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SEARCHING FOR SOLUTIONS IN TIMES OF GLOBAL INSTABILITY AND UNCERTAINTY

Róbert Štefko - Richard Fedorko - Eva Benková (Eds.)

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A Novel Hybrid IBA-OSCD Approach for Multi-Criteria Inventory Classification

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Abstract

Research background: Inventory management plays a crucial role in manufacturing organizations as it enables continuity of production, adequate response to customer demand, financial optimization of inventory and overall adequate organizational liquidity. Inventory management is highly dependent on inventory classification as it allows simplification of the inventory management process by assigning inventory management policies based on categories rather than individual items.
Purpose of the article: In this article, a novel hybrid approach for multi-criteria inventory classification is proposed. The approach considers two groups of logically related criteria: One group focuses on inventory ordering dynamics, i.e., lead time, average demand, current inventory quantity, and coefficient of variation, while the other focuses on inventory quantity and value, including average demand, unit price, and dollar usage value. The method follows the ABC classification convention and is used to categorize 290 inventory items into three classes.
Methods: The classification process is conducted in two steps. First, each set of criteria is evaluated and aggregated using logical aggregation based on Interpolative Boolean Algebra, allowing for the integration of both logic-based and statistical relationships within the data during aggregation. The resulting values are then further aggregated using ordinal sums of conjunctive and disjunctive functions to perform upward or downward reinforcement , depending on the input values.
Findings & Value added: This study demonstrates the novel logic-based approach to multi-criteria inventory classification, which aims to explore a different perspective on inventory management by considering multiple sets of logically related criteria.

Keywords: Inventory management, Inventory classification, Hybrid multi-criteria approach, Interpolative Boolean algebra, Ordinal sums of conjunctive and disjunctive functions

JEL classification: M11, C38, C00

1. Introduction

Inventory is defined as the stored instances of transformed resources within a production or service operation (Slack et al., 2010, p. 368) due to timing mismatches between supply and demand (Slack et al., 2010, p. 368). It is essential for ensuring smooth production or service availability, enabling the company to meet the needs of customers in an appropriate manner (Nowotyńska, 2013). For manufacturing-oriented companies, inventory and its appropriate management play a crucial role in maintaining ongoing production and meeting customer needs (Nowotyńska, 2013). This includes maintaining an adequate inventory of raw materials, work in progress and finished goods to achieve cost efficiency and reliable

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supply (Pandya & Thakkar, 2016), while controlling stock levels to accommodate any fluctuations in demand (Priniotakis & Argyropoulos, 2018). Inventory management has a significant financial impact as it directly affects an organisation's performance through its influence on procurement, sales and logistics. Due to this financial impact, inventory management is of great importance from both a theoretical and practical perspective, as it is both capital-intensive and time-consuming (Razavi Hajiagha et al., 2021).

For organizations that may have up to several thousand different inventory items, it is both economically inefficient and logistically impractical, if not impossible, to devote equal and maximum attention to each individual item. For this reason, inventory classification is often recommended in the literature as a strategy to address this issue (Rakicevic et al., 2024). Instead of managing each item individually, this approach involves companies grouping their inventory items into categories and applying appropriate management policies to each individual item (Mohammaditabar et al., 2012).

Numerous numerical methods have been proposed in the literature to improve inventory classification. Probably the most important and widely used method is the ABC method, which classifies inventory into three categories (Ramanathan, 2006). For classification, ABC analysis primarily considers the inventory value of each item or the variability of demand, i.e. a single criterion. Over the years, more advanced multi-criteria ABC analysis approaches have been developed (Ravinder & Misra, 2014). However, these approaches are mainly based on simple aggregation functions, i.e. weighted sums, and more sophisticated aggregations, i.e., logic-based aggregations, are yet to be explored.

In this paper, we present a novel approach to multi-criteria inventory classification that combines Interpolative Boolean Algebra (IBA) and its logic-based aggregation capabilities with Ordinal Sums of Conjunctive and Disjunctive (OSCD) functions. Specifically, we use the IBA framework for Boolean consistent modeling and the computation of lower-level partial logical requirements defined by a domain expert. In addition, OSCD functions with three different parameter settings are applied to aggregate values at a higher level to make a clear distinction between inventory classes. With the proposed approach, we incorporate both logical and statistical dependencies in the data to obtain more credible results.

