LOSS-FREE COMPRESSION OF WORD EMBEDDINGS VIA DEEP COMPOSITIONAL CODE LEARNING

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ABSTRACT

Natural language processing (NLP) models suffer from a large storage or memory footprint due to the massive number of parameters used in word embeddings. Deploying neural NLP models to mobile devices requires compressing the word embeddings without sacrificing the performance too much. For this purpose, we propose a novel hashing-based approach that constructs the embedding vectors for all in-vocabulary words using few basis vectors. The composition of basis vectors is controlled by the hash code assigned to each word. To maximize the compression rate, we adopt the compositional coding approach instead of usual binary codes. Each code is composed by multiple discrete numbers, such as $(3, 2, 1, 8)$, where the value of each component is limited in a fixed range. We propose to directly learn the discrete codes in an end-to-end neural network by reconstructing the pre-trained embeddings using the Gumbel-softmax trick. Our experiments show the loss-free compression rate achieves 98% in sentiment analysis task and over 94% in machine translation task. In sentiment analysis task, the reconstructed embeddings improve the classification accuracy by around 1%. Comparing to other approaches such as character-level segmentation, the proposed method is language-independent and does not require modifications to the model architecture.

1 INTRODUCTION

In neural-based Natural Language Processing models, word embeddings play an important role. Neural word embeddings encapsulate the necessary linguistic information in continuous vectors for all words in vocabulary. However, as each word is assigned an independent embedding vector, the number of parameters in the embedding matrix can be tremendously large. For example, the network has to hold 100M embedding parameters to represent 200K words, when each embedding has 500 dimensions.

As only a small portion of the word embeddings is selected in the forward pass, the giant embedding matrix usually does not cause a speed issue. However, having a massive number of parameters in the neural network results in a large storage or memory footprint. When other components of the neural network are also large, the word embedding layer may fail to fit into GPU memory during training. Moreover, as the demand for low-latency neural computation rises for mobile platforms, some neural-based models are expected to run on mobile devices. It becomes more important to compress the size of NLP models for deploying them to devices with limited memory capacity.

In this work, we attempt to reduce the number of parameters used in word embeddings without hurting the performance of the model. We hypothesize that learning independent embeddings for all words causes the redundancy in embedding vectors, as the inter-similarity among words is ignored. Some words are very similar regarding the semantics. For example, “dog” and “dogs” have almost the same meaning except one is plural. To efficiently represent these two words, it is desirable to share information between the two embeddings. However, a small portion in both vectors have to be trained independently to capture the difference in syntactic roles.

Follow the intuition of creating partially shared embeddings, instead of assigning each word a unique id, we represent a word w with a code C_w composed of M components. Each component C_w^i is an integer number in $[1, K]$. Ideally, similar words shall have similar codes. For example, we may want $C_{\text{dog}} = (3, 2, 4, 1)$ and $C_{\text{dogs}} = (3, 2, 4, 2)$. Once we obtained such compact codes for

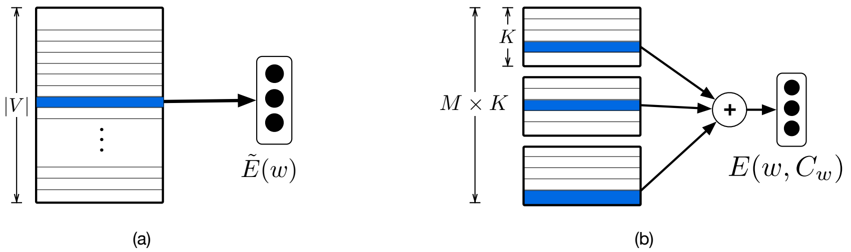


Figure 1: A comparison of embedding computation between the conventional approach (a) and compositional coding approach (b)

all words in the vocabulary, we assign embedding vectors to the components in the codes rather than unique words. More specifically, we create M codebooks, and each codebook contains K codeword vectors. The embedding of a word $E(w)$ is computed by summing up the codewords for all components in the code as

$$E(w, C_w) = \sum_{i=1}^{M} E_i(C_w^i), \tag{1}$$

where $E_i(\cdot)$ returns a codeword vector for i-th component. In this way, the embedding matrix will have $M \times K$ vectors, which is usually much smaller than the vocabulary size. Fig. 1 gives a intuitive comparison between our coding approach and the conventional approach (assigning unique ids).

