# Convolutional Neural Networks for Text Categorization: Shallow Word-level vs. Deep Character-level

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#### Abstract

This paper reports the performances of shallow word-level convolutional neural networks (CNN), our earlier work (2015) [3, 4], on the eight datasets with relatively large training data that were used for testing the very deep character-level CNN in Conneau et al. (2016) [1]. Our findings are as follows. The shallow word-level CNNs achieve better error rates than the error rates reported in [1] though the results should be interpreted with some consideration due to the unique pre-processing of [1]. The shallow word-level CNN uses more parameters and therefore requires more storage than the deep character-level CNN; however, the shallow word-level CNN computes much faster.

## 1 Introduction

Text categorization is the task of labeling documents, which has many important applications such as sentiment analysis and topic categorization. Recently, several variations of *convolutional neural networks* (*CNNs*) [7] have been shown to achieve high accuracy on text categorization (see e.g., [3, 4, 9, 1] and references therein) in comparison with a number of methods including linear methods, which had long been the state of the art. *Long-Short Term Memory* networks (LSTMs) [2] have also been shown to perform well on this task, rivaling or sometimes exceeding CNNs [5, 8]. However, CNNs are particularly attractive since, due to their simplicity and parallel processing-friendly nature, training and testing of CNNs can be made much faster than LSTM to achieve similar accuracy [5], and therefore CNNs have a potential to scale better to large training data. Here we focus on two CNN studies that report high performances on categorizing long documents (as opposed to categorizing individual sentences):

- Our earlier work (2015) [3, 4]: shallow word-level CNNs (taking sequences of words as input), which we
  abbreviate as word-CNN.
- Conneau et al. (2016) [1]: very deep *character-level CNNs* (taking sequences of characters as input), which we abbreviate as *char-CNN*.

Although both studies report higher accuracy than previous work on their respective datasets, it is not clear how they compare with each other due to lack of direct comparison. In [1], the very deep char-CNN was shown to perform well with larger training data (up to 2.6M documents) but perform relatively poorly with smaller training data; e.g., it underperformed linear methods when trained with 120K documents. In [3, 4] the shallow word-CNN was shown to perform well, using training sets (most intensively, 25K documents) that are mostly smaller than those used in [1]. While these results imply that the shallow word-CNN is likely to outperform the deep char-CNN when trained with relatively small training sets such as those used in [3, 4], the shallow word-CNN is untested on the training sets as large as those used in [1]. Hence, the purpose of this report is to fill the gap by testing the shallow word-CNNs as in [3, 4] on the datasets used in [1], for direct comparison with the results of very deep char-CNNs reported in [1].

**Limitation of work** In this work, our new experiments are limited to the shallow word-CNN as in [3, 4]. We do not provide new error rate results for the very deep CNNs proposed by [1], and we only cite their results. Although it may be natural to assume that the error rates reported in [1] well represent the best performance that the deep char-CNNs

can achieve, we note that in [1], documents were clipped and padded so that they all became 1014 characters long, and we do not know how this pre-processing affected their model accuracy. To experiment with word-CNN, we handle variable-sized documents as variable-sized as we see no merit in making them fixed-sized, though we reduce the size of vocabulary to reduce storage requirements. Considering that, we emphasize that this work is not intended to be a rigorous comparison of word-CNNs and char-CNNs; instead, it should be regarded as a report on the shallow word-CNN performance on the eight datasets used in [1], referring to the results in [1] as the state-of-the-art performances.

## 1.1 Preliminary

We start with briefly reviewing the very deep word-CNN of [1] and the shallow word-CNN of [3, 4].

#### 1.1.1 Very deep character-level CNNs of [1]

[1] proposed very deep char-CNNs and showed that their best performing models produced higher accuracy than their shallower models and previous deep char-CNNs of [9]. Their best architecture consisted of the following:

- Character embedding of 16 dimensions.
- 29 convolution layers with the number of feature maps being 64, 128, 256, and 512.
- Two fully-connected layers with 2048 hidden units each, following the 29 convolution layers.
- One of the following three methods for downsampling to halve the temporal size: setting stride to 2 in the convolution layer, k-max pooling, or max-pooling with stride 2. Downsampling was done whenever the number of feature maps was doubled.
- k-max pooling with k=8 to produce 4096-dimensional input (per document) to the fully-connected layer.
- Batch normalization.

