Utilizing the One-Sense-per-Discourse Constraint for
Fully Unsupervised Word Sense Induction and Disambiguation

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Abstract
Recent advances in word sense induction rely on clustering related words. In this paper, instead of using a clustering algorithm, we suggest to perform a Singular Value Decomposition (SVD) which can be guaranteed to always find a global optimum. However, in order to apply this method to the problem of word sense induction, a semantic interpretation of the dimensions computed by the SVD is required. Our finding is that in our specific setting the first dimension relates to semantic similarities between words, and the second dimension distinguishes between the two main senses of an ambiguous word. Based on this result we present an algorithm for fully unsupervised word sense induction and disambiguation.

1. Introduction
Past work on word senses has concentrated on disambiguation, i.e. on choosing among a predefined set of senses when given an ambiguous word in context. However, hardly any work was done on sense induction, that is the automatic discovery of the possible senses for a word. Only recently a number of papers have been published on this topic, among them Pantel & Lin (2002), Neill (2002), Dorow & Widdows (2003), and Rapp (2003).

All these papers rely on the distributional hypothesis, i.e. the observation that words with similar meanings tend to have similar lexical surroundings. In that they use global co-occurrence vectors, i.e. vectors that represent the overall behavior of a word in an entire corpus, they also have a common limitation: Since most words are semantically ambiguous, the observed vectors reflect a mixture of the contextual behavior of a word’s senses.

Therefore, when starting from global vectors the task of sense induction requires determining the co-occurrence vectors of the senses given the co-occurrence vector of an ambiguous word. This is a difficult problem that can be approached in different ways:

1. Pantel & Lin (2002) cluster all words in a vocabulary, then deduce a word’s co-occurrence vector from the centroid of its cluster, and finally look at the similarity of the differential vector to other clusters.

2. Rapp (2003) postulates that the best descriptors for the senses of an ambiguous word can be found by looking for words whose co-occurrence vectors are as dissimilar as possible but nevertheless add up to the co-occurrence vector of the ambiguous word.

3. A similar approach is to look at the co-occurrence vectors of the, say, 20 strongest first-order associations to the ambiguous word, and to cluster the product vectors resulting from all 190 possible pairs. The clustering works especially well if we consider binary vectors and eliminate all vector positions that are not significantly associated with the ambiguous word.

4. Rapp (2004) assumes that the sense distribution of an ambiguous word varies with genre. On the basis of three corpora from different domains for each word he derives three co-occurrence vectors that are considered to be different mixes of the underlying senses. He then uses independent component analysis to recover the vectors of the senses from the observed mixtures.

However, since reconstructing the sense vectors from the mixtures is difficult and often suffers from the sparse data problem, the question is if we really need to base our work on mixtures or if there is some way to directly observe the contextual behavior of the senses, thereby avoiding the mixing beforehand. For this we suggest two possibilities:

1. Some semantic ambiguities (usually the coarser ones) can be resolved by syntactic considerations. For example, the word sound can be used as a noun, a verb, or an adjective and has a different sense in each case. This kind of ambiguity can be taken into account by working with a part-of-speech tagged or a parsed corpus and by using different co-occurrence vectors for each possible part of speech (Pantel & Lin, 2002).

2. We can look at local instead of global co-occurrence vectors. As can be seen from human performance, in almost all cases the local context of an ambiguous word is sufficient to disambiguate the word. From this observation we conclude that the local context of a word usually carries no ambiguities.

The first approach has already been applied by Pantel & Lin (2002) with reasonably good results for finding the main senses of a word. Therefore, in this paper we will concentrate on the second approach. It is closely related to the one-sense-per-discourse constraint formulated by Gale et al. (1992) that has been proven effective in word sense disambiguation. The argument here is that in a given discourse an ambiguous word usually tends to occur in only a single sense. By looking at close neighborhoods instead of entire documents we take this position to an extreme. The aim of this paper is to show how the one-sense-per-discourse constraint, whose application tends to suffer from the sparse data problem, can be successfully exploited for word sense induction.

