NATURAL LANGUAGE PROCESSING METHODS FOR CONCEPT MAP MINING: THE CASE FOR ENGLISH, KAZAKH AND RUSSIAN TEXTS

Concept maps are used for knowledge visualization via representing an input text or domain at the conceptual level. Concept maps reflect the systemic relations between key concepts of a text/domain and thereby contribute to a deeper understanding of text/domain ideas, save time spent on reading and analysis. However, the process of concept maps construction is laborious and time consuming. Currently, there is a lot of research on the idea of automatic generation concept map from natural language texts. The problem has a high practical value, but in theoretical terms, methods for its solution are mainly language-dependent. Such methods require high-quality annotated linguistic resources, which is a serious problem for low-resource languages like Kazakh. In this work, we analyze the issues related to language-dependent approaches and present our experimental work on automatic generating concept maps from English, Kazakh and Russian texts. We use a well-known language-dependent method called ReVerb which was originally developed for English, and on the example of this method we explore the issues that we have encountered in the case of Kazakh and Russian languages.

Key words: concept maps, concept map mining, natural language processing, low-resource languages, R language.

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Концепт-карталарды өндіруге арналған табиғи тілді әдістері: әгъылып, қазақ және өрсөс мәтіндерінің ықтималдылығы
орыс тілдерінде мәтіндерден концепт-карталарды автоматты түрде қуру бойынша жасалған эксперименттік жұмыс ұсынылған. Қосымша белгілі бастанқыда ағылшын тілін үшін әзірленген тілге әсерді ReVerb әдісін колданамыз және осы әдістің мысалына оны қазақ және орыс тілдеріне аудару маселелерін қалайыз.

Түйін сөздер: концепт-карталар, концепт-картаны өндіру, табиғи тілді оқу, ресурстары шектеулемі тілдер, R тілі.

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Методы обработки естественного языка для извлечения концепт-карт: кейс для текстов на английском, казахском и русском языках

Концепт-карты используются для визуализации знаний посредством представления входного текста или предметной области на концептуальном уровне. Концепт-карты отражают системные отношения между ключевыми понятиями текста/предметной области и тем самым способствуют более глубокому пониманию идей предметной области, экономией времени, затрачиваемое на чтение и анализ. Однако сам процесс построения концептуальных карт трудоемок и требует много времени. В настоящее время проводятся много исследований, связанных с идеей автоматической генерации концепт-карт из текстов на естественном языке. Задача имеет высокую практическую ценность, но теоретически методы ее решения в основном являются языко-зависимыми. Такие методы требуют качественных лингвистических ресурсов с аннотациями, что представляет серьезную трудность для таких малоресурсных языков, как казахский. В этой работе мы анализируем проблемы, связанные с языко-зависимыми подходами, и представляем нашу экспериментальную работу по автоматической генерации концептуальных карт из текстов на английском, казахском и русском языках. Мы используем хорошо известный, языко-зависимый метод ReVerb, который изначально был разработан для английского языка, и на примере этого метода анализируем проблемы его переноса на казахский и русский язык.

Ключевые слова: концепт-карты, извлечение концепт-карт, обработка естественного языка, малоресурсные языки, язык R.

1 Introduction

As powerful knowledge visualization tools, concept maps allow representing a text and its domain at a conceptual level. They link the key concepts and ideas of a text into a single conceptual framework, which is a kind of guide to a given text and contributes to a deeper understanding of it. Well-built concept maps allow reducing the mental and physical stress on a human, saving time spent on reading and analyzing. The latter actualizes the problem of automatic generation and embedding of concept maps into digital reading services. The problem is at the junction of three disciplines at once – human-computer interaction, natural language processing and digital reading, and largely inherits the challenges of each of them. First, there are challenges posed by the high creative variability inherent in the concept mapping process. There is no single correct way of constructing concept maps, and therefore no unambiguous assessment criteria: this is a creative process, during which new ideas and new, previously non-verbalized relations are generated [2]. Second, there are the challenges posed by traditional natural language processing issues. Generating concept maps from natural language texts involves solving problems such as text preprocessing, open information
extraction, co-reference resolution, etc. [3]. Third, these are the challenges caused by the
novelty of the problem of digital reading [4].