The rest of the article is organized as follows: In the literature review section, three distinct topics are discussed. First, inventory classification and its importance to the inventory management process as well as the most common approaches to inventory classification are presented. Next, the basis of IBA and its logical aggregation capabilities are discussed. Finally, the basis of OSCD functions are presented. In the methodology section, a step-by-step explanation of the item classification process is presented. There is an explanation given for each individual step and its necessity for adequate classification of items. In the fourth section, the explained methodology is implemented in a real-world scenario to better understand each individual step of its implementation. The results obtained are presented, discussed and a general recommendation is given on how the model can help and be interpreted by the expert. The final section concludes the paper. Implications of the research and further research perspectives are outlined.

2. Literature review

The literature review section is divided into three sections: inventory classification, logical aggregation based on Interpolative Boolean Algebra and Ordinal Sums of Conjunctive and Disjunctive functions. Each section provides an overview of the most important concepts and relevant research in the respective area.

Inventory classification

Inventory classification serves as a fundamental step in inventory management and forms the basis for the selection of appropriate inventory control policies tailored to their respective categories (Razavi Hajiagha et al., 2021). The reason for using classification is the observation that in most situations it is not possible to develop a separate strategy for each individual item due to the large number of items in stock (Teunter et al., 2010). One of the fundamental components of effective inventory management is precisely this process of classifying items, which helps companies allocate their limited resources more strategically and determine appropriate inventory control policies (Anđelić et al., 2024). By classifying inventory, companies can prioritize those items that contribute the most to achieving their operational and financial goals (Mohammaditabar et al., 2012).

The first approach to inventory classification was the original ABC analysis of inventory, a name that has become synonymous with the process of inventory classification (Ramanathan, 2006). The original ABC analysis classifies items into categories A, B, and C based on their importance, which is measured solely by dollar usage value (Nallusamy et al., 2017). Conventional ABC analysis is based on the Pareto principle (Park et al., 2014), which states that a small proportion of items usually account for the majority of inventory value, while the majority of items make only a small contribution. Accordingly, Class A items are considered very important, Class B items are considered moderately important and Class C items are considered relatively insignificant (Douissa & Jabeur, 2016). The traditional ABC classification is still one of the most commonly used methods for categorizing items by importance (Nallusamy et al., 2017), mainly because of its ease of use and understanding.

While the aforementioned reliance on a single criterion (Teunter et al., 2010) is what makes the method so intuitive and easy to use, it is also its main source of criticism (Muller, 2019), where it is often pointed out that the method does not adequately reflect the different priorities of different departments within an organization and completely disregards non-financial factors. Therefore, inventory classification is increasingly being explored in a multi-criteria framework (Razavi Hajiagha et al., 2021), a direction supported by many scholars (Lolli et al., 2019). Muller (2019) suggests that at least two criteria should be considered. These could be ordering cost, item criticality, lead time, shelf life, substitutability and demand variability, paving the way for a multidimensional approach to inventory classification (Park et al., 2014).

Taking all this into account, more advanced multi-criteria approaches have emerged, incorporating both financial and non-financial variables that reflect the greater complexity of real-world inventory systems (Silver et al., 1998). Over time, three general methods for implementing multi-criteria ABC analysis have emerged (Ravinder & Misra, 2014). The first is based on subjective weighting and scoring of criteria, where a decision maker assigns weights and methods such as the Analytic Hierarchy Process (AHP), often enhanced by fuzzy logic, are used to combine the scores (Paredes Rodríguez et al., 2023). The second approach is based on linear optimization, which bypasses subjectivity by deriving the weights directly from the data so that a predefined cost function is minimized. Data Envelopment Analysis (DEA) is often used in this context (Xu & Xu, 2020). The third approach uses artificial intelligence such as clustering techniques, genetic algorithms and neural networks that learn from existing data provided by experienced managers (Zhang et al., 2019).

Logical aggregation based on Interpolative Boolean Algebra

One of the distinct approaches that aim to incorporate logical and statistical dependencies into aggregation and decision-making is logical aggregation based on IBA (Radojevic, 2008). LA combines individual inputs based on user-defined logical rules to obtain a consistent and interpretable collective outcome. This procedure is both multi-valued and Boolean consistent, since IBA (Radojevic, 2000) serves as the foundation of this approach.

