Class Vectors: Embedding representation of Document Classes

Devendra Singh Sachan  
Enixta Innovations  
Hyderabad, India  
devendras@enixta.com

Shailesh Kumar  
Enixta Innovations  
Hyderabad, India  
shkumar@enixta.com

Abstract

Distributed representations of words and paragraphs as semantic embeddings in high dimensional data are used across a number of Natural Language Understanding tasks such as retrieval, translation, and classification. In this work, we propose "Class Vectors" - a framework for learning a vector per class in the same embedding space as the word and paragraph embeddings. Similarity between these class vectors and word vectors are used as features to classify a document to a class.

In experiment on several sentiment analysis tasks such as Yelp reviews and Amazon electronic product reviews, class vectors have shown better or comparable results in classification while learning very meaningful class embeddings.

1 Introduction

Text classification is one of the important tasks in natural language processing. In text classification tasks, the objective is to categorize documents into one or more predefined classes. This finds application in opinion mining and sentiment analysis (e.g. detecting the polarity of reviews, comments or tweets etc.) (Pang and Lee, 2008), topic categorization (e.g. aspect classification of web-pages and news articles such as sports, technical etc.) and legal document discovery etc.

In text analysis, supervised machine learning algorithms such as Naive Bayes (NB) (McCallum and Nigam, 1998), Logistic Regression (LR) and Support Vector Machine (SVM) (Joachims, 1998) are used in text classification tasks. The bag of words (Harris, 1954) approach is commonly used for feature extraction and the features can be either binary presence of terms or term frequency or weighted term frequency. It suffers from data sparsity problem when the size of training data is small but it works remarkably well when size of training data is not an issue and its results are comparable with more complex algorithms. (Wang and Manning, 2012).

Using the co-occurring words information, we can learn distributed representation of words and phrases (Morin and Bengio, 2005) in which each term is represented by a dense vector in embedding space. In the skip-gram model (Mikolov et al., 2013), the objective is to maximize the prediction probability of adjacent surrounding words given current word while global-vectors model (Pennington et al., 2014) minimizes the difference between dot product of word vectors and the logarithm of words co-occurrence probability.

One remarkable property of these vectors is that they learn the semantic relationships between words i.e. in the embedding space, semantically similar words will have higher cosine similarity. For example, the word "gpu" will be more similar to "processor" than to "camera". To use these word vectors in classification tasks, Le et al. (2014) proposed the Paragraph Vectors approach, in which they learn the vectors representation for documents by stochastic gradient descent and the gradient is computed by backpropagation of the error from the word vectors. The document vectors and the word vectors are learned jointly. Kim (2014) demonstrated the application of Convolutional Neural Networks in sentence classification tasks using the pre-trained word embeddings.

Taking inspiration from the paragraph vectors approach, we propose class vectors method in which we learn a vector representation for each class. These class vectors are semantically simi-
lar to vectors of those words which characterizes the class and also give competitive results in document classification tasks.

2 Model

We use skip-gram model (Mikolov et al., 2013) to learn these vectors. In the skip-gram approach, we learn the parameters of model to maximize the prediction probability of the cooccurrence of words. Let the words in the corpus be represented as $w_1, w_2, w_3, \ldots, w_n$. The objective function is defined as,

$$ L = \sum_{i=1}^{N_c} \sum_{c \in \{-w, w\}, c \neq 0} \log p(w_{i+c}/w_i) \quad (1) $$

where $N_c$ is the number of words in the sentence (corpus) and $L$ denotes the likelihood of the observed data. $w_i$ denotes the current word, while $w_{i+c}$ is the context word within a window of size $w$. The prediction probability $p(w_{i+c}/w_i)$ is calculated using the softmax classifier as below,

$$ p(w_{i+c}/w_i) = \frac{\exp(v_{w_i}^T v_{w_{i+c}})}{\sum_{w=1}^{T} \exp(v_{w_i}^T v_{w})} \quad (2) $$

$T$ is number of unique words selected from corpus in the dictionary, $v_{w_i}$ is the vectors representation of the current word from inner layer of neural network while $v_{w_i}'$ is the vector representation of the context word from the outer layer of the neural network. In practice, since the size of dictionary can be quite large, the cost of computing the denominator in the above equation can be very expensive and thus gradient update step becomes impractical.

