Unsupervised Abbreviation Disambiguation
Contextual disambiguation using word embeddings

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Abstract

Abbreviations often have several distinct meanings, often making their use in text ambiguous. Expanding them to their intended meaning in context is important for Machine Reading tasks such as document search, recommendation and question answering. Existing approaches mostly rely on manually labeled examples of abbreviations and their correct long-forms. Such data sets are costly to create and result in trained models with limited applicability and flexibility. Importantly, most current methods must be subjected to a full empirical evaluation in order to understand their limitations, which is cumbersome in practice.

In this paper, we present an entirely unsupervised abbreviation disambiguation method (called UAD) that picks up abbreviation definitions from unstructured text. Creating distinct tokens per meaning, we learn context representations as word vectors. We demonstrate how to further boost abbreviation disambiguation performance by obtaining better context representations using additional unstructured text. Our method is the first abbreviation disambiguation approach with a transparent model that allows performance analysis without requiring full-scale evaluation, making it highly relevant for real-world deployments.

In our thorough empirical evaluation, UAD achieves high performance on large real-world data sets from different domains, and outperforms both baseline and state-of-the-art methods. UAD scales well and supports thousands of abbreviations with multiple different meanings within a single model.

In order to spur more research into abbreviation disambiguation, we publish a new data set, that we also use in our experiments.

1 Introduction

Abbreviations are shortened forms of phrases or single words, employed most often in written language. When the text denoting a concept is long and an author must refer to it multiple times, it is easier for the author to only use the abbreviation. Thus, abbreviations are many-to-one mappings from long-forms to short-forms, used when space or human limitations make the short-form
more convenient. Due to the many-to-one mapping, abbreviation usage can cause problems for automated, computer based, readers and represents a challenge for various natural language understanding tasks. For example, PCB is an abbreviation for: Polychlorinated biphenyl, Printed Circuit Board, Pakistan Cricket Board and a few other concepts. Without domain knowledge, the meaning of PCB in the sentence: The environmental measures taken include limiting the use of substances such as cadmium, lead, PCB, and Azo pigments, cannot be correctly inferred to be Polychlorinated biphenyl.

Resolving the intended meaning of an abbreviation in a given context is crucial for search engines, question answering systems, document recommendation systems, or text analytics. All systems addressing Natural Language Understanding tasks are expected to automatically know which concept a sentence refers to, even if only an abbreviation (i.e. short-form) is used to denote said concept. If a search engine is given a query like effects of Polychlorinated biphenyl on the environment, one would expect the search engine to return documents referring to Polychlorinated biphenyl either with its long-form or with its short-form. Similarly, recommender systems suggesting further literature on the topic of Printed Circuit Boards should not suggest only documents where the authors employ exclusively the long-form, but also those where the short-form PCB is used to denote the same meaning.

Previous abbreviation disambiguation methods have relied on corpora of manually annotated meanings and used hand-designed features [10, 11, 20, 21]. Such approaches have two major weaknesses. First, the cost of annotating abbreviation meanings is high as it involves human labor, often from domain experts. Secondly, models trained on such corpora can only disambiguate abbreviations that have been manually annotated. In order for such systems to support new abbreviations, more human work from domain experts is necessary to create more annotations, leading to higher costs. Similarly, if disambiguation is needed for a new domain, different domain experts are required to first manually annotate a corpus. Human annotation costs have prevented the scaling up of abbreviation disambiguation to large collections of abbreviations spanning multiple domains. Indeed, most data sets for abbreviation disambiguation are quite small [2, 5, 13, 21].

Our method is completely unsupervised. It automatically extracts short-forms and their possible long-forms from unstructured text. We then define new tokens to represent the distinct meanings for each short-form, thereby handling ambiguity. We learn word embeddings for each token that identifies a long-form, and for all context words, in order to create semantic representations of the possible long-forms and the context in which they are used. Using this representation space, our method can easily identify the most likely intended long-form for an ambiguous abbreviation based on the context the abbreviation is used in. As the first method in this field, we provide an analysis of the expected disambiguation performance that does not require costly and cumbersome empirical evaluation studies on manually annotated test data. Additionally, we introduce a technique that can boost the quality of the context representations using external text corpora for learning. In summary, our method is completely
unsupervised, generally applicable, flexible in terms of application domains and
text content, as well as easy to review and to update.

In this paper, we present the following contributions: (1) the Unsupervised
Abbreviation Disambiguation (UAD), our disambiguation method that is unsupervised and does not employ hand-designed features, (2) a data set for evaluating
performance on the abbreviation disambiguation task. For paper review purposes, the data set and evaluation scripts are available at http://bit.ly/2DTkMh7. They will be moved to the Harvard Open DataVerse before camera ready.

2 Related Work

Supervised approaches to abbreviation disambiguation require sense-annotated
data sets, usually annotated manually, by domain experts. These methods often
rely on hand-designed feature vectors co-occurrence (e.g., with other words in
the corpus), number of uppercase letters etc [10, 11, 20]. These features are
usually designed using domain knowledge or are language-specific. Our method
does not use hand-designed features.

One approach to avoiding hand-designed features is to use word embeddings
to represent words and long-forms. A short paper by Li, Ji, and Yan [5] briefly
sketches this idea and presents two models built using word2vec vectors [9].
Both models represent long-forms using a single vector calculated as a weighted
average of vectors of all words observed in the context of each long-form, in
all training examples. The two models differ in the underlying word2vec model
and the weighing strategy. The first model, TBE, averages CBOW-derived word
vectors of surrounding words using TF-IDF scores. It also limits the terms used
in the average computation to the top \( n \) in the window surrounding a long-
form usage. The other, SBE, represents context as sum of vectors of contextual
words over all encountered occurrences in the training data, but uses Skip-gram-
derived word vectors. Thus, for both models proposed by Li, Ji, and Yan, vectors
for long-forms are calculated as an average or surrounding context words, given
all observations of each long-form. Once vectors have been computed for each
long-form, disambiguating an abbreviation use reduces to picking that long-form
candidate whose vector has the smallest cosine distance to the average of vectors
of words surrounding an abbreviation use. Li, Ji, and Yan show experimentally
that the SBE model outperforms TBE. More recently, Charbonnier and Wartena
[3] present a variation of TBE that replaces weighing by TF-IDF with weighing
by IDF only. Unlike these two methods, in our model, vectors for long-forms
are not averages of observed contexts, but trained in relation to their context,
at the same time as the rest of vector space. Thus, their value is established
by the language model trained by word2vec, and their vectors influence those
of words forming the context around each long-form usage.

