YAŞAR UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

MASTER THESIS

GENERATING LEARNING CONCEPTS IN INTELLIGENT TUTORING SYSTEMS

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2016

I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a dissertation for the degree of master of science.

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I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a dissertation for the degree of master of science.

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ABSTRACT

GENERATING LEARNING CONCEPTS

IN INTELLIGENT TUTORING SYSTEMS

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In the first section of this thesis, concept maps and intelligent tutoring systems are defined, studies in literature are explained and the goal of this thesis is indicated. In the second chapter, methods and definitions for the solution are given. In the third chapter, the experimental results of these methods obtained from by using the computer program are presented in tables. Finally, in fourth chapter a conclusion is given.

Keywords: Concept Maps, Intelligent Tutoring Systems, k-NN Algorithm, Feature Extraction, Learning Concepts

ÖZET

ZEKİ ÖĞRETİM SİSTEMLERİNDE ÖĞRENME KAVRAMLARI OLUŞTURMA

Enver ÇİLENGİROĞLU
Yüksek Lisans, Matematik Bölümü
Tez Danışmanı: Yrd. Doç. Dr. Refet POLAT
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Haziran 2016, 25 sayfa

Bu tezin ilk bölümünde kavram haritalarından, zeki öğretim sistemlerinden ve tarihsel gelişiminden bahsedilmiş ve tezin amacı belirtilmiştir. İkinci bölümünde çözüme ulaşmak için gerekli metotlar ve tanımlar verilmiştir. Üçüncü bölümde bu metotların bilgisayarda elde edilen test sonuçları tablolar halinde sunulmuştur. Son olarak dördüncü bölümde sonuç verilmiştir.

Anahtar sözcükler: Kavram Haritaları, Zeki Öğretim Sistemleri, k-NN Algoritması, Öznitelik Çıkarımı, Öğretici Kavramlar

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İzmir, 2016

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TEXT OF OATH

I declare and honestly confirm that my study, titled “GENERATING LEARNING CONCEPTS IN INTELLIGENT TUTORING SYSTEMS” and presented as a Master’s Thesis, has been written without applying to any assistance inconsistent with scientific ethics and traditions, that all sources from which I have benefited are listed in the bibliography, and that I have benefited from these sources by means of making references.

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1 INTRODUCTION

Today, there are different libraries on software industry with developed applications to provide support for their users. However, existing contexts include detailed information without helping people to learn these technical documents. Since the concepts in large scale data are not connected, a road map is needed to make the learning process easier. One of the tools for facilitating this process in educational technologies is concept maps. These concept maps are generated by experts. Nevertheless, large scale data makes the process of generating concept maps complicated, time consuming and expensive.

Concept maps are graphical tools for organizing information. They generally consist of concepts (including words or sentences) and directed or undirected arrows showing the relations between these concepts. These arrows are labeled with verbal expression. The relation between two concepts is called proposition (Novak, Canas, 2008). The concept maps can be used as road maps laying out the learning plan for an individual learning process. Once these propositions are validated and the concepts and their relations are learned, then the learning goals are achieved.

The automatic extraction of concept maps are called "Concept Map Mining" (Villalon and Calvo, 2010). Concept map mining aims to visualize the extracted information from raw texts for teachers and students. There are different aspects of concept map mining. These can be summarized as Educational utility, Simplicity, Semi-formality and Subjectivity. Educational utility is about producing concept maps which provide accurate information about student's knowledge. Hence it should follow Novak's definition of concept maps (Novak, 2008). Simplicity is about summarising the educational text by restricting the number of learning concepts. According to Novak's definition this number should be less than or equal to 25 (Novak, 2008). Semi-formality is about computationally represent concept maps. Subjectivity is about the consistency between the information in a concept map and the educational text of which the concept map is extracted. It also means that the parts of concept map should not be influenced by external knowledge. (Villalon and Calvo, 2008 and 2010).

Mathematical definition of a concept map forms a triplet $\{C, R, G\}$. In this triplet, C is the set of concepts, i.e. $C = \{c_1, c_2, \dots, c_n\}$, R is the set of relations between these concepts, i.e. $R = \{r_1, r_2, \dots, r_k\}$, and G is a sorted set of generalization levels, i.e.

$G = g_1, g_2, \dots, g_m$. Every concept c_i in C is unique and represents a word or phrase. Every relation r_i in R consists of a set of two different concepts from C and one label of a relation from R. Hence, r_i is defined as a triplet of $r_i = (c_p, c_q, l_i)$. In this triplet, c_p and c_q are concepts in C and l_i is label of the relation r_i in R. Each generalization level g_i refers to a set of concepts $g_i = c_1, c_2, \dots, c_s$. Here all these c_i's share the same level of generalization (Villalon and Calvo, 2008).

Intelligent tutoring systems are simply defined as systems that determines who can learn which material in which way. Although studies on intelligent tutoring systems begin with artificial intelligence studies, at the beginning, the researchers could not dare to enter this field due to the lack of knowledge in cognitive models and semantics (Self, 1995). Most of the studies on intelligent tutoring systems in literature have the goal of classifying the students depending on their learning speeds and styles (Drigas, Argyri, Vrettaros, 2009). Intelligent tutoring systems should generate concept maps from raw text materials. On the other hand, there are many studies on the comparison of the impacts of experts and intelligent tutoring systems on individual learning.

