Network of Natural Terms Hierarchy as a Lightweight Ontology

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***Abstract* — This paper describes the construction methodology of a network of natural terms hierarchy based on the analysis of a homogeneous or heterogeneous text corpus. It also presents a criterion for the evaluation of paper relevance to a particular scientific conference. The proposed method is illustrated by the examples from the heterogeneous corpus of the STIDS 2013 conference proceedings.**

Keywords* — *language network, compactified horizontal visibility graph, term hierarchy, scientific trend.

I. INTRODUCTION

It is a very complex and resource-demanding problem to construct a large domain-specific ontology. Therefore for various natural language processing (NLP) tasks (e.g., information extraction, information retrieval, question answering), e-commerce-related problems, etc. so called lightweight ontologies are used [4]. Meanwhile the problem of fully unsupervised ontology learning is still unsolved [12]. It is especially important for languages without good ontology or semantic recourses, for example, for Russian – although there are a few initiatives, no open ontologies are available [3].

Our aim is to develop the construction methodology of a lightweight domain-specific ontology. In this paper we propose an approach to the construction of the terms hierarchy network which is actually a lightweight domain-specific ontology. Our approach is unsupervised and data-driven and does not involve any specific linguistic analysis. We propose a method of constructing a terminological basis for the technological science domain.

Another problem – that of the formal estimation of relevance of the works of scientists to different scientific trends – is also addressed. We introduce the corresponding formal criterion based on the extension of the terms network model.

We conducted preliminary research based on the Russian data (homogeneous "Corpora Conference" proceedings) [11]. However, the data for this paper is derived from the heterogeneous corpus of STIDS'2013 proceedings (in contrast to the previous one); we suppose it illustrates the proposed method better.

II. RELATED WORK

Hierarchy is a natural form of complex self-organizing systems organization that can produce a strong differentiation in capacity (power and size) between the parts of the system (e.g., in biological, technological, social and language networks). However, detecting, identifying and comparing hierarchies is difficult [13] [16]. The construction of the network of natural terms hierarchy (NNHT) is fully based on the text corpora content of the appropriate orientation and does not include any special methods of semantic analysis [10].

There are several works addressing the problem of a lightweight ontology construction.

In [18] an approach to learning ontologies from different sources is proposed. Thus, external sources of knowledge are employed as well as in-domain ones. Ontology construction process is organized as follows. First, a seed set of terms is proposed by the experts, after which the term extraction stage takes place. Second, relations and then their labels are detected. Such framework includes part of speech (POS) tagging and verbs normalization. The term learning procedure is based on the use of co-occurring patterns.

Cross-language ontology learning is discussed in [7]. Terms are extracted using existing tools for English and Mutual Information metric (MI) for under-resourced languages. To identify relations, distributional similarity models and statistical machine translation methods are employed.

Lightweight ontology learning is also described in [6]. Terms are extracted from the collection of documents. They are considered similar if they occur in the same documents, and similarity scores are calculated using Salton Index [17].

In [1] an ontology is learned from the Wikipedia plain-texts. The authors collect word definitions from Wikipedia and use a special term extraction tool. Having constructed a hypernym graph, they weigh its edges and then apply a Kruskal's algorithm adaptation to build maximal covering forest from a graph.

In [15] Wikipedia definitions are also learned. The authors proposed Word-Class Lattices model which is a word lattice extension to the model definitions of words with classes mainly based on the POS tags. Their ap-

978-1-4799-9900-2/15 $31.00 © 2015 IEEE
DOI 10.1109/MICAI.2014.9

proach, above all, involves sentences extraction, POS-tagging and sentence-clustering. Such procedures are difficult in the sense that they demand complex efforts and much time.

In fact, most papers describe either the application of lexico-syntactic patterns to the terms and definitions extraction (see [5], for example) or employ graph theory (e.g., [1]). Most NLP-based techniques rely on POS-tagging and sometimes syntactic parsing, in some cases seed term sets are predefined [21].

