Automatic Generation of Concept Maps Based on Collection of Teaching Materials

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Abstract: The aim of this work is demonstration of usefulness and efficiency of statistical methods of text processing for automatic construction of concept maps of the pre-determined domain. Statistical methods considered in this paper are based on the analysis of co-occurrence of terms in the domain documents. To perform such analysis, at the first step we construct a term-document frequency matrix on the basis of which we can estimate the correlation between terms and the designed domain. At the second step we go on from the term-document matrix to the term-term matrix that allows to estimate the correlation between pairs of terms. The use of such approach allows to define the links between concepts as links in pairs which have the highest values of correlation. At the third step, we have to summarize the obtained information identifying concepts as nodes and links as edges of a graph and construct a concept map as resulting graph.

1 INTRODUCTION

Concept maps or semantic maps are a means of visualization of subject knowledge. The main figures of concept maps are concepts (key notions of the domain) put in circles or boxes. Concepts can be connected with each other by relations represented in the form of lines. The relations can be signed by words or word combinations expressing their purpose and meaning. In the broad sense, concept maps can be treated as visual means of presenting ontologies and thesauri of domains. However, their main purpose is to contribute to a deeper understanding of the subject and allow to represent the structure of the subject knowledge on the conceptual level.

The work (Sherman, 2003) reports the results of experimental investigations verifying the practical value and efficiency of using concept maps as a strategy of teaching. Unfortunately, the complexity of a manual construction of the concept maps greatly reduces the advantages of their using in the educational process. As a result, when preparing courses studies, teachers often renounce the use of concept maps or have to simplify their representation decreasing the number of concepts in the map or designating only the clearest and the most important relations between concepts.

Owing to the mentioned arguments, of special importance is the task of automatic or semi-automatic construction of concept maps on the basis of their extraction from a collection of text documents. Following the authors of (Villalon et.al, 2008) example this task got the name Concept Map Mining (CMM) similar to Data Mining (retrieval of useful information from large data files) and Text Mining (retrieval of useful information from large text arrays). In general case the process of CMM consists of three subtasks: extraction of concepts, extraction of links and summarization (Villalon et.al, 2010) (see Figure 1).

Concepts extraction
Relations extraction
Summarization

Figure 1: The subtasks of concept map mining process.

The aim of this work is demonstration of usefulness and efficiency of statistical methods of text processing for automatic construction of concept maps of the pre-determined domain. One of the most important virtues of statistical techniques is that they can be directly applied to any domain and any language, i.e. they are invariant in regard to the most important attributes of teaching courses, such as the field of knowledge and language of teaching.

Statistical methods considered in this paper are based on the analysis of co-occurrence of terms in the domain documents. To perform such analysis, at the first step we construct a term-document frequency matrix on the basis of which we can estimate the correlation between terms and the designed domain. We suppose that the more often a certain term occurs in the documents of the given subject domain and the sparser in the documents of other themes, the closer it is to the given domain, i.e. the higher is the correlation between the term and the domain. The use of such approach allows us to define concepts as terms which have a high level of correlation with the domain documents. At the second step we go on from the term-document matrix to the term-term matrix that allows to estimate the correlation not between terms and documents but between pairs of terms. The use of such approach allows to define the links between concepts as links in pairs which have the highest values of correlation. Thus, we have a concrete two-step algorithm for extraction of concepts and links between them. At the third step, we have to summarize the obtained information identifying concepts as nodes and links as edges of a graph and construct a resulting graph (see Figure 2).

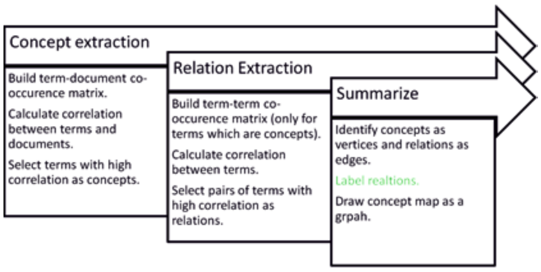

Concept extraction
Build term-document co-occurence matrix.
Calculate correlation between terms and documents.
Select terms with high correlation as concepts.
Relation Extraction
Build term-term co-occurence matrix (only for terms which are concepts).
Calculate correlation between terms.
Select pairs of terms with high correlation as relations.
Summarize
Identify concepts as vertices and relations as edges.
Label realtions.
Draw concept map as a grpah.

