Inventory classification enhancement with demand associations

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Abstract—**The most common method for classifying inventory items is the annual dollar usage ranking method (ABC classification), which assumes, accordingly to the Pareto principle, that a small number of items account for a large share of the cost-volume, an intermediate category of moderate cost-volume items and a large number of low cost or usage items. However, using only one criterion for decision making, in some cases, may lead to mismanaging the assets. To reconcile these conflicts, instead of using multiple criteria with analytic hierarchy process, we look at the alternative options available for improving the classification performance. The intent of this paper is to discuss several aspects of well-known inventory classification strategies, and to propose a demand association criterion for classification enhancement. Experimental results for two warehouse datasets are included and analyzed.**

Index Terms— **inventory management, ABC classification, Pareto, annual-dollar-usage ranking method.**

I. Introduction

Achieving effective inventory control is critical to help ensure the success of manufacturing and distribution companies. Large number of stock-keeping units (SKUs) make it unfeasible to manage items individually. Therefore, they are commonly grouped together and generic inventory stock control policies are applied for each group. The most common method for classifying and prioritizing items is the annual dollar usage ranking method [1], which is based on the Pareto's Principle. Vilfredo Pareto was an Italian economist who made an observation [2] that a preponderance of the wealth was concentrated in the hands of a relatively small percentage of the population. In the context of inventory control, Pareto's Principle is important because it recognizes that all the individual items which comprise the total inventory are not of equal relative importance. It implies that effort, time, money, and other assets to be spent or used in the control of an inventory should be allocated among the items in proportion to their relative importance [5].

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This work was supported in part by the Estonian Information Technology Foundation under Grant 05-03-99-11.

The classical single criterion ABC inventory classification is simple, straightforward and practical. Regardless of advances in inventory management methodologies, most of the companies are still using the basic single-criterion ranking method [10].

However, using only one criterion for decision making, in some cases, may lead to mismanaging the assets. Several other factors have been suggested [3],[4],[7] that may override dollar value: availability, criticality, scarcity, obsolescence, substitutability, lead time, average unit cost. From the business perspective, they are all necessary, but multi-criteria decisions pose completely different obstacles - besides investment justification, common understanding and trust in priority coefficients has to be introduced. One could resolve those issues by letting the inventory manager to go back through all items and reclassify any that they felt were misclassified. Large number of stock-keeping units make such an approach ineffective or even unfeasible.

Previous inventory classification methods share another common property - product-centered approach for classification procedure. However, the paradigm shift from product-centered thinking to customer-centered thinking has been gaining acceptance in marketing [23]. In order to be effective, the shift has to be supported also at the operational level, including inventory management. To narrow this gap, current paper presents a different and more customer-centered approach for the inventory classification problem.

We will discuss several aspects of well-known inventory classification methodologies (in section 2) and propose an efficient demand association criterion (in section 3), which is implementable both in single and multi-criteria classification environment. Experimental results are given in sections 4, followed by the conclusion.

II. Related Work

The term "ABC Inventory Analysis" was first coined in early 1950s by H. F. Dickie [1], who gave an overview about the analysis in general and results of implementation in General Electric Company. Success stories in direct inventory reduction and turnover increasement were presented.

Zimmerman [5] warned about using single criteria

1-4244-0318-9/06/$20.00 ©2006 IEEE

approaches to complex inventory problems and emphasized the common fallacy - misuse of a statistical technique. Current paper and the methodology hopes to overcome exactly those specific problems brought out in [5] - some "C" items should be closely monitored regardless of their ABC classification. We will call such classification situations *conflicts* that must be reconciled by reclassification, rather than making exceptions in the system.

Another common classical ABC classification fallacy that was also mentioned in [5] has become the main issue addressed in all the following papers [3],[4],[6]-[13] - distribution by value as the only criterion can lead to gross errors and mismanaging the assets.

Flores and Whybark [3],[4] suggested that multiple criteria ABC classification can provide more comprehensive managerial approach, allowing consideration of other criteria such as lead time and criticality. They presented a joint criteria matrix procedure that could help the management to derive combined criteria (usually a combination from dollar value and criticality). Unfortunately, the method only works the best with two criteria - if all criteria are important and need to be incorporated in the analysis, the task may become unmanageable [3], if not impossible.