Although the number of embedding vectors can be greatly reduced by using such coding scheme, we want to avoid the performance loss comparing to using normal embeddings. In other words, given a set of normal word embeddings $\tilde{E}(w)$, we want to find a set of codes $\hat{C}_w$ that can achieve the same effectiveness of $\tilde{E}(w)$ with $E(w, \hat{C}_w)$ for all words. A safe and straight-forward way is to minimize the squared distance between the baseline embeddings and the composed embeddings as

$$\hat{C}_w = \underset{C_w}{\text{argmin}} \frac{1}{|V|} \sum_{w \in V} ||E(w, C_w) - \tilde{E}(w)||^2 \tag{2}$$

$$= \underset{C_w}{\text{argmin}} \frac{1}{|V|} \sum_{w \in V} ||\sum_{i=1}^{M} E_i(C_w^i) - \tilde{E}(w)||^2 , \tag{3}$$

where $|V|$ is the vocabulary size. The baseline embeddings can be a set of pre-trained vectors such as word2vec (Mikolov et al., 2013) or Glove (Pennington et al., 2014) embeddings.

In Eq. 2, the baseline embedding matrix $\tilde{\mathbf{E}}$ is approximated by M codewords selected from M codebooks. The selection of codewords is controlled by the code C_w. Such problem of learning compositional compact codes with multiple codebooks is formalized and discussed in the research field of compression-based source coding as *multi-codebook quantization* (Jégou et al., 2011; Babenko & Lempitsky, 2014; Du & Wang, 2014; Martinez et al., 2016). Previous works learn compact codes to perform efficient similarity search of vectors. In this work, we utilize the compact codes for a different purpose, that is, constructing word embeddings with fewer parameters.

Due to the discreteness in the hash codes, it is usually difficult to directly optimize the objective in Eq. 2 for code learning. In this paper, we propose a simple and straight-forward method to directly learn the codes in an end-to-end neural network. We utilize the Gumbel-Softmax trick (Maddison et al., 2016; Jang et al., 2016) to find the best code composition that forces the model to assign similar codes to the words with similar embeddings.

The contribution of this paper can be summarized as three folds:

- We propose to utilize the compositional coding approach to construct the word embeddings with drastically fewer parameters. In the experiments, we show that over 98% of the embedding parameters can be eliminated in sentiment analysis task without hurting performance. The compression rate in machine translation task also reaches 94%.

- We propose a way to directly learn the codes in an end-to-end neural network, with a Gumbel-softmax layer to encourage the discreteness.
- The source code for code learning will be packaged into a tool. With the learned codes and basis vectors, the computation graph for composing embeddings is fairly easy to implement, which does not require modifications to other parts in the neural network.

2 RELATED WORK

Existing works for compressing neural networks include low-precision computation (Vanhoucke et al., 2011; Hwang & Sung, 2014; Courbariaux et al., 2014; Anwar et al., 2015), quantization (Chen et al., 2015; Han et al., 2015a; Zhou et al., 2017), network pruning (LeCun et al., 1989; Hassibi & Stork, 1992; Han et al., 2015b; Wen et al., 2016) and knowledge distillation (Hinton et al., 2015). Network quantization is a technique to reduce the number of real weights. HashedNet (Chen et al., 2015) forces each weight matrix to have few real weights. For each position in the weight matrix, the assignment of real weights is determined by a hash function. To solve the problem that HashedNet does not capture the non-uniform nature of the networks, DeepCompression (Han et al., 2015a) groups weight values into clusters based on a pre-trained weight matrix. The weights in the same cluster share a same value. The weight assignments for each position in the weight matrix are stored in the form of Huffman codes. However, as the embedding matrix is tremendously big, the number of hash codes a model need to maintain is still very large even with Huffman coding.

Network pruning works in different way that makes a network sparse. Iterative pruning (Han et al., 2015b) prunes a weight value if its absolute value is smaller than a threshold. The remaining network weights are retrained after pruning. Some recent works (See et al., 2016; Zhang et al., 2017) also apply iterative pruning to prune 80% of the connections for neural machine translation models. In this paper, we compare the proposed method with iterative pruning. Please note that as our method produces a dense matrix composed of $M \times K$ basis vectors, there is room to further apply quantization or pruning techniques to achieve a even higher compression rate.

