Ranking Reusable Learning Objects With Rough Sets Based Methods

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Abstract: Many educational institutions collaborate for developing joint bachelor, master and PhD programs. Quite often in the process of completing learning materials, included in an intelligent tutoring system f. ex. they have to choose among different learning objects developed by different teams and originally intended to be presented to different type of students. In order to be effective this process should involve both content providers and IT experts. The objective of this paper is to show how a rough set theory based approach can facilitate the process of ranking available learning objects.

Key–Words: Rough sets approximations, knowledge, intelligent systems

1 Introduction

A large number of definitions of learning objects can be found in the literature since 1994. One way to describe them is to say that they are small entities meant to be used in learning and teaching situations. Examples of learning objects include animation, Java applets, interactive simulations, quizzes, etc. In order to make them reusable it should be possible to store and retrieve them from a database and allow them to be part of different management systems. Important characteristics of learning objects are discussed in details in [1].

Many educational institutions collaborate for developing joint bachelor, master and PhD programs. Quite often in the process of completing learning materials, included in an intelligent tutoring system f. ex. they have to choose among different learning objects developed by different teams and originally intended to be presented to different type of students. In order to be effective this process should involve both content providers and IT experts. Technical aspects of learning objects are presented in [2], [3], [4], [5], [6], and [11].

The objective of this paper is to show how a rough set theory based approach can facilitate the process of ranking available learning objects.

The rest of the paper is organized as follows. Section 2 contains definitions of terms used later on. Section 3 illustrates our approach. Section 4 contains the conclusion of this work.

2 Background

2.1 Rough Sets

Rough Sets were originally introduced in [7]. The presented approach provides exact mathematical formulation of the concept of approximative (rough) equality of sets in a given approximation space. An approximation space is a pair \( \mathcal{A} = (U, R) \), where \( U \) is a set called universe, and \( R \subseteq U \times U \) is an indiscernibility relation.

Equivalence classes of \( R \) are called elementary sets (atoms) in \( \mathcal{A} \). The equivalence class of \( R \) determined by an element \( x \in U \) is denoted by \( R(x) \). Equivalence classes of \( R \) are called granules generated by \( R \).

The following definitions are often used while describing a rough set \( X, X \subseteq U \):

- the \( R \)-upper approximation of \( X \)
  \[ R^*(x) := \bigcup_{x \in U} \{R(x) : R(x) \cap X \neq \emptyset\} \]
- the \( R \)-lower approximation of \( X \)
  \[ R_*(x) := \bigcup_{x \in U} \{R(x) : R(x) \subseteq X\} \]
- the \( R \)-boundary region of \( X \)
  \[ RN_R(X) := R^*(X) - R_*(X) \]
An information system is a pair \( S = (U, A) \), where \( U \) and \( A \), are non-empty finite sets called the universe, and the set of attributes, respectively such that \( a : U \to V_a \), where \( V_a \), is the set of all values of a called the domain of \( a \). Any subset \( B \) of \( A \) determines a binary relation \( I(B) \) on \( U \), which will be called an indiscernibility relation, and defined as follows: \( (x, y) \in I(B) \) if and only if \( a(x) = a(y) \) for every \( a \in A \), where \( a(x) \) denotes the value of attribute \( a \) for element \( x \). Obviously \( I(B) \) is an equivalence relation. The family of all equivalence classes of \( I(B) \), i.e., a partition determined by \( B \), will be denoted by \( U/I(B) \), or simply by \( U/B \); an equivalence class of \( I(B) \), i.e., block of the partition \( U/B \), containing \( x \) will be denoted by \( B(x) \) and called \( B \)-granule induced by \( x \), [9].

If \( (x, y) \) belongs to \( I(B) \) we will say that \( x \) and \( y \) are \( B \)-indiscernible (indiscernible with respect to \( B \)). Equivalence classes of the relation \( I(B) \) (or blocks of the partition \( U/B \)) are referred to as \( B \)-elementary sets or \( B \)-granules, [9].

