The Computation of Semantically Related Words:
Thesaurus Generation for English, German, and Russian

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Abstract. A method for the automatic extraction of semantically similar words is presented which is based on the analysis of word distribution in large mono-lingual text corpora. It involves compiling matrices of word co-occurrences and reducing the dimensionality of the semantic space by conducting a singular value decomposition. This way problems of data sparseness are reduced and a generalization effect is achieved which considerably improves the results. The method is largely language independent and has been applied to corpora of English, German, and Russian, with the resulting thesauri being freely available. For the English thesaurus, an evaluation has been conducted by comparing it to experimental results as obtained from test persons who were asked to give judgements of word similarities. According to this evaluation, the machine generated results come close to native speaker's performance.

1 Introduction

In his paper "Distributional Structure" Zelig S. Harris [3] hypothesized that words that occur in the same contexts tend to have similar meanings. This finding is often referred to as *distributional hypothesis*. It was put into practice by Ruge [12] who showed that the semantic similarity of two words can be computed by looking at the agreement of their lexical neighborhoods. For example, the semantic similarity of the words *street* and *road* can be derived from the fact that they both frequently co-occur with words like *car*, *drive*, *map*, *traffic*, etc. If on the basis of a large corpus a matrix of such co-occurrences is compiled, then the semantic similarities between words can be determined by comparing the vectors in the matrix. This can be done using any of the standard vector similarity measures such as the cosine coefficient.

Since Ruge's pioneering work, many researchers, e.g. Schütze [14], Rapp [9], and Turney [16] used this type of distributional analysis as a basis to determine semantically related words. An important characteristic of some algorithms (e.g. [12, 2, 7]) is that they parse the corpus and only consider co-occurrences of word pairs that are in a certain relation to each other, e.g. a head-modifier, verb-object, or subject-object relation. Others do not parse but perform a *singular value decomposition* (SVD) on the co-occurrence matrix, which also could be shown to improve results [4, 5]. As an alternative to the SVD, Sahlgren [13] uses *random indexing* which is computationally less demanding.

In the current paper we use an improved variant of the Landauer & Dumais algorithm as described in Rapp [10, 11]. It does not perform a syntactic analysis but

reduces the dimensionality of the semantic space by performing an SVD. The program is applied to corpora of three languages, namely English, German, and Russian, and large thesauri of related words are generated for each of these languages.

2 Corpora

Since our algorithm is based on a similarity measure relying on co-occurrence data, corpora are required from which the co-occurrence counts can be derived. If – as in this case – a measure for the success of the system is the results' plausibility to human judgment, it is advisable to use corpora that are as typical as possible for the language environment of native speakers.

For English, we chose the *British National Corpus* (BNC), a 100-million-word corpus of written and spoken language that was compiled with the intention of providing a balanced sample of British English [1]. As for the German corpus, due to lack of a balanced corpus, we used 135 million words of the newspaper *Frankfurter Allgemeine Zeitung* (years 1993 to 1996). For Russian, we used the *Russian Reference Corpus*, a corpus of about 50 million words.[1]

Since these corpora are relatively large, to save disk space and processing time we decided to remove all function words from the texts. This was done on the basis of a list of approximately 600 German and another list of about 200 English function words. These lists were compiled by looking at the closed class words (mainly articles, pronouns, and particles) in an English and a German morphological lexicon (for details see [6]) and at word frequency lists derived from our corpora. In the case of the Russian Reference Corpus, part-of-speech information was given for all words, and function words were removed on this basis. By eliminating function words, we assumed we would lose little information: Function words are often highly ambiguous and their co-occurrences are mostly based on syntactic instead of semantic patterns.

We also decided to lemmatize our corpora. Since we were interested in the similarities of base forms only, it was clear that lemmatization would be useful as it reduces the sparse-data problem. For English and German we conducted a partial lemmatization procedure that was based only on a morphological lexicon and did not take the context of a word form into account. This means that we could not lemmatize those ambiguous word forms that can be derived from more than one base form. However, this is a relatively rare case. (According to [6], 93% of the tokens of a German text had only one lemma.) In the case of Russian, no special processing was necessary since lemma information was already given in the corpus as provided by Serge Sharoff.