There has been many studies on concept map mining and intelligent tutoring systems since 1970s. Carbonell (1970) developed SCHOLAR in order to teach students the geography of South America. SCHOLAR is the first intelligent tutoring system ever known. Brown (1974) used an intelligent tutoring system named SOPHIE to design electrical circuits. The intelligent system WHY was developed by Collins, Adams and Pew (1978) and was a the extension of SCHOLAR. It was system based on students' dialogues. Suppes (1981) designed an intelligent tutoring system BUGGY that helped teachers in understanding where students misunderstand mathematical concepts. WEST system developed by Brown, Burton and deKleer (1982) provided suggestions to students about how to win the game after analyzing how they play the game. Anderson and Reiser (1985) developed a LISP Tutor system which teaches LISP language by using ACT theory. Lisp Tutor is the first study that uses the fundamental principles of ACT theory. MAIS designed by Tennyson, Christensen and Park (1984) adjusts the difficulty of lectures according to the students' performances. Clancey (1987) developed GUIDON for medically diagnosing bacterial infections. Project LISTEN (1993) aimed to help people to read texts with their own voices and correct their mistakes. PACT was developed by Aleven, Koedinger, Sinclair and Snyder (1998) to teach and apply basic principles of geometry. Thepchai, Akiko, Mitsuru and Riichiro (1999) developed OGF to create a corporate or team learning environment.

ILEX developed by Cox, O'Donnell and Oberlander provided an online learning in museums. Meyer, Miller, Steuck and Kretschmer (1999) developed ISIS to provide students biological and echological information. AHAM developed by Bra, Houben and Wu (1999) is an example of applying intelligent tutoring systems to hypermedia. Schulze and et al (2000) started ANDES in 1995. ANDES teaches students physics visually by using Bayes networks. The project VET helped a group of students to achieve their goal corporately (Johnson, Rickel and Lester, 2000). The project AUTO TUTOR used a module of voice recognition that Works with an intelligent agent. This project was supported by the Secretary of Defense of the United States of America and National Science Foundation in the USA (Graesser, et al., 2001; Graesser, Jackson and McDaniel, 2007).

In 2004, concept maps were used to support reading and writing activities. This is called Text Concept Mapping (TCM)(Nurit Nathan, 2004). Valerio and Leake (2006) proposed concept map mining for several applications such as overcoming the large amount of available data to facilitate the organization of information in digital libraries (Shen, Richardson et al. 2005). Villalon, Kearney et al. (2008) suggested that TCM could be used to support authors' reflections during their writing process. Günel and Aşlıyan (2010) proposed 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, Jeong, Khan and Lee (2011) used Affinity Propagation Algorithm for automatic acquisition of domain concepts. Günel and et al. (2014) explored the support vector classifiers to solve the problem of extracting learning concepts from a single educational text.

The first step of constructing a concept map is to extract learning concepts from educational texts. In this thesis, it is aimed to model an intelligent tutoring system which generates learning concepts from raw text materials.

2 METHODS AND MATERIALS

Extracting a learning concept begins with the pre-processing of the given corpora. In this stage, all the punctuation marks, numbers and special symbols are eliminated in the corpora. Then, the most frequent n-grams are extracted. Afterwards, each document for each subject is pre-processed the same way and the candidate learning concepts are generated. By the help of experts, these candidate learning concepts are evaluated whether they are real learning concepts. The next step is to generate feature vectors for each candidate. After feature extraction, all these feature vectors are normalized and then Principal Component Analysis is applied in order to find the aspects of these feature vectors. At the last stage, k-Nearest Neighbor Algorithm, which is the fundamental and one of the easiest method of data mining, is used as supervised learning method. The reason for this choice is that k-NN one of the most successful method in this area despite its long training process. The general view of the architecture is given in Figure 2.1 (Günel et al., 2016).

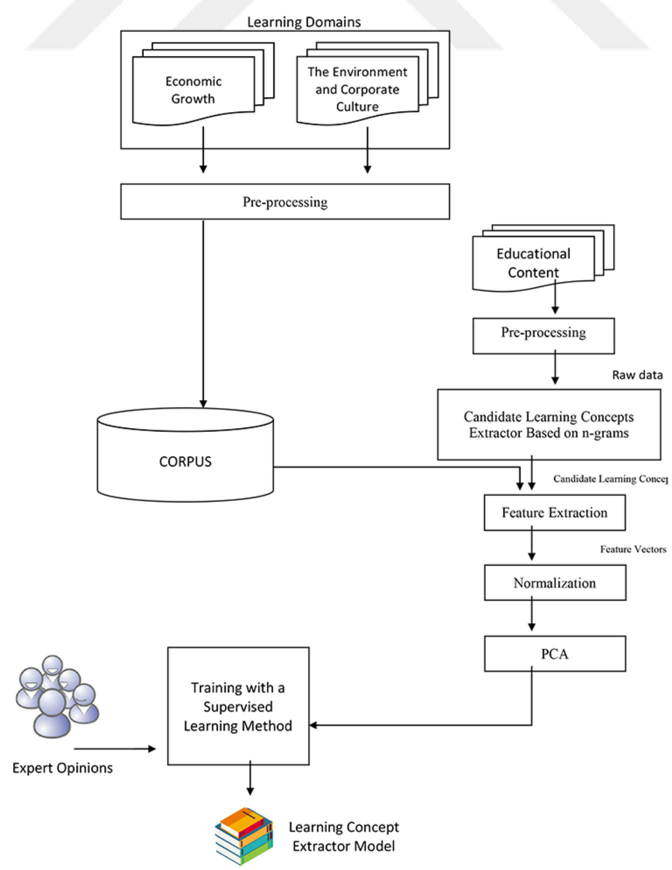


Figure 2.1 System architecture

2.1 Corpus

In this thesis, two different corpora are constructed through text books for each corpus. These corpora are about "Economic Growth" and "Organizational Environment". For each of these corpora, three text books/lecture notes which have been provided by the expert tutors are used. The number of words and sentences in these documents is calculated and presented in Table 2.1 and Table 2.2.