From the technical point of view, LA consists of two steps:

i) Normalization of attributes' values to the unit interval;
ii) Aggregation of normalized values by means of a logical/pseudo-logical function.

In the general case, the aggregation function may be pseudo-logical, i.e. weighted sum of partial logical demands $\underset{i=1}{\overset{m}{LA}}(x_i) = \sum_{j=1}^{m} w_j \cdot \varphi_j^{\otimes}(x_1,...,x_m)$, where *m* is number of attributes, φ_j is a logical function of attributes $x_1,...,x_m$, and w_j are corresponding weights.

Before making a final aggregation, each logical expression φ should be treated within IBA framework on symbolic and valued level. First, on the symbolic IBA level, any logical function φ of attributes $x_1,...,x_m$, is transformed to the generalized Boolean polynomial (GBP) $\varphi^{\otimes}$.

$$\varphi \mapsto \varphi^{\otimes}, \quad \varphi(x_1,...,x_m) = \varphi^{\otimes}(x_1,...,x_m) \qquad (1)$$

The transformation procedure (Radojevic, 2000) is performed according to the IBA transformation rules, either manually or using a software solution (Milošević et al., 2014). Variables in GBP are observed attributes, while the operators are standard +, standard – and generalized product (GP). The structural transformations of the expression ends with obtaining the shortest form of GBP.

On the valued level, the GP is considered a subclass of *t*-norms that satisfy an additional non-negativity condition, i.e. GP may be realized as any *t*-norm that produces the result from the following interval (Radojevic, 2008):

$$\max(x+y-1,0) \le x \otimes y \le \min(x,y) \qquad (2)$$

According to the nature of attributes to be aggregated and their and statistical dependencies, three realizations of GP are distinguished in practice (Čolić et al., 2024; Milošević et al., 2021). Attributes of the same/similar nature and high statistical dependency should be aggregated with the min function. For independent, uncorrelated attributes, the product is used as a suitable operator. GP is realized as Lukasiewicz t-norm if the attributes are negatively correlated. Attributes of the same nature should be aggregated first, followed by negatively correlated attributes if more attributes are to be aggregated using GP. The choice and application of GP together with the final value calculation completes the valued level of the IBA framework.

In the general case, LA is not monotonic and therefore does not satisfy all the properties required to be considered an aggregation operator. On the one hand, this can be seen as an opportunity to model unusual situations, e.g. similarity or dissimilarity. On the other hand, certain special cases of logical aggregation are monotonic and can be used in a conventional way as they generalize the arithmetic mean, the weighted sum, the minimum function and both the discrete and the generalized Choquet integrals. This approach is utilized both in practice and in the literature, e.g. (Anđelić et al., 2024; Milošević et al., 2024), because it is transparent, well-defined, easy to use and has numerous mathematical properties.

Ordinal Sums of Conjunctive and Disjunctive functions

Mixed aggregation functions are appropriate when one category of elements is to be emphasized as crucial, e.g. class A, the second category as more or less relevant (class B) and the third category downplayed as the least relevant (class C). The ordinal sum of conjunctive and disjunctive functions could be the solution to this exact problem (De Michele & Pierri, 2020; Hudec et al., 2021). One form of ordinal sums is as follows:

$$A(x,y) = A_1(a \wedge x, a \wedge y) + A_2(a \vee x, a \vee y) + a \qquad (3)$$

where x and y are intensities of satisfying categories, and $a \in [0,1]$ expresses the separation between upward and downward reinforcements. Then holds the following observations:

$$\text{for } x,y \in [0,a]^2 \text{ we get } A(x,y) = A_1(x,y) \qquad (4)$$
$$\text{for } x,y \in [a,1]^2 \text{ we get } A(x,y) = A_2(x,y) \qquad (5)$$

The key observation is that if A1 is a conjunctive function (downward renifircement) and A2 is a disjunctive function (upward renforecmeent) (Durante and Sempi, 2005), the remaining two sub-areas are covered by the averaging function, since:

$$\text{for } x,y \in [0,a] \times [a,1] \text{we get } A(x,y) = A_v(x,y) = x + y - a \qquad (6)$$
$$\text{for } x,y \in [a,1] \times [0,a] \text{we get } A(x,y) = A_v(x,y) = x + y - a \qquad (7)$$

These functions are depcted in Figure 1.