The kernel size ('region size' in our wording) was set to 3 in every convolution layer. In addition, the results obtained by two more shallower architectures were reported. [1] should be consulted for the exact architectures.

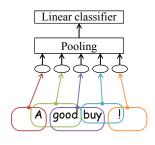
## 1.1.2 Shallow word-level CNNs as in [3, 4]

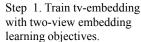
Two types of word-CNN were proposed in [3, 4], which are illustrated in Figure 1. One is a straightforward application of CNN to text (the base model), and the other involves training of *tv-embedding* ('tv' stands for two views) to produce additional input to the base model. The models with tv-embedding produce higher accuracy provided that sufficiently large amounts of unlabeled data for tv-embedding learning are available. As discussed in [5], the shallow word-CNN can be regarded as a special case of a general framework which jointly trains a linear model with a non-linear feature generator consisting of 'text region embedding + pooling', where *text region embedding* is a loose term for a function that converts regions of text (word sequences such as "good buy") to vectors while preserving information relevant to the task of interest.

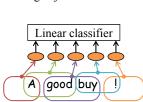
**Word-CNNs without tv-embedding (base model)** In the simplest configuration of the shallow word-CNNs, the region embedding is in the form of

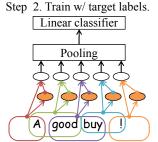
$$f(\mathbf{x}) = \sigma \left( \mathbf{W} \mathbf{x} + \mathbf{b} \right)$$

where  $\sigma$  is a component-wise nonlinear function (typically  $\sigma(x) = \max(x,0)$ ), input x represents a text region via either the concatenation of one-hot vectors for the words in the region or the bow representation of the region, and weight matrix W and bias vector b (shared within a layer) are trained. Note that when x is the concatenation of one-hot vectors, Wx can be interpreted as summing *position-sensitive* word vectors, and when x is the bow representation of the region, Wx can be interpreted as summing *position-insensitive* word vectors. Thus, in a sense, the region embedding f(x) above *internally* and *implicitly* includes word embedding, as opposed to having an *external* and









(a) word-CNN (base model).

(b) word-CNN with tv-embedding.

Figure 1: Shallow word-level CNNs. In each oval, computation in the form of  $\sigma(\mathbf{W}\mathbf{x} + \mathbf{b})$  takes place, where  $\mathbf{x}$  is input, parameters  $\mathbf{W}$  and  $\mathbf{b}$  (shared within a layer) are trained, and  $\sigma$  is component-wise nonlinearity, typically  $\sigma(x) = \max(0, x)$ . In the base model in (a), input  $\mathbf{x}$  is one-hot representation of each text region (e.g., "good buy"). In (b) we first train tv-embedding with two-view embedding learning objectives and then use it to produce additional input to the base model.

explicit word embedding layer before a convolution layer as in, e.g., [6], which makes x the concatenation of word vectors. See also the supplementary material of [4] for the representation power analysis.

As illustrated in Figure 1 (a),  $f(\mathbf{x})$  is applied to the text regions at every location of a document (ovals in the figure), and pooling aggregates the resulting region vectors into a document vector, which is used as features by a linear classifier.

In our experiments with word-CNN without tv-embedding reported below, the one-hot representation used for  $\mathbf{x}$  was fixed to the concatenation of one-hot vectors with a vocabulary of the 30K most frequent words, and the dimensionality of region embedding (i.e., the number of feature maps) was fixed to 500. That is, our one-hot vectors were 30K-dimensional while any out-of-vocabulary word was converted to a zero vector, and the region embedding  $f(\mathbf{x})$  produced 500-dimensional vectors for each region. Region size (the number of words in each region) was chosen from  $\{3,5\}$ . Based on our previous work, we performed max-pooling with k pooling units (each of which covers 1/k of a document) while setting k=1 on sentiment analysis datasets and choosing k from  $\{1,10\}$  on the others. The models described here also served as the base models of the word-CNN with tv-embedding described next.

