Diachronic Word Embeddings for Semantic Shifts Modeling: How to Trace Changes of Meaning in Time

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AINL
Tartu, Estonia
November 20, 2019

Who I am?

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`https://www.mn.uio.no/ifi/english/people/aca/andreku/`

Contents

What is this about?

Computational Linguistics and Intellectual Technologies:
Proceedings of the International Conference "Dialogue 2019"

Moscow, May 29—June 1, 2019

TRACING CULTURAL DIACHRONIC SEMANTIC SHIFTS IN RUSSIAN USING WORD EMBEDDINGS: TEST SETS AND BASELINES

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The paper introduces manually annotated test sets for the task of tracing diachronic (temporal) semantic shifts in Russian. The two test sets are complementary in that the first one covers comparatively strong semantic changes occurring to nouns and adjectives from pre-Soviet to Soviet times, while the second one covers comparatively subtle socially and culturally de-

[Fomin et al., 2019]

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Task:

- Diachronic semantic shift detection
- Lexical semantic change detection (LSC) [Schlechtweg et al., 2019]

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- Temporal cultural and linguistic changes influence the contexts
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Task:

- Diachronic semantic shift detection
- Lexical semantic change detection (LSC) [Schlechtweg et al., 2019]

Can also be used to analyze synchronic cross-domain semantic shifts [Kutuzov and Kuzmenko, 2015].

SemEval-2020 (at COLING)

Task 1: Unsupervised Lexical Semantic Change Detection

- `https://competitions.codalab.org/competitions/20948`
    1. classification task
    2. ranking task
- German, English, Swedish, Latin

For an overview of the phases, please see the 'Phases' page.

Timeline (updated)

- Trial data ready July 31, 2019
- Test data ready ~~December 3, 2019~~ January 15, 2020
- Evaluation start ~~January 10, 2020~~ February 19, 2020
- Evaluation end ~~January 31, 2020~~ March 11, 2020
- Paper submission due ~~February 23, 2020~~ April 17, 2020
- Notification to authors ~~March 29, 2020~~ June 10, 2020
- Camera ready due ~~April 5, 2020~~ July 1, 2020
- SemEval workshop on September 13-14 (colocated with COLING)

Contents

Previous work

- Linguistics: hand-picking examples
  [Traugott and Dasher, 2001, Daniel and Dobrushina, 2016]

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  - Training models jointly across time bins
    [Bamler and Mandt, 2017, Yao et al., 2018, Rosenfeld and Erk, 2018]
  - ...

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    [Bamler and Mandt, 2017, Yao et al., 2018, Rosenfeld and Erk, 2018]
  - ...
- Distributional approaches to diachronic semantics are surveyed in

  [Kutuzov et al., 2018, Tang, 2018].

Contents

Russian datasets

What we did?

- Re-packing a dataset of long-term semantic shifts for nouns and adjectives during the Soviet period
- Dataset of short-term semantic shifts in Russian adjectives, based on news texts
- Experimenting with well-established baseline algorithms for semantic shift detection, testing them on the datasets

Russian datasets

‘Micro’ dataset

- 2000 — 2014: 15 years of Russian news texts
- 20 adjectives for each year pair (2000-2001, 2001-2002, etc...)
- selected randomly, biased towards the words chosen by the *Global Anchors* method (more details further)
- 14 year pairs $\times$ 20 words = 280 entries
- Manual annotation by 3 annotators
- 3 class labels:

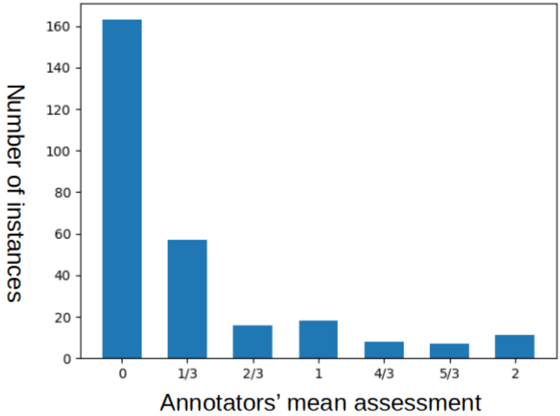
Label	**Meaning**
0	no semantic shift
1	somewhat shifted
2	significantly shifted

