss the limitations of the previous PROFSET model. More details can be found elsewhere [3].

## 2.1 Limitations

The previous PROFSET model was specifically developed for market basket data from automated convenience stores. Data sets of this origin are characterized by small market baskets (size 2 or 3) because customers typically do not purchase many items during a single shopping visit. Therefore, the profit margin generated per frequent purchase combination ( $X$ ) could accurately be approximated by adding the profit margins of the market baskets ( $T_j$ ) containing the same set of items, i.e.  $X = T_j$ . However, for supermarket data, the existing formulation of the PROFSET model poses significant problems since the size of market baskets typically exceeds the size of frequent itemsets. Indeed, in supermarket data, frequent itemsets mostly do not contain more than 7 different products, whereas the size of the average market basket is typically 10 to 15. As a result, the existing profit allocation heuristic cannot be used anymore since it would cause the model to heavily underestimate the profit potential from cross-selling effects between products. However, getting rid of this heuristic is not trivial and it will be discussed in detail in Section 3.1.

A second limitation of the existing PROFSET model relates to principles of category management. Indeed, there is an increasing trend in retailing to manage product categories as separate strategic business units [6]. In other words, because of the trend to offer more products, retailers can no longer evaluate and manage each product individually. Instead, they define product categories and define marketing actions (such as promotions or store layout) on the level of these categories. The generalized PROFSET model takes this domain knowledge into account and therefore offers the retailer the ability to specify product categories and place restrictions on them.

## 3 The Generalized PROFSET Model

In this section, we will highlight the improvements being made to the previous PROFSET model [3].

### 3.1 Profit Allocation

Avoiding the equality constraint  $X = T_j$  results in different possible profit allocation systems. Indeed, it is important to recognize that the margin of transaction  $T_j$  can potentially be allocated to different frequent subsets of

that transaction. In other words, how should the margin  $m(T_j)$  be allocated to one or more different frequent subsets of  $T_j$ ?

The idea here is that we would like to know the purchase intentions of the customer who bought  $T_j$ . Unfortunately, since the customer has already left the store, we do not possess this information. However, if we can assume that some items occur more frequently together than others because they are considered complementary by customers, then frequent itemsets may be interpreted as purchase intentions of customers. Consequently, there is the additional problem of finding out which and how many purchase intentions are represented in a particular transaction  $T_j$ . Indeed, a transaction may contain several frequent subsets of different sizes, so it is not straightforward to determine which frequent sets represent the underlying purchase intentions of the customer at the time of shopping. Before proposing a solution to this problem, we will first define the concept of a maximal frequent subset of a transaction.

**Definition 1.** Let  $F$  be the collection of all frequent subsets of a sales transaction  $T_j$ . Then  $X \in F$  is called *maximal*, denoted as  $X_{max}$ , if and only if  $\forall Y \in F : |Y| \leq |X|$ .

Using this definition, we will adopt the following rationale to allocate the margin  $m(T_j)$  of a sales transaction  $T_j$ .

If there exists a frequent set  $X = T_j$ , then we allocate  $m(T_j)$  to  $M(X)$ , just as in the previous PROFSET model. However, if there is no such frequent set, then one maximal frequent subset  $X$  will be drawn from all maximal frequent subsets according to the probability distribution  $\Theta_{T_j}$ , with

$$\Theta_{T_j}(X_{max}) = \frac{\text{support}(X_{max})}{\sum_{Y_{max} \in T_j} \text{support}(Y_{max})}$$

After this, the margin  $m(X)$  is assigned to  $M(X)$  and the process is repeated for  $T_j \setminus X$ . In summary:

Table 1: Frequent Subsets of  $T_{100}$ 

Frequent Sets	Support	Maximal	Unique
{cola}	10%	No	No
{peanuts}	5%	No	No
{cheese}	8%	No	No
{cola, peanuts}	2%	Yes	No
{peanuts, cheese}	1%	Yes	No

```

for every transaction  $T_j$  do {
  while ( $T_j$  contains frequent sets) do {
    Draw  $X$  from all maximal frequent subsets
    using probability distribution  $\Theta_{T_j}$ ;
     $M(X) := M(X) + m(X)$ 
    with  $m(X)$  the profit margin of  $X$  in  $T_j$ ;
     $T_j := T_j \setminus X$ ;
  }
}
return all  $M(X)$ ;

```

Say, during profit allocation, we are given a transaction

$$T = \{\text{cola, peanuts, cheese}\}.$$

Table 1 contains all frequent subsets of  $T$  for a particular transaction database. In this example, there is no *unique* maximal frequent subset of  $T$ . Indeed, there are two maximal frequent subsets of  $T$ , namely {cola, peanuts} and {peanuts, cheese}. Consequently, it is not obvious to which maximal frequent subset the profit margin  $m(T)$  should be allocated. Moreover, we would not allocate the entire profit margin  $m(T)$  to the selected itemset, but rather the proportion  $m(X)$  that corresponds to the items contained in the selected maximal subset.

