An adaptive hierarchical questionnaire based on the Index of Learning Styles

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Abstract. One of the main concerns when providing learning style adaptation in Adaptive Educational Hypermedia Systems is the number of questions the students have to answer. With respect to learning styles, it is possible to decrease the number of versions taking into account the general tendency of the student and not the specific score obtained in each dimension. In this paper we present a new approach to reduce the number of questions of Index of Learning Styles (ILS) questionnaire based on Felder-Silverman's Learning Style Model (FSLSM). The results obtained in a case study with 330 students are very promising. It was possible to predict students' learning styles with high accuracy and only a few questions.

1 Introduction

In order to provide adaptation, Adaptive Hypermedia Systems (AHSs) [3] need to store and maintain information about the user, which constitutes the user model [9]. Building user models implies gathering information about the users and transferring this information into the model. Many systems use questionnaires for detecting users' features while others try to infer them from user interactions with the system.

In the area of Adaptive Educational Hypermedia (AHE), one of the students' features frequently used for adaptation purposes is that of their learning style. In recognition of the fact that individuals learn in different ways, a body of research and techniques has been developed, which attempts to categorize individual variations while satisfying different learning style preferences.

Felder and Silverman created a learning style model (FSLSM) [4] that has been widely used in technology-enhanced learning. It describes learning styles distinguishing between preferences on four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global). Information about these preferences can be extracted from the corresponding questionnaire (ILS) [5], which contains 44 questions. We have used FSLSM and ILS in previous works [1] [10] [12].

Even when information about learning styles is very useful for adapting the education material to each student, answering the 44 questions from the ILS is a time con-

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suming and boring task. That is especially relevant if the system requires more information from the students, beside the learning style. In this paper we propose an approach to reduce the number of questions needed to determine the learning style of each student.

Next section describes the goal of the work in detail. Section 3 and 4 explain how the study was developed, while section 5 presents the results. Section 6 describes some related work and finally section 7 presents the conclusions.

2   The goal

Most of the current AEHSs that provide adaptation based on learning styles use the ILS questionnaire to obtain the learning style model of each student. ILS produces information about 4 dimensions of learning styles, using 11 questions for each dimension. The score are obtained by subtracting the number of answers related to one category from the number of answers related to the opposite category. In this way, the final results from the test are four scores (odd numbers ranging from -11 to 11), one for each dimension. That is, there are 12 possible different results for each one.

This information provides many opportunities for adaptation, because an AEHS could deliver 12 different versions of the educational material considering only one dimension of the learning style model. On the negative side, adapting to learning styles requires the student to answer 44 questions about his/her preferences, which many times it is considered a heavy additional burden.

However, most of the times there is not a different version of the course for every possible value of the questionnaire, but students are clustered in classes covering different values. For example, Felder et al. [5] recommend grouping the students into five categories for every dimension.If a student gets a score from 1 to 3 in any dimension, he/she has a mild preference but his/her learning style is well balanced. Differently, if the score is from 5 to 7, the student has a moderate preference and he/she will learn more easily in teaching systems that favor that dimension. Finally, if the student scores from 9 to 11, he/she could have difficulties when learning through a system that does not support this preference.

In previous experiences with adaptive courses, we have found that authors use to prefer to classify the students into three categories for every dimension: **low**, **neutral** and **high**. In this case, students having, for example, values between -11 and -5 in a given dimension would be provided with the same version of the adaptive course, students with values between -3 and 3 would receive a second version and students having between 5 and 11 would receive a third one.

In this context, the system only needs to know the class of a given student for every dimension, but not the exact value. As a consequence, it does not need to ask the student the 11 questions of the ILS, but only enough questions to discriminate his/her class. The problem is: which questions (among the 11) would provide enough information about the student learning style?

This problem is a variation of the general question approached by the Item Response Theory (ITR) [13]. ITR mostly focuses on the problem of analyzing the power of a question or a whole test to evaluate, for example, knowledge or IQ of a person.