One problem affecting unsupervised abbreviation disambiguation is that of
identifying valid long-forms. Many unsupervised methods identify valid long-
forms by first identifying definitions of abbreviations. Such methods must ac-
count for inconsistencies in writing long-form definitions. In the biomedical
domain, Okazaki, Ananiadou, and Tsujii [15] found that many long-forms represent the same sense even when lexically different, e.g. pathologic complete response and pathologically complete responses. They propose a supervised clustering method, which normalizes the long-forms into clusters of senses using a similarity measure trained on term variations observed by a domain expert. Disambiguation is based on hand-designed features built from unigrams and bigrams. Experiments show the value of clustering long-forms and limiting their variations. In contrast, the normalization step used in our method is simpler and does not require any labeled data.

There have been some attempts to formulate abbreviation disambiguation as a classification problem. Since the set of labels (i.e. long-forms) is specific to each short-form, Wu et al. [21] express abbreviation disambiguation as a series of classification problems, one for each abbreviation (i.e. short-form). Their system combines word embeddings with hand-designed features and uses a Support Vector Machine to train a classifier for each supported short-form. However, only distinct 75 abbreviations are included in the system. Such a method is impractical for industrial settings that require support for thousands of distinct abbreviations with, potentially, tens of thousands of long-forms. By contrast, our system builds a single model that allows disambiguation of all abbreviations and does not use hand-designed features, making it generally applicable, including for multiple languages.

Entity Linking (EL), often referred to as Record Linking, Entity Resolution or Entity Disambiguation, is a Natural Language Processing task that addresses ambiguities in text and bears some similarity to Abbreviation Disambiguation. The EL task consists of identifying entity mentions in text and providing links from the mentions to knowledge base entries. Entity Linking can target named entities (i.e., names that uniquely refer to entities of predefined classes such as person, location or organization), or common entities (also referred to as Wikification) where all noun phrases determining entities must be linked to concepts in a given knowledge base. The choice of entities to disambiguate depends on downstream tasks which can, for example, be to track named entities for document indexing, relation extraction, or question answering [6, 19].

Both Abbreviation Disambiguation and Entity Linking, establish connections between a lexical form and one of potentially many meanings. Despite this similarity, the two tasks differ on fundamental aspects. In Entity Linking ambiguity, at least in part, is due to partial forms which exist due to pre-established context (e.g. referring to George Washington as George, or Washington), metonymy (e.g. using the name of a country or its capital city as a substitute for its government), or entity overlap (e.g. mentioning a city together with its geographic location, such as Madison, Wisconsin) [6, 12, 17]. Often, in Entity Linking, the disambiguation task is simplified by the possibility of finding the correct linking via co-reference resolution.

Another core difference lies in the fact that Entity Linking is based on few distinct types (traditionally place, organization, person) that are insufficient to differentiate between different meanings of abbreviations [17]. More importantly, Entity Linking is a supervised task and requires ground truth, entity
types for proper linking, as well as access to a knowledge base. In Abbreviation Disambiguation such types are not available and are not practical due to the large number of types and their granularity. And, as mentioned before, our method is entirely unsupervised, and does not require a knowledge base.

3 Method

In this section, we present Unsupervised Abbreviation Disambiguation (UAD), a method that requires only a corpus of unstructured text from which it extracts examples of abbreviation uses together with the intended meanings. Because of its simple input requirements, UAD can scale to large corpora and can easily be adapted to new domains by providing it with a corpus of unstructured text from the new domain. UAD exploits properties of word vectors (also called word embeddings) in order to represent the dependency between long-forms and the contexts in which they are used. UAD does not rely on hand-designed features.

The Abbreviation Disambiguation task can be formalized as follows. Given an input triple $(sf_x, LFS(sf_x), s)$, where $sf_x$ represents a short-form, the function $LFS(sf_x)$ returns a set of all known long-forms associated with a given short-form. Let $s$ be a sentence containing a use of $sf_x$, a disambiguator should return the long-form $lf_y \in LFS(sf_x)$ that represents the concept denoted by $sf_x$ in $s$. Please note that in all our experiments we only focus on ambiguous abbreviations. That is, short-forms $sf_x$ for which $|LFS(sf_x)| \geq 2$. We do not consider unambiguous abbreviations, meaning those short-forms that are only ever observed to map into a single long-form, i.e., $|LFS(sf_x)| = 1$. Since unambiguous abbreviations can easily be expanded using a dictionary lookup, their expansion does not involve any form of disambiguation. A study by Liu, Lussier, and Friedman [7] finds that 76.9% of abbreviations in the Unified Medical Language System ontology, a popular ontology in the field of medicine, are unambiguous, and thus, require no disambiguation.

3.1 Word embeddings

Word embeddings like those of word2vec [9] are obtained by training a language model using a shallow neural network.

In word2vec’s Continuous Bag-Of-Words (CBOW) context model, the probability of a word $w_i$ is estimated using information from the surrounding window of length $n$ on both sides of $w_i$ as:

$$P(w_i|s) = p(w_i|w_{i-1}, \ldots, w_{i-n+1}, w_{i+1}, \ldots, w_{i+n})$$

In the Skip-gram model, a word $w_i$ is used as input and the model attempts to predict the surrounding words. In order to encode the language model, word2vec learns a representation of words in a multi-dimensional continuous space. Word representations can be used as inputs to the neural network in order to predict words according to the language model.

word2vec requires many word repetitions in order to appropriately estimate a vector for each word.
3.2 Unsupervised Disambiguation

Our method is based on the central idea of learning to represent words such that context can be used to predict presence of often co-occurring words. We use this idea to express the disambiguation problem as a prediction problem. We start by obtaining sentences containing ambiguous short-forms in which the intended meaning is well-known. We call these sentences unambiguous uses of ambiguous abbreviations since the short-form is ambiguous (i.e., known to map to multiple long-forms), but the intended expansion is known because it is defined locally in the text. Unlike previous work, we do not rely on any human-annotated data sets to learn mappings. Instead, we extract them from text using an extension of the patterns defined by Schwartz and Hearst [18]. The core idea is that abbreviations are often defined using the pattern long-form (short-form) or short-form (long-form). For example, A printed circuit board (PCB) is a support for electronic components that also provides physical conductive connections is an unambiguous use of the ambiguous abbreviation PCB, here meaning Printed Circuit Board. From this sentence, we extract the tuple $(<sentence>, PCB, Printed Circuit Board)$. Thus, the input is unstructured text in the form of a sentence $s$ and the output is a tuple $(s, short-form, long-form)$. Please note that one of the strengths of our approach is that it performs well even in the presence of some erroneous or missed definitions, because we identify consistent repeated definitions from large corpora.