Now how can one determine to which of both frequent subsets of  $T$  this margin should be allocated? As we have already discussed, the crucial idea here is that it really depends on what has been the purchase intentions of the customer who purchased  $T$ . Unfortunately, one can never know exactly

since we haven't asked the customer at the time of purchase. However, the support of the frequent subsets of  $T$  may provide some probabilistic estimation. Indeed, if the support of a frequent subset is an indicator for the probability of occurrence of this purchase combination, then according to the data, customers buy the maximal subset {cola, peanuts} two times more frequently than the maximal subset {peanuts, cheese}. Consequently, we can say that it is more likely that the customer's purchase intention has been {cola, peanuts} instead of {peanuts, cheese}. This information is used to construct the probability distribution  $\Theta_{T_j}$ , reflecting the relative frequencies of the frequent subsets of  $T$ . Now, each time a sales transaction {cola, peanuts, cheese} is encountered in the data, a random draw from the probability distribution  $\Theta_{T_j}$  will provide the *most probable* purchase intention (i.e. frequent subset) for that transaction. Consequently, on average in two of the three times this transaction is encountered, maximal subset {cola, peanuts} will be selected and  $m(\{\text{cola, peanuts}\})$  will be allocated to  $M(\{\text{cola, peanuts}\})$ . After this,  $T$  is split up as follows:  $T := T \setminus \{\text{cola, peanuts}\}$  and the process of assigning the remaining margin is repeated as if the new  $T$  were a separate transaction, until  $T$  does not contain a frequent set anymore.

### 3.2 Category Management Restrictions

As pointed out in Section 2.1, a second limitation of the previous PROFSET model is its inability to include category management restrictions. This sometimes causes the model to exclude even all products from one or more categories because they do not contribute enough to the overall profitability of the optimal set. This often contradicts with the mission of retailers to offer customers a wide range of products, even if some of those categories or products are not profitable enough. Indeed, customers expect supermarkets to carry a wide variety of products and cutting away categories/departments would be against the customers' expectations about the supermarket and would harm the store's image. Therefore, we want to offer the retailer the ability to include category restrictions into the generalized PROFSET model.

This can be accomplished by adding an additional index  $k$  to the product variable  $Q_i$  to account for category membership, and by adding constraints on the category level. Several kinds of category restrictions can be introduced: which and how many categories should be included in the optimal set, or how many products from each category should be included. The relevance of these restrictions can be illustrated by the following common practices in

retailing. First, when composing a promotion leaflet, there is only limited space to display products and therefore it is important to optimize the product composition in order to maximize cross-selling effects between products and avoid product cannibalization. Moreover, according to the particular retail environment, the retailer will include or exclude specific products or product categories in the leaflet. For example, the supermarket in this study attempts to differentiate from the competition by the following image components: *fresh*, *profitable* and *friendly*. Therefore, the promotion leaflet of the retailer emphasizes product categories that support this image, such as fresh vegetables and meat, freshly-baked bread, ready-made meals, and others. Second, product category constraints may reflect shelf space allocations to products. For instance, large categories have more product facings than smaller categories. These kind of constraints can easily be included in the generalized PROFSET model as will be discussed hereafter.

### 3.3 The Generalized PROFSET Model

Bundling the improvements suggested in Sections 3.1 and 3.2 results in the generalized PROFSET model as presented below.

Let categories  $C_1, \dots, C_n$  be sets of items,  $L$  the set of frequent itemsets, and let  $P_X, Q_i \in \{0, 1\}$  be the decision variables for which the optimization routine must find the optimal values.  $P_X$  specifies whether an itemset  $X$  will positively contribute to the value of the objective function, and  $Q_i$  equals 1 as soon as any itemset  $X$  in which it is included is set to 1 ( $P_X = 1$ ) by the optimization routine. Let  $\text{Cost}_i$  be the inventory and handling cost of item  $i$ . The objective of the following formula is to maximize all profits from cross-selling effects between products:

$$\max \left( \sum_{X \in L} M(X) P_X - \sum_{c=1}^n \sum_{i \in C_c} \text{Cost}_i Q_i \right)$$

which is subject to the following constraints

$$\sum_{c=1}^n \sum_{i \in C_c} Q_i = \text{ItemMax} \quad (1)$$

$$\forall X \in L, \forall i \in X : Q_i \geq P_X \quad (2)$$

$$\forall C_c : \sum_{i \in C_c} Q_i \geq \text{ItemMin}_{C_c} \quad (3)$$

Constraint 1 determines how many items are allowed to be included in the optimal set. The ItemMax parameter, specified by the retailer, will depend on the retail environment in which the model is being used. For instance, it may be the number of eye-catchers (products obtaining special display space) in the supermarket or the number of facings in a promotion leaflet. Constraint 2 is analogous to the one in the previous PROFSET model and specifies the relationship between the frequent sets and the products contained in them. Finally, constraint 3 specifies the number of categories and the number of products that are allowed, within each category, to enter the optimal set.

