Acronym Expansion: A Domain Independent Approach

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Abstract

Acronyms are present in usually all documents to express information that is repetitive and well known. But acronyms can be ambiguous because there can be many expansions of the same acronym. In this paper, we propose a general system for acronym expansion that can work on any acronym given some context information it is used in. We present methods for retrieving all the possible expansions of an acronym from Wikipedia and AcronymsFinder.com. We propose to use these expansions to collect the context in which these acronym expansions are used and then score them using a deep learning technique called Doc2Vec. All these things collectively lead to achieving an accuracy of 90.9% in selecting the correct expansion for given acronym on a dataset we scraped from Wikipedia with 707 distinct acronyms and 14,876 disambiguations.

1 Introduction

Acronyms are short descriptors made from important initial letters of a phrase. The phrase here is referred as an expansion of that acronym. Acronyms are used within these documents to shorten complicated or oft-repeated terms.

Acronym usage is becoming more and more common in emails, tweets, blog posts, etc. And with the increasing popularity of mobile devices, the use of acronyms on social platforms has increased even more because typing in these devices is difficult and acronyms provide a succinct way to express information.

Usually, acronyms will be conveniently defined at the point of the first usage, but sometimes a document will omit the definition entirely, assuming the readers familiarity with the acronym. For example, WHO is often used as an acronym for World Health Organization and usually people are expected to know the expansion of it. Or take CSS as an example, most of the documents wont even mention the expansion of CSS because its such a common acronym for Cascading Style Sheets. But CSS can also mean Content-Scrambling System, Closed Source Software, and Cross-Site Scripting.

Also, many natural language processing applications require preprocessing of a document. Text normalization is one of the most important phase of these preprocessing tasks. The basic task of text normalization is to convert non-standard words like numbers, abbreviations, dates, etc. into standard words, though depending on the task and the domain a greater or lesser number of these non-standard words may need to be normalized. In this phase of text normalization, we need to expand all the acronyms in the document. Acronyms are typically ambiguous because several expansions exist for the same acronym as we saw in the example before. For example, Cable News Network and Convolutional Neural Network are both expansions for the common acronym CNN. To disambiguate these acronyms, we can use context paragraphs that surround these acronyms to find the actual expansion. [1]

In our work, we have studied and created an information retrieval system which takes any acronyms along with some context words and then will expand the acronym based on the score it gives to all the possible expansions on the acronym. As shown in the figure, the system will search for all the possible expansions of the given acronym on Wikipedia and Acronymfinder.com. Once it has the list of all the expansions then it will start finding occurrences of those phrases in Wikipedia to get all the contexts in which it is used. Our system will then represent each poss-

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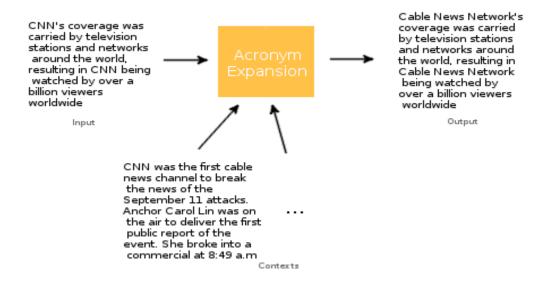[1] [*] indicates these author is an equal contributor to this work

Figure 1: Acronym Exoansion from Input to Output

bile expansion using a deep learning technique called Doc2Vec (Mikolov et al., 2014) in high dimensional vector space. Doc2Vec (Mikolov et al., 2014) which is used in our system can be seen as a distributional semantic representation and this representation is proved to be effective to compute the semantic similarity between words based on the context without any labeled data. The Doc2Vec (Mikolov et al., 2014) embeddings represents the expansions of acronyms in vector space. The placement of each acronym expansion depends on the context that it is used in. Once the system has represented all the possible context vectors associated with each expansion using Doc2Vec (Mikolov et al., 2014), we can pick the expansion whose context vector has the highest cosine similarity score with the input context vector which will then be our expansion for that given acronym.

To the best of our knowledge, we are the first to apply Doc2Vec (Mikolov et al., 2014) embeddings to this task. Experimental results show that our system achieves a comparable accuracy of 90.9% accuracy and is close to humans performance.

Our paper is mainly divided into the following sections:

- In Section 1, we begin with an introduction to the task of acronym expansion and briefly describe our approach.

- In Section 2, we mention the issues with acronym expansion and provide an overview of the past approaches to the same problem.

- In Section 3, we descibe our proposed ap-323

proach to the task of acronym expansion and the creation of document embeddings from context of acronym usage which is at the core of our model.

- In Section 4, we explain our experimental setup, describe how we gathered the dataset and give results and observations of testing on the datasets.

- In Section 5, we give our conclusions from the experiments and also describe methods to extend our approach to similar problems.

