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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 өңдеу әдістері: ағылшын, қазақ және орыс мәтіндерінің мысалында

Концепт-карталар концептуалды деңгейде кіріс мәтінін немесе пәндік аймақты ұсыну арқылы білімді визуализациялау үшін қолданылады. Концепт-карталар мәтіннің/пәндік аймақтың негізгі ұғымдары арасындағы жүйелік қатынасты көрсетеді және сол арқылы оқу мен талдауға кететін уақытты үнемдей отырып, пәндік аймақтың идеяларын тереңірек түсінуге ықпал етеді. Алайда, концепт-карталарды құру процесі еңбек пен және уақытты көп қажет етеді. Қазіргі уақытта табиғи тілдегі мәтіндерден концепт-карталарды автоматты түрде құру идеясына байланысты көптеген зерттеулер жүргізілуде. Мәселе жоғары практикалық құндылыққа ие, бірақ теориялық тұрғыдан оны шешу әдістері негізінен тілге тәуелді. Мұндай әдістер аннотациялары бар сапалы лингвистикалық ресурстарды талап етеді, бұл қазақ тілі сияқты ресурстары шектеулі тілдер үшін елеулі қиындық туғызады. Бұл жұмыста тілге тәуелді тәсілдерге байланысты проблемаларға талдау жасалған және ағылшын, қазақ,

орыс тілдеріндегі мәтіндерден концепт-карталарды автоматты түрде құру бойынша жасалған эксперименттік жұмыс ұсынылған. Көпшілікке белгілі бастапқыда ағылшын тілі үшін әзірленген тілге тәуелді ReVerb әдісін қолданамыз және осы әдістің мысалында оны қазақ және орыс тілдеріне аудару мәселелерін талдаймыз.
Түйін сөздер: концепт-карталар, концепт-картаны өндіру, табиғи тілді өңдеу, ресурстары шектеулі 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, экономя время, затрачиваемое на чтение и анализ. Однако сам процесс построения концептуальных карт трудоемок и требует много времени. В настоящее время проводится 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 it 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 condidates recongnition 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]

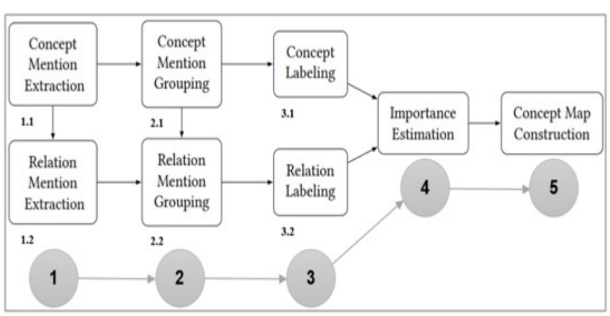


Figure 1: General scheme for solving the problem of automatic generation of concept maps from texts in natural language [49] (task numbering is ours)

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).

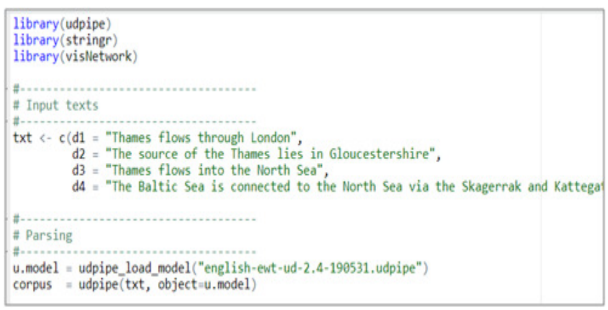
ReVerb which we use in this work, is exactly the kind of such language-dependent methods. It takes as input a POS-tagged sentence and returns a set of *(x,r,y)* extraction triples [5]. The method first identifies relation phrases that satisfy syntactic and lexical constraints, and then finds a pair of 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 God". The method does not provide relations that are located differently in the text, for example: "In 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., *write*), VP (a verb followed by a preposition, e.g., *written by*), VN?P (a verb followed by a noun and ended with a preposition, e.g., *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 it 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).

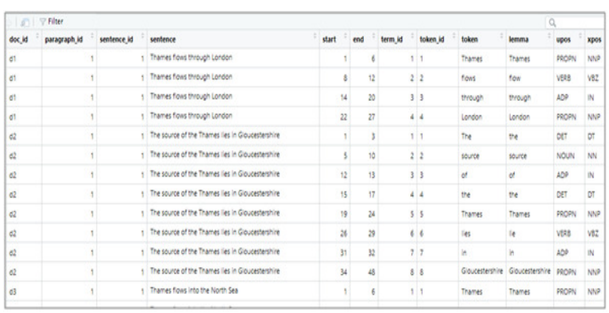


```
library(udpipe)
library(stringr)
library(visNetwork)

#------------------------------------
# Input texts
#------------------------------------
txt <- c(d1 = "Thames flows through London",
         d2 = "The source of the Thames lies in Gloucestershire",
         d3 = "Thames flows into the North Sea",
         d4 = "The Baltic Sea is connected to the North Sea via the Skagerrak and Kattegat

#------------------------------------
# Parsing
#------------------------------------
u.model = udpipe_load_model("english-ewt-ud-2.4-190531.udpipe")
corpus  = udpipe(txt, object=u.model)
```