Our goal is to provide AEHSs with the ability to classify the learning style of a given student with so few questions as possible. Eventually, we seek to obtain an algorithm capable of asking different questions to different students: the next question to be posed is calculated considering the answers given so far by the student (figure 1). It is important to highlight that we do not attempt to propose new questions for finding the student learning style, but only to select the more relevant ones **for each student** from the ILS.
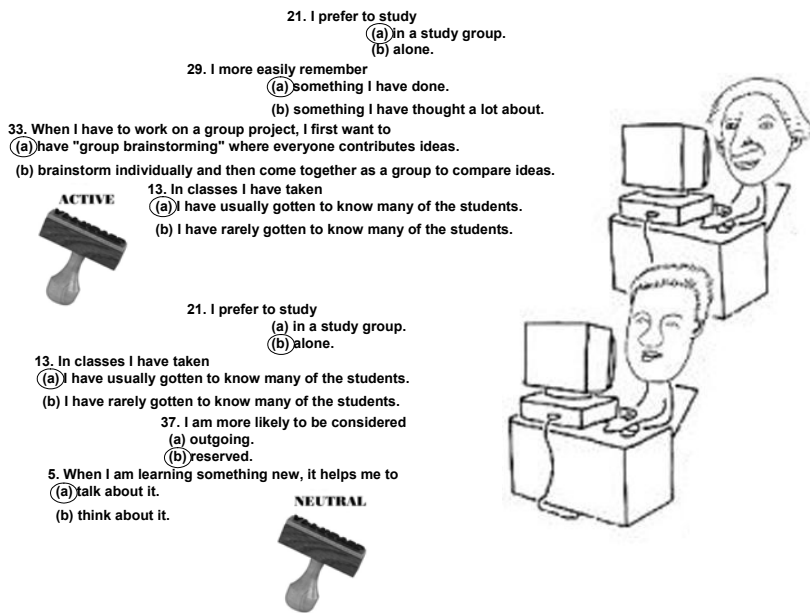

Fig. 1. Different questions for different students

Classification is one of the main goals of data mining techniques [15]. In general, these techniques learn a classification model from the observation of (already classified) instances. Once the model has been learnt, it can be used to classify new instances whose class is unknown.

This work shows how classification techniques can be used to learn which questions should be asked to each student in order to reduce the number of answers needed to classify his/her learning style.

3 Data collection

Data mining techniques are based on the analysis of samples in order to find patterns in the data; this knowledge can be used to classify new examples, considering the class of similar patterns in the sample.

Samples of students belonging to three different populations were used to generate the results presented on this work.

- Sample 1: 42 students from Secondary School level (IES "Agora", Madrid).
- Sample 2: 80 students from a Vocational School (post-secondary level, CIFP "Jose Luis Garci", Madrid). They were studying audio-visual technology.
- Sample 3: 200 students from the Computer Science and Engineering degree at the Universidad Autónoma de Madrid.

As a result, the study is based on the answers to the ILS questionnaire from 330 students who were between 15 and 30 years old. In the rest of the paper, the term "sample" will make reference to the whole set of students, considering the aggregation of the three samples described above.

Figure 2 shows the frequency of each ILS dimension for the sample. Dim1 to dim4 correspond to the Active/reflective, Sensing/intuitive, Visual/verbal and Sequential/global dimensions, respectively. These frequencies do not follow the normal distribution, but fortunately this is not a requirement of the techniques used to analyze the data. Not surprisingly, data distributions fairly accurate to the distributions found on a previous experiment with similar population [1]. Regarding the distribution between genders, 101 were women and 229 were men.
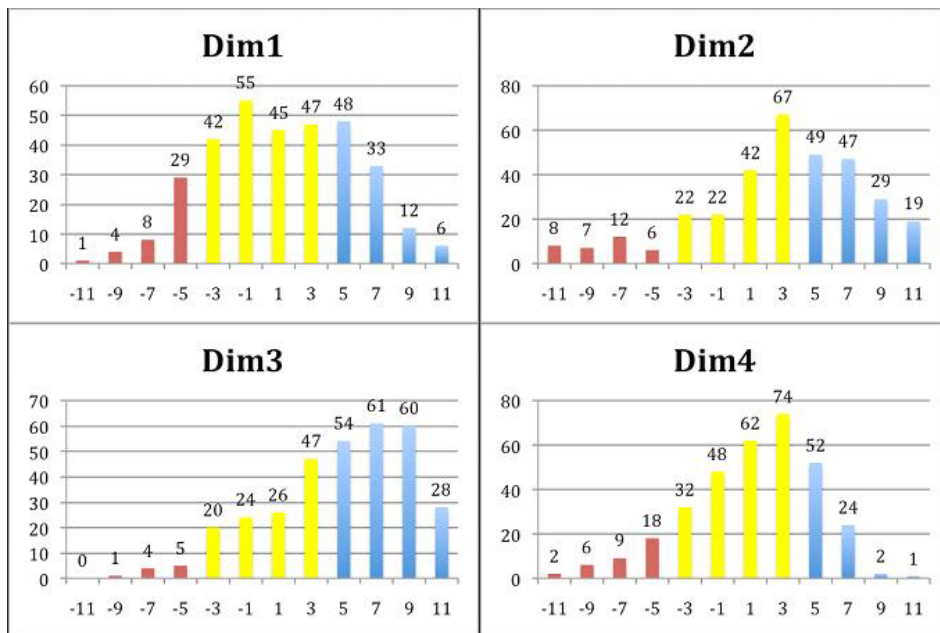