Long-forms can sometimes be inconsistent due to spelling (British vs. American English), different prepositions in long-forms or inconsistent use of hyphens, spaces or plurals. For example, in the Wikipedia data we found every single possible hyphenation of White Anglo-Saxon Protestants (WASP). To address this problem, we normalize long-forms. In order to determine if two long-forms for the same short-form refer to the same concept we first strip them of spaces, hyphens and endings in $s$ or $es$ (e.g. Amino Acid and amino-acids are rewritten to aminoacid). All stripped long-forms for a given short-form are then compared with each other. If the ratio between the Levenshtein distance [4] and the length of the longest long-form is low, we replace the less frequent long-form with the more popular one. Formally:

\[
\forall s_{fx} \text{ and } \forall (lf_i, lf_j) \in \{LFS(s_{fx}) \times LFS(s_{fx})\} :
\]

\[
\text{rw}(lf_i, lf_j) = \begin{cases} 
\text{arg max}_x \text{freq}(x), & \text{if } \frac{\text{lev}(lf_i, lf_j)}{\text{max}(|lf_i|, |lf_j|)} \leq t \\
null, & \text{otherwise}
\end{cases}
\] (1)

where $|lf_x|$ is the length of $lf_x$. Threshold $t$ was set to 0.2 in order to keep rewrites conservative. A rewrite null is ignored.

Normalization is important to avoid ambiguities before the actual learning of mappings. The two spelling variations of Amino Acid mentioned above would otherwise be mapped to similar embedding vectors, which would make disambiguation difficult. Note that our normalization step is simpler than the logistic classifier clustering step in [13] and does not require any labeled data from which
to learn a similarity measure.

During training, we build a word2vec space that represents the similarities and dissimilarities in the corpus for all words and tokens that uniquely identify each long-form. Note that if we were to learn one representation per short-form, we would not be able to distinguish different meanings. In SBE and Dist. Sim. vector compositionality is combined with weighing methods to construct representations for long-forms. We represent each long-form with a unique placeholder token so that, at training time, each long-form is allocated its own unique vector in the vector space. The placeholder tokens are represented in relation to their contexts following word2vec’s learning approach. Both placeholder tokens and words that often appear surrounding them, are represented in the vector space in such a way that their relationship is automatically encoded in the vectors due to word2vec’s underlying language model.

We disambiguate a short form by comparing its context with those of its candidate long-forms. More precisely, we average the vectors corresponding to words constituting the short-form’s context, and calculate vector-cosine distance to all candidate long-forms in the word2vec space to find the closest one:

\[
\text{disambiguate}(s_{fx}, v_{ctx}) = \arg \min_{l_{fi} \in LFS(s_{fx})} \cosine(v_{ctx}, l_{fi})
\]  

Using this method, we can disambiguate any number of abbreviations without requiring data annotated by domain experts or hand-designed features. The only requirement is that a long-form is observed a sufficient number of times in the corpus before it can be reliably represented in the vector space. In our experiments we consider 50 observations to be sufficient for word2vec to construct stable and reliable vector representations. Since new short-forms and long-forms are introduced all the time, approaches relying on traditional, human-annotated data, require new manual annotations in order to support disambiguation of new abbreviations. UAD requires only a large corpus of unstructured text that contains uses with definitions of new abbreviations. Similarly, adaptation to a new domain only requires a corpus from that domain.

Global Vectors (GloVe) \cite{le2014distributed} is a method for learning word embeddings that is often considered an alternative to word2vec. It aims to combine the benefits of matrix factorization methods (i.e., the use of global corpus co-occurrence statistics as opposed to only information that is available in the local window) with word2vec’s skip-gram model in order to improve performance of resulting word vectors in tasks such as word similarity and analogy, or Named Entity Recognition. Both similarity and analogy tasks try to mimic the overall human perception of similarity of arbitrary pairs of words or of analogous relationships between pairs of words, respectively.

In principle, GloVe vectors can be used as a drop-in replacement to word2vec in our disambiguation method. However, we expect that GloVe’s prioritization of global co-occurrence to be detrimental to the representation of long-forms as a function of their context. The core idea in UAD is to build a local context model to disambiguate abbreviations, which fits with the window model in word2vec. In other words, for abbreviation disambiguation, we expect the
words surrounding a short-form or long-form to be of much greater importance for correctly identifying the semantics than overall frequencies or co-occurrence as is the case for similarity and analogy tasks. In Section 4.3.6, we study experimentally GloVe as a drop-in replacement for word2vec as the word embedding generation method.

3.3 Pre-evaluation analysis

In the previous section we presented \textit{UAD}, a method that can learn in an unsupervised manner which abbreviations are present in a corpus and how to disambiguate them based on context. In this section, we present a property of \textit{UAD} that addresses practical aspects of deploying abbreviation disambiguation in industrial settings.

Tailoring abbreviation disambiguation to a specific domain can improve performance by allowing the model to learn abbreviation meanings that are specific to the domain, or to drop meanings that are not used in a specific domain. For example, the \textit{Pakistan Cricket Board} meaning for the abbreviation \textit{PCB} mentioned earlier, is improbable to appear in chemical scientific literature. Automatically removing this meaning from the disambiguation model would eliminate the possibility of wrongly emitting the meaning and, in some cases, it will reduce the number of possible long-forms for an abbreviation to 1, thus making the disambiguation process straight-forward. \textit{UAD} allows domain adaptation to be done with little effort due to its unsupervised nature.

Usually, after training a disambiguation model on a new corpus (or for a new domain), expensive, extensive evaluation is required to properly understand overall performance, and identify individual problematic cases, such as abbreviations whose long-forms are easily confused. Typically, this is done by repeated cycles of training, evaluation on test cases (for which costly manual labels are needed), followed by gathering, clearing, and potentially labeling of new data. This iterative process can take considerable effort and time. Unfortunately, such tedious cycles are the norm for adapting existing methods to new domains \cite{11, 20, 21}. In industrial environments, where deployment speed of disambiguation models is crucial, costly, full-scale, evaluations on domain data may prove impractical. A method that does not require such expensive evaluation cycles would allow for faster and more flexible deployment in new domains and for efficient model updates.