Figure 2: Proposed realization of concept map mining process.

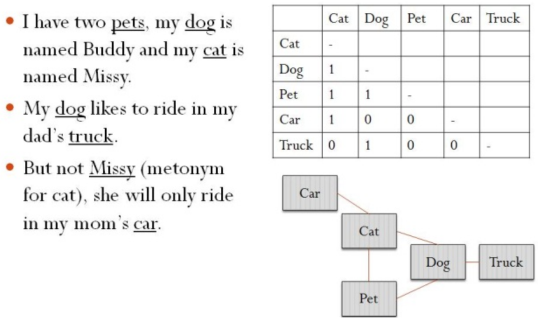
Automatically created concept maps we plan to integrate in e-learning environments as a learning activity aimed to student's active and deep learning of the subject. In (Akhmed-Zaki et al., 2014) we represent our conception of such e-learning environment, and in this paper we investigate one of its meaningful elements.

The remaining part of the work has the following structure. The second section presents a brief review of works related to the considered problem of automatic construction of concept maps. The approach proposed in this work is described in detail in the third section. The results of experimental testing of the proposed approach are given in the fourth section. The fifth section contains brief conclusions on the work done and presents a plan of further investigations.

2 RELATED WORKS

The resent decade is characterized by the growth of interest to investigations devoted to automatic extraction of concept maps from collections of text materials. Among these investigations, of high rank are the works based on the use of statistical techniques of processing a natural language. As is mentioned in (Zubrinic et al., 2012), the methods focused on statistical processing of texts are simple, efficient and well portable, however, they possess a decreased accuracy as they do not consider latent semantics in the text.

The mentioned simplicity and efficiency of statistical approaches are illustrated well in (Clariana et al., 2004). The authors construct a term-term matrix based on a short list of key words selected manually for the considered domain. They fill in the matrix on the basis of terms co-occurrence in sentences. If two elements occur in on sentence, the matrix element is equated to 1, otherwise – to 0. Then they display this matrix in the concept map, as shown in Figure 3. Obviously, such approach is good for chamber teaching courses consisting of materials limited in volume. For weighty courses such approach is very inefficient.



- I have two pets, my dog is named Buddy and my cat is named Missy.
- My dog likes to ride in my dad's truck.
- But not Missy (metonym for cat), she will only ride in my mom's car.

	Cat	Dog	Pet	Car	Truck
Cat	-				
Dog	1	-			
Pet	1	1	-		
Car	1	0	0	-	
Truck	0	1	0	0	-

Figure 3: Mapping the term-term matrix to the concept map.

These authors applied their methodology for constructing concept maps based on students' text summaries. The obtained concept maps were used by instructor to analyze how students learned the training material. In particular, the purpose of the analysis was selection of correct, incorrect or missing propositions in the students' summaries.

The authors of (Chen et al., 2008) extract concepts from scientific articles using the principal component analysis. For the extracted concepts they introduce the notion “relation strength” with the help of which they describe correlation between two concepts calculated on the basis of distance between these concepts in the text and on the basis their co-occurrence in one sentence. They display the extracted concepts in concept maps connecting those concepts “relation strength” between which does not exceed 0.4. Like the authors of (Clariana et al., 2004), the authors of this work do not label the related elements (do not sign them). These authors used some papers in scientific journals and conference proceedings, dedicated to the field of e-learning, as data sources for the construction of concept maps. According to them, constructed concept maps can be useful for researchers who are beginners to the field of e-learning, for teachers to develop adaptive learning materials, and for students to understand the whole picture of e-learning domain.

Generally speaking, labeling of related elements extracted from the texts being analyzed is a very complex problem that requires execution semantic analysis of texts. That is why many researchers note the limitedness of statistical approaches and try to combine statistical and linguistic tools and use the knowledge base suitable for semantic analysis. In particular, the authors (Oliveira et al., 2001) use thesaurus WordNet for part-of-speech analysis of texts. Due to determination of parts of speech in sentences they extract a predicate (the main verb) from each sentence and form for each predicate a triplet “subject-predicate-object”. The subject and object are interpreted as concepts and the predicate – as a link between the subject and object (see Figure 4). The authors of the paper were interested in building a concept map concerning biological kingdoms.

