Document Classification by Inversion of Distributed Language Representations

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Abstract

There have been many recent advances in the structure and measurement of *distributed* language models: those that map from words to a vector-space that is rich in information about word choice and composition. This vector-space is the distributed language representation.

Given the success of such approaches, researchers have proposed models and algorithms to adapt them for use in document classification; e.g., for predicting sentiment. The goal of this note is to point out that any distributed representation can be turned into a classifier through inversion via Bayes rule. The approach is simple and modular, in that it will work with any language representation whose training can be formulated as optimizing a probability model. In our application to 2 million sentences from Yelp reviews, we also find that it performs as well as or better than complex purpose-built algorithms.

1 Introduction

Distributed, or vector-space, language representations $\mathcal{V}$ consist of a location for every vocabulary *word* in $\mathbb{R}^K$, where K is the dimension of the latent representation space. These locations are learned to optimize (or approximately optimize) an objective function defined on the original text, such as a likelihood for word occurrences.

A popular example is the Word2Vec machinery of Mikolov et al. (2013). This trains the distributed representation to be useful as an input layer for prediction of words from their neighbors in a Skip-gram likelihood. That is, to maximize

$$\sum_{k \neq t,\ j=t-b}^{t+b} \log \mathrm{p}_{\mathcal{V}}(w_{sj} \mid w_{st}) \qquad (1)$$

summed across all words w_{st} in all sentences $\mathbf{w}_s$, where b is the skip-gram window (possibly truncated by the end or beginning of the sentence) and the function $\mathrm{p}_{\mathcal{V}}(w_{sj}|w_{st})$ is a neural network classifier that takes vector-space representations for w_{st} and w_{sj} as input (see Section 2).

Distributed language representations have been studied since the early work on neural networks (Rumelhart et al., 1986) and have long been applied in natural language processing (Morin and Bengio, 2005). The models are generating much recent interest due to the large performance gains from the newer systems, including Wor2Vec and the Glove model of Pennington et al. (2014), observed in tasks such as word prediction, word analogy identification, and named entity recognition.

Given the success of these new models, researchers have begun searching for ways to adapt the representations for use in document classification tasks such as sentiment prediction or author identification. One naive approach is be to use aggregated word vectors across a document (e.g., a document's average word-vector location) as input to a standard classifier (e.g., logistic regression). However, a document is actually an *ordered* path of locations through $\mathbb{R}$, and simple averaging destroys much of the available information.

More sophisticated aggregation is proposed in Socher et al. (2011; 2013), where recursive neural networks are used to combine the word vectors through the estimated parse tree for each sentence. Alternatively, Le and Mikolov's Doc2Vec (2014) adds document labels to the conditioning set in (1) and has them influence the skip-gram likelihood through a latent input vector location in $\mathcal{V}$. In each case, the end product is a distributed representation for every sentence (or document for Doc2Vec) that can be used as input to a generic classifier.

1.1 Bayesian Inversion

These approaches all add considerable model and estimation complexity to the original underlying distributed representation. They require careful engineering and are not just add-ons to existing systems. We are proposing a simple alternative that turns fitted distributed language representations into document classifiers without any additional modeling or estimation.

Write the probability model that the representation $\mathcal{V}$ has been trained to optimize (likelihood maximize) as $\mathrm{p}_{\mathcal{V}}(d)$, where document $d = \{\mathbf{w}_1, ...\mathbf{w}_S\}$ is a set of sentences – ordered vectors of word identities. For example, in Word2Vec the skip-gram likelihood in (1) yields

$$\log \mathrm{p}_{\mathcal{V}}(d) = \sum_s \sum_t \sum_{k \neq t,\ j=t-b}^{t+b} \log \mathrm{p}_{\mathcal{V}_y}(w_{sj} \mid w_{st}). \tag{2}$$

Even when such a likelihood is not explicit it will be implied by the objective function that is optimized during training.

Now suppose that your training documents are grouped by class label, $y \in \{1 \dots C\}$. We can train *separate* distributed language representations for each set of documents as partitioned by y; for example, fit Word2Vec independently on each sub-corpus $D_c = \{d_i : y_i = c\}$ and obtain the labeled distributed representation map $\mathcal{V}_c$. A new document d has probability $\mathrm{p}_{\mathcal{V}_c}(d)$ if we treat it as a member of class c, and Bayes rule implies

$$\mathrm{p}(y|d) = \frac{\mathrm{p}_{\mathcal{V}_y}(d)\pi_y}{\sum_c \mathrm{p}_{\mathcal{V}_c}(d)\pi_c} \tag{3}$$

where π_c is our prior probability on class label c.

