MULTIPLE FEATURES FOR MULTIWORD EXTRACTION: A LEARNING-TO-RANK APPROACH

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This paper describes the extraction of multiword expressions (MWEs) from corpora for inclusion in a large online lexical resource for Russian. The novelty of the proposed approach is twofold: 1) we use two corpora—the Russian National Corpus and Russian Wikipedia—in parallel and 2) employ an extended set of features based on both data sources. To combine syntactic and statistical features derived from two corpora, we experiment with several learning-to-rank (LETOR) methods that have been proven to be highly effective in information retrieval (IR) scenarios. We make use of bigrams from existing dictionaries for learning, which leads to very sparing manual annotation efforts. Evaluation shows that machine-learned rankings with rich features significantly outperform traditional corpus-based association measures and their combinations. Analysis of resulting lists supports the claim that multiple features and diverse data sources improve the quality of extracted MWEs. The proposed method is language-independent.

Key words: multiword expressions (MWEs), collocations, lexical acquisition, learning-to-rank methods (LETOR), thesaurus, Russian language

ИЗВЛЕЧЕНИЕ МНОГОСЛОВНЫХ ВЫРАЖЕНИЙ НА ОСНОВЕ МНОЖЕСТВЕННЫХ ПРИЗНАКОВ И МЕТОДОВ МАШИННОГО ОБУЧЕНИЯ РАНЖИРОВАНИЮ

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1. Introduction

Multiword expressions (MWEs) are heavily underrepresented in existing Russian lexical resources. We encountered the problem of MWE extraction within a project aimed at creating a new wordnet for Russian. The study described in the paper deals with nominal bigrams—the most common MWE type. Since the pioneering work by Church and Hanks (1989) the problem of MWE extraction has been studied in depth, and various statistical association measures (AMs) have been proposed. Despite the task seems to be solved, larger datasets and advanced statistical methods available nowadays offer opportunities for a more efficient solution.

The proposed approach includes three components: 1) we use two different corpora—the Russian National Corpus (364M tokens) and Russian Wikipedia (1.2M articles, 318M tokens)—in parallel; 2) MWE candidates are described with a rich set of features (various corpus-based statistics, link-based Wikipedia features, phrase structure, Web statistics, etc.); 3) we formulate the MWE ranking task in terms of multiple 'queries' and 'documents' and apply learning-to-rank (LETOR) algorithms that showed good results in information retrieval (IR) scenario. Our approach deals with different kinds of MWEs—collocations, idioms, set phrases, etc. (see classification in Baldwin and Kim (2010))—in a uniform way. We took several thousands of nominal bigrams from existing Russian dictionaries and manually labeled them as positive and negative examples. This routine allowed us to minimize manual labeling efforts and is more advantageous than such alternatives as labeling output of an automatic method, which can potentially introduce bias towards presented results, or asking an expert to produce a list of good and bad examples from scratch, which is very labor-intensive. Using limited training data, we were able to rank the whole set of candidate MWEs extracted from both

corpora and cut them off at desired level (our estimate of the target number of MWEs for the wordnet under development is around 40K). Evaluation showed that proposed approach outperformed existing AMs, as well as classification-based methods. Manual probes proved that high-ranked MWEs are good enough to be included in the resource with minimal manual intervention. The method is language-independent—it relies only on the availability of a large corpus, Wikipedia, and a part-of-speech (POS) tagger. Furthermore, the method is highly flexible and can be applied to other MWE types.

2.   Related Work

There is a large body of literature on extraction of multiwords, collocations, and keyphrases; Hasan (2014) and Ramisch (2015) provide an extensive overview of the field. Three groups of approaches related to our work can be distinguished: (i) methods based on purely statistical AMs; (ii) machine-learned classification; (iii) Wikipedia-based approaches to terminology extraction.