Taken together, all these challenges determine the scientific complexity of the problem
of automatic generation of concept maps from natural language texts. They determine the
fact that, despite the enormous practical significance, in theoretical terms, this problem is
not fully resolved. In this article, we review 20 years of research in the field of automatic
concept map generation and analyze the issues related to language-dependent approaches
such as ReVerb [5]. We use a well-known language-dependent method called ReVerb which
was originally developed for English, and on the example of this method we explore the issues
that we have encountered in the case of Kazakh and Russian languages.

2 Related work

During the period from 2001 to 2020, about fifty works were published, directly related to
the topic of automatic construction of concept maps based on texts in natural language.
Table 1 presents 45 of the most famous publications, of which 24 are conference reports,
20 are journal articles, and 1 is a doctoral dissertation. Previously, these publications were
compared with publications included in the review of related works given in [44]. The authors
of this thorough and in-depth review covered the period from 2001 to 2016 and highlighted 30
relevant publications; this table supplements their overview with uncovered years and works.
Most of the publications listed in the table use methods of morphological and syntactic
analysis to identify concepts and relations contained in the text [6, 7], [11, 12], [18], [20],
[22], [25–27], [29,30], [36], [38], [40–42]. Typically, these are techniques such as POS tagging,
syntax tree building, and morpho-syntactic patterns extraction. These methods are often
supplemented by co-reference resolution, synonym extraction, and named entity recognition
[6,18,26,27,30,36,40]. Several publications use the search for association rules to extract
relations [9,28,39,50].

The extracted concepts and relations are often grouped into larger categories and/or
ranked in order of importance. For grouping, as a rule, clustering methods are used [6,16,30,
32], and for ranking – statistical methods such as TF-IDF [32,36,42,48,49], LSA [6,17,32],
PCA [16], HARD [39], VF-ICF [30], two articles use a method for measuring bursts in text
streams [42,49].

Ultimately, the most significant concepts and the relations connecting them are combined
into a single map, which from the mathematical point of view is a graph [39,49]. In most
publications, this stage is not described or described superficially, with the exception of [49],
in which the construction of the graph is considered as NP-complete optimization problem
with constraints imposed on the size and connectivity of the graph, and with an objective
function that maximizes the total significance of vertices and edges included in the graph. It
should be noted that [49] is notable not only for the detailed consideration of the final stage
of assembling a concept map from previously extracted fragments (by constructing a graph).
The author of this work also painstakingly considers all stages of generating concept maps,
and combines them into a single logical scheme, consisting of five subtasks of the first level
and eight subtasks of the second level (Figure 1). Through its comprehensive decomposition,
the scheme provides a universal basis for comparing different approaches.
Table 1: List of related research for the period of 2001-2020

