A fuzzy methodology to alleviate information overload in eLearning

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Abstract

Some aspects of eLearning experience can be enhanced in a very natural way by using the basic tools offered by fuzzy logic. As a matter of example, consider the uncontrolled growth of information produced in a collaborative-oriented context, in which each participant (e.g. students, teachers) is able to insert and share new contents (e.g. comments, texts) concerning a university course. All the incrementally added pieces of information can be evaluated in several ways: by the intervention of a “dictator” (e.g. the teacher), using a rating form, or even according to the frequency of access. As contents rapidly become unusable for the effects of information overload, basic tools of fuzzy logic such as membership functions and measures of fuzziness can help to distinguish between relevant and trivial content, without thereby canceling any contribution. This very same idea can of course also be applied to different contexts.

Keywords: eLearning, info overload, Fuzziness.

1. Introduction

The aim of the present paper is to outline a path which allows to save possible comments and revisions to a presentation of certain subjects so that all the past history of the teaching of a certain topic could be never lost.

The idea for this is the most trivial one: “add every comment to every notion when this happens to be done in a incremental way”. The simplicity and triviality of this procedure is also at the origin of its main defect: the information can grow in an uncontrollable way putting all the information at the same level without distinguishing between a very meaningful and a trivial information.

We propose to use the basic feature of fuzzy sets (graded membership) to classify and discriminate among all the incremental clarifications provided to a given text (we limit ourselves to the most basic elements of the notion of fuzzy set). One plans finally to provide a quantitative evaluation of how much the additional information can be easily distinguished and divided between interesting/not interesting by using the theory of “measures of fuzziness”. Those fuzzy sets which have a low index are good candidate for easily eliminating the uninteresting comments, those with a high index show that the comments are more graded and a solution can be provided by more complex procedures. It could be also the case that a real major complexity of the topic in question emerges naturally in this way.

This paper is organized as follows: in the next section we shall fix the basic notation and terminology used; some measures of fuzziness will also be briefly introduced. In the third section we shall shortly survey the state of the art, listing some recent results and the tools used in literature in the fields of collaborative eLearning and evaluation of user-generated contents. In the fourth section we will describe our approach to the problem through the use of examples. The last section presents some conclusion and shows some possible developments of this work.

2. Fuzzy logic

In the present section we shall present and fix the basic notation that will be used later.

2.1. Notation and terminology

A fuzzy set $A$ in the universe of discourse $U$ is usually determined by his membership function

$$\mu_A : U \rightarrow [0, 1]$$

(1)

that maps each element $x \in U$ to its degree of membership to the set $A$. $\mathcal{F}(U) = \{\mu \text{ such that } \mu : U \rightarrow [0, 1]\}$ is the set whose elements are all the possible membership functions of fuzzy sets in the universe $U$.

The support of a fuzzy set $A$ is defined as

$$s(A) = \{x \in U : \mu_A(x) > 0\}$$

(2)

and $A$ is called a finite fuzzy set if its support is finite. Its crisp part or kernel is

$$c(A) = \{x \in U : \mu_A(x) = 1\}$$

(3)

and, finally, its $\alpha$-cuts are

$$A^\alpha = \{x \in U : \mu_A(x) \geq \alpha\}$$

(4)

for $\alpha \in [0, 1]$. 

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A classical set $B$ can be considered as a fuzzy set described by his characteristic function and, vice-versa, a fuzzy set having a membership function whose range is $\{0, 1\}$ is called a crisp set.

The original way of defining union and intersection between two sets $A$ and $B$ and the complement of a set $A$ is the following:

$$
\mu_{A\cup B}(x) = \max(\mu_A(x), \mu_B(x))
$$

(5)

$$
\mu_{A\cap B}(x) = \min(\mu_A(x), \mu_B(x))
$$

(6)

$$
\mu_{\neg A}(x) = 1 - \mu_A(x)
$$

(7)

These are the original definitions by Zadeh [1]. Let us remember that in the same paper, Zadeh presented also alternative possible ways of defining such operators and that subsequently there has been a huge and profound work for introducing and studying generalized connectives (see [2, 3] for a more comprehensive survey); however, in what follows it suffices to consider the basic definitions just introduced.