Traditional approaches rank a list of MWEs according to their co-occurrence frequencies or statistical AMs (Evert and Krenn, 2005; Pecina and Schlesinger, 2006). Krenn and Evert (2001) evaluated Mutual Information (MI), Dice coefficient, Student's t-score and log-likelihood ratio for adjective-noun pairs. Pecina and Schlesinger (2006) evaluated 82 measures on a Czech corpus. Some studies suggested different strategies for handling low-frequency and high-frequency items (Evert and Krenn, 2001; Evert and Krenn, 2005; Bouma, 2009). Wermter and Hahn (2006) showed that the most advanced AMs perform similarly to raw frequency.

State-of-the-art studies consider the MWE extraction task as a classification problem (Pecina and Schlesinger, 2006; Fothergill and Baldwin, 2011; Karan et al., 2012; Ramisch, 2015). Pecina and Schlesinger (2006), Ramisch et al. (2010) and Karan et al. (2012) employed support vector machines (SVM) with frequency counts, traditional AMs, and POS patterns as features. These supervised approaches are different from ours in that Karan et al. (2012) and Ramisch (2015) created a training set consisting of positive and negative MWE examples, while Fazly and Stevenson (2007) and Fothergill and Baldwin (2011) assigned MWE categories. Feature-rich ranking of keyphrases extracted from a document is close to our approach (Jiang et al., 2009). However, extracting keyphrases from a document exploits quite a different set of document-level features such as position of the first occurrence, document field (e.g. title, section heading, anchor text), and text highlighting (e.g. boldface). Document-level keyphrase extraction task differs from our setting in that the same word sequence occurring in different documents can be a good keyphrase in one case, but not suitable in other cases.

Many studies explored Wikipedia as an external knowledge resource for terminology extraction (Hartmann et al., 2012; Vivaldi et. al., 2012) and keyphrase extraction (Medelyan et al., 2009). Medelyan et al. (2009) used a machine learning approach with Wikipedia-based semantic features to determine whether the document can be annotated with a given keyphrase. Hartmann (2012) considered n-grams that appeared in Wikipedia titles and anchor text as candidates for subsequent ranking by AMs. (Vivaldi et al., 2012) used Wikipedia categories to validate term candidates extracted from scientific texts.

Due to limited space we do not survey a large body of literature on learning to rank and feature selection for IR; Liu (2009) gives a nice overview of approaches and methods. In our work we follow the feature selection approach proposed by Geng et al. (2007) that combines two scores: importance of individual features and similarity between features.

3. Data

In our study, we use two corpora—Russian National Corpus[1] (RNC) and Russian Wikipedia[2]. RNC has genre subdivisions—scientific texts, classical literature, legal and official documents, religious texts, children's literature, nonfiction, news, etc.—that we use for feature calculation. We treat Wikipedia both as a "plain text corpus" to calculate MWE statistics and as semi-structured data: we make use of Wikipedia links, redirects, categories, and page titles. Lemmatization and POS-tagging is performed with *mystem* library[3].

We consider all bigrams conforming to one of six morpho-syntactic patterns—*Adjective + Noun, Noun + Adjective, Participle + Noun, Noun + Participle, Noun + Noun (genitive)*, and *Noun + Noun (instrumental)*—as candidate MWEs. Moreover, a candidate MWE must occur at least ten times in the RNC or to be a Wikipedia title.

We also collected nominal bigram entries from three dictionaries: Wiktionary[4] (3,155), Small Academic Dictionary (2,955), and Ushakov's Dictionary (2,506), which resulted in 7,751 unique bigrams in total. Manual inspection revealed that the list contained many archaisms (e.g. *книга живота*—*book of life*, *духовное брашно*—*spiritual repast*), narrowly used metaphorical expressions (e.g., *деревянный макинтош*—*coffin* (literally—*wooden mackintosh*), *белый друг*—*toilet bowl* (*white friend*)), joking expressions (e.g., *губозакаточная машинка*—*lip-rolling machine*), as well as named entities (e.g. *Амурская область*—*Amur Region*). The list underwent manual labeling by two lexicographers. Lexicographers labeled MWEs as positive (suitable for a general-purpose thesaurus) and negative (otherwise). Manual labeling resulted in an approximately equal number of positive and negative examples. Table 1 summarizes the data used in the study.