Saaty's Analytic Hierarchy Process (AHP) was used in [7] to reduce multiple criteria to a univariate and consistent measure. AHP allows decision maker(s) with a finite set of alternatives to combine multiple objectives [14],[15]. Inventory management can include several criteria and reduce them to a single variable, using a linear combination of the variables. Clear drawback of the approach [7] is that more managerial time is needed to understand the process and to develop more information for each inventory item.

Neural networks and genetic algorithms [8],[9],[11] are very effective with inventory classification when it comes to optimizing a set of parameters that represent the weights of criteria. Nevertheless, a possible limitation of such approaches is that they generate black box models - the structure of weights is never explained.

Contrasting unsupervised approach was presented in [6], where Cohen and Ernst presented the ORG method, suggesting clustering of the items based on 40 operational attributes about each item. They formulated the SKU-based control problem as an optimization problem where the objective is to obtain the minimum number of groups which satisfy both operational performance (the penalty associated with the application of generic policies relative to individual-based policies) and constraints (a minimal level of statistical discrimination). Such approach enables the generation of operations-related groups, which are based on the common properties and features of items, but it could fail to notice the non-product-based associations between items.

In this paper we suggest a different and more customer-centered approach for solving the problem - using demand associations for classification. With both main previous approaches, single and multiple criteria ABC analysis, the demand association method is suggested as an enhancement, not as a replacement.

III. Proposed Methodology

This paper proposes the use of association rules framework [16]-[21] (also known as *market basket analysis*) for calculating the demand association criterion. Items, which are frequently bought, assembled or used together, should be applied with the same management policy and classified in the same class. The criterion is measured in ordinal scale and can represent either non-existent, normal (from classical ABC analysis category "B" to "A" or "C" to "B") or strong (from "C" to "A") recommendation for reclassification. In most cases no recommendation is given, which allows better managerial concentration on special cases.

We provide a formal model for association rules framework with required restrictions. Let I = $i_1,i_2,\ldots,i_m$ be a set of binary attributes, called items. Let D be a set of transactions. Each transaction t is represented as a binary vector, with $t[k]=1 \leftrightarrow i_k \in t$ if i_k was bought, assembled or used in transaction t. We also have annual dollar usage value for the item i_k.

By an association rule, we mean an implication of the form $X \rightarrow i_j$, where X is a single item from I, and i_j is a single item in I that is not X. The number of items as an antecedent and consequent is restricted to one. The *confidency* of a rule is the conditional probability that a randomly chosen transaction from D that matches X also matches i_j. It should be noted [22] that the symbol $\rightarrow$ is a bit misleading since such a rule does not correspond to real implications, the confidence measure is merely an estimate of the conditional probability of i_j given X.

In this formulation, the problem of calculating the demand association criterion can be decomposed into three subproblems:

1. After data acquisition and pre-processing, generate all two-item association rules that have fractional transaction confidency above a certain threshold, which is based on managerial judgement.
2. Classify all items in I, using the annual dollar usage ranking method.
3. Calculate the demand association criterion for all items in I, using the following algorithm. The recommendation for reclassification for an item i_k is:
   - *non-existent*, if no rules exist where the item is associated with an item from different annual dollar usage ranking ABC class;
   - *normal*, if at least one rule exists where the item is associated with an item from different annual dollar usage ranking ABC class - item from "B" associated with an item from "A" or item from "C" with an item from "B";

- *strong*, if at least one rule exists where the item is associated with an item from different annual dollar usage ranking ABC class - item from "C" associated with an item from "A".

Hence, we are interested in rules, where antecedent and consequent are from the different ABC classes.

A. Numerical Example

Let us look at the following numerical example. Table 1 shows four items referred to as i_1 to i_4. Each transaction t is represented as a binary vector, with $t[k]=1 \leftrightarrow i_k \in t$ if i_k was bought, assembled or used in transaction t. The quantity of each item in the transaction history record is ignored, as we are concerned about the association. *DollarValue* of an item (in the last row) is the result of the classical ABC analysis, which is independently calculated of the binary transaction data. In most cases, annual dollar-usage value can be extracted from the summary or ABC analysis reports, depending on the inventory management software.

TABLE 1
TRANSACTIONS AND DOLLAR-USAGE VALUES

	i_1	i_2	i_3	i_4
t_1	1	0	0	1
t_2	0	1	0	0
t_3	0	0	1	0
t_4	0	0	1	0
t_5	0	1	0	0
t_6	1	0	0	1
DollarValue	36	6	1	1

We can see that items i_1 and i_4 are twice (rows 1 and 6) bought, assembled or used together, therefore the conditional probability that a randomly chosen transaction from table 1 with i_1 also has i_4, is 100%. This indicates that no transactions exist where item i_1 did not co-occur with i_4.