Documents	Authors	Number of Words	File Size
d_1	Durmuş Özdemir, Ph.D	4.635	407 Kb
d_2	Matthias Doepke, Andreas Lehnert, and Andrew Sellgren	6.007	131 Kb
d_3	Daron Acemoğlu	107.586	4 Mb
d_4	Robert J. Barro AND Xavier Sala-i-Martin	261.441	6.3 Mb
d_5	Robert M. Solow	10.026	2.4 Mb

Table 2.1 Statistical information about the corpus for Economical Growth

Documents	Authors	Number of Words	File Size
d_1	Richard L. Daft	386.922	21.4 Mb
d_2	Thomas G. Cummings and Christopher G. Worley	17.133	4.6 Mb
d_3	Robert B. Duncan	8.413	2.5 Mb
d_4	Warren R. Plunkett, Raymond F. Attner, Gemmy S. Allen	344.070	15.9 Mb
d_5	Esra Akta, Işık Çiçek, Mithat Kıyak	7.109	257 Kb

Table 2.2 Statistical information about the corpus for Organizational Environment

Expert tutors who provided these corpora materials also constructed a concept map related to these corpora. These corpora are shown in Figure 2.1 and Figure 2.2. These concept maps are used in comparing and validating the results obtained by the methods used in this thesis.

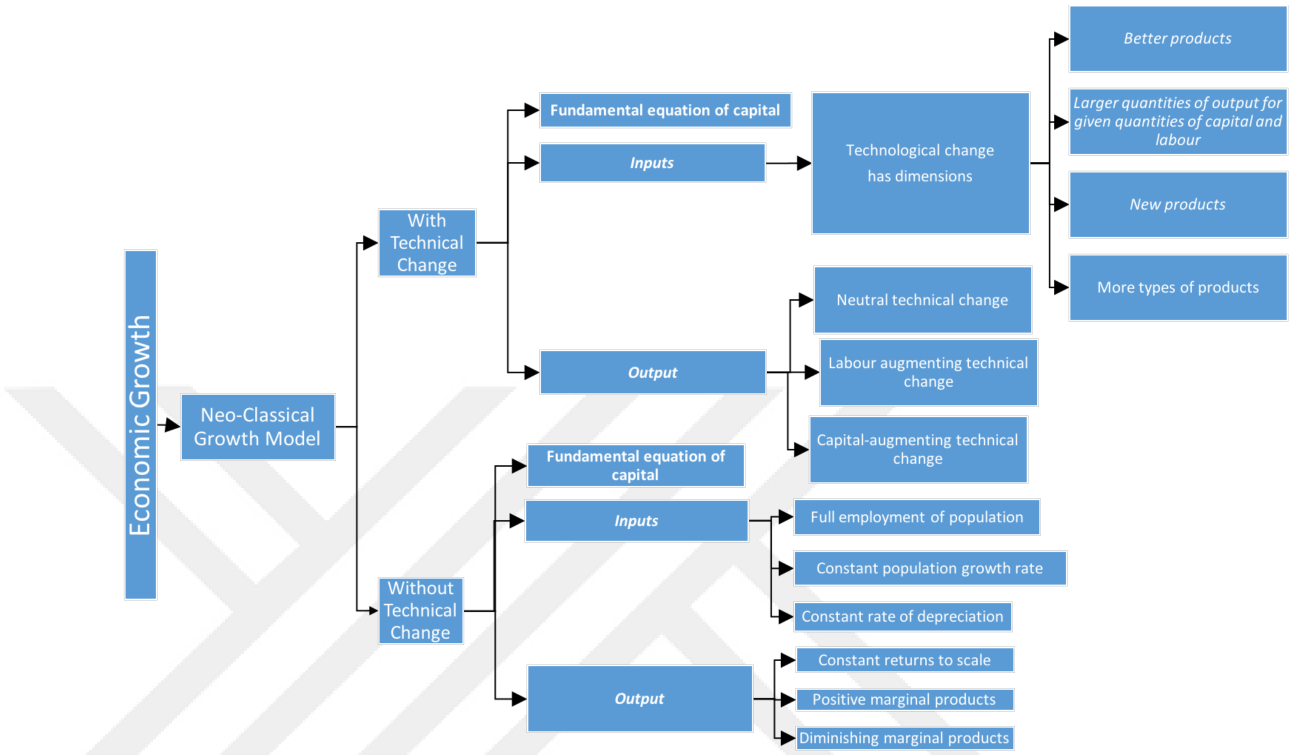


Figure 2.2 A concept map for Economical Growth corpus constructed by an expert tutor

