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

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Detection of grammatical aspect in Russian

- Differentiation between perfective (PFV) and imperfective (IMPF) verbs:
  - derivational pairs
  - derivational affixes
- Distribution of derivational pairs in a vector-space model

Main Questions

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Q1

- Does morphological form contribute to distinguishing grammatical aspect in Russian?
  - derivational affixes
    - typically modify the lexical meaning of the verb stem they are added to
    - often modify argument structure of the verb stem

Q2

- How well is grammatical aspect detected by the distributional semantics model?
  - subword (morphology-based) information
  - distributional vector space
  - visualization of clustering

Outline

I. Theoretical background

- Grammatical Aspect
- Derivational pairs
- Prefixes and Suffix -Nu-
- Distributional Semantics: Methods

II. Experiment

- FastText
- Tools
- Derivational data
- Processing
- Vector space of Russian aspect
- Error analysis

III. Conclusions and future work

I. Theoretical background

Grammatical Aspect

Perfective versus Imperfective Distinction

- IMPERFECTIVE: verb *čitat'* 'read'

Ja	*čital*	*knigu*	dva	dnja.
I	read.IMPF.PST	book	two	day

'I have been reading the book for two days.'

- PERFECTIVE: verb ***pro**čitat'* 'read; read over'

Ja	***pro**čital*	*knigu*	za	dva	dnja.
I	read.PFV.PST	book	in	two	day

'I read the book in two days.'

Grammatical Aspect

Semantics: Klein (1994)

- Aspect is the relation between event and topic time
- PFV aspect
  - event time within topic/reference time
- IMPF aspect
  - topic/reference time within event time or
  - overlap with event time

Grammatical Aspect

Perfective-imperfective opposition

- Derivationally related verbs (Dahl, 1985; Filip, 1993/1999; Filip, 2000; Weimer & Seržant, 2017)
  - "derivational pairs"
  - simplex imperfective – derivationally complex perfective
- Aspectual form and affixation (Filip, 2000, 1993/1999, 2003, 2005)
  - derivational prefixes and semelfactive suffix *-nu-*
  - imperfectivizing suffix*
  - affixes as modifiers of eventuality types denoted by verbal predicates

*The suffix has multiple allomorphic realizations such as *-(o)va-*, *-v-*, etc.

Derivational Pairs: Examples

Simplex IMPF

- *kopat'* ‘to dig’

Dnem	Fedor	kopal	zemlju
day	Fedor	dig.IMPF.PST	ground

‘At daytime Fedor dug ground.’

Derived PFV

- ***za-**kopat'* ‘to dig in, bury’

Piraty	**za**kopali	klad
pirates	dig.PFV.PST	treasure

‘Pirates buried treasure.’

- ***pere-**kopat'* ‘to dig again’

Grjadki	my	**pere**kopali
garden.bed	we	dig.PFV.PST

‘We dug again garden beds.’

- *kop-**nu-**t'* to dig up’

Ja	lopatoj	kop**nul**	čto-to	zvjaknulo
I	spade	dig.PFV.PST	something	clink

‘I dug up with the spade, something clinked.’

Examples from RUSSIAN WEB 2017 (RUTENTEN17) corpus

Prefixes and the Suffix *-nu-*

Extension of lexical meaning

- *za-:* completive or inceptive meaning (i.a.)
- *pere-:* distributive or iterative meaning (i.a.)
- *-nu-*: semelfactive suffix

Change of argument structure

- *kopat' zemlju* 'to dig the ground'
- ***za**kopat' #zemlju* 'to bury #the ground'
  versus ***za**kopat' klad v zemlju* 'to bury a/the treasure into the ground'
- ***pere**kopat' #klad* 'to dig over/again #the treasure'
  versus ***pere**kopat' zemlju* 'to dig over/again the ground'

here is "uninterpretable", "odd", "unacceptable"

Distributional Semantics: Methods

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Linguistic items with similar meanings have similar distributions (Firth, 1957)

- fastText method (Bojanowski et al., 2017)
  - non-contextual (static) word embeddings unique for each word
  - word representations: internal structure of words
- t-SNE: t-Distributed Stochastic Neighbor Embedding (van der Maaten and Hinton 2008)
  - unsupervised non-linear dimensionality reduction technique for exploratory analysis
  - visualization of word embeddings generated by fastText

Distributional Semantics: Methods

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fastText

- Form similarity in addition to context similarity
- Captures lexically similar words
- Internal subword information
  - less-resourced and inflected languages

