Analyzing Learning Concepts in Intelligent Tutoring Systems

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Abstract: *The information that is increasing and changing rapidly at the present day, and the usage of computers in educational and instructional processes has become inevitable. With the rapid progress in technology, research gives more importance to integrate intelligent issues with educational support systems such as distance learning and learning management systems. Such studies are considered as applications of the artificial intelligence on educational processes. Regarding this viewpoint, some supervised learning models which is able to recognize the learning concepts from a given educational content presented to a tutoring system has been designed, in this study. For this aim, firstly, three different corpora constructed from educational contents related to the subject titles such as calculus, abstract algebra and computer science have been composed. For each candidate learning concepts, the feature vectors have been generated using a relation factor in addition to tf-idf values. The relation factor is defined as the ratio of the total number of the most frequent substrings in the corpus that appear with a candidate concept in the same sentence within an educational content to most frequent substring in the corpus. The achievement of this system is measured according to the F-measure.*

Keywords: *Educational technology, artificial intelligence on education, machine learning, intelligent tutoring.*

Received April 26, 2014; accepted September 9, 2014; published online April 1, 2015

1. Introduction

Today, most of governments have begun to develop some national educational technology policy and the integrating intelligent issues with educational technology are becoming an increasingly more important research area [9, 20, 26, 31]. Across the literature on measuring the effectiveness of using technology in educational purpose, researchers emphasize engaging the student and increasing of students' performance by supporting the traditional class based education [3, 8, 11, 13, 30]. We firmly believe that educational support systems should automatically detect what to teach to students because they should act as a real teacher in class; they must teach the learning concepts in an educational content according the students' learning speed and learning style. Most of time, extracting learning concepts within a specific learning domain is a difficult, controversial, time consuming and highly non-trivial process, even for an expert in this field [25].

Al-Zoube and Khasawneh [2] present an adaptive course composer to build adaptive course based on specific learning goals, prior knowledge, and context of a learner preferences. Automatically detecting learning goals is a major problem in e-learning systems. The system should know what to teach to the students, or which learning concepts should be learned by students. Extracting keywords or terms from a given document is not a new research area at all, and several techniques and methods have been developed [4, 15, 18, 19, 24, 27, 29]. However, these approaches have begun to use within educational technologies in last decade. Daille uses a combination of linguistic filters and statistical methods to extract concepts from corpora [10]. Frantzi *et al*. [14] developed a method, which uses C-value/NC-value to extract multiword terms automatically [14]. Cimiano and Völker [7] developed a tool that uses Probabilistic Ontology Model to extract terms for ontology development on a particular domain. Zouaq and Nkambou [32] present a semiautomatic methodology for knowledge acquisition from text to produce domain concept maps in e-learning. Villalon and Calvo [28] present a new approach for automatic concept extraction from students' essays, using grammatical parsers and latent semantic analysis. Gunel and Asliyan [16] propose an approach that uses the statistical language models together with content vectors to extract the minimal set of learning concepts within an educational content. Qasim *et al*. [25] use affinity propagation algorithm for automatic acquisition of domain concepts. Gunel *et al*. [17] use support vector machines as a supervised learning algorithm to detect learning concepts from an educational content.

The focus of this study is to present an analysis of detecting the learning concepts from a given educational content using the well-known supervised learning methods in artificial intelligence. In this way, the educational content becomes significant, and it gains a meaning semantically for the system.

Therefore, the system knows that what students should learn. Briefly, the proposed approach extracts candidate concepts from a given document, and generates a feature vector for each candidate concept. For this aim, firstly, three corpora constructed from educational contents related to some learning domains. The system uses normalized feature vectors to make a decision whether the candidate is a learning concept or not.

The remainder of the paper is organized as follows. In the methods section, the method of extracting candidate concepts from a document is introduced. After that the method of generating the related feature vectors and the supervised learning approaches for detecting learning concepts among the candidates are described, briefly. The experimental results on selected methods over the learning domains are summarized in the experimental results section. Finally, conclusions are given.

2. Methods

In this study, firstly, three different corpora are constructed by quoting from seven books for each one. These corpora correspond to the “Abstract Algebra”, “Calculus” and “Neural Networks” as learning domains, and have 803490, 1777067 and 868490 words and 92870, 241315 and 122027 sentences respectively. In fact, it does not matter of the selection of learning domains for the proposed approach. However, the closely related subjects have been selected for obtaining more realistic test results, in the study.