For \textit{UAD}, we propose a novel, straightforward, rapid evaluation of the expected disambiguation quality, e.g. when updating to newly discovered abbreviations or moving to a new application domain. Specifically, \textit{UAD} can provide fully unsupervised insights into performance on target data, without requiring labeled data or creation of actual test cases. Our pre-evaluation method is based on the observation that issues with abbreviation disambiguation performance translate directly into selecting incorrect long-forms for a given short-form and context. Consequently, we study which pairs of long-forms are difficult to disambiguate based on their context models. We show how this can be done using only the vector representations. If two long-forms of the same short-form have
similar representations in the vector space, they are clearly difficult to disam-
biguate. Given two long-form vectors $lf_i$ and $lf_j$ of the same short-form $s_x$, if
the vectors are similar under cosine distance, then any context vector $c_v$ that is
similar to one of them, will also be similar to the other. Please note that we only
need to consider $lf_i$ and $lf_j$ which belong to the same short-form $s_x$ because
UAD disambiguates only candidate long-forms of a given short-form. Thus,
pairs of long-forms that belong to different short-forms do not cause problems
for disambiguation. Formally, for the set $L$ containing all unordered pairs of
long-forms that share the same short-form:

$$L = \{\{lf_i, lf_j\} \mid \exists s_{f_x} : lf_i, lf_j \in LFS(s_{f_x})\} \quad (3)$$

we construct a ranking $P_L$ of the unordered pairs based on their cosine dis-
tance. In other words, the unordered pair $\{lf_i, lf_j\}$ is more problematic than
the unordered pair $\{lf_k, lf_l\}$ if and only if:

$$\text{cosine}_{\text{dist}}(lf_i, lf_j) < \text{cosine}_{\text{dist}}(lf_k, lf_l) \quad (4)$$

The ranking $P_L$ can be easily reviewed for problematic long-form pairs with-
out requiring costly evaluation on labeled test cases. Note that the two un-
ordered pairs $\{lf_i, lf_j\}$ and $\{lf_k, lf_l\}$ need not share the same short-form as we
are ordering pairs based on how difficult it is for UAD to distinguish between the
elements of each pair, and not between pairs. Our pre-evaluation based on the
ranking $P_L$ only uses the trained disambiguation model and no labeled data. In
the Experiments Section we demonstrate how cosine distances of long-forms are
correlated to disambiguation performance. Existing abbreviation disambigua-
tion methods whose models are opaque to explanations [21], cannot provide such
insights into the model, and thus need to be subjected to a full scale evaluation
on ground truth data.

3.4 Context Representations

Proper context representation is critical to the performance of UAD. In the
following, we discuss how to create word embeddings that effectively capture
context.

3.4.1 Augmentation with background text

As described previously, for vector space training, UAD is provided with input
consisting of only the extracted examples. Small and targeted corpora may ex-
hibit relatively high vocabulary to corpus length ratios which means that words
in the vocabulary are observed relatively few times in the corpus. This can be
problematic for unsupervised word representation methods such as word2vec.
The small number of word uses may not provide enough information about the
relation of words to their contexts, leading to non-representative vector spaces.
In order to give word2vec a better chance to reach a stable vector space config-
uration, and to improve disambiguation performance, we augment the corpus
used for vector space training. We supplement the set of abbreviation usage examples with an extra corpus of unstructured text. We aim for as high a vocabulary overlap with the abbreviation examples as possible in order to provide the maximum word usage information. The addition of background text helps stabilize the location of words that appear in both corpora. Since the location of long-form placeholders is influenced by that of all other words in the vocabulary through context-sharing, the locations of long-form placeholders will also be influenced, leading to overall improvements in abbreviation disambiguation. For maximal benefit, the augmentation text should share the same domain and writing style as the abbreviation examples. This can be achieved by extracting the background text from the same large corpus as the abbreviation examples. In experiments where we use background text, we denote such augmentations with $TXT$.

### 3.4.2 Stop-word removal

Tokens that often occur in language use, such as prepositions, articles, punctuation etc. (often called stop-words) can reduce vector space quality. At training time, word2vec will adjust vectors of words surrounding stop-words to increase its performance in predicting stop-words. This behavior is undesired since it leads to lower quality vectors for tokens that are not stop words. Moreover, our disambiguator ($UAD$) will compound this issue because at disambiguation time, it computes an average vector of all contextual tokens where content-bearing words have the same weight as stop-words.

In order to eliminate these undesired effects, we remove stop-words from the learning corpora. This has the side effect of effectively increasing the window size for word2vec as every stop-word removed allows another token to enter the window, if any is left in the sentence.

### 4 Experiments

#### 4.1 Data Sets

We used two data sets for all experiments: one based on the English Wikipedia and one based on PubMed. All of English Wikipedia as of 1st of August 2017 was downloaded, and all text content was extracted using WikiExtractor [1]. For the PubMed data set, we downloaded the Commercial Use Collection of the Open Access Subset of PubMed [14] and extracted only the text content from each article.

From each corpus, we selected only sentences with unambiguous abbreviation usage and normalized long-forms using the methods described above. We kept only those short-forms that had at least two long-forms (i.e. ambiguous abbreviations), each of which occurred in at least 50 examples. All sentences containing uses of ambiguous abbreviations were distributed into 10 bins for the purpose of 10-fold cross-validation. Since we know the intended long-form for each of our extracted and normalized examples, we can perform 10-fold cross-validation.
Table 1: Overview of data sets. TXT refers to the background text created from each corpus. GNEWS refers to the precomputed Google News vectors.

without requiring manual labels. In order to provide some more in-depth evaluation, we manually annotated a subset of the 10th fold of our Wikipedia data set. This evaluation is discussed separately. The manually labeled data set is published together with the full Wikipedia data set and evaluation scripts.

For every data set, we also extracted a collection of sentences that is used as background corpus to derive higher quality word vectors (the background corpus is denoted TXT in all experiments).