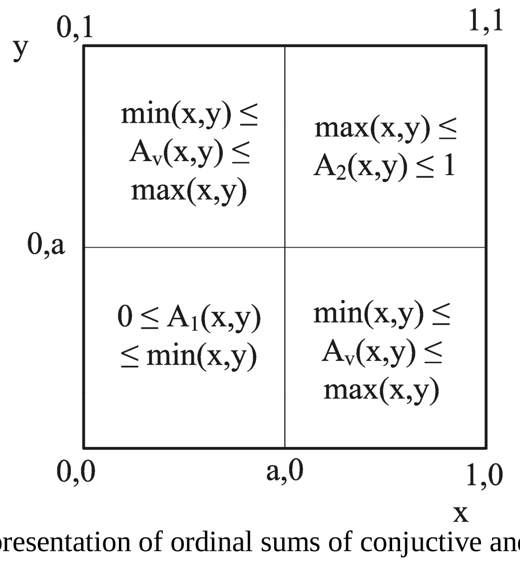

Figure 1. Graphical representation of ordinal sums of conjuctive and doisjunctve functions

For the aggregation function, we should keep the borderline cases, i.e., $A(0, 0) = 0$ and $A(1, 1) = 1$. It holds for averaging functions, but if the functions are conjunctive, we should keep $A(a, a) = a$, because this is the borderline case of the lower left sub-square. It is solved by adjusting strict conjunctive function (e.g., product t-norm $T(x, y) = xy$) through transformation (Beliakov et al., 2007)

$$A_1(x,y) = aT\left(\frac{x}{a},\frac{y}{a}\right) \qquad (8)$$

or $A_1(x,y) = \frac{1}{a}xy$ (Figure 1). When the space is divided into equal sized subsquares we get $A_1(x,y) = 2xy$. Analogously, for nilpotent conjunction (e.g., Lukasiewich t-norm $T(x, y) = \max(0, x + y - 1)$) we get $A_1(x, y) = \max(0, x + y - a)$ (Hudec et al., 2021).

In the same way, we adopted the disjuctive functions as $A_2(x,y) = -1 + \frac{1}{a}x + \frac{1}{a}y - \frac{1}{a}xy$ for strict probabilistic sum t-norm and $A_2(x, y) = \min(0, x + y - a)$ for Lukasiewicz t-conorm. For the averaging part, we can keep the neutral arithmetic mean $A_v = (x + y - a)$ or adjust the inclination toward conjunctive or disjunctive behaviour (Hudec et al., 2022).

3. Methodology

Figure 2 displays all the steps necessary for appropriate inventory item classification, which further allows the definition of appropriate inventory management strategies.

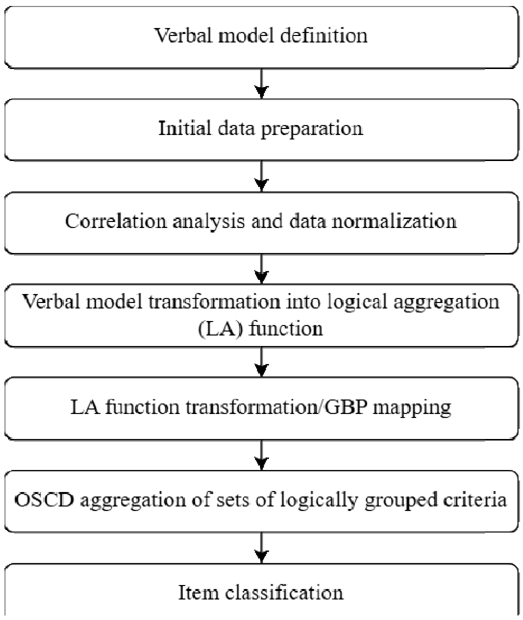

Figure 2. Graphical representation of methodological steps for item classification
Source: own processing

In the first step, an expert from the field verbally defines the considerations as to which criteria influence the perceived importance of a particular inventory item. The expert also provides information on how these criteria are interconnected, i.e. what logical connections, if any, exist between certain criteria.

