Tracing cultural diachronic semantic shifts in Russian using word embeddings: test sets and baselines

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Introduction

TL:DR

- Word meaning ≈ word contexts [Firth, 1957]
- Changes in contexts ≈ changes in meaning
  - a.k.a. semantic shifts.

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- Word meaning ≈ word contexts [Firth, 1957]
- Changes in contexts ≈ changes in meaning
  - a.k.a. semantic shifts.
- Cultural changes influence the contexts
- Studies in automatic tracing of semantic shifts for Russian require publicly available datasets and strong baselines.
- We provide those.

Introduction

Contributions

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

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Previous work

- Hand-picking examples
  [Traugott and Dasher, 2001, Daniel and Dobrushina, 2016]

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  - Training models incrementally [Kim et al., 2014]

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- Various algorithms of semantic shift tracing using word embeddings:
  - Training models incrementally [Kim et al., 2014]
  - Training models separately for each time bin:
    - Comparing distances between a given word and all others (second-rank similarity) [Yin et al., 2018]
    - Aligning embedding spaces [Hamilton et al., 2016]

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    - Comparing distances between a given word and all others (second-rank similarity) [Yin et al., 2018]
    - Aligning embedding spaces [Hamilton et al., 2016]
  - Training models jointly across time bins
    [Bamler and Mandt, 2017, Yao et al., 2018]

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Our 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

Our 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'*

Our datasets

Examples of words labeled as 2 in the 'Micro' dataset

Years	Adjective	English translation
2000—2001	македонский	'*Macedonian*'
2006—2007	несогласный	'*Dissident*'
2008—2009	свиной	'*Swine*'
2009—2010	греческий	'*Greek*'
2011—2012	координационный	'*Coordinating*'

Our datasets

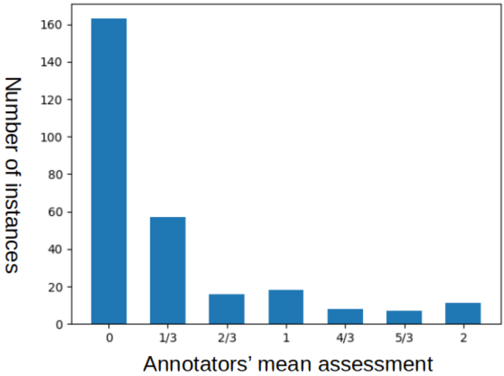

Figure: Mean values of annotators' scores, 'Micro' dataset

Our datasets

'Macro' dataset

- Originally from [Kutuzov and Kuzmenko, 2018]
- We publish it in a machine-readable form.
- Changes from Pre-Soviet through Soviet times
-

	Nouns	Adjectives
Target	38	5
Filler	152	20

- 2 class labels (no shift / shift)

Our 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

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Our corpora

The corpora we used correspond to the datasets.

‘Micro’ dataset

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

‘Macro’ dataset

- 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)

Our corpora

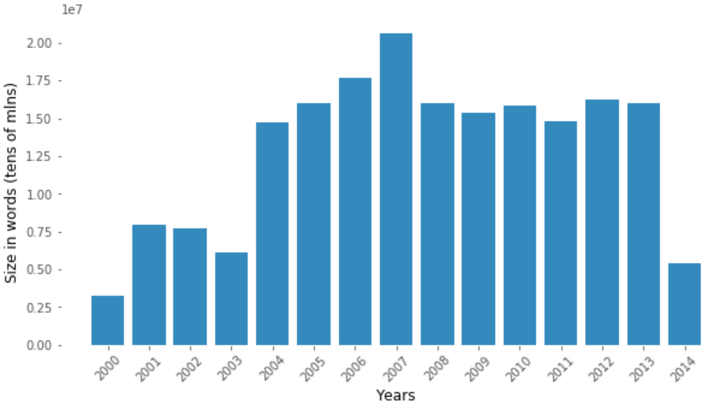

Figure: 'Micro' corpora sizes per year

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Word embeddings

Distributional models for baselines 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.