The authors of (Valerio et al., 2008) analyze the structure of sentences by constructing trees of dependences. They divide each sentence into a group of members dependent on nouns and a group of members dependent on the verb. They display verbs in the links and the nouns in concepts, as shown in Figure 5. The final goal of the authors is to develop intelligent user interfaces to help understanding of complex project documents and contextualization of project tasks.

The work (Kornilakis H. et al., 2004) describes the approach based on the use of thesaurus WordNet, too. The authors of this work use the lexical power of WordNet to provide the construction of an interactive concept maps by students.

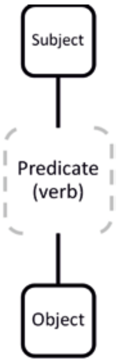


Figure 4: The extracted triplet.

Using WordNet the authors perform processing of different student responses revealing the meaning of the concepts with the help synonyms, hyponyms, meronyms, holonyms existing in the lexical base of WordNet.

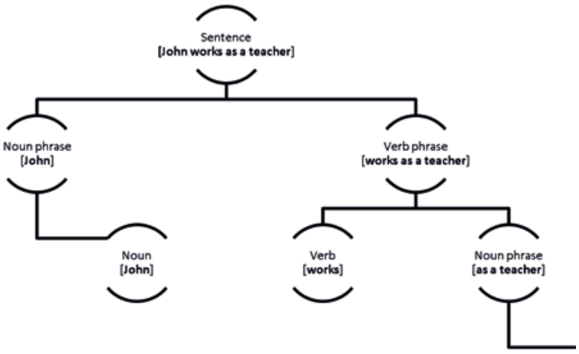


Figure 5: Dependency tree for semantic analysis.

Like the authors of (Clariana et al., 2004), the authors of (K.Rajaraman et al., 2002) search for structures noun-verb-noun in sentences. They use verbs as designations of links and display nouns in concepts. The authors of (Valerio et al, 2012) use not only verbs but also prepositional groups of the English language which designate possessiveness (of), direction (to), means (by), etc. for designation of links.

All the enumerated works demonstrate quite good results for extraction of concepts and relations. The problem only occurs when marking relations, i.e. when allotting semantics to relations. Interpretation of verbs and prepositional groups as relations is one of the ways to solve this problem which requires the use of linguistic tools and dictionaries.

3 PROPOSED APPROACH

We have already used the approach proposed in this work for another purpose - to build an associative thesaurus (Nugumanova et al., 2014). In our opinion, the difference between thesauri and concept maps is that concept maps are more subjective, they depend on the point of view of their creator, while thesauri are intended to be used as a tool of standardization and unification of the vocabulary of the domain.

3.1 Extraction of concepts

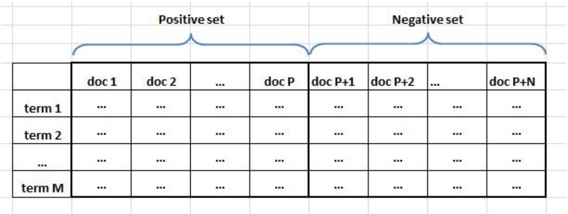
The first step of our approach is extraction of concepts. We consider the words which are characterized by a strong attachment to the domain as concepts. To find and select such words, we use Pearson's criterion, one of the applications of which is the test for independence of two events (Zheng et al., 2009). In our case, this test allows to estimate independence of a word and the domain. The null hypothesis of the test is that there is no dependence (link) between a word and domain that means that the considered word occurs with approximately equal frequency in the texts of the domain and the texts of other themes. Consequently, an alternative hypothesis is that there is dependence between a word and the domain that means that the frequency of the word occurrence in the texts of the domain is higher than in the texts of other themes.

All of the above means that Pearson's criterion for independence compares distribution of the word in two sets of documents: a positive set (the documents of the domain) and a negative one (the documents of other themes). The formula that allows to estimate such distribution for each word has the following form:

$$\chi^2 = \frac{(A+B+C+D)(AD-BC)^2}{(A+B)(A+C)(B+D)(C+D)}$$

where A is the number of documents of the positive set containing this word, B is the number of documents of the negative set containing the word, C is the number of documents of the positive set not containing this word, D is the number of documents of the negative set not containing the word.