  (Finnish, Turkish, Russian, etc.)
  - suffixes and prefixes
  - out of vocabulary words
  - infrequent words

t-SNE

- Clustering method
  - clusters of similar points
- Nominal inflection, paradigm cell-filling issues in Finnish and Russian (Nikolaev et al. 2023, Chuang et al., 2023)
  - e.g. model for the conceptualization of Finnish inflected nouns

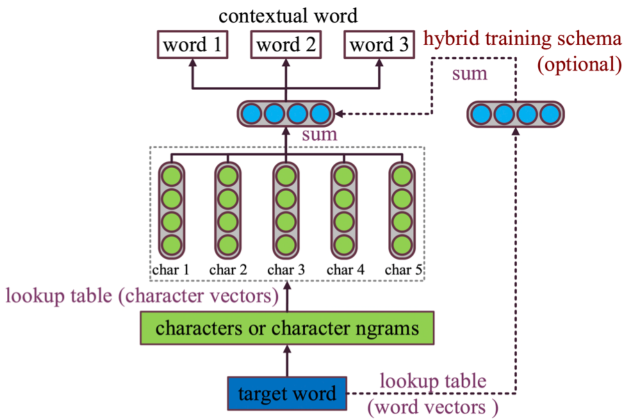
II. Experiment

FastText

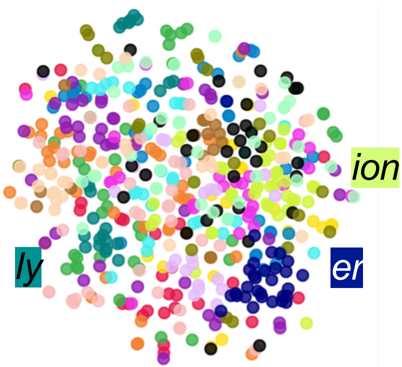
Subword-level model

- Prediction of target word from its form/context
  - word: N-gram characters (subword information)
  - context: sum of all vectors of N-gram characters
  - result: high-dimensional vector space

- T-SNE visualization
  - mapping data from high-dimensional vector space to lower-dimensional space
  - representation of datapoints in a lower-dimensional space (2D plane)
  - visual verification of predicition results via clusters



FastText model (Li et al., 2018: 40)



Cluster visualization of different English affixes by color, FastText model (Li et al., 2018: 44)

Tools

RusVectores pre-trained model (Kutuzov and Kuzmenko, 2017)

- fastText distributional model
  - Continuous Bag of Words (CBOW) architecture
  - Vocabulary size: 195,782 words
  - Vector dimension size: 300
  - Web-corpus Araneum Russicum Maximum 2018: 10 billion words
- *Gensim, sklearn* packages

Derivational Data

Resources

- Exploring Emptiness Database (Janda 2007)
- Database of Russian Verbal Aspect
  (OSLIN database; Borik and Janssen, 2012)
- Essex Database of Russian Verbs and their Nominalizations
  (Essex database; Spencer and Zaretskaya 2017)

Derivational Data

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Counts

- 4032 derivational pairs:
  - 3976 prefixes
  - 56 inst. of suffix *-nu-*
- 3986 PFV verbs
- 1766 IMPF verbs

IMPF	PFV	Affix type	Affix
вить	**с**вить	prefix	с
влажнеть	**по**влажнеть	prefix	по
возить	**от**возить	prefix	от
гаркать	гарк**ну**ть	suffix	ну
двигать	дви**ну**ть	suffix	ну+alt
дёргаться	дер**ну**ться	suffix	ну
…	…	…	…