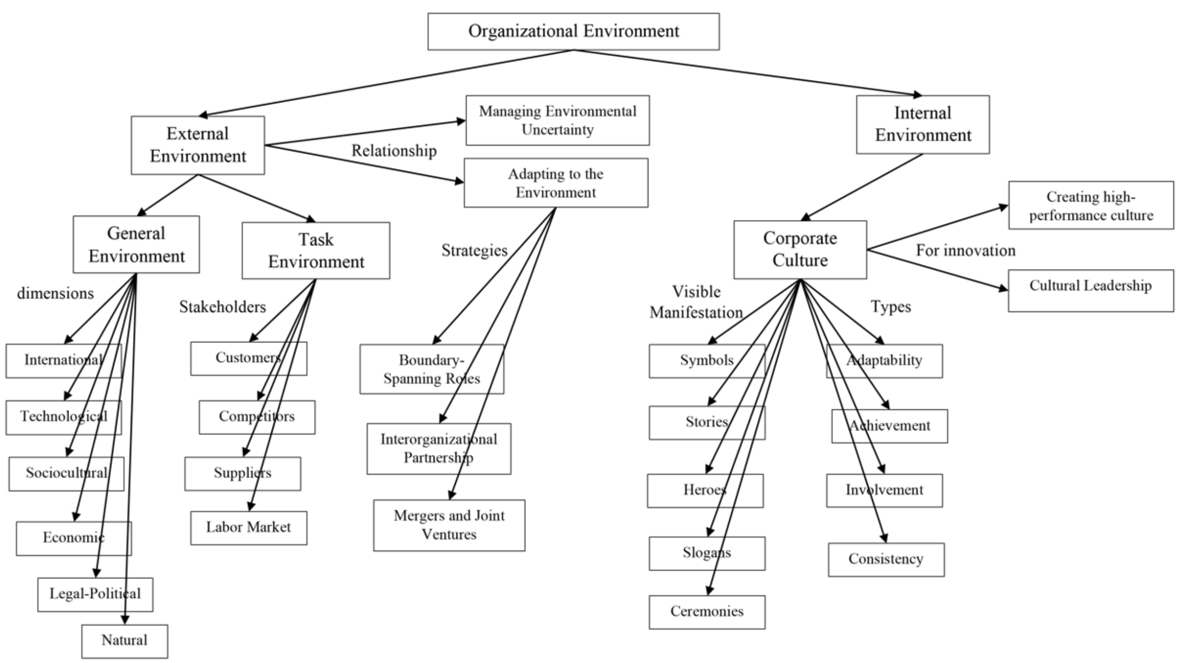


Figure 2.3 A concept map for Organizational Environment corpus constructed by an expert tutor

2.2 Pre-processing

In this stage, first of all, the documents received from the expert tutors are converted into text files. Since graphics, equations and figures cannot be considered as learning concepts, they are eliminated by this file format conversion.

In these text files, punctuation marks, numbers, special characters and extra spaces are removed and then rest of the text is converted to lowercase letters. Since stop words are used as inputs in training neural networks, they are not removed from the texts. Furthermore, not only words but also sentences are extracted for feature extraction (Günel et al., 2016).

2.3 n-Gram Extractor

After pre-processing, the most frequent n-grams (for $1 \leq n \leq 5$) from the corpora are extracted. n-gram model is used for predicting the next word, in such a sequence $w_{i-(n-1)}, w_{2-(n-1)}, \ldots, w_{i-1}, w_i$, in a corpus with a probability. This probability is calculated as given in Equation 1:

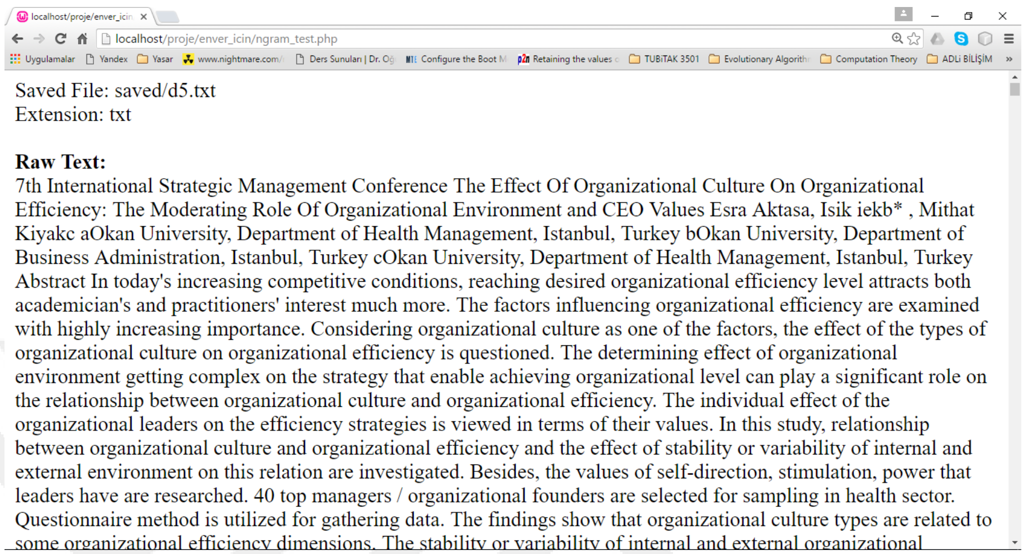
$$P\left(w_i \middle| w_{i-(n-1)} \ldots w_{i-1}\right) = \frac{C\left(w_{i-(n-1)} \ldots w_{i-1} w_i\right)}{C\left(w_{i-(n-1)} \ldots w_{i-1}\right)}$$

Equation 1.

In this equation, $C(w_{i-(n-1)}, w_{2-(n-1)}, \ldots, w_{i-1})$ indicates the number of occurences of the string $w_{i-(n-1)}, w_{2-(n-1)}, \ldots, w_{i-1}$, whereas $C(w_{i-(n-1)}, w_{2-(n-1)}, \ldots, w_{i-1}, w_i)$ specifies the number of occurences of the string $w_{i-(n-1)}, w_{2-(n-1)}, \ldots, w_{i-1}, w_i$ in a corpus. In a corpus, the set of the most frequent 500 n-grams are named G_1 (Günel et al., 2016).