Morin et al. (2005) proposed Hierarchical Softmax to speed up the training. They construct a binary Huffman tree to compute the probability distribution which gives logarithmic speedup $\log_2(T)$. Mikolov et al. (2013) proposed negative sampling which approximates $\log p(w_{i+c}/w_i)$ as,

$$ \log \sigma(v_{w_i}^T v_{w_{i+c}}') + \sum_{j=1}^{k} \mathbb{E}_{w_j \sim P_n(w)} \left( \log \sigma(-v_{w_i}^T v_{w_j}') \right) $$

$$ \sigma(x) \) is the sigmoid function, the word $w_j$ is sampled from probability distribution over words $P_n(w)$. The word vectors are updated by maximizing the likelihood $L$ using stochastic gradient ascent.

Our model, shown in Figure 1, learns a vector representation for each of the classes along with word vectors in the same embedding space. We represent each class vector by its id (class_id). Each class id co-occurs with every sentence and thus with every word in that class. Basically, each class id has a window length of the number of words in that class. We call them as Class Vectors (CV). Following eq(1) new objective function becomes,

$$ \sum_{i=1}^{N_c} \sum_{c \in \{-w, w\}, c \neq 0} \log p(w_{i+c}/w_i) + \lambda \sum_{j=1}^{N_c} \sum_{i=1}^{N_j} \log p(w_i/c_j) \quad (4) $$

$N_c$ is the number of classes, $N_j$ is the number of words in class $j$, $c_j$ is the class id of the class $j$. We use skipgram method to learn both the word vectors and class vectors.

**Figure 1: Class Vectors model. While training each class vector is represented by an id. Every word in the sentence of that class co-occurs with its class vector. Class vectors and words vectors are jointly trained using skip-gram approach.**

2.1 Class Vector based scoring

Converting class vector to word similarity to probabilistic score using softmax function

$$ s(w_j/c_i) = \frac{\exp(v_{c_i}^T v_{w_j})}{\sum_{w=1}^{T} \exp(v_{c_i}^T v_{w_j})} \quad (5) $$

$v_{c_i}$ and $v_{w_j}$ are the inner un-normalised $i$th class vector and $j$th word vector respectively. To predict the class of test data, we use different ways as described below

- We do summation of probability score for all the words in sentence for each class and predict the class with the maximum score. (CV Score)

$$ \text{arg max}_{i=1, \ldots, C} \sum_{j=1}^{N_w} \log s(w_j/c_i) $$

- We take the difference of the probability score of the class vectors and use them as
features in the bag of words model followed by Logistic Regression classifier. For example, in the case of sentiment analysis, the two class are positive and negative. So, the expression becomes, (CV-LR) 
\[ f(w) = \log(s(w/c_{pos})) - \log(s(w/c_{neg})) \]

\[ w \] is the vector of the words in vocabulary.

- We compute the similarity between class vectors and word vectors after normalizing them by their l2-norm and using the difference between the similarity score as features in bag of words model. (norm CV-LR) 
\[ f(w) = v_{c_{pos}}^T v_w - v_{c_{neg}}^T v_w \]

**2.2 Feature Selection**

Important features in the corpus can be selected by information theoretic criteria such as conditional entropy and mutual information. We assume the entropy of the class to be maximum i.e. \( H(C) = 1 \) irrespective of the number of documents in each class. Realized information of class given a feature \( w_i \) is defined as,
\[ I(C; w = w_i) = H(C) - H(C/w = w_i) \]

where conditional entropy of class, \( H(C/w = w_i) \) is,
\[ H(C/w = w_i) = - \sum_{c_i} \frac{N_c}{N} \log_2 p(c_i/w_i) \]

\[ p(c_i/w_i) = \frac{\exp(w_i^T v_{c_i})}{\sum_{c_i} \exp(w_i^T v_{c_i})} \]

We calculate expected information \( I(C; w) \) also called mutual information for each word as,
\[ I(C; w) = H(C) - \sum_w p(w) H(C/w) \]

\( p(w) \) is calculated from the document frequency of word. We plot expected information vs realized information to see the important features in the dataset.