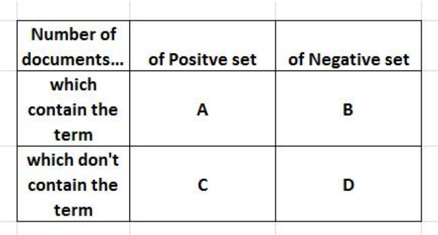
For a technical realization of the test we should prepare a collection of documents consisting of two parts: a positive set of documents containing teaching materials from a subject domain and a negative set of documents containing various texts from other desirable more general themes (culture, news, events, etc.). Then we should carry out tokenization of the obtained texts, i.e. division into words, lemmatization (reduction of words to normal forms) and removal of stop-words. As result of such preprocessing we obtain a list of unique words (terms) of the collection. After that we can construct a term-document matrix the lines of which correspond to terms, columns – to documents and elements – to frequencies of using terms in documents (see Figure 6).



	Positive set				Negative set			
	doc 1	doc 2	...	doc P	doc P+1	doc P+2	...	doc P+N
term 1	...	...	...	...	...	...	...	...
term 2	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...
term M	...	...	...	...	...	...	...	...

Figure 6: Term-document co-occurrence matrix.

Now, for each chosen term we can calculate the values A, B, C, D as described above (see Figure 7), after that, using the formula we can calculate the value of Pearson's criterion. If the value of Pearson's criterion appears to be higher than a threshold we will use this term as a concept.



Number of documents...	of Positve set	of Negative set
which contain the term	A	B
which don't contain the term	C	D

Figure 7: The contingency table for the Chi-squared test.

3.2 Extraction of relations

The obtained term-document matrix contains information concerning links between terms and documents. To extract relations between concepts, we should concentrate on links between terms, i.e. go on to a term-term matrix. For this, we should find pairwise distances between terms which are presented by vectors-lines in the initial term-document matrix. The distance can be calculated using the cosine measure:

$$c = \cos(\bar{x}, \bar{y}) = \frac{\bar{x} \cdot \bar{y}}{|x| \cdot |y|}$$

where c is the sought for distance; x, y are any two lines in the initial term-document matrix corresponding to the pair of terms. The obtained values (distances) between the terms are measured by figures in the range from 0 to 1. The higher the proximity between vectors-terms, the less is the angle, the higher is the cosine of the angle (cosine measure). Consequently, maximum proximity is equal to 1, and minimum one is equal to 0.

The obtained term-term matrix measures the proximity between terms on the basis of their co-occurrence in documents (as coordinates of vectors-terms are frequencies of their use in documents). The latter means that the sparser the initial term-document matrix, the worse is the quality of the term-term proximity matrix. Therefore, it is expedient to save the initial matrix from information noise and rarefaction with the help of the latent semantic analysis (Deerwester et al., 1990). The presence of noise is conditioned by the fact that, apart from the knowledge about the subject domain, the initial documents contain the so-called "general places" which, nevertheless, contribute to the statistics of distribution.

We use the method of latent semantic analysis for clearing up the matrix from information noise. The essence of the method is based on approximation of the initial sparse and noised matrix by a matrix of lesser rank with the help of singular decomposition. Singular decomposition of matrix A with dimension $M \times N$, $M > N$ is its decomposition in the form of product of three matrices – an orthogonal matrix U with dimension $M \times M$, diagonal matrix S with dimension $M \times N$ and a transposed orthogonal matrix V with dimension $N \times N$:

$$A = USV^T.$$

Such decomposition has the following remarkable property. Let matrix A be given for which singular decomposition $A = USV^T$ is known and which is needed to be approximated by matrix A_k with the pre-determined rank k. If in matrix S only k greatest singular values are left and the rest are substituted by nulls, and in matrices U and V^T only k columns and k lines are left, then decomposition

$$A_k = U_k S_k V^T{}_k$$

will give the best approximation of the initial matrix A by matrix of rank k. Thus, the initial matrix A with the dimension $M \times N$ is substituted with matrices of lesser sizes $M \times k$ and $k \times N$ and a diagonal matrix of k elements. In case when k is much less than M and N there takes place a significant compression of information but part of information is lost and only the most important (dominant) part is saved. The loss of information takes place on account of neglecting small singular values, i.e. this loss is the higher, the more singular values are discarded. Thus, the initial matrix gets rid of information noise introduced by random elements.