Russian datasets

Socio-cultural semantic shifts in adjectives in 2014, as compared to 2013 (excerpts from the 'Micro' dataset)

Class	Adjective	English translation
2	крымский	'*Crimean*'
2	приёмный	'*1) adopted; 2) something receiving*'
2	луганский	'*of Luhansk*'
1	правый	'*1) right; 2) right-wing*'
1	кипрский	'*Cyprian, Cypriot*'
0	серый	'*gray*'
0	балетный	'*of ballet*'

Russian datasets



Mean values of annotators' scores, 'Micro' dataset

Russian datasets

‘Macro’ dataset

- Originally from [Kutuzov and Kuzmenko, 2018]
- We liberated it from behind the paywall and published in a convenient form.

Russian datasets

‘Macro’ dataset

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- Semantic shifts from Pre-Soviet through Soviet times:
-

	Nouns	**Adjectives**
Target	38	5
Filler	152	20

- 2 class labels (no shift / shift)

Russian datasets

word	label	word	label
отделение	1	тюрьма	0
секция	1	влияние	0
богадельня	1	весна	0
особа	1	уверенность	0
уклон	1	красавица	0
молодец	1	жених	0
передовой	1	заказ	0

Table: Example entries from the ‘Macro’ dataset

Russian datasets

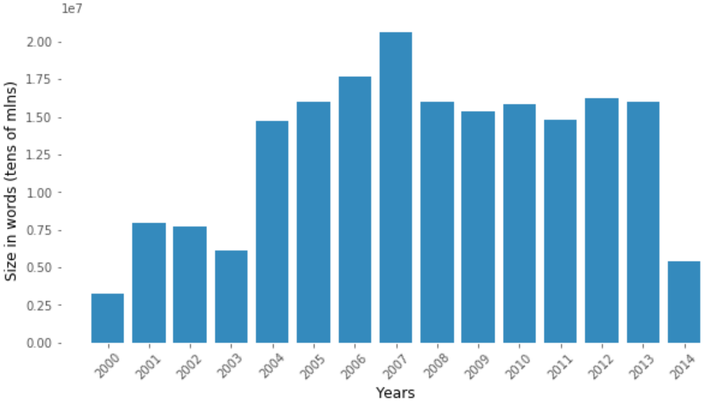
‘Micro’ corpus

- Newspaper subcorpus of RNC + lenta.ru
  - News texts produced in 2000,
  - News texts produced in 2001,
  - ...,
  - News texts produced in 2014,

‘Macro’ corpus

- Main body of RNC:
  - Texts produced before 1917 (75 millions tokens),
  - Texts produced in 1918—1990 (96 millions tokens),
  - Texts produced after 1991 (85 millions tokens)

Russian datasets



'Micro' corpora sizes per year

Contents

Distributional models for evaluation

- ‘Static’ models:
  - Model trained on time bin tb_0,
  - Model trained on time bin tb_1,
  - ...
  - Model trained on time bin tb_n
- ‘Incremental’ models
  - Model trained on time bin tb_0,
  - Model trained on time bin tb_1, initialized with tb_0 weights,
  - ...
  - Model trained on time bin tb_n, initialized with tb_{n-1} weights.

