Improving Neural Metaphor Detection with Visual Datasets

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Abstract

We present new results on Metaphor Detection by using text from visual datasets. Using a straightforward technique for sampling text from Vision-Language datasets, we create a data structure we term a visibility word embedding. We then combine these embeddings in a relatively simple BiLSTM module augmented with contextualized word representations (ELMo), and show improvement over previous state-of-the-art approaches that use more complex neural network architectures and richer linguistic features, for the task of verb classification.

Keywords: Metaphor Detection, Visual datasets, Visibility word embeddings, neural models

1. Introduction

Metaphors play a special role in human language and thought, as they evoke a complex array of hidden connotations, past experiences, feelings, and humor, in the service of helping the speaker convey their message in a way that is easier to relate to. However, by their very nature, metaphors continue to pose a challenge to Natural Language Processing (NLP) systems, and their identification is crucial for many tasks, such as Machine Translation, Information Retrieval, and others.

In most cases, metaphor identification is done at the sentence level, where the input consists of some or all of the words in the sentence, and the output refers to the metaphoricity of the word(s) in the specific context. Often, Metaphor Identification takes the form of one of two tasks: (1) Sequence Labeling, in which each token in the sentence is classified as either “metaphorical” or “literal” (multiple outputs per sentence), or (2) Classification of a specific target word, usually the main verb (one output per sentence).

In this paper, we deal with the second task, which more formally takes a sentence \( w_1, \ldots, w_n \) and a verb index \( i \) as input, and outputs a label for the target verb \( w_i \) of either “metaphorical” or “literal”, in relation to its role in the sentence (See Figure 1 for examples for non-metaphorical (literal) and metaphorical usages of the same verb in different contexts).

In our approach to improve metaphor detection, we follow Black (1979)'s observation that a metaphor is essentially an interaction between two terms, creating an “implication-complex” to resolve two incompatible meanings. Operationally, we follow Turney et al. (2011) and their adoption of Lakoff and Johnson (1980)'s notion that metaphor is a way to move knowledge from a concrete domain to an abstract one. Hence, there should be a correlation between the “degree of abstractness in a word’s context [...] with the likelihood that the word is used metaphorically” (Turney et al., 2011). Recent studies have suggested that there is a strong correlation between the concreteness scores of words, as annotated by humans, and the visibility of words, as calculated as a function of their occurrences in a visual corpus (Kehat and Pustejovsky, 2017). In the present paper, we take this notion one step further and use visibility of words directly as a feature of the system.

More specifically, we further improve on the recently presented results by Gao et al. (2018) on the task of verb classification for metaphor detection. In their work, Gao et al. (2018) used contextual information, in the form of contextualized word embeddings (ELMo) (Peters et al., 2018), as well as the GloVe embeddings (Pennington et al., 2014), both concatenated and fed as an input to a simple BiLSTM. We use a number of popular Vision-Language Datasets to create what we call Visibility Embeddings. These embeddings are created by a simple sampling technique from visual corpora (the textual part of vision-language datasets, usually in the form of a list of image-caption sentences). We show that these Visibility Embeddings are useful when combined in a simple concatenation manner with the previously presented architecture by Gao et al. (2018). Our code is available at https://github.com/gititkeh/visibility_embeddings.

2. Background and Related Work

2.1. Metaphor Detection

Currently, neural methods are dominating the task of Metaphor Detection, with recent state-of-the-art results by Gao et al. (2018) and Mao et al. (2019), using BiLSTMs and contextualized word embeddings (ELMo) (Peters et al., 2018), demonstrated on a number of popular annotated Metaphor Detection datasets by Mohammad et al. (2016) (MOH-X), Steen et al. (2010) (the VU Amsterdam Metaphor Corpus (VUA)) and Birke and Sarkar (2006) (TROFI). In the recent 2018 VUA Metaphor Detection Shared Task, several neural models with different architectures were introduced. Most of the teams in the task used LSTM’s combined with other linguistic features, such as part-of-speech tags, WordNet data, concreteness scores and more (Wu et al., 2018; Swarnkar and Singh, 2018; Pramanick et al., 2018; Bizzoni and Ghanimifard, 2018).