2.2. Defuzzification

In most applications, one needs to infer precise numerical values from imprecise statements represented by means of fuzzy sets. Among many possibilities, we shall here present only some basic methods: the centre of gravity method (COG), and the maxima-based methods.

The COG method obtains a crisp value $y$ by means of a weighted average:

$$
y = \frac{\sum_{x \in U} x \cdot \mu_A(x)}{\sum_{x \in U} \mu_A(x)}
$$

(8)

while maxima methods are based on various statistical features of the set of those $x$ such that $\mu_A(x)$ is maximal. For example, the mean of maxima method (MOM) is defined as follows:

$$
y = \frac{\sum_{x \in M} x}{|M|}
$$

(9)

in which $M = \{x : \mu_A(x) = \max_{x \in U} \mu_A(x)\}$ and $|M|$ is its cardinality. In a similar way it is possible to define methods such as first of maxima (FOM), last of maxima (LOM) and median/centre of maxima (COM).

See Figure 1 to get an instantaneous description of these methods.

Figure 1: Centre of gravity (COG) and mean of maxima (MOM) of a fuzzy set

2.3. Measures of fuzziness

The idea behind a fuzzy set is to specify how much is certain that a given element belongs to a given set. It is therefore natural to ask for the degree of fuzziness of a set, or, to put it another way, the global difficulty of deciding which elements belong to a set. The answer is given by the theory of “measures of fuzziness”, firstly proposed in [4]. For a survey of this theory see [5]. A measure of fuzziness is a non-negative mapping $d : \mathcal{F}(U) \to [0, +\infty]$ satisfying at least the following conditions:

- Sharpness: $d(A) = 0$ if and only if $A$ is a crisp set
- Maximaliy: $d(A)$ is maximal when $\mu_A(x) = 1/2$ for each $x \in U$
- Resolution: $d(A^*) \leq d(A)$, with $A^*$ being a sharpened version of $A$, that is: $\mu_{A^*}(x) \leq \mu_A(x)$ when $\mu_A(x) \leq 1/2$ and $\mu_{A^*}(x) \geq \mu_A(x)$ when $\mu_A(x) \geq 1/2$.

Other reasonable conditions that can be adopted are:

- Symmetry: $d(A) = d(A^C)$
- Valuation: $d(A \cup B) + d(A \cap B) = d(A) + d(B)$

Ebanks has shown that, by adding a further technical condition (called generalized additivity), the measure of fuzziness provided by $d(A) = \sum_{x \in U} \mu_A(x)|1 - \mu_A(x)|$ is unique [6].

The following are some particular measures of fuzziness $d$ given a finite universe $U = \{x_1, x_2, ..., x_n\}$:

- Fuzzy Entropy [4]:

$$
d(A) = \frac{1}{n} \sum_{x \in U} S(\mu_A(x))
$$

(10)

where $S(x) = -x \ln x - (1 - x) \ln(1 - x)$ is the Shannon function. The value $\frac{1}{n}$ normalizes $d(A)$ into the range $[0, 1]$ if the logarithm in base 2 is taken.
- Linear index of fuzziness [7]:
  \[ d(A) = \frac{2}{n} \sum_{x \in U} |\mu_A(x) - \mu_{A^{0.5}}(x)| \] 
  (11)

  in which \( \mu_{A^{0.5}} \) is the membership function of the 0.5-cut of \( A \). Ultimately, \( d(A) \) is the distance between \( A \) and its closest crisp version \( A^{0.5} \).

- Quadratic index of fuzziness [7]:
  \[ d(A) = \sqrt{\frac{4}{n} \sum_{x \in U} [\mu_A(x) - \mu_{A^{0.5}}(x)]^2} \] 
  (12)

3. State of the art

3.1. Collaborative eLearning

The use of electronic instruments in the field of teaching has recently gained attention for his proven capacity of increasing the fruition of contents and the learning quality [8, 9]. This mixture of technology and learning is usually known as eLearning. Its applications range from the simple use of computer-aided technologies during lessons to hybrid learning and pure online learning.