Our approach is graph-based like the one proposed in [1] and is actually based on terms co-occurrence like the one in [6] but it demands neither any complex linguistic procedures nor special parsing tools. Our method is also language-independent and can be based on either homogeneous or heterogeneous corpus. Unlike the approaches presented in [6] and [18], ours does not demand any external sources of knowledge (e.g., synonyms or hypernyms thesauri) apart from the in-domain ones. Moreover, in our approach, as a side effect of the ontology construction, the terms are classified into the central and peripheral ones with regard to the domain.

The terms hierarchy construction method proposed in this paper includes a series of stages. It reflects the following tasks (the parts of our research):

- node weighting, i.e. TF-IDF calculation for words (unigrams), bigrams and trigrams;
- the construction of a compactified horizontal visibility graph (CHVG), recalculation of weights for unigrams, bigrams and trigrams [8] so that the new weight of a term would be equal to the corresponding node degree; terms sorting in accordance with calculated weights;
- the network of natural terms hierarchy construction (introducing part-whole relations) [10].

III. DATA

In our research we experimented with the data consisting of the proceedings of the 8th International Conference on Semantic Technologies for Intelligence, Defense, and Security (STIDS 2013)[1]. We constructed the terms hierarchy networks for the whole corpus as well as for each separate paper. In this paper we only consider the following four papers (see the author, the title and the keywords respectively):

- Boury-Brisset A. -C. Managing Semantic Big Data for Intelligence (intelligence, data integration, knowledge extraction, ontology, Big Data);
- Haberlin R. J. A Reference Architecture for Probabilistic Ontology Development (intelligence, data integration, knowledge extraction, ontology, Big Data);
- Moten R. Analyzing Military Intelligence Using Interactive Semantic Queries (semantic search; military intelligence; analytics; type theory; ontology; semantic modeling; interactive theorem proving);
- Mehmet M., Wijesekera D. Data Analytics to Detect Evolving Money Laundering (data analytics; social network analysis; anti money laundering; dynamic risk model; money laundering risk).

IV. METHODS

A. Method 1. How to Construct the Network of Natural Terms Hierarchy?

The network of natural terms hierarchy (NNTH) is based on information-intensive text elements, pivot words and word combinations. The methodology of identification of these elements is described in [8], [19]. The usage of such elements allows constructing information pictures and embracing specific knowledge domains. Pivot words and word combinations are selected on the base of their TF-IDF values. However this feature is not enough for the construction of a terms ontology of high quality. Sometimes other words – in particular, the most frequent words from the chosen domains (such as “Information”, “Data” and “Ontology” from semantic technologies domains) turn out to be very important for the tasks considered in this article.

The network of natural terms hierarchy is constructed on the base of the text corpora of a particular domain. We call it natural as it does not include any special methods of semantic analysis (including part of speech tagging). All the relations in our network are determined by the relative positions of words and word combinations, which are extracted from the texts of statistically significant size. A terms hierarchy which is built completely automatically can be considered a base for the further automatic ontology construction with the experts.

Let us consider the stages of building a network in detail:

1. The corpus preprocessing procedure includes the division of a text into fragments (separate reports, paragraphs, sentences, words, bigrams, and trigrams), the deletion of analphabetical symbols and cutting off inflexions – stemming (as optional).
2. Each term (a unigram, bigram or trigram) gets a weight (TF-IDF in its canonical form).
3. For the obtained terms sequences and their TF-IDF weights compactified horizontal visibility graphs (CHVG) are constructed. Then on the base of the CHVG algorithm new weights (namely, node degrees) are attributed to the terms. This procedure allows taking into account not only the terms with high TF-IDF but also high-frequency terms which are rather important for the common subject of text corpus.