3 TOEFL data for evaluation

As described in Rapp [11], it is desirable to evaluate the results of the different algorithms for computing semantic similarity. For doing so, many possibilities can be

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[1] See http://corpus.leeds.ac.uk/serge/bokrcorpora/index-en.html. This corpus was kindly provided by Serge Sharoff.

thought of and have been applied in the past. For example, [2] used available dictionaries as a gold standard, Lin [7] compared his results to WordNet, and [4] used experimental data taken from the synonym portion of the *Test of English as a Foreign Language* (TOEFL). As described by Turney [17], the advantage of the TOEFL data is that it has gained considerable acceptance among researchers.

The TOEFL is an obligatory test for non-native speakers of English who intend to study at a university with English as the teaching language. The data used by Landauer & Dumais had been acquired from the *Educational Testing Service* and comprises 80 test items. Each item consists of a problem word embedded in a sentence and four alternative words, from which the test taker is asked to choose the one with the most similar meaning to the problem word. For example, given the test sentence *"Both boats and trains are used for transporting the materials"* and the four alternative words *planes*, *ships*, *canoes*, and *railroads*, the subject would be expected to choose the word *ships*, which is supposed to be the one most similar to *boats*.

Landauer & Dumais [4] found that their algorithm for computing semantic similarities between words has a success rate comparable to the human test takers when applied to the TOEFL synonym test. Whereas the algorithm got 64.4% of the questions right (i.e. the correct solution obtained the best rank among the four alternative words), the average success rate of the human subjects was 64.5%.[2] Other researchers were able to improve the performance to 69% [9], 72% [13], 74% [16] and 81.25% [15]. This gives the impression that the quality of the simulation is above human level.

However, it has often been overlooked that the 64.5% performance figure achieved by the test takers relates to non-native speakers of English, and that native speakers perform significantly better. On the other hand, the simulation programs are usually not designed to make use of the context of the test word, so they neglect some information that may be useful for the human subjects.

In order to approach both issues, we presented a test sheet with the TOEFL test words, together with the alternative words, but without the sentences, to five native and five non-native speakers of English, drawn from staff at the Macquarie University in Sydney [11] We asked them to select among the alternative words the one that, according to their personal judgment, was closest in meaning to the given word. Two of the native speakers got all 80 items correct, another two got 78 correct, and one got 75 correct. As expected, the performance of the non-native speakers was considerably worse. Their numbers of correct choices were 75, 70, 69, 67, and 66.

On average, the performance of the native speakers was 97.75%, whereas the performance of the non-native speakers was 86.75%. Remember that the performance of the non-native speakers in the TOEFL test, although they had the context of each test word as an additional clue, was only 64.5%. The discrepancy of more than 20% between our non-native speakers and the TOEFL test takers can be explained by the fact that most of our subjects had spent many years in English speaking countries and thus had a language proficiency far above average. More importantly, our native speakers' results indicate that the performance of the above mentioned algorithms is clearly below human performance. So the impression from the Landauer & Dumais [4] paper that human-like quality has been obtained is obviously wrong unless one only looks at second language learners with a relatively poor proficiency.

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[2] This performance figure was provided by the Educational Testing Service, with the number of test takers being unknown.

As we did not have any data comparable to the TOEFL synonym test for German and Russian, the evaluation was only conducted for English.