Processing and Prediction

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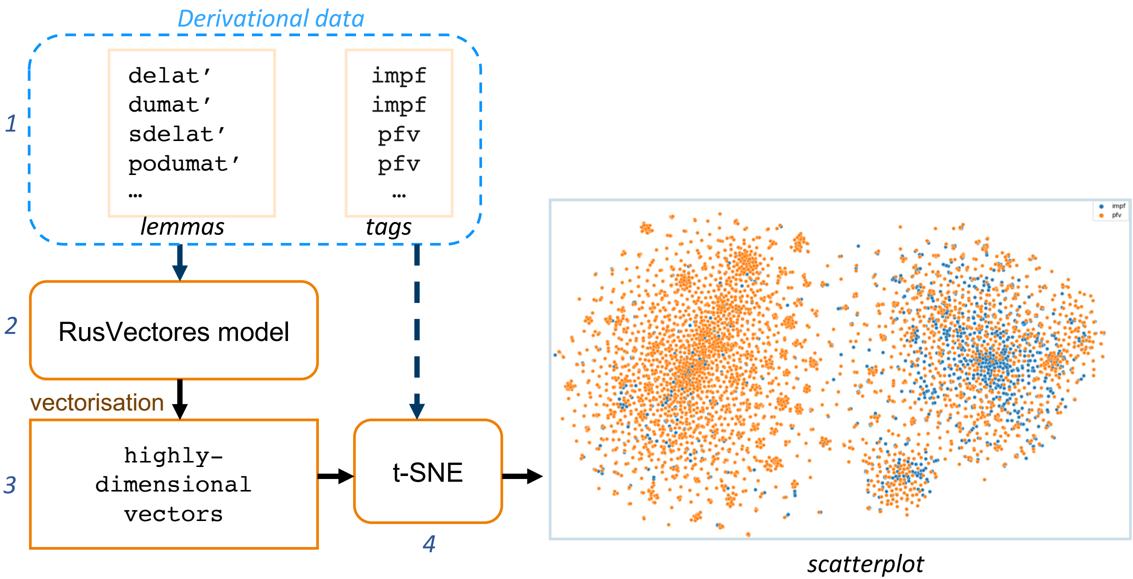

Scattered clusters: Aspect

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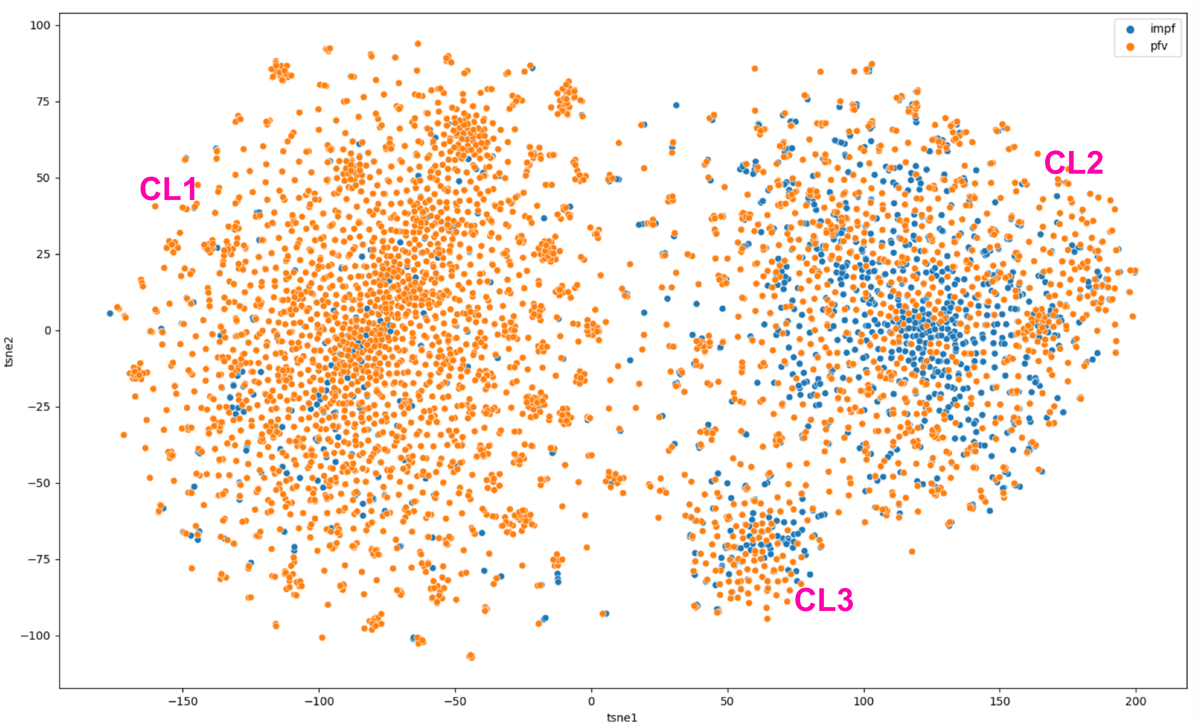
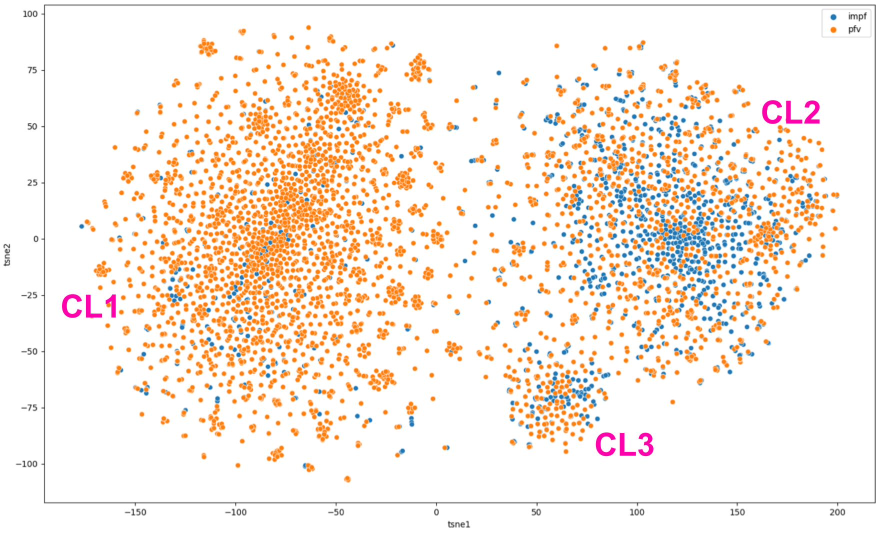
Perfective lemmas (CL1), imperfective lemmas (CL2, 3)