Elements in the index set \( A = a_1, a_2, ..., a_m \) are the importance degree of attribute set where each index in the system is determined by:

\[
S_A(a_i) = \frac{|POS_A(a_i)| - |POS_{A-a_i}(A)|}{|U|}
\]

where \( i = 1, 2, 3, ..., m \) and the weight of index \( a_i \) is given by

\[
w_i = \frac{S_A(a_i)}{\sum_{i=1}^{m} S_A(a_i)}
\]

and finally, we can get the institution assessment model which is defined by

\[
P_j = \sum_{i=1}^{m} w_i f_i
\]

where \( P_j \) is the comprehensive assessment value of assessed \( j \)th object \( f_i \) is the assessment values of \( i \)th index \( a_i \) according to the comprehensive assessment value, each object can easily be assessed, [10].

### 3 Learning objects

In this section we consider the problem of automated ranking of several reusable learning objects with respect to a number of predetermined criteria. The goal is to find the best reusable learning object from a set of available learning objects. A team of educational and technical experts contributed for the content in Table 1. The original data was delivered in a text form, i.e. high, medium and low level was assigned to each learning object with respect to the five attributes. The text is converted to numbers by saying that high corresponds to 3, medium corresponds to 2, and low corresponds to 1.

The five attributes used to evaluate learning objects in this work reflect level of: usability (A1), being self-contained (A2), being suitable for current types of learners (A3), flexibility (A4), and interoperability (A5).

The following granules are extracted from Table 1:

\[
U/I(A) = \{\{A1\}, \{A2\}, \{A3\}, \{A4\}, \{A5\}, \{A6\}, \{A7\}, \{A8\}, \{A9\}, \{A10\}\}
\]

\[
U/I(A - A1) = \{\{A1, A4, A9\}, \{A2\}, \{A3\}, \{A5\}, \{A6\}, \{A7\}, \{A8\}, \{A9\}, \{A10\}\}
\]

\[
U/I(A - A2) = \{\{A1\}, \{A2\}, \{A3\}, \{A4\}, \{A5, A7\}, \{A6\}, \{A8\}, \{A9\}, \{A10\}\}
\]

\[
U/I(A - A3) = \{\{A1\}, \{A2, A6, A9\}, \{A3\}, \{A4\}, \{A5\}, \{A7\}, \{A8\}, \{A9\}, \{A10\}\}
\]

\[
U/I(A - A4) = \{\{A1\}, \{A2\}, \{A3\}, \{A4\}, \{A5\}, \{A6\}, \{A7, A8\}, \{A9\}, \{A10\}\}
\]

\[
U/I(A - A5) = \{\{A1, A3\}, \{A2\}, \{A4\}, \{A5\}, \{A6\}, \{A7\}, \{A8\}, \{A9\}, \{A10\}\}
\]

The positive regions are

<table>
<thead>
<tr>
<th>Table 1: Learning objects</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A4</th>
<th>A5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lo1</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Lo2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Lo3</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Lo4</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Lo5</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Lo6</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Lo7</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Lo8</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Lo9</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Lo10</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>
\[ POS_A(A) = \{\{A1, A2, A3, A4, A5\}, \{A6, A7, A8, A9, A10\}\} \]

\[ POS_{A-A1}(A) = \{\{A2, A3, A5\}, \{A6, A7, A8, A10\}\} \]

\[ POS_{A-A2}(A) = \{\{A1, A2, A3, A4\}, \{A6, A8, A9, A10\}\} \]

\[ POS_{A-A3}(A) = \{\{A1, A3, A4, A5\}, \{A7, A8, A10\}\} \]

\[ POS_{A-A4}(A) = \{\{A1, A2, A3, A4\}, \{A5, A6, A9, A10\}\} \]

\[ POS_{A-A5}(A) = \{\{A2, A4, A5, A6\}, \{A7, A8, A9, A10\}\} \]