A summary of the data sets is provided in Table 1. We created the two data sets used in our experiments to address shortcomings in existing evaluations. Many data sets used in previous studies are too small to provide an accurate image of real-life disambiguation performance and some have artificial biases. For example, the MSH-WSD subset used by Li, Ji, and Yan \cite{5} has a low degree of ambiguity (2.11) and is heavily balanced, i.e., an almost equal number of usage examples are provided for each long-form. We do not consider such data sets sufficient for accurately assessing disambiguation performance. None the less, we have run experiments with the MSH-WSD subset from Li, Ji, and Yan \cite{5} for repeatability, which we include in Section 4.3.2 below. The data of Charbonnier and Wartena \cite{3} is not publicly available, but we have, of course, also evaluated their method, DistSim in our experimental study.

Even the smaller of our data sets, Wikipedia, is up to one order of magnitude larger than the ones used in previous literature \cite{2, 13, 21}. The larger size of our data sets helps gain a better view of performance as they contain more varied test and learning examples. The ratio between examples of the various long-forms in either of our data sets is not artificially balanced, i.e., they represent the relative popularity of the long-forms as observed in the corpora. We made the Wikipedia data set available online together with the evaluation script used in our experiments.
4.2 Performance measures

We measured performance as follows. For every long-form we calculated precision and recall as:

\[ \text{precision} = \frac{TP}{TP + FP} \]
\[ \text{recall} = \frac{TP}{TP + FN} \]

Where TP stands for true positives, FP for false positives and FN stands for false negatives.

Performance for each short-form is calculated as the weighted and unweighted average over precision and recall of the associated long-forms. Weights are provided by the observed frequency of each long-form in the learning set. Performance for each fold is calculated as the weighted and unweighted average of short-form performance. Overall scores are averages of each fold. Besides precision and recall, we also calculate the F1 score for easier comparisons between the different experiments. We calculated both weighted and unweighted metrics in order to better understand the observed performance. Weighted precision, recall and F1 provide an estimation of real-life performance as abbreviations that occur more often matter more. On the other hand, unweighted measures describe how many abbreviations are properly disambiguated. For example, if an experiment leads to an increase in unweighted precision, but a drop in the weighted one, we can conclude that the new version handles less frequent abbreviations better, to the detriment of some frequent ones. The evaluation script that calculates all performance metrics is made available together with the Wikipedia data set.

4.3 Results

4.3.1 Setup

UAD only requires those hyper-parameters specific to word2vec. More specifically, in all experiments we set \( w=10, i=10, \text{size}=300, \text{neg}=5 \) and the model to Skip-gram, unless stated differently.

4.3.2 Comparisons with baseline and existing methods

In the following experiments we compare our method, UAD, with a simple, but efficient baseline and two state-of-the-art methods: SBE [5] and DistSim [3]. The baseline (FREQUENCY) outputs the most frequent long-form for a given short-form. Its statistics are calculated based on the frequencies observed in the 9 folds available for learning. We implement SBE [5], and its variation, Distr. Sim. [3]. We train both vector methods using the parameters given in the original papers.

Li, Ji, and Yan [3] use a specifically constructed small subset of MSH WSD containing abbreviations with little ambiguity (average ambiguity 2.11) and artificially balanced (the average ratio of long-form examples to total examples for each short-form is 1 : 2). On this data set, UAD outperforms both SBE [5] and DistSim [3].
and DistSim \textsuperscript{3}, see Table \textsuperscript{2}. Due to the small size and artificial balancing of MSH WSD subset, we do not consider this to be representative of abbreviation disambiguation evaluation, and therefore proceed on larger unbiased data.

Table \textsuperscript{2} shows results of experimental comparisons on the Wikipedia and PubMed data sets. For both data sets, the \textit{FREQUENCY} baseline manifests a discrepancy between the weighted and unweighted measures. This is due to the disambiguation strategy which always disambiguates to the most popular long-form. Thus, it achieves perfect scores when disambiguating the most popular long-form for each short-form. Weighted performance is higher since the less frequent long-forms matter less in that measure. \textit{SBE} achieves performance results similar to what is reported in the original paper. \textit{Distr. Sim.} is weaker than \textit{SBE} in all measures. This is expected as \textit{Distr. Sim.} is a variation of \textit{TBE}, a weaker sibling of \textit{SBE}, both proposed at the same time by Li, Ji, and Yan \textsuperscript{5}. Our model, \textit{UAD}, outperforms the baseline and both competitors in all measures, on both data sets.

\subsection*{4.3.3 Effect of background information}

As described earlier, we expected both data sets to exhibit relatively high ratios between vocabulary and corpus length. Indeed, in Table \textsuperscript{1} we can see that for the \textit{Wikipedia} data set, the ratio between vocabulary size and corpus length is 1 : 73, while it is 1 : 266 for the \textit{PubMed} data set. Given the relatively high ratio of vocabulary to corpus length, especially for the \textit{Wikipedia} data set, \textit{word2vec} might not see each word in the vocabulary enough times in order to properly place each word in the vector space in relation to its context.

We evaluated the benefit of augmenting with background knowledge in two ways: directly and indirectly. The former consists of generating a background corpus of sentences extracted from the same data set as the examples of abbreviation use. Thus, it provides the same text style as the corpus of ambiguous abbreviation usage. The indirect method aims to study whether performance can be improved without increasing training time. For this, we used the \textit{GNEWS} pre-computed vector space \textsuperscript{8}. The \textit{GNEWS} space is trained on news items, so it does not share writing style with either of our corpora, but we consider it highly relevant since it was trained on a large corpus. Table \textsuperscript{4} shows the vocabulary overlap of the learning text corpus (consisting of the examples extracted

| Disambiguator  | Precision | Recall | F1 score | P\textsubscript{UW} | R\textsubscript{UW} | F1\textsubscript{UW} |
|----------------|-----------|--------|----------|------------------|------------------|------------------|
| 1 FREQUENCY    | 30.04     | 54.14  | 38.64    | 26.74            | 47.80            | 34.29            |
| 2 SBE \textsuperscript{5} | 83.07     | 82.48  | 82.77    | 82.69            | 82.68            | 82.68            |
| 3 Distr. Sim. \textsuperscript{3} | 80.87     | 80.19  | 80.53    | 80.45            | 80.67            | 80.56            |
| 4 UAD with TXT | \textbf{92.28} | \textbf{90.62} | \textbf{91.44} | \textbf{91.53}   | \textbf{91.54}   | \textbf{91.53}   |

Table 2: Competitor comparisons on the subset of MSH WSD used by Li, Ji, and Yan \textsuperscript{5}
from Wikipedia and PubMed) with the background text (denoted TXT) and with GNEWS.

