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Fuzzy Classification Approach to Select Learning Objects Based on Learning Styles in Intelligent E-Learning Systems

Ibtissam Azzi [1,*], Abdelhay Radouane [2], Loubna Laaouina [3], Adil Jeghal [4], Ali Yahyaouy [5] and Hamid Tairi [5]

1 Department of Informatics, CRMEF de l'Oriental, Nador 62000, Morocco
2 Department of Informatics, CRMEF de Fez Meknes, Fez 30000, Morocco; radouaneabdelhay@yahoo.fr
3 LISA Laboratory, National School of Applied Science, Sidi Mohamed Ben Abdellah University, Fez 30000, Morocco; loubna.laaouina@usmba.ac.ma
4 LISAC Laboratory, National School of Applied Science, Sidi Mohamed Ben Abdellah University, Fez 30000, Morocco; adil.jeghal@usmba.ac.ma
5 LISAC Laboratory, Faculty of Sciences Dhar El Mehraz, Sidi Mohamed Ben Abdellah University, Fez 30000, Morocco; ayahyaouy@yahoo.fr (A.Y.); htairi@yahoo.fr (H.T.)
* Correspondence: ibtissam.azzi@usmba.ac.ma

Abstract: In e-learning systems, even though the automatic detection of learning styles is considered the key element in the adaptation process, it does not represent the main goal of this process at all. Indeed, to accomplish the task of adaptation, it is also necessary to be able to automatically select the learning objects according to the detected styles. The classification techniques are the most used techniques to automatically select the learning objects by processing data derived from learning object metadata. By using these classification techniques, considerable results are obtained via several approaches and consist of mapping the learning objects into different teaching strategies and then mapping these strategies into the identified learning styles. However, these approaches have some limitations related to robustness. Indeed, a common feature of these approaches is that they do not directly map learning object metadata elements to learning style dimensions. Moreover, they do not consider the fuzzy nature of learning objects. Indeed, any learning object can be suitable for different learning styles at varying degrees of suitability. This highlights the need to find a way to remedy this shortcoming. Our work is part of the automatic selection of learning objects. So, we will propose an approach that uses the fuzzy classification technique to select learning objects based on learning styles. In this approach, the metadata of each learning object that complies with the Institute of Electrical and Electronics Engineers (IEEE) standard are stored in a database as an Extensible Markup Language (XML) file. The Fuzzy C Means algorithm is used, on one hand, to assign fuzzy suitability rates to the stored learning objects and, on the other hand, to cluster them into the Felder and Silverman learning styles model categories. The experiment results show the performance of our approach.

Keywords: Intelligent e-learning systems; learning objects selection; learning styles; Felder–Silverman learning style model; IEEE learning objects metadata; fuzzy C means clustering algorithm

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1. Introduction

E-learning systems expand upon traditional computerized learning platforms by integrating intelligence to enhance the learner experience, thereby facilitating the better achievement of learning goals. This typically involves personalized learning, leveraging factors such as the learner's knowledge, emotions, or learning style to customize the sequence and style of learning materials [1,2]. However, in a typical e-learning environment, learners lack the immediate intervention of a teacher when needed. Human tutors have the flexibility to adjust teaching strategies to align with learners' styles and needs [3,4]. On the other hand, learners in e-learning environments face the additional challenge of maintaining interest in learning without direct encouragement from a teacher.

To address these challenges, the concept of intelligent e-learning systems was introduced, leveraging computational intelligence in web-based education [5,6]. To meet learners' needs, intelligent e-learning systems must fulfill various requirements, including the selection of suitable learning objects (LOs) to structure courses according to each learner's style [7–10]. Indeed, the selection of LOs is a crucial step in course design and sequencing. It involves automatically selecting these objects from a database while considering the styles of the learners [11,12]. Then, the major challenge lies in how to select LOs according to the learners' learning styles. To address this problem, the primary approach involves mapping the learning objects (LOs) to different teaching strategies and then aligning these strategies with identified learning styles [13,14]. In this context, numerous studies have investigated various learning style models, including the Kolb model [15] and the Felder and Silverman model [16]. These studies have employed different classification techniques to automatically select LOs by analyzing data derived from LO characteristics [17–19]. IEEE learning objects' metadata (LOM) are commonly used in these techniques to describe LO characteristics and enable their retrieval [20].

