Towards a new approach for constructing concept maps based on fuzzy logic

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Abstract—In recent years, adaptive learning systems rely increasingly on concept maps to customize the educational logic developed in their courses. Most approaches do not take into account the possibility of combining the concept maps predefined by experts of field and those developed automatically using the Fuzzy Sets Theory. In this article, we present a hybrid approach using on the one hand the feedback from experts of domain to select, prioritize relevant concepts and create prerequisite relationships to get the initial concept map, on the other hand we use the fuzzy logic to measure relevance degree of all relationships existing in this concept map, these links are considered as fuzzy relationships. With this approach we got two types of prerequisite relationships between concepts, the first type can be classified as relationships correctly established by the expert. These relationships must be kept in the final concept map. The second type can be considered as relationships incorrectly established by the expert, because the concepts involved in these relationships are independent, in this case these relations must be deleted or substituted with the inverse of the original relations, or because the items used in evaluations of these concepts, connected by erroneous relations, are inappropriate and must to be reviewed.

Keywords—Concept map; Fuzzy Sets Theory; Adaptive Learning Environments; Fuzzy prerequisites relationships; Data mining.

I. INTRODUCTION

Since 1998, Novak developed the theory of meaningful learning, based on the concept maps to facilitate the students for understanding certain scientific concepts [1-2], this theory gave birth to teaching by objectives. The big idea of this pedagogy involves cutting of knowledge in as many teachable units, the selection criterion is, above all, the possibility of acquisition related to the evaluation and the knowledge that if you cut enough, it is always possible for a learner to learn and the tutor to assess the acquisition [3]. Concept maps have the advantage of reproducing the conditions of development of thought, as presupposed by the assimilation theory [4] and these concept maps are an excellent teaching tool in adaptive learning systems. In fact relations between the prerequisite relationships among concepts in the map must beings established with maximum certainty that allows the learner to follow a logical process of learning. However, it is not easy to predict in some way a link between two concepts is a prerequisite relationships or not. Indeed the Fuzzy Sets Theory (Fuzzy Sets Theory - FST) is the most appropriate technical to build fuzzy prerequisite relationships with their relevance degree among learning concepts for creating the concept map in a particular field [5].

The following section presents a brief overview of some existing approaches for the concept maps constructing process and discusses their limits.

II. SOME EXISTING APPROACHES FOR THE CONCEPT MAPS CONSTRUCTING PROCESS

A. Approach based on methods of neuro linguistic programming (NLP)

This approach, using methods of neural linguistic programming NLP are used in information retrieval. This approach is generally used in areas such as construction of automatic summarization, information retrieval in documents and metadata documents [6], and the creation of conceptual maps for unstructured sources data [7]. It is also used to extract a summary of an original document without any change [8]. This approach is applicable only for the language is technical tools and methods are not available for many languages.

B. Approach based on Fuzzy Sets Theory (FST)

Several learning systems use this approach on a number of different methods of fuzzy logic [9-13]. Sue et al. used a two-phase method that extracts the association rules between the concepts by applying fuzzy logic to convert the grades learners into three levels of difficulty and construct a concept map [14]. Bai and Chen simplified and improved the latter method in adaptive way [15]. Wang based on the FST has developed another method for the non-explicit links between concepts [16]. These methods mentioned above do not take into account the possibility of combining the concept maps predefined by experts of field and the automatic generation of these concepts map from the evaluation results obtained by learners during of process learning.

In this paper, a new approach is proposed to build fuzzy prerequisite relationships with their relevance degree among learning concepts for creating the concept map in a particular area.
III. FUZZY SETS THEORY (FST)

Since 1965, the Fuzzy Sets Theory has advanced in a variety of ways and in many disciplines. Fuzzy sets were introduced by Zadeh [17, 18, and 19] to represent mathematically the vagueness on certain classes of objects and provide the basis for fuzzy logic.

The fuzzy sets were introduced to model human knowledge representation, and thus improve the performance of systems that use this modeling decision. Fuzzy sets admit gradation such as all tones between black and white. A fuzzy set has a graphical description that expresses how the transition from one to another takes place. This graphical description is called a membership function.

A fuzzy part (or fuzzy set) of a set E is an application

\[ \mu_A(x) : E \rightarrow [0, 1] \]

Fig. 1. \( \mu_A(x) \): A membership function. The gray level indicates the degree of membership

IV. OUR PROPOSED APPROACH

In our approach we follow three phases to build the concept map of a specific area. The first phase determines an initial predefined concept map, the second phase mine the association rules between the concepts from the numeric testing records of learners, in the third phase we propose to build fuzzy prerequisite relationships with their relevance degree among learning concepts.

