#### New Method of Automated Terminology Extraction: Case Study of Russian-language Textbooks

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## Traditional statistical approach

Two corpora are employed:

- the target corpus from which the terminology is extracted,
- the reference corpus, normally the national corpus of the relevant language.

# Disadvantages of traditional approach:

- it does not extract low-frequency terms,
- it results in a list of terms ordered by frequency, but does not provide a comprehensive image of the terminological system these terms belong to,
- the resulting lists of term-candidates are plagued with infrequent lexical units which are for some reason widely represented in the target corpus under consideration.

## Modern trends

- Context holds crucial information about the semantics of the word.
- Measure of specific lexemes' semantic proximity is calculated as the probability of their co-occurrence within a certain distance of each other.

## Research corpus of textbooks in Russian

- 212 items in 21 subjects; 14,370,000 words.
- By discipline: algebra 18 textbooks; astronomy 2 textbooks; **biology**-21 textbooks; **chemistry**-13 textbooks; **computer science**-6 textbooks; **crafts**-4 textbooks; **fine** arts-8 textbooks; geography-8 textbooks; geometry-8 textbooks; **law**-2 text- books; **literature**-36 textbooks; mathematical analysis – 14 textbooks; mathematics – 10 textbooks; **music**-4 textbooks; **natural science**-2 textbooks; **physical education**-7 textbooks; **physics**-15 textbooks; **Russian**-4 textbooks; **social studies**-12 textbooks; world art culture – 2 textbooks; world history and Russian history – 17 textbooks.

### Automatic Terminology Extraction

- Reference corpus—Russian Web 2011 Sample (*ruTenTen11*), 900 millions of words.
- Different selection principles for individual words (*keywords* in Sketch Engine) and multi-word expressions (*terms* in Sketch Engine).

## Automatic Terminology Extraction: Keywords Score

((Lt \* 1,000,000 / Ct) +1) / ((Lr \* 1,000,000 / Cr) +1),

where

Lt is the frequency of the lexical unit in the focus corpus,

Ct is the total number of tokens in the focus corpus,

Lr is the frequency of the lexical unit in the reference corpus,

Cr is the total number of tokens in the reference corpus.

## Automatic Terminology Extraction: Terms Score

**14 + log(2(|X∩Y|) / (|X| + |Y|))**,

where

**|X|** is the absolute frequency of the first element of the combination in the focus corpus,

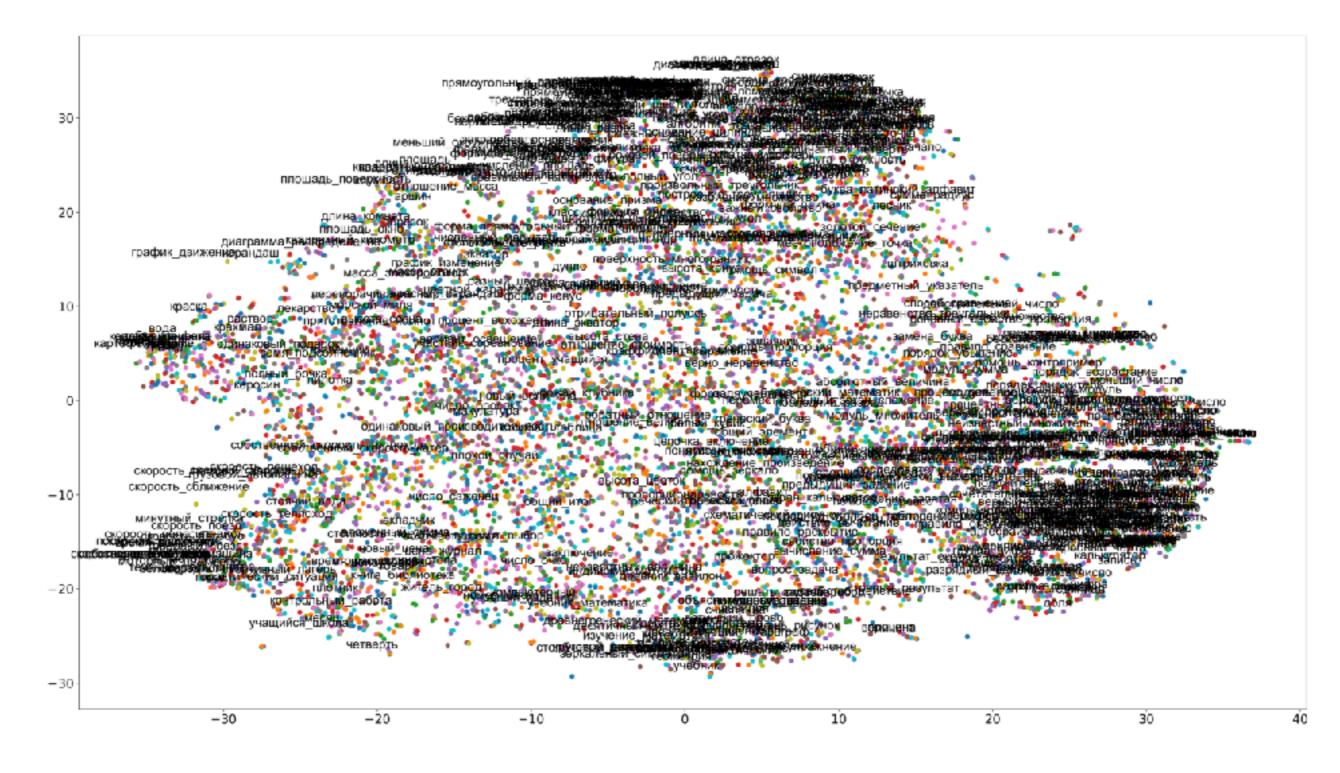
**Y** is the absolute frequency of the second element of the combination in the focus corpus,

 $|X \cap Y|$  is the absolute frequency of the whole combination in the focus corpus.