Previous work by Turney et al. (2011), Tsvetkov et al. (2014) and Köper and im Walde (2017) showed concreteness scores to be effective for Metaphor Detection. Embedding-based approaches such as in Köper and im Walde (2017) and Rei et al. (2017) also proved to work effectively on several annotated datasets. Different types of word embeddings were studied by researchers, including
embeddings trained on corpora representing different levels of language mastery (Stemle and Onysko, 2018), and embeddings representing different dictionary categories in the form of binary vectors for each word (Mykowiecka et al., 2018).

In our work, we study the effect of using embeddings created from visual datasets, which were shown to be useful in Metaphor Detection (Shutova et al., 2016), as well as in the task of estimating concreteness scores (Kehat and Pustejovsky, 2017).

2.2. Vision-Language datasets

The field of Vision and Language has become extremely popular in the last several years. New tasks involving both images and texts were introduced to both the Computer Vision and Natural Language Processing communities, such as Visual Question Answering (Antol et al., 2015) and visual entailment (Krishnamurthy, 2015). This growing interest has led to an explosion of datasets combining visual and textual information, mostly in the form of an image (or segmented regions of an image) and its corresponding or associated textual caption. Many of the most popular vision-language datasets are based on extensive crowdsourcing. The most famous ones to date are the Visual Genome (Krishna et al., 2016) (See examples in Figure 1), Microsoft COCO (Lin et al., 2014), Imagenet (Deng et al., 2009), which is a visual version of WordNet (Miller, 1995), and Flickr30K (Young et al., 2014). Other vision-language datasets, like the SBU dataset (Ordonez et al., 2011) were created automatically by simply querying the web.

In our work we use what we call “visual corpora”, which are the text-only parts of vision and language datasets. These texts tend to represent words and ideas of higher concreteness on average, helping us to solve concreteness-related tasks such as metaphor detection (Kehat and Pustejovsky, 2017).

2.3. Word Concreteness

The concreteness of a word commonly refers to what extent the word represents things that can be perceived directly through the five senses (Brysbaert et al., 2014; Turney et al., 2011), such as water and blue. Accordingly, an abstract word represents a concept that is far from immediate perception, or alternatively, could be explained only by other words (as opposed to being demonstrated through image, taste, etc.), like decision and fun.

The most common resources for concreteness ratings of English words are the list of 40K scores by Brysbaert et al. (2014), with assigned concreteness scores between 1.0-5.0, and the MRC psycholinguistic database (Coltheart, 1981) that contains over 4K words and their concreteness scores (range from 158 to 670), given by human subjects through psychological experiments.

3. Improving Metaphor Detection

As presented in previous work, certain lexical features, like concreteness scores, have been shown to improve metaphor detection models (Mykowiecka et al., 2018; Turney et al., 2011). Nevertheless, these models were based on hand-annotated resources, such as the MRC Psycholinguistic Corpus (Coltheart, 1981). One of the major disadvantages of using these lists is the fact that they contain a limited number of words and are usually available and evaluated for English only and are hard to reproduce for other languages, as noted by Mykowiecka et al. (2018).

In order to introduce information about the concreteness of word to the models without having to use an annotated dataset or a dictionary, we take a similar approach to Kehat and Pustejovsky (2017), and use vision-language datasets as a reference. Many of the available vision-language datasets were created by crawling image-sharing social networks like Flickr (Ordonez et al., 2011), which are already popular among users throughout the web.
In the following sections, we show our results on two commonly used annotated datasets for metaphor detection:

**The dataset by Mohammad et al. (MOH)** (Mohammad et al., 2016), was created as part of a bigger dataset that also contains annotations about the emotional level and emotional polarity of words. In this dataset, about 1,600 sentences were annotated in a binary fashion, as either “metaphorical” or “literal”, in relation to a certain verb occurrence. The MOH dataset is commonly cut into a smaller dataset, called the MOH-X dataset, which contains only about 650 sentences, and is more balanced in terms of the number of labels for each class (the original MOH dataset contains many more “literal” annotations than “metaphorical” ones).

**the VU Amsterdam Metaphor Corpus (VUA)** (Sleen et al., 2010) is the largest available metaphor dataset to date. In this dataset, every word (not just a target verb) is labeled through an exhaustive annotating scheme. We use the Verbs subset of the VUA metaphor dataset, as used in the 2018 shared task (See section 2.1). This subset consists of more than 17K training samples and over 5K test samples, taken from the British National Corpus (BNC).