| Year | Publication title, reference |
|------|------------------------------|
| 2001 | Automatic reading and learning from text [6] |
| 2002 | Knowledge discovery from texts: a concept frame graph approach [7] |
| 2003 | Concept maps as visual interfaces to digital libraries: summarization, collaboration, and automatic generation [8] |
| 2004 | A new approach for constructing the concept map [9] |
| 2005 | Using concept maps in digital libraries as a cross-language resource discovery tool [10] |
| 2006 | Jump-starting concept map construction with knowledge extracted from documents |
|      | Concept mining for indexing medical literature [12] |
| 2007 | A new approach for constructing the concept map [13] |
| 2008 | Automatically constructing concept maps based on fuzzy rules for adapting learning systems [14] |
|      | Building domain ontologies from text for educational purposes [15] |
|      | Mining e-Learning domain concept map from academic articles [16] |
|      | Concept map mining: A definition and a framework for its evaluation [17] |
|      | Mining knowledge from natural language texts using fuzzy associated concept mapping [18] |
| 2009 | Concept extraction from student essays, towards concept map mining [19] |
|      | Toward a fuzzy domain ontology extraction method for adaptive e-learning [20] |
|      | A concept map extractor tool for teaching and learning [21] |
| 2010 | Concept Maps core elements candidates recogniton from text [22] |
|      | Mining concept maps from news stories for measuring civic scientific literacy in media [23] |
|      | Analysis of a Gold Standard for Concept Map Mining – How Humans Summarize Text Using Concept Maps [24] |
| 2011 | Generating concept map exercises from textbooks [25] |
| 2012 | The automatic creation of concept maps from documents written using morphologically rich languages [26] |
|      | English2mindmap: An automated system for mindmap generation from English text [27] |
| 2013 | Constructing concept maps for adaptive learning systems based on data mining techniques [28] |
|      | Document analysis based automatic concept map generation for enterprises [29] |
|      | Concept map construction from text documents using affinity propagation [30] |
| Year | Publication title, reference |
|------|-----------------------------|
| 2014 | A practical approach for automatically constructing concept map in e-learning environments [31] |
|      | Automatic concept maps generation in support of educational processes [32] |
|      | Burst analysis of text document for automatic concept map creation [33] |
|      | Evaluation of concept importance in concept maps mined from lecture notes [34] |
| 2015 | Burst analysis for automatic concept map creation with a single document [35] |
|      | Implementation of method for generating concept map from unstructured text in the Croatian language [36] |
|      | An automatic construction of concept maps based on statistical Text Mining [37] |
|      | Exploiting concept map mining process for e-content development [38] |
| 2016 | Using prerequisites to extract concept maps from textbooks [39] |
|      | Automatic construction of concept maps from texts [40] |
| 2017 | Bringing structure into summaries: crowdsourcing a benchmark corpus of concept maps [41] |
|      | Utilizing automatic predicate-argument analysis for concept map mining [42] |
| 2018 | Research on a new automatic generation algorithm of concept map based on text clustering and association rules mining [43] |
|      | Towards technological approaches for concept maps mining from text [44] |
| 2019 | Improving an AI-based algorithm to automatically generate concept maps [45] |
|      | Concept map mining approach based on the mental models retrieval [46] |
|      | Fuzzy concept map generation from academic data sources [47] |
|      | Using a recommender system to suggest educational resources and drawing a semi-automated concept map to enhance the learning progress [48] |
|      | Automatic structured text summarization with concept maps [49] |
| 2020 | Research on a new automatic generation algorithm of concept map based on text analysis and association rules mining [50] |

Figure 1: General scheme for solving the problem of automatic generation of concept maps from texts in natural language [49] (task numbering is ours)
3 Material and methods

3.1 ReVerb relation extraction method

Over the past two decades, the solution to the problem of automatic generation of concept maps from natural language texts has been largely based on the methods of parsing. Since these methods are language-dependent, the degree of their elaboration directly depends on the status and resource availability of the language used. Most of the cited publications use language-dependent methods designed for English language [39,48]. In other words, there is a clear imbalance not only between language-dependent and language-independent methods of generating concept maps (not in favor of the latter), but also between high-resource and low-resource languages (also not in favor of the latter).

ReVerb which we use in this work, is exactly the kind of such language-dependent methods. It takes as input a POS-tagged sentence and returns a set of \((x, r, y)\) extraction triples [5]. The method first identifies relation phrases that satisfy syntactic and lexical constraints, and then finds a pair of entities (noun phrases) for each relation phrase. The method retrieves only sequences of tokens expressing a verb relation located between two entities, for example: “We trust in \textbf{God}”. The method does not provide relations that are located differently in the text, for example: "In \textbf{God} we trust". Given an input sentence \(s\), ReVerb follows the next algorithm:

- **Step 1.** For each verb \(v\) in the sentence \(s\), find the longest sequence of words \(r_v\) such that
  - \(r_v\) starts at the verb \(v\),
  - \(r_v\) satisfies the syntactic constraint,
  - \(r_v\) satisfies the lexical constraint.
  - \(r_v\) satisfies the lexical constraint. If any pair of verbal sequences \(r_{v1}\) and \(r_{v2}\) are adjacent or overlap in the sentence \(s\), they are merged into a single sequence. Therefore, the relation phrase must be a contiguous span of words in the sentence.