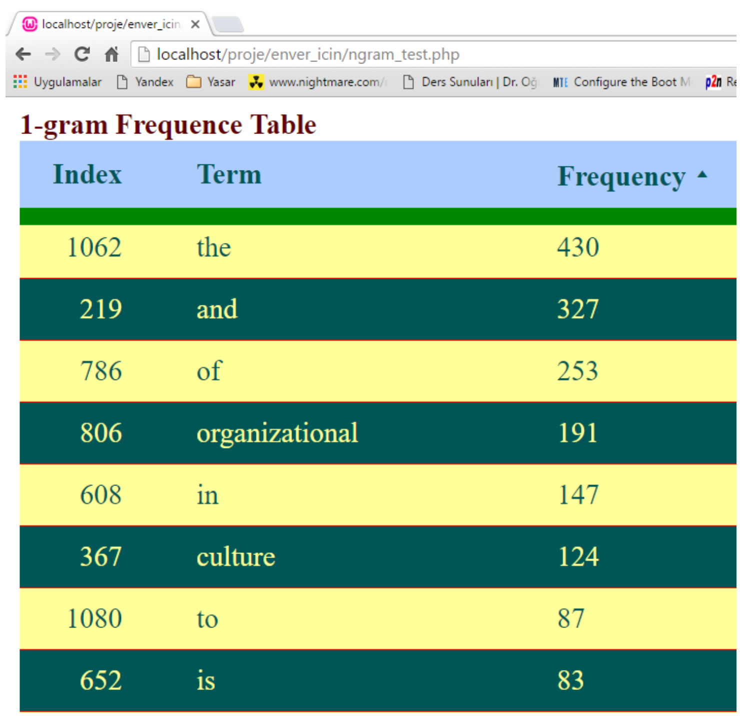
The same process is applied to all documents for each corpus. The over all most frequent 500 n-grams are called G_2. Each word in G_2 is a candidate learning concept. These candidate learning concepts are used as inputs for the proposed system.

A PHP program is used for extracting n-grams (for $1 \leq n \leq 5$) for each document. Sample screenshots are shown from Figures 2.4 to 2.9.


Saved File: saved/d5.txt
Extension: txt

Raw Text:
7th International Strategic Management Conference The Effect Of Organizational Culture On Organizational Efficiency: The Moderating Role Of Organizational Environment and CEO Values Esra Aktasa, Isik iekb* , Mithat Kiyakc aOkan University, Department of Health Management, Istanbul, Turkey bOkan University, Department of Business Administration, Istanbul, Turkey cOkan University, Department of Health Management, Istanbul, Turkey Abstract In today's increasing competitive conditions, reaching desired organizational efficiency level attracts both academician's and practitioners' interest much more. The factors influencing organizational efficiency are examined with highly increasing importance. Considering organizational culture as one of the factors, the effect of the types of organizational culture on organizational efficiency is questioned. The determining effect of organizational environment getting complex on the strategy that enable achieving organizational level can play a significant role on the relationship between organizational culture and organizational efficiency. The individual effect of the organizational leaders on the efficiency strategies is viewed in terms of their values. In this study, relationship between organizational culture and organizational efficiency and the effect of stability or variability of internal and external environment on this relation are investigated. Besides, the values of self-direction, stimulation, power that leaders have are researched. 40 top managers / organizational founders are selected for sampling in health sector. Questionnaire method is utilized for gathering data. The findings show that organizational culture types are related to some organizational efficiency dimensions. The stability or variability of internal and external organizational

Figure 2.4 Raw data of document d_5 of Internal Environment Subject


1-gram Frequence Table

Index	Term	Frequency
1062	the	430
219	and	327
786	of	253
806	organizational	191
608	in	147
367	culture	124
1080	to	87
652	is	83

Figure 2.5 1-gram statistics for document d_5 of Internal Environment Subject

2-gram Frequence Table

Index	Term	Frequency
1829	organizational culture	55
1329	in the	48
1733	of organizational	39
1748	of the	34
1832	organizational efficiency	33
1831	organizational effectiveness	32
807	culture and	27
2388	the organizational	26
467	and organizational	25

Figure 2.6 2-gram statistics for document d_5 of Internal Environment Subject

3-gram Frequence Table

Index	Term	Frequency
2897	the relationship between	15
910	culture and organizational	12
2184	organizational culture and	12
2802	the effect of	11
2439	relationship between organizational	11
700	between organizational culture	11
2194	organizational culture types	10
2041	of organizational culture	10
501	and organizational efficiency	9

Figure 2.7 3-gram statistics for document d_5 of Internal Environment Subject

4-gram Frequence Table

Index	Term	Frequency
2552	relationship between organizational culture	10
2277	organizational culture and organizational	8
3045	the relationship between organizational	8
716	between organizational culture and	8
2195	on the relationship between	7
934	culture and organizational efficiency	6
320	academy of management journal	6
3403	x org env f	6
2763	stability or variability of	5

Figure 2.8 4-gram statistics for document d_5 of Internal Environment Subject

5-gram Frequence Table

Index	Term	Frequency
3087	the relationship between organizational culture	8
723	between organizational culture and organizational	8
2588	relationship between organizational culture and	7
2223	on the relationship between organizational	5
2310	organizational culture and organizational efficiency	4
1143	effect on the relationship between	4
2800	stability or variability of internal	3
3448	x org env f 1	3
2254	or variability of internal and	3

Figure 2.9 5-gram statistics for document d_5 of Internal Environment Subject

2.4 Feature Extraction

The next step is to generate feature vectors for each candidate learning concept. The first of these feature vectors is "term frequency – inverse document frequency value" $(tf\ x\ idf)$. This value measures the weight of the important words of a document. It is calculated as in Equation 2.

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

Equation 2.

In this equation, while $tf(t, d)$ indicates candidate learning concept's frequency, D indicates the learning domain as a corpus. Here, t is an element of G_2 and is extracted from the document d (Günel et al., 2016).

The second feature vector is the Equation 3.

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

Equation 3.

This equation is the logarithm of the ratio of total number of sentences over the number of sentences. In this ratio, the candidate learning concept is also included. Here, d and t are elements of G_2 and s indicates any sentence of the document (Günel et al., 2016).

The third feature vector is obtained as it is shown in Equation 4.

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

Equation 4.

Again, here t is an element of G_2 and all x is the element of G_1. The function in this equation produces binary outputs such as:

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

Here, t is one of the most frequent n-gram occured in the educational content as a document d whereas x is one of the most frequent n-gram occured in the learning domain as corpus. The output of this function is a relation matrix which is obtained by using G_1 and G_2 (Günel et al., 2016).