Rows 3 of Tables 4 and 5 show that, indeed, addition of background text improves the weighted precision on both data sets with up to 0.2 percentage points, although less on the PubMed data set (compare row 1 vs. 2 in both tables). On the Wikipedia data set, performance is increased on all measures. On the PubMed data set only weighted precision increases, while the other measures decrease slightly. The background text has a positive effect on positioning of both high- and low-frequency long-forms for the Wikipedia data set. For PubMed, its effect is limited to weighted precision which suggests that performance improvements are limited to high-frequency long-forms. We believe the lower scores in weighted recall as well as unweighted measures are partly due to the smaller vocabulary overlap between PubMed and the background text (34.47% as opposed to 54.10% for the Wikipedia data set).

Following, we initialized the vector space to the GNEWS pre-computed vector space and then trained with our examples. Since the GNEWS space is trained on a large collection of news items, we expected initialization with this vector space to bring our own word embeddings closer to a convergence point. The results for this experiment are presented in row 3 of Tables 4 and 5 (compare row 1 vs. 3 in both tables). The changes in performance are more nuanced. While for Wikipedia most measures improve, for PubMed augmentation with GNEWS leads to a slight decrease in performance for most measures. We believe the smaller improvements (and the drops in performance) are partly due to the lower vocabulary overlap with the GNEWS vectors (24.85% and 3.4%) compared to the background text (54.10% and 34.47%), see Table 1.

Finally, rows 4 of Tables 4 and 5 contain results obtained when we utilized both kinds of augmentation. For both data sets, this leads to mixed results with the disambiguator benefiting more on the Wikipedia data set. We can conclude that the benefits from the two augmentations are not complementary. In fact, as we have seen that augmentation with text of the same style is more beneficial than vectors computed on different style text, we can conclude that the style differences (especially for scientific text such as PubMed) are large enough that combining the two kinds of augmentations can be detrimental.

The results of these experiments reveal an important aspect of our proposed unsupervised method: Disambiguation performance can be improved by adding word usage information. Both augmentations are easy to employ as more vector spaces pre-computed over large corpora are becoming available.

4.3.4 Effect of stop-word removal

In order to evaluate the impact of stop-words, we re-processed our data sets and removed stop-words. A list of the removed tokens is made available together with the Wikipedia data set and the evaluation script at http://bit.ly/2DTkMh7.

Tables 6 and 7 show the results of disambiguation on the data sets without stop-words. For both data sets, the non-augmented vector spaces lead to disambiguation precision and recall that are higher than the augmented ones.
### Wikipedia (no stop-words)

| Disambiguator       | Precision | Recall | F1 score | P_UW | R_UW | F1_UW |
|---------------------|-----------|--------|----------|------|------|-------|
| 1 FREQUENCY         | 64.82     | 78.31  | 70.93    | 30.7 | 45.37| 36.62 |
| 2 SBE [5]           | 93.40     | 89.54  | 91.43    | 85.82| 89.13| 87.44 |
| 3 Distr. Sim. [3]   | 92.81     | 88.99  | 90.86    | 84.34| 88.06| 86.16 |
| 4 UAD with TXT      | **96.15** | **94.19** | **95.16** | **91.30** | **93.51** | **92.39** |

### PubMed (no stop-words)

| Disambiguator       | Precision | Recall | F1 score | P_UW | R_UW | F1_UW |
|---------------------|-----------|--------|----------|------|------|-------|
| 1 FREQUENCY         | 59.54     | 73.41  | 65.75    | 24.67| 35.25| 29.03 |
| 2 SBE [5]           | 89.20     | 69.83  | 78.34    | 75.75| 83.39| 79.39 |
| 3 Distr. Sim. [3]   | 87.35     | 63.29  | 73.40    | 70.63| 80.00| 75.02 |
| 4 UAD with TXT      | **92.41** | **77.62** | **84.37** | **80.49** | **87.15** | **83.69** |

Table 3: Baseline and competitor comparisons

### Table 4: UAD performance on the Wikipedia data set. w2v trained with $w=10$, $i=10$, size=300, neg=5

| Augmented      | Precision | Recall | F1 score | P_UW | R_UW | F1_UW |
|----------------|-----------|--------|----------|------|------|-------|
| 1 No           | 94.76     | 90.23  | 92.44    | 87.22| 90.2 | 88.68 |
| 2 TXT          | **94.98** | **91.42** | **93.17** | **88.50** | **90.30** | **89.39** |
| 3 GNEWS        | 94.76     | 90.39  | 92.52    | 87.26| 90.19| 88.70 |
| 4 TXT + GNEWS  | 94.91     | 91.18  | 93.01    | 88.35| 90.1 | 89.22 |

### Table 5: UAD performance on the PubMed data set. w2v trained with $w=10$, $i=10$, size=300, neg=5

| Augmented      | Precision | Recall | F1 score | P_UW | R_UW | F1_UW |
|----------------|-----------|--------|----------|------|------|-------|
| 1 No           | 91.63     | **71.16** | **80.11** | **78.27** | **83.45** | **80.78** |
| 2 TXT          | **91.74** | 67.28  | 77.63    | **77.03** | **83.05** | **79.93** |
| 3 GNEWS        | 91.71     | 68.73  | 78.57    | 77.81| **83.60** | **80.60** |
| 4 TXT + GNEWS  | 91.73     | 67.09  | 77.50    | 77.06| 83.20| 80.01 |

### Table 6: UAD performance on Wikipedia without stop-words. w2v trained with $w=10$, $i=10$, size=300, neg=5

| Augmented      | Precision | Recall | F1 score | P_UW | R_UW | F1_UW |
|----------------|-----------|--------|----------|------|------|-------|
| 1 No           | 95.90     | 93.07  | 94.46    | 90.09| 92.94| 91.49 |
| 2 TXT          | 96.15     | 94.19  | 95.16    | 91.30| 93.51| 92.39 |
| 3 GNEWS        | 95.89     | 93.38  | 94.62    | 90.22| 92.94| 91.56 |
| 4 TXT + GNEWS  | **96.19** | **94.31** | **95.24** | **91.43** | **93.65** | **92.53** |

