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DISTRIBUTIONAL SEMANTIC FEATURES IN RUSSIAN VERBAL METAPHOR IDENTIFICATION[1]

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Our experiment is aimed at evaluating the performance of distributional semantic features in metaphor identification in Russian raw text. We apply two types of distributional features representing similarity between the metaphoric/literal verb and its syntactic or linear context. Our approach is evaluated on a dataset of nine Russian verb context, which is made available to the community. The results show that both sets of similarity features are useful for metaphor identification, and do not replicate each other, as their combination systematically improves the performance for individual verb sense classification, reaching state-of-the-art results for verbal metaphor identification. A combined verb classification demonstrates that the suggested features effectively generalize over metaphoric usage in different verbs, shows that linear coherence features perform as well as the combined feature approach. By analyzing the errors we conclude that syntactic parsing quality is still modest for raw-text metaphor identification in Russian, and discuss properties of semantic models required for high performance.

Keywords: Metaphor identification, Russian language, distributional semantics, contextual anomaly

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ДИСТРИБУТИВНАЯ СЕМАНТИКА В АВТОМАТИЧЕСКОМ ВЫЯВЛЕНИИ ГЛАГОЛЬНОЙ МЕТАФОРЫ В РУССКОМ ЯЗЫКЕ

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1. Introduction

Metaphor processing has in recent years gained high popularity, both for practical and fundamental reasons. Not only is it indispensable to account for metaphor in various language processing tasks, but it is also commonly accepted that metaphor is a pervasive process in human language and thought (Lakoff and Johnson, 2008), with numerous effects in cognitive disciplines. There have been various effective approaches to automatic identification of linguistic metaphor, mostly relying on a consideration that metaphor is a violation of contextual selectional restrictions. Recent approaches to metaphor identification escape the subjectivity and sparseness of hand-coded semantic resources by applying distributional semantic models.

We evaluate word-embeddings distributional semantic features in the task of metaphor identification on a raw text dataset of Russian verbs. Our goal is to assess a range of distributional features in a real-world text processing task. Syntax-based features presented in previous work are extended and combined with linear contextual anomaly detection techniques. While preserving the original selectional restriction violation view on metaphor, in practice we also position it in a range of phenomena characterized by contextual anomaly. Our features reach state-of-the-art performance, proving that distributional semantic features are an important technique in metaphor detection.

2. Related Work

2.1. Word Meaning Representation in Metaphor Identification

Most of the work on automatic metaphor identification is aimed at uncovering specific relations between metaphorically used words and their context. The idea is formulated in its strict version in the selectional restriction approach to metaphor (Mason, 2004; Shutova, 2010). Methods of analyzing the metaphor-context relations make use of two main information sources: symbolic and numeric. Symbolic approaches apply hand-coded data from external resources such as WordNet, FrameNet, MetaBank, as features representing word meaning (Martin, 1994; Mason, 2004; Peters and Peters, 2000; Gedigian et al., 2006; Krishnakumaran and Zhu, 2007; Shutova, 2010; Klebanov et al., 2016). Numeric approaches usually involve assessing word meaning on numeric scales representing different aspects of meaning, of which particularly useful are concreteness, imageability, animateness (Turney et al., 2011; Gandy et al., 2013; Tsvetkov et al., 2014).

There has been some important work on metaphor identification in Russian, reaching high performance of up to 0.77–0.85 F1; however, most of it has been focused on large hand-coded databases or dictionaries (Ovchinnikova et al., 2014; Mohler et al., 2014; Tsvetkov et al. 2014).

2.2. Distributional Features in Metaphor Identification

Distributional semantic modeling allows to evaluate relations between word meanings in their entirety, automatically build conceptual domain knowledge, at the same time overcoming subjectivity and data sparseness characteristic of hand-coded resources. Authors of (Heintz et al., 2013) have used LDA topic modeling to automatically induce source domains for metaphors in political domain. In (Strzalkowski et al., 2013) candidates for metaphoric usage are identified by excluding the ’topic chains’ forming the main topical structure of a text. Klebanov et al. (2016) evaluate corpus-based distributional semantic features against hand-coded resources. Shutova et al. (2016) have applied word-embeddings to measuring metaphoricity in word pairs. They classified verb-subject, verb-object and noun-attribute word pairs as metaphorical or literal, based on semantic relatedness measures between the paired words, achieving best performance among linguistic methods (F1 = 0.71–0.76).