A. First phase: define an initial concept map

For an expert in a particular field, the presentation of the methodology and sequence to be used for the construction of concept maps is achievable by following the steps below described by Novak [2]:

Step 1: Identify all the domain concepts, then make a classification of these concepts in descending order of importance.

Step 2: Start building the map starting with the more general concept (at the top of the map) to go to the most specific concept (located at the bottom of the map), by establishing, progressively, the all relationships that may appear between the relevant concepts.

At the end we will have an initial concept map as shown in figure below:

The Figure 2 shows an example of a concept map of a course containing 10 relevant concepts, and prerequisite relationships among them.

From the links of the concept map we define the matrix \( M \) of prerequisites between concepts, where the value of each element \( M_{ij} \) is calculated as below:

\[ M_{ij} = 1 \] means the concept « i » is a prerequisite of the concept « j ».

\[ M_{ij} = 0 \] means the concept « i » is not a prerequisite of the concept « j ».

« i » represents the rows and « j » the columns.

Table 1 below, shows a matrix representation (\( M_{ij} \)) of initial predefined concept map of the figure 2.

For example, the first line means that the concept A is a prerequisite of the concepts B and C.

<table>
<thead>
<tr>
<th>( M_{ij} )</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>C</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>D</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
B. Second phase: fuzzification of learners’ testing records

1) Retrieving digital data

In this sub-phase, we retrieve the numerical grades obtained during assessments of each student in each concept in a learning process [20]. These grades are collected in a matrix called the matrix grades: Grades (Learner (Si), Concept (i)) such as:

<table>
<thead>
<tr>
<th>Grades</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>S_1</td>
<td>10</td>
<td>10</td>
<td>1</td>
<td>3</td>
<td>7</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>S_2</td>
<td>11</td>
<td>12</td>
<td>5</td>
<td>7</td>
<td>11</td>
<td>11</td>
<td>7</td>
</tr>
<tr>
<td>S_3</td>
<td>10</td>
<td>11</td>
<td>5</td>
<td>3</td>
<td>8</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>S_4</td>
<td>13</td>
<td>10</td>
<td>6</td>
<td>6</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>S_5</td>
<td>15</td>
<td>18</td>
<td>10</td>
<td>12</td>
<td>16</td>
<td>16</td>
<td>15</td>
</tr>
<tr>
<td>S_6</td>
<td>19</td>
<td>18</td>
<td>6</td>
<td>10</td>
<td>14</td>
<td>19</td>
<td>13</td>
</tr>
<tr>
<td>S_7</td>
<td>12</td>
<td>11</td>
<td>1</td>
<td>5</td>
<td>6</td>
<td>10</td>
<td>4</td>
</tr>
<tr>
<td>S_8</td>
<td>3</td>
<td>4</td>
<td>0</td>
<td>2</td>
<td>5</td>
<td>7</td>
<td>5</td>
</tr>
<tr>
<td>S_9</td>
<td>15</td>
<td>16</td>
<td>6</td>
<td>10</td>
<td>11</td>
<td>18</td>
<td>13</td>
</tr>
<tr>
<td>S_10</td>
<td>12</td>
<td>14</td>
<td>5</td>
<td>3</td>
<td>0</td>
<td>13</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 2 shows an example of 10 students and their grades within 7 concepts that constitute the initial conceptual map. Where:

The maximum score that a student can have in an assessment is equal to 20.

2) Measure of variation of grades

In this sub-phase, we measure the variation of grades of all prerequisite relationships of initial predefined concept map. The Matrix of variation of grades ∆Grades (i, j) is calculated using the both matrix:

- Matrix Grades (Learner (Si), Concept (i))
- Matrix Mij

\[ \Delta \text{Grades} (i, j)_{\text{Learner}} = [\text{Grade} (j) - \text{Grade} (i)] \] with \( M_{ij} = 1 \) i.e the concept « i » is a prerequisite of the concept « j ».

And \( -20 \leq \Delta \text{Grades} \leq 20 \)

In table bellow we propose an example of matrix ∆Grades (i, j) based on the data of the tables 1 and 2:

<table>
<thead>
<tr>
<th>∆Grades</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>D</th>
<th>D</th>
<th>D</th>
<th>D</th>
<th>D</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>S_1</td>
<td>0</td>
<td>-9</td>
<td>-1</td>
<td>2</td>
<td>6</td>
<td>4</td>
<td>-4</td>
<td>0</td>
<td>6</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3) Prerequisite relationships fuzzification

The fuzzy set theory is used to simplify the analysis of the numerical results of the evaluations of learners with transforming their digital data in membership functions. In our approach this theory is applied to the prerequisite relationships of initial concept map.