Most advanced LETOR algorithms (so-called pair-wise and list-wise methods, see (Liu, 2009)) optimize ranking in the context of individual queries and respective result lists in contrast to earlier point-wise approaches that model relevance as global regression or classification task. In order to apply modern LETOR algorithms to the MWE extraction task, we represent the data as a set of "queries" and "documents". Our hypothesis is that 'divide and conquer' approach helps deal with MWEs of different types and frequency ranges in a unified way in the learning phase. For "queries", we took 5,871 unique words from labeled examples to create individual lists of MWE candidates ("documents") containing the "query" (see Table 2). 56.5% of all

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[1]   http://ruscorpora.ru/en

[2]   http://ru.wikipedia.org

[3]   https://tech.yandex.ru/mystem

[4]   http://ru.wiktionary.org

candidates were included at least in one list. We randomly sampled 80% of the 'queries' for training and held out 20% for testing.

Table 1. Candidate MWEs and labeled data
(overlapping bigrams have at least one common word)

# of positive examples	3,981
# of negative examples	3,770
# of unique words in labeled examples	5,871
# of positive examples in the test set	1,322
# of candidate MWEs from the RNC	190,416
# of candidate MWEs from Wikipedia	157,748
# of unique candidate MWEs from both corpora	329,866
# of candidate MWEs overlapping with labeled set (RNC)	82,456
# of candidate MWEs overlapping with labeled set (Wiki)	117,837
# of unique candidate MWEs overlapping with labeled set	188,441

Table 2. 'Queries' (single words from labeled bigrams) and 'documents'
(overlapping candidate MWEs); positive examples are underlined

word ('query')	overlapping bigrams ('documents')
неправильный	неправильная установка (wrong installation), неправильная постановка (wrong statement), неправильная музыка (wrong music), неправильная галактика (wrong galaxy), неправильная переменная (wrong variable), <u>неправильная дробь</u> (improper fraction)
струна	слабая струна (weak string), натянутая струна (tense string), гетеротическая струна (heterotic string), бозонная струна (bosonic string), квантовая струна (quantum string), золотая струна (gold string), космическая струна (cosmic string), <u>спинная струна</u> (notochord)
корова	белая корова (white cow), старая корова (old cow), черная корова (black cow), синяя корова (blue cow), священная корова (sacred cow), <u>дойная корова</u> (milk cow), <u>морская корова</u> (sea cow)
вещество	специальное вещество (special substance), обычное вещество (usual substance), рабочее вещество (working substance), солнечное вещество (solar substance), сухое вещество (solid), белое вещество (white substance), мягкое вещество (soft substance), полярное вещество (polar substance), компактное вещество (compact substance), радиоактивное вещество (radioactive material), живое вещество (live substance), лекарственное вещество (medicinal substance), действующее вещество (active ingredient), <u>вредное вещество</u> (harmful substance), <u>серое вещество</u> (gray substance), <u>простое вещество</u> (simple substance), <u>органическое вещество</u> (organic), <u>химическое вещество</u> (chemical agent)

4. Methods

To apply a ranking algorithm to the data we have to present each MWE candidate as a feature vector. Note that, in the IR scenario a vector represents a query-document pair, i.e. there are features depending on the query, document, or both. In our case, all features describe an individual MWE independently from the "query", which allows us to apply the obtained ranking function later to the global set of candidates (hundreds of thousands items). The feature set used in the study (42 features in total) is described below.

RNC features (14): RNC global frequency, ten frequencies in genre subcorpora (reflects specificity of the MWE), first and second words' frequencies, the presence of the candidate in the corpus.

Wikipedia-based features (20) included: Wikipedia frequency, the presence of a redirect with the given MWE, match with a Wikipedia title, the number of in- and out-links, the number of categories assigned to the page, the presence of an infobox, 11 binary features corresponding to the infobox type[5], and capitalization (the latter three features aimed at capturing named entities).