### Table 7: UAD performance on PubMed without stop-words. w2v trained with $w=10$, $i=10$, size=300, neg=5

| Augmented      | Precision | Recall | F1 score | P_UW | R_UW | F1_UW |
|----------------|-----------|--------|----------|------|------|-------|
| 1 No           | 92.41     | **75.03** | **84.61** | **80.73** | **87.15** | **83.82** |
| 2 TXT          | 92.41     | 77.62  | 84.37    | 80.49| 87.15| 83.69 |
| 3 GNEWS        | **92.51** | 72.04  | 81.00    | 79.68| 87.17| 83.26 |
| 4 TXT + GNEWS  | 92.42     | 75.68  | 83.22    | 80.16| **87.21** | **83.54** |
for spaces that contain the stop-words. Given the way word2vec’s underlying language model works, removal of stop-words eliminates noise from the window around each long-form meaning and has the side effect that is allows new (potentially relevant) words to enter the window. Results also show that it is highly important that the vector for each long-form is constructed only out of those words in the context that are semantically relevant.

4.3.5 Comparison with Continuous Bag of Words

word2vec supports two models for learning of word embeddings: Continuous Bag of Words Model (CBOW) and Skip-gram. In Tables 9 to 12 we provide experiments using the CBOW model instead of Skip-gram. These experiments are using the same setup as our Skip-gram experiments in Tables 4 to 7.

UAD using the Skip-gram model performs better for UAD using CBOW on both of our data sets. We believe this is due to the learning strategy in CBOW where a context vector is constructed and, from the context vector, a prediction is made. During training, a prediction error is assigned to the context vector. Since it is not possible to determine which word member of the context window is responsible for the error, the same vector correction is applied to the vectors of all words in the window. In the Skip-gram model pairs of words are trained and, thus, vector corrections are applied proportionately to prediction error of each word’s vector. Our experimental observation is in line with the original work of Mikolov et al. [9], who also conclude that word2vec with the Skip-gram model leads to more qualitative vector spaces.

However, some tendencies can be observed between our CBOW and Skip-gram experiments. First, addition of background data in the form of text or initialization with pre-trained vectors tends to improve disambiguation quality showing the importance of using more text in order to derive word embeddings (e.g. row 2 in Table 9). However, augmentation text from the same corpus generally leads to the highest disambiguation performance, probably due to matching text styles (e.g. in Table 11 row 2 has a higher performance increase than row 3). Secondly, we observe that just as with Skip-gram, the CBOW based UAD performs worse on the PubMed data set, probably due to the more complex language (e.g. row 2 in Table 12 shows weaker disambiguation performance than row 2 in Table 11).

4.3.6 Comparisons between word2vec and GloVe

As discussed before, Global Vectors [16] is a method for unsupervised construction of word embeddings from large text corpora which attempts to combine word2vec’s Skip-gram analogy capabilities with global corpus co-occurrence information. It is often considered an alternative to word2vec, especially for Named Entity Recognition or tasks that involve similarity.

In Table 13 we show a version of Table 3 that includes results from disambiguating with UAD, but using GloVe as a drop-in replacement for word2vec used for construction of word vectors (see line 4). As mentioned earlier, we
### Table 9: UAD performance on the Wikipedia data set. w2v trained with \( \text{model=CBOW, w}=10, \text{i}=10, \text{size}=300, \text{neg}=5 \)

| Augmented | Precision | Recall | F1 score | P\_UW | R\_UW | F1\_UW |
|-----------|-----------|--------|----------|--------|--------|--------|
| 1 No       | 92.19     | 76.88  | 83.84    | 82.07  | 85.98  | 83.98  |
| 2 TXT      | 92.48     | 80.14  | 85.87    | 83.12  | 86.28  | 84.67  |
| 3 GNEWS    | 92.19     | 76.98  | 83.90    | 82.05  | 85.92  | 83.94  |
| 4 TXT + GNEWS | 92.43 | 79.94  | 85.73    | 83.1   | 86.27  | 84.66  |

### Table 10: UAD performance on the PubMed data set. w2v trained with \( \text{model=CBOW, w}=10, \text{i}=10, \text{size}=300, \text{neg}=5 \)

| Augmented | Precision | Recall | F1 score | P\_UW | R\_UW | F1\_UW |
|-----------|-----------|--------|----------|--------|--------|--------|
| 1 No       | 86.81     | 71.23  | 78.25    | 70.97  | 76.49  | 73.63  |
| 2 TXT      | 86.88     | 69.78  | 77.40    | 70.66  | 76.51  | 73.47  |
| 3 GNEWS    | 86.81     | 71.16  | 78.21    | 70.94  | 76.47  | 73.60  |
| 4 TXT + GNEWS | 86.88 | 69.79  | 77.40    | 70.65  | 76.53  | 73.47  |

### Table 11: UAD performance on the Wikipedia data set without stop-words. w2v trained with \( \text{model=CBOW, w}=10, \text{i}=10, \text{size}=300, \text{neg}=5 \)

| Augmented | Precision | Recall | F1 score | P\_UW | R\_UW | F1\_UW |
|-----------|-----------|--------|----------|--------|--------|--------|
| 1 No       | 88.94     | 74.69  | 81.19    | 75.31  | 82.32  | 78.66  |
| 2 TXT      | 88.89     | 75.74  | 81.79    | 75.63  | 82.10  | 78.73  |
| 3 GNEWS    | 88.94     | 73.10  | 80.25    | 75.18  | 82.34  | 78.60  |
| 4 TXT + GNEWS | 88.90 | 75.39  | 81.59    | 75.66  | 82.16  | 78.78  |

### Table 12: UAD performance on the PubMed data set without stop-words. w2v trained with \( \text{model=CBOW, w}=10, \text{i}=10, \text{size}=300, \text{neg}=5 \)

- Table 9: UAD performance on the Wikipedia data set.
- Table 10: UAD performance on the PubMed data set.
- Table 11: UAD performance on the Wikipedia data set without stop-words.
- Table 12: UAD performance on the PubMed data set without stop-words.
expect GloVe vectors to be less suited for abbreviation disambiguation, as the local context is of decisive importance for the representation of abbreviation meanings.