Despite the significant results obtained, these approaches have limitations related to robustness. One common limitation is the lack of direct mapping between LO metadata elements and learning style dimensions. Additionally, these approaches often overlook the fuzzy nature of learning objects. Logically, any LO can be suitable for different learning styles to varying degrees of suitability. For instance, an LO that is highly suitable for active learners may be less suitable for others [21–23]. Following this, a robust approach for automatically selecting suitable learning objects (LOs) based on learning styles must assign fuzzy suitability rates to LOs. Considering the limitation mentioned above, we propose, in this paper, an approach that utilizes fuzzy classification techniques to select LOs based on learning styles. We adopt the Felder and Silverman learning styles model (FSLSM) for the mapping process. The LOs are mapped to the identified learning styles using the Fuzzy C Means (FCM) algorithm.

The remainder of this paper is structured as follows: In Section 2, we present related works concerning the automatic selection of learning objects in e-learning systems. The Section 3 outlines the proposed approach. Following that, the Section 4 provides details of the tests conducted on our approach and presents the analysis of the results. Finally, in Section 5, we conclude this paper.

2. Related Works

The automatic selection of suitable learning objects (LOs) plays a crucial role in designing and sequencing courses within intelligent e-learning systems. To positively impact the learning process, it is essential to consider the characteristics of the learners [24–26]. Therefore, it becomes necessary to explore the correlations between LOs and learner characteristics and subsequently provide mechanisms for selecting LOs to facilitate adaptation processes in intelligent e-learning systems. In this context, various approaches have been proposed, including the development of personalized LO recommendation systems or the generation of personalized learning paths.

In the case of recommendation systems, these systems are employed to suggest content within e-learning platforms to learners based on their individual needs, establishing similarity between them and the available content. In the existing literature, various approaches have been explored, with classification techniques being prominently used, particularly those based on decision trees. However, these techniques often result in the generation of numerous rules that the system can utilize to identify suitable learning objects (LOs) [27–31].

In the case of learning path generation, the approaches developed aim to find the best possible match between each learner and the learning objects (LOs) in order to minimize the individual learning path. Many studies in the literature have proposed the use of evolutionary algorithms, such as genetic algorithms [32–34] or ant colony optimization [35–37], to address learning path adaptation based on the satisfaction of learners' needs.

While these studies present a promising approach for solving learning path optimization problems, it is worth noting that the proposed intelligent evolutionary algorithms can be computationally intensive.

Other investigations that search for correlations between learning objects (LOs) and learner characteristics have highlighted the close relationship between learning styles and LOs [38–41]. According to these studies, the vast amount of available LOs in e-learning systems can contribute to cognitive overload for learners, potentially leading to disorientation. Therefore, utilizing intelligent analyses can facilitate the connection of suitable LOs with learners' learning styles. This has paved the way for the development of approaches for automatically selecting appropriate LOs by matching LOs with learning styles [42–44]. Generally, these approaches primarily rely on classification techniques to categorize LOs according to learning styles.

In a study conducted by Anitha and Deisy [45], the authors proposed an approach for delivering suitable learning objects (LOs) according to learners' learning styles. Their approach complies with the IEEE LOM standard, and it involves classifying and selecting LOs for different learning styles proposed by Felder and Silverman. The classification is executed using a rule-based algorithm, where various metadata elements of LOs are considered to cover all the features of LOs. Initially, the LOs are categorized into teaching strategy groups based on the values of the metadata elements, and then they are mapped to the corresponding learning styles. However, the authors note that this classification mechanism does not directly map LOs into learning style categories, nor does it consider the fuzzy nature of LOs.

In another study [46], the authors built upon the previous approach and incorporated the fuzzy nature of learning objects (LOs). They introduced a fuzzy-based scheme for assigning suitability ratings and classifying LOs under different learning styles proposed by Felder and Silverman. Additionally, the authors utilized two factors to determine the suitability rating: fuzzy ratings calculated using a fuzzy-based scheme with metadata elements and expert ratings of LO suitability. By combining these factors, one could determine the suitability ratings of LOs for each learning style dimension proposed by Felder and Silverman. While this approach introduced the fuzzy nature of LOs into the LO selection process, it still required expert intervention to assign the suitability rate to LOs, which raises concerns about the automatic nature of the approach.