The problem of learning compact codes described in this paper is closely related to learning to hash (Weiss et al., 2008; Kulis & Darrell, 2009; Liu et al., 2012), which aims to learn the hash codes for vectors to facilitate the approximate nearest neighbor search. The fundamental difference between learning to hash and our approach is the objective. The hashing methods mainly aim to maintain the distance of input vectors in the Hamming space. Therefore, a majority of the methods in learning to hash use pairwise similarity as the objective function. In contrast, we use reconstruction loss as the objective function.

The codes in learning to hash methods are usually presented in the binary form. Initiated by product quantization (Jégou et al., 2011), few succeeding works such as additive quantization (Babenko & Lempitsky, 2014) and compositional coding (Du & Wang, 2014) explore the use of multiple codebooks for compression-based source coding. We also adopt the compositional coding scheme for the storage efficiency. Previous works employ alternating optimization as the learning algorithm, which alternatively optimizes the codebooks and the discrete codes. In this work, we propose a method to learn the codes directly in an end-to-end neural network.

Some recent works (Xia et al., 2014; Liu et al., 2016; Yang et al., 2017) in learning to hash also utilize neural networks as hash functions to produce the binary codes. These methods impose binary constraints in the code layer (e.g., sigmoid function) to encourage the discreteness. However, such constraints cannot be applied to the compositional coding approach. In our work, we encourage the discreteness with Gumbel-Softmax trick.

As an alternative to our approach, one can also reduce the number of unique word types by forcing a character-level segmentation. Kim et al. (2016) proposed a character-based neural language model, which applies a convolutional layer after the character embeddings. Botha et al. (2017) propose to use char-gram as input features, which are further hashed to save space. Generally, using character-level inputs requires modifications to the model architecture. Moreover, some Asian languages such as Japanese and Chinese have a large vocabulary even in character level, which makes the character-based approach difficult to be applied. In contrast, our approach does not suffer from these limitations.

3 Compositional Compact Codes

In this section, we give a formal description of the compositional coding approach and analyze its merits. We represent a word w with a compact code C_w that is composed of M components s.t. $C_w \in Z_+^M$. Each component C_w^i is constrained to have a value in $[1, K]$, which also indicates that it takes $\log_2 K$ bits to store each code. For convenience, K is selected to be a number of a multiple of 2, so that the codes can be efficiently stored.

If we restrict each component C_w^i to take 0 or 1, the code for each word C_w will be a binary code. In this case, the code learning problem is equivalent to a matrix factorization problem with binary components. Forcing the compact codes to be binary numbers can be beneficial as the learning problem is usually easier to solve in the binary case, and some existing optimization algorithms in learning to hash can be reused. However, the compositional coding approach produces shorter codes and is thus more storage efficient.

In addition to the embedding vectors, the model also has to store the hash codes for all in-vocabulary words. The footprint of the hash codes depends on the vocabulary size and the number of bits for every single code. Suppose we wish the model to have a set of N basis vector, then the code length with be $N/2$ bits in the binary case. For the compositional codes, if we can find a $M \times K$ decomposition such that $M \times K = N$, then each code will have $M \log_2 K$ bits. For example, a binary code will have a length of 256 bits to support 512 basis vectors. In contrast, a 32 × 16 compositional coding scheme will produce codes of only 128 bits.

	#basis	**computation**	**code length (bits)**
conventional	$\lvert V \rvert$	1	-
binary	N	$N/2$	$N/2$
compositional	MK	M	$M \log_2 K$

Table 1: A comparison of different coding approaches in terms of the number of basis vectors, code length and the number of vectors need to be indexed when constructing a word embedding

A comparison of different coding approaches is summarized in Table 1. The conventional approach assigns a unique id to each word. Therefore, the number of basis embedding vectors is identical to the vocabulary size and the computation is basically a single indexing operation. In the case of binary codes, the computation for constructing an embedding is a summation over $N/2$ basis vectors. For the compositional approach, the number of vectors required to construct an embedding vector is M. Both the binary and compositional approach has significantly fewer basis vectors. The compositional coding approach provides the better balance between the number of basis vectors and the code length.