Fig. 2. Distribution for every dimension

4 Methods

The data were processed and the students divided into three classes: **high** (from 11 to 5), **neutral** (from 3 to -3), and **low** (from -5 to -11). This dataset was analysed using the *Weka* workbench of data mining algorithms [15].

Classification algorithms learn a model based on the instances of the dataset, where each instance is described as a collection of attributes. In this case, an instance or example was formed by the data of a given student: the answer (*a* or *b*) he/she gave to each of the ILS questions and the class assigned to each leaning style dimension.

Considering the goal of this work, decision trees are very convenient tools. Nodes in a decision tree involve testing a particular attribute of the instance to be classified. Depending on the attribute value, the corresponding descendent branch is followed. This procedure is recursively applied until a leaf is reached. Usually, each leaf has a label with the class to be assigned to the instances that reach that leaf. As a consequence, along each path from the root to a leaf they can be used, potentially, different attributes from the instance to be classified.

Next subsection provides some technical details about the method used to build classification trees, while §4.2 explains how this implementation supports our goals.

4.1 C4.5 algorithm

An implementation of the C4.5 algorithm [11] (called J4.8 [15]) for building decision trees was used with the aim of identifying the most relevant questions from ILS. C4.5 builds decision trees from a set of training data using the concept of **Information Entropy**. This concept is a measure of the uncertainty associated with a random variable. In the context of this work it is a measure of the average information content the recipient is missing when the value of the random variable is unknown. Given a set *S* of instances, each one with the class it belongs to, the *Entropy(S)* can be thought of as a measure of how random the class distribution is in *S*.

Information gain is a measure given to an attribute *a*. Attribute *a* can separate *S* into subsets $S_{a1}, S_{a2}, S_{a3}, ..., S_{an}$. The information gain of *a* is then *Entropy(S)* − *Entropy(S_{a1})* − *Entropy(S_{a2})* − ... − *Entropy(S_{an})*. In other words, the information gain of *a* measures how much information (about the class of an instance) is obtained in the average by learning the value of attribute *a* for the given instance.

In this way, C4.5 examines the normalized information gain that results from choosing an attribute for splitting the data. The attribute with the highest normalized information gain is the one used to make the decision. The algorithm then recurs on the smaller sublists. It usually stops when all the samples in the list belong to the same class. Once this happens, it simply creates a leaf node for the decision tree, telling the class of the instances that reach this point. If none of the features gives any information gain, C4.5 creates a decision node higher up the tree using the expected value of the class.

An important consideration when building classification models is to avoid overfitting, that is, to build models which provide good results only with the training data. To this end, 10 folds cross-validation [15] was used. This method provides estimations about the predicted behavior of the model with data different from the training set. Results obtained by applying the method are presented in section 5.

4.2 Properties of decisions trees

Decisions trees built with the classification algorithm described in the previous section have two properties that are well suited for the goal of this work:

- The criterion for choosing the next attribute to be used to split the data is to maximize the information gain. In other words, they select the most relevant attribute for a given subset of the sample.
- Decision trees provide an explicit representation of the classification model, enabling the construction of dynamic tests based on the attributes (questions) used by the tree.

