Automatic detection of grammatical aspect of Russian verbs based on their morphological properties

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Abstract

The goal of this study is to explore whether the properties of the morphological form of Russian verbs can be used to automatically predict their grammatical status as perfective or imperfective. We rely on a vector space model pre-trained with a non-contextual method of Distributional Semantics. The model largely succeeded in correctly identifying the grammatical aspect of derivationally related perfective and imperfective forms based on their morphological form. The study demonstrates that the internal structure of verbs captured by the model can identify whether a given Russian verb form is perfective or imperfective. Our results are especially relevant for computational studies using distributional semantic representations for aspect prediction and analysis of morphological patterns in languages with verbs that exhibit a complex morphological structure.

1 The Main Topic and Questions

This study proposes an approach that automatically differentiates between simplex imperfective and morphologically complex perfective forms in Russian derived from them by means of prefixes or the semelfactive suffix *-nu-*, referred henceforth as 'derivational pairs'.[1] We pose the following questions:

i Does the morphological form contribute to distinguishing grammatical aspect of Russian?

ii How well does the distributional semantics approach handle grammatical aspect detection?

Our approach relies on visualizing the distribution of verb vector representations in a vector space. It is built using a distributional semantic model pre-trained using a fastText non-contextual method, which is specifically adjusted for the analysis of morphological patterns. The method generates vectors for verb lemmas based on their internal subword (morphological) information in the form of character n-grams. It is important to note that Slavic verbs in derivational pairs most often differ in lexical semantics, not just in grammatical aspect, therefore members of a derivational pair may not always have distributionally close vector space representations.

2 Linguistic Assumptions

The perfective-imperfective opposition in Russian, as in other Slavic languages, is largely lexicalized, and manifested in relations between forms that are derivationally related by means of affixation (Dahl, 1985; Filip, 1993/1999, 2000; Wiemer and Seržant, 2017). Examples of derivational pairs we are interested in are given in (1).[2]

(1) a. *gavkat'* IMPF ⇒ ***pro**-gavkat'* PFV
bark-INF PX-bark-INF
'(be) bark(ing)' 'bark [several times]'

b. *gavkat'* IMPF ⇒ *gavk-**nu**-t'* PFV
bark-INF bark-SX-INF
'(be) bark(ing)' 'bark [once]'

[1] The word 'pair' in this study refers to two derivationally related verbs (an imperfective verb and an affixed perfective counterpart) and does not refer to 'an aspectual pair', in support of the hypothesis proposed by Isačenko (1960); Timberlake (2004).

[2] We use the following glossing abbreviations: INF (an infinitival form), PX (a prefix), and SX (a suffix).

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The derivational pair in (1-a) consists of an underived (simplex or primary) imperfective *gavkat'* with no overt morphological marking of aspect and its perfective counterpart *progavkat'* derived with the perdurative prefix *pro-* 'through' which refers to temporal duration (e.g., Tolskaya, 2015; Naumov, 2019). (1-b) illustrates a minor derivational pattern where the semelfactive suffix *-nu-* is added to an imperfective simplex (or primary) imperfective verb *gavkat'* denoting a set of singular events or a plurality thereof, and derives a perfective verb *gavknut'* restricting its denotation to a set of singular events. Russian grammatical aspect, the derivational affixes by which perfective and imperfective verb forms are built, and their semantic, syntactic, and morphological properties, have been studied in theoretical linguistics (e.g., Filip, 2003 and references therein), corpus linguistics (e.g., Janda, 2007), computational linguistics (e.g., Drozd et al., 2015) and rule-based translation (Sonnenhauser and Zangenfeind, 2016). There is an emerging agreement that there are no dedicated markers of perfective aspect in Russian and other Slavic languages, which would consistently mark perfectivity of the verb in all their occurrences; while the semelfactive suffix *-nu-* consistently occurs on perfective verbs, it is a derivational morpheme that only delimits a minor derivational pattern (Filip, 2000, 2003, 2005).