3.3 Summary

The extracted concepts and relations must be plotted on a concept map. Let us repeat that as concepts or nodes of a graph we use all terms for which Pearson's criterion is higher than a certain threshold value determined experimentally. In literature the value of 6.6 is indicated as a threshold but by varying this value it is possible to reduce or increase the list of concepts. For example, a too high value of the threshold will allow to leave only the most important terms which have the highest values of Pearson's criterion.

In the same way the number of extracted relations can be varied. If among all pairwise distances in the term-term matrix, the values lower than a certain threshold are nulled, the edges (links) will connect only the concepts the proximity between which is higher than the indicated threshold.

4 EXPERIMENTS

To carry out experiments, we chose the subject domain "Ontology engineering". The documents representing chapters from the textbook (Allemang, D. et al, 2011) formed a positive set of the teaching collection. Besides, some articles from other themes formed a negative set of the teaching collection. Tokenization and lemmatization from the collection resulted in a thesaurus of unique terms. The use of Pearson's criterion with the threshold value of 6.6 allowed to select 500 key concepts of the subject domain. Table 1 presents the first 10 concepts with the greatest value of the criterion.

Then the constructed term-document matrix was approximated by a matrix of the rank 100 with the help of singular decomposition.

Table 1: The first 12 concepts of the subject domain.

No	Concept	Chi-square test value
1	semantic	63.69
2	Web	59.95
3	property	59.87
4	manner	57.08
5	model	53.74
6	class	52.40
7	major	51.71
8	side	50.78
9	word	50.59
10	query	44.09
11	rdftype	37.41
12	relationship	35.71

On the basis of the obtained matrix, pairwise distances between terms-lines were calculated using cosine measure. Thus, the transfer from a term-document matrix to a term-term matrix was carried out. Table 2 presents, as an example, some pairs of terms with different indexes of proximity. Only the links the proximity values of which exceeded 0.3 were left as relations significant for construction of a concept map.

Table 2: The samples of various extracted relations.

No	First concept	Second concept	Relation strength
1	OWL	Class	0.54
2	OWL	Modeling	0.34
3	OWL	member	0.37
4	Property	Class	0.35
5	Result	Pattern	0.37
6	Term	Relationship	0,33

Having obtained all concepts and links, we constructed a graph of the concept map. The concepts were taken as nodes of the graph and relations between concepts were taken as edges. As the general structure of the map is too large for analysis, we present a fragment of this map in Figure 8.

The results demonstrate one important limitation of our approach, it is strongly influenced by the selection of negative set. This is one of the problematic aspects that need to be investigated in the future works.

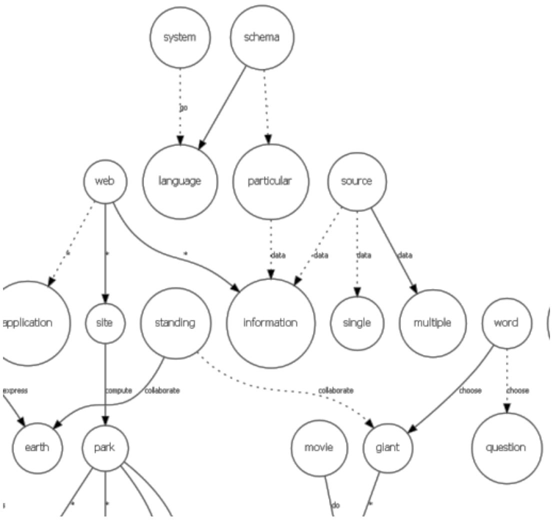


Figure 8: Fragment of the concept map.

5 CONCLUSION

The results of experiments were submitted for analysis to two independent experts in the subject domain. The experts noted the following advantages of automatic generation of concept maps: quickness, effectiveness, completeness and actuality. However, they marked that large dimensions of concept maps require more intellectual methods of their processing; the further work will be related to this theme.

This work is part of a project carried out in the Al-Farabi Kazakh National University and East Kazakhstan State Technical University, the goal of which is to develop efficient algorithms and models of semi-structured data processing, on the basis of modern technologies in the field of the Semantic Web using the latest high-performance computing achievements to obtain new information and knowledge from unstructured sources, large amounts of scientific data and texts.

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