3. Experiment

3.1. Metaphor Annotation

The metaphoric occurrences of verbs were defined in accordance with the Vrije Universiteit Metaphor Identification Procedure (MIPVU) (Steen et al., 2010). MIPVU defines the three major types of metaphor-related words: Indirect Metaphor, Possible Personification, and Direct Metaphor.

Indirect Metaphor is attested when the contextual meaning of a word is not basic. The basic meaning of a word “is defined as a more concrete, specific, and human-oriented sense in contemporary language use” (ibid., p. 35).

For example, the basic meaning of ‘взорвать’ — to blow up — is ‘to explode smth, to destroy smth by an explosion’. The non-basic meanings are:

1. ‘to make a sensational impression on smb, to astonish smb’;
2. ‘to outrage, to scandalize smb’;
3. ‘to trigger a sudden and drastic change’ (Evgenyeva, 1981).

Thus, Indirect Metaphor in MIPVU covers the cases of conventional lexicalized metaphor, e.g.:

(1) *'Обещания премьера … взорвали блогосферу.' — Prime Minister's promises have … exploded the blogosphere.*

Direct Metaphor is attested when lexical units are used in their direct sense, but they are "incongruous" with the 'overall referential and/or topical framework' of their context, so their use can be 'potentially explained by cross-domain mapping' (ibid., p. 38):

(2) *'Мы … тебе особую, яркую судьбу выкраивали.' — It was an extraordinary and outstanding destiny that … we were cutting out for you.*

Besides, Direct Metaphor in MIPVU includes the cases of simile; they are termed as 'flagged' metaphor-related words:

(3) *Словно бы я желал выкроить из бумаги твое пение! — As if I wanted to cut your singing out of paper!*

MIPVU's Possible Personification covers the two types of occurrences: a) when an argument of a word is expressed metonymically and b) when an argument violates the selectional preference of a word for animate arguments:

(4) *Департамент их [деньги] пилит. — The department is sawing (=embezzling) the money.*

(5) *Прошлогодняя гигантская лавина … аккуратно «причесала» … все оставшиеся кустики и деревья… — Last year's gigantic avalanche … thoroughly 'combed' … the remaining shrubs and trees …*

Indirect and Direct Metaphor, and Possible Personification together constitute a single class of metaphor-related words forming a binary opposition with non-metaphoric occurrences. Our experimental corpus contains Indirect Metaphor and Possible Metonymic Personification (including examples (1), (4)), while Direct Metaphor (examples 2,3) and Metaphoric Personification (5) were excluded from the analysis.

Although graphic cues (such as quotation marks) are not distinguished in MIPVU as signals of metaphor, they definitely serve as supplementary factors that enable annotators to identify metaphoric occurrences.

MIPVU, designed to provide an explicit and standardized protocol for metaphor identification, has shown reliable levels of inter-annotator agreement: Fleiss' kappa > 0.79 in English and Dutch (Steen et al., 2010), and 0.9 in Russian texts (Badryzlova et al., 2013).

3.2. Dataset

We experimented with nine Russian polysemous transitive verbs: *бомбардировать* — 'bombardirovat' — to bombard, *очертить* — 'ochertit' — to outline, *пилить* — 'pilit' — to saw, *распылять* — 'raspylyat' — to diffuse, *разбавлять* — 'razbavlyat' — to dilute, *выкраивать* — 'vykraivat' — to cut out, *взорвать* — 'vzorvat' — to blow up, *взвесить* — 'vzvesit' — to weigh, and *зажигать* — 'zazhigat' — to ignite.

The dataset contained 990 full sentences (roughly about 100 sentences per verb), with an approximately equal number of metaphoric and non-metaphoric occurrences for each target verb.

The sentences were randomly sampled from RuTenTen, a Russian web corpus accessed via the Sketch Engine tool[2]. The sentences were manually annotated as metaphoric or non-metaphoric by a native Russian speaker who is a trained linguist[3].

Table 1 shows the number of sentences for each verb, and the majority class occurrence.