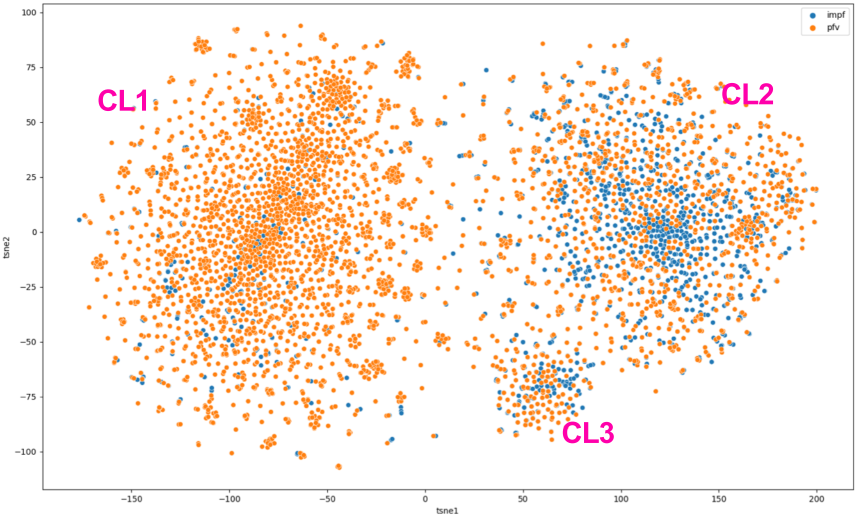
Observation: CL1 and CL2



- Clear-cut separation of PFV and IMPF verbs
  - significant similarity by morphological form

- PFV verbs that co-occur with IMPF verbs in CL2
  - e.g. ***za**molčat'* ‘to get silent’, ***po**buret'* ‘to turn brown’, *mig**nut'*** ‘to wink’

Observation: CL1, 2, 3



Lack of similarity (CL2, 3)

- by morphological form
- by verb semantics
  - (verb classes; Levin, 1993)

Diverse lexical semantic classes

- manner of speaking (*prokvakat'* 'to croak', CL1)
- measure (*sosčitat'* 'to count'; CL1)
- gestures involving body parts (*mignut'* 'to wink [once]'; CL2),
- contact by impact (*užalit'* 'to sting'; CL2)
- creation/transformation (e.g., *vygravirovat'* 'to engrave'; CL3)

Overlap of semantic classes

- psychological state (*zainteresovat'* 'to interest', *pozavidovat'* 'to envy'; CL1, 2)
- psychological state/inchoative (*obozlit'sja* 'to get angry', *obradovat'sja* 'to become glad'; CL1, 2)
- change of state (*prixvornut'* 'to get [a bit] sick', *poburet'* 'to turn brown', *otremontirovat'* 'to repair'; CL1, 2, 3)

Error Analysis

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Corpus frequency effect

- Higher frequency counts
  - higher similarity scores (Asudani et al., 2023)
  - increased model's bias to one category over another (Caliskan et al., 2022, Brunet et al., 2019)
- Araneum Russicum Maximum 2019
- Zipf transformation measure (Van Heuven et al., 2014):
  - low frequency verbs (rank 1, 2, 3)

    raw freq 4 > 1.94 > rank 2 > low freq
  - high frequency verbs (rank 4, 5, 6, 7)

    raw freq 46899 > 5.92 > rank 6 > high freq
- t-SNE clusters of frequency ranks

Biaspectual verbs, CL3

- Borrowed biaspectual *-ova-* verbs
  - function as PFV or IMPF verbs dependent on context
  - *kristallizir**ova**t'* 'to crystallize', *modelir**ova**t'* 'to model', *transkribir**ova**t'* 'to transcribe'