The fourth feature vector is the function in Equation 5. This function points out the relation between a canditate learning concept t and the corpus as a learning domain. It also helps to eliminate the useless words such as stop words from the candidate learning concept set.

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

Equation 5.

Here, $|t|$ and $|t'|$ denote the number of words in t and t' respectively. r_3 is needed to weigh the candidate learning concepts based on their lengths (i.e. the number of words in the candidates) (Günel et al., 2016).

Once feature extraction process is completed, a normalization procedure is applied to all feature vectors. First, the original range of feature vectors are mapped to the range $[-1, 1]$ having its mean 0 and standard deviation 1. And then, in order to find aspects of the candidates Principal Component Analysis (PCA) is applied. The aspects of the candidates are necessary in identification of learning concepts. In this thesis, these vectors obtained from normalization process are used as inputs for the proposed system (Günel et al., 2016).

2.5 k-Nearest Neighbor Algorithm

In this thesis, k-Nearest Neighbor (k-NN) with majority voting are used as supervised methods. k-NN is a simple and fundamental method for a classification study when there is little or no prior knowledge about the distribution of the data. Therefore, k-NN is a non-parametric and instance-based classification method. k-NN algorithm specifies the new observation class as a feature vector by calculating the distance between this class and all the training examples and then gathering the k units which have the smallest distance. Since all neighbors are calculated with respect to k, the appropriate class of observation must be selected. In order to do that, the k-NN with majority voting method is used.

3 EXPERIMENTAL RESULTS

At this stage, the experimental results of training and testing of the techniques mentioned in the previous section are presented. In order to train, validate and test the models, five documents for each subject are collected. The subjects are "Neo Classical Growth", "Technological Change", "External Environment" and "Internal Environment". Then, G_2 is generated by pre-processing all these five documents. This pre-processing resulted in providing learning concept candidates. These learning concept candidates are examined and decided whether these concepts are real learning concepts by the experts.

For training and testing, two different methods are used: k Nearest Neighbour (k-NN) with majority voting algorithm for $k = 3$ and $k = 5$. From the set G_2, only the first 500 n-grams with highest frequency in the first document (d_1) are used for training and the first 500 n-grams with highest frequency in the documents d_2, d_3, d_4 and d_5 are used for testing. In training stage, 10-fold cross validation is used. In this validation method, the original sample is randomly partitioned in 10 equal sized samples. One of these samples is used for testing the model and the rest is used for training the data. This cross validation process is repeated 10 times and each sample is used as validation data once. The ratio of learning concepts in G_2 for each domain is given in Table 3.1.

Documents	Learning Domains			
	Neo-Classical Growth	Technological Change	External Environment	Internal Environment
d_1	0,032	0,034	0,068	0,028
d_2	0,038	0,020	0,030	0,020
d_3	0,028	0,038	0,032	0,014
d_4	0,034	0,048	0,046	0,032
d_5	0,030	0,036	0,026	0,038

Table 3.1 The ratio of learning concepts in G_2 for each domain

In testing stage, the documents d_2, d_3, d_4 and d_5 are used and the expert decisions are compared with the outputs of supervised methods that use recall, precision and f-measure scores. Table 3.2 shows these scores. Recall score is the ratio of the number of all positive predictive concepts to the total number of candidate concepts in an educational content. Precision score is the ratio of true positive concepts to the total number of candidate concepts in reality. f-measure is the harmonic mean of precision and recall to measure test's accuracy. Table 3.2 shows the recall, precision and f-measure scores of the testing stage for $k = 3$ and $k = 5$ in k-NN algorithm used in testing (Hripcsak, G., Rothschild, A.S. 2005).

		3-NN with Weighed Voting				5-NN with Weighed Voting			
Subject	**Docs.**	**Accuracy**	**Recall**	**Precision**	**f-Measure**	**Accuracy**	**Recall**	**Precision**	**f-Measure**
Neo-Classical Growth	d_2	0,934	0,842	0,348	0,492	0,976	0,947	0,621	0,750
	d_3	0,986	0,857	0,706	0,774	0,960	0,786	0,393	0,524
	d_4	0,996	0,941	0,941	0,941	0,954	0,882	0,417	0,566
	d_5	0,966	0,867	0,464	0,605	0,924	1,000	0,283	0,441
Technological Change	d_2	0,980	1,000	0,500	0,667	0,956	1,000	0,313	0,476
	d_3	0,970	0,895	0,567	0,694	0,958	0,895	0,472	0,618
	d_4	0,962	0,958	0,561	0,708	0,978	0,833	0,741	0,784
	d_5	0,922	0,923	0,267	0,414	0,974	0,889	0,593	0,711
External Environment	d_2	0,982	1,000	0,625	0,769	0,964	0,933	0,452	0,609
	d_3	0,712	0,875	0,090	0,163	0,700	0,813	0,081	0,148
	d_4	0,662	0,826	0,103	0,184	0,648	0,826	0,099	0,178
	d_5	0,788	0,500	0,081	0,140	0,872	0,846	0,151	0,256
Internel Environment	d_2	0,974	0,500	0,435	0,465	0,932	0,700	0,184	0,292
	d_3	0,986	1,000	0,500	0,667	0,958	1,000	0,250	0,400
	d_4	1,000	1,000	1,000	1,000	0,972	0,875	0,538	0,667
	d_5	0,942	0,947	0,391	0,554	0,954	0,789	0,441	0,566

Table 3.2 Recall, precision and f-measure scores of the testing stage for $k = 3$ and $k = 5$ in k-NN algorithm

The confusion matrices of the methods used for each subject and corpora are shown in tables below. Confusion matrix is a table which lays out the visualization of the performance of a method or an algorithm. In the confusion matrix below, True Positive shows the number of n-grams that are truly determined as learning concepts in real and its ratio to the total number of n-grams. False Positive shows the number of n-grams that are falsely determined as learning concepts in real and its ratio to the total number of n-grams. False Negative shows the number of n-grams that are not determined as learning concepts in the system but should be real learning concepts and its ratio to the total number of n-grams. True Negative shows the number of n-grams that are correctly determined as not learning concepts in the system and its ratio to the total number of n-grams.