Table 1: Dataset summary

Verb	Sentences	Majority, %
бомбардировать — bombard	120	55
очертить — outline	99	53
пилить — saw	106	52
распылять — diffuse	112	50
разбавлять — dilute	115	51
выкраивать — cut out	110	53
взорвать — blow up	96	50
взвесить — weigh	133	51
зажигать — ignite	99	53
All	990	50

3.3. The task of distributional metaphor classification

The goal of the work is to evaluate the performance of distributional semantic measures in Russian verbal metaphor identification. The task is to distinguish metaphoric from literal usage of a verb in raw, full sentence context. To achieve this, we apply a number of distributional measures characterizing the semantic relations between the verb and the context.

Our setting is crucially different from the tasks described by Shutova et al. (2016) and Tsvetkov et al. (2014) in that we process raw contexts of verbs, and not hand-picked syntactically related word pairs. Another complication of the raw-text task is that a verb paired with it's syntactic dependency cannot always be unambiguously resolved in terms of metaphoricity/literacy, unlike the unequivocally annotated word-pairs in previous work. Consider example (6), where the direct object *круг — circle* does not resolve the metaphoricity/literacy ambiguity: (6a) is an ambiguous word pair and can only be resolved by using broader context, as illustrated by (6b, c):

(6a) *очертить круг — to outline a circle*
(6b) *очертить круг обязанностей — to outline a circle of responsibility*
(6c) *очертить круг палкой на песке — to outline a circle on the ground with a stick*

2 http://www.sketchengine.co.uk/

3 The dataset is available for download at http://web-corpora.net/~badryzlova/VERB_DATASET/.

Our task is thus complicated by the following steps necessary for real-world metaphor identification in raw text:

- identifying related syntactic arguments;
- overcoming the absence or ambiguity of specific syntactic arguments, or the parser's failure to identify them, by using broader context features.

We apply the following distributional features:

- a set of syntax-based features presented by Shutova et al. (2016);
- an extension of the syntax-based features to include all the significant dependency types;
- linear topic coherence features proposed by Newman et al. (2010).

We are concerned with the question how well can distributional measures perform in the real-world task of classifying contextual metaphoricity by applying the available state-of-the-art morphosyntactic processing and semantic modeling in Russian.

To our knowledge, this is the first work on automatic metaphor identification in Russian raw text samples by applying distributional techniques without relying on large-scale hand-crafted resources. It is also the first attempt to apply a Russian word-embeddings model with various contextual and syntax-based distributional semantic measures to metaphor identification. Our evaluation data is made available to the community.

3.4. Distributional Semantic Features

Distributional semantic models: Our distributional features are based on word-embeddings semantic models. We evaluate two pre-trained models presented in (Kutuzov and Andreev, 2015)[4]:

- RNC: a model trained with the Russian National Corpus texts containing 107M tokens, dimensionality = 300.
- WikiRNC: a larger model trained with a combined RNC + Russian Wikipedia dump corpus of 280M tokens, dimensionality = 500.

Both models have been trained using CBOW algorithm and window size 2.

Semantic Similarity (Sim): Semantic similarity features are based on the consideration that metaphor is a Selectional Preference violation, which is effectively captured as semantic deviance between the metaphoric verb and its main arguments (Shutova et al., 2016). The assumption is that a verb used in a literal sense belongs to the same conceptual domain as its immediate arguments, whereas metaphoric verb usage implies arguments belonging to a different conceptual domain. The semantic similarity features involve cosine similarity values between the verb and its syntactic dependencies: предик — Subject (Subj), компл-1 — Direct object (Obj), компл-2 — Indirect object (Obj2), сочин — Coordinate (Coord), and обст — Circumstance (Circ). Syntactic dependencies are identified by MaltParser (Sharov and Nivre, 2011). Semantic similarity features are calculated as follows:

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[4] Freely available for download at http://ling.go.mail.ru/dsm/en/about#models

$$\mathrm{Sim}_{\mathrm{rel}} = \cos(\mathrm{verb}, \mathrm{w}_{\mathrm{rel}}) \quad (1),$$

where *rel* is the syntactic relation in {Subj, Obj, Obj2, Coord, Circ}, *verb* is the keyword verb, and w_{rel} is the syntactically dependency of the keyword verb in the current relation.