4 Code Learning with Gumbel-Softmax

Let $\tilde{\mathbf{E}} \in \mathbb{R}^{|V| \times H}$ be the original embedding matrix, where each embedding vector has H units. By using the reconstruction loss as the objective in Eq. 2, we are actually finding an approximate matrix factorization $\tilde{\mathbf{E}} \approx \sum_{i=0}^{M} \boldsymbol{D^i A_i}$, where $\boldsymbol{A_i} \in \mathbb{R}^{K \times H}$ is a basis matrix for the i-th component. $\boldsymbol{D^i}$ is a $|V| \times K$ code matrix, where each row is an K-dimensional one-hot vector. Let $\boldsymbol{d_w^i}$ be the one-hot vector corresponding to the component C_w^i, the computation of the word embeddings can be reformulated as

$$E(w, C_w) = \sum_{i=0}^{M} \boldsymbol{A_i}^\top \boldsymbol{d_w^i}. \tag{4}$$

Therefore, the learning problem of discrete codes C_w is converted to a problem of finding a set of optimal one-hot vectors $\boldsymbol{d_w^1}, ..., \boldsymbol{d_w^M}$ and source dictionaries $\boldsymbol{A_i}$ that minimize the reconstruction loss in Eq. 2. The Gumbel-softmax reparameterization trick (Maddison et al., 2016; Jang et al., 2016) is an useful tool to parameterize a discrete distribution such as the K-dimensional one-hot vectors $\boldsymbol{d_w^i}$ in Eq. 4. By applying the Gumbel-softmax trick, the k-th elemement in $\boldsymbol{d_w^i}$ is computed

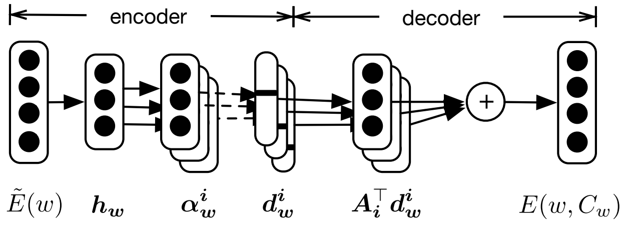


Figure 2: The network architecture for learning compositional compact codes. The Gumbel-softmax computation is marked with dashed lines.

by

$$\left(\boldsymbol{d_w^i}\right)_k = \mathrm{softmax}_\tau(\log \boldsymbol{\alpha_w^i} + G)_k \tag{5}$$

$$= \frac{\exp((\log\,(\boldsymbol{\alpha_w^i})_k + G_k)/\tau)}{\sum_{k'=1}^{K} \exp((\log\,(\boldsymbol{\alpha_w^i})_{k'} + G_{k'})/\tau)}\;, \tag{6}$$

where G_k is a noise term that is sampled from a Gumbel distribution $-\log(-\log(\mathrm{Uniform}[0,1]))$, whereas τ is the temperature of the softmax. In our model, the vector $\boldsymbol{\alpha_w^i}$ is computed by a simple neural network with a single hidden layer as

$$\boldsymbol{h_w} = \tanh(\boldsymbol{\theta}^\top \tilde{E}(w) + \boldsymbol{b}), \tag{7}$$

$$\boldsymbol{\alpha_w^i} = \mathrm{softplus}(\boldsymbol{\theta_i'}^\top \boldsymbol{h_w} + \boldsymbol{b_i'})\,. \tag{8}$$

In our experiments, the hidden layer $\boldsymbol{h_w}$ always has a size of $MK/2$. As described in Eq. 6, the Gumbel-softmax trick is applied to $\boldsymbol{\alpha_w^i}$ to obtain $\boldsymbol{d_w^i}$. Finally, the model reconstructs the embedding $E(w, C_w)$ with Eq. 4 and compute the reconstruction loss in Eq. 2. The model architecture of the end-to-end neural network is illustrated in Fig. 2, which is effectively an auto-encoder with a Gumbel-softmax middle layer. The whole neural network for coding learning has five parameters $(\boldsymbol{\theta}, \boldsymbol{b}, \boldsymbol{\theta'}, \boldsymbol{b'}, \boldsymbol{A})$.