5 Results

Table 1 shows the average path from the root to the leaves in the classification tree for each dimension, considering the number of training examples that reached each leaf. That is, each length represents the expected number of questions the AEHS should ask before being able to classify a student for that dimension.

Table 1. Estimated number of questions for each LS dimension.

	Active/Reflective	Sensing/Intuitive	Visual/Verbal	Sequential/Global
Questions	4.97	4.06	4.96	4.28

The questions posed to each student are selected on the fly, accordingly to the classification tree generated for each dimension. Figure 3 shows, for example, the classification tree generated by the C4.5 algorithm from the sample for the *Sensing/intuitive* dimension.

Figures 3, 4, 5, and 6 show the trees for dimensions 1 (active/reflective), 2 (sensing/intuitive), 3 (visual/verbal) and 4 (sequential/global), respectively. These trees can be interpreted in a top-down way. The questions are represented by circles (Q xx) and always has two different paths, depending on the answer of the student (a or b), where xx is the number of question in ILS. When a specific answer classifies students, it conduces to a leaf. These leaves can be high (H xx and six sides polygon), neutral (N xx and five sides polygon), and low (L xx and four sides polygon), where xx is the number of students classified in our population.
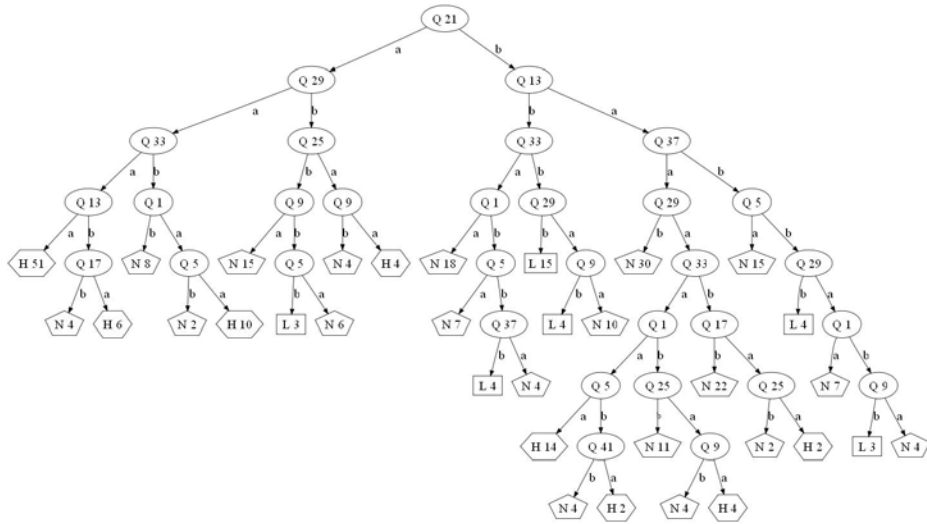
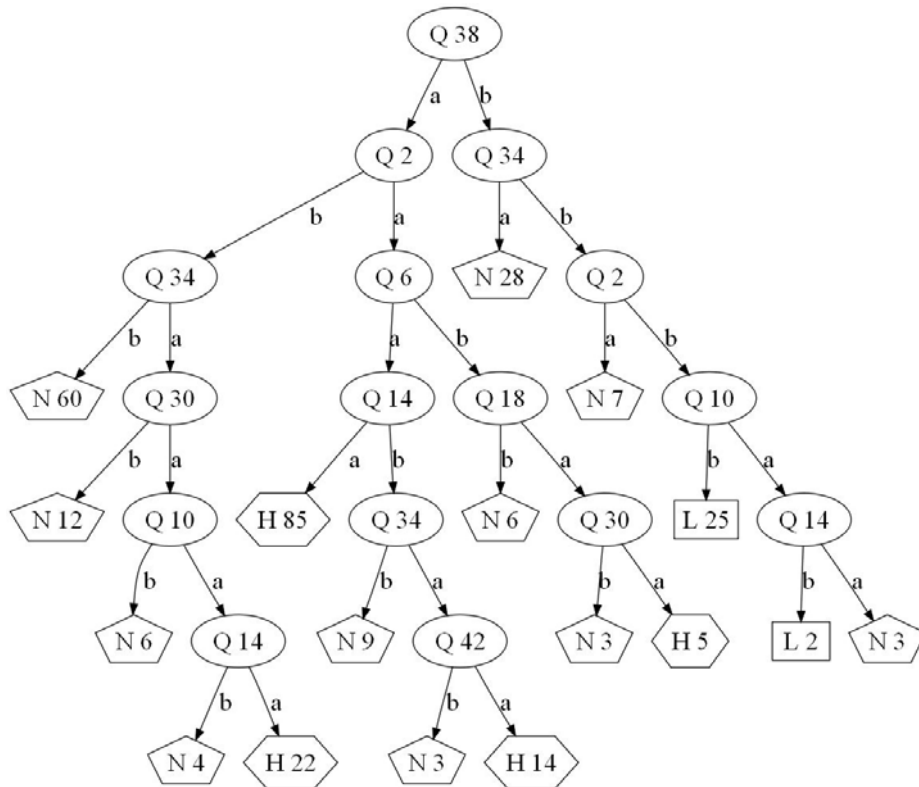**Fig. 3.** Decision tree for the *Active/reflective* dimension.