Prefixes have a derivational function, occur on both perfective and imperfective verbs to which they often contribute additional lexical meanings and/or change argument structure (ibid.). For instance, the perfective verb ***vy**igrat'* 'to win' prefixed with the completive *vy-* can select the direct object *priz* 'prize' as in ***vy**igrat' priz* 'to win a prize', while its imperfective counterpart *igrat'* 'to play' cannot, cf. *igrat' *priz'* 'to play a prize'. As is well-known, prefixes often extend the core meaning of the base verb by adding a variety of modifications, such as spatial and temporal dimensions (largely due to the prepositional origin of most of them) and may also add affective connotations. Semantically speaking, prefixes can be uniformly analyzed as modifiers of eventuality types denoted by verb bases they are applied to (Filip, 2005). While most perfective verbs are morphologically complex, either prefixed or suffixed, as in the examples above, there are a few perfective root (or primary) verbs (e.g., *past'* 'to fall', *dat'* 'to give'). All Slavic languages have morphologically complex secondary imperfectives derived from perfective verbs by the imperfectivizing suffix (realized in allomorphs *-yva-*, *-va-*, *-a-*, as in *perečit**yva**t'* 'to read over'), but they are not part of this study. When it comes to the semantic analysis of perfectivity and imperfectivity, many rely on Klein's (1994) idea (within the Reichenbachian tradition) that grammatical aspect concerns the relationship in which: (i) event time is included within topic/reference time (perfective aspect), (ii) topic/reference time is within event time, or overlaps with it (imperfective aspect).

3 Experiment

3.1 Overview of methodology

The experiment for exploring whether the morphological form of Russian verbs can be exploited in automatic determination of their aspectual class was conducted as follows. First, we compiled a list of derivational pairs from existing databases. Second, the distribution of pre-trained word embeddings associated with these perfective and imperfective verbs was presented in a vector space (Mikolov et al., 2013), relying on the distributional hypothesis that linguistic items with similar meanings have similar distributions (Firth, 1957). Vector representations of derivational pairs were constructed using a fastText algorithm integrating with the Continuous Bag of Words architecture (CBOW), which predicts the target word according to its context represented by its n-grams. The visualization of word embeddings was done using the Distributed Stochastic Neighbor Embedding (t-SNE), an unsupervised clustering technique (van der Maaten and Hinton, 2008).

The fastText algorithm (Bojanowski et al., 2017) constructs a semantic vector space capturing semantic relations between words based on their formal similarity and their context similarity.[3] It computes non-contextual word embeddings that are unique for each word regardless of context and do not change in downstream tasks (Si et al., 2019; Zhou et al., 2022). In a fastText model, the vector for a word is a sum of all vectors of its n-gram characters. This property enables fastText to achieve higher predictive performance for morphologically rich languages and rare words (Onan, 2020). t-SNE is used for visual verification of generated word embeddings by reducing dimension into a two-dimensional plane for

[3]Formal similarity is numerical representation of sub-word information, while context similarity is distance in vector space.

fastText embeddings (Sanjanasri et al., 2021) and has been applied to exploring Russian and Finnish inflectional paradigms (Chuang et al., 2023; Nikolaev et al., 2023). Nikolaev et al. use t-SNE for assessing the accuracy of clusters of inflected Finish nouns in a vector space generated by fastText-based models. By using fastText and t-SNE, we expect the model to be able to separate perfective verbs from their imperfective counterparts by their morphology, rather than by context similarity. We visualize a vector space of derivational pairs to observe if it would exhibit distinct patterns in the form of clusters.

3.2 Derivational data

The data used in the experiment were collected and compiled from existing aspectual databases in Russian: the *Exploring Emptiness* (*EE*) database, the database of Russian Verbal Aspect (OSLIN database; Borik and Janssen, 2012), and the Essex Database of Russian Verbs and their Nominalizations (Essex database; Spencer and Zaretskaya, 1999).[4] We compiled our database by extracting entries with derivational pairs of Russian verbs and the affixes by which they are related. We extracted 2899 entries from the Essex Database, 1981 entries from the *EE* database, and 529 entries from the OSLIN database. The data were then transliterated, sorted and cleaned from duplicates. It contains 4032 derivational pairs, as is illustrated in Table 1, 3976 verb forms related by prefixes, and 56 verb forms by the semelfactive suffix *-nu-*.