Once the coding learning model is trained, the code C_w for a word can be easily obtained by applying argmax to the one-hot vectors $\boldsymbol{d_w^i}$. The basis vectors (codewords) for constructing the embeddings are exactly the row vectors in the matrix $\boldsymbol{A}$, which is a decoder parameter in the code learning model.

For general NLP tasks, one can learn the compositional codes from public available word vectors such as Glove vectors. However, for some tasks such as machine translation, the word embeddings are usually jointly learned with other parts of the neural network. For such tasks, one has to train a normal model first to obtain the embeddings for all in-vocabulary words. Then based on the trained embedding matrix, one can learn a set of task-specific codes. As the reconstructed embeddings are not identical to the original embeddings, the model parameters other than the embedding matrix have to be retrained again.

5 Experiments

5.1 Experiment Settings

In our experiments, we focus on evaluating the maximum loss-free compression rate of word embeddings on two typical NLP tasks: sentiment analysis and machine translation. We compare the model performance and the size of embedding layer with the uncompressed baseline mode and the iterative pruning method (Han et al., 2015b). Note that the sizes of other parts in the neural networks are not included in our results. For dense matrices, the report the size of dumped numpy arrays. For the sparse matrices, we report the size of dumped *compressed sparse column matrices* (`csc_matrix`) in scipy. All float numbers take 32 bits storage. We enables the compressing option when dumping the matrices, without this option, the file size is about 1.1 times bigger.

5.2 Code Learning

To learn efficient compact codes for each word, our proposed method requires a set of baseline embedding vectors. For the sentiment analysis task, we learn the codes based on the publicly available Glove vectors. For the machine translation task, we first train a neural machine translation (NMT) model with a normal embedding layer to obtain task-specific word embeddings. Then we learn the codes using the pre-trained embeddings.

We train the end-to-end network described in Section 4 to learn the codes automatically. In each iteration, a small batch of the embeddings is sampled uniformly from the baseline embedding matrix. The network parameters are optimized to minimize the reconstruction loss of the sampled embeddings. In our experiments, the batch size is set to 128. We use Adam optimizer (Kingma & Ba, 2014) with a fixed learning rate of 0.0001. The training is run for 200K iterations. Every 1,000 iterations, we examine the loss on a fixed validation set and save the parameters if the loss decreases. We evenly distribute the model training to 4 GPUs using the *nccl* package, so that one round of code learning takes around 12 minutes to complete.

5.3 Sentiment Analysis

Dataset: For sentiment analysis, we use a standard separation of IMDB movie review dataset (Maas et al., 2011), which contains 25k reviews for training and 25K reviews for testing purpose. We lowercase and tokenize all texts with the *nltk* package. We choose the 300-dimensional uncased Glove word vectors (trained on 42B tokens of Common Crawl data) as our baseline embeddings. The vocabulary for the model training contains all words appears both in the IMDB dataset and the vocabulary of Glove vectors, which results in around 75K words. We truncate the texts of reviews to assure they are not longer than 400 words. In this task, we attempt to learn an efficient compositional codes based on the Glove vectors to achieve comparable performance, but with significantly less embedding parameters.

Model architecture: Both the baseline model using Glove vectors and the small model has the same computational graph except the embedding layer. The model is composed of a single LSTM layer with 150 hidden units and a sof"tmax layer for predicting the binary label. For the baseline model, the embedding layer contains a large $75K \times 300$ embedding matrix initialized by Glove embeddings. For the small model, suppose we use a 32×16 code decomposition. The embedding matrix will then have shape 512×300, which is initialized by the concatenated basis matrix $[\boldsymbol{A_1}; \boldsymbol{A_2}; ...; \boldsymbol{A_M}]$. The embedding parameters for both models remain fixed during the training.

Training details: The models are trained with Adam optimizer for 15 epochs with a fixed learning rate of 0.0001. At the end of each epoch, we evaluate the model performance on a small validation set. The parameters with lowest validation loss are saved.

Results: For different settings of the number of components M and the number of codeword candidates K, we train the code learning network. The average reconstruct loss (least-squares error) on a fixed validation set is summarized in the left of Table 2. For reference, we also report the final size (MB) of embedding layer in the right table, which is the total size of embedding vectors and compact codes (Eq. (ref)). We can see that increasing either M or K can effectively improve the reconstruction loss. However, setting M to a large number will result in longer codes for representing each word, thus significantly increase the size of embedding layer. Hence, it is important to choose a correct setting of M and K to balance the performance and model size.