		Predicted Conditions	
		Positive	Negative
True Conditions	Positive	True Positive 57 88%	False Negative 8 12%
	Negative	False Positive 51 3%	True Negative 1884 97%

Table 3.3 The confusion matrix of k-NN method for k = 3 used for Neo-Classical Growth subject in Economic Growth corpus

		Predicted Conditions	
		Positive	Negative
True Conditions	Positive	True Positive 62 94%	False Negative 4 6%
	Negative	False Positive 74 4%	True Negative 1855 96%

Table 3.4 The confusion matrix of k-NN method for k = 3 used for Technological Change subject in Economic Growth corpus

		Predicted Conditions	
		Positive	Negative
True Conditions	Positive	True Positive 57 79%	False Negative 15 21%
	Negative	False Positive 418 22%	True Negative 1515 78%

Table 3.5 The confusion matrix of k-NN method for k = 3 used for External Environment subject in Organizational Environment corpus

		Predicted Conditions	
		Positive	Negative
True Conditions	Positive	True Positive 51 82%	False Negative 11 18%
	Negative	False Positive 48 2%	True Negative 1900 98%

Table 3.6 The confusion matrix of k-NN method for k = 3 used for Internal Environment subject in Organizational Environment corpus

		Predicted Conditions	
		Positive	Negative
True Conditions	Positive	True Positive 59 91%	False Negative 6 9%
	Negative	False Positive 87 4%	True Negative 1848 96%

Table 3.7 The confusion matrix of k-NN method for $k = 5$ used for Neo-Classical Growth subject in Economic Growth corpus

		Predicted Conditions	
		Positive	Negative
True Conditions	Positive	True Positive 63 89%	False Negative 8 11%
	Negative	False Positive 59 3%	True Negative 1870 97%

Table 3.8 The confusion matrix of k-NN method for $k = 5$ used for Technological Change subject in Economic Growth corpus

		Predicted Conditions	
		Positive	Negative
True Conditions	Positive	True Positive 57 85%	False Negative 10 15%
	Negative	False Positive 398 21%	True Negative 1535 79%

Table 3.9 The confusion matrix of k-NN method for $k = 5$ used for External Environment subject in Organizational Environment corpus

		Predicted Conditions	
		Positive	Negative
True Conditions	Positive	True Positive 43 83%	False Negative 9 17%
	Negative	False Positive 83 4%	True Negative 1865 96%

Table 3.10 The confusion matrix of k-NN method for $k = 5$ used for Internal Environment subject in Organizational Environment corpus

4 CONCLUSION

In this thesis, it is shown that it is possible to extract learning concepts from a raw educational material by using a machine learning technique in educational technology. Generating concept maps with large scale data is a difficult and cumbersome process for experts. Doing this process automatically by machine learning and artificial intelligence techniques by computers speeds up the process and helps both students and experts to learn the concepts rather than the subject. Once this intelligent tutoring system is generated and trained well enough, the relations between the learning concepts can be generalized and reinforced. This way students would be assisted efficiently in evaluating the learning concepts and the course materials in future.

In this thesis, it is observed that the proposed k-NN method is suffcient in extracting learning concepts by feature vectors used in this study. As it is seen in experimental results, the learning concepts have been extracted with an accurracy ratio of 92.3% in average for $k = 3$ and an accurracy ratio of 91.8% in average for $k = 5$. This study, however, can be developed with different methods and techniques, and they can be compared with each other, as well.

This study is important for filling the gap in literature on automatically extracting learning concepts and constructing concept maps. In this way, learning paths depending on the educational contents can be constructed for educational technologies. Accordingly, the systems used in educational technologies can be restructured. Furthermore, customized and appropriate tests, self evaluation systems, etc. can be developed.

REFERENCES

Aleven, V., Koedinger, K. R., Sinclair, H.C. and Snyder, J. 1998. “Combatting shallow learning in a tutor for geometry problem solving”, 4th International Conference of Intelligent Tutoring Systems, ITS ’98, San Antonio, Texas, USA, August, 16-19.

Anderson, J. and Reiser, B. 1985. “The LISP Tutor”, Byte, 10(4), 159-175.

Bra, P.D., Houben, GJ. and Wu, H. 1999. “AHAM: A Dexter-based Reference Model for Adaptive Hypermedia”, Proceedings of ACM Hypertext 99, Darmstadt, Germany, February, 147-156.

Brown, J.S. 1974. “Sophisticated Instructional Environment for Teaching Electronic Troubleshooting”. Final Report, Report period covered January 1973-March 1974, Air Force Human Resources Lab., Brooks AFB, TX.

Brown, J.S., Burton, R.R. and deKleer, J. 1982. “Pedagogical natural language, and knowledge engineering techniques in SOPHIE I, II and III”, In: D. Sleeman, J.S. Brown, eds., Intelligent Tutoring Systems, Newyork Academic Pub., 227-282.

Carbonell, J.R. 1970. “AI in CAI: An artificial intelligence approach to computer-assisted instruction”, IEEE Transaction on Man-Machine Systems, 11(4), 190-202.

Clancey, W.J. 1987. Knowledge-based tutoring: the GUIDON program, MIT Press, Cambridge, MA, USA.

Collins, A., Adams, M.J., and Pew, R.W. 1978. “The effectiveness of an interactive map display in tutoring geography”, Journal of Educational Psychology, 70(1), 1-7.