Word embeddings

Distributional models for evaluation

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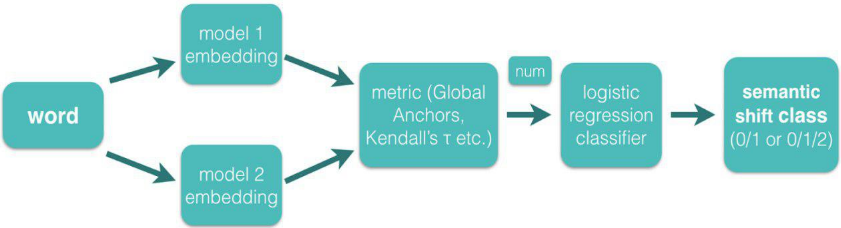
word2vec CBOW [Mikolov et al., 2013], context window = 5, vector size 300

Comparing words across embedding models



Experimental workflow

Conceptual types of methods

Local methods for semantic shift detection

Comparing words' nearest neighbors:

- Jaccard similarity [Jaccard, 1901]
- Kendall's τ [Kendall, 1948]

Global methods for semantic shift detection

Comparing words' vectors (or semantic spaces in general):

- Procrustes alignment [Hamilton et al., 2016b]
- Global Anchors [Yin et al., 2018]

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...and many more by now!

Local methods

Jaccard similarity

[Jaccard, 1901]

$$J(X, Y) = \frac{|X \cap Y|}{|X \cup Y|} \quad (1)$$

Nearest neighbors for 'вежливый':

- X = приветливый, общительный, уравновешенный, отзывчивый, добродушный
- $X + 1$ = камуфляж, неравнодушный, порядочный, здравомыслящий, незнакомый

$J(X, X + 1) = 0$

Can you guess the years for X and $X + 1$?

Kendall's τ

Takes into account the ranking of neighbors [Kendall, 1948]

$$\tau = \frac{2}{n(n-1)} \sum_{i<j} sgn(x_i - x_j)\, sgn(y_i - y_j) \tag{2}$$

Nearest neighbors for 'луганский' ($x = 2013, y = 2014$):

x_1: иркутский → y_1: донецкий

… → …

x_7: донецкий → y_{17}: иркутский

Local methods

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... $\longrightarrow$ ...

x_7: донецкий $\qquad$ y_{17}: иркутский

Local Neighborhood Distance: calculate similarity between cosine similarities of nearest neighbors [Hamilton et al., 2016a].

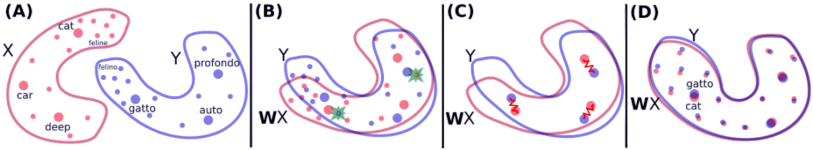
Orthogonal Procrustes Analysis

First, we ‘align’ two models:
Given embedding matrices A and B, find an orthogonal matrix R that maps A to B [Hamilton et al., 2016b].

$$B^T A = M$$

$$M = U \Sigma V^T$$

$$R = UV^T$$



Global methods

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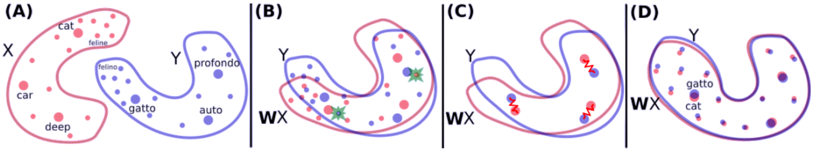

Then, simple cosine similarity between $word^A$ and $word^B$ is calculated

Global Anchors

[Yin et al., 2018]

Semantic shift of word *w* from year *x* to year *y*:

$$similarities_x = (x_1, ..., x_n)$$

$$similarities_y = (y_1, ..., y_n)$$

- x_i and y_i are cosine similarities between the word *w* and the i^{th} word in the intersection of *x* and *y* vocabularies.

Global methods

Global Anchors

[Yin et al., 2018]

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- x_i and y_i are cosine similarities between the word *w* and the ith word in the intersection of *x* and *y* vocabularies.
- We compare global positions of *w* in the semantic space.
- Semantic similarity between different time periods = $cos(similarities_x, similarities_y)$
- No explicit alignment needed.