To see how the reconstructed loss translates to the classification accuracy, we train the sentiment analysis model for few settings of code learning and report the results in Table 3. The baseline model using 75k Glove embeddings achieves an accuracy of 87.18. The uncompressed size of the embedding matrix is 85.94MB when each float number takes 32 bits of storage. For the models using code decomposition, we can observe a clear trade-off between the accuracy and the size of embedding layer.

Surprisingly, the model using reconstructed embeddings starts to outperform the baseline using original Glove-based embeddings with a 16×32 code decomposition. In this case, the size of 512 vectors is 0.58 MB, whereas the codes of 75k words take 0.71 MB of storage. The uncompressed size of embedding layer is 1.30 MB, achieving a reduction rate of 98.4%. Increasing the code length is shown to improve the classification performance, which also results in larger model sizes as a byproduct.

loss	M=8	M=16	M=32	M=64
K=8	29.1	25.8	21.9	15.5
K=16	27.0	22.8	19.1	11.5
K=32	24.4	20.4	14.3	9.3
K=64	21.9	16.9	12.1	7.6

size (MB)	M=8	M=16	M=32	M=64
K=8	0.28	0.56	1.12	2.24
K=16	0.41	0.83	1.67	3.34
K=32	0.62	1.24	2.48	4.96
K=64	0.95	1.91	3.82	7.64

Table 2: Reconstruction loss and the size of embedding layer (MB) of difference settings

	#vectors	**vector size**	**code len**	**code size**	**total size**	**accuracy**
Glove baseline	75102	78 MB	-	-	78 MB	87.18
prune 80%	75102	21 MB	-	-	21 MB	86.25
prune 90%	75102	11 MB	-	-	11 MB	84.96
prune 95%	75102	5.31 MB	-	-	5.31 MB	83.88
8 × 8 coding	64	0.06 MB	24 bits	0.21 MB	0.27 MB	82.84
8 × 16 coding	128	0.13 MB	32 bits	0.28 MB	0.41 MB	83.77
16 × 8 coding	128	0.13 MB	48 bits	0.42 MB	0.55 MB	85.21
8 × 64 coding	512	0.52 MB	48 bits	0.42 MB	0.94 MB	86.66
16 × 32 coding	512	0.52 MB	80 bits	0.71 MB	**1.23 MB**	**87.37**
32 × 16 coding	512	0.52 MB	128 bits	1.14 MB	**1.66 MB**	**87.80**
64 × 8 coding	512	0.52 MB	192 bits	1.71 MB	**2.23 MB**	**88.15**

Table 3: Trade-off between the model performance and the size of embedding layer in IMDB sentiment analysis task

5.4 Machine Translation

Dataset: For machine translation tasks, we experiment on IWSLT 2014 German-to-English translation task (Cettolo et al., 2014) and ASPEC English-to-Japanese translation task (Nakazawa et al., 2016). The IWSLT14 training data contains 178K sentence pairs, which is a small dataset for machine translation. We utilize moses toolkit (Koehn et al., 2007) to tokenize and lowercase both sides of the texts. Then we concatenate all five TED/TEDx development and test corpus to form a test set containing 6750 sentence pairs. We apply byte-pair encoding (Sennrich et al., 2016) to transform the texts to subword level so that the vocabulary has a size of 20K for each language. For evaluation, we report *tokenized BLEU* using "multi-bleu.perl".

The ASPEC dataset contains 300M bilingual pairs in the training data with the automatic estimated quality scores provided for each pair. We only use the first 150M pairs for training the models. The English texts are tokenized by moses toolkit whereas the Japanese texts are tokenized by kytea (Neubig et al., 2011). The vocabulary size for each language is reduced to 40K using byte-pair encoding. The evaluation is performed using a standard post-processing script for this dataset.