**Word-CNNs with tv-embedding** Training of word-CNNs with tv-embedding is done in two steps, as shown in Figure 1 (b). First we train region tv-embedding ('tv' stands for two views) in the form of  $f(\mathbf{x})$  above, with a two-view embedding learning objective such as 'predict adjacent text regions (one view) based on a text region (the other view)'. This training can be done with unlabeled data. [4] provides the definition and theoretical analysis of tv-embeddings. Next, we use the tv-embedding to produce additional input to the base model and train it with labeled data. This model can be easily extended to use multiple tv-embeddings, each of which, for example, uses a distinct vector representation of region, and so the region embedding function in the final model (hollow ovals in Figure 1 (b)) can be written as:

$$g(\mathbf{x}, {\{\mathbf{x}^{(i)}\}_i}) = \sigma \left( \mathbf{W}\mathbf{x} + \sum_i \mathbf{W}^{(i)}\mathbf{x}^{(i)} + \mathbf{b} \right).$$

 $\mathbf{x}^{(i)}$  is the output of the tv-embedding indexed by i applied to the corresponding text region. In [4], tv-embedding training was done using unlabeled data as an additional resource; therefore, the proposed models were semi-supervised models.

In the experiments reported below, due to the lack of standard unlabeled data for the tested datasets, we trained tv-embeddings on the labeled training data ignoring the labels; thus, the resulting models are supervised ones. We trained four tv-embeddings with four distinct one-hot representations of text regions (i.e., input to orange ovals in Figure 1 (b)): bow representation with region size 5 or 9, and bag-of-{1,2,3}-gram representation with region size 5 or 9. To make bow representation for tv-embedding, we used a vocabulary of the 30K most frequent words, and to make the bag-of-{1,2,3}-gram representation, we used a vocabulary of the 200K most frequent {1,2,3}-grams. The

dimensionality of tv-embeddings was 300 unless specified otherwise, and the dimensionality of  $g(\cdot)$  was 500 (as in the base model); thus, we note that the dimensionality of internal vectors are comparable to those of the deep char-CNN of [1], which are 64, 128, 256, and 512 as shown below. The rest of the setting was the same as the base model above.

**Other two-step approaches** Another two-step approach with word-CNNs was studied by [6], where the first step is pre-training of the word embedding layer (substituted by use of public word vectors in [6]), which is followed by a convolution layer. One potential advantage of our tv-embedding learning is that it can learn more complex information (embedding of *word sequences*) than word embedding (embedding of *single words in isolation*).

# 2 Experiments

We report the experimental results of the shallow word-CNNs in comparison with the results reported in [1]. The experiments can be reproduced using the code available at riejohnson.com/cnn\_download.html.

## 2.1 Data and data preprocessing

The eight datasets used in [1] are summarized in Table 1 (a). AG and Sogou are news, Dbpedia is an ontology, and Yelp and Amazon (abbreviated as 'Ama') are reviews. '.p' (polarity) in the names of review datasets indicates that labels are either positive or negative, and '.f' (full) indicates that labels represent the number of stars. Yahoo contains questions and answers from the 'Yahoo! Answers' website. On all datasets, classes are balanced. Sogou consists of Romanized Chinese. The others are in English though some contain characters of other languages (e.g., Chinese, Korean) in small proportions.

To experiment with the deep char-CNNs, [1] converted upper-case letters to lower-case letters and used 72 characters (lower-case alphabets, digits, special characters, and special tokens for padding and out-of-vocabulary characters). They *padded* the input text with a special token to a fixed size of 1014.

To experiment with the shallow word-CNNs, we also converted upper-case letters to lower-case letters. Unlike [1], we handled variable-sized documents as variable-sized without any shortening or padding; however, we limited the vocabulary size to 30K words and 200K {1,2,3}-grams, as described above. To put it into perspective, the size of the complete word vocabulary of the largest training set (Ama.p) is 1.3M, and when limited to the words with frequency no less than 5, it is 221K. By comparison, a vocabulary of 30K sounds rather small, but it covers about 98% of the text on Ama.p, and it appears to be sufficient for obtaining good accuracy.