A general view of the logical system architecture is given in Figure 1. In the pre-processing stage, punctuation marks, numbers and special symbols in the corpora are eliminated. However, the stop-words are not eliminated from the corpora, because these tokens are also used to train neural networks as inputs. After the pre-processing, there is only a blank between two words in a corpus, and all characters are lowercase. In addition, all sentences of the corpora are extracted from the corpus for feature extraction.

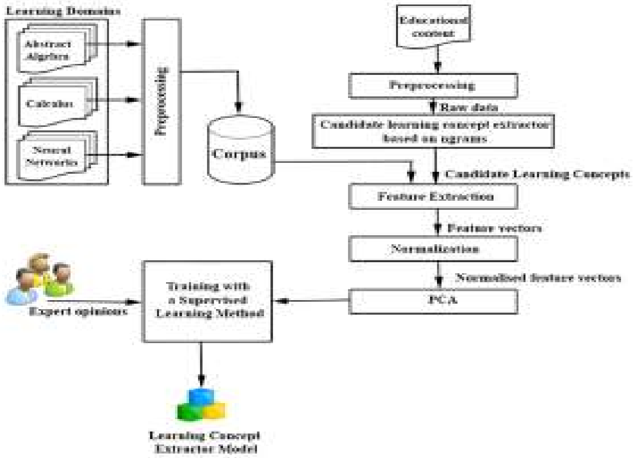

Figure 1. System architecture.

The next step is to extract the most frequent n-grams from a corpus for $1\leq n\leq 5$. n-gram model is a probabilistic language model [22], and the model predicts the next word, w_i, in such a sequence $w_{i-(n-1)}\ldots w_{i-1}$ as given in the Equation 1.

$$P\left(w_i \mid w_{i-(n-1)}\cdots w_{i-1}\right)=\frac{C\left(w_{i-(n-1)}\cdots w_{i-1}w_i\right)}{C\left(w_{i-(n-1)}\cdots w_{i-1}\right)} \tag{1}$$

Where $C(w_{i-(n-1)}\ldots w_{i-1})$ specifies the number of occurrences of the string $w_{i-(n-1)}\ldots w_{i-1}$, and $C(w_{i-(n-1)}\ldots w_{i-1}w_i)$ represents the number of occurrences the $w_{i-(n-1)}\ldots w_{i-1}w_i$ word sequences in a corpus. The set of first 500 most frequent n-grams in a corpus is called as G_1 in the study.

To detect the learning concepts in a given educational content, the document is pre-processed with the same procedure, which applied to the corpora. The set of first 500 most frequent n-grams in the educational content is called as G_2. Each element of G_2 is considered as a candidate learning concepts. We have consulted with experts about whether these candidates are real learning concepts in the learning domain or not. The expert reports obtained from G_2 have been used to train the networks with supervised learning method in the study.

After that, the feature vectors are generated for each candidate. First component of feature vectors is the term frequency-inverse document frequency ($tf\times idf$) value which is simply a weight measure to evaluate the important words in a document within a collection [22], and it is calculates as in the Equation 2.

$$tf\times idf(t,d,D)=tf(t,d)\times\log\left(\frac{|D|}{1+\left|\{d\in D: t\in d\}\right|}\right) \tag{2}$$

Where D denotes the learning domain as a corpus, the value $tf(t, d)$ indicates the frequency of the candidate learning concept, $t\in G_2$ extracted from the document, d. The second one is the logarithm of the ratio of the total number of sentences to the number of sentences, which includes the candidate, $t\in G_2$ as shown in the Equation 3.

$$r_1(t,d)=log\left(\frac{|s|}{1+\left|\{s\ occurred\ in\ d: t\ is\ a\ substring\ of\ s\}\right|}\right) \tag{3}$$

Where s denotes a sentence of the document, d and $t\in G_2$. Another feature is obtained with a function with binary outputs for all $x\in G_1$ and $t\in G_2$ as given in the Equation 4.

$$r_2(t,d)=\sum_{x\in G_1}M(t,x) \tag{4}$$

Such that:

$$M(t,x)=\begin{cases}1 & t\ and\ x\ are\ occurres\ together\ in\ any\ sentence\ of\ a\ corpus\\ 0 & otherwise\end{cases}$$

Where x is one of the most frequent n-gram occurred in the learning domain as a corpus, D and t is one of the most frequent n-gram occurred in the educational content as a document, d. This function generates a relation matrix using G_1 and G_2. The last component of feature vectors is obtained using the number of words in n-gram as given in the Equation 5. The importance of this approach is to point out the relevance between a candidate learning concept, $t \in G_2$, and the corpus as a learning domain. It also assists to eliminate the unwanted words such as stop-words from the set of candidates.

$$r_3(t) = \frac{|t|}{max\left\{|t'| \text{ such that } t' \in G_2\right\}}, t \in G_2 \quad (5)$$

Where |.| operation represents the number of words in a token. r_3 is required for weighting the candidate learning concepts according to their lengths in the meaning of the number of words contained by the candidates.