Thus distributed language representations trained separately for each class label yield directly a document classification rule via (3). This approach has a number of attractive qualities.

Modularity: The inversion strategy works for any model of language that can (or its training can) be interpreted as a probabilistic model. This makes for easy implementation in any system that has already been engineered to fit such language representations. In business applications, this will lead to faster deployment and lower development costs. The strategy is also very interpretable: whatever intuition one has about the distributed language model can be applied directly to the resulting inversion-based classification rule.

Scalability: when fitting distributed representations for massive corpora it can be necessary to split the data into pieces for use in distributed optimization. Our model of classification via inversion provides a convenient top-level partitioning of the data. An efficient system could be designed to fit separate by-class language representations, which will provide for document classification as in this article as well as class-specific answers for NLP tasks such as word prediction or analogy. When one wishes to treat a document as unlabeled, NLP tasks can be answered through an ensemble aggregation of the class-specific answers.

Performance: We find that, in our Yelp review classification examples, inversion of Word2Vec yields lower misclassification rates than both Doc2Vec-based classification and the multinomial inverse regression (MNIR) of Taddy (Taddy, 2013c), another framework for mapping from documents to a vector space for use in classification. We did not anticipate such outright performance gain. Moreover, we expect that with careful calibration of the *many* various tuning parameters available when fitting both Word and Doc 2Vec the performance results will change. Indeed, we find that all methods are often outperformed by phrase-count logistic regression with rare-feature up-weighting and carefully chosen regularization. However, the completely untuned out-of-the-box performance of Word2Vec inversion argues for its consideration as a simple default or strong strawman in document classification.

The remainder of the paper outlines how inversion works with the specific Word2Vec framework and provides an illustration of the ideas in classification of Yelp reviews. The implementation requires only a small extension of the popular `gensim` python library's Word2Vec capability; the extended library as well as code to reproduce all of the results and plots in this paper are available at `github.com/taddylab`. In addition, the yelp data is publicly available as part of the correspond data mining contest at `kaggle.com`.

2 Implementation

As outlined in the introduction, Word2Vec trains $\mathcal{V}$ to maximize the skip-gram likelihood of summed word log probabilities in (1). We work with the Huffman softmax specification (Mikolov et al., 2013), which includes a pre-processing step to en-

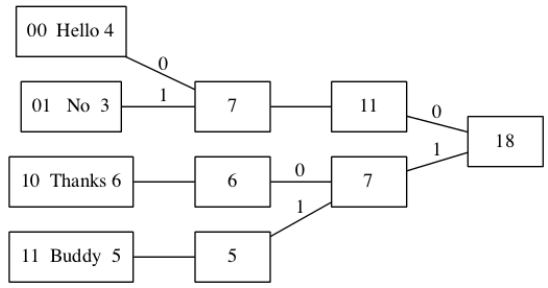

Figure 1: Binary Huffman encoding of a 4 word vocabulary, based upon 18 total utterances. At each step proceeding from left to right the two nodes with lowest count are combined into a parent node. Binary encodings are read back off of the splits moving from right to left.

code each vocabulary word in its representation via a binary Huffman tree (see Figure 1).

Each individual probability is then

$$\mathrm{p}_{\mathcal{V}}(w|w_t) = \prod_{j=1}^{L(w)-1} \sigma\Big(\mathrm{ch}\left[\eta(w, j+1)\right] \mathbf{u}_{\eta(w,j)}^{\top} \mathbf{v}_{w_t}\Big) \tag{4}$$

where $\eta(w, i)$ is the i^{th} node in the Huffman tree path, of length $L(w)$, for word w; $\sigma(x) = 1/(1 + \exp[-x])$; and $\mathrm{ch}(\eta) \in \{-1, +1\}$ translates from whether η is a left or right child to +/- 1. Every word thus has both input and output vector coordinates, $\mathbf{v}_w$ and $[\mathbf{u}_{\eta(w,1)} \cdots \mathbf{u}_{\eta(w,1)}]$. Typically, only the input space $\mathbf{V} = [\mathbf{v}_{w_1} \cdots \mathbf{v}_{w_p}]$, for a p-word vocabulary, is reported as the distributed language representation – these vectors are used as input for NLP tasks. However, the full representation $\mathcal{V}$ includes mapping from each word to both $\mathbf{V}$ and $\mathbf{U}$.