## 2.2 Experimental details of word-level CNNs

On all datasets, we held out 10K data points from the training set for use as validation data. Models were trained using the training set minus validation data, and model selection (or hyper parameter tuning) was done based on the performance on the validation data.

Tv-embedding training was done as in [4]; weighted square loss was minimized without regularization while the target regions (adjacent regions) were represented by bow vectors, and the data weights were set so that the negative sampling effect was achieved. Tv-embeddings were fixed (i.e., no weight updating) during the final training with labeled data.

Training with labels (either with or without tv-embedding) was done as follows. A log loss (or cross entropy) with softmax was minimized. Optimization was done by mini-batch SGD with momentum 0.9 and the mini-batch size was set to 100. The number of epochs was fixed to 30 (except for AG, the smallest, for which it was fixed to 100), and the learning rate was reduced once by multiplying 0.1 after 24 epochs (or 80 epochs on AG). In all layers, weights were initialized by the Gaussian distribution of zero mean and standard deviation 0.01. The initial learning rate was treated as a hyper parameter. Regularization was done by applying dropout with 0.5 to the input to the top layer and having a L2 regularization term with parameter 0.0001 on the top layer weights.

#### (a) Data statistics

	AG	Sogou	Dbpedia	Yelp.p	Yelp.f	Yahoo	Ama.f	Ama.p
# of training documents	120K	450K	560K	560K	650K	1.4M	3M	3.6M
# of test documents	7.6K	60K	70K	38K	50K	60K	650K	400K
# of classes	4	5	14	2	5	10	5	2
Average length (words)	45	578	55	153	155	112	93	91
Average length (characters)	219	2709	298	710	718	519	441	432

#### (b) Error rates (%)

Models	depth	AG	Sogou	Dbpedia	Yelp.p	Yelp.f	Yahoo	Ama.f	Ama.p
Linear model best [9]	0	7.64	2.81	1.31	4.36	40.14	28.96	44.74	7.98
char-CNN best [1]	9+2	9.17	3.58	1.35	4.88	36.73	27.60	37.95	4.70
	29+2	8.67	3.18	1.29	4.28	35.28	26.57	37.00	4.28
word-CNN w/o tv-embed.	1	6.95	2.21	1.12	3.44	34.21	26.06	37.51	4.27
word-CNN w/ tv (300-dim)	2	6.57	1.89	0.84	2.90	32.39	24.85	36.24	3.79

Table 1: (a) Data statistics. (b) Error rates (%).

'depth' counts the hidden layers with weights in the longest path. [9] reported the results of several linear methods, and we copied only the *best* results. [1] reported the results of deep char-CNN with three downsampling methods, and we copied only the *best* results. The word-CNN results are our new results. The best (or second best) results are shown in bold (or italic) font, respectively.

#### 2.3 Performance results

**Error rates** In Table 1 (b), we show the error rate results of the shallow word-CNN in comparison with the best results of the deep char-CNN reported in [1] and the best results of linear models reported in [9]. On each dataset, the best results are shown in bold and the second best results are shown in the italic font.

On all datasets, the shallow word-CNN with tv-embeddings performs the best. The second best performer is the shallow word-CNN without tv-embedding on all but Ama.f (Amazon full). Whereas the deep char-CNN underperforms traditional linear models when training data is relatively small, the shallow word-CNNs with and without tv-embedding clearly outperform them on all the datasets. We observe that, as in our previous work [4], additional input produced by tv-embeddings led to substantial improvements.

The performances of word-CNN without tv-embedding might be further improved by having multiple region sizes [3, 6], but for simplicity, we did not attempt it in this work.