Authors like Nafea et al. [41] presented, in 2019, an algorithm that recommends personalized learning objects (LOs) based on learners' learning styles. They utilized the Felder and Silverman learning styles model (FSLSM) to represent both the learner learning styles and the LO profiles. The K-means clustering algorithm was employed to cluster the LOs into groups with similar profiles. Cosine similarity metrics and the Pearson correlation coefficient were used to calculate similarities between the clusters. Subsequently, the obtained clusters were utilized as inputs to a recommender algorithm, which provided the best prediction of learner ratings for any LO. Although the proposed algorithm demonstrated improved classification accuracy and facilitated direct mapping of LOs to different learning styles, it did not account for the fuzzy nature of LOs.

Based on the studies of related works, it is evident that classification techniques play a crucial role in the development of approaches aimed at automatically selecting learning objects (LOs) based on learning styles. The utilization of metadata elements of LOs can notably enhance performance in terms of the accuracy of classification techniques used. However, it is noteworthy that in these studies, the predominant approaches focus on matching LOs to the learning style of the learner without giving due consideration to the fuzzy nature of LOs.

3. Proposed Approach for Automatically Selecting Learning Objects

In e-learning systems, the primary challenge lies in establishing a correspondence between the characteristics of the learner and the sequence of the learning content. This is a complex task because it entails selecting suitable material from a vast pool of available learning resources. Moreover, performing this process manually is challenging, as it requires both technical and pedagogical expertise.

Our proposed approach aimed to address this challenge by developing an automatic selection algorithm for personalized learning objects (LOs) in e-learning systems. This approach imbues the e-learning system with intelligence, enabling it to emulate the role of an instructional designer in course design. The algorithm classifies any LO compliant with the IEEE LOM standard into different learning styles proposed by Felder and Silverman. To achieve this, the preferred learning style of each learner was identified and recorded in the learner profile database in XML format. The LOs, designed with numerous metadata elements, were stored in the LO repository, also in XML format.

To map the LOs to the corresponding learning styles, we employed the FCM clustering algorithm. This mechanism enabled us to perform classification while considering the fuzzy nature of LOs. In practical terms, our approach involved two steps. The first step involved preparing the data to serve as inputs for the FCM clustering algorithm. The second step entailed mapping the LOs into the identified learning styles.

3.1. Methodology

To accomplish the first step, we identified the learning styles of individual learners according to the FSLSM. This can be carried out either by having learners respond to the interactive learning style (ILS) questionnaire [47] or automatically using predefined criteria [48]. Subsequently, the identified learning styles were stored in the learner profile database in XML format. Table 1 illustrates the various categories of learning styles according to the FSLSM [16].

Table 1. Felder–Silverman Model of Learning Style.

Learning Style	Explanation
Active	learners prefer to test and solve problems
Reflective	learners prefer to think, assess, and solve problems on their own
Sensing	learners prefer concrete, practical, and procedural information, i.e., they seek out the facts
Intuitive	learners prefer concrete, innovative, and theoretical information, i.e., they seek meaning
Visual	learners prefer graphs, pictures, and diagrams, i.e., they look for visual representations of information
Verbal	learners prefer to read or hear information, i.e., they look for explanations in words
Sequential	learners prefer information to be presented in a linear and orderly fashion
Global	learners prefer a systematic approach, i.e., they first constitute a global idea and then go into the details

Following that, to acquire the metadata values of the various learning objects (LOs) associated with the course that learners intend to undertake, the stored XML files linked with each LO were collected from the LO repository and parsed, for instance, using Java code. Once the metadata values were extracted, vectors comprising these metadata values were created and then designated as inputs for the classification algorithm. Thus, for each LO, the constructed vector was defined based on the metadata values, with each vector containing a vector id, topic id, LO id, and the set of metadata elements along with their corresponding metadata values.

The IEEE LOM metadata elements selected for the classification of LOs were technical format, interactivity type, learning resource type, interactivity level, and Relationship Kind. These elements were chosen as they represent the criteria influencing the selection of

LOs [49,50]. Table 2 illustrates the categories of LOM considered in our approach, along with their associated elements, their descriptions of each element, and the possible values that they can take.

Table 2. LOM categories considered and their associated elements.