2. Approach
The basic idea is that we do not cluster the global co-occurrence vectors of the words (on the basis of an entire corpus) but local ones which are based on the contexts of a single word. That is, our matrix is derived from the concordance of this word. Also, we do not consider a term/term but a term/context matrix. For each word in our vocabulary we obtain an entire matrix whose context vectors when summed up form one global vector. When for all
words of a vocabulary such matrices are constructed, by
putting them together one could speak of a three di-

men sional array, with two dimensions being the words
in the corpus and the third dimension being all contexts.
Let us exemplify this using the ambiguous word palm
with its tree and hand senses. If we assume that our cor-

pus has six occurrences of palm, i.e. there are six local
corpus contexts, then we can derive six local co-occurrence
vec-

tors for palm. Considering only strong associations to

palm, these vectors could, for example, look as in table 1.

| arm | beach | coconut | finger | hand | shoulder | tree |
|-----|-------|---------|--------|------|----------|------|
| c1  | •     | •       | •      | •    | •        | •    |
| c2  | •     | •       | •      | •    | •        | •    |
| c3  | •     | •       | •      | •    | •        | •    |
| c4  | •     | •       | •      | •    | •        | •    |
| c5  | •     | •       | •      | •    | •        | •    |
| c6  | •     | •       | •      | •    | •        | •    |

Table 1. Context matrix for the word palm.

The dots in the matrix indicate if the respective word
occurs in a context or not. We use binary vectors since we
assume short contexts where words usually occur only
once. By looking at the matrix it is easy to see that con-
texts c1, c3, and c6 seem to relate to the hand sense of
palm, whereas contexts c2, c4, and c5 relate to the tree
sense. Our intuitions can be resembled by using a method
for computing vector similarities, for example the (binary)
Jaccard-measure. If we then applied an appropriate clus-
tering algorithm to the context vectors, we would probably
obtain the two expected clusters, and the words closest to
the geometric centers of the clusters should be good de-
scriptors for the senses of palm.

However, as matrices of the above type can be very
large and extremely sparse, clustering is a difficult task,
and common algorithms often deliver sub-optimal results
because they can easily get stuck in local minima. Fortu-
nately, the problems of matrix size and sparseness can be
minimized by reducing the dimensionality of the matrix.
An appropriate algebraic method that has the capability
to reduce the dimensionality of a rectangular or square ma-
trix in an optimal way is SVD. As shown by Landauer &
Dumais (1997), Schütze (1997), Rapp (2003), and others,
by reducing the dimensionality a generalization effect
is achieved that can improve results. As Schütze (1997:190)
puts it: “The role of SVD is to transform distributional
matrices in order to bring out generalizations in distribu-
tional patterns that the original matrix does not show due
to natural randomness in sampling from a corpus.”

As this method is rather sophisticated, we can not go
into the details here. Good descriptions can be found in
Landauer & Dumais (1997), Manning & Schütze (1999),
and Press et al. (1992). The essence is that by computing
the singular values of a matrix and by truncating the
smaller ones, SVD allows to significantly reduce the
number of columns, thereby (in a least squares sense) op-
timally preserving the euclidean distances (and angles)
between the lines (Schütze, 1997:191). Alternatively, it is
also possible to reduce the number of lines thereby pres-
serving the distances between the columns.

A more or less obvious way to utilize SVD in our set-
ting would involve reducing the number of lines (con-
texts) to, say, 100, and then applying a clustering algo-

rithm to the column vectors of the resulting matrix. This
approach should work well since it is a strength of SVD to
reduce the effect of sampling errors and to close gaps in
the data. However, since our local matrices (based on the
concordance of a word) are smaller and more sparse than
the global co-occurrence matrices used in other studies, it
is probably advisable to use fewer dimensions. Depending
on the corpus frequency of the given word, we suggest to
use 50 to 100 dimensions, which compares to 200 or 300
dimensions used in the literature for co-occurrence ma-

trices of global vectors derived from a full corpus (Rapp,
2003).

However, in the work described here we did not fur-
ther pursue this approach but instead decided to imple-
ment a more innovative method. It has the potential of
being easier to implement, more elegant, and more accu-
rate, but also rises difficult questions.

Our claim is that we don’t need a separate clustering
algorithm since the process of SVD involves an implicit
clustering. However, to see this we need to semantically
interpret the dimensions of the reduced space. This is a
difficult problem, as can have been seen from the follow-
ing citation (Schütze, 1997:195): “I have not been able to find
good interpretations of the dimensions of the reduced
SVD-spaces. Apparently, meaningful generalizations can
only be made about patterns of values that involve all di-

mensions. This is precisely what the clustering techniques
I have used do.”

Of course, from algebra we know that the dimension-
ality reduced vectors form an orthonormal basis of the
vector space (Press et al. 1992:61), which means that all
column vectors are orthogonal to each other (linearly in-
dependent) and their lengths are 1.

But what does this mean for the semantic interpreta-
tion of the reduced vectors? One could think that SVD
collapses those columns of our matrix that correspond to
the same senses. Therefore, if in the matrix of table 1 we
reduced the number of columns to two, this would mean
that one column of the reduced matrix should correspond
to the columns for arm, finger, hand, and shoulder in the
original matrix, and the other to beach, coconut, and tree.
However, this is a misinterpretation of what SVD does.