After feature extraction step, the normalization procedure with following steps is applied for each feature vectors. The first transformation maps from the original range of feature vectors to range [-1, 1] with its mean and standard deviations to 0 and 1 respectively. Next, Principal Component Analysis (PCA) is applied to find the aspects of candidates, which are important for identification of learning concepts. Briefly, PCA transforms a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables. The obtained vectors at the normalization stage are used to train the presented supervised models in the study.

k-Nearest Neighbour (k-NN) with majority voting, Multi-Layer Perceptron Network (MLP) with Levenberg-Marquardt optimization and Radial Basis Function (RBF) Networks methods are used as supervised methods within the study. k-NN is one of the most fundamental, instance-based and non-parametric classification methods [12]. In the algorithm, the class of new observation value as a feature vector is determined by calculating the distance metrics, and selecting maximum number of units among k units of observation which have the smallest distance such that k is the number of the nearest neighbours in the previously identified training samples. In k-NN, chosen class may not always be appropriate because neighbours are determined only with respect to k. Therefore, the k-NN with majority voting method, which is a subset of k-NN method, is used in this study [1].

The second training method used in the study is MLP with the Levenberg-Marquardt algorithm, which is used for optimization of the neural network weights via Newton's approximation method [21, 23]. In the study, two hidden layers used with the transfer functions, tangent sigmoid and logarithmic sigmoid functions respectively. The learning rate is selected 0.8 with the number of maximum epochs, 10000. The measure of network performance is measured according to mean of squared errors with the error goal, 10^{-3}.

The last method used in the study is RBF network, which is is an artificial neural network that uses RBFs as activation functions [5, 6]. Any real valued function, f that satisfies the property $f(x) = f(\|x\|)$ is called radial function. RBF networks can require more neurons than standard feed-forward backpropagation networks; however, they work best when many training vectors are available. In the study, we use the spread value of RBFs, 0.01 as a network parameter with the maximum number of neurons in the hidden layer, 300000. The measure of RBF performance is also measured according to mean of squared errors with the error goal, 10^{-3}.

In the next section, the experimental results for each method are presented and compared with each other.

3. Experimental Results

In this section, we present our experimental results of applying supervised learning techniques for detecting learning concepts within a given educational content. To train, validate and test the models, firstly, six documents in four different subjects were collected. The total size of documents is 3.56MB. All documents were pre-processed, and the set G_2 was generated for each document as described in the preceding section. The elements of G_2 were considered as the candidates of learning concepts, and these elements were presented to experts. Experts decide whether or not the candidate concepts is real learning concept in the domain. Train data set includes 296, 422, 200 and 554 samples with respect to the subject, "Group Theory", "Derivation", "Limits and Continuity" and "Multi-layer per MLP ceptrons with backpropagation algorithm" respectively.

In this study, four different methods were applied: k-NN with majority voting algorithm for k=3 and k=5, MLP with Levenberg–Marquardt, RBF network. The set, G_2 obtained from the documents, d_1 and d_2 together in each subject were used for training the systems and other documents were used for testing. However, not all the elements of G_2 were used in the training. The elements of G_2 were chosen such that the number of learning concepts according to the expert opinions is equal to other n-grams. This approach provides a better learning of the system in the training stage. After training the models, we have randomly selected half of the elements in G_2 to validate the systems. The ratio of learning concepts in G_2 for each domain is given in Table 1, and the validation scores as *F-measure* are given in the Table 2.

Table 1. Ratio of learning concepts in G_2 for each domain.

Documents	Learning Domains			
	Group Theory	Derivation	Limits and Continuity	MLP with Backpropagation
d_1	0.140	0.244	0.120	0.280
d_2	0.156	0.178	0.080	0.274
d_3	0.160	0.194	0.174	0.252
d_4	0.148	0.232	0.144	0.190
d_5	0.156	0.188	0.090	0.250
d_6	0.150	0.122	0.062	0.280

Table 2. F-measure scores for validation stage of the methods.