Linear Semantic Coherence (Coh): Semantic coherence features are evaluated as the topic coherence measure proposed by (Newman et al., 2010). The intuition is that a metaphoric verb is semantically deviant from its linear context window, affecting mean semantic similarity between the words in the window in a negative way, whereas a literally used verb belongs to the same conceptual domain as its context, making the contextual sub-space denser and adding to mean similarity (Herbelot and Kochmar, 2016). We apply 3 features representing linear semantic coherence:

$$\mathrm{Coh}_{\mathrm{win}} = \frac{1}{\mathrm{length(Win)}} \sum_{\mathrm{w_i, w_j \in Win}} \mathrm{Sim}\left(\mathrm{w_i}; \mathrm{w_j}\right) \quad (2),$$

$$\mathrm{CohV}_{\mathrm{win}} = \frac{1}{\mathrm{length(Win)}} \sum_{\mathrm{w_i, w_j \in Win, w_i \neq verb, w_j \neq verb}} \mathrm{Sim}\left(\mathrm{w_i}; \mathrm{w_j}\right) \quad (3),$$

$$\mathrm{CohDiff}_{\mathrm{win}} = \mathrm{Coh}_{\mathrm{win}} - \mathrm{CohV}_{\mathrm{win}} \quad (4);$$

where *Sim* is the cosine similarity measure in the distributional semantic space; and *Win* is the context window consisting of [-x; x] content words (nouns, verbs, adjectives or adverbs) around the keyword verb.

One the one hand, Coherence features reproduce the conceptual domain similarity information provided by the Sim values, without relying on the syntactic subtleties, including the syntactic parsing quality. On the other hand, being effectively applied to lexical error detection (Herbelot and Kochmar, 2016), Coherence features render the task of metaphor identification as a case of lexical anomaly detection in linear context.

The features are combined to perform binary metaphoricity/literalness classification using Support Vector Machine (SVM) classification with linear kernel[5]. We applied 3-fold cross-validation in experiments with individual verbs; in the combined dataset experiment we used 30-fold cross-validation in order to maintain comparable training/test set volume between all the experiments.

4. Metaphor Identification Results

Metaphor identification results based on Sim and Coh features are presented in Table 2, with the results for two distributional models following the format "RNC / WikiRNC result", and the highest performance for a single verb/combined verbs highlighted in bold.

[5] LinearSVC, as implemented in scikit-learn, (Pedregosa et al., 2011).

Table 2: Metaphor classification results, accuracy, in %

Verb	Sim				Coh	Coh+ Sim
	Subj	Obj	Subj+Obj	All		
бомбардировать — bombard	59 / 55	57 / 56	59 / 58	59 / 58	63 / 55	**68** / 58
очертить — outline	53 / 53	52 / 51	51 / 49	52 / 49	**58** / 57	55 / 53
пилить — saw	50 / 53	61 / 60	62 / 61	64 / 65	71 / 64	**74** / 71
распылять — diffuse	51 / 54	44 / **71**	43 / **71**	46 / **71**	46 / 54	49 / 68
разбавлять — dilute	56 / 54	68 / 70	70 / 73	72 / 77	90 / 83	90 / **93**
выкраивать — cut out	53 / 53	53 / 53	53 / 53	53 / 55	57 / 52	**58** / 53
взорвать — blow up	59 / 60	74 / 69	78 / 75	77 / 75	78 / 63	**81** / 75
взвесить — weigh	51 / 50	48 / 48	47 / 47	**56** / 50	54 / 50	**56 / 56**
зажигать — ignite	55 / 56	69 / 70	71 / 72	71 / 72	**80** / 78	76 / 77
All	53 / 52	57 / 57	59 / 59	62 / 62	**68** / 67	**68 / 68**

Evaluated **Sim** feature sets include Subj, Obj, their combination, and all five dependency features Subj, Obj, Obj2, Coord, Circ. **Coh** feature results are illustrated for context window = 2 (other window sizes have resulted in the same pattern with insignificant differences). In the joint **Coh+Sim** classification we apply **Coh** feature set combined with the set of all five **Sim** dependency features. The best classification result for all the verbs combined reaches **68% Accuracy** or **F1 = 0.71** for the Metaphor class.

5. Discussion

5.1. Distributional verb representation

The best results for different verbs range from just above the majority baseline (**53%**) to very accurate classification (**93%**). The combined classification performs reasonably high (**68%**), reaching the level of medium-hard individual verbs: this proves that the applied features can be generalized over different verbs, reflecting not only individual peculiarities in verb meanings, but common patterns of metaphoric/literal usage.