Structural features (7) included six binary features corresponding to the above mentioned extraction patterns plus bigram length in characters (indirectly reflects the bigram specificity).

Web document frequency (1) refers to the number of documents returned to MWE as a phrase query by a search engine (SE) through an API[6].

We used three algorithms implemented in the RankLib library[7] to obtain MWE rankings: MART (Friedman, 2001), RankBoost (Freund et al., 2003), and LambdaMART (Wu et al., 2007) with default parameters. To improve efficiency of the training, we applied a feature selection (Geng et al., 2007). We held out 20% of the training set as validation set to optimize the number of features. First, according to the method, we computed importance of each feature using *mean reciprocal rank* (MRR). We measured similarity between features with Kendall's τ for pairs of corresponding rankings. Second, we maximized the sum of the importance scores of individual features and minimized the total similarity score between the features using a greedy search algorithm. Finally, five groups of features with the best results on the validation set were used to evaluate LETOR models on the test set.

5. Evaluation

We evaluated multiple intermediate rankings with artificial queries using two measures: 1) *mean reciprocal rank* (MRR) and 2) *bpref*, an evaluation measure suited for incomplete judgments (Buckley and Voorhees, 2004). MRR is an average

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[5]   http://en.wikipedia.org/wiki/Wikipedia:List_of_infoboxes

[6]   https://xml.yandex.ru/

[7]   http://sourceforge.net/p/lemur/wiki/RankLib

of inverse ranks of the first positive example in each 'query'; while *bpref* accounts for inversions—cases, when 'relevant' items are ranked lower than 'non-relevant' ones. Both measures were averaged over 1,449 lists in the test set.

We compared our approach to state-of-the-art collocation extraction methods based mainly on frequency (Pecina and Schlesinger, 2006; Ramisch et al., 2010; Karan et al., 2012). In particular, we implemented the best-performing method for keyphrase extraction (Jiang et al., 2009) based on SVM-rank[8] algorithm and following features: POS patterns, MWE frequency, and 20 AMs calculated using UCS toolkit[9] on (i) RNC, (ii) Wikipedia, (iii) both corpora. We also implemented AMs (t-score, log-likelihood, and MI) as baselines. Evaluation results are presented in Table 3.

Table 3. MRR and *bpref* measures computed on the test set

Ranking method	MRR	*bpref*
MI	0.440	0.353
t-score	0.615	0.321
log-likelihood	0.620	0.353
Wikipedia frequency	0.625	0.467
RNC frequency	0.624	0.328
SVM-rank (RNC)	0.644	0.550
SVM-rank (Wikipedia)	0.609	0.492
SVM-rank (RNC+Wikipedia)	0.635	0.483
MART	0.639	0.545
MART + feature selection	0.639	0.480
LambdaMART	0.679	0.742
LambdaMART + feature selection	0.684	0.546
RankBoost	0.739	0.742
RankBoost + feature selection	**0.758**	**0.825**

As the results show, LambdaMART and RankBoost scored best compared to MART, SVM-Rank and AMs. SVM-rank and MART scores are comparable. Impact of feature selection is mixed: it improved both MRR and *bpref* for RankBoost, but degraded LambdaMART and MART *bpref* scores. Best LambdaMART results were obtained with all features except for the Wikipedia title feature and four Wikipedia infobox features. RankBoost scored best using the Wikipedia title feature, number of categories, and presence of candidate in the corpus. Table 4 illustrates the contribution of different feature groups to the overall performance. The results support our initial hypothesis that multiple data sources improve results.