A sample illustrating the structure of the compiled database is given in Table 2. We see that the imperfective verbs *bajukat'* 'to sing lullabies, to cradle', *kapat'* 'to drip' and their perfective correspondents *ubajukat'* 'to lull [to sleep]' and *kapnut'* 'to drop, to let fall a drop' are followed by the type of affix by which they are related (prefix and suffix) and the specific affix form, here *u-* and *nu-*. The latter count reflects the well-known empirical fact that in Russian the number of prefixed perfective verbs is larger than that of verbs formed with the semelfactive suffix *-nu*.

#Der.Prs.	**#Prefixes**	**#Suffix**
4032	3976	56

Table 1: Counts of derivational pairs, prefixes, and the suffix *-nu-* in the compiled database.

IMPF verb	**PFV verb**	**Affix type**	**Affix**
bajukat'	*ubajukat'*	prefix	*u*
kapat'	*kapnut'*	suffix	*nu*

Table 2: Examples of two entries in the compiled database.

Overall, the database contains about 700 imperfective verbs that have more than one corresponding perfective verb in the compiled database. Table 3 below illustrates an excerpt with a few imperfective verbs that have two or more perfective counterparts. For example, from the imperfective simplex verb

IMPF verb	**PFV verb**	**Affix**	**#**
bespokoit' 'worry'	*obespokoit'* 'trouble', *pobespokoit'* 'bother'	*o*, *po*	2
bit' 'hit'	*pobit'* 'beat up', *probit'* 'break through', *razbit'* 'break'	*po*, *pro*	3
lepit' 'mould'	*zalepit'* 'seal', *vylepit'* 'mould', *nalepit'* 'stick', *slepit'* 'sculpt'	*za*, *vy*, *na*, *s*	4
dumat' 'think'	*podumat'* 'think about', *nadumat'* 'imagine', *pridumat'* 'invent', *obdumat'* 'think through', *razdumat'* 'change one's mind'	*po*, *na*, *pri*, *ob*, *raz*	5
mazat' 'smear'	*pomazat'* 'anoint', *vymazat'* 'cover', *izmazat'* 'stain', *zamazat'* 'cover up', *namazat'* 'spread', *promazat'* 'miss'	*po*, *vy*, *iz*, *za*, *na*, *pro*	6

Table 3: Examples of imperfective verbs with two to six prefixed perfective derivationally related verbs in the compiled database.

dumat' 'to think' we can derive five perfective verbs by means of five different prefixes, each with a different lexical meaning: *podumat'* 'to think over', *nadumat'* 'to think, to imagine', *obdumat'* 'to think through', *pridumat'* 'to invent, to come up with', *razdumat'* 'to change one's mind'.

[4] The databases are available at: http://emptyprefixes.uit.no/project_eng.htm, http://ru.oslin.org, https://reshare.ukdataservice.ac.uk/852633/.

3.3 Visualizing the vector space of Russian aspect

Representations of derivational pairs were constructed on the basis of pre-trained fastText embeddings provided by the RusVectores project. The RusVectores model (Kutuzov and Kuzmenko, 2017)[5] was trained using the fastText algorithm with the Continuous Bag of Words (CBOW) architecture on the Araneum Russicum Maximum 2018 of 10 billion words from Russian texts crawled from Internet domains; its vocabulary contains 195,782 words with vector size of 300. The vector space representations of verb lemmas sorted by their tags (*impf* versus *pfv*) were then visualized with t-SNE. For the visualization, we used 4032 derivational pairs consisting of 3896 perfective verbs and 1766 imperfective verbs amounting to the total of 5662 verbs.[6] Figure 1 illustrates the distributional space of perfective (*pfv*) and imperfective (*impf*) verbs visualized by t-SNE. The visualized space contains data points grouped by *pfv* and *impf* aspect forming distinctly separated clusters. The first major cluster to the left is formed by perfective verbs while the second major cluster to the right consists of imperfective verbs surrounded by some perfective verbs, although the right-side cluster at the bottom of Figure 1 is a mixture of imperfective and perfective verbs.