Contents

Baseline results for Russian

'Macro' dataset (pre-Soviet to post-Soviet)

Models	Glob.Anchors	Procrustes	Kendall	Jaccard	combined
Separate	0.675	**0.767**	0.504	0.646	0.722
Incremental	0.598	0.681	0.475	0.576	0.617
Random choice					
$\approx$ 0.5					

- Global methods work better
- Local methods are still applicable
- Procrustes analysis is clearly the best
- Incremental models are worse than separate.

Baseline results for Russian

‘Micro’ dataset (2000-2014)

Models	Glob.Anchors	Procrustes	Kendall	Jaccard	combined
Separate	0.453	0.468	0.136	0.301	**0.503**
Incremental	0.462	0.459	0.194	0.326	0.442
Random choice					
≈ 0.33					

- Global methods clearly win on granular timespans
- Local methods sometimes worse than random
- Combining methods is a good idea
- Still no (significant) profit from incremental models
- Great results from Procrustes: in line with [Schlechtweg et al., 2019]

Baseline results for Russian

Please re-use:

- Two manually annotated datasets with diachronic semantic shifts for Russian:
  - A short-term 'Micro' dataset, scale = years (adjectives only)
  - A long-term 'Macro' dataset, scale = centuries (nouns and adjectives)
- Datasets and baseline implementations:

`https://github.com/wadimiusz/diachrony_for_russian`

Contents

Recent ideas

Temporal referencing

- Time labels as tags [Dubossarsky et al., 2019]
- When training, each target word is replaced with a time-specific token:
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Recent ideas

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Contradicting reports: [Schlechtweg et al., 2019] say it fails on German data.

Recent ideas

What else can be done?

- Semantic shifts are related to word senses

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- [Giulianelli, 2019] tries to compare clusters of BERT embeddings for word occurrences across the Corpus of Historical American English (COHA).
- We did the same with ELMo top layer representations.
- Variation coefficient: mean cosine distance between all embeddings of a word occurrences in a corpus and their average (centroid).

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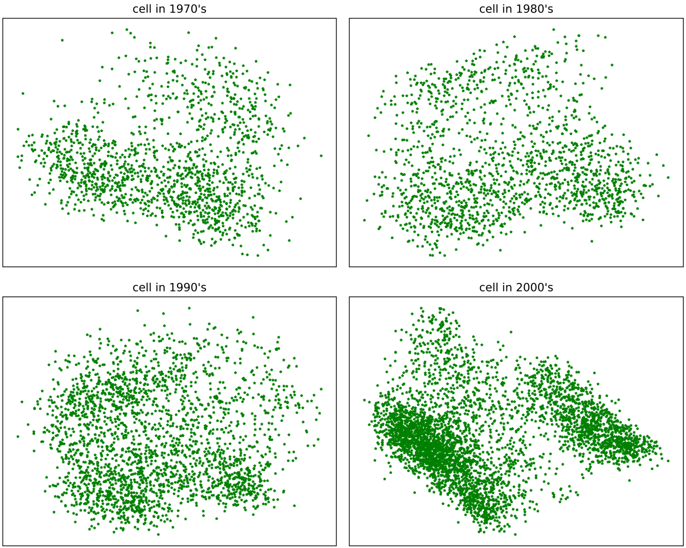
NB: '*dispersion measures are strongly influenced by frequency and very sensitive to different corpus sizes*' [Schlechtweg et al., 2019]

Recent ideas



ELMo representations of each occurrence of the word *'cell'* in 4 decades: actual semantic shift. Diversity significantly increased in 2000s.

Old senses

Prison cell

1. '...the chief turnkey on duty, for over ten years, but you wouldn't have known it from the way he processed me for the cells.'
2. 'It also happened to me in a jail cell, Peb.'
3. 'If she had been writing to somebody in the darkness of her prison cell, what had she done with the message?'