A CHVG is constructed in three stages [8] (and the network construction takes one more step):

[1] http://stids.c4i.gmu.edu/

1. At first a number of nodes are marked on the horizontal axis; each node corresponds to the word as it occurs in the text. On the vertical axis there are TF-IDF values. Between these TF-IDF values and their projections on the x-axis vertical lines are drawn. Thus, we come up with a series of vertical lines.
2. Secondly a traditional horizontal visibility graph is built [14]. We consider two nodes to be connected if they are in "direct visibility", i.e., if they can be connected by a horizontal line which does not cross any vertical line.
3. The graph is compactified. All the nodes with the same word are merged into a single one. All the edges of such nodes are also united. There is no more than one edge between any two nodes, as multiple edges are deleted. New weights for the words are calculated as the degrees of the corresponding nodes in the CHVG. Then all the terms are sorted according to their new weights in descending order. Stop words are excluded from the further analysis: they are rather important for text coherence, but do not have a great sense load. As a rule, such words present a fixed set of auxiliary words. In this paper we use stop words sets which are available on the following web resources:

- https://code.google.com/p/stop-words/downloads/list;
- http://www.ranks.nl/stopwords/;
- http://www.textfixer.com/resources/common-english-words.txt.

4. The network size (denoted by N) is suggested by the experts. Then N unigrams, N bigrams and N trigrams with the largest weights in the CHVG are selected (3*N elements). The nodes are constructed from the chosen elements, where the nodes are the terms by themselves, and the links present part-whole relations between some two terms. Fig. 1 illustrates the terms hierarchy construction. Different geometric figures present different words. The first column consists of unigrams (i.e., words), while bigrams and trigrams occupy the second and the third columns respectively. If a unigram is a part of some bigram or trigram, we suppose that there is a relation between them and denote it by the link in the form of an arrow. The set of nodes (terms) and links (relations) forms a three-level network of natural terms hierarchy.

B. Method 2. How to Use Visualization of Network of Natural Terms Hierarchy?

To illustrate network visualization, we select top-20

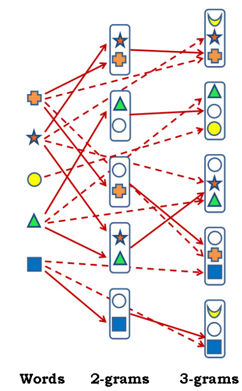

Figure 1. Relations construction in a three-level term hierarchy network.

terms with the largest weights from the network constructed on the base of corpus (see table 1). It should be noted that in Table 1 the rows do not correspond to the fixed triples of n-grams. Each column represents an independent list of n-grams sorted according to their weights. It can be seen that the terms in Table 1 evidently reflect the main themes of a semantic technology-related conference.

As soon as the term hierarchy network is constructed, we visualize it using graph analysis tools, namely, Gephi system[2]. To load this network into a database we represent it by an incidence matrix in ".csv" format, see results of the visualization – Fig. 2, 3, etc. – in the Results section.

V. Results

In Table 1 the list of 20 terms with the largest weights from the STIDS 2013 corpus is given (3*20: 20 unigrams, 20 bigrams and 20 trigrams). Fig. 2 is an illustration of a small network with 20 terms (20+20+20 in total) visualized using Gephi system.

Table 1. Top-20 terms with largest CHVG weights

№	Unigrams	Bigrams	Trigrams
1	data	decision making	social network analysis
2	information	big data	human decision makers
3	decision	data source	dynamic risk model
4	ontology	semantic web	decision making process
5	context	probabilistic ontology	big data technologies
6	based	intelligence analysis	probabilistic ontology development
7	model	real time	open information extraction
8	event	international conference	navigation assistance framework
9	intelligence	decision support	decision support systems
10	knowledge	static risk	decision development kes
11	time	cyber argus	cyber impact assessment
12	semantic	access control	additional unexploded