What actually happens is that SVD determines the
main dimensions of our semantic space. In the following
explanations, for simplicity we assume that the columns of
our reduced matrix are sorted according to the size of their
corresponding singular values, i.e. the first column cor-

responds to the most important dimension, the second to the
next important dimension, and so on.

A dimension can be characterized by a scale which is
best described by its extremes. In our setting, the first di-
mension seems to relate to the contextual similarity to-
wards the given word, i.e. to palm. Therefore, at one end of
the first dimension’s scale we have words that are simi-
lar to palm, for example tree or hand, at the other end
words that are not similar, for example synthesis or vol-

ce.

In determining the second dimension, SVD removes
the first dimension from the data. What we then find is
that the extremes of the second dimension’s scale are the
two meanings of palm, i.e. at one end we find tree and at
the other we find hand.

Now if SVD also removes this second dimension from
the data, one could hope that the third dimension gives us
further distinctions. For example, given the tree sense of
palm, one could distinguish products (palm oil) and names (Palm Beach). Or given the hand sense, further distinctions could be body part versus handheld computer. So the third and following dimensions would capture the next strongest regularities hidden in the data that only become visible after removal of the previous dimensions.

However, since with higher dimensions the effects become less clear and sampling errors tend to dominate, we have not yet been able to clearly support this view empirically. In what follows we therefore restrict our discussion to the first and the second dimensions.

Having formulated interpretations concerning the dimensions of the reduced space, the question is for what kinds of applications this is of relevance, and in how far this view leads to useful practical results. Let us therefore briefly look at the computation of semantically similar words and then move on to the tasks mentioned in the title of the paper, namely word sense induction and word sense disambiguation.

3. Word similarities and sense induction

Our computations are based on a partially lemmatized version of the British National Corpus (BNC) which has the function words removed (Rapp, 2002). With partial lemmatization we mean that only those words in the corpus have been replaced by their root forms that, according to a large lexicon of English, can be unambiguously assigned to a stem. This makes the corpus more manageable, the computations faster, and reduces the sparse data problem without introducing errors (other than those resulting from errors or omissions in the lexicon). Our vocabulary consists of all 374240 different word forms occurring in this corpus after lemmatization.

Next we have to specify how we define a context. Since the documents in the BNC are rather long (average sample size is 24274 words), it is probably better to choose shorter contexts, for example sentences, paragraphs, or text windows of a fixed size. We decided to use text windows of ±20 words around the given word. Since function words were removed from our corpus, this corresponds to a larger window size of perhaps ±40 words in the original corpus if we assume that roughly every second word is a function word.

Due to space constraints, the following considerations and results will be exemplified by only a single test word. We chose the word palm which has already been used in the previous examples. In our corpus, palm occurs 2054 times. Note that this occurrence frequency relates to several inflected forms of palm (e.g. palms and palm ing) as the corpus has been lemmatized.

Using the window size of ±20 words we created a concordance of palm, with each line in the concordance relating to one context window. From this concordance we computed a term/context-matrix whose binary entries indicate if a word occurs in a particular context. When constructing the matrix, for the lines we took all 2054 contexts of palm into account, but restricted the columns to those words other than palm that have a corpus frequency of at least 100 in the lemmatized BNC. The reason for this restriction is that the following SVD can be computationally demanding, and that in a previous study the omission of infrequent words seemed to have little impact on the results (Rapp, 2003). The resulting matrix had a size of 2054 lines \times 10610 columns.

As proposed in other papers (e.g. Landauer & Dumais, 1997; Rapp, 2003), we considered applying some association measure to the matrix entries. However, simply adopting the association formulas used elsewhere seemed not appropriate, as we are working with a different type of matrix that consists of local instead of global vectors. Unfortunately, finding the best formula is difficult, as many considerations must be taken into account. Possibilities include replacing the matrix entries by the association strengths of the respective word to palm, or to simply use the salience of a word which can, for example, be expressed by its entropy, by the standard deviation of its distribution, or possibly by the logarithm of its inverse frequency. Since we have not yet completed these experiments, the results that we present below are based on the unmodified binary matrix.

We applied the SVD to this matrix and reduced its number of columns from 10610 to 2, whereas the number of lines remained at 2054. This took only a few seconds of computing time, and the singular values that we obtained were 62.9 and 25.7 (subsequent values are 22.1 and 19.7).