2 Related Work

The task of acronym expansion has been intensively studied by various researchers using supervised learning algorithms. However, the performance of these supervised methods depends on a large amount of labeled data which is extremely difficult to obtain.

In Hippocratic Abbreviation Expansion (Roark et al., 2014) paper, they have used SVM, N-Gram, and many hand-crafted feature engineering techniques to identify the correct expansion of an acronym.

In Acronym-Expansion Recognition and Ranking on the Web (Jain et al., 2007), they use a very similar technique of information retrieval to find all the expansions of any acronyms and then ranked them using co-occurence between acronym and expansion, popularity and reliability of sources.

One other difference between the work we report from much of the recent work cited above is that our work focuses on a more general system to solve the problem. Most of the recent works we have mentioned before are focused on some particular domain and hence use some domain specific techniques to achieve better accuracy. Our system on the other hand only uses the textual data present on Wikipedia to understand the context and outputs the closest expansion similar to input context.

3   Proposed Approach

Owing to the recent success in deep learning frameworks, we sought to apply the techniques to Acronym Expansion problem. But, the main challenge in these approaches is to identify the correct expansion inspite of the many expansions for the same acronym.

We propose to use the vast amount of data available on the internet to identify the correct expansion for any acronym. Our approach involves using Document embeddings to understand the context in which an acronym is used. Document embeddings (Mikolov et al., 2014) are a direct extrapolation of the concept of Word Embeddings (Mikolov et al., 2013). We extract the paragraphs where the acronym was used and supply it to our model. These paragraphs are then embedded in high dimensional vector space, where vector proximity is a direct measure of similarity of context. This concept is explained further in detail in the following sections.

Input Acronym
with context

Scraping
Documents

Possible Expansions
with Contexts

Model

Correct Expansion

Figure 2: Our Approach

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3.1   Crawling Data

As shown in Figure 3, an acronym is given to our system as input. The input is then used to search for all the expansions that we can find for it. To identify, whether any phrase is an expansion of the given acronym, we have made 3 conditions that it must follow:

- The first letters of the words must match the acronym on the sequence

- The words can be separated using space ( ), underscore($\_$) or dash (-)

- It can consist of stop words in between if the first letters do not match

Implementing these rules, we were able to crawl almost all the expansions that are possible of an acronym.

After finding all the expansions that we could crawl, we had a list of expansions that were possible expansions for the given input. Now, to find the correct expansion, we wanted some contextual data that was used when these expansions were mentioned in any document. Our system would then use the list of expansion to further search for all the occurrences of that expansion and collected some data that surrounds it. This surrounding data is the contextual data that we need to identify the correct expansion of the acronym given to us. The amount of data (words) that we picked surrounding the expansion was of size ranging from 2000-5000 characters (at max). By 2000, we mean that words in 1000 characters before the expansions and words in 1000 characters after the expansion.

It might happen that our system would select an expansion-context pair even if the same expansion has already been fetched. We have purposely allowed it because even if the expansion is same, the context will be different in which the acronym is used. The different contexts for same expansion helps the system to find the correct expansion.

3.2   Model

It has become common practice to use word embeddings (Mikolov et al., 2013) for semantic analysis, the most famous implementations being Googles Word2Vec (Mikolov et al., 2013) and Stanfords GloVe (Pennington et al., 2014). However, researchers have been experimenting, with great success, with sentence/paragraph/document
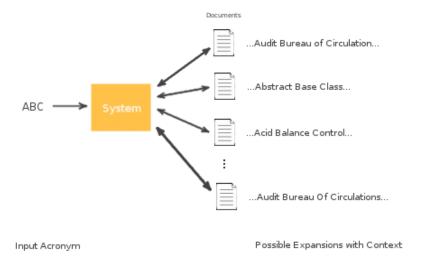
Figure 3: Crawling and finding possible expansions

embeddings - commonly known as thought vectors - for the past few years. Our model is based on Googles Doc2vec (Mikolov et al., 2014) model. It is a neural network architecture that outputs N (number of paragraphs) labelled vectors each of M dimensions.

We have trained our datasets on both the models proposed by Doc2Vec (Mikolov et al., 2014), namely the distributed memory model and distributed bag of words model. The distributed memory model takes into account the context of the surrounding words while predicting a word, while the distributed bag of words model does not.

According to Doc2Vec (Mikolov et al., 2014), given a set of training words, we maximise average log likelihood as:

$$\frac{1}{T}\sum_{t=k}^{T-k}\log p(w_t|w_{t-k},...,w_{t+k})$$

As per their model, prediction is handled by a multiclass classifier (softmax) :

$$p(w_t|w_{t-k},...,w_{t+k}) = \frac{e^{y_{w_t}}}{\sum_i e^{y_i}}$$

We got marginally better results on the Doc2Vec model, as compared to the Distributed Bag of Words model.

As mentioned earlier, our implementation was based on the Doc2vec model.