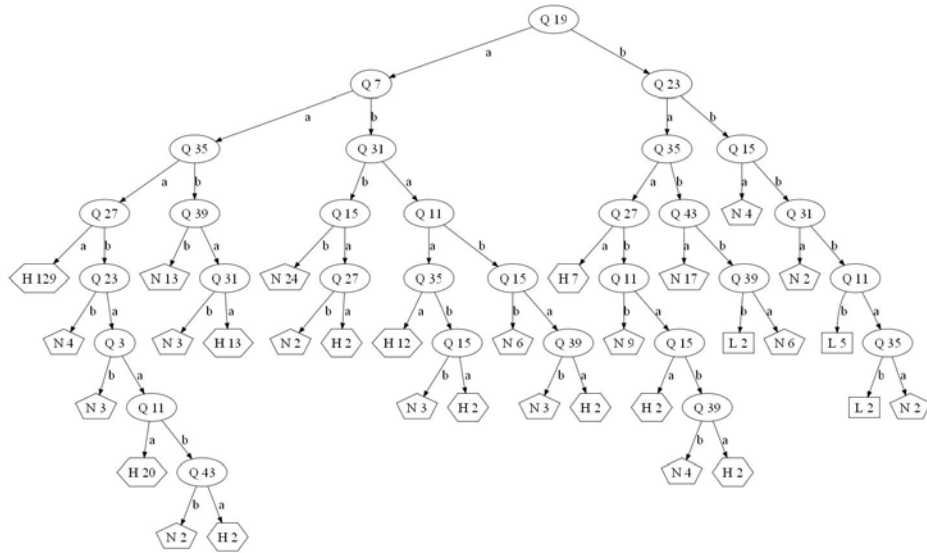**Fig. 4.** Decision tree for the *Sensing/intuitive* dimension.

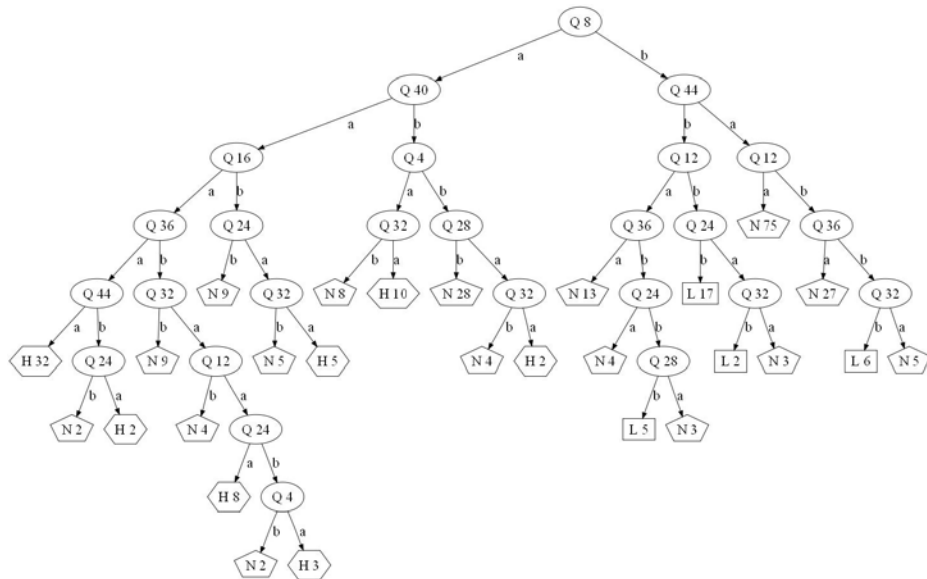**Fig. 5.** Decision tree for the *Visual/verbal* dimension.