It is obvious that the results differ considerably between individual verbs, i.e. there are certain ’easy’ and ’difficult’ verbs for classification. A range of factors affect the individual performance:

- The better the verb is represented in the training corpus of the distributional model, the higher the resulting classification accuracy. Spearman’s r between verb frequency and the RNC-based joint **Sim+Coh** (window = 2) classification results reaches a moderate correlation value of 0.37. Moreover, the two most under-represented verbs occurring less than 200 times in RNC, *diffuse* and *cut out*, have the lowest RNC-based classification performance.
- Qualitative representation of the keyword verbs in the models affects the performance. The verb representation in the distributional models has been manually analyzed by evaluating the most similar verbs to the keyword verbs. The

models representing mostly the literal/technical sense of a verb give higher performance in metaphor classification, than those representing broader, metaphoric sense (cf. *diffuse*: *распыляться* — diffuse(refl), *абсорбировать* — absorb, *ожижать* — liquify, *перенасыщать* — supersaturate (WikiRNC), *уничтожать* — destroy, *сосредотачивать* — focus, *мобилизовать* — mobilize, *превращать* — transform, *разгонять* — scatter (RNC)).
- For most of the verbs, **Sim** and **Coh** features both contribute to the result, achieving higher performance when **Sim** and **Coh** are combined. However, as the strict regularities erode into broader common patterns in the all-verb classification, fine-grained syntax-based **Sim** features give no additional advantage over the linear **Coh** features.

5.2. Error Analysis

We have classified reasons for wrong classification in the case of **Sim** Subj+Obj features. The main error types are presented in Table 3.

Table 3: Error type statistics in Sim Subj+Obj classification results

Verb	Sparsity	Syntactic	Semantic
Total	40	55	5
Combined	48	44	8

Errors are attributed to data sparsity when either Subj or Obj was not represented in the data, or either of them was not expressed by a noun, making semantic similarity measurement impossible. Classification errors due to failures in syntactic parsing occurred when the parser incorrectly identified either Subj or Obj, or both of them. Semantic errors are the errors when both nominal Subj and Obj are present in the data and correctly parsed, but the wrong classification is due to a failure of the semantic model or the classifier algorithm.

The most common error in **Sim** Subj+Obj are errors due to inadequate syntactic parsing: they explain about 55% of overall errors, ranging from 39 to 73% across the verbs, or 44% in the combined verb classification. Syntactic errors are followed by errors due to data sparsity which comprise 40–48% of all errors in total.

6. Conclusions and Future Work

We have performed metaphor identification with raw contexts of nine Russian verbs by applying distributional semantic features based on similarity to the main arguments and linear coherence. Both feature sets have proven to be useful with considerable performance in the task well above the majority baseline, reaching **63–93% Accuracy** for individual verbs. More importantly, the suggested distributional features generalize reasonably well in a combined classification of nine verbs, reaching **68% Accuracy**, or F1 = 0.71. The result is comparable to the reported state-of-the-art results for Russian and reaches that reported for a similar resource-free setting

(F1 = 0.71 for verbal metaphor by Shutova et al. (2016)). We consider the performance reasonably high, taking into account the raw-text setting of our experiment and the absence of hand-coded dictionary resources among our features.

One of the main difficulties of the task is the sparsity of main verb arguments, including genuine absence of arguments in the sentence and failure of the syntactic parser to identify them; it is effectively overcome by adding linear semantic coherence features. A high quality distributional semantic representation of a keyword verb for metaphor identification should reflect primarily the literal meaning of the verb, i.e. the metaphoric sense should not be too conventionalized in the model.

Distributional semantic features are a useful source of information in metaphor identification. In future work aimed at high-quality performance of metaphor identification, other features should be added, including explicit selectional preference encoding and word-meaning aspects such as concreteness, imageability.

We have shown that algorithms capturing contextual anomaly both in terms of syntactic pairs and linear context are effective in describing metaphor. As the same algorithms have been applied to identifying non-compositional constructions (Bukia et al., 2016) and L2-learner errors (Herbelot and Kochmar, 2016), it is clear that these phenomena share similar distributional properties with metaphoric usage. However, it is important in future work to draw a line between the three different phenomena representing contextual anomaly.

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