Categories	Elements	Description	Values
4. Technical	4.1 Format	Technical data type(s) of (all the components of) this learning object. This data element shall be used to identify the software needed to access the learning object.	Video/mpeg, application/xtoolbook, text/html, audio, example, image, model
5. Educational	5.1 Interactivity Type	Predominant mode of learning supported by this learning object.	Active, expositive, mixed
	5.2 Learning Resource Type	Specific kind of learning object. The most dominant kind shall be first.	Exercise, simulation, questionnaire, diagram, figure, graph, index, slide, table, narrative text, exam, experiment, problem statement, self-assessment, lecture
	5.3 Interactivity Level	Degree of interactivity characterizing this learning object.	Very low, low, medium, high, very high
7. Relation	7.1 Relationship Kind	Nature of the relationship between a learning object and others	Ispartof, haspart, isversionof, hasversion, isformatof, hasformat, references, isreferencedby, isbasedon, isbasisfor, requires, isrequiredby

To accomplish the second step, our proposed approach employed the Fuzzy C Means (FCM) clustering algorithm to map the constructed vectors into the FSLSM. Figure 1 provides a summary of the proposed approach.

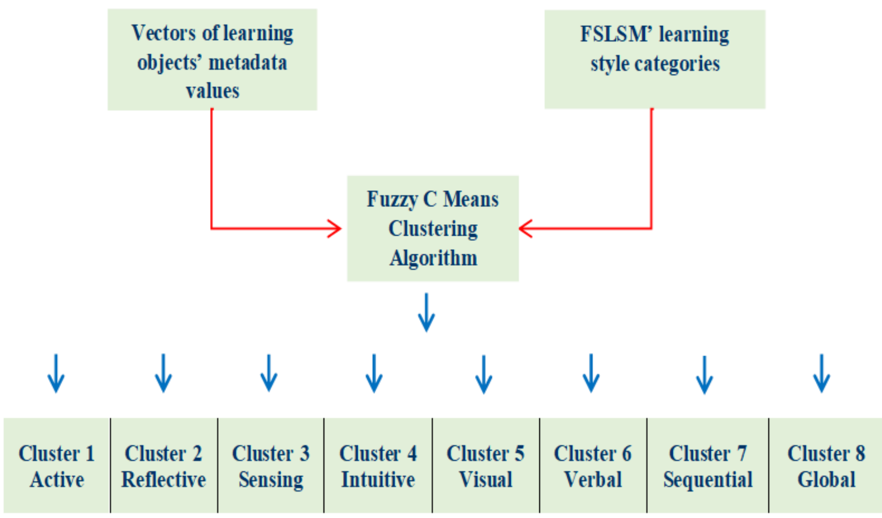

Figure 1. The proposed approach for selecting LOs based on learning styles.

Once the LOs were selected based on learning style, the e-learning system could provide the appropriate LOs for each learner according to their learning style.

The LOs labeling as per the FSLSM and the FCM clustering algorithm are described in the following subsections.

3.2. Labeling LOs

To have the mapping of LOs into the FSLSM's learning styles categories, practically all metadata values of each LO needed to be labeled according to permissible values, which were defined in previous studies [51–53]. Table 3 shows the labeling of the IEEE LOs metadata values as per the FSLSM.

Table 3. Labeling of LOs metadata values as per the FSLSM.

Learning Styles Categories	IEEE LO Metadata Elements and the Corresponding Metadata Values	
	Metadata Elements	**Metadata Values**
Active	5.1. Interactivity Type	Active
	5.3. Interactivity Level	High, Med
Reflective	5.1. Interactivity Type	Mixed, Expositive
	5.3. Interactivity Level	Med, Low
Sensing	5.2. Learning Resource Type	Simulation, Experiment
Intuitive	5.2. Learning Resource Type	Exercise, Problem Statement, Lecture
Visual	4.1. Technical Format	Application, Image, Model, Video
	5.2. Learning Resource Type	Diagram/Figure/Graph
Verbal	4.1. Technical Format	Audio, Text
	5.2. Learning Resource Type	Narrative Text/Lecture
Sequential	5.2. Learning Resource Type	Others
	7.1. Relationship Kind	Others
Global	5.2. Learning Resource Type	Index
	7.1. Relationship Kind	Has Part

After labeling, the constructed vectors of the metadata values of each LO were classified into any one of the eight learning styles by using the FCM algorithm.