Model architecture: In our preliminary experiments, we found a 32 × 16 coding works well for a vanilla NMT model. As it is more meaningful to test on a high-performance model, we applied several techniques to improve the performance. The model has a standard bi-directional encoder composed of two LSTM layers similar to Bahdanau et al. (2014). The decoder contains two LSTM layers. Residual connection (He et al., 2016) with scaling factor of $\sqrt{1/2}$ is applied to the two decoder states to compute the outputs. All LSTMs and embeddings have 256 hidden units in IWSLT14 task and 1000 hidden units in ASPEC task. The decoder states are firstly linearly transformed to 600-dimensional vectors before computing the final softmax. Dropout with a rate of 0.2 is applied everywhere except the recurrent computation. We apply Key-Value Attention (Miller et al., 2016) to the first decoder, where the query is the sum of the feedback embedding and the previous decoder state and the keys are computed by linear transformation of encoder states.

Training details: All models are trained by Nesterov's accelerated gradient (Nesterov, 1983) with an initial learning rate of 0.25. We evaluate the smoothed BLEU (Lin & Och, 2004) on a validation set composed of 50 batches every 7,000 iterations. The learning rate is reduced by a factor of 10 if no improvement is observed in 3 validation runs. The training ends after the learning rate is reduced three times. Similar to the code learning, the training is distributed to 4 GPUs, each GPU computes a mini-batch of 16 samples.

We firstly train a baseline NMT model to obtain the task-specific embeddings for a total of 40K words in both languages. Then based on these baseline embeddings, the obtain the hash codes and basis vectors for constructing embedding vectors by training the code learning model. Finally, the NMT models using compositional coding are trained by plugging in the reconstructed embeddings. Note that the embedding layer is fixed in this phase, other parameters are retrained from random initial values.

Results: The experimental results are summarized in Table 4. All translations are decoded by the beam search with a beam size of 5. With the high-performance model, the 32 × 16 coding scheme fails to match the performance of the baseline in IWSLT14 task. This may indicate that the embedding vectors contain more information in a larger model, which is difficult to be compressed. When a 64 × 16 coding is used, the performance reaches the baseline model with a 94% reduction rate of the size. Note that the sizes of NMT models are still quite large due to the big softmax layer and recurrent layers, which are not reported in the table. Please refer to some existing works (Zhang et al., 2017) for the techniques of compressing layers other than word embeddings.

	coding	**#vectors**	**vector size**	**code len**	**code size**	**total size**	**BLEU(%)**
De → En	baseline	40000	35 MB	-	-	35 MB	29.45
	prune 90%	40000	5.21 MB	-	-	5.21 MB	29.34
	prune 95%	40000	2.63 MB	-	-	2.63 MB	28.84
	32 × 16	512	0.44 MB	128 bits	0.61 MB	1.05 MB	29.04
	32 × 32	1024	0.89 MB	160 bits	0.76 MB	1.65 MB	29.17
	64 × 16	1024	0.89 MB	256 bits	1.22 MB	**2.11 MB**	**29.56**
En → Ja	baseline	80000	274 MB	-	-	274 MB	37.93
	prune 90%	80000	41 MB	-	-	41 MB	?
	prune 95%	80000	? MB	-	-	? MB	?
	32 × 16	512	1.75 MB	128 bits	1.22 MB	2.97 MB	38.10
	64 × 16	1024	3.50 MB	256 bits	2.44 MB	**5.94 MB**	**38.89**

Table 4: Trade-off between the model performance and the size of embedding layer in IWSLT 2014 German-to-English translation task

6 Qualitative Analysis

6.1 Examples of Learned Codes

In Table 5, we show some examples of learned codes based the 300-dimensional uncased Glove embeddings used in the sentiment analysis task. We can see that similar words have similar codes for both categories of words. Such a code-sharing mechanism can largely reduce the redundancy of the word embeddings, thus help to achieve a high reduction rate.

