Arbitrariness of Linguistic Sign Questioned: Correlation between Word Form and Meaning in Russian

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Introduction

Since Ferdinand de Saussure, we know that the linguistic sign is arbitrary:
▶ any meaning can be conveyed by any sequence of sounds or characters;
▶ form and semantics are not related.

Image from https://seminalthought.blogspot.ru/
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There are exceptions from this law:

- Onomatopoeia (imitating the sound with the word form);
- ‘мяукать’
- Phonaesthemes (parts of words with consistently linked form and meaning):
  - ‘gl-’ related to vision and light in English [Bergen, 2004];
  - ‘-стр-’ related to quickness or streaming in Russian [Mikhalev, 2008];
- etc...

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<tr>
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<td>但...</td>
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- the strength of this correlation shows how systematic is the vocabulary we deal with;

Findings for Russian

- We analyzed the link between the graphic forms and meanings of frequent monosyllabic Russian nouns;
- There is a strongly statistically significant systematicity in this data;
- The correlation is even higher than the one reported in similar experiments for English.
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Some previous work

- The form space and meaning in English were shown to be related in [Monaghan et al., 2014];
- Indeed, there are regions in the lexicon, where the arbitrariness principle is violated;
- [Gutierrez et al., 2016] further proved this with modern word embedding models and kernel regression (best paper award at ACL-2016);
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- The problem was studied in [Zhuravlev, 1991] and other works of the same author;
- The results were unstable, hardly verifiable and generally disputable.

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Data sources

4 test sets were produced from the Russian National Corpus (RNC):

1. Mono: all monosyllabic nouns with frequency > 100 (1,729 words);
2. Bi: monosyllabic and bisyllabic words with frequency > 1,000 (2,900 words);
3. Bi_NoDim: the same as Bi, w/o the nouns ending with the diminutive suffixes ‘-ок’, ‘-ек’ and ‘-ка’; (2,633 words);
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- For **orthographic differences**, the edit distance is enough;

Continuous Skipgram model [Mikolov et al., 2013] was trained on the lemmatized and PoS-tagged RNC:

- vector size 300;
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- other hyperparameters set as default.
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Measuring correlation

**Workflow**

1. calculate pairwise orthographic and semantic distances between words;

   - **Semantic distance**: $1 - \text{CosSim}$, where $\text{CosSim} = 0$ if $\text{CosSim} < 0$ (the distance is always within $[0...1]$)

   - for $n$ words, the number of pairs is $n \times (n - 1) / 2$:
     - **Mono**: 1,493,856 distances
     - **Bi_NoDim**: 3.5 million distances
     - **Bi**: 4 million distances
     - **All**: 22.5 million distances

2. for each dataset, produce 2 sets of distances (edit and cosine):
   - **Edit** ($квас, пас$) = 2
   - **Cosine** ($квас, пас$) = 0.89

3. calculate Spearman rank correlation ($\rho$) between these 2 sets;

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NB: the distances are skewed to the right and not normally distributed:

Distribution of pairwise cosine distances in the All dataset
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Testing significance

Pairwise distances are not independent: changing one character in a word will change several distances, not one; Spearman correlation must be additionally tested for significance; we use Mantel permutation test [Mantel, 1967].

Mantel test randomly shuffles the values in one of the two sets; does it $x$ times; $x$ correlation values are computed for $x$ 'possible lexicons'.

How many random lexicons produced higher correlation than the real one?

If the real data does contain systematicity, the random lexicons will very rarely exhibit the same.
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Our results: Mantel test with 1 000 random permutations

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<tr>
<th>Dataset</th>
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<tbody>
<tr>
<td>Mono</td>
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Correlations between edit distances and semantic distances
▶ $p = 0.001$ means that none of the 1 000 random lexicons exhibited correlation more or equal to the real one.
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Localizing systematicity

Why this highly significant correlation is so low?

We split the Mono dataset into subsets corresponding to the initial two-character sequences (arguably, phonaesthemes):

- nouns starting with 'ст-',
- nouns starting with 'ха-',
- etc...

This gave us 321 subsets.

Filtered out:

- 159 subsets containing less than 3 nouns;
- 18 subsets with no variance in pairwise edit distances (for example, all distances equal to 1).

144 'valid subsets' in the end: calculated correlations separately for each of them.
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In many cases, the correlation $\rho$ was high, but not statistically significant;

For example, 'тв-\subset' ('тварь', 'твердь', 'твист'); $\rho = 1$,

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This is especially true for negative correlations (difficult to interpret anyway).

Can we prove this is not a simple fluctuation?

Comparison with randomly generated subsets of comparable sizes:

- Random subsets follow normal distribution of correlations, concentrate around zero, no outliers;
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Top subsets by the correlation $\rho (\rho < 0.05)$:
## Localizing systematicity

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<th>$\rho$</th>
<th>$p$</th>
<th>Subset size</th>
<th>Examples</th>
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<tbody>
<tr>
<td>ха-</td>
<td>0.57</td>
<td>0.011</td>
<td>9</td>
<td>хай, хам, харч, хадж...</td>
</tr>
<tr>
<td>дж-</td>
<td>0.43</td>
<td>0.047</td>
<td>7</td>
<td>джей, джим, джин...</td>
</tr>
<tr>
<td>ше-</td>
<td>0.39</td>
<td>0.015</td>
<td>9</td>
<td>шелк, шерсть, шейх, шельф...</td>
</tr>
<tr>
<td>фо-</td>
<td>0.35</td>
<td>0.019</td>
<td>9</td>
<td>фон, фонд, фок, форс...</td>
</tr>
<tr>
<td>ва-</td>
<td>0.33</td>
<td>0.017</td>
<td>10</td>
<td>вал, вальс, вар, вамп...</td>
</tr>
<tr>
<td>ло-</td>
<td>0.32</td>
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<td>лесть, лещ, лед, лев...</td>
</tr>
<tr>
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<td>0.26</td>
<td>0.029</td>
<td>16</td>
<td>кайф, казнь, кадр, кант, кат...</td>
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- the principle of the **arbitrariness of linguistic sign in general still holds**;
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▸ the principle of the *arbitrariness of linguistic sign in general still holds*;

▸ however, there are *regular exceptions*, manifested throughout the lexicon;
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- the principle of the arbitrariness of linguistic sign in general still holds;
- however, there are regular exceptions, manifested throughout the lexicon;
- most of the correlations can probably be explained with rigorous diachronic research:
  - words in the pairs can be cognates, etc..
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- the principle of the **arbitrariness of linguistic sign in general still holds**;
- however, there are **regular exceptions**, manifested throughout the lexicon;
- most of the correlations can probably be explained with rigorous diachronic research:
  - words in the pairs can be cognates, etc..
- still, these ‘**pockets of sound symbolism**’ [Gutierrez et al., 2016] deserve a deeper analysis.
Instead of conclusion

- Graphic form and semantics of Russian nouns do correlate in the present state of language.
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The datasets and calculated pairwise distances:
http://ltr.uio.no/~andreku/arbitrariness/
Arbitrariness of Linguistic Sign Questioned: Correlation between Word Form and Meaning in Russian

Thank you for your attention! Questions are welcome.

Andrey Kutuzov
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Dialogue’17

May 31, Moscow, Russia