As expected, the experiments show that UAD using GloVe vectors performs significantly worse than UAD using word2vec vectors. This observation is also in line with Charbonnier and Wartena [3] who also tested GloVe as part of DistSim and noticed a performance decrease. These results suggest that even though word2vec and GloVe are drop-in replacements for one-another in tasks that rely heavily on word similarity, that is not the case for abbreviation disambiguation, where a local context is of high relevance.

### 4.3.7 Evaluation against human-labeled data

Both our learning and testing data are automatically extracted. In order to evaluate the reliability of results on these data sets, we manually label 7000 examples from one of the 10 folds from the Wikipedia data set. We then train our disambiguator using only the other 9 folds under the Skip-gram model with background text augmentation.

On this manually labeled subset, UAD achieves a weighted precision and recall of 97.62 and 95.18, respectively, and unweighted precision and recall of 93.24 and 94.09. These results are close to the ones in Table 6, which indicates that the automatically extracted data set is of high quality and confirms the results we presented earlier.

Since the labeled data set is much smaller than the ones automatically created, it better lends itself to detailed error analysis. We used 5 categories to classify each disambiguation error. Of the 337 errors, 2.33% are due to multi-level abbreviations (e.g. Communist_Party_of_the_United_States vs. Communist_Party_USA). 9.67% are due to inconsistencies in long-forms that our normalization step cannot handle (e.g. Average Annual Daily Traffic vs. Annual Average Daily Traffic). A portion of 5.33% represent language mismatches in long-forms that mean the same thing (e.g. Federation_of_Association_Football vs. Fédération_Internationale_de_Football_Association). The second-largest source of error is due to incorrect long-form mappings in our pipeline (e.g. Advanced Placement Program instead of Advanced Placement). We believe most of these
errors can be solved in the future through improved pre-processing.

Of the remaining mistakes, many are made for long-forms that appear in sufficiently different contexts while only a minority represent difficult cases that have similar contexts such as American Broadcasting Company versus Australian Broadcasting Corporation.

### 4.3.8 Pre-evaluation analysis

In order to demonstrate how UAD supports efficient and cost-effective pre-evaluation analysis, we investigate the correlation between cosine distance of long-forms pairs and their misclassification rate. For each of the data sets, we selected the models corresponding to row 2 in Tables 6 and 7. For each pair of long-forms we calculated the cosine distance and the misclassification rate between the two long-forms and then both their Pearson and Spearman correlation coefficients. The Pearson Correlation Coefficient $\rho_P$ is defined as:

$$\rho_P = \frac{\text{cov}(X, Y)}{\sigma_x \sigma_y}$$

While the Spearman Correlation Coefficient $\rho_S$ is defined as:

$$\rho_S = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

While Pearson evaluates the linear relationship between two variables and assumes normally distributed data, Spearman evaluates the monotonic relationship. For example, if an increase in one variable leads to an increase in the other, but the relationship is not linear, the Pearson correlation coefficient will show a weaker correlation, while Spearman will not be affected by the lack of linearity. We therefore measure both correlation coefficients in order to obtain a clearer picture. Analysis results are shown in Table 8.

Both the Pearson and Spearman correlation coefficients show that, on both data sets, there is strong negative correlation between cosine distance and misclassification rate. In other words, the closer two long-forms are to each other, the more likely it is that UAD will have difficulties selecting the correct disambiguation. This follows the hypothesis presented in Section 3.3 if two long-forms have similar representatives, then a context vector aligned with one of them, will also align with the other.

Pairs of close long-forms provide information as to how disambiguation performance can be improved.

In fact, we identify all pairs of problematic long-forms given as examples in Section 4.3.8. More specifically cases where long-forms represent the same meaning, but are considered different due to: lack of support for multi-level abbreviations(e.g. United States Geological Survey and U.S. Geological Survey) for USGS, language mismatches, difficult edge cases for long-form normalization (e.g. words swapped around like in House Committee on Un-American Activities and House Un-American Activities Committee for HUAC). Finally,
we also observe examples from cases where more data is required for proper disambiguation due to long-forms that are difficult to disambiguate due to them denoting concepts in the same domains (e.g. Metropolitan Railway and Midland Railway or American Broadcasting Company and Australian Broadcasting Corporation).

The pre-evaluation analysis feature of UAD is extremely useful in practice as it allows the identification of abbreviations that are potentially difficult to disambiguate without requiring expensive evaluations, such as the 10-fold cross-validation we performed in this article. Abbreviations that are difficult to disambiguate can either be removed from the models, investigated for potential pre-processing errors or noise. They can be used to target corpus acquisition towards gathering more examples of the specific abbreviations, which can lead to better representations for the long-forms and, thus, higher disambiguation performance.

Finally, for pairs of long-forms that denote the same meaning, the model can either be retrained after normalizing the long-forms to a single lexical representation, or the model can be updated directly by replacing the two long-form vectors with one that represents their average, thus completely avoiding spending time on model retraining.

5 Conclusion

We presented the Unsupervised Abbreviation Disambiguation (UAD), a fully unsupervised method for abbreviation disambiguation that does not require hand-designed features or labeled data. UAD automatically identifies abbreviations used in a large corpus of unstructured text, determining their meanings and disambiguating between distinct meanings.

UAD creates word vector space embeddings for representation of long-forms relative to their context, by introducing distinct tokens for distinct long-forms of the same short-form. The relation between long-form representations and the context surrounding ambiguous abbreviations thus captures the information required for successful disambiguation.

We demonstrate in a thorough empirical evaluation that UAD outperforms realistic baseline and state-of-the-art methods. We perform our evaluation on two data sets that are at least one order of magnitude larger than previously used data sets, that are more ambiguous, that have not been artificially balanced, and that are thus much more representative of real-world performance.

We also presented methods to further improve UAD’s performance through augmentation with easy to acquire, ubiquitous background knowledge in the form of unstructured text or pre-computed vector spaces.

This the first method that supports insights into disambiguation performance without requiring full-scale evaluation through pre-evaluation analysis which can help identify problematic abbreviations, help target corpus acquisition and in some cases allow for model adjustments that do not require retraining.
Both augmentation and pre-evaluation analysis make UAD highly relevant for real-world use, especially in domains with thousands of ambiguous abbreviations or those that lack large sets of manually annotated data.

As our contribution to the research community, we publish a data set containing abbreviation annotations, which is at least an order of magnitude larger than current similar resources. We hope the data set will support repeatability and further research in abbreviation disambiguation.

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