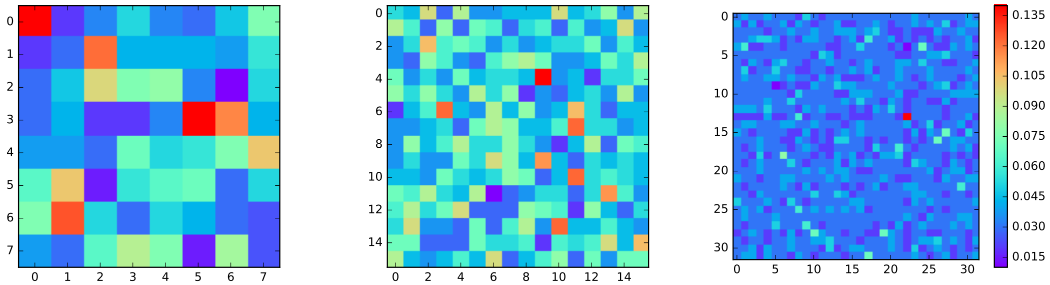
category	**word**	8 × 8 **code**	16 × 16 **code**
animal	dog	0 7 0 1 7 3 7 0	7 7 0 8 3 5 8 5 B 2 E E 0 B 0 A
	cat	7 7 0 1 7 3 7 0	7 7 2 8 B 5 8 C B 2 E E 4 B 0 A
	penguin	0 7 0 1 7 3 6 0	7 7 E 8 7 6 4 C F D E 3 D 8 0 A
verb	go	7 7 0 6 4 3 3 0	2 C C 8 2 C 1 1 B D 0 E 0 B 5 8
	went	4 0 7 6 4 3 2 0	B C C 6 B C 7 5 B 8 6 E 0 D 0 4
	gone	7 7 0 6 4 3 3 0	2 C C 8 0 B 1 5 B D 6 E 0 2 5 A

Table 5: Examples of learned compositional codes based on Glove embedding vectors

6.2 Code Balance

Besides the performance of learned codes, we also care about the storage efficiency of the codes. If the model produces unbalance codes, then some codewords will be overused, while some codewords will be used only by few words. In our experiments, we found 31% of the words have a subcode of "0" for the first component when using a 8 × 8 code decomposition, whereas the subcode "1" is only used by 5% of the words.

Figure 3 gives a visualization of code balance for different settings. Each cell shows the percentage of a specific subcode, thus the values in each column sum to one. We found that the learned codes for a tight code decomposition are unbalanced for some components. However, when a large code decomposition such a 32 × 32 is used, the problem is largely mitigated.



(a) 8 x 8

(b) 16 x 16

(c) 32 x 32

Figure 3: Visualization of code balance for different settings. Each cell in the heat map shows the percentage of a specific subcode. The results indicates the codes are evenly assigned to the words in the vocabulary when a large code decomposition (e.g., 32 × 32) is used.

7 Conclusion

In this work, we propose a novel way to reduce the number of parameters of word embeddings. Instead of assigning each unique word an embedding vector, we compose the embedding vectors using a small set of basis vectors. The selection of basis vectors is governed by the hash code of each word. We the compositional coding approach to maximize the storage efficiency. The proposed method works by eliminating the redundancy caused by representing similar words with independent embeddings. In our work, we also propose a simple way to directly learn the discrete codes in a neural network with Gumbel-softmax trick. The results show that the size of embedding layer can be reduced by 98% in IMDB sentiment analysis task and 94% in machine translation task without hurting performance.

Our approach achieves a high loss-free compression rate by considering the semantic inter-similarity among different words. In qualitative analysis, we found the learned codes of similar words are very close in Hamming space. As our approach maintains a dense basis matrix, it has the potential to be further compressed by applying quantization or pruning techniques to the dense matrix. The advantage of compositional coding approach will be more significant when the size of embedding layer is dominated by the hash codes.

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A APPENDIX: SHARED CODES

In both tasks, when we use a small code decomposition, we found some hash codes will be assigned to multiple words. Table 6 shows some samples of shared codes with their corresponding words in the sentiment analysis task. This phenomenon does not cause a problem in both tasks, as the words only have shared codes when they have almost same sentiments or target translations.

However, the shared codes cause problems when we attempted to compress the weight matrix of the softmax layer in NMT models, which is another source of large model size. When the weights are same for two different words, the model can no longer discriminate between the words, which we believe is partially the reason why the proposed method cannot be successfully applied to the softmax layer.

shared code	**words**
4 7 7 0 4 7 1 1	homes cruises motel hotel resorts mall vacations hotels
6 6 7 1 4 0 2 0	basketball softball nfl nascar baseball defensive ncaa tackle nba
3 7 3 2 4 3 3 0	unfortunately hardly obviously enough supposed seem totally ...
4 6 7 0 4 7 5 0	toronto oakland phoenix miami sacramento denver minneapolis ...
7 7 6 6 7 3 0 0	yo ya dig lol dat lil bye

Table 6: Examples of words sharing same codes when using a 8×8 code decomposition