During data preparation, the raw data is transformed on the basis of the verbal model so that it is suitable for further analysis. The data is cleaned, potential errors are handled accordingly, duplicates are removed and, if necessary, composite metrics are calculated based on multiple input parameters.

In the third step, a correlation analysis is performed between the individual criteria, as this later influences the transformation of the generalized Boolean polynomial into a corresponding mathematical expression. The data is also normalized to ensure a proportional and meaningful contribution to the final classification results.

In the fourth step, the verbal model previously defined by the expert is transformed into appropriate logical functions. This step is crucial as it enables the subsequent logical and mathematical operations to adequately reflect the expert's input and opinions.

In the fifth step, the logical expressions are translated into a generalized Boolean polynomial according to the IBA transformation rules. This step essentially provides a mathematical representation of the previously defined logical groupings.

In the sixth step, the individually modeled groups of criteria are further aggregated using ordinal sums of conjunctive and disjunctive functions. In this step, the input of an expert is not as crucial, as this class of functions naturally emphasize and rank key items with high values when both categories are high (class A), downplay non-crucial items resulting in low values when both categories are low (class C) and averages the feature ranks the other itmes (class B).

The final result of this aggregation is the individual groupings of the inventory items into corresponding classes.

4. Results and discussion

In a **verbal model definition**, an expert gives his opinion on how certain criteria influence the importance of an item. In this case, the expert has given two general indications that an inventory item is of high importance. One reason has to do with order dynamics. If an item has a long lead time and the average ordering demand is high, combined with the fact that the inventory level is high, which means that a lot of capital is tied up in inventory, the expert believes that this item is of high importance. Even if this is not the case, if the average ordering demand is high, but the individual demand quantities fluctuate greatly from case to case, an item is of high importance, as an appropriate demand forecast can be extremely difficult in this case. The second line of reasoning concerns the financial aspects of inventory management. An item is of high importance if it is expensive and the demand for this item is high. Even if this is not the case, an item is still of high importance if a lot of capital is “trapped” in this item and the value of the total item stock is high. This expert input forms the basis for further implementation steps.

During **data preparation**, the raw data, i.e. the item-level data on prices, inventory quantities, demand, etc., is cleansed, transformed and organized in such a way that further analysis is possible. An important aspect of data preparation in this case is the identification and calculation of indicators that adequately reflect the experts' input. While in some cases this is only a technical issue, e.g. lead time is an indicator that already exists in the company data, in some cases appropriate calculations had to be made. For example, the expert pointed out that an item is of great importance if the demand for that item fluctuates greatly. This characteristic was modeled with the coefficient of variability, as it accurately reflects the expert's assessment.

The following step comprises the **correlation analysis and the normalization of the data**. The correlation analysis is a mandatory step as it serves as input for further transformation of the logically aggregated criteria into a mathematical relationship. Data normalization must be performed to rescale different criteria to comparable scales. In this case, many of the individual scales had data with vastly different orders of magnitude and several outliers skewing the normalized values. For this reason, similar to (Milošević et al., 2024), a data normalization based on the interquartile distribution was performed to exclude the outliers.

In the next step, the previously described **verbal model is transformed** into a logical expression, or in this case into functions, one for each of the two rationales. Based on the description of the importance of items by the expert in the context of order dynamics, the verbal model is represented by the following LA function:

$$LA_1 = (ALT \wedge AD \wedge CSQ) \vee (CoV \wedge AD) \qquad (9)$$

Where ALT is average lead time, AD is average demand, CSQ is current stock quantity, and CoV is the coefficient of variability. The financial aspects related to inventory item importance are represented with the following LA function:

$$LA_2 = (UP \wedge AD) \vee DUV \qquad (10)$$

where UP is unit price, AD is average demand, and DUV represents dollar usage value, i.e. unit prices multiplied by current stock quantity.