Next comes the essential step which is to find out about the semantic interpretations of the two computed columns. This we did by comparing each of the two column vectors of the reduced matrix to all column vectors (words) of the original binary matrix and by ranking the results according to the similarities obtained. As our similarity measure we used the well known cosine coefficient (Rapp, 2003) which computes the cosine of the angle between two vectors.

The resulting ranked word list obtained from the comparison with the first vector of the reduced space (first dimension) is shown in table 2, and the list relating to the second dimension is shown in table 3. For each word, the tables show its similarity value (cosine coefficient) and its rank among all words in the vocabulary. As we have a large vocabulary, we had to restrict the lists to a selection of words. As such we took the top 30 words with the strongest associative relationship to palm. These first-order associations had been automatically computed using the log-likelihood ratio as our association measure and the lemmatized BNC as our corpus. The exact procedure is described in Rapp (2002).

| RK | COS | WORD   | RK | COS | WORD   |
|----|-----|--------|----|-----|--------|
| 1  | 0.57| hand   | 104| 0.20| upward |
| 3  | 0.45| back   | 109| 0.20| lip     |
| 6  | 0.42| hands  | 127| 0.19| gently  |
| 10 | 0.38| tree   | 134| 0.18| facing  |
| 13 | 0.35| hold   | 164| 0.17| fist    |
| 15 | 0.33| finger | 170| 0.17| island  |
| 16 | 0.32| head   | 200| 0.16| thumb   |
| 21 | 0.30| eyes   | 206| 0.16| elbow   |
| 53 | 0.24| arms   | 243| 0.15| slap    |
| 56 | 0.24| beach  | 252| 0.15| oil     |
| 62 | 0.23| shoulder | 328| 0.14| coconut |
| 63 | 0.23| mouth  | 459| 0.12| frond   |
| 64 | 0.23| white  | 600| 0.11| attacker|
| 90 | 0.21| skin   | 611| 0.11| Florida |
| 97 | 0.21| slowly | 633| 0.10| breathe |

Table 2. Cosine similarities between the column vectors of the original matrix and the first column (first dimension) of the reduced matrix.
If we look at table 2, we can see that our first dimension seems to correspond to association strength, as all of our 30 test words are among the top 633 in our ranked list of altogether 374240 words. Of course, ideally one could have hoped that all test words would end up on exactly the top 30 positions. But this is unrealistic, as different methods for computing association strengths (in our case log-likelihood versus SVD) will always lead to variations in results. Also, one should keep in mind that these results have been achieved by applying the SVD to a binary co-occurrence matrix that had not been transformed using any association measure.

When considering the results for the second dimension as shown in table 3, we see that 22 of our 30 test words are ranked among the top 119, but that 8 are among the bottom 72. Interestingly, according to our judgement, all of the top words relate to the hand sense of palm, and all of the bottom words relate to its tree sense. This is a result that is extremely unlikely to occur incidentally. Moreover, the best descriptors for the two senses of palm, namely hand and tree, are placed at the very first respectively last position of our ranked list. From this it becomes clear that the second dimension that SVD computed is capable of distinguishing between the two main senses of palm.

### 4. Word sense disambiguation

A nice feature of the proposed SVD-based method for word sense induction is that it implicitly performs sense disambiguation for each of the 2054 contexts of palm. The second column in our reduced matrix (i.e. the one that distinguishes between the senses) represents the results of this disambiguation process. Remember that this vector has a length of 2054 so that each value corresponds to one of the contexts. If we now assume that a positive value in this vector indicates that palm is used in the sense of hand in the respective context, and that a negative value indicates the use of palm in the sense of tree, then according to our judgment for the first 100 occurrences of palm in the BNC we get 87 correct predictions.

If we want to disambiguate the sense of palm given a new context, we can either add this context to our original matrix and redo the SVD. Alternatively, there is also the possibility of mapping the new context into the reduced space, as described in Manning & Schütze (1999:563).

### 5. Summary and conclusions

We have presented a method for fully automatic word sense induction and disambiguation from text. It relies on the semantic interpretation of a dimensionality reduced matrix of contexts. As this is ongoing work, there are many open questions: Can the results that have been presented here for a single example be generalized? Will the dimensions that SVD computes always agree with our intuitions? What is the meaning of the third and the following dimensions? What happens if several singular values are of similar size? What about ambiguous words with more than two senses?

Nevertheless, the simplicity of the approach is surprising, and SVD has the advantage that it is an analytical method that always finds optimal dimensions. If the hypothesis of this paper, namely that SVD dimensions agree with human intuitions, can be confirmed, then this could be useful for solving many problems in natural language processing. Other applications that we have started to explore include language identification in mixed language corpora, text categorization, and part-of-speech induction.

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