**3 Dataset description**

We did experiments on Amazon Electronic Reviews corpus and Yelp Restaurant Reviews. The task is to do sentiment classification among 2 classes (i.e. each review can belong to either positive class or negative class).

- **Amazon Electronic Product reviews**: This dataset is a part of large Amazon reviews dataset McAuley et al.,(2013). This dataset (Johnson and Zhang, 2015) contains training set of 392K reviews split into various various sizes and a test set of 25K reviews. We pre-process the data by converting the text to lowercase and removing some punctuation characters.

- **Yelp Reviews corpus**: This reviews dataset was provided by Yelp as a part of Kaggle competition. Each review contains star rating from 1 to 5. Following the generation of above IMDB Movie Reviews and Amazon Electronic Product Reviews data we considered ratings 1 and 2 as negative class and 4 and 5 as positive class. We separated the files into ratings and do pre-processing of the corpus. In this way, we obtain around 193K reviews for training and around 20K reviews for testing.

| Dataset         | Pos Train | Neg Train | Test Set |
|-----------------|-----------|-----------|----------|
| Amazon          | 196000    | 196000    | 25000    |
| Yelp            | 154506    | 38172     | 19931    |

**Table 1**: Dataset summary. Pos Train: Number of training examples in positive class. Neg Train: Number of training examples in negative class. Test Set: Number of reviews in Test Set

**4 Experiments**

We do phrase identification in the data by two sequential iterations using the approach as described in Kumar et al. (2014). We select the top important phrases according to their frequency and coherence and annotate the corpus with phrases. To do experiments and train the models, we consider those words whose frequency is greater than 5. We use this common setup for all the experiments.

We did experiments with following methods. In the bag of words(bow) approach in which we an-

1. http://riejohnson.com/cnn_data.html
2. http://snap.stanford.edu/data/web-Amazon.html
3. https://www.kaggle.com/c/yelp-recruiting/data
4. We use the code available at https://github.com/TaddyLab/deepir/blob/master/code/parseyelp.py
notate the corpus with phrases as mentioned earlier. We report the best results among the bag of words in Table 2. In the bag of words method, we extract the features by using

1. presence/absence of words (binary)
2. term frequency of the words (tf)
3. inverse document frequency of words (idf)
4. product of term frequency and inverse document frequency of words (tf-idf)

We also evaluate some of the recent state of the art methods for text classification on the above datasets

1. naive bayes features in bag of words followed by Logistic Regression (NB-LR) [Wang and Manning, 2012]
2. inversion of distributed language representation (W2V inversion) [Taddy, 2015]  
3. Convolutional Neural Networks for text categorization (CNN) [Johnson and Zhang, 2015]
4. Paragraph Vectors - Distributed Bag of Words Model (PV-DBOW) [Le and Mikolov, 2014]

Class Vector method based scoring and feature extraction. We extend the open-source code https://code.google.com/p/word2vec/ to implement the class vectors approach. We learn the class vectors and word embeddings using these hyperparameter settings (window=10, negative=5, min_count=5, sample=1e-3, hs=1, iterations=40, λ=1). For prediction, we experiment with the three approaches as mentioned above. (2.7)

After the features are extracted we train Logistic Regression classifier in scikit-learn [Pedregosa et al., 2011] to compute the results. Results of our model and other models are listed in Table 2.

