Evaluation of Twitter as semantic analysis resource

Abstract

In this paper we evaluate the use of Russian-speaking Twitter segment as a resource for distributional semantic analysis. Though gold-standard for task of semantic relatedness of Russian language does not yet exist, some tweaks may be done to substitute it. There are several gold-standards for English, German and other languages. We translate WordSim353 and evaluate it against two corpora - the one of Twitter stream and corpus made of contemporary Russian literature.

1 Introduction

One of the vital goals in task of distributional semantics of Russian language is building a gold-standard, analogous to WordSim353 (Finkelstein et al., 2001), ZG222 (Zesch and Gurevych, 2006) and others. Such datasets are composed with use of expert knowledge. At first, researcher composes pairs of words, either related somehow (meronymy, hyponymy, hyperonymy, antonymy, etc.), or unrelated. Next, a group of individual experts are given the task to estimate relatedness of those pairs. Estimations may vary, e.g. four distinct grades, or fraction from 0.0 to 1.0. Typical group size is about 10-15 people.

Apparently, researchers wanting to make such datasets for other languages may try to use existing ones as basis, e.g. by simply translating them, because reengineering it from scratch would be much more complicated. Some did try, but as far as we know there was no proper evaluation of translated word-sim datasets.

Semantic analysis was under study for decades, starting with Latent Semantic Analysis (Landauer et al., 1998), Latent Semantic Indexing, finally Explicit Semantic Analysis (Gabrilovich and Markovitch, 2007), and numerous Wordnet and Wikipedia-based works (Zesch et al., 2008).

Early models, like LSA, worked well on smaller dataset, compared to those we have nowadays. Tremendous shift in efficient vector-space models estimation was made by (Mikolov et al., 2013), with use of simplified neural network models, Continuous Bag-of-Words and Continuous Skip-gram. It was evaluated on word-similarity task.

On the other hand, increasing popularity of social networks, and in particular Twitter, enables users to communicate instantly, and researchers to analyse their activity. The area is "hot ground", there are works such as elections prediction (Metaxas et al., 2011), sentiment analysis and so on.

1.1 Goals of this paper

In this paper we focus on word-to-word similarity task for Russian language. The primary goal is to evaluate applicability of Twitter stream in this NLP task. The secondary goals are construction and validation of word similarity dataset for Russian based on WordSim353 translated subset, and cross-checking it with corpus of Russian literature.

Alias	Word count	ρ_P
`01`	1.2M	0.25
`01_10`	12.5M	0.27
`01_20`	22.5M	0.28
`books`	450K	0.31

Table 1: Corpus under study. (Here ρ_P is Pearson correlation with WordSim)

2 Input data and algorithm

2.1 Input data

Twitter data is mined from Twitter streaming API[1]. It is assumed to be random subset of actual Twitter stream.

Big picture of algorithm:

- fetch tweets
- filter non-Cyrillic ones
- stemming (each tweet as one sentence)
- remove stopwords
- store words in database.

All fetched data is stored in daily chunks, $\approx$ 450k Tweets per day.

We detect Russian words by simply counting cyrillic symbols. We use Yandex Tomita Parser[2] for stemming.

Algorithm for parsing books slightly differs: it splits continuous text by sentence.

2.2 Counting distributions

The word distribution matrix has word-by-word structure. Each row is frequency distribution of word context. Every cell X in row Y describes number of sentences with both x and y.

Each cell in matrix is then weighted with entropy: $-\sum p \log p$, as stated by (Landauer et al., 1998).

Semantic relatedness is computed as cosine similarity between word distributions (which is common for such task). We will use notation where 0.0 is no similarity, and 10.0 is identically similar, as in WordSim353.

[1] https://dev.twitter.com/streaming/overview

[2] https://tech.yandex.ru/tomita/

3 Evaluation

Common approach for evaluation of word semantic relatedness is to use several datasets (3-4 typically). Since we want to evaluate if translated one is worthwhile, it's enough to translate just one. We make an assumption that bias of translation would be more significant than the one of a dataset.

3.1 Method of translation

First of all, we consider only 2000 most frequent words in our Twitter corpus. We make list of words from WordSim353 combined set. For each word we manually lookup translation with dictionary [3] and write down short-list of possible translations. If translation is not present in 2000 list, we remove it. Empty translation lists are removed. Pairs from WordSim with partial or none translation are also removed.

Still we managed to translate roughly 250 words out of 450, giving us 100 translated pairs. This is the baseline for all our subsequent experiments.

3.2 Twitter corpus

Twitter corpus under study consists of 20 chunks since 1 to 20 August, 2014, one chunk per day. Each chunk contains $\approx 1.3M$ words. We also consider joined chunks, namely `01_10`, `11_20` containing 10 days each, and `01_20` containing entire corpus. We use Pearson correlation coefficient to estimate accuracy of our method.

4 Experimental results

First measurements of Pearson correlation for single-day chunk, without using stopwords, showed as low as 0.20, in contrast with 0.6 being state-of-the-art accuracy for this task (Mikolov et al., 2013).

This low accuracy may be in result of following factors:

- errors in translation
- algorithm issues
- corpus quality

[3] slovari.yandex.ru

#	Pair		Δbooks	Δ01_10
1	psychology (психолог)	depression (депрессия)	6.25	-0.14
	psychology (психология)		5.32	1.48
2	precedent (случай)	group (группа)	-3.13	-7.11
	precedent (прецедент)		0.04	-2.55
3	network (сеть)	hardware (техника)	7.21	0.35
		hardware (оборудование)	5.10	1.77

Table 2: Translation errors. (Here: $\Delta\texttt{books} = m_{WordSim353} - m_{\texttt{books}}$, $\Delta\texttt{01\_10} = m_{WordSim353} - m_{\texttt{01\_10}}$)

- size of corpus

Usage of stopwords helped us to make 0.25.