[2] https://gephi.org

№	Unigrams	Bigrams	Trigrams
			bombs
13	query	social media	attribute value pairs
14	set	data integration	event ontology extension
15	evidence	money laundering	sketch data model
16	cyber	knowledge base	natural language processing
14	risk	context representation	intelligence data integration
15	level	event ontology	weakly recursive datalog
16	source	intelligence data	basic formal ontology
17	approach	decision variables	big data analytics
18	analysis	knowledge representation	evidence based reasoning
19	example	context aware	models decision making
20	system	risk model	real life cases

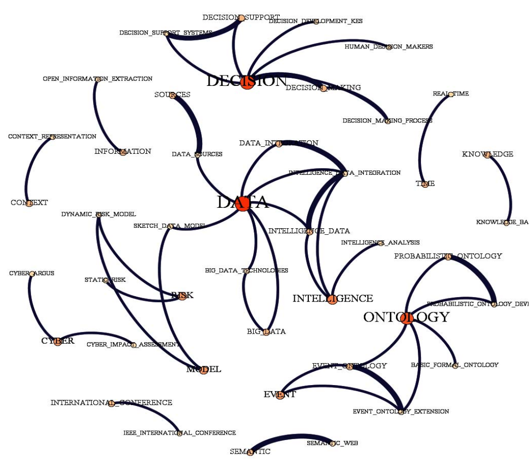

Figure 2. Network of Natural Terms Hierarchy (20+20+20).

It can be seen that in Fig. 2 the terms in large print (e.g., "data", "decision", "ontology") refer to the top-most positions in Table 1 as they represent the nodes with the largest weights. The unigram nodes are connected to the bigram and trigram nodes (and the bigram nodes – to the trigram nodes) according to the principle outlined in section 4.1 and illustrated by Fig. 1. The term "information", although its position in Table 1 is high, does not appear in Fig. 2 because it has no connections to the other terms (i.e., it is not a part of top-20 bigrams and trigrams). Arc thickness in Fig. 2 is proportional to the joint frequency of the terms (i.e., n-grams) it unites.

We can take a larger example of a conference-based network, consisting of 200 terms of each type (unigrams, bigrams and trigrams). Fig. 3 represents such a fragment of the network of natural terms hierarchy. The fragment in Fig. 2 can be considered a "figure" and the fragment of Fig. 3 – a "background" in terms of Gestalt psychology.

Though the network becomes very dense, the top-most terms (at least unigrams) are still visualized as the largest ones, while multiple smaller nodes are added (in comparison with 20+20+20 network).

According to the proposed algorithm, one node can have 5 ingoing links at most (for the network in our example, see Fig. 2). Unigrams have 0 ingoing links, bigrams – 2 ingoing links at most and trigrams – 5 ingoing links at most (with 3 links inherited from each word of a trigram and other 2 inherited from the two bigrams a trigram consists of). Top-20 nodes with the largest ingoing degrees for 200+200+200 network of natural terms hierarchy are shown in Table 2.