According to annual dollar-usage ranking, item i_1 is classified as "A", i_2 as "B", i_3 and i_4 as "C". Despite, we see a situation that we would call *a demand association conflict* within the initial classification. An item from category C (according to *DollarValue*) is always bought, assembled or used together (according to association rules) with the item from category A. Therefore, a strong recommendation for reclassification is given for i_4 under such circumstances.

Previous example illustrated the motivation for demand association approach in single criterion environment. It is also possible to implement the recommendation as one objective in multiple criteria classification environment based on Analytic Hierarchy Process [7].

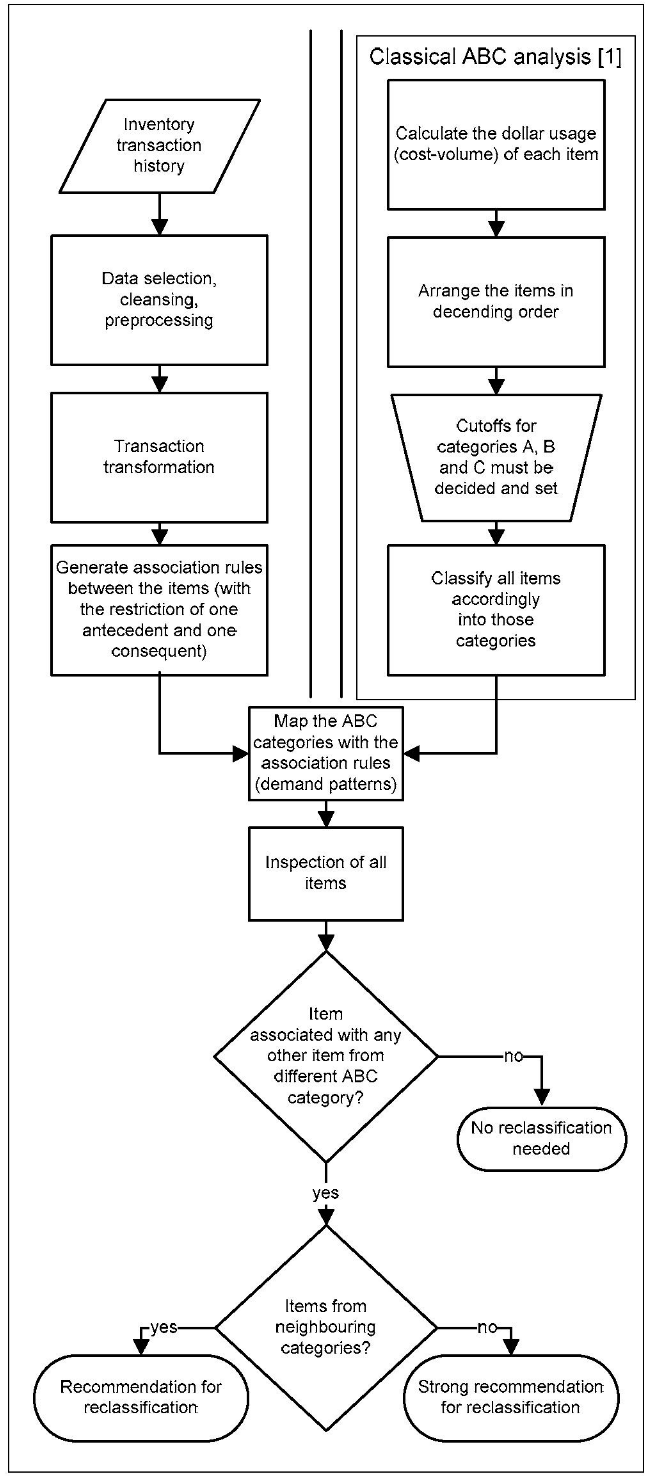

Figure 1. Proposed demand association approach

IV. EXPERIMENTAL RESULTS

The aim of the experiments is to investigate how common demand association conflicts are in real world scenarios. Therefore, we evaluate the given method with respect to the initial classification results and enumerate demand associations between items from different categories.

Two wholesale companies participated in the study, anonymized datasets are available upon request for benchmarking and research purposes.

The number of SKUs in the organizations were 234 (Dataset 1) and 1601 (Dataset 2), respectively. Data were gathered and prepared from the transaction history records in the inventory management software of each organization.