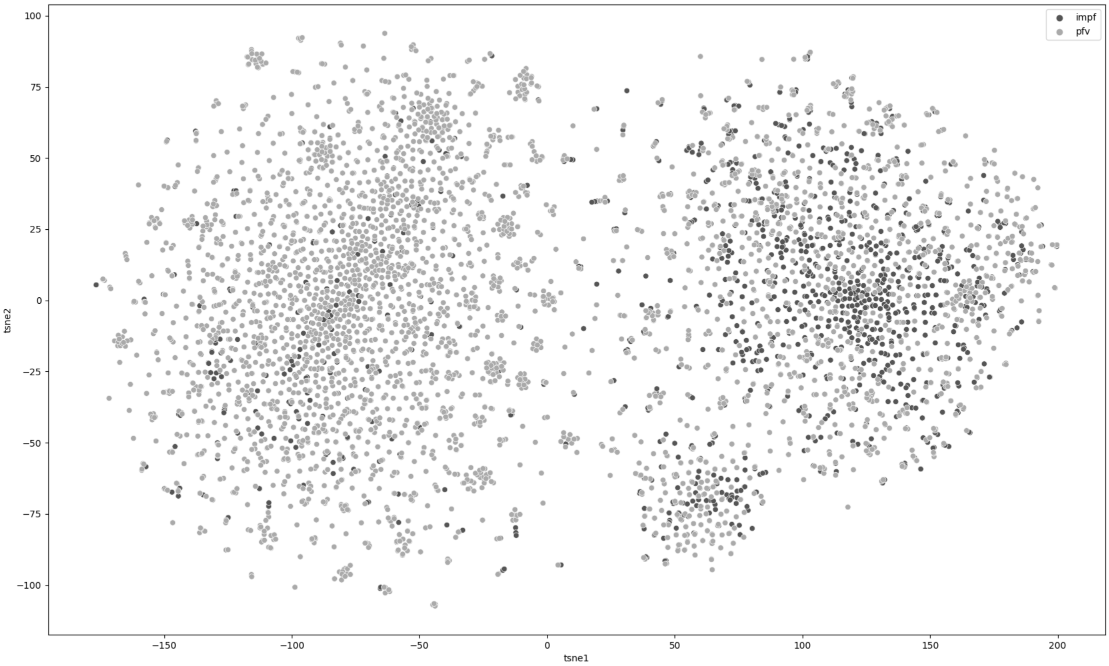

Figure 1: Scattered clusters of perfective (*pfv*; grey dots) and imperfective (*impf*; black dots) verbal lemmas based on high-dimensional vectors of word embeddings from the pre-trained RusVectores fastText model.

We observed quite a few perfective verbs scattered around the main right imperfective cluster, which led us to exploring whether these groupings were motivated by their semantic similarity, i.e., alignment with classes of verbs developed in accordance with their meanings and syntactic behavior by Levin (1993). Following Levin's (1993) semantically coherent classification of verbs, the clusterings of perfective verbs (grey dots) in the main left and right clusters fall into the classes of verbs listed in Tables 4 and 5 below. As can be seen, the verb classes in both clusters are notionally quite diverse. Change of state verbs such as *obozlit'sja* 'to become angry', *obradovat'sja* 'to become glad', and *ozveret'* 'to become engared' also belong to the class of psychological state. Verbs of these classes occur both in the perfecitve and imperfective clusters.

The perfective verbs in the minor cluster on the bottom right side are mostly borrowed verbs derived by prefixation from *-ova-* imperfective verbs,[7] and there are also some non-borrowed verbs. Levin (1993)

[5] araneum_none_ fasttextcbow_300_5_2018, available at: `https://rusvectores.org/en/models/`

[6] In this experiment, we used verb lemmas as they were presented in the compiled derivational database.

[7] The borrowed verbs in this cluster are classified as perfective in the Reverse Dictionary of Russian (Ševeleva, 1974, p.

classifies these verbs as verbs of change of state (e.g., *otremontirovat'* 'to repair', *proventilirovat'* 'to ventilate'), and creation and transformation (e.g., build verb *vygravirovat'* 'to engrave'), among other cases.