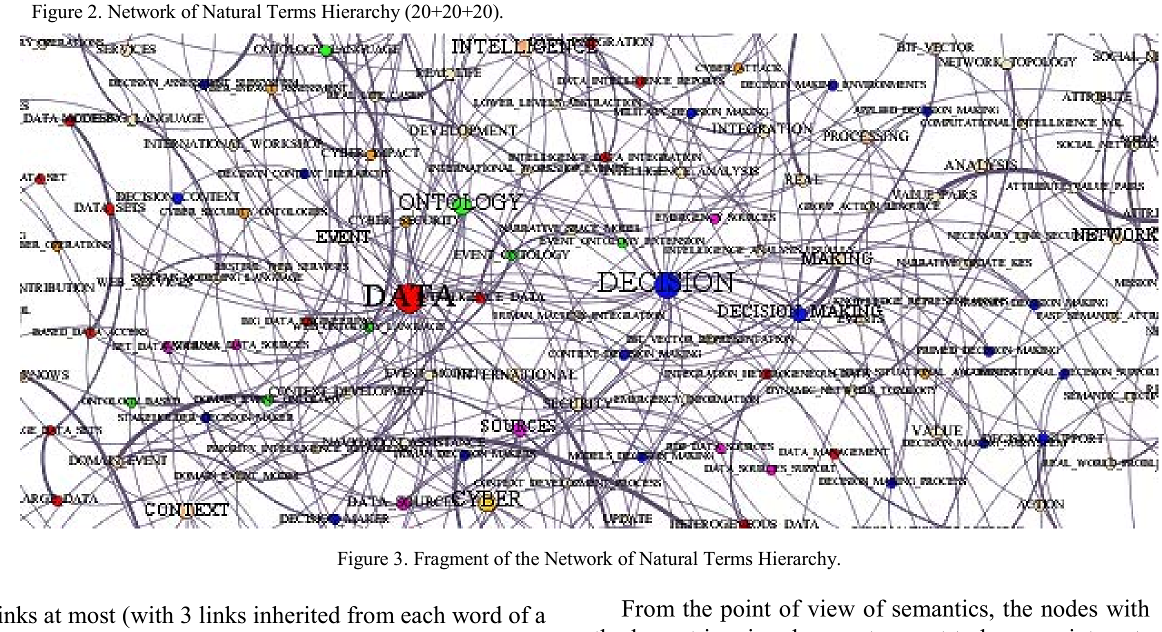

Figure 3. Fragment of the Network of Natural Terms Hierarchy.

From the point of view of semantics, the nodes with the largest ingoing degrees turn out to be more interesting than any other ones. Such nodes include word combinations like "social network analysis", "probabilistic ontology development", "military intelligence analysis", "intelligence data integration" and "dynamic risk model".

Therefore, due to space limits in this paper we show the results of the experiments conducted on the four papers (from the STIDS'2013 proceedings corpus) which contain the mentioned word combinations and interrelations for these papers.

We calculate CHVG weights for unigrams, bigrams and trigrams and construct networks for some papers. Fig. 4 illustrates the NNTH visualization for the paper by Mehmet & Wijesekera (the paper from the periphery of the conference domain).

Terms interrelations from these four papers are represented in Fig. 5. Here the terms correspond to each paper (see the nodes marked with the names of the authors). In the central part of the figure there are the terms which these papers share, while specific terms are at the periphery. The central zone does not necessarily include the terms from all the papers: they can appear only in some threshold portion of the papers (e.g., one half).

The more terms the central zone of a paper includes, the closer this paper is to the main topics of the conference, and the most relevant it is. The paper by Anne-Claire Boury-Brisset appears to be the most relevant one to the main topics of the conference (see Fig. 5) as it is in the central zone of the conference domain.

VI. Paper Relevance Criterion. Node degree distribution

We propose the following criterion – an empirical heuristics for the paper relevance to the central topics of a conference: the more terms of a paper there are in the central part of the term interrelation network, the more relevant this paper is to the central subdomain (or the set of the main topics) of the conference. In other words, paper relevance is proportional to the number of its terms in the central zone of the term interrelation network (see fig. 5). Thus, the paper by Mehmet & Wijesekera turns out to be the most central one to the domain of the conference.

TABLE 2. TOP-20 NODES WITH THE LARGEST INGOING DEGREE

Ingoing degree	Node
5	social network analysis, probabilistic ontology development, military intelligence analysis, intelligence data integration, dynamic risk model, evidence based reasoning, domain event ontology, domain event model, cyber impact assessment, big data analytics
4	web ontology language, systems modeling language, support decision making, static risk model, social network environment, sketch data model, rdf data sources, multiple model types, large data sets, military decision making