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

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Baseline results

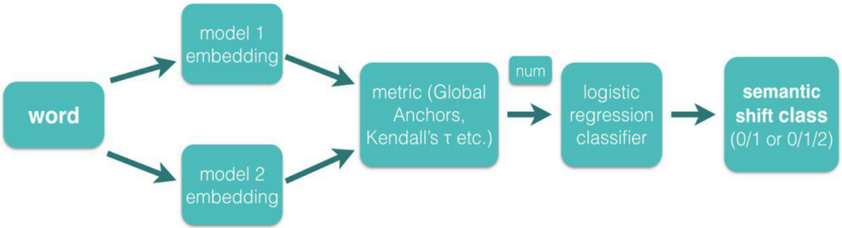


Figure: Experimental workflow

Baseline results

Local methods for semantic shift detection

Comparing words' nearest neigbors:

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

Global methods for semantic shift detection

Comparing overall structure of semantic spaces:

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

Baseline results

Kendall's τ

[Kendall, 1948]

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

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

x_1: иркутский → y_1: донецкий

…   …

x_7: донецкий y_{17}: иркутский

Baseline results

Jaccard distance

[Jaccard, 1901]

$$J(X, Y) = \frac{|X \cap Y|}{|X \cup Y|} \quad (2)$$

Nearest neighbors for ‘вежливый’:
X = приветливый, общительный, уравновешенный, отзывчивый, добродушный
Y = камуфляж, неравнодушный, порядочный, здравомыслящий, незнакомый

Can you guess the years for X and Y?

Baseline results

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 word *w* and i^th word in vocabulary in the years *x* and *y*
- We compare global positions of *w* in the semantic space.
- Semantic similarity between different time periods = $cos(similarities_x, similarities_y)$

Baseline results

Orthogonal Procrustes Analysis

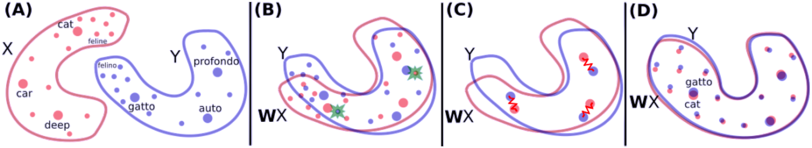
[Hamilton et al., 2016]

Given embedding matrices A and B, find an orthogonal matrix R that maps A to B.

$$B^T A = M$$

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

$$R = UV^T$$



Baseline results

Macro F1 scores, ‘Macro’ dataset

Models	Glob.Anchors	Procrustes	Kendall	Jaccard	combined
Static	0.675	**0.767**	0.504	0.646	0.722
Incremental	0.598	0.681	0.475	0.576	0.617
Random choice					
≈ 0.5					

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

Baseline results

Macro F1 scores, 'Micro' dataset

Models	Glob.Anchors	Procrustes	Kendall	Jaccard	combined
Static	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 guessing
- Combining methods is a good idea
- Still no (significant) profit from incremental models

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  - A short-term 'Micro' dataset, scale = years
  - A long-term 'Macro' dataset, scale = centuries
- Evaluating 4 algorithms, 2 of which have never been tested on Russian data

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- Evaluating 4 algorithms, 2 of which have never been tested on Russian data
- Providing solid ground for further studies.

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- Please outperform our baselines! :-)

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- Evaluating 4 algorithms, 2 of which have never been tested on Russian data
- Providing solid ground for further studies.
- Please outperform our baselines! :-)
- Datasets and code available:

https://github.com/wadimiusz/diachrony_for_russian

Conclusion

Future work

- Looking into word features

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- Looking into word features
- Using models with continuous time variables
  [Rosenfeld and Erk, 2018]

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- Contextualized word embeddings [Peters et al., 2018]

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Future work

- Looking into word features
- Using models with continuous time variables [Rosenfeld and Erk, 2018]
- Contextualized word embeddings [Peters et al., 2018]
- Sense-aware semantic shifts detection

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