4 Algorithm

Our algorithm is a modified version of Landauer & Dumais [4] and consists of the following four steps (see also [10, 11]):

1. Counting word co-occurrences
2. Applying an association measure to the raw counts
3. Singular value decomposition
4. Computing vector similarities

4.1 Counting Word Co-occurrences

For counting word co-occurrences, as in most other studies a fixed window size is chosen and it is determined how often each pair of words occurs within a text window of this size. Choosing a window size usually means a trade-off between two parameters: specificity versus the sparse-data problem. The smaller the window, the more salient the associative relations between the words inside the window, but the more severe the sparse data problem. In our case, with ±2 words, the window size looks rather small. However, this can be justified since we have reduced the effects of the sparse data problem by using a large corpus and by lemmatizing the corpus. It also should be noted that a window size of ±2 applied after elimination of the function words is comparable to a window size of ±4 applied to the original texts (assuming that roughly every second word is a function word).

Based on the window size of ±2, we computed the co-occurrence matrix for the corpus. By storing it as a sparse matrix, it was feasible to include all of the approximately 375 000 lemmas occurring in the BNC.

4.2 Applying an Association Measure

Although semantic similarities can be successfully computed based on raw word co-occurrence counts, the results can be improved when the observed co-occurrence-frequencies are transformed by some function that reduces the effects of different word frequencies. For example, by applying a significance test that compares the observed co-occurrence counts with the expected co-occurrence counts (e.g. the log-likelihood test) significant word pairs are strengthened and incidental word pairs are weakened. Other measures applied successfully include TF/IDF and mutual information. In the remainder of this paper, we refer to co-occurrence matrices that have been transformed by such a function as *association matrices*. However, in order to further improve similarity estimates, in this study we apply a *singular value decomposition* (SVD) to our association matrices (see section 4.3). To our surprise, our experiments clearly showed that the log-likelihood ratio, which was the transformation function that gave good similarity estimates without SVD [9], was not optimal when using

SVD. Following Landauer & Dumais [4], we found that with SVD some entropy-based transformation function gave substantially better results than the loglikelihood ratio. This is the formula that we use:

$$A_{ij} = \log(1 + f_{ij}) \cdot \left(-\sum_k p_{kj} \log(p_{kj}) \right) \text{ with } p_{kj} = \frac{f_{kj}}{c_j}$$

Hereby f_{ij} is the co-occurrence frequency of words i and j and c_j is the corpus frequency of word j. Indices i, j, and k all have a range between one and the number of words in the vocabulary n. The right term in the formula (sum) is entropy. As usual with entropy, it is assumed that $0 \log(0) = 0$. The entropy of a word reaches its maximum of $\log(n)$ if the word co-occurs equally often with all other words in a vocabulary, and it reaches its minimum (zero) if it co-occurs only with a single other word.

Let us now look at how the formula works. The important part is taking the logarithm of f_{ij} thus dampening the effects of large differences in frequency. Adding 1 to f_{ij} provides some smoothing and prevents the logarithm from becoming infinite if f_{ij} is zero. A relatively modest, but noticeable improvement (in the order of 5% when measured using the TOEFL-data) can be achieved by multiplying this by the entropy of a word. This has the effect that the weights of rare words that have only few (and often incidental) co-occurrences are reduced.

Note that this is in contrast to Landauer & Dumais [4]who suggest not to multiply but to divide by entropy. The reasoning is that words with a salient co-occurrence distribution should have stronger weights than words with a more or less random distribution. However, as shown empirically, in our setting multiplication leads to clearly better results than division.

4.3   Singular Value Decomposition

Landauer & Dumais [4] showed that the results can be improved if before computing semantic similarities the dimensionality of the association matrix is reduced. An appropriate mathematical method to do so is singular value decomposition. As this method is rather sophisticated, we can not go into the details here. A good description can be found in Landauer & Dumais [4]. The essence is that by computing the Eigenvalues of a matrix and by truncating the smaller ones, SVD allows to significantly reduce the number of columns, thereby (in a least squares sense) optimally preserving the Euclidean distances between the lines [14].

For computational reasons, we were not able to conduct the SVD for a matrix of all 374,244 lemmas occurring in the BNC. Therefore, we restricted our vocabulary to all lemmas with a BNC frequency of at least 20. To this vocabulary all problem and alternative words occurring in the TOEFL synonym test were added. This resulted in a total vocabulary of 56,491 words. In the association matrix corresponding to this vocabulary all 395 lines and 395 columns that contained only zeroes were removed which led to a matrix of size 56,096 by 56,096.