**Model size and computation time** In Table 2, we observe that, *compared with the deep char-CNN*, *the shallow word-CNN has more parameters but computes much faster*. Although the table shows computation time and error rates on one particular dataset (Yelp.f), the observation was the same on the other datasets. The shallow word-CNN has more parameters because the number of parameters mostly depends on the vocabulary size, which is large with word-CNN (30K and 200K in our experiments) and small with char-CNN (72 in [1]). Nevertheless, computation of the shallow word-CNN can be made much faster than the deep char-CNN for three reasons<sup>1</sup>. First, with implementation to handle sparse data efficiently, computation of shallow word-CNN does *not* depend on the vocabulary size. For example, when x is the concatenation of p one-hot vectors of dimensionality v (vocabulary size), computation time of  $\mathbf{W}\mathbf{x}$  (the most time-consuming step) depends *not* on v (e.g., 30K) but on p (e.g., 3) since we only need to multiply nonzero elements of x with the weights in  $\mathbf{W}$ . Second, character-based methods need to process about five times more text units than word-based methods; compare the rows of average length in words and characters in Table 1 (b). Third, a deeper network is less parallel processing-friendly since many layers have to be processed sequentially.

If we reduce the dimensionality of tv-embedding from 300 to 100, the number of parameters can be reduced to a half with a small degradation of accuracy, as shown in Table 2; more error rate results with 100-dim tv-embedding are

<sup>&</sup>lt;sup>1</sup> Computation time depends on the specifics of both implementation and environment including hardware. Our discussion here assumes parallel processing and efficient handling of sparse matrices (whose components are mostly zero), and otherwise it is general.

		Depth	Dimensionality of	#param	Time	Error
		Берш	layer outputs (#layers)	πραιαιιι		rate(%)
		9+2	16(1), 64(3), 128(2),	2.2M	†215	36.73
char-CNN [1]		972	256(2), 512(2), 2048(2)	2.2111	213	30.73
		29+2	16(1), 64(11), 128(10),	4.6M	‡700	35.28
			256(4), 512(4), 2048(2)	1.0111	+700	33.20
	w/o tv-embed.	1	500(1)	45M	6	34.21
word-CNN	w/ 2 tv (100-dim)	2	100(2), 500(1)	68M	21	32.77
	w/ 4 tv (100-dim)	2	100(4), 500(1)	91M	36	32.55
	w/ 4 tv (300-dim)	2	300(4), 500(1)	184M	72	32.39

Table 2: Model size and computation time. 'Time': Elapsed time (seconds) for testing on the Yelp.f test data using Tesla M2070. It excludes preprocessing for input vector generation including one-hot vector manipulation (concatenation/bow generation) for word-CNN. Error rates are also on Yelp.f. The shallow word-CNN has more parameters but computes faster than the deep char-CNN. Information on the deep char-CNN is from [1] except for 'Time'.

† Processing time depends on implementation, and test time of the deep char-CNN was measured using our implementation. As described in [1], we clipped and padded documents so that the documents all became 1014 characters long.

	AG	Sogou	Dbpedia	Yelp.p	Yelp.f	Yahoo	Ama.f	Ama.p
word-CNN w/ 4 tv (100-dim)	6.57	1.96	0.84	2.97	32.55	25.14	36.52	3.90
word-CNN w/ 4 tv (300-dim)	6.57	1.89	0.84	2.90	32.39	24.85	36.24	3.79

Table 3: Error rates of the shallow word-CNN with tv-embeddings of 100 dimensions ('w/ 4 tv(100-dim'). 'w/ 4 tv (300-dim)' was copied from Table 1 (b) for easy comparison.

shown in Table 3. Reducing the number of tv-embeddings from four to two also reduces the number of parameters with a small degradation of accuracy ('w/ 2 tv (100-dim)' in Table 2).

### Summary of the results

- The shallow word-CNNs as in [3, 4] generally achieved better error rates than those of the very deep char-CNNs reported in [1].
- The shallow word-CNN computes much faster than the very deep char-CNN. This is because the deep char-CNN needs to process more text units as there are many more characters than words per document, and because many layers need to be processed sequentially. This is a practical advantage of the shallow word-CNN.
- The shallow word-CNNs use more parameters and therefore require more storage, which is a drawback in storage-tight situations. Reducing the number and/or dimensionality of tv-embeddings reduces the number of parameters though it comes with the expense of a small degradation of accuracy.

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