Training continuous space language models: some practical issues

Le Hai Son and **Alexandre Allauzen** and **Guillaume Wisniewski** and **François Yvon**
Univ. Paris-Sud, France and LIMSI/CNRS
BP 133, 91403 Orsay Cedex
Firstname.Lastname@limsi.fr

Abstract

Using multi-layer neural networks to estimate the probabilities of word sequences is a promising research area in statistical language modeling, with applications in speech recognition and statistical machine translation. However, training such models for large vocabulary tasks is computationally challenging which does not scale easily to the huge corpora that are nowadays available. In this work, we study the performance and behavior of two neural statistical language models so as to highlight some important caveats of the classical training algorithms. The induced word embeddings for extreme cases are also analysed, thus providing insight into the convergence issues. A new initialization scheme and new training techniques are then introduced. These methods are shown to greatly reduce the training time and to significantly improve performance, both in terms of perplexity and on a large-scale translation task.

1 Introduction

Statistical language models play an important role in many practical applications, such as machine translation and automatic speech recognition. Let $\mathcal{V}$ be a finite vocabulary, statistical language models define distributions over sequences of words w_1^L in $\mathcal{V}^\star$ usually factorized as:

$$P(w_1^L) = P(w_1) \prod_{l=1}^{L} P(w_l | w_1^{l-1})$$

Modeling the joint distribution of several discrete random variables (such as words in a sentence) is difficult, especially in real-world Natural Language Processing applications where $\mathcal{V}$ typically contains dozens of thousands words.

Many approaches to this problem have been proposed over the last decades, the most widely used being back-off n-gram language models. n-gram models rely on a Markovian assumption, and despite this simplification, the maximum likelihood estimate (MLE) remains unreliable and tends to underestimate the probability of very rare n-grams, which are hardly observed even in huge corpora. Conventional smoothing techniques, such as Kneser-Ney and Witten-Bell back-off schemes (see (Chen and Goodman, 1996) for an empirical overview, and (Teh, 2006) for a Bayesian interpretation), perform back-off on lower order distributions to provide an estimate for the probability of these unseen events. n-gram language models rely on a discrete space representation of the vocabulary, where each word is associated with a discrete index. In this model, the morphological, syntactic and semantic relationships which structure the lexicon are completely ignored, which negatively impact the generalization performance of the model. Various approaches have proposed to overcome this limitation, notably the use of word-classes (Brown et al., 1992; Niesler, 1997), of generalized back-off strategies (Bilmes et al., 1997) or the explicit integration of morphological information in the random-forest model (Xu and Jelinek, 2004; Oparin et al., 2008).

One of the most successful alternative to date is to use *distributed word representations* (Bengio et al., 2003), where distributionally similar words are represented as neighbors in a continuous space. This

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turns n-grams distributions into smooth functions of the word representations. These representations and the associated probability estimates are jointly computed in a multi-layer neural network architecture. This approach has showed significant and consistent improvements when applied to automatic speech recognition (Schwenk, 2007; Emami and Mangu, 2007; Kuo et al., 2010) and machine translation tasks (Schwenk et al., 2006). Hence, continuous space language models are becoming increasingly used. These successes have revitalized the research on neuronal architectures for language models, and given rise to several new proposals (see, for instance, (Mnih and Hinton, 2007; Mnih and Hinton, 2008; Collobert and Weston, 2008)). A major difficulty with these approaches remains the complexity of training, which does not scale well to the massive corpora that are nowadays available. Practical solutions to this problem are discussed in (Schwenk, 2007), which introduces a number of optimization and tricks to make training doable. Even then, training a neuronal language model typically takes days.

In this paper, we empirically study the convergence behavior of two multi-layer neural networks for statistical language modeling, comparing the standard model of (Bengio et al., 2003) with the log-bilinear (LBL) model of (Mnih and Hinton, 2007). Our contributions are the following: we first propose a reformulation of Mnih and Hinton's model, which reveals its similarity with extant models, and allows a direct and fair comparison with the standard model. For the standard model, these results highlight the impact of parameter initialization. We first investigate a re-initialization method which allows to escape from the local extremum the standard model converges to. While this method yields a significative improvement, the underlying assumption about the structure of the model does not meet the requirement of very large-scale tasks. We therefore introduce a different initialization strategy, called *one vector initialization*. Experimental results show that these novel training strategies drastically reduce the total training time, while delivering significant improvements both in terms of perplexity and in a large-scale translation task.