Figure 2: Applying UDPipe to English texts



doc_id	paragraph_id	sentence_id	sentence	start	end	term_id	token_id	token	lemma	upos	xpos
d1	1	1	Thames flows through London	1	6	1	1	Thames	Thames	PROPN	NNP
d1	1	1	Thames flows through London	8	12	2	2	flows	flow	VERB	VBZ
d1	1	1	Thames flows through London	14	20	3	3	through	through	ADP	IN
d1	1	1	Thames flows through London	22	27	4	4	London	London	PROPN	NNP
d2	1	1	The source of the Thames lies in Gloucestershire	1	3	1	1	The	the	DET	DT
d2	1	1	The source of the Thames lies in Gloucestershire	5	10	2	2	source	source	NOUN	NN
d2	1	1	The source of the Thames lies in Gloucestershire	12	13	3	3	of	of	ADP	IN
d2	1	1	The source of the Thames lies in Gloucestershire	15	17	4	4	the	the	DET	DT
d2	1	1	The source of the Thames lies in Gloucestershire	19	24	5	5	Thames	Thames	PROPN	NNP
d2	1	1	The source of the Thames lies in Gloucestershire	26	29	6	6	lies	lie	VERB	VBZ
d2	1	1	The source of the Thames lies in Gloucestershire	31	32	7	7	in	in	ADP	IN
d2	1	1	The source of the Thames lies in Gloucestershire	34	48	8	8	Gloucestershire	Gloucestershire	PROPN	NNP
d3	1	1	Thames flows into the North Sea	1	6	1	1	Thames	Thames	PROPN	NNP

Figure 3: The output of UDPipe for English texts

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

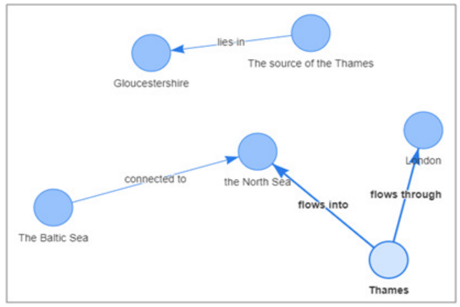
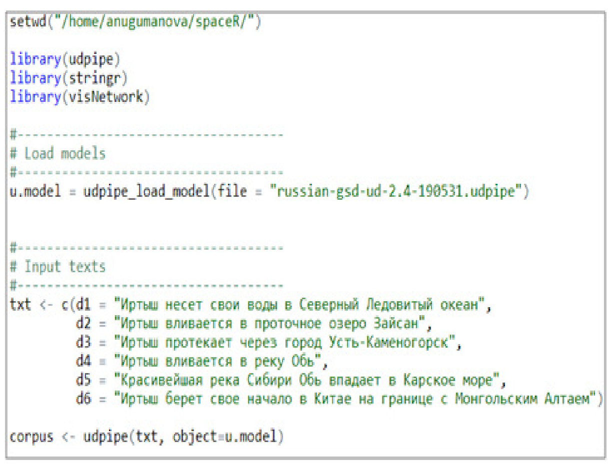


Figure 4: The final concept map based on English texts

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").



```
setwd("/home/anugumanova/spaceR/")

library(udpipe)
library(stringr)
library(visNetwork)

#-----------------------------------
# Load models
#-----------------------------------
u.model = udpipe_load_model(file = "russian-gsd-ud-2.4-190531.udpipe")


#-----------------------------------
# Input texts
#-----------------------------------
txt <- c(d1 = "Иртыш несет свои воды в Северный Ледовитый океан",
         d2 = "Иртыш вливается в проточное озеро Зайсан",
         d3 = "Иртыш протекает через город Усть-Каменогорск",
         d4 = "Иртыш вливается в реку Обь",
         d5 = "Красивейшая река Сибири Обь впадает в Карское море",
         d6 = "Иртыш берет свое начало в Китае на границе с Монгольским Алтаем")

corpus <- udpipe(txt, object=u.model)
```

Figure 5: Applying UDPipe to Russian texts

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).