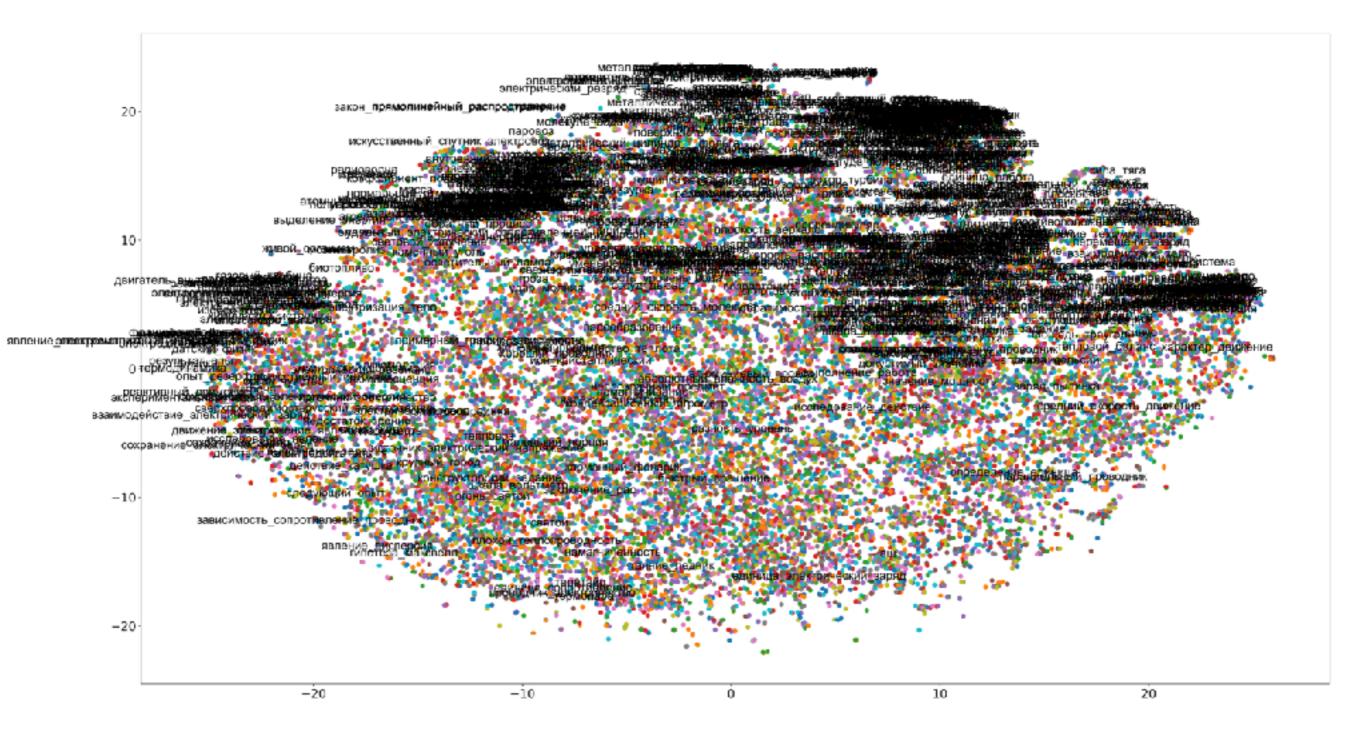
### Automatic Terminology Extraction: Word Embedding Models

- Target corpus was vectorised.
- Word-embedding models were trained for each area of knowledge.
- Maps reflecting the relative position of term-candidates in the obtained models were created and projected from a high-dimensional vector space into a two-dimensional plane using the t-distributed stochastic neighbour embedding (t-SNE) method.

#### Automatic Terminology Extraction: t-SNE space visualisation



#### Automatic Terminology Extraction: t-SNE space visualisation



### Automatic Terminology Extraction: Clustering

Clusters labelling was based on the following factors:

- the proportion of lexemes that occur within a cluster both as separate units and as part of word combinations (the hypothesis was that terminological clusters are characterised by a higher degree of repetition than nonterminological clusters),
- the proportion of multi-word combinations within a cluster (the hypothesis was that the number of multi-word units is higher in terminological clusters because automatic extraction of multi-word terms demonstrates a higher level of accuracy than extraction of individual terms).

Based on these factors, one common metric with a value for each cluster varying from 1 to 7200 was calculated. A value of 1 indicates that term-candidates in this cluster are highly likely to be terms. A value of 7200 indicates that term-candidates in this cluster are highly likely to be false terms.