We apply the `gensim` Python implementation of Word2Vec, which fits the model via stochastic gradient descent (SGD), under default specification. This includes a vector space of dimension $K = 100$ and a skip-gram window of size $b = 5$.

2.1 Word2Vec Inversion

Given Word2Vec trained on each of C corpora $D_1 \ldots D_C$, leading to C distinct language representations $\mathcal{V}_1 \ldots \mathcal{V}_C$, classification for new documents is straightforward. Consider the S-sentence document d: each sentence $\mathbf{w}_s$ is given a *probability* under each representation $\mathcal{V}_c$ by applying the calculations in (1) and (4). This leads to the $S \times C$ matrix of sentence probabilites, $\mathrm{p}_{\mathcal{V}_c}(\mathbf{w}_s)$, and the document probabilities are obtained as the column means

$$\mathrm{p}_{\mathcal{V}_c} = \frac{1}{S} \sum_s \mathrm{p}_{\mathcal{V}_c}(\mathbf{w}_s). \tag{5}$$

Finally, class probabilities are calculated via Bayes rule as in (3). We use priors $\pi_c = 1/C$, so that classification proceeds by assigning the class

$$\hat{y} = \mathrm{argmax}_c \ \mathrm{p}_{\mathcal{V}_c}(d). \tag{6}$$

3 Illustration

We consider a corpus of reviews provided by Yelp for a contest on `kaggle.com`. The text is tokenized simply by converting to lowercase before splitting on punctuation and white-space. The training data are 200,000 reviews containing a total of 2 million sentences. Each review is marked by a number of *stars*, from 1 to 5, and we fit separate Word2Vec representations $\mathcal{V}_1 \ldots \mathcal{V}_5$ for the documents at each star rating. The validation data consists of 20,000 reviews, and we apply the inversion technique of Section 2 to score each validation document d with class probabilities $\mathbf{q} = [q_1 \cdots q_5]$, where $q_c = \mathrm{p}(c|d)$.

The probabilities will be used in three different classification tasks; for reviews as

a. negative at 1-2 stars, or positive at 3-5 stars;

b. negative at 1-2 stars, neutral at 3 star, or positive at 4-5 stars;

c. corresponding to each of 1 to 5 stars.

In each case, classification proceeds but summing across the relevant sub-class probabilities. For example, in task a, $\mathrm{p}(\texttt{positive}) = q_3 + q_4 + q_5$. We emphasize that the same five fitted Word2Vec representations are used for each task; all that differs is the outcome to be predicted.

We consider three comparator techniques.

Doc2Vec is also fit via `gensim`, using the same latent space specification for Word2Vec: $K = 100$ and $b = 5$. As recommended in the documentation, we apply repeated SGD over 20 reorderings of each document set (for comparability, this was also done when fitting Word2Vec). Le and Mikolov provide two alternative Doc2Vec specifications: distributed memory (DM) and distributed bag-of-words (DBOW). We follow the original paper by fitting both on the training data, then training vector representations for validation

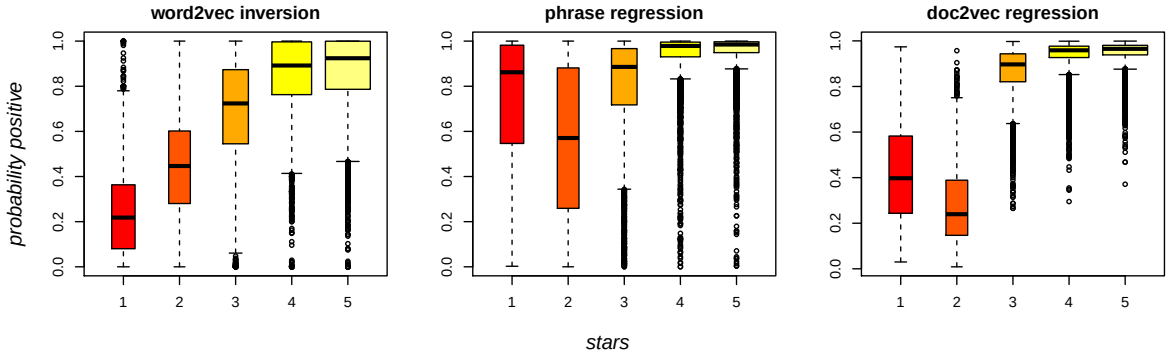

Figure 2: Out-of-Sample fitted probabilities of a review having greater than 2 stars.

documents without updating the word-vector elements of the models. This leads to 100 dimensional vectors for each document for each of the DM and DCBOW models. We train maximum likelihood logistic regression for each and for the combined 200 dimensional DM+DBOW representation, leading to three candidate Doc2Vec classifiers for each task.