By using a version of Mike Berry's SVDPACK[3] software that had been modified by Hinrich Schütze, we transformed the 56,096 by 56,096 association matrix to a matrix of 56,096 lines and 300 columns. This smaller matrix has the advantage that all subsequent similarity computations are much faster. As discussed in Landauer &

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[3] http://www.netlib.org/svdpack/

Dumais [4], the process of dimensionality reduction, by combining similar columns (relating to words with similar meanings), is believed to perform a kind of generalization that is hoped to improve similarity computations (even critics concede at least a smoothing effect).

4.4 Computation of Semantic Similarity

The computation of the semantic similarities between words is based on comparisons between their dimensionality reduced association vectors. Our experience is that the sparse data problem is usually by far not as severe for the computation of vector similarities (second-order dependency) as it is – for example – for the computation of mutual information (first-order dependency). The reason is that for the computation of vector similarities a large number of association values are taken into account, and although each value is subject to a sampling error, these errors tend to cancel out over the whole vector. Since association measures such as mutual information usually only take a single association value into account, this kind of error reduction cannot be observed here.

For vector comparison, among the many similarity measures found in the literature, we decided to use the cosine coefficient. The cosine coefficient computes the cosine of the angle between two vectors.

5 Results and Evaluation

The processing of the German and the Russian corpus was done in analogy to English as described above. That is, the size of vocabulary has been chosen to be in the same order of magnitude,[4] and all parameters remained the same. Only for Russian the number of dimensions was chosen to be 250 instead of 300. The reason is that the Russian corpus is considerably smaller than the English and the German ones. It therefore carries less information and requires fewer dimensions.[5]

To give a first impression, Table 1 shows the top most similar words to a few English examples as computed using SVD, the cosine-coefficient, and a vocabulary of 56,096 words. Although these results look plausible, a quantitative evaluation is always desirable. For this reason we used our system for solving the TOEFL synonym test and compared the results to the correct answers as provided by the Educational Testing Service. Remember that the subjects had to choose the word most similar to a given stimulus word from a list of four alternatives. In the simulation, we assumed that the system made the right decision if the correct answer was ranked best among the four alternatives. This was the case for 74 of the 80 test items which gives us an accuracy of 92.5%. For comparison, recall that the performance of our human subjects had been 97.75% for the native speakers and 86.75% for our highly proficient non-native

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[4] For German the 39,745 words with a corpus frequency of 100 or higher were chosen, for Russian the 57,058 words with a frequency above 19.

[5] After removal of the function words, the English corpus contained 50,486,400 tokens, the German corpus 59,307,629, and the Russian corpus 42,792,750.

speakers. This means our program's performance is in between the two levels with about equal margins towards both sides.

Results analogous to Table 1 are given for German and Russian in Tables 2 and 3. To make the interpretation easier, for all words appearing in the tables translations are provided. For the Russian data this has been kindly done by Alexander Perekrestenko. Note that for Russian the transliteration from the Cyrillic to the Latin alphabet as already provided by the Russian Reference Corpus has been used.

Table 1. Semantic similarities for some English words as computed. The lists are ranked according to the cosine coefficient.

enor-mously	greatly (0.52), immensely (0.51), tremendously (0.48), considerably (0.48), substantially (0.44), vastly (0.38), hugely (0.38), dramatically (0.35), materially (0.34), appreciably (0.33)
flaw	Shortcomings (0.43), defect (0.42), deficiencies (0.41), weakness (0.41), fault (0.36), drawback (0.36), anomaly (0.34), inconsistency (0.34), discrepancy (0.33), fallacy (0.31)
issue	question (0.51), matter (0.47), debate (0.38), concern (0.38), problem (0.37), topic (0.34), consideration (0.31), raise (0.30), dilemma (0.29), discussion (0.28)
build	building (0.55), construct (0.48), erect (0.39), design (0.37), create (0.37), develop (0.36), construction (0.34), rebuild (0.34), exist (0.29), brick (0.27)
discrep-ancy	disparity (0.44), anomaly (0.43), inconsistency (0.43), inaccuracy (0.40), difference (0.36), shortcomings (0.35), variance (0.34), imbalance (0.34), flaw (0.33), variation (0.33)
essen-tially	primarily (0.50), largely (0.49), purely (0.48), basically (0.48), mainly (0.46), mostly (0.39), fundamentally (0.39), principally (0.39), solely (0.36), entirely (0.35)