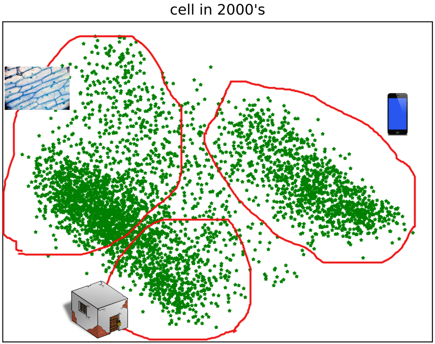
Biological cell

1. 'The sexual cells of Pyronema show this in ascomycetes.'
2. '...how a cell decides whether it becomes a muscle cell or...'
3. 'If those cells are found to be cancerous after being sent to a lab...'

A new sense

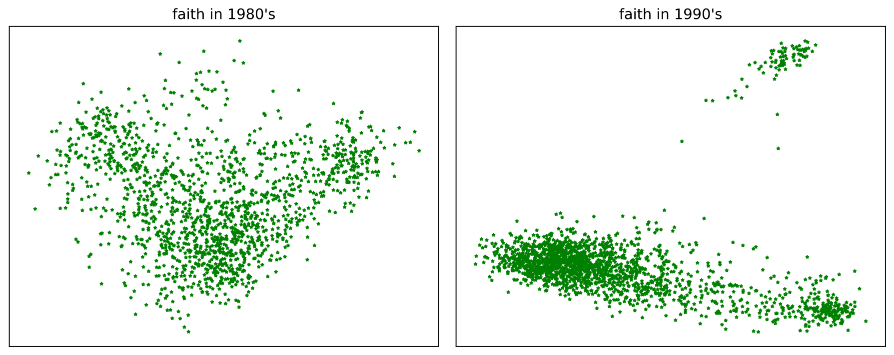
Cell phone (2000s only)

1. '...service providers fulfill that objective, and what about the other health and safety risks... that the growing use of cell phones raise?'
2. 'Gilles swatted Adriana on the upper arm... nearly dislodging the cell phone she had balanced between her chin and her left shoulder.'
3. 'You still have the same cell number.'



Bad example

But...



ELMo representations of each occurrence of the word ‘faith’ in 2 decades: diversity also significantly increased. WTF?

Recent ideas

Sentences from the new cluster:

1. ‘Maybe we could - - 64 -   *FAITH* (waving down a cab) Thank you, but this is a personal matter.’
2. ‘ *FAITH* (nodding) Like a detective.’
3. ‘Perhaps you misunderstood ?   *FAITH* (trying not to panic) Are you absolutely sure he’s gone? Maybe you made a mistake.’

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- Script of the 1994 movie 'Only You', where 'FAITH' is one of the main characters!
- Often accompanied by parentheses and non-breaking space ( ).
- Contextualized representations heavily influenced by surface forms and punctuation.
- False flag!

Empirical results (correlations)

Model	Pearson ρ	Spearman ρ
Topic modeling (Bayesian) methods		
SCAN [Fermann and Lapata, 2016]	-	**0.377**
Frozen BERT [Giulianelli, 2019]		
Mean distance	0.224	0.293
Jensen-Shannon distance	0.231	0.224
Incremental ELMo models (ours)		
Variation coefficients	**0.233**	0.285

- Human-annotated dataset from [Gulordava and Baroni, 2011] (English shifts between the 1960s and the 1990s).
- ELMo models trained on the COHA subcorpora.
- [Frermann and Lapata, 2016] trained on the DATE corpus.

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Thanks! Questions?

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- Clone the code to detect similarity between words in two different models:
  - `https://github.com/wadimiusz/diachrony_for_russian`
- Calculate change scores for all words in the models' vocabularies (`model.wv.vocab`).
- Submit your top-changed words as pull requests to the same *Github* repository.

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