The rest of this paper is organized as follows. We first describe, in Section 2, the standard and the LBL language models. By reformulating the latter, we show that both models are very similar and emphasize the remaining differences. Section 2.4 discusses complexity issues and possible solutions to reduce the training time. We then report, in Section 3, preliminary experimental results that enlighten some caveats of the standard approach. Based on these observations, we introduce in Section 4 novel and more efficient training schemes, yielding improved performance and a reduced training time both on small and large scale experiments.

2 Continuous space language models

Learning a language model amounts to estimate the parameters of the discrete conditional distribution over words given each possible history, where the history corresponds to some function of the preceding words. For an n-gram model, the history contains the $n-1$ preceding words, and the model parameters correspond to $P(w_l|w_{l-n+1}^{l-1})$. Continuous space language models aim at computing these estimates based on a distributed representation of words (Bengio et al., 2003), thereby reducing the sparsity issues that plague conventional maximum likelihood estimation. In this approach, each word in the vocabulary is mapped into a real-valued vector and the conditional probability distributions are then expressed as a (parameterized) smooth function of these feature vectors. The formalism of neural networks allows to express these two steps in a well-known framework, where, crucially, the mapping and the model parameters can be learned in conjunction. In the next paragraphs, we describe the two continuous space language models considered in our study and present the various issues associated with the training of such models, as well as their most common remedies.

2.1 The standard model

In the following, we will consider words as indices in a finite dictionary of size V; depending on the context, w will either refer to the word or to its index in the dictionary. A word w can also be represented by a 1-of-V coding vector $\mathbf{v}$ of $\mathbb{R}^V$ in which all elements are null except the w^{th}. In the standard approach of (Bengio et al., 2003), the feed-forward network takes as input the $n-1$ word history and delivers an estimate of the probability $P(w_l|w_{l-n+1}^{l-1})$

as its output. It consists of three layers.

The first layer builds a continuous representation of the history by mapping each word into its real-valued representation. This mapping is defined by $\mathbf{R}^T\mathbf{v}$, where $\mathbf{R} \in \mathbb{R}^{V\times m}$ is a *projection matrix* and m is the dimension of the continuous projection word space. The output of this layer is a vector $\mathbf{i}$ of $(n-1)m$ real numbers obtained by concatenating the representations of the context words. The projection matrix $\mathbf{R}$ is shared along all positions in the history vector and is learned automatically.

The second layer introduces a non-linear transform, where the output layer activation values are defined by $\mathbf{h} = \tanh\left(\mathbf{W_{ih}}\mathbf{i} + \mathbf{b_{ih}}\right)$, where $\mathbf{i}$ is the input vector, $\mathbf{W_{ih}} \in \mathbb{R}^{H\times(n-1)m}$ and $\mathbf{b_{ih}} \in \mathbb{R}^H$ are the parameters of this layer. The vector $\mathbf{h} \in \mathbb{R}^H$ can be considered as an higher (more abstract) representation of the context than $\mathbf{i}$.

The third layer is an output layer that estimates the desired probability, thanks to the *softmax* function:

$$P(w_l = k|w_{l-n+1}^{l-1}) = \frac{\exp(\mathbf{o_k})}{\sum_{k'}\exp(\mathbf{o_{k'}})} \quad (1)$$

$$\mathbf{o} = \mathbf{W_{ho}}\mathbf{h} + \mathbf{b_{ho}}, \quad (2)$$

where $\mathbf{W_{ho}} \in \mathbb{R}^{V\times H}$ and $\mathbf{b_{ho}} \in \mathbb{R}^V$ are respectively the projection matrix and the bias term associated with this layer. The w^{th} component in $\mathbf{P}$ corresponds to the estimated probability of the w^{th} word of the vocabulary given the input history vector.