3.3. Fuzzy C Means (FCM) Algorithm

To classify learning objects (LOs), we employed the FCM clustering algorithm to group the constructed vectors of LOs metadata values into eight clusters corresponding to the FSLSM categories. Each vector was then labeled according to the FSLSM category to which it belongs. This methodology is supported by previous studies such as those conducted by Joshi et al. [54] and Dung et al. [55], where vectors were grouped based on feature values. In our approach, the clustering was accomplished by utilizing IEEE LO metadata values.

In this algorithm, a membership is assigned to each vector corresponding to each singular cluster center. This membership indicates the degree of suitability of the vector of metadata values associated with an LO for a particular learning style category.

Let μ_{ik} be the membership of kth vector in ith cluster. Then, this membership value satisfies the following conditions:

$$\mu_{ik} \in [0 \ \ 1] \ \text{ and } \ \sum_{i=1}^{c} \mu_{ik} = 1 \ , \ 1 \le i \le c \ , \ 1 \le k \le N$$

where c is the number of cluster centroids and N is the number of vectors of data points.

This means that the membership value may be in the range of 0 to 1, in which 0 indicates the lower suitability level and 1 indicates higher suitability level. This is how we defined fuzzy clustering in our approach and, therefore, how we considered the fuzzy nature of LOs.

Thereafter, by revising iteratively the membership and the cluster centers until convergence, the FCM algorithm led to grouping the vectors of the LOs' metadata values based on the center value selection. Algorithm 1 shows the steps of FCM clustering.

Algorithm 1 FCM clustering algorithm for mapping vectors of LOs' metadata values

Initialize m = real number greater than 1
$M_{ij} =$ degree of membership function x_i in cluster j
$F_i =$ input vector, $C_j =$ center of cluster, $\varepsilon =$ threshold value

Step 1 : Initialize the membership function
$M = \left[M_{ij}\right],\ M^{(0)}$

Step 2: Calculate the center value by assigning weights to vectors of learning objects' metadata values

$C^k = C_j$ with $M^{(k)}$ where $k =$ number of center values calculated based on feature values
$C_j = \frac{\sum_i^n M_{ij}^m F_i}{\sum_i^n M_{ij}}$

Step 3 : Update the membership function M^k and M^{k+1}
$M_{ij} = \frac{1}{\sum_{k=1}^{c}\left[\frac{\left\|F_i - C_j\right\|}{\left\|F_i - C_k\right\|}\right]^{\frac{2}{m-1}}}$

Step 4 : if $\left|M^{k+1} - M^k\right| < \varepsilon$ then stop, else go to step 2

4. Experimental Test and Result Analysis

The experiment that we are conducting aims to evaluate the proposed approach for selecting learning objects (LOs) to comprise a specific course, while also considering the learning styles of individual learners. In this experiment, we conduct a simulation test where we generate metadata values corresponding to the elements prescribed by the IEEE LOM standard for various types of LOs. The course that we anticipate learners will undertake consists of eight topics, each containing 12 types of LOs. Thereafter, for each LO, the metadata values corresponding to technical format, interactivity type, learning resource type, interactivity level, and Relationship Kind elements are randomly generated. Table 4 displays the random generation of metadata values for each element of the learning objects (LOs) within the various topics. Additionally, a portion of the generated data is presented in Table 5, illustrating the metadata values for the elements of the LOs within the topic identified by the ID as equal to 1.

Table 4. Random generation of metadata values of IEEE LOM elements.

		Metadata Values of IEEE LOM Elements				
Topic id	LO id	Format	Interactivity Type	Learning Resource Type	Interactivity Level	Relationship Kind
i	j	x	y	z	v	w

where i = 1. . .7 and j = 1. . .10, and values x, y, z, v, and w are given by the following:
x = Rand (video/mpeg, application/xtoolbook, text/html, audio, example, image, model)

y = Rand (Active, expositive, mixed)

z = Rand (Exercise, simulation, questionnaire, diagram, figure, graph, index, slide, table, narrative text, exam, experiment, problem statement, self-assessment, lecture)

v = Rand (Very low, low, medium, high, very high)

w = Rand (Ispartof, haspart, isversionof, hasversion, isformatof, hasformat, references, isreferencedby, isbasedon, isbasisfor, requires, isrequiredby).