Scattered clusters: Frequency rank

Low-frequency PFV verbs, high-frequency PFV verbs

Error Analysis

Frequency rank bias

- High-frequency PFV verbs: IMPF cluster
  - *e.g. **raz**budit'* ‘to wake up’
- Low-frequency PFV verbs: PFV cluster
  - *e.g. **za**torcevat'* ‘to pave with wood blocks’

Error Analysis

Context similarity

- Biaspectual borrowed verbs, which are integrated into the Russian verb system with the suffix *-ova-*
  - e.g. *orientirovat'* ‘to orient(ate)’, ‘to guide’, ‘to aim’, ‘to walk s.o. through’, *kooperirovat'sja* ‘to cooperate, to partner with’
- They co-occur with derived prefixed PFV counterparts in CL3
  - e.g., ***s****orientirovat'*, ***s****kooperirovat'sja*

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III. Conclusions and future work

Conclusions

Correct prediction of Russian aspect by RusVectores model

- Morphological structure: significant criterion for determing the grammatical aspect of the verb
  - Lexical semantic classes: unsignificant criterion
- CL2: fastText model's bias to high-frequency PFV verbs
- CL3: context similarity for borrowed biaspectual *-ova-* verbs and their PFV derivates

Future work

- Cosine similarity scores using different word embedding model (e.g. contextual ELMo model)
- Identify best predictors of aspect for derivational pairs, e.g.
  - Random Forests
  - Generalized logistic regression
- Prediction of sematic relations between derived perfectives and their imperfective bases (see e.g. Bonami and Naranjo, 2023)

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Appendix

Corpus Frequency Transformation

- Frequency rank of a lemma in a corpus
  - log-transformation of raw frequencies counts
  - scaling of log-transformed frequency values
  - frequency rank of lemmas (low frequency, high frequency; van Heuven et al., 2014)

blestet' ‘shine’ (IMPF verbal lemma)
corpus frequency: 756

vypisat' ‘write down’ (PFV verbal lemma)
corpus frequency: 1019

logarithmic transformation

4.66510116

4.253130176

Frequncy Rank

Van Heuven et al. SUBTLEX-UK (2014: 1180)

Table 1. *The Zipf scale of word frequency*

Zipf value	*fpmw*	*Examples*
1	0.01	antifungal, bioengineering, farsighted, harelip, proofread
2	0.1	airstream, doorkeeper, neckwear, outsized, sunshade
3	1	beanstalk, cornerstone, dumpling, insatiable, perpetrator
4	10	dirt, fantasy, muffin, offensive, transition, widespread
5	100	basically, bedroom, drive, issues, period, spot, worse
6	1000	day, great, other, should, something, work, years
7	10,000	and, for, have, I, on, the, this, that, you

Note: The Zipf scale is a word frequency scale going from 1 to 7. Words with Zipf values of 3 or lower are low-frequency words; words with Zipf values of 4 and higher are high-frequency words. Examples are based on the SUBTLEX-UK word frequencies. fpmw = frequency per million words.

1, 2, 3 – low-frequency
4, 5, 6, 7 – high-frequency

Zipf Transformation

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```
Zipf = log10((rawFreqSmooth/(corpusSizePm + typesNbPm)) + 3.0
```

Zipf smoothing   Laplace smoothing   scaling for ipm values

Lemma	Raw Freq	Laplace smoothing	Zipf Smoothing	Scaling (+3)	Rank
бацнуть	16	17	-0,5250134	2	Low freq
выездить	64	65	0,05745064	3	Low freq
выдрессировать	1521	1522	1,42694083	4	High Freq
вызубрить	2099	2100	1,56674106	5	High Freq
выкупить	99544	99545	3,24179872	6	High Freq
…	…	…	…	…	…

Corpus examples

- PERFECTIVE: verb ***pere**čitat'* ‘reread’

Ja perečital ètu frazu raz desjat' .

I **read.**pfv.pst this phrase time ten

‘I **reread** this phrase ten times.’

- PERFECTIVE: verb ***na**čitat'* ‘read (aloud)’

Igor' načital 3 knigi Verdona.

Igor' ***read**$_{PFV.PST}$* three book Verdon

‘Igor' *has read/read three Verdon’s books.’*

Examples from RUSSIAN WEB 2017 (RUTENTEN17) corpus