MNIR, the multinomial inverse regression of Taddy (2013c; 2013b; 2013a), is applied as implemented in the `textir` package for R. MNIR maps from text to the class-space of interest through a multinomial logistic regression of word (or phrase) counts onto variables relevant to the class-space. Here, we regress word counts onto stars expressed both numerically and as a 5-dimensional indicator vector, leading to a 6-feature multinomial logistic regression. The MNIR procedure then uses the $6 \times p$ matrix of feature-word regression coefficients to map from word-count to feature space, resulting in 6 dimensional 'sufficient reduction' statistics for each document. As for Doc2Vec, these statistics are then input to maximum likelihood logistic regressions.

Phrase regression applies logistic regression of the response classes directly onto word or phrase counts. The phrases are obtained using `gensim`'s phrase builder, which simply combines highly probable pairings; for example, it yields `first_date` and `chicken_wing` in this corpus (these phrases are also used as the bag-of-words input to MNIR). The logistic regressions are then fit under L_1 regularization with the penalties weighted by phrase-count standard deviation (feature scaling) and selected according to the corrected AICc criteria (Flynn et al., 2013), using the `gamlr` R package of Taddy (2014). For multi-class tasks $b - c$, we use `gamlr` in distribution via the `distrom` R package of Taddy (2013a).

	a (NP)	b (NNP)	c (1-5)
W2V inversion	.099	**.189**	.439
Phrase regression	**.084**	.200	**.410**
D2V DBOW	.144	.282	.496
D2V DM	.179	.306	.549
D2V combined	.148	. 284	.5
MNIR	.095	.254	.508

Table 1: Out-of-sample misclassification rates.

3.1 Results

Misclassification rates for each task on the validation set are reported in Table 1. We see that the simple phrase-count regression is consistently the strongest performer, bested only by Word2Vec inversion on task b. This is partially due to the relative strength of discriminative (e.g., logistic regression) vs generative (e.g., all others here) classifiers outlined in Ng and Jordan (2002) (and in Taddy (2013d) in the specific context of MNIR). Given the large amount of training text in this corpus, asymptotic efficiency of logistic regression will start to work in its favor over the finite sample advantages of generative discrimination. However, the comparison is also a bit unfair to Word2Vec and Doc2Vec as models: both phrase regression and MNIR are optimized exactly according to sophisticated AICc penalty selection, while Word and Doc 2Vec have only been approximately optimized under a single non-optimized model specification. As we are finding with the current rise of deep learning algorithms, many of these models only begin to shine after a period of careful engineering.

After phrase regression, Word2Vec inversion

outperforms the other alternatives (except, by a narrow margin, MNIR if task a). Doc2Vec inversion under DBOW specification and MNIR both do worse, but not by a large margin. Their similar performance might be expected: both have a version of logistic (or closely related softmax) regression for word-counts as their first step. MNIR regresses the words onto the observed class information, while Doc2Vec regresses onto a latent vector space. In contrast to the Le and Mikolov examples, we find here that the more complex Doc2Vec DM model does much worse than DBOW.

Looking at the fitted probabilities in detail we see that Word2Vec provides a more realistic document *ranking* than any comparator, including phrase regression. For example, Figure 2 shows the probabilities for task a as a function of the true star rating for each validation review. Although phrase regression does slightly better on this task in terms of misclassification rate, it does so at the cost of classifying many terrible (1 star) reviews as positive. Word2Vec inversion is the *only* method that yields positive-document probabilities that are clearly increasing in distribution with the true star rating. It is not difficult to envision a misclassification cost structure that favors these nicely ordered probabilities over those coming from, say, phrase regression.

4 Discussion

The goal of this note is to point out how inversion should be considered as a single step for turning distributed language representations into classification rules. We are not arguing for the supremacy of Word2Vec inversion in particular, and the approach will work nicely with alternative representations. Moreover, we are not even arguing that it will always outperform purpose-built classification tools. However, it is a simple, scalable, interpretable, and effective option for classification whenever you are working with such distributed representations.

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