Next comes the **LA transformation and its mapping into a Generalized Boolean Polynomial**, based on the IBA transformation rules, taking into consideration the fact that in the IBA framework $a \otimes a = a$, and as a consequence, $a \otimes (1-a) = 0$. Based on this, our LA functions are transformed in the following manner:

$$GBP_1 = ALT \otimes AD \otimes CSQ + CoV \otimes AD - ALT \otimes AD \otimes CSQ \otimes CoV \qquad (11)$$

$$GBP_2 = UP \otimes AD + DUV - UP \otimes AD \otimes DUV \qquad (12)$$

In the context of IBA, the correlation coefficient is interpreted as a measure of the nature and dependence of the inputs. The correlation results show that there is a single strong correlation between the coefficient of variation and the average demand, and for these attributes a minimum is used as a generalized product operator, while in all other cases a standard product is used. On this basis, the GBPs mentioned above are transformed into the following mathematical relationships that allow the final aggregation of each attribute into their respective groups:

$$F_1 = \min(AD, CSQ) \cdot ALT + CoV \cdot AD - \min(AD, CSQ) \cdot ALT \cdot CoV \qquad (13)$$

$$F_2 = UP \cdot AD + DUV - UP \cdot AD \cdot DUV \qquad (14)$$

Now that the individual groups are aggregated, the final step is the **aggregation of the groups themselves using OSCD.** In this instance, the following variation of conjunction, discjuntion and averaging functions is chosen based on their desired behaviour of upward/downward reinforcement and averaging capabilities with respect to aggregated values (Hudec et al., 2021):

$$A(x,y) = \begin{cases} 2xy, \ x,y \in [0,a]^2 \\ -1 + 2x + 2y - 2xy, \ x,y \in [\,a,1]^2 \\ x + y - \mathrm{a}, otherwise \end{cases} \qquad (15)$$

Based on the aggregated measure, the **individual inventory items are ranked** according to the classic ABC inventory classification and assigned to a class A, B or C, so that the first 20% of the items belong to class A, 30% to class B and the remaining 50% to class C. The aggregation was performed with three different values for the parameter a, 0.3, 0.5 and 0.7, to compare the final item classifications and to investigate which inventory items occupy a gray area and may require special attention. Although this was not the case in this instance, the expert could provide indications of a stronger preference for class A, resulting in a lower value for parameter a, or a stronger leaning from class B to C, resulting in a higher value for the parameter, or another averaging function with a higher tendency for conjunction, such as the goemtric or harmonic mean. The final classification results are shown in Table 1.

Table 1. Inventory classification model agreeableness

N = 290	Inventory classification agreeableness				
Class	A	A/B gray area	B	B/C gray area	C
Number of items	40	36	40	58	116
% of items	13,79%	12,41%	13,79%	20,00%	40,00%

Source: Authors own research

All three models agree that 13.79% of items unequivocally belong to class A, 13.79% of the items belong to class B and 40% of items belong to class C. This distribution roughly corresponds to the basic premise of the ABC classification according to the Pareto principle (Nallusamy et al., 2017). Gray areas represent items that cannot be clearly assigned to a single category. An item is assigned to this category if at least one of the models indicates that it belongs in a different category. In this case, the A/B gray area is of particular interest, as a misclassification in this case could potentially lead to the most important items being treated inadequately, i.e. not receiving enough attention. It is important to note that there is no A/C gray area, which is excellent, as misclassification in this case could result in a very important item receiving virtually no attention. Since the basic premise of this method is expert input and opinion, the results could be further refined so that the expert decides in which category an item should be classified.

Conclusion

Modern manufacturing companies manage an enormous number of different items in stock, often tens of thousands. The records of these items are usually managed using Excel spreadsheets or Enterprise Resource Planning systems. Individually reviewing such a large number of items can be extremely tiring and time-consuming, which is why organizations apply classification methods based on various criteria. In this study, a novel approach to inventory classification is presented. It approaches the problem of multi-criteria inventory classification from a different perspective, focusing on logical aggregation based on the IBA framework of individual criteria and OSCD aggregation rather than purely mathematical relationships. This approach is presented using a real-world scenario where the experts' imput and opinion is considered to optimize the classification of items based on his previous experiences. The proposed method shows reasonable consistency with the classical ABC analysis and can be a valuable asset in the decision-making process where appropriate inventory management strategies can be developed for each category rather than on a per-item basis. Overall, the research presented in this study contributes to the body of knowledge on inventory classification and offers practical implications for companies seeking to optimize their inventory costs. Their effectiveness and impact on organizational performance represent future areas of research.

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