	Learning Domains			
Method	Group Theory	Derivation	Limits and Continuity	Feed-forward Backpropagation Networks
3-NN with Majority Voting	1.000	1.000	1.000	1.000
5-NN with Majority Voting	1.000	1.000	1.000	1.000
Levenberg-Marquardt	0.993	0.977	1.000	0.975
RBF	1.000	1.000	1.000	0.996

In testing stage, the set G_2 extracted from the documents d_3, d_4, d_5 and d_6 was used, and the expert opinions were compared with outputs of supervised methods using recall, precision, and *F-measure* scores. The recall score is the ratio of number of concepts that are required to be extracted by the system to the total number of candidate concepts in an educational content. The precision score is the ratio of the number of concepts that are required to be extracted by the system to total number of extracted concepts by the system in reality. The *F-measure* is a measure of a test's accuracy. The traditional balanced *F-measure* is to combine recall and precision into single measure of overall performance and is the harmonic mean of precision and recall. Recall, precision and *F-measure* score results are shown in Table 3 where *C* represents the number of concepts that are required to be extracted by the system, *T* is the total number of candidate concepts in an educational content, and *R* describes the total number of extracted concepts by the system in reality.

Table 3. Recall, precision and *F-measure* scores in the testing stage of the methods.

		3-NN with Weighted Voting			5-NN with Weighted Voting			MLP with Levenberg-Marquardt			RBF		
Subject	Docs.	C/T	R/T	F-measure	C/T	R/T	F-measure	C/T	R/T	F-measure	C/T	R/T	F-measure
Group Theory	d_3	1.00	0.95	0.97	1.00	0.95	0.97	0.60	0.24	0.34	0.24	0.58	0.34
	d_4	1.00	0.96	0.98	1.00	0.96	0.98	0.64	0.20	0.31	0.26	0.56	0.35
	d_5	1.00	1.00	1.00	1.00	1.00	1.00	0.47	0.29	0.36	0.04	1.00	0.07
	d_6	1.00	0.96	0.98	1.00	0.96	0.98	0.64	0.20	0.30	0.32	0.62	0.42
Limits and Continuity	d_3	1.00	0.98	0.99	1.00	0.98	0.99	0.75	0.20	0.32	0.30	0.30	0.30
	d_4	1.00	1.00	1.00	1.00	1.00	1.00	0.64	0.17	0.27	0.36	0.30	0.33
	d_5	1.00	1.00	1.00	1.00	1.00	1.00	0.58	0.10	0.18	0.36	0.25	0.29
	d_6	1.00	1.00	1.00	1.00	1.00	1.00	0.68	0.08	0.14	0.45	0.19	0.26
Derivative	d_3	1.00	0.97	0.98	1.00	0.97	0.98	0.98	0.26	0.41	0.58	0.34	0.43
	d_4	1.00	1.00	1.00	1.00	1.00	1.00	0.65	0.30	0.41	0.48	0.41	0.44
	d_5	1.00	0.98	0.99	1.00	0.98	0.99	0.67	0.21	0.23	0.49	0.34	0.40
	d_6	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.16	0.28	0.51	0.25	0.34
MLP with Back propagation	d_3	1.00	0.91	0.95	1.00	0.91	0.95	0.57	0.28	0.38	0.23	0.30	0.26
	d_4	1.00	0.85	0.92	1.00	0.85	0.92	0.69	0.20	0.31	0.15	0.19	0.17
	d_5	1.00	0.98	0.99	1.00	0.98	0.99	0.62	0.27	0.38	0.31	0.28	0.29
	d_6	1.00	1.00	0.99	1.00	0.97	0.98	0.74	0.27	0.40	0.25	0.29	0.27

4. Conclusions

This study demonstrated that extracting of learning concepts from given educational material is possible using the artificial intelligence methods in educational technology. The development of learning domain models is a difficult task, and extracting them automatically would help human users in a number of tasks such as understanding the concept hierarchy and generating the concept map. The approach can be taught as the first step of concept mapping, and it assists the development of the automatic concept mapping tools. The next step should be developing a concept hierarchy component to complete such tools.

The other advantage of the extracting the learning concepts is to relate the educational material to the concepts which can serve to students and teachers as a recommender to learn the concepts rather than a subject. Let us consider, two different educational contents related to "set theory" are given to an e-learning system, and one of them provides good examples and presents the concept, "subset" better than the other one. Also, claim that the second one gives more detailed description about the concept, "complement of a set". The learning concept extractor models can give a weight to relate the concept with the educational material, and then a recommender system can assist students by evaluating the learning concepts and the course materials in future.

In the present study, the three different models with supervised learning algorithm were compared with each other. The experimental results showed that the k-NN with majority voting method was generally found to perform better than the neural network models as MLP with Levenberg-Marquadt and RBF networks. The study further show that the k-NN with majority voting algorithm has advantages to other methods according to independence of learning domains. However, the selection of feature vectors and the training samples can be prevail on the detection of learning concepts via neural networks.

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