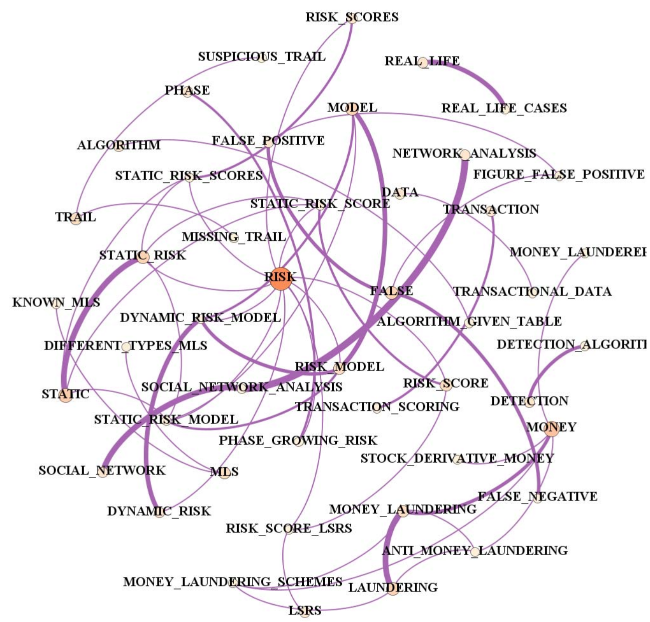

Figure 4. The Terms Hierarchy Network (20+20+20) for Mehmet & Wijesekera paper.

As we experimented with networks of different size we also deduced that node degree distribution (for outgoing links only) follows the power law ($p(k) = Ck^{\alpha}$).

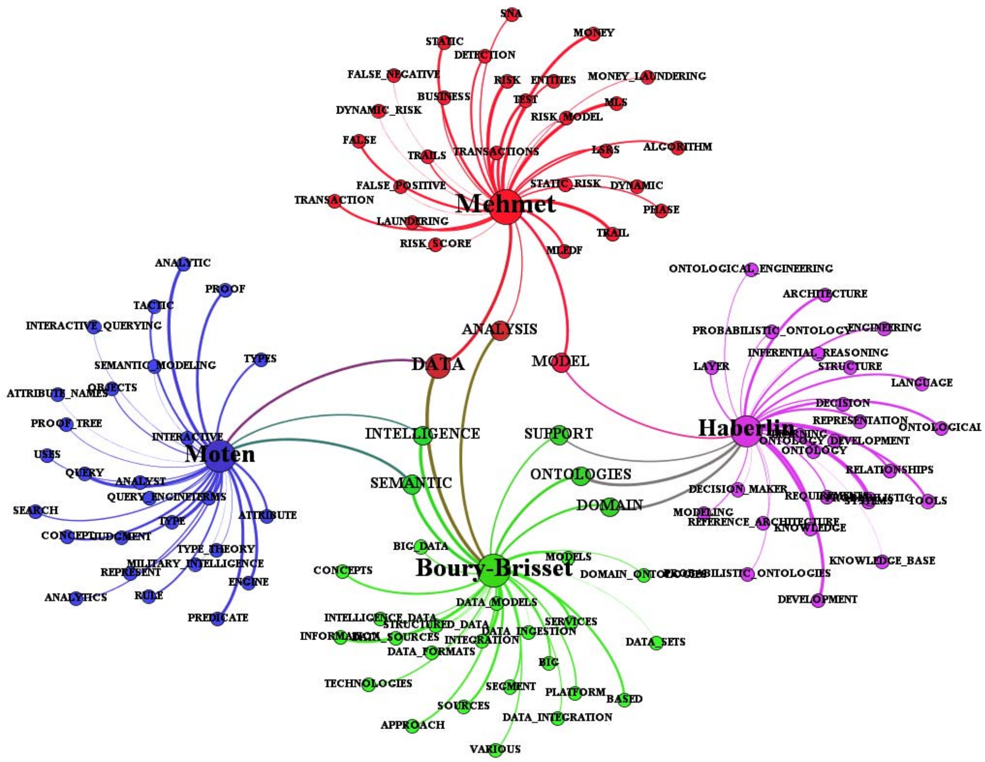

Figure 5. The Term Interrelation Network for the four papers.