Verb class	Example
Manner of speaking	*prokvakat'* 'croak'
Measure (price)	*vyčislit'* 'estimate'
Putting (fill)	*zamaskirovat'* 'cover up'
Cutting	*rascarapat'* 'scratch all over'
Psychological state (amuse type)	*zainteresovat'* 'interest'
	obesslavit' 'dishonor'
Social interaction	*izbalovat'* 'pamper'
Separating/Disassembling	*razdelit'* 'split, separate'
Change of state	*obozlit'sja* 'become angry'
	prixvornut' 'get [a bit] sick'

Table 4: Examples of Levin's (1993) verb classes for perfective verbs in the *pfv* cluster.

Verb class	Example
Psychological state	*pozavidovat'* 'envy'
Desire	*vozvzelat'* 'desire'
Social interaction	*podrat'sja* 'get into a fight'
Gestures w/ body parts	*mignut'* 'wink [once]'
Negative judgment	*nakazat'* 'punish'
Change of state	*poburet'* 'turn brown'
	obradovat'sja 'become glad'
	ozveret' 'become engared'
Contact by impact	*oblobyzat'* 'kiss'
	užalit' 'sting'
	pokusat' 'bite'

Table 5: Examples of Levin's (1993) verb classes for perfective verbs in the *impf* cluster.

Change of state verbs are also known as verbs with 'affected objects' and creation, contact by impact verbs as 'effected objects', both types of objects are traditionally subsumed under the Patient thematic relation. Hence, in so far as these two classes of verbs denote eventualities during the course of which the referents of their direct object arguments undergo some change, they are semantically similar.

3.4 Error analysis

To analyze the errors produced by the RusVectores model, we considered the properties of perfective and imperfective verbs connected to their contextual use. This is why we examined the distributional representations of the verbs based on their corpus frequencies and bi-aspectual uses. First, we labeled perfective verbs with their frequency ranks (high- versus low frequency) based on their corpus frequencies and visualized the distribution via t-SNE. Second, we checked for bi-aspectual perfective/imperfective verbs in the minor right-side cluster as many borrowed verbs were observed in this cluster in Section 3.3.

We used corpus frequencies to analyze the RusVectores' errors because they affect similarity scores in word embedding. That is, the model would perform better with verbs that have higher frequencies than with verbs with lower frequencies. For example, for the BOW architecture models with increasing frequency counts, similarity score increases generating the same vector for different sentences disregarding context and word order (Asudani et al., 2023). For the list of word list of all perfective verbs, we extracted their raw corpus frequencies from the *Araneum Russicum III Maximum 2019* corpus[8] using the NoSketch Engine corpus query tool (Rychlỳ, 2007; Kilgarriff et al., 2014). The frequencies of these verbs were normalized and log-transformed on the scale from one to seven using the Zipf measure proposed by (van Heuven et al., 2014).[9] This measure converts normalized (item per million) frequencies into more understandable values on the scale from 1 to 7; the values from 1 to 3 are associated with low-frequency words while the ones from 4 to 7, with high-frequency verbs (van Heuven et al., 2014, 1180).

Figure 2 shows that low-frequency verbs are on the left-side cluster while high-frequency verbs are on the right-side cluster (left-side perfective and right-side imperfective clusters on Figure 1, respectively).

611, 607, 604). Their imperfective unprefixed counterparts, *remontirovat'* 'to repair', *ventilirovat'* 'to ventilate', *gravirovat'* 'to engrave', are borrowings and integrated into Russian by means of the *-ova-* suffix. There is no general agreement whether the borrowed unprefixed verbs are imperfective or biaspectual. Their prefixed counterparts are often taken to be perfective (Horiguchi, 2018, 62; Bunčić, 2013, cited in Olsson, 2018), but some treat many of them as biaspectual (Schuler, 1996 and Horiguchi, 2018).

[8]The corpus is based on texts crawled from the Russian Web (more than 19 billion tokens). This is the newer version of the corpus the RusVectores model was pre-trained on. The corpus description is available at: `http://aranea.juls.savba.sk/aranea_about/index.html`.