The standard model has two hyper-parameters (the dimension of projection space m and the size of hidden layer, H) that define the architecture of the neural network and a set of free parameters $\mathbf{\Theta}$ that need to be learned from data: the projection matrix $\mathbf{R}$, the weight matrix $\mathbf{W_{ih}}$, the bias vector $\mathbf{b_{ih}}$, the weight matrix $\mathbf{W_{ho}}$ and the bias vector $\mathbf{b_{ho}}$.

In this model, the projection matrices $\mathbf{R}$ and $\mathbf{W_{ho}}$ play similar roles as they define maps between the vocabulary and the hidden representation. The fact that $\mathbf{R}$ assigns similar representations to history words w_1 and w_2 implies that these words can be exchanged with little impact on the resulting probability distribution. Likewise, the similarity of two lines in $\mathbf{W_{ho}}$ is an indication that the corresponding words tend to have a similar behavior, i.e. tend to have a similar probabilities of occurrence in all contexts. In the remainder, we will therefore refer to $\mathbf{R}$ as the matrix representing the **context space**, and to $\mathbf{W_{ho}}$ as the matrix for the **prediction space**.

2.2 The log-bilinear model

The work reported (Mnih and Hinton, 2007) describes another parameterization of the architecture introduced in the previous section. This parameterization is based on Factored Restricted Boltzmann Machine. According to (Mnih and Hinton, 2007), this model, termed the *log-bilinear* language model (LBL), achieves, for large vocabulary tasks, better results in terms of perplexity than the standard model, even if the reasons beyond this improvement remain unclear.

In this section, we will describe this model and show how it relates to the standard model. The LBL model estimates the n-gram parameters by:

$$P(w_l|w_{l-n+1}^{l-1}) = \frac{\exp(-E(w_l; w_{l-n+1}^{l-1}))}{\sum_w \exp(-E(w; w_{l-n+1}^{l-1}))} \quad (3)$$

In this equation, E is an *energy function* defined as:

$$E(w_l; w_1^{l-1}) = -\left(\sum_{k=l-n+1}^{l-1} \mathbf{v_k}^T\mathbf{R}\mathbf{C}_k^T\right)\mathbf{R}^T\mathbf{v}_l \quad (4)$$

$$- \mathbf{b_r}^T\mathbf{R}^T\mathbf{v}_l - \mathbf{b_v}^T\mathbf{v}_l$$

$$= -\mathbf{v}_l^T\mathbf{R}\left(\sum_{k=l-n+1}^{l-1}\mathbf{C}_k\mathbf{R}^T\mathbf{v_k} + \mathbf{b_r}\right)$$

$$- \mathbf{v}_l^T\mathbf{b_v} \quad (5)$$

where $\mathbf{R}$ is the projection matrix introduced above, $(\mathbf{v}_k)_{l-n+1\le k\le l-1}$ are the 1-of-V coding vectors for the history words and $\mathbf{v}_l$ is the coding vector for w_l; $\mathbf{C}_k \in \mathbb{R}^{m\times m}$ is a combination matrix and $\mathbf{b_r}$ and $\mathbf{b_v}$ denote bias vectors. All these parameters need to be learned during training.

Equation (4) can be rewritten using the notations introduced for the standard model. We then rename $\mathbf{b_r}$ and $\mathbf{b_v}$ respectively $\mathbf{b_{ih}}$ and $\mathbf{b_{ho}}$. We also denote $\mathbf{i}$ the concatenation of the $(n-1)$ vectors $\mathbf{R}^T\mathbf{v_k}$; likewise $\mathbf{W_{ih}}$ denotes the $H \times (n-1)m$ matrix obtained by concatenating row-wise the $(n-1)$ matrices $\mathbf{C}_k$. With these new notations, equations (4)

and (3) can be rewritten as:

$$\mathbf{h} = \mathbf{W_{ih}}\mathbf{i} + \mathbf{b_{ih}}$$
$$\mathbf{o} = \mathbf{R}\mathbf{h} + \mathbf{b_{ho}}$$
$$P(w_l = k|w_{l-n+1}^{l-1}) = \frac{\exp(\mathbf{o_k})}{\sum_{k'} \exp(\mathbf{o_{k'}})}$$

This formulation allows to highlight the similarity of the LBL model and the standard model. These two models differ only by the activation function of their hidden layer (linear for the LBL model and tangent hyperbolic for the standard model) and by their definition of the prediction space: for the LBL model, the context space and the prediction space are the same ($\mathbf{R} = \mathbf{W_{ho}}$, and thus $H = m$), while in the standard model, the prediction space is defined independently from the context space. This restriction drastically reduces the number of free parameters of the LBL model.