Cox, R., O’Donnell, M., Oberlander, J. 1999. Dynamic versus static hypermedia in museum education: an evaluation of ILEX, the intelligent labelling explorer, Proceedings of the Conference on Artificial Intelligence in Education (AI-ED 1999), Le Mans, 181-188.

Drigas, A., Argyri, K. and Vrettaros, J. 2009. “Decade Review (1999-2009): Artificial Intelligence Techniques in Student Modeling”, Communications in Computer and Information Science Series, 49, Springer-Verlag, In: Second World Summit on the Knowledge Society, WSKS, Chania, Crete, Greece, September 16-18, 552-564.

Graesser, A.C., Jackson, G.T., and McDaniel, B. 2007. “AutoTutor holds conversations with learners that are responsive to their cognitive and emotional states”, Educational Technology, 47, 19-22.

Graesser, A.C., VanLehn, K., Rosé, C.P., Jordan, P.W. and Harter, H. 2001. "Intelligent tutoring systems with conversational dialogue", AI Magazine, 22(4), 39-51.

Günel, K. 2010. Intelligent Tutoring Systems: Conceptual Map Modeling (Paperback), LAP Lambert Academic Publishing, Saarbrücken, Germany, ISBN-13: 978-3838352299.

Günel K., Aşlıyan R. 2010. "Extracting Learning Concepts from Educational Texts in Intelligent Tutoring Systems Automatically", Expert Systems with Applications, 37(7), 5017-5022.

Günel K., Aşlıyan, R., Polat, R., Kurt, M., Öziş, T. 2014. "Dealing with Learning Concepts via Support Vector Machines", Seventh International Conference on Management Science and Engineering Management, Eds. Jiuping Xu, John A. Fry, Benjamin Lev, Asaf Hajiyev, Lecture Notes in Electrical Engineering Volume 241, Springer Berlin Heidelberg, 61-71.

Günel K., Polat, R., Kurt, M. 2016. "Analyzing Learning Concepts in Intelligent Tutoring Systems", The International Arab Journal of Information Technology, Volume 13, 281-286.

Hripcsak, G., Rothschild, A.S. 2005, "Agreement, the f-measure, and reliability in information retrieval", Journal of the American Medical Informatics Association, 12(3), 296-298.

Johnson, W.L., Rickel, J.W. and Lester. J.C. 2000. "Animated pedagogical agents: Face-to-face interaction in interactive learning environments", International Journal of Artificial Intelligence in Education, 11, 47-78.

Meyer, T.N., Miller, T. M., Steuck, K. and Kretschmer, M. 1999. "A multi-year large-scale field study of a learner controlled Intelligent Tutoring System", In: Artificial Intelligence in Education, Edited by Susanne P. Lajoie and Martial Vivet, IOS Press, Frontiers in Artificial Intelligence and Applications.

Nurit Nathan, E. K. 2004. "Text concept mapping: The contribution of mapping characteristics to learning frombtexts", First International Conference on Concept Mapping, Pamplona, Spain.

Novak, J. D. & Cañas, A.J. 2008. "The theory underlying concept maps and how to construct and use them", Technical report, IHMC CmapTools 2006-01, Rev 01-2008, Florida Institute for Human and Machine Cognition, Pensacola Fl.

Qasim I., Jeong J. W., Khan S., Lee D. H., 2011. “Exploiting Affinity Propagation for Automatic Acquisition of Domain Concept in Ontology Learning,” 7th International Conference on Emerging Technologies (ICET), Islamabad, Pakistan, pp. 1 – 6.

Self, J., 1990. “Theoretical foundations for intelligent tutoring systems”, AAI/AI-ED Technical Report, No.45, Journal of Artificial Intelligence in Education, 1(4), 3-14.

Schulze, K.G., Shelby, R.N., Treacy, D.J., Wintersgill, M.C., VanLehn, K. and Gertner, A. 2000. “Andes: An intelligent tutor for classical physics”, The Journal of Electronic Publishing, University of Michigan Press, Ann Arbor, MI, 6(1).

Suppes, P., 1981. “Future educational uses of interactive theorem proving”, In P. Suppes (Ed.), University-level Computer-assisted Instruction at Stanford: 1968-1980, Stanford, CA: Stanford University, Institute for Mathematical Studies in the Social Sciences, 165-182.

Tennyson, R.D., Christensen, D.L., Park, S.I., 1984. “The Minnesota Adaptive Instructional System: An intelligent CBI system”, Journal of Computer-Based Instruction, 11(1), 2-13.

Thepchai S., Akiko I., Mitsuru I., Riichiro M. 1999. “Learning goal ontology supported by learning theories for Opportunistic Group Formation”, Proc. of AIED99, 67-74.

Shen, R., R. Richardson, et al. 2005. “Using Concept Maps in Digital Libraries As A Cross-Language Resource Discovery Tool”, Proceedings of the 5th ACM/IEEE-CS joint conference on Digital libraries.

Valerio, A. and D. Leake 2006. “Jump-Starting Concept Map Construction with Knowledge Extracted from Documents”, Proceedings of the Second International Conference on Concept Mapping.

Villalon, J. J., Calvo, R. A. 2008. “Concept map mining: A definition and a framework for its evaluation”, in ‘Proceedings of the International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)’, Vol. 3, IEEE Computer Society, Los Alamitos, CA, USA, 357–360.

Villalon, J. J., Calvo, R. A. 2010. “Analysis of a gold standard for concept map mining – how humans summarize text using concept maps”, in ‘Proceedings of Fourth Int. Conference on Concept Mapping’, Viña del Mar, Chile, 14-22.

Villalon, J., P. Kearney, et al. 2008. “Glosser: Enhanced feedback for student writing”, Proceedings of the International Conference on Advanced Learning Technologies, Santander, Spain.

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