## 3.1 Visibility Embeddings

In their work, [Kehat and Pustejovsky (2017)] showed that visual corpora (text derived from vision-language datasets) tend to have higher “concreteness level”, and used this fact to automatically estimate concreteness scores of words, by checking if the given word and its nearest neighbors (in a semantic vector space) are contained in the visual corpus. We aim to improve upon the suggested model by [Gao et al., 2018](2018) by adding our own Visibility Embeddings to the set of embeddings mapped to each word in a given sentence.

These inherently carry information about the semantic vector space structure and neighbors. Therefore, our approach is even simpler, and checks only if the specific given word is in the visual corpus.

We base our sampling method on the shown relatively high differences in the “concreteness level” of different visual and non-visual corpora. The concreteness level of a corpus is calculated as follows: given a concreteness score list (usually the 40K or MRC), we divide the words in the list into two non-overlapping sets (words contained in the corpus and words not contained in the corpus), and calculate the average concreteness score of each set, as well as the difference of the two averages normalized by the score range of the list (‘Diff/Range%’).

Table 1 contains the Diff/Range percentages of several visual and non-visual corpora and their subsets (as sets of words). Like [Kehat and Pustejovsky (2017)] , we refer to the **BVC** as the Big Visual Corpus, a unified corpus consists of several common visual corpora, which showed to have the higher Diff/Range ratio. As a balanced non-visual corpus, we take the Brown corpus (Francis and Kucera, 1964), which showed to have the smaller, almost zero, Diff/Range ratio (means, it is balanced in terms of concreteness).

| Corpus     | D/R% 40K | D/R% MRC |
|------------|----------|----------|
| **BVC**    | 25.49%   | 24.53%   |
| Brown      | 2.74%    | -0.28%   |
| Brown - BVC| -17.30%  | -24.44%  |
| Brown&BVC  | 14.84%   | 13.34%   |

Table 1: The Diff/Range% of the Big Visual Corpus (BVC), the Brown corpus, and their subsets. Higher Diff/Range ratio indicates the corpus is more concrete on average.

### 3.2 The Construction of the Visibility Embeddings

In this section, we show how to build word embeddings out of the visual and non-visual corpora discussed above. In the next section, we show how to plug these vectors in a BiLSTM model, improving existing results.

For each seen word in a sentence, we build a vector of length $l$, consisting of $l$ values sampled from a normal distribution around mean $m$ with variance $v$. We choose $m$ such that it can have one of three values, $-1.0, 0.0$ or $1.0$, where $-1.0$ aims to represent abstractness and $1.0$ aims to represent concreteness.

In order to determine $m$, we use several of the corpora in Table 1 as reference. Based on the Diff/Range ratios, we determine $m$ as follows:

For each word in a sentence:

- If the word is a stopword or punctuation:
  assign $m = 0.0$.
- Else, if the word is in Brown - BVC:
  assign $m = -1.0$.
- Else, if the word is in BVC:
  assign $m = 1.0$.
- Else:
  assign $m = 0.0$.

First we check if a word is in Brown - BVC since this sub-corpus is small with a very low Diff/Range ratio. We continue checking if the word is in the BVC (we don’t check for BVC - Brown since, according to our calculations, it is less concrete on average than the BVC). If the word is in neither corpora or if it is a stopword, we choose $m$ to be the neutral $0.0$.

Following [Kehat and Pustejovsky (2017)] and [Gao et al. (2018)] , we do not normalize the tokens before building the visibility embeddings (or generally inputting them into the system). Our experiments show that without special handling of contextual ambiguity, too much information is lost, due to the derivative nature of the English language. For example, for the lemma “woman”, we can construct both “women” and “womanize”, which are highly different in terms of concreteness scores.

### 3.3 Experiment Setting and Results

We further build on the model proposed by [Gao et al. (2018)] by adding our own Visibility Embeddings to the set of embeddings mapped to each word in a given sentence. Originally, [Gao et al. (2018)] concatenated three types of vectors: embeddings created with ELMo (of dimension
1024), GloVe embeddings (Pennington et al., 2014) (of dimension 300), and binary verb embeddings (of dimension 50) which indicated the verb index in the sentence. We kept the same structure and dimensions of the vectors and also added the new Visibility Embeddings of dimension 50 (See Figure 2).

Figure 2: The embeddings used in the model consist of the ELMo output, GloVe, Verb Index binary embeddings, and Trinary Visibility Embeddings.