Next obvious step was to determine if we can improve accuracy with just more data.

It gave us another 2-3% (Table 1), with 20 times larger corpus. Apparently, enlarging it further doesn't make much sense.

Still we had to mitigate possible translation issues and corpus-related ones.

4.1 Russian literature corpus

To overcome translation issues we mined different corpus, using publicly available words of Russian contemporary authors (late 20th century - beginning of 21th, for list of them see Appendix A). In this paper we address it `books`.

Size of corpus was chosen empirically: we stopped adding texts when no significant improvement in accuracy could be noticed.

It's top was around 0.30, which is slightly better than `01_20`, and much better than `01`.

Inter-correlation between `01_20` and `books` appeared to be 0.63 (on the set of pairs from translated WordSim). Hence Twitter may be used as linguistic resource (as far as literature may).

On the other side, considering that `books` is 50 times smaller than `01_20`, it's closest contestant with 0.28 accuracy, one may conclude that literature is more information-dense linguistic resource. Which is not surprising.

4.2 Language issues

In order to validate our word translations, we count errors for estimated relatedness values. Some of them can be seen at Table 2 (translation comes in parenthesis). This table helps to get the picture of how translation influences the error of relatedness estimation.

The first row for each WordSim pair comes with original translation, and second row is for adjusted translation.

"Psychology" was originally translated as "psychologist", the *occupation*, not the *science*, "hardware" — as general "technics", and "precedent" as "case", rather than, literally, precedent.

After adjusting translation for these three words, we measured accuracy again, and saw significant shift. Firstly, $\rho_{\texttt{books}}$ jumped to 0.39, but somehow $\rho_{\texttt{01\_20}}$ bumped down to 0.23. `books` and `01_20` correlation also declined to 0.51.

Such big shift in just 12 out of 100 pairs (these words occur in 12 wordsim pairs) tells us that our translated version of WordSim isn't robust enough, and a posteriori tweaks are dangerous, because outcome can be easily manipulated.

For this reason correlation with translated WordSim cannot be compared with state-of-the-art values.

4.3 Corpus issues

Another interesting observation deals with over- and under-estimation of semantic relatedness.

Let the value of word pair relatedness be *underestimated* if its standard value is more than 3 points higher, than generated by algorithm, and *overestimated* if it is more than 3 points lower.

It turns out that `books` underestimate value in 45% cases, and never overestimate; `01_10` overestimate value in 35% cases, and never underestimate.

They both give large estimation error in only 2% cases, i.e. they guess wrong in different

#	**Pair**		Relatedness estimation
1	Maidan (майдан)	Ukraine (украина)	8.70
2	Maidan (майдан)	people (народ)	8.58
3	Maidan (майдан)	war (война)	8.58
1	iPhone (айфон)	telephone (телефон)	7.63
2	iPhone (айфон)	computer (комп)	7.17
3	iPhone (айфон)	internet (интернет)	7.09
1	internet (интернет)	work (работать)	8.44
2	internet (интернет)	problem (проблема)	8.41
3	internet (интернет)	inet (инет)	8.36

Table 3: Terms defined by Twitter corpus

cases. Hence their estimations can be combined to improve accuracy:

$m_{combo} = (m_{\texttt{books}} + m_{\texttt{01\_10}})/2$

Its correlation with WordSim happens to be 0.32, the best observed. So these corpora can be considered complementing each other.

4.4 Empirical study

Taking into account that Twitter posts are often related to current events and terms, we assume that it is possible to identify these events and get some knowledge of what do they look like.

Here we present few words with their most related (according to `01_10`) allies. They may be seen at Table 3.

The first case describes term Maidan, which shifted from general "square" meaning to something related to situation in Ukraine.

The last one, *internet*, is actually more blurred, and seem unrelated, but it can be explained that people often post Tweets about problems with internet link quality.

5 Conclusion

During this research we evaluated the translated version of WordSim353. It turned out that such method can be used to estimate accuracy of semantic relatedness algorithm.

Although term *accuracy* seems a little bit confusing, because it cannot be compared to that of state-of-the-art (the absolute value). It still can be used as relative quality measure, e.g. for estimating quality change between two versions of same algorithm.

We also evaluated Twitter stream as linguistic resource, which performed slightly worse than same algorithm trained with set of several Russian contemporary literature texts. However, Twitter-based dataset was an order of magnitude larger than former one.

Twitter stream can also be used to estimate meaning of new words. It also may be considered to detect word semantic change.

6 Future work

There are number of ways to continue this work.

WordSim353 can be translated completely and analogous evaluation performed.

Several other resources may be tried, e.g. Wikipedia articles, Wictionary and WordNets.

Several modifications may be applied to the algorithm, including different `td-idf` modifications, different stopword lists, and usage of methods introduced by (Mikolov et al., 2013).

Twitter-based semantic relatedness may be combined with trend analysis to produce trending topics.

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Appendix A. Texts in `books` corpus.

B. Akunin. Almaznaya kolesnitsa.

B. Akunin. Vneklassnoe chtenie.

D. Granin. Zubr.

V. Pelevin. Prince gosplana.

V. Pelevin. Pokolenie ”P”.

S. Lukianenko. 13 gorod.

S. Lukianenko. Pristan zheltih korablei.

A. Strugatsky, B. Strugatsky. Ponedelnik nachinaetsa v subbotu.

A. Strugatsky, B. Strugatsky. Ulitka na sklone.

M. Veller. Vse o zhizni.

A. Zhitinksi. Ditia epokhi.