6 Discussion

In section 3 the performances of some other systems that also had been evaluated on the TOEFL synonym test have been given. The best performance of corpus-based systems we are aware of was reported by Terra & Clarke [15] which is 81.25%. It was obtained using a terabyte web corpus (53 billion words) and pointwise mutual information as the similarity measure. Although our corpus is several orders of magnitude smaller, by using SVD with a performance of 92.5% we were able to significantly improve on this result, which is an indication that the generalization effect claimed for SVD actually works in practice. This finding is also confirmed by our previous performance of only 69% achieved on the BNC without SVD [9].

Given these results, for the task of computing semantically related words it seems not essential to perform a syntactical analysis beforehand in order to determine the dependency relations between words, as for example done by Pantel & Lin [8]. Although – depending on the corpus used – the results can be somewhat noisy, it should be noted that – in case only paradigmatic relations are of interest – there is the

possibility of filtering the output lists according to part of speech which should remove most of the noise.

But even if no filtering is performed, the results of the fully unsupervised approach which only relies on algebra largely agree with human intuition. Neglecting the pre-processing step of partial lemmatization, which essentially served the purpose of keeping our co-occurrence matrix small enough for SVD processing, no linguistic resources, neither a lexicon nor syntactic rules, are required. The algorithm considers any string of characters that is delimited by blanks or punctuation marks as a word, applies the SVD to an association matrix derived from the co-occurrences of the words in a corpus, and finally comes up with lists of similar words that highly agree with human intuitions.

Table 2. Semantic similarities for some German words as computed. For each word, an English translation is given in square brackets.

ärgerlich [angry]	peinlich [embarrassing](0.51), bedauerlich [regrettable] (0.47), unangenehm [unpleasant] (0.45), empörend [infuriating] (0.44), bedenklich [precarious] (0.42), ärgern [to annoy] (0,41), unverständlich [incomprehensible] (0.39), nerven [to annoy] (0.39), skandalös [scandalous] (0.39), deprimieren [to depress] (0.38)
Dar-steller [per-former]	Schauspieler [actor] (0.64), Regisseur [director] (0.57), Sänger [vocalist] (0.56), Hauptrolle [leading part] (0.55), inszenieren [to stage-manage] (0.49), Filmemacher [moviemaker] (0.49), Tänzer [dancer] (0.48), Choreograph [choreographer] (0.47), Komödie [comedy] (0.47), filmen [filming] (0.45)
dennoch [never-theless]	gleichwohl [nonetheless] (0.76), trotzdem [although] (0.64), indes [however] (0,60), zwar [indeed] (0.59), allerdings [but] (0.57), deshalb [therefore] (0.56), immerhin [anyhow] (0.56), freilich [sure enough] (0.55), indessen [meanwhile] (0.54), zudem [furthermore] (0.51)
Gesang [sing-ing]	Lied [song] (0.62), singen [to sing] (0.53), Klang [sound] (0.52), Melodie [melody] (0.49), Musik [music] (0.47), Trommeln [drumming] (0.46), Orgel [organ] (0.46), Hymnus [hymn] (0.46), Arie [aria] (0.45), Ballade [ballad] (0.45)
Magi-strat [magi-strate]	Stadtparlament [city parliament] (0.60), Stadtverordnetenversammlung [city council meeting] (0.58), Stadtrat [city council] (0.55), Stadtver-ordnete [city councillor] (0.48), Gemeinderat [municipal council] (0.48), Abgeordnetenhaus [house of representatives] (0.46), Bürgermeisterin [mayoress] (0.46), Kreistag [district council] (0.45), Bürgerschaft [citizenship] (0.41), Stadtoberhaupt [mayor] (0.41)
Spott [ridi-cule]	Häme [malice] (0.54), Empörung [outrage] (0.46), Neid [enviousness] (0.43), Mitleid [compassion] (0.42), Unverständnis [lack of under-standing] (0.41), Polemik [polemic] (0.41), Wut [fury] (0.41), Zorn [anger] (0.41), ironisch [ironical] (0.39), Unmut [displeasure] (0.39)