The model consists of three main layers (See Figure 3): (1) A Bidirectional-LSTM layer; (2) An attention layer, in which we apply linear softmax on the result and then calculate the similarity of the created vector and the matrix created from the Bi-LSTM output; (3) A classification layer, a feed-forward layer with softmax log to get the classification label of each sentence.

We implemented the model in Python using the AllenNLP package for deep semantic NLP (Gardner et al., 2017). The input for each learning iteration of the model is a batch of embedded sentences. We also apply three dropout factors: before the Bi-LSTM layer, inside the Bi-LSTM layer, and before the classifier layer. To accommodate the new embeddings, we also changed a few constants, such as learning rates, dropout, and number of epochs, but kept the structure of the model and all the other parameters as in Gao et al. (2018).

We note the difficulty in the evaluations of the results reported by Gao et al. (2018). Though not mentioned in their paper, the code that was made available online suggested that the 10-fold cross-validation was performed without shuffling. Also, the reported maximal score was computed by sampling within a given number of iterations (rather than in the end of every epoch). When running their code, we discovered a steady difference between running on the same pre-chosen sets over unshuffled samples (like they apparently did), and randomly choosing the validation set (as traditionally done by researchers), with the right sampling in the end of each epoch. Therefore, to maintain consistency with future results, we also bring our models’ performances when tested on randomly chosen 10-fold cross-validation sets, which are, in fact, the ones we should report.

In general, we can observe that the higher results are on the MOH-X dataset. This is due to the fact that for this dataset, only the metaphoricity of the target verb is known, and the sentences are relatively short. Other methods, such as labeling each token of a sentence, give better results on datasets like the VUA.

We fine-tuned the hyperparameters of the models for each of the discussed metaphor detection datasets. We can notice that by just adding our simply constructed visibility vectors to the already existed model by Gao et al. (2018), we can achieve significant improvement over their previous results on both the MOH-X and VUA datasets.

For the MOH-X dataset shown in Table 2 we can see that by simply adding our visibility vectors, we can gain +1.36 to the F1-score. We experimented also with variations of the models that do not include the GloVe embeddings (i.e., of dimension 1024+50+50), and found the system to perform better in this settings for the MOH-X dataset (though not for the VUA dataset). These results are shown in the last rows of Table 2.

| Model                  | P    | R    | F1  |
|------------------------|------|------|-----|
| Lexical Baseline       | 39.1 | 26.7 | 31.3|
| Mao et al. (2019)      | 77.5 | 83.1 | 80.0|
| Gao et al. (2018)      | 75.3 | 84.3 | 79.1|
| Gao et al. (2018)+Vis  | 79.5 | 81.8 | 80.46|
| Gao et al. (2018)+Vis (rand) | 80 | 80.62 | 80.02|
| Elmo+verb+Vis          | 79.35 | 84.6 | 81.57|
| Elmo+verb+Vis (rand)   | 81.16 | 81.03 | 80.85|

Table 2: Results on the MOH-X dataset. Our model improves upon the previous state of the art by Mao et al. (2019).

For the VUA dataset, we also experiment with the already existed model by Gao et al. (2018), we can achieve significant improvement over their previous results on both the MOH-X and VUA datasets.

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Specifically for the VUA dataset, we also experiment with...
actual concreteness scores annotated by humans, from the list of 40K concreteness ratings by [Brysbaert et al. (2014)]. For each word, we build a similar normalized vector using the concreteness score from the list as the mean $m$. To set up the variance, we tried to use both the inter-annotators standard deviation as appears in the list, and a constant standard deviation (as in the Visibility Vectors case), and found the last one to give better results. All the means and variances were normalized to have the same range as the visibility embeddings, and the results are shown in the last row of Table 4.

We found that using the concreteness scores directly showed less improvement than using the Visibility Embeddings. The overall F1-score is lower because of a lower recall, yet the precision is higher. We hypothesize that the high variance of the concrete and non-concrete terms in our construction of the Visibility Embeddings is more significant than the finer differences naturally occurring in the human annotation, hence their effect as part of the vectorized input is more noticeable.

4. Summary
In this paper, we have presented a simple and direct way to use visual corpora as a reference to certain visibility properties of words. We showed that by adding Visibility Embeddings, built in the same way, to existing deep learning models for metaphor detection, we can compare with or improve upon most classification scores for the task of verb classification. Furthermore, our approach is much simpler than previous models, and is not limited to English.

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