Preprocessing activities included data selection, cleansing and transformation. The goal was to have two distinct input files for the method:

- Results of the classical ABC analysis (cutoffs for ABC categories and items in descending order with respect to dollar-usage values or any other chosen criterion).
- Transaction data in suitable format for the extraction process of association rules.

The following steps were performed for both datasets:

1. All the association rules were extracted from the transactions. For exploratory purposes different rule confidencies were tested (25%, 50%, 60%, 70%, 75%, 80%, 85%, 90%).
2. ABC categories for dollar-usage were developed, distributions of dollar-usage values for both datasets are shown in figure 2.

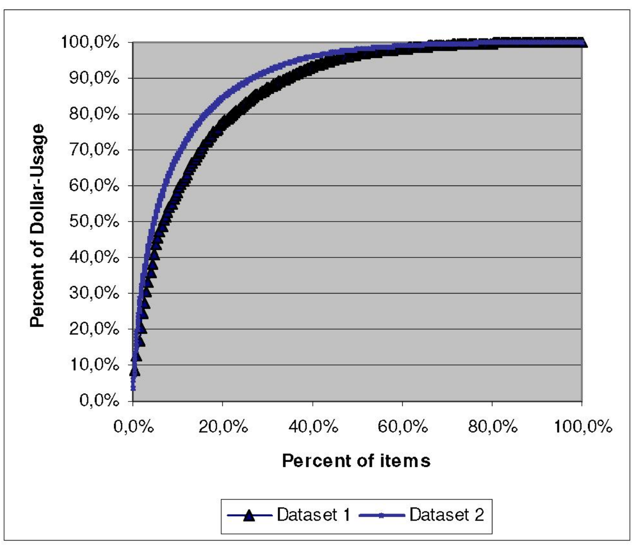

Figure 2. Distribution of Dollar-Usage Values

3. For both organizations ABC categories were defined as 75%, 15%, and 10% of the dollar-usage, respectively.
4. We enumerated all the rules (for all tested confidencies), where antecedent and consequent were from different ABC categories.
5. Demand association criteria were calculated for all items and confidencies, which allows managers to perform a subjective evaluation in order to find the optimal confidency threshold.

TABLE 2

DATASET 1 AND ENUMERATION RESULTS

	25 %	*50 %*	*60 %*	*70 %*	*75 %*	*80 %*	*85 %*	*90 %*
A→B	103	6	6	4	0	0	0	0
A→C	1	0	0	0	0	0	0	0
B→A	549	102	35	12	11	7	2	1
B→C	7	1	0	0	0	0	0	0
C→A	69	11	3	0	0	0	0	0
C→B	19	5	2	1	1	0	0	0

TABLE 3

DATASET 2 AND ENUMERATION RESULTS

	25 %	*50 %*	*60 %*	*70 %*	*75 %*	*80 %*	*85 %*	*90 %*
A→B	1813	334	114	26	15	5	3	1
A→C	271	1	0	0	0	0	0	0
B→A	2629	629	239	95	65	26	15	6
B→C	396	16	2	1	1	1	0	0
C→A	436	98	30	14	6	1	1	0
C→B	177	61	24	8	3	0	0	0

Enumeration results for both organizations are shown in tables 2 (Dataset 1) and 3 (Dataset 2), associations within the same category were not included. The values should be interpreted as numbers of demand association conflicts, relevant confidency level to be chosen depends on the managerial judgement. The results should illustrate the relative amount of ABC classification conflicts with the current prerequisites. Several items with strong recommendations for reclassification were found.

V. CONCLUSIONS

Regardless of advances in inventory management methodologies, managers are accustomed to working with simple and practical ABC inventory classification, although using single criteria approaches to complex inventory problems may lead to mismanaging the assets.

In this paper we suggest a different and more customer-centered approach for solving several fallacies of the classical ABC analysis - using demand associations for classification enhancement. In addition to the annual dollar usage ranking method, items which are frequently bought, assembled or used together, should be applied with the same management policy and classified in the same category. Using the approach in single and multiple criteria systems can both be considered. It provides inventory managers a straightforward remedy to reduce dependency conflicts in the results of the classical ABC analysis.

The presented results with two warehouse datasets justify the demand association approach and illustrate the need for considering non-product-based associations between items.

ACKNOWLEDGMENT

We would like to thank Rein Kuusik, Leo Vohandu, Enn Ounapuu from Tallinn University of Technology, Illimar Paul from Estonian Logistics Association and other anonymous reviewers for insightful comments and suggestions.

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