Table 3. Semantic similarities for some Russian words as computed. For each word, an English translation is given in square brackets.

festivalq [festi-val]	koncert [concert] (0.62), vystavka [exhibition] (0.58), spektaklq [performance, show] (0.57), teatr [theater] (0.52), balet [ballet] (0.51), konkurs [competition] (0.49), forum [forum] (0.49), opera [opera] (0.49), gastrolq [(performance) tours] (0,49), kamernyj [chamber (adj.)] (0.48)
'dolzh-nostq' [post]	post [post] (0.59), zvanie [rank] (0.49), naznachatq [to appoint] (0.46), otstavka [resignation] (0.46), naznachenie [appointment] (0.45), oklad [salary] (0.45), uvolqnjatq [to fire] (0.42)
dom [house]	kvartira [flat] (0.59), ulica [street] (0.54), zdanie [building] (0.54), dvor [garden] (0.53), gorod [town] (0.48), komnata [room] (0.45), domik [small house] (0.43), dacha [summer cottage] (0.39), semqja [family] (0.38), derevnja [village] (0.38)
doma-shnij [dome-stic]	domashnie [domestic] (0.55), koshka [cat] (0.32), zhivotnoe [animal] (0.31), kompqjuter [computer] (0.31), privychnyj [accustomed] (0.30), ujut [coziness] (0.29), kuxnja [kitchen] (0.29), xozjajstvo [facilities] (0.28), piwa [food] (0.27), kurica [hen] (0.27)
begatq [to run]	xoditq [to walk] (0.53), prygatq [to jump] 0.53, gonjatq [to race] (0.52), metatqsja [to race in panic] 0.50, nositqsja [to rush] (0.49), broditq [to wander] (4.5), gonjatqsja [to chase] (0.40), pobezhalyj [the color of a burnt steel] (0.40), polzatq [to creep] (0,40), chistitq [to clean] (0.40)
davno [long ago]	pora [period] (0.55), nedavno [recently] (0.46), davnym-davno [very long ago] (0.44), uzkij [narrow] (0,43), sej [sow! (imperative)] (0,42), kogda-to [once upon a time] (0.39), navsegda [forever] (0.38), nikogda [never] (0.38), rano [early] 0.35, teperq [now, nowadays] 0.34

7 Summary and Prospects

We have presented a statistical method for the corpus-based automatic computation of related words which has been evaluated on the TOEFL synonym test. Its performance on this task favorably compares to other purely corpus-based approaches and suggests that sophisticated and language dependent syntactic processing is not essential.

The automatically generated sample thesauri of related words for English, German and Russian, each comprising in the order of 50,000 entries, are freely available from the author. Although, unlike other thesauri, at the current stage they do not distinguish between different kinds of relationships between words, there is one advantage over manually created thesauri: Given a certain word, not only a few related words are listed. Instead, all words of a large vocabulary are ranked according to their similarity to the given word. Since even at the higher ranks the distinctions obtained seem meaningful, this is an important feature that is indispensable for some kinds of machine processing, e.g. for word sense disambiguation and induction.

Future work that we envisage includes applying our method to corpora of other languages, adding multi-word units to the vocabulary, and to find solutions to the problem of word ambiguity that has not been dealt with here.

Acknowledgements

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