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[8]   http://www.cs.cornell.edu/people/tj/svm_light/svm_rank.html

[9]   http://www.collocations.de/software.html

Table 4: MRR for highest and lowest positive items ranked with
LambdaMART: contribution of different feature groups

	MRR highest	MRR lowest
all features	0.679	0.598
w/o RNC-based features	0.565	0.497
w/o Wikipedia-based features	0.609	0.543
w/o structural features	0.671	0.592
w/o results from the search engine	0.678	0.602

Top-40K lists ranked by LambdaMART, SVM-Rank, and RNC-based frequency contain 634, 472, and 452 positive examples (out of 990 'relevant' MWEs in the initial global list), respectively. In the top-40K MWEs ranked by LambdaMART, 43% items occur in both corpora, 35% and 22% occur in Wikipedia or RNC only, respectively. This again illustrates the benefit of using two data sources in parallel. Figure 1 presents ROC curves for the top-40K candidate MWEs ranked by LambdaMART, SVM-Rank, and RNC-based frequency (note that the total number of true positives differs for these 40K-lists, see above). Table 5 shows MWEs at different levels of the global list ranked by LambdaMART.
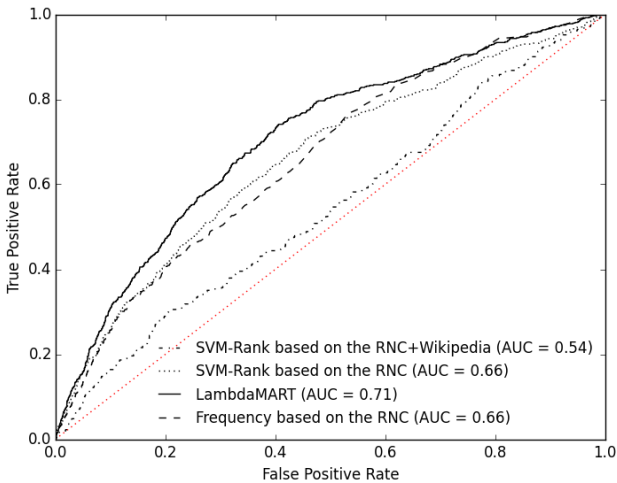

Fig. 1: ROC curves for four methods

Table 5: Examples of MWEs at different levels of the global ranking

Cut-off level = 100	Cut-off level = 1,000
земная кора (Earth's crust) программное обеспечение (software) основные фонды (basic assets) биологические науки (bioscience) общественное мнение (public opinion)	подсадная утка (decoy-duck) народный дух (national character) разговорная речь (spoken language) публичная библиотека (public library) братская могила (mass grave)
Cut-off level = 2,500	**Cut-off level = 5,000**
диалектическая логика (dialectical logic) барионный заряд (baryon charge) врождённые идеи (innate idea) гонка вооружений (arms race) адский огонь (hellfire)	фразовое ударение (phrasal stress) блуждающие огни (will-o'-the-wisp) золотой телец (golden calf) циркуляция крови (blood motion) кольцевые гонки (circuit race)
Cut-off level = 10,000	**Cut-off level = 30,000**
грудная железа (breast gland) критическая теория (critical theory) чесменский бой (battle of Chesma) автоматический огонь (automatic fire) личное дворянство (personal nobility)	концептуальное искусство (conceptual art) институциональный инвестор (institutional investor) земские марки (zhemstvo stamps) агглютинативные языки (agglutinative language) ненасыщенный пар (unsaturated steam)
Cut-off level = 100,000	**Cut-off level = 150,000**
шлиховой анализ (panning) облеченный тон (invested tone) дардские народы (dardsky people) трамвайная археология (tram archeology) глухой удар (bump)	ноги прохожих (feet of passers-by) разделенный экран (divided screen) воркутинская улица (Vorkuta street) осетинская церковь (Ossetian church) старый базар (old market)

6. Conclusion

In this paper, we described an experiment on MWE extraction from corpora. The novelty of the approach lays in the use of two data sources in parallel, a rich set of features, and advanced learning-to-rank methods applied to the task. The proposed approach outperforms traditional association measures and state-of-the-art classification methods. The method is language-independent and employs limited training data. In the future, we plan to apply the method to the extraction of verbal MWEs.

Acknowledgments

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