token	lemma	upos	xpos	feats
Иртыш	Иртыш	PROPN	NNP	Animacy=Anim|Case=Nom|Gender=Masc|Numbe
несет	несть	VERB	VBC	Aspect=Imp|Mood=Ind|Number=Sing|Person=3|T
свои	свой	DET	PRP$	Animacy=Inan|Case=Acc|Number=Plur
воды	вода	NOUN	NN	Animacy=Inan|Case=Acc|Gender=Fem|Number=F
в	в	ADP	IN	NA
Северный	северный	ADJ	JJL	Animacy=Inan|Case=Acc|Degree=Pos|Gender=Ma
Ледовитый	Ледовитый	ADJ	JJL	Animacy=Inan|Case=Acc|Degree=Pos|Gender=Ma
океан	океан	NOUN	NN	Animacy=Inan|Case=Acc|Gender=Masc|Number=
Иртыш	Иртыш	PROPN	NNP	Animacy=Anim|Case=Nom|Gender=Masc|Numbe
вливается	вливаться	VERB	VBC	Aspect=Imp|Mood=Ind|Number=Sing|Person=3|T
в	в	ADP	IN	NA
проточное	проточный	ADJ	JJL	Case=Acc|Degree=Pos|Gender=Neut|Number=Si
озеро	озеро	NOUN	NN	Animacy=Inan|Case=Acc|Gender=Neut|Number=
Зайсан	Зайсан	NOUN	NN	Animacy=Inan|Case=Nom|Gender=Masc|Number

Figure 6: The output of UDPipe for Russian texts

	token	type
1	Иртыш	noun_phrase
4	свои воды	noun_phrase
8	Северный Ледовитый океан	noun_phrase

Figure 7: Entities (noun phrases) extracted from the sentence "Иртыш несет свои воды в Северный Ледовитый океан"

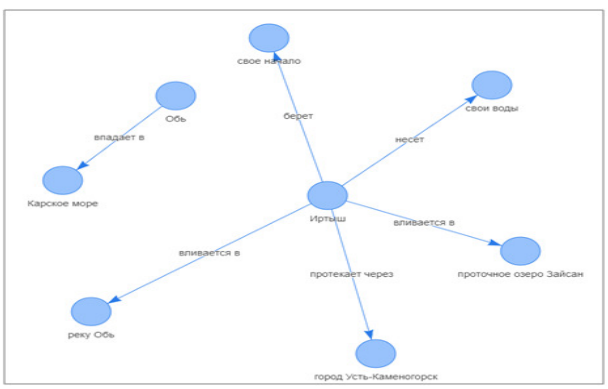


Figure 8: The final concept map based on Russian texts

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

```
#------------------------------------
# Load models
#------------------------------------
u.model = udpipe_download_model(language="kazakh",
                                udpipe_model_repo='jwijffels/udpipe.models.ud.2.0')


#------------------------------------
# Input texts
#------------------------------------
txt <- c(d1 = "Ертіс Обь өзеніне құяды",
         d2 = "Қара Ертіс өзені Қытайдан басталады",
         d3 = "Ертіс өзені Өскемен арқылы өтеді",
         d4 = "Әдемі Павлодар қаласы Ертіс өзенінің жанында орналасқан")

corpus <- udpipe(txt, object=u.model)
corpus[corpus$token=="Ертіс", "upos"] = "PROPN"
corpus[corpus$token=="өзені", "upos"] = "NOUN"
```

Figure 9: Applying UDPipe to Kazakh texts

token	lemma	upos
Ертіс	Ертіс	NUM
Обь	Обь	NOUN
өзеніне	өзеніне	PRON
құяды	құя	VERB
Қара	Қара	NOUN
Ертіс	ертіс	NUM
өзені	өзені	ADJ
Қытайдан	Қытайдан	NOUN

Figure 10: The output of UDPipe for Kazakh texts

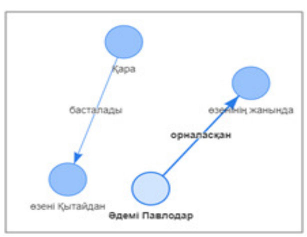


Figure 11: The output of UDPipe for Kazakh texts. An incorrect version of a concept map based on wrong preprocessing of Kazakh texts

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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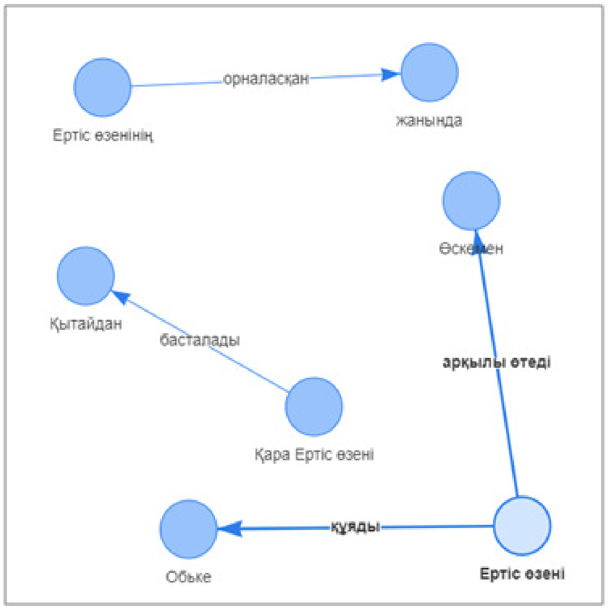

Figure 12: A version of a concept map based on manual preprocessing of Kazakh texts

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