It is finally noteworthy to outline the similarity of this model with standard maximum entropy language models (Lau et al., 1993; Rosenfeld, 1996). Let $\mathbf{x}$ denote the binary vector formed by stacking the (n-1) 1-of-V encodings of the history words; then the conditional probability distributions estimated in the model are proportional to $\exp F(x)$, where F is an affine transform of $\mathbf{x}$. The main difference with MaxEnt language models are thus the restricted form of the feature functions, which only test one history word, and the particular representation of F, which is defined as:

$$F(\mathbf{x}) = \mathbf{R}\mathbf{W_{ih}}\mathbf{R'}^T\mathbf{v} + \mathbf{R}\mathbf{b_{ih}} + \mathbf{b_{ho}}$$

where, as before, $\mathbf{R'}$ is formed by concatenating $(n-1)$ copies of the projection matrix $\mathbf{R}$.

2.3 Training and inference

Training the two models introduced above can be achieved by maximizing the log-likelihood $\mathcal{L}$ of the parameters Θ. This optimization is usually performed by stochastic back-propagation as in (Bengio et al., 2003). For all our experiments, the learning rate is fixed at 5×10^{-3}. The learning weight decay and the the weight decay (respectively 1×10^{-9} and 0) seem to have a minor impact on the results. Learning starts with a random initialization of the parameters under the uniform distribution and converges to a local maximum of the log-likelihood function. Moreover, to prevent overfitting, an early stopping strategy is adopted: after each epoch, training is stopped when the likelihood of a validation set stops increasing.

2.4 Complexity issues

The main problem with neural language models is their computational complexity. For the two models presented in this section, the number of floating point operations needed to predict the label of a single example is[1]:

$$((n-1) \cdot m + 1) \times H + (H+1) \times V \quad (6)$$

where the first term of the sum corresponds to the computation of the hidden layer and the second one to the computation of the output layer. The projection of the context words amounts to select one row of the projection matrix $\mathbf{R}$, as the words are represented with a 1-of-V coding vector. We can therefore assume that the computation complexity of the first layer is negligible. Most of the computation time is thus spent in the output layer, which implies that the computing time grows linearly with the vocabulary size. Training these models for large scale tasks is therefore challenging, and a number of tricks have been introduced to make training and inference tractable (Schwenk and Gauvain, 2002; Schwenk, 2007).

Short list A simple method to reduce the complexity in inference and in learning is to reduce the size of the output vocabulary (Schwenk, 2007): rather than estimating the probability $P(w_l = w|w_{l-n+1}^{l-1})$ for all words in the vocabulary, we only estimate it for the N most frequent words of the training set (the so-called *short-list*). In this case, two vocabularies need to be considered, corresponding respectively to the *context vocabulary* $\mathcal{V}_c$ used to define the history; and the *prediction vocabulary* $\mathcal{V}_p$. However, this method fails to deliver any probability estimate for words outside of the prediction vocabulary, meaning that a fall-back strategy needs to be defined for those words. In practice, neural network

[1] Recall that learning requires to repeatedly predict the label for all the examples in the training set.

language models are combined with a conventional n-gram model as described in (Schwenk, 2007).

Batch mode and resampling Additional speed-ups can be obtained by propagating several examples at once through the network (Bilmes et al., 1997). This "batch mode" allows to factorize the matrix operations and cut down both inference and training time. In all our experiments, we used a batch size of 64. Moreover, the training time is linear in the number of examples in the training data[2]. Training on very large corpora, which, nowadays, comprise billions of word tokens, cannot be performed exhaustively and requires to adopt *resampling* strategies, whereby, at each epoch, the system is trained with only a small random subset of the training data. This approach enables to effectively estimate neural language models on very large corpora; it has also been observed empirically that sampling the training data can increase the generalization performance (Schwenk, 2007).