- **Step 2.** For each relation phrase \(r\) identified in Step 1,
  - find the nearest noun phrase \(x\) to the left of \(r\) in a sentence \(s\) such that \(x\) is not a relative pronoun,
  - find the nearest noun phrase \(y\) to the right of \(r\) in a sentence \(s\). If such an \((x, y)\) pair could be found, return \((x, r, y)\) as an extraction.

The syntactic constraint requires for English relation phrases to match POS-tag patterns such as V (a verb, e.g., \textit{write}), VP (a verb followed by a preposition, e.g., \textit{written by}), VN?P (a verb followed by a noun and ended with a preposition, e.g., \textit{is a part of}), and so forth. The lexical constraint separates valid relation phrases from over-specified ones using an external relation database.
3.2 Experimental work

We realize ReVerb method with the help of R language and UDPipe text processing models. UDPipe is a pipeline which is based on Universal Dependencies 2.4 Models and provides pre-trained language models for various languages [51]. Experiments on English texts have been carried out using the joint model “english-ewt-ud-2.4-190531”. Tokenizer, POS tagger, lemmatizer and parser models have been applied to input texts (see Figure 2). The output was a preprocessed corpus (see Figure 3). Then POS-tagging patterns have been applied to corpus tokens in order to extract relations (verb phrases) and entities (noun phrases). For example, the pattern <VB>?<IN> has been applied to extract relations like “flows” or “flows into”, and the pattern <DT>?<PRP>?<JJ>*<NN> has been applied to extract entities like “The Baltic Sea”. Matched relations and entities phrases have been sorted in the order they appeared in the sentences, and if they formed a sequence “noun phrase – verb phrase – noun phrase” they have been extracted as a triplet. Finally, a concept map has been constructed from found triplets (see Figure 4).

Experiments on Russian texts have been carried out using the joint model “russian-gsd-ud-2.4-190531” from Universal Dependencies 2.4 Models. Tokenizer, POS tagger, lemmatizer and parser models have been applied to input texts (see Figure 5). The output was a preprocessed corpus (see Figures 6-7). The POS-tag patterns, as is the case with English, have been applied to tokens, and a concept map has been constructed from found triplets (see Figure 8). Despite the fact that there are some parsing errors in the corpus, these errors generally do not affect
the result of extracting relations and entities. Logical errors of the ReVerb algorithm are more serious. In particular, from the sentence "Иртыш несет свои воды в Северный Ледовитый океан" ("Irtysh carries its water to the Arctic Ocean") three entities, viz. “Иртыш” ("Irtysh"), “свои воды” ("its water") and “Северный Ледовитый океан” ("the Arctic Ocean"), and one relation “несет” ("carries") are extracted, so the resulting triplet is constructed as “Иртыш – несет – свои воды” ("Irtysh – carries – its water"). However, the correct version should be “Иртыш – несет свои воды в – Северный Ледовитый океан” ("Irtysh – carries its water to – the Arctic Ocean").

Experiments on Kazakh texts have been carried out using the joint model “kazakh-ud-2.0-170801” from Universal Dependencies 2.0 Models (there is no models for Kazakh language in the Universal Dependencies 2.4 Treebank). Tokenizer, POS tagger, lemmatizer and parser models have been applied to input texts (see Figure 9). The output was a preprocessed corpus, and as it shown in Figure 10, there are a number of serious POS tagging errors which leads to a very low performance in triple extraction (see Figure 11). At the same time, manually correcting POS tags results in a more believable concept map (see Figure 12).
4 Conclusion

In this paper, we considered an algorithm for extracting triplets of the "entity - relation - entity" type from texts in English, Kazakh and Russian. The algorithm is based on the use of syntax patterns and depends on the availability of annotated linguistic resources. It demonstrates acceptable results for Russian and English. However, experiments carried out for Kazakh texts have shown that the algorithm demonstrates very low quality in the
absence of such linguistic resources. In our future work, we plan to explore alternative ways of constructing concept maps for low-resource languages such as Kazakh.

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Figure 12: A version of a concept map based on manual preprocessing of Kazakh texts

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