[9]For example, for *posmuglet'* 'to become tanned' the raw frequency of 4 is normalized, log-transformed (base 10) to -1.056, and scaled to 2, which represents low-frequency rank. For *posmet'* 'to dare', the raw frequency of 46899 is normalized, log-transformed to 2.915, and scaled to 6 representing the rank of high-frequency verbs.

High-frequency perfective verbs ranked 5–6 found in the *highFreq* cluster are, for example, *obnaglet'* ‘to become arrogant’, *razbudit'* ‘to wake [someone] up’, *mignut'* ‘to wink [once]’, *užalit'* ‘to sting’, *počtit'*‘to commemorate’. Some perfective low frequency verbs with ranks 2–3 from the *lowFreq* cluster include *sfantazirovat'* ‘to fantasize’ (rank 3), *srepetirovat'* ‘to rehearse’ (rank 2), *zatorcevat'* ‘to pave with wood blocks’ (rank 2). The vector-space distribution of high- and low-frequency perfective verbs implies that the RusVectores model may show a bias in separating to low- and high-frequency verbs. In general, the model separated perfective and imperfective verbs according to low- versus high frequency (same as in Figure 2), but in this section we only addressed the distributional representations related to the frequency of perfective verbs.

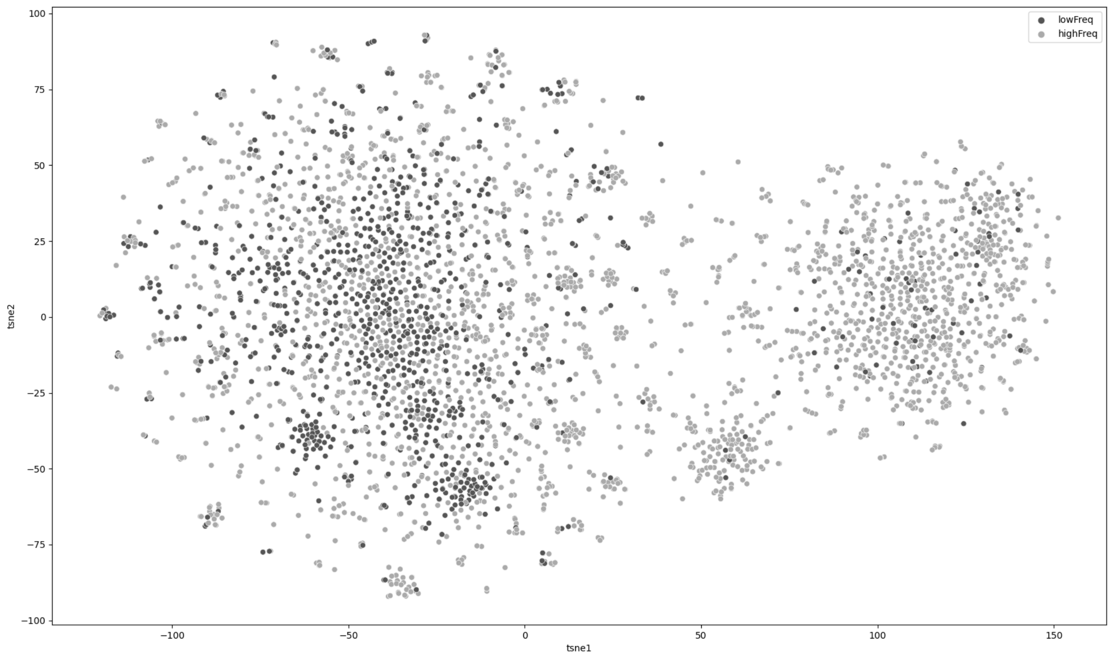

Figure 2: Scattered clusters of high frequency (*highFreq*; grey dots) and low frequency (*lowFreq*; black dots) perfective lemmas based on high-dimensional vectors of word embeddings from the pre-trained RusVectores fastText model. The frequency ranks of these verbs are based on the raw frequency values from the Araneum Russicum corpus log-transformed and scaled by means of the Zipf measure.