Let \( X \) a set of prerequisite relationships of initial concept map. Let CPR a fuzzy subset of prerequisite relationships that can be classified as a correct prerequisite relationships between concept « i » and concept « j ».

\[ \text{CPR} = \{ k | \mu_{\text{CPR}} (k) / k \in X \} \]

Where:

\( \mu_{\text{CPR}} (k) \) Is the membership function of CPR, the values of this function present the relevance degree of each link « k » in the fuzzy set CPR.

Let RPR a fuzzy subset of links that can be classified as wrong prerequisite relationships between concept « i » and concept « j », but can be classified also as a correct prerequisite relationships between concept « j » and concept « i ».

\[ \text{RPR} = \{ k | \mu_{\text{RPR}} (k) / k \in X \} \]

Where:

\( \mu_{\text{RPR}} (k) \) is the membership function of RPR, the values of this function present the relevance degree of each link « k » in the fuzzy set RPR.
This result will be denoted matrix of fuzzy prerequisite relationships (M-FPR).

\[
\begin{array}{c|c|c|c|c|c|c|c|c|c|c}
\hline
k & A & B & C & D & E & F \\
\hline
& \mu(CPR) & \mu(RPR) & \mu(CPR) & \mu(RPR) & \mu(CPR) & \mu(RPR) & \mu(CPR) & \mu(RPR) & \mu(CPR) & \mu(RPR) \\
\hline
0 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline
1 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline
2 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline
3 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline
4 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline
5 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline
6 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline
7 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline
8 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline
9 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline
10 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline
\end{array}
\]

Table 4 shows the result of prerequisite relationships fuzzification.

4) Results of prerequisite relationships fuzzification

Table 4 shows the result of prerequisite relationships fuzzification.
2) **Fuzzy data mining**

In last step we use the algorithm above for mining the prerequisite relationships with their relevance degree and generate the final concept. Input data of the algorithm are:

- Matrix of fuzzy prerequisite relationships (M-FPR)
- A threshold minimum of prerequisite relationships is a threshold that indicates the prerequisite relationships meaningful in the construction process.

At first, the final concept map is empty. For each link « k » existing in the matrix of fuzzy prerequisite relationships we test:

- If the value of maximum of average of each membership functions \( \mu_{FPR}^{k} \) and \( \mu_{RPR}^{k} \) is greater or not than the threshold minimum.

At the end, the link (k) may be:

- Add in the final concept map in the same direction between his two concepts with a relevance degree equal to \( \alpha_{k} \).
- Add in the final concept map in the opposite direction of the initial link with a relevance degree equal to \( \alpha_{k} \).
- Delete and it is not included in the final concept map.

3) **Example of Concept map constructing process**

We will apply this algorithm to the data (M-FPR) of the table 4.

Input data of the algorithm are:

- Matrix of fuzzy prerequisite relationships (M-FPR) of table 4.
- A threshold minimum \( \alpha_{c} = 0.5 \)

Thus, the final concept map is:

![Initial concept map of Java](image)

In this section, we propose an implementation of our approach in the Java programming language field.

A. **Define an initial concept map of JAVA programming language**

1) **Concepts chosen for the course of the JAVA programming language**

For this course were selected following 12 concepts:

1) Elementary of Java
2) Objects and Classes
3) Packages
4) Inner Classes
5) Flux I/O
6) Exceptions
7) Inheritance
8) Serialization
9) Interfaces
10) Polymorphism
11) Threads
12) Collections

2) **Initial concept map of the JAVA programming language:**

Figure below shows the initial conceptual map selected:
VI. CONCLUSION

In this paper we present a new hybrid approach to construct the concept map of a specific field, this approach is based on using a predefined expert concept map and we measure the degree of relevance of all relationships existing in this predefined expert concept map. This new approach improves the educational protocol to obtain two kinds of prerequisite relationships, the first type can be classified as relationships correctly established by the expert. These relationships must be kept in the final concept map. The second type can be considered as relations incorrectly established by the expert, these relations must be deleted or substituted with the inverse of the original relationships. For the second type we conclude that there is no correlation between the results obtained and the skills of learners, which can be explained by one or both of the following reasons:

- The use of inappropriate items in the tests of the two concepts
- The two concepts of this relationship are completely independent.

The results obtained from the application of this new approach on the course of JAVA programming language are good.

REFERENCES