Table 5. Part of the generated metadata values of IEEE LOM elements.

	Metadata Values of IEEE LOM Elements					
Topic id	**LO id**	**Format**	**Interactivity Type**	**Learning Resource Type**	**Interactivity Level**	**Relationship Kind**
1	1	Image	Mixed	Simulation	Low	Is part of
	2	Video	Active	Index	Med	References
	3	Model	Active	Graph	Low	Has part
	4	Text	Mixed	Problem statement	Low	Is part of
	5	Audio	Active	Narrative	High	References
	6	Text	Mixed	Problem statement	High	Is part of
	7	Application	Expositive	Graph	Med	Is part of
	8	Application	Expositive	Exercise	Med	Is part of
	9	Image	Expositive	Figure	Med	Is part of
	10	Image	Mixed	Exercise	High	Has part

Next, metadata values are inputted for the required IEEE LOM elements for each learning object (LO). Subsequently, the dataset used as the input for our clustering algorithm is created by forming vectors of the metadata values of the LOs, following the proposed methodology.

Clustering of the Vectors of LOs' Metadata Values Based on FCM Algorithm

Following the application of the FCM clustering algorithm, the vectors are grouped into eight clusters corresponding to the following FSLSM categories: Active, Reflective, Sensing, Intuitive, Visual, Verbal, Sequential, and Global. The final clusters are derived after 50 iterations with a threshold value $\varepsilon = 0.001$. The clustering results are depicted in Table 6.

Table 6. Results of the clustering.

Clusters	Number of Vectors
Active	17
Reflective	11
Sensing	15
Intuitive	11
Visual	13
Verbal	11
Sequential	8
Global	10

The classification results demonstrate that the FCM algorithm yields the best outcomes, with rapid convergence being achieved. Merely 50 iterations were necessary for the algorithm to converge. This observation is directly attributed to the limited amount of input data utilized in our simulation test. In real cases, the number of learning objects

(LOs) employed in course design on e-learning platforms is significantly higher, resulting in a larger volume of input data and, thus, a longer convergence time.

This classification result can be directly utilized to offer appropriate learning objects (LOs) to each learner based on their learning style. Certainly, as the metadata vectors include details such as the identifiers of the LOs and the identifiers of the topics, we can retrieve these data from all the classified vectors. Consequently, we can determine the appropriate LOs for each learner with a specific style for every topic included in the course.

For example, for the Active cluster, it suffices to extract the identifiers of the Los, as well as the identifiers of the topics, from the 17 metadata vectors classified in this category and subsequently provide suitable LOs for learners belonging to this category.

5. Conclusions

This paper introduces an approach for automatically selecting learning objects in intelligent e-learning systems based on the learning styles of the learner. To address the challenge posed by the fuzzy nature of learning objects (LOs), a fuzzy classification technique is employed for LO selection. This approach enables the classification of any LO conforming to the IEEE LOM standard into various learning styles proposed by Felder and Silverman. The learning styles of learners are identified and stored in a learner profile database in XML format. LOs, designed with multiple metadata elements, are stored in an LO repository, also in XML format. The XML metadata elements of LOs are parsed to form the input data for the clustering algorithm. The Fuzzy C Means (FCM) algorithm is utilized to cluster the LOs into the categories defined by the Felder and Silverman learning styles model (FSLSM). The experimental results demonstrate the effectiveness of our approach.

Therefore, through the implementation of our approach, we can surpass the limitations observed in prior research, notably the challenges concerning robustness. This includes the necessity to account for the fuzzy characteristics of learning objects in the selection process, as well as the requirement to address the direct mapping between learning object metadata elements and learning style dimensions.

Among other things, the proposed approach offers another advantage: it can be easily integrated into various e-learning platforms, including free-license platforms like Moodle. As a result, this approach empowers the e-learning system to attain intelligence, enabling it to mimic the actions of an instructional designer in course design completion.

Furthermore, it is true that our work addresses the problem of learning object selection in e-learning systems; however, it only considers selection based on learning styles. To attempt to cover the various parameters influencing selection, we plan to consider other parameters in future work, namely learner prerequisites and their levels of learning acquisition.

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