It means that such networks are scale-free (see Fig. 4). The power coefficient α varies from 2.1 to 2.3 for networks of different size (e.g., from 20+20+20 to 500+500+500) that in general complies with the Language Networks structure [2].

Our assumptions regarding the informational importance of term combinations for the network construction were confirmed during the series of experiments with assessors. For each of the four papers a standard instruction was given: «Read the text. Think about its content. Write down 10-15 words which are most important for text understanding». For each of these papers more than 10 assessors were questioned [9]. To confirm that keywords and word combinations which we obtained as the nodes (terms) during the process of the network construction are really semantically important for our topics there was another experiment, when the assessors were invited to analyze the lists (such as given in Tables 1, 2, etc.) and detect the mains topics of the conference or the analyzed papers [20]. We asked them to read the keywords which we obtained during the process of the network construction and suggest the topics of the conference which these keywords can be associated with (more than 10 assessors were questioned).

The assessors gave different responses while detecting the conference subject due to the fact that for our purpose we used a heterogeneous corpus. The corpus consists of papers of absolutely different subjects: biology, social networks, risk analytics, human, money and so on. Such a structure of our corpus makes the research more interesting from the scientific point of view. The construction of an ontology for one specific domain is a problem which is widely considered nowadays; meanwhile the problem of an ontology construction for a variety of domains is studied little.

Here are the examples of the most informative responses (representing the sets of the conference topics):

1. Big data, data mining, ontologies, artificial intelligence
2. Decision making systems, social networks
3. Data mining, information extraction, ontologies learning
4. Artificial intelligence, decision systems, ontologies, social networks, big data
5. Computational linguistics, data security, ontologies
6. Social networks, data security, artificial intelligence
7. Data mining, social networks, ontologies

TABLE 3. THE KEYWORDS OF STIDS'2013 DETECTED BY THE ASSESSORS

Terms (bigrams & unigrams)
ontologies
social networks artificial intelligence, data mining, data security
big data, decision (making) systems computational linguistics, information extraction, learning (ontologies), reasoning

8. Reasoning, ontologies, data security, social networks, etc.

The intersection of the results of the assessors experiment and the list of topics from the conference site consists of more than 25% topics (keywords). The intersection of the top of terms with the largest CHVG weights (see Table 1) and topics from the conference site consists of more than 38% topics (keywords). The comparisons (the well-described and the others) confirm that keywords and word combinations which we obtained as the top nodes (terms) during the process of the network construction are really semantically important for our topics. Further experiments with other types of corpora and more detailed evaluation are going to be a part of our future work.

VII. Conclusion

Thereby the contributions of the paper are as follows:

- We propose a method of constructing the network of natural terms hierarchy – a lightweight domain-specific ontology – without complex linguistic procedures.
- We give examples of networks of natural terms hierarchy constructed for technical conference proceedings (it was deduced empirically that the minimal text size for a representative network of natural terms hierarchy is about 20 KB).
- During the computational experiments it is shown that the network of natural terms hierarchy is scale-free (while considering outgoing links).
- The empirical criterion of the paper relevance to a conference theme is proposed.
- The language network, constructed according to the proposed method, can be used as 1) a basis for the further ontology construction (e.g., for the semantic technologies domain), 2) a tool for database navigation and 3) a tool for organizing user prompts in the information retrieval systems.

Our future work directions include experiments with different languages, heterogeneous and homogeneous corpora of different size and domain to confirm the relevance criterion proposed in this paper. The first step of the future research includes the comparison of the results obtained on the STIDS proceedings corpora (different size corpora: 2013 and 2011-2014 years) for English (this paper) and on the “Corpora Conference” proceedings for Russian.

Acknowledgment

The authors acknowledge Saint-Petersburg State University for a research grant 30.38.305.2014.

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