As mentioned in Section 3.3, we identified a pattern of borrowed *-ova-* verbs in the minor right-side cluster. We (manually) extracted 221 perfective and imperfective verbs from this cluster and checked if they were bi-aspectual according to the annotation in the verb database based on Zaliznyak’s dictionary (1987).[10] Out of 221 verbs that we analyzed, 49 were marked as bi-aspectual *-ova-* verbs in the verb database, 47 of which were borrowed, and only two non-borrowed (e.g., *zaimstvovat'* ‘to borrow’, *usoveršenstvovat'sja* ‘to improve oneself’). The bi-aspectual borrowed verbs include *kristallizovat'* ‘to crystallize’, *modelirovat'* ‘to model’, *transkribirovat'* ‘to transcribe’, *kooperirovat'* ‘to cooperate’, *orientirovat'* ‘to orientate’, *degustirovat'* ‘to taste’, among others. Many perfective verbs had close distributional properties with their bi-aspectual counterparts and were placed close to each other in the minor cluster. The examples of such derivational pairs (biaspectual–perfective) include *orientirovat'–sorientirovat'* ‘to walk someone through’, *degustirovat'–prodegustirovat'* ‘to taste’, *zaimstvovat'–pozaimstvovat'* ‘to borrow’. It should be noted we observed few *-ova-* verbs in the main right-side cluster compared to the the minor cluster that contained predominantly *-ova-* bi-aspectual verbs. The verbs in the main right-side cluster were mostly perfective and imperfective verbs with stems ending with theme vowels *-e-* (as in *ter**e**t'* ‘to rub’), *-a-* (as in *pačk**a**t'* ‘to make dirty’), *-i-* (as in *sverl**i**t'* ‘to drill’).

We may speculate that the clustering that we observe reflects similarities in the distributional properties

[10]The database was compiled by Slioussar (2012) based on the grammatical dictionary of Russian (Zaliznyak, 1987) and contains 27409 verbs. Available at: `http://www.slioussar.ru/verbdatabase.html`

of verbs, rather than similiarities in their morphological form. It is possible that these are the cases where fastText generated vector representations based more on context similarity than form similarity, which in turn might be due to high frequency of verbal lemmas and the use of biaspectual verbs and their perfective counterparts in similar contexts.

4 Results and discussion

The experiment showed that the distributional model separated perfective and imperfective verbs into two distinct clusters. As the model was built by the non-contextual fastText method, this confirmed our hypothesis that the morphological structure of Russian verbs should be a significant criterion for distinguishing the grammatical aspect of Russian verbs. The semantic examination of clusterings of perfective verbs based on Levin's (1993) classification of verbs revealed diverse semantic classes of these verbs. Although the clusterings of these verbs may have been based on context similarity of these perfective verbs, and therefore have similar lexical meanings, they do not seem to constitute coherent systematic lexical semantic classes.

The error analysis revealed that the RusVectores model had a bias towards corpus frequency of perfective verbs. This resulted in highly frequent verbs being placed in the right-side imperfective cluster, while low-frequency verbs were placed in the perfective left-side cluster. Verbs with higher frequency are likely to have higher similarity scores and cluster with imperfective base verbs. The error analysis also confirmed that the minor cluster consisted mostly of borrowed *-ova-* verbs including bi-aspectual verbs. These observations suggest that perfective verbs tended to cluster with their respective bi-aspectual verbs due to their context similarity as both perfective and bi-aspectual verbs would appear in similar contexts. That is, perfective *-ova-* verbs are semantically closer to their biaspectual counterparts.

For the future work, it would be relevant to assess how semantically close the members of a derivational pair are, and to explain the clusters of perfective verbs observed around the *impf* cluster. We would use similarity measures (e.g., cosine similarity) to compute how similar perfective and imperfective verbs are to each other based on their distributional representations. We could also carry out a logistic regression analysis to identify which factor(s), morphological/semantic properties or their interaction, predict(s) best the grammatical aspect of the members of the derivational pair. Cosine similarity scores, morphological properties, semantic classes could serve as input to the analysis.

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