Recently eLearning, supported by the new instruments that are being available as internet and ICT grow up (e.g. wikis, forums, mind-maps, social networks...), is moving towards a new – more collaborative – way of handling and communicating knowledge.

In fact, statistical evidence seem to prove that the “new millennium learner” wants/needs to be an active, collaborative part of the learning process [10, 11]. This has progressively led to a new approach that is called Computer-supported collaborative learning (CSCL) [12].

In such a collaborative context each user is generally able to add new contents, and/or remove and modify existing ones (as it happens, for example, on Wikipedia). For this kind of interaction to be effective, several strategies and organizational patterns are to be applied, e.g. synchronous or asynchronous writing, parallel or single-writing [13, 14, 15]. Furthermore, in order to gain knowledge one needs to fetch useful information [16] among a great amount of data produced by many different sources, a phenomenon known as information overload, while at the same time trying to build a single and coherent shared source of knowledge.

As we shall see in the following section, this very problem – that is the one we are mostly concerned with – has yet been addressed in several ways involving (automated) evaluation of contents.

3.2. Evaluation

Evaluation of content has been recently studied for its wide range of applicability. As a matter of example, evaluation of books, movies and other commercial products has a great importance in business and e-commerce [17, 18]. This kind of evaluation is mainly based on users’ ratings (e.g. Likert-like scales [19], star systems [17]) and hence on their previous experiences. The typical aims of this systems employed in evaluation are to use information about customers to suggest personalized recommendations [20, 18] and to assess a second party’s reliability [21, 22]. However, since we are here concerned with university courses, this approach is not suitable for our purposes because a significative portion of our audience is renewed periodically and moreover we have completely different intents. For this reason, we shall exclusively concentrate on evaluation of contents.

Having a qualitative evaluation of a single content in an unstructured collection of data can be useful in order to discriminate between related pieces of information with different quality [23, 24].

The vast use of wiki technologies (e.g. Wikipedia) allowed researchers to study evaluation of user-generated contents [25, 26]. A series of studies was conducted to rate wiki pages in a fully manual way [27, 28]; more recently, some instruments like Wikipedia’s “Article Feedback Tool” [29] try to assess the quality of a page in a e-commerce-like fashion.

4. Our model

We set ourselves in the case in which all the users are able to incrementally add contents (that are related to the same subject or topic) in an uncontrolled way. Our main aim is to describe a CSCL platform for eLearning in which fuzzy methodologies are used to rise relevant pieces of information above less considerable ones. The basic steps of the process are essentially the following:

1. Contents’ features are evaluated.
2. Evaluations are defuzzified.
3. Fuzzy measures and further statistics are extracted and exploited to identify and isolate most interesting pieces of information.

Let us now consider the example of a university course in which students are invited to add different explanations for a given topic, which in our example is represented by the Productivity of a Turing Machine (TM), a concept connected to the well-known

<table>
<thead>
<tr>
<th>U1</th>
<th>U2</th>
<th>U3</th>
<th>Entropy</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>simple</td>
<td>1</td>
<td>0.7</td>
<td>0.62</td>
<td>0.77</td>
</tr>
<tr>
<td>correct</td>
<td>0.9</td>
<td>0.1</td>
<td>0.3</td>
<td>0.93</td>
</tr>
<tr>
<td>clear</td>
<td>0.8</td>
<td>0.6</td>
<td>0.5</td>
<td>0.7</td>
</tr>
<tr>
<td>interesting</td>
<td>1</td>
<td>0.7</td>
<td>0.83</td>
<td></td>
</tr>
<tr>
<td>illustrative</td>
<td>0.9</td>
<td>0.0</td>
<td>0.3</td>
<td>0.33</td>
</tr>
</tbody>
</table>

Table 1: From linguistic attribution to defuzzification. We have used (10) as our Entropy function.
User 1:

Given a TM, we define its productivity as the number of 1's on its tape at the end of a correct computation (i.e., the machine halts correctly and with the further tie that M has no input symbol on its tape when the computation begins). If the computation does not halt, then the productivity of the given machine is 0.