4   Experiments

We wanted to be absolutely comprehensive in our approach, so we scraped 707 distinct acronyms

with their occurences and context in which they had occured.

We got marginally better results on the distributed memory model, as compared to the distributed bag of words model.

For each acronym, we train a model with all the context possibilities. We then calculate the cosine similarity between every input-context and crawled-context pair. Following that, we extract the pair with the highest cosine similarity value. To give some physical intuition, this means that this pair of vectors are the closest together in vector space. We predict that the full form associated with the context selected above is the same as the full form associated with the meaning. Using pythons in built sequence matcher, we match the predicted expansion with the expansion associated with the input context to verify the models prediction and calculate accuracy.

So, for example, if CNN is the acronym at hand, we have one context paragraph and a expansion (Convolutional Neural Network) associated with it, and several crawled context paragraphs (i.e. places on Wikipedia articles where the acronym CNN has occurred). Each context paragraph also has a distinct expansion associated with it. Lets take two distinct context paragraphs, one with a expansion of "Cable News Network" associated with it, and another with the expansion "Convolutional Neural Network" associated with it.

We plot all 3 paragraphs in vector space, and calculate the cosine similarity of the input context and all the crawled-contexts pair-wise. So

Doc2Vec Model	Embedding Size.	Context/Source	Length of Source/Context	Traning Epochs	Accuracy
Distributed Bag of Words	500	Context	-	12	88.9%
Distributed Bag of Words	500	Context	-	12	89.7%
Distributed Bag of Words	500	Context	2000	12	90.7%
Distributed Bag of Words	500	Context	2000	12	90.6%
Distributed Bag of Words	200	Source	2000	12	**90.9%**
Distributed Memory	200	Context	5000	12	88.4%
Distributed Memory	750	Context	2000	15	89.7%
Distributed Memory	200	Source	5000	15	86.1%
Distributed Memory	500	Context	5000	15	**90.9%**

Table 1: Results of experiments

here, cos_sim(input_context, crawled_context_1) and cos_sim(input_context, crawled_context_2) are compared. Now we select the pair with the highest cosine similarity, lets say, (input_context, crawled_context). meaning has a full form of "Convolutional Neural Network" associated with it. If crawled_context also has a full form of "Convolutional Neural Network" associated with it, then our model has worked successfully, otherwise not.
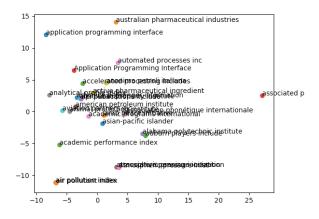

Figure 4: Doc2Vec (Mikolov et al., 2014) Plot for Acronym 'API'

The Figure 4 is an approximate plot of the vector space for the acronym API. This was achieved using Principal Component Analysis. Keeping in mind that 500 dimensions are being condensed to 2 dimensions, this plot is for representation purposes only, and is in no way indicative of the models accuracy.

Using the dataset mentioned before, we ran our model on a total of 14,876 disambiguations for 707 distinct acronyms. We achieved an accuracy of 90.9%.

4.1 Experimental Setup

We use this architecture for the network because of the constraint on the dataset size caused by

scarcity of labelled data. We used a NVIDIA 970 GTX GPU and a 4.00 GHz Intel i7-4790 processor with 64GB RAM to train our models. As the datasets in this domain expand, we would like to scale up our approach to bigger architectures. The results obtained on different experiments are given in Table 1. We are able to achieve comparable accuracies without using any domain specific feature engineering.

4.2 Observations

A crawled input for our model ranges from 200 characters to 60,000 characters, as we wanted to simulate real life scenarios as much as possible. A learning rate of 0.025 was found to be ideal, coupled with 12 epochs of training the same model. Less than 10 epochs proved to cause a significant decrease in accuracy due to undertraining. Greater than than 15 epochs of training caused the same problem, but due to overtraining, vectors of 500 dimensions for Distributed Memory model and vectors of 200 dimensions for Distributed Bag of Words model proved to be ideal on our datasets. On smaller paragraphs, smaller dimensions of vectors (100-150) seemed to lead to more accurate predictions, whereas on larger prargraphs, larger dimension vectors(800-1000) worked better.

In some special cases, if an acronym is found in contexts with other acronyms, the models accuracy decreases. For example, in case of acronym "ETC", it can found in context of "European Travel Commission" also. So the cosine similarity score of "European Travel Commission" will be very close to that of "Et Cetera". [2]

5 Conclusion

The experimental results have shown that document embeddings are a promising solution to the acronym disambiguation problem. The results we

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[2]Code available at: https://github.com/adityathakker/AcronymExpansion

achieved are stable even without using any hand-crafted feature engineering which proves that it's a general data-oriented system.

For further work, we want to try this approach to make recommendation engines that use such contextual data that surrounds any (product) name to identify similar (product) names and recommend them to users.

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