## 4 Empirical Study

The empirical study is based on a data set of 18 182 market baskets obtained from a sales outlet of a Belgian supermarket chain over a period of 1 month. The store carries 9 965 different products grouped in 281 product categories. The average market basket contains 10.6 different product items. In total, 3 381 customers own a loyalty card of the supermarket under study.

First, frequent sets and association rules were discovered from the market baskets with a minimum absolute support threshold of 30 transactions. The motivation behind this is that a product or set of products should have been sold at least, approximately, once a day to be called frequent. Slightly more than 87% of the products are sold less than once a day.

The retailer in question is interested in finding the optimal set of eye-catchers such that the profit from cross-selling these eye-catchers is maximized. Hence, this should be represented by the objective function as described in the previous section. However, because of limited shelf-space for each product category, the retailer specified that each product category can only delegate one product to the optimal set, represented by the category constraint (i.e. constraint 3). Subsequently, it is the goal of the generalized PROFSET model to select the most profitable set of products in terms of cross-selling opportunities between the delegates of each category.

For 54 (24, 7%) of the 218 product categories, the generalized PROFSET model selects a different product than the one with the highest individual profit ranking within each category. This suggests that for these products, there must be some cross-selling opportunity with eye-catchers from other categories which cause these products to get *promoted* in the profitability

Table 2: Cross-selling profit improvements

Category	Improvement
Washing-up liquid	21%
Baby food	49%
Margarine 1	189%
Coffee biscuits	14%
Sandwich filling	43%
Candy bars	588%
Canned fish	N/A
Canned fruit	3%
Packed-up bread	8%
Newspapers and magazines	55%
...	...

Table 3: Own and cross-selling profit figures (in BEF) per product

Product	Own profit	Cross-selling profit	Total profit
1. MILKY WAY MINI	37 808	2 350	40 158
2. MELO CAKES	34 333	0	34 333
3. LEO 3-PACK	28 728	0	28 728
4. LEO 10-PACK 10+2	12 028	264 228	276 256

ranking.

Due to space limitations Table 2 shows the relative improvements in cross-selling profit for only some categories, expressed as the percentage of improvement in cross-selling profits by choosing the optimal products from the generalized PROFSET model instead of selecting the product with the highest individual profitability within each category.

It would lead us too far to discuss the profit improvements in detail for all categories. Therefore, we will highlight one of the most striking results to illustrate the power of the model. Analogous conclusions can be obtained for other categories. Note that N/A means that there is no alternative product available in that category that has enough support to be frequent, such that comparison with the product, selected by the generalized PROFSET model, is not applicable. For instance, for the category candy bars, the profit from cross-selling the selected eye-catcher of this category with eye-catchers of

other categories would increase cross-selling profits by 588%. This can be observed in Table 3 (only relevant products are included).

Table 3 illustrates that product 4 in the candy bars category is ranked last when looking at its own profit. However, due to large cross-selling effects with eye-catchers of other product categories, this product becomes much more important when looking at the total profit. This illustrates that for the eye-catchers application, it is better to display product ‘Leo 10-pack 10+2’ than to display one of its competing products in the same category. In contrast, if the objective would be the selling volume of the individual product, then it would be better to select product 1 as eye-catcher, but since the retailer wants the customer to buy other products with it, product 4 will definitely be the best choice. The association rules discovered during the mining phase validate these conclusions.

MILKY WAY $\Rightarrow$ VEGETABLE/FRUIT

(sup=0.17%, conf=50.82%)

MEAT PRODUCT AND LEO 10-PACK  $\Rightarrow$ CHEESE PRODUCT

(sup=0.396%, conf=55%)

Note that the products included in the rules are all eye-catchers such as determined by the generalized PROFSET model. The reason that the other items contained in the association rules carry a rather abstract name, such as “cheese product”, is because this is a collective noun for products that do not have an own barcode, like for instance different cheese products that are weighed at the check-out after which they are grouped into an abstract product name such as “cheese product”.

Finally, for those product categories that do not contain frequent products, the generalized PROFSET model will choose the product with the highest individual profit in order to maximize the overall profitability of the eye-catcher set.

## 5 Further Research

The authors plan to test the proposed model in practice and externally validate its performance based on a real world experiment in cooperation with the Belgian supermarket chain. Furthermore, additional improvements to the model will be considered. More specifically, it will be studied how promotion coupons affect the composition of the optimal set of products and

whether it is possible to measure the effect of the value price reduction on the cross-selling profitability of products.

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