Its productivity is 4, as we can see from a complete computation:

```
0 0 0 0 A
0 0 0 0 B
0 0 0 0 0 1
0 0 0 0 1
0 0 0 0 0
```

Moreover, it is easy to see that the machine depicted below never halts; thus, its productivity is 0.

User 2:

We define productivity of a given TM M as the number of 1's that lie on the tape at the end of M's computation starting with blank tape. If the machine does not halt, we'll say that its productivity equals 0.

Let us now define the function \( p(n) \) as the maximum productivity that a \( n \)-state machine can reach. One can now ask: is it possible to build a TM that calculates \( p(n) \) for each value of \( n \)?

The answer – as we can expect from some previously proved theorems – is no: this problem is unsolvable.

User 3:

The productivity \( \sigma(M) \) of a TM M is the number of ones left on its tape at the end of a computation starting with no symbols on the input tape. We have \( \sigma(M) = 0 \) in the following two cases:

1. M does not reach a final state
2. M does not halt

Let us now define the function \( p(n) \) as the maximum productivity that a \( n \)-state machine can reach. One can now ask: is it possible to build a TM that calculates \( p(n) \) for each value of \( n \)?

The answer – as we can expect from some previously proved theorems – is no: this problem is unsolvable.
statistical measures.

In particular, we want to stress the following point: an high index of fuzzy entropy (or, in general, of any appropriate fuzzy measure – in Table 1 we simply have used Equation 10; it is possible however to consider different measures, such as those described in Equations 11 and 12 to obtain more pregnant, better results) naturally suggests that, to a certain extent, the specified feature is controversial and more complex to handle; conversely, a low index of fuzzy entropy indicates that the particular feature is solid as it is, and good and bad contributions to the topic can be easily distinguished. Ideally, as the course is updated from year to year, the entropy should converge to zero. In addition, it is possible to consider some appropriate statistical measures – e.g. mean, variance – to get a further characterization of the considered features.

In our view, these indications are useful to have a better understanding of the present state of the course, its strengths and its weaknesses; moreover, most relevant contributions can be immediately identified and used to make the course’s entropy convergence faster. In fact, we can infer from Table 1 that the most problematic aspects related to the considered lesson are “clarity” and “simplicity” (fuzzy entropy is significantly greater than 0.5), while “correctness” is a better assessed aspect having a low fuzzy entropy index; it is important to note here that despite the “illustrative” parameter has a low mean, the entropy of the corresponding set is lower than 0.5, indicating that the corresponding feature is well assessed – in fact, contributions to the topic are only “very illustrative” or “not illustrative at all”; the teacher can then consider improving the course by refining the so highlighted aspects. Furthermore, it is possible to exploit the fuzzy set representation to browse relevant contents through the use of α-cuts. In our example, \( \alpha_{0.8}^{\text{user 3}} = \{ \text{User 3} \} \), indicating that the third user’s contribution can be taken into account for its simplicity.

As a further detail, we want to highlight the fact that especially in the initial stages of the course, only a few evaluated comments could be available. In order to avoid making inferences from data that is still not significant, a (possibly fuzzy) threshold can be included.

5. Conclusions

In this contribution we have discussed contents and evaluations as fuzzy sets. As we have shown in the previous section, this approach lead to a simplified treatment of the information overload due to the activity of many users contributing to incrementally build a single source of knowledge, without the need to eliminate any content. Even better, this kind of representation allows to highlight and point out which features of the considered topic are solid and well assessed, and also gives us a way of determine which topics are the most controversial and complex, through the use of fuzzy measures.

It is remarkable that this methodology can be applied not only to university courses and classes, but also to situations where one needs to evaluate a great amount of data originated from different sources – e.g. reviews and criticism of books, films, works of art. In fact, as we have already seen in Subsection 2.3, the theory of “measures of fuzziness” allows to define many different measures of entropy of a fuzzy set, and such measures can be applied to a whole host of diverse disciplines [32, 33, 34, 35, 36, 37, 38].

In future works we shall implement the described platform in a web-based application in order to apply and test this methodology to real cases such as university courses, aiming to collect data and evidence about its effectiveness in a comparative study.

References