| Model          | Amazon  | Yelp   |
|----------------|---------|--------|
| bow binary     | 91.29   | 92.48  |
| bow tf         | 90.49   | 91.45  |
| bow idf        | 92.00   | 93.98  |
| bow tf-idf     | 91.76   | 93.46  |
| Naive Bayes    | 86.25   | 89.77  |
| NB-LR          | 91.49   | 94.68  |
| W2V inversion  | –       | 93.3   |
| CNN            | 92.86   | –      |
| PV-DBOW        | 90.07   | 92.86  |
| CV Score       | 84.06   | 87.85  |
| norm CV-LR     | 91.58   | 94.91  |
| CV-LR          | 91.70   | 94.83  |

Table 2: Comparison of accuracy scores for different algorithms

5 Results and Discussion

1. We found that annotating the corpus by phrases is important to give better results. For example, the accuracy of PV-DBOW method on Yelp Reviews increased from 89.67% (without phrases) to 92.86% (with phrases) which is more than 3% increase in accuracy.
2. Class vectors have high cosine similarity with words which discriminate between classes. For example, when trained on Yelp reviews, positive class vector was similar to words like "very very good", "fantastic" while negative class vector was similar to words like "awful", "terrible" etc. More results can be seen in Table 3 and Table 4.
3. In Figure 2, we see that class informative words have greater values of both expected information and realized information. One advantage of class vectors based feature selection method over document frequency based method is that low frequency words can have high mutual information value.
4. On Yelp reviews dataset, we find that the class vectors based approach (CV-LR and norm CV-LR) performs much better than normalized term frequency (tf), tf-idf weighted bag of words, paragraph vectors and W2V inversion and it achieves competitive results in sentiment classification.
5. On Amazon reviews dataset, bow idf performs surprisingly well and outperforms all other methods except CNN based approach.
6. Shuffling the corpus is important to learn high quality class vectors. When learning the class vectors using only the data of that class, we find that class vectors lose their discriminating power. So, it is important to jointly learn the model using full dataset.

6 Conclusion and Future Work

We learned the class vectors and used its similarity with words in vocabulary as features effectively in text categorization tasks.

There is a lot of scope for further work and research such as using pre-trained word vectors to compute the class vectors. This will help in cases when training data is small. In order to use more than 1-gram as features we need approaches to compute the embeddings of n-grams from the composition of its uni-grams. Recursive Neural Networks of Socher et al. (2013) can be applied in these case. We can also work on generative models of class based on word embeddings and its application in text clustering and text classification.

| Amazon Electronic Product Reviews | Top Similar Words to |
|-----------------------------------|----------------------|
| Pos class vector                  | Neg class vector      |
| very_pleased                      | unfortunately        |
| product_works_great               | very_disappointed    |
| awesome                           | piece_of_crap        |
| more_than_i_expected             | piece_of_garbage     |
| very_satisfied                    | hunk_of_junk         |
| great_buy                         | awful_service        |
| so_good                           | even Worse           |
| great_product                     | sadly                |
| very_happy                        | worthless            |
| am_very_pleased                   | terrible             |
| a_great_value                     | useless              |
| it_works_great                    | never_worked         |
| works_like_a_charm                | horrible             |
| great_purchase                    | terrible_product     |
| fantastic                         | wasted_my_money      |

Table 3: Top 15 similar words to the positive class vector and negative class vector.
Table 4: Top 15 similar words to the positive class vector and negative class vector.

| Pos class vector  | Neg class vector       |
|-------------------|------------------------|
| very, very, good  | awful                  |
| fantastic         | terrible               |
| awesome           | horrible               |
| very, yummy       | fine, but              |
| great, too        | food, wa, cold         |
| excellent         | awful, service         |
| real, good        | horrib                 |
| spot, on          | not, very, good        |
| great             | pathetic               |
| food, wa, fantastic| mediocre, at, best     |
| very, good, too   | unacceptable           |
| love, the, place  | disgust                |
| food, wa, awesome | food, wa, bland        |
| very, good        | crappy, service        |

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