Fig. 6. Decision tree for the *Sequential/global* dimension.

Even if all the examples on the sample are well classified, the classifier is assumed to make some mistakes when classifying new instances (students). In order to estimate the predicted classification error, ten fold cross-validation was used [15]. Table 2 shows the estimated prediction error for each dimension.

Table 2. Estimated classification error for each LS dimension.

	Active/Reflective	Sensing/Intuitive	Visual/Verbal	Sequential/Global
Error (%)	4.29	1.36	2.92	3.41

It should be noted that classification mistakes happen with students having values on the border between classes. For example, sometimes a student with a value -5 in a given dimension is wrongly assigned to the *neutral* category, instead of *low*. This type of mistakes is not severe, because a student with a value -5 will probably be well assisted by a "neutral" version of the educational material.

During the data analysis it was also observed that training the classification trees with less examples produced both larger errors and longer paths from the root to the leaves. Even though it is possible that significant larger samples would produce shorter trees with the same level of confidence, the tests developed do not seem to indicate that.

It is also interesting to describe the results when the three original samples were individually analyzed. Even if the expected error increased, the learning algorithm mostly selected the same attributes (questions) for the higher portions of the trees. This fact indicates two things:

a) The relevance of a question does not vary significantly with the age of the student.

b) The trees seem to converge to a common tree, independently from the origin of the sample, or at least to a common subset of questions.

6   Related work

The use of questionnaires, although usually provides accurate information, can be very time-consuming. Some works have investigated the use of Bayesian networks [6], behavior patterns [7], user-mouse interaction [2], and feed-forward neural networks [12] to detect learning styles starting from information of user behavior in educational websites (tasks done, time spent, scores obtained). However not all characteristic behavior described in the learning style model can be mapped and identified from the behavior in a specific learning system.

A previous work [8] tried to identify the five most representative questions for each dimension of the ILS according to frequencies analysis. Nevertheless they investigate the relationship between these questions and semantic groups established by them instead of trying to reduce the number of questions of ILS. Comparing their ranking and our decision trees we can see that those relevant questions in [8] are in the four highest levels of the trees.

7 Discussion

In this work we have presented a new approach to predict students' learning styles that reduces the number of questions of ILS questionnaire that each student has to answer. It must be highlighted that the goal of this paper is not to provide

The results of the case study show that some questions from the ILS are more relevant that others, in the sense that they provide more information about the general tendency of the student along the corresponding dimension. Particularly, using a sample with 330 students, we were able to build classification trees that need, on the average, between 4 and 5 questions to classify a learning style dimension for each student. These results are very promising since the prediction accuracy obtained is very high (between 95.71 and 98.64% depending on the dimension).

Even if different samples could produce different classification trees, considering that each tree is concerned only with 11 questions, the size of the sample is enough to consider that classification trees would not be much different for other samples. Actually, the three individual samples show very little difference of distribution among them and the classifications trees built for individual samples tend to use the same discriminating questions.

Even so, an author intending to use the best possible sequence of questions to classify students' learning style could build classification trees based on samples from her target population. However, if the sample is not large enough, these "specific" trees would produce more errors than generic ones.

A possible bias of the studied sample is the proportion of men to women (more than 2 to 1). However, results from the case study show no significant difference between the results of the ILS for men and women. Moreover, none of the classification trees used the gender as a discerning attribute. In other words, knowing the gender of a student does not provide information about his/her learning style.

It is also possible to create more classes for each dimension, for example the five categories proposed by Felder and Silverman. However, it would be needed to ask more questions in order to refine the classification. Besides, additional example instances would be needed in order to reach good precision levels with more classes.

We plan to extend our study collecting and analyzing data from different groups of students. In addition, we plan to eventually combine information extracted from ILS questionnaire with that related to the type of information selected, activities done, time spent on each one, mouse movements and so on.

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