Table 2: Indexes’ weights

<table>
<thead>
<tr>
<th>Indexes</th>
<th>(a_1)</th>
<th>(a_2)</th>
<th>(a_3)</th>
<th>(a_4)</th>
<th>(a_5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weights</td>
<td>0.3</td>
<td>0.2</td>
<td>0.3</td>
<td>0.2</td>
<td>0.2</td>
</tr>
</tbody>
</table>

\[ P_1 = 0.3 \times 2 + 0.2 \times 1 + 0.3 \times 3 + 0.2 \times 2 + 0.2 \times 1 = 2.3 \]

\[ P_2 = 0.3 \times 1 + 0.2 \times 1 + 0.3 \times 1 + 0.2 \times 2 + 0.2 \times 1 = 1.4 \]

\[ P_3 = 0.3 \times 2 + 0.2 \times 1 + 0.3 \times 3 + 0.2 \times 2 + 0.2 \times 2 = 2.5 \]

\[ P_4 = 0.3 \times 2 + 0.2 \times 2 + 0.3 \times 1 + 0.2 \times 2 + 0.2 \times 3 = 2.3 \]

\[ P_5 = 0.3 \times 3 + 0.2 \times 1 + 0.3 \times 3 + 0.2 \times 2 + 0.2 \times 1 = 2.6 \]

\[ P_6 = 0.3 \times 1 + 0.2 \times 1 + 0.3 \times 2 + 0.2 \times 2 + 0.2 \times 1 = 1.7 \]

\[ P_7 = 0.3 \times 3 + 0.2 \times 2 + 0.3 \times 3 + 0.2 \times 2 + 0.2 \times 1 = 2.8 \]

\[ P_8 = 0.3 \times 3 + 0.2 \times 2 + 0.3 \times 3 + 0.2 \times 3 + 0.2 \times 1 = 3.0 \]

\[ P_9 = 0.3 \times 1 + 0.2 \times 1 + 0.3 \times 3 + 0.2 \times 2 + 0.2 \times 1 = 2.5 \]

\[ P_{10} = 0.3 \times 1 + 0.2 \times 2 + 0.3 \times 1 + 0.2 \times 2 + 0.2 \times 2 = 1.8 \]

Index importances are listed below:

\[ S_A(a_1) = \frac{|POS_A(A)| - |POS_{A-A1}(A)|}{|U|} = \frac{10 - 7}{10} = 0.3 \]

\[ S_A(a_2) = \frac{|POS_A(A)| - |POS_{A-A2}(A)|}{|U|} = \frac{10 - 8}{10} = 0.2 \]

\[ S_A(a_3) = \frac{|POS_A(A)| - |POS_{A-A3}(A)|}{|U|} = \frac{10 - 7}{10} = 0.3 \]

\[ S_A(a_4) = \frac{|POS_A(A)| - |POS_{A-A4}(A)|}{|U|} = \frac{10 - 8}{10} = 0.2 \]

\[ S_A(a_5) = \frac{|POS_A(A)| - |POS_{A-A5}(A)|}{|U|} = \frac{10 - 8}{10} = 0.2 \]

Thus the weight of index \(a_1\) and index \(a_3\) is

\[ w_1 = \frac{S_A(a_1)}{\sum_{i=1}^{m} S_A(a_i)} = \frac{0.3}{1.2} = 0.25 = w_3 \]

and the weight of indexes \(a_2\), \(a_4\), and \(a_5\) are

\[ w_2 = w_4 = w_5 = \frac{0.2}{1.2} = 0.17 \]

Table 2 summarizes calculations of indexes’ weights.

Assessment values for objects \(Lo1, ..., Lo10\)

The best three learning objects are \(Lo8\), \(Lo7\), and \(Lo5\) with corresponding assessment values 3, 2.8, and 2.6. The least desirable is object \(Lo2\) with assessment value 1.4.
4 Conclusion

There is a definite need to find and implement an efficient way of evaluating learning objects before starting to work on including them in a system and consecutively suggesting them to learners. The presented approach is easy to implement. It is interesting to note that the five attributes coupled with assessment values are still not quite sufficient to order the whole set of learning objects. More attributes have to be used if a finer ordering of the objects is needed. This however would immediately lengthen the preliminary work. In our opinion this method can useful for simple filtering and in case of need for further tuning we would recommend some more sophisticated data mining techniques.

References:


