A Knowledge-based Recommendation Framework using SVN Numbers

Roddy Cabezas Padilla1, José González Ruiz2, Milton Villegas Alava3, Maikel Leyva Vázquez4

1Universidad de Guayaquil, Facultad de Ciencias Administrativas, Guayaquil Ecuador. E-mail: roddy.cabezasp@ug.edu.ec
2Universidad de Guayaquil, Facultad de Ciencias Matemáticas y Físicas, Guayaquil Ecuador. E-mail: jose.gonzalezr@ug.edu.ec
3Universidad de Guayaquil, Facultad de Ciencias Administrativas, Guayaquil Ecuador. E-mail: mleyvaz@gmail.com
4Universidad de Guayaquil, Facultad de Ciencias Matemáticas y Físicas, Guayaquil Ecuador. E-mail: roddy.cabezasp@ug.edu.ec

Abstract:
Current knowledge based recommender systems, despite proven useful and having a high impact, persist with some shortcomings. Among its limitations are the lack of more flexible models and the inclusion of indeterminacy of the factors involved for computing a global similarity. In this paper, a new knowledge based recommendation models based SVN number is presented. It includes database construction, client profiling, products filtering and generation of recommendation. Its implementation makes possible to improve reliability and include indeterminacy in product and user profile. An illustrative example is shown to demonstrate the model applicability.

Keywords: recommendation systems, neutrosophy, SVN numbers.

1 Introduction
Recommendation systems are useful in decision making process providing the user with a group of options that meet expectations [1]. Based on the information and the algorithms used to generate the recommendations, various techniques can be distinguish [2, 3]: Knowledge Based Recommender Systems use the knowledge about users’ necessities to infer recommendations not requiring a great amount of data like another approaches [4]. They use cases based reasoning techniques frequently. In this paper, a new framework for including neutrosophic in knowledge based recommender system is presented.

This paper is structured as follows: Section 2 reviews some important preliminary concepts about Single valued neutrosophic numbers (SVN number). In Section 3, is presented a knowledge based recommendation model framework based on SVN numbers. Section 4 shows a case study of the proposed model. The paper ends with conclusions and further work recommendations.

2.2 SVN-numbers
Neutrosophy [5] is a mathematical theory developed for dealing with indeterminacy. Neutrosophy has been the base for developing new methods to handle indeterminate and inconsistent information like neutrosophic sets and SVNS were developed.

The truth value in neutrosophic set is as follows [8]:

\[ T \]

\[ F \]

\[ I \]

\[ 0 \leq T(x) + F(x) + I(x) \leq 3 \] for all x \( x \in X \).

The implementation makes possible to improve reliability and include indeterminacy in product and user profile. An illustrative example is shown to demonstrate the model applicability.

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The implementation makes possible to improve reliability and include indeterminacy in product and user profile. An illustrative example is shown to demonstrate the model applicability.
Profiles of product $a_j$, is expressed using the linguistic scale expressed $S$, $v_k^j \in S$ where $S = \{s_1, ..., s_8\}$ is the linguistic term set for evaluating the characteristic $c_k$ using SVN. Having described the products:

$$A = \{a_1, ..., a_i, ..., a_n\}$$

(5)

Then, are stored in a database.

### 3.2 Acquisition of the user profile

The proposed framework presents a fundamental difference with previous proposals, it is focused in the fact that most of this information is collected using SVN numbers this information is stored in the database:

$$P_k = \{p_{k_1}^1, ..., p_{k_n}^n\}$$

(6)

This profile will be composed of a set of attributes:

$$C^e = \{c_1^e, ..., c_k^e, ..., c_l^e\}$$

(7)

### 3.3 Filtering

In this activity, products according to the similarity with the user profile are filtered to find out which are the most appropriate for the student. The similarity between user profile, $P$, product $a_j$ is calculated. For the calculation of the overall similarity, the similarity measure can be obtained from a distance measurement, if $d(x, y) \in [0, \text{max}]$ then [16] :

$$\text{sim}(p_k, v_k^j) = 1 - \frac{d(p_k^e, v_k^j)}{\text{max}}$$

(8)

In this case similarity is calculated as follows:

$$S_i = 1 - \left( \frac{1}{3} \sum_{j=1}^{n} \left( \frac{1}{2} \sum_{i=1}^{n} \left[ (|a_i^* - a_j^*|)^2 + (|b_i^* - b_j^*|)^2 + (|c_i^* - c_j^*|)^2 \right] \right) \right)^{\frac{1}{2}}$$

(9)

Where function $S$ calculate similarity among user profile and products profiles [17].

### 3.4 Recommending

In this activity, a set of products that match with the user profiles is suggested. After calculating the similarity products are ordered and represented with the following similarity vector:

$$S = \{s_1, ..., s_n\}$$

(10)

The best is that best meet the needs of the user profile (greater similarity).

### 4 Case study

To show the applicability of the model, a case study is developed.

Initially a database of products is created:

$$A = \{a_1, a_2, a_3, a_4, a_5\}$$

described with the following attributes:
\[ C = \{c_1, c_2, c_3, c_4, c_5\} \]

Attributes are evaluated in the linguistic scale shown in Table 1 and stored in the database.

<table>
<thead>
<tr>
<th>Linguistic terms</th>
<th>SVNSs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely good (EG)</td>
<td>(1,0,0)</td>
</tr>
<tr>
<td>Very very good (VVG)</td>
<td>(0.9, 0.1, 0.1)</td>
</tr>
<tr>
<td>Very good (VG)</td>
<td>(0.8,0,15,0.20)</td>
</tr>
<tr>
<td>Good (G)</td>
<td>(0.70,0.25,0.30)</td>
</tr>
<tr>
<td>Medium good (MG)</td>
<td>(0.60,0.35,0.40)</td>
</tr>
<tr>
<td>Medium (M)</td>
<td>(0.50,0.50,0.50)</td>
</tr>
<tr>
<td>Medium bad (MB)</td>
<td>(0.40,0.65,0.60)</td>
</tr>
<tr>
<td>Bad (B)</td>
<td>(0.30,0.75,0.70)</td>
</tr>
<tr>
<td>Very bad (VB)</td>
<td>(0.20,0.85,0.80)</td>
</tr>
<tr>
<td>Very very bad (VVB)</td>
<td>(0.10,0.90,0.90)</td>
</tr>
<tr>
<td>Extremely bad (EB)</td>
<td>(0,1,1)</td>
</tr>
</tbody>
</table>

Table 1. Linguistic terms used to provide the assessments [13].

Database used in this example is shown in Table 2.

<table>
<thead>
<tr>
<th>α_1</th>
<th>α_2</th>
<th>α_3</th>
<th>α_4</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDB</td>
<td>M</td>
<td>MMB</td>
<td>B</td>
</tr>
<tr>
<td>B</td>
<td>MD</td>
<td>MB</td>
<td>M</td>
</tr>
<tr>
<td>MMB</td>
<td>M</td>
<td>M</td>
<td>B</td>
</tr>
<tr>
<td>M</td>
<td>B</td>
<td>MMB</td>
<td>B</td>
</tr>
</tbody>
</table>

Table 2: Products database.

If user \( u_a \), wish to receive recommendation expressing his/her preferences in this case:

\[ P_u = \{\text{MDB, MB, MMB, MB}\} \]

The next step in this case is the calculation of similarity between user profile and products profiles stored in database.

<table>
<thead>
<tr>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
<th>( \alpha_3 )</th>
<th>( \alpha_4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.44</td>
<td>0.76</td>
<td>0.42</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Table 3: Similarity calculation

A ranking of products based on similarity calculation is:

\[ \{α_4, α_2, α_1, α_3\} \]

In case that the recommendation of two products was needed it is as follows:

\[ α_4, α_2 \]

This example shows the applicability of the proposal

5 Conclusions

In this paper, a product recommendation model was presented following the knowledge-based approach. It is based on the use of SVN numbers to express linguistic terms.

Future work will be related to the creation of the database from multiple experts, as well as obtaining the weights of the characteristics using group evaluations. In addition, we will work on the integration of more complex aggregation models, as well as hybridization with other models of recommendation.

References


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