3 A head-to-head comparison

In this section, we analyze a first experimental study of the two neural network language models introduced in Section 2 in order to better understand the differences between these models especially in terms of the word representations they induce. Based on this study, we will propose, in the next section, improvements of both the speed and the prediction capacity of the models. In all our experiments, 4-gram language models are used.

3.1 Corpus

The data we use for training is a large monolingual corpus, containing all the English texts in the parallel data of the Arabic to English NIST 2009 constrained task[3]. It consists of 176 millions word tokens with $532,557$ different word types as the size of vocabulary. The perplexity is computed with respect to the 2006 NIST test data, which is used here as our development data.

[2]Equation (6) gives the complexity of inference for a single example.

[3]http://www.itl.nist.gov/iad/mig/tests/mt/2009/MT09_ConstrainedResources.pdf

3.2 Convergence study

In a first experiment, we trained the two models in the same setting: we choose to consider a small vocabulary comprising the $10,000$ most frequent words. The same vocabulary is used to constrain the words occurring in the history and the words to be predicted. The size of hidden layer is set to $m = H = 200$, the history contains the 3 preceding words, we use a batch size of 64, a resampling rate of 5% and no weight decay.

Figure 1 displays the perplexity convergence curve measured on the development data for the standard and the LBL models[4]. The convergence perplexities after the combination with the standard back-off model are also provided for all the models in table 2 (see section 4.3). We can observe that the LBL model converges faster than the standard model: the latter needs 13 epochs to reach the stopping criteria, while the former only needs 6 epochs. However, upon convergence, the standard model reaches a lower perplexity than the LBL model.

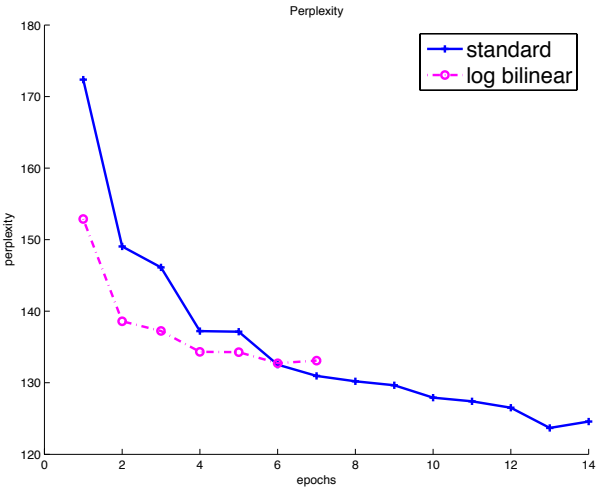


Figure 1: Convergence rate of the standard and the LBL models evaluated by the evolution of the perplexity on a development set

As described in Section 2.2, the main difference between the standard and the LBL model is the way the context and the prediction spaces are defined: in the standard model, the two spaces are distinct; in

[4]The use of a back-off 4-model estimated with the modified Knesser-Ney smoothing on the same training data achieves a perplexity of 141 on the development data.

the LBL model, they are bound to be the same. With a smaller number of parameters, the LBL model can not capture as many characteristics of the data as the standard model, but it converges faster[5]. This difference in convergence can be explained by the scarcity of the updates in the projection matrix $\mathbf{R}$ in the standard model: during backpropagation, only those weights that are associated with words in the history are updated. By contrast, each training sample updates all the weights in the prediction matrix $\mathbf{W_{ho}}$.

3.3 An analysis of the continuous word space

To deepen our understanding, we propose to further analyze the induced word embeddings by finding, for some randomly selected words, the five nearest neighbors (according to the Euclidian distance) in the context space and in the prediction space of the two models. Results are presented in Table 1.

If we look first at the standard model, the global picture is that for frequent words (*is*, *are*, and, to a lesser extend, *have*), both spaces seem to define meaningful neighborhood, corresponding to semantic and syntactic similarities; this is less true for rarer words, where we see a greater discrepancy between the context and prediction spaces. For instance, the date *1947* seems to be randomly associated in the context space, while the 5 nearest words in the prediction space form a consistent set of dates. The same trend is also observed for the word *Castro*. Our interpretation is that for less frequent words, the projection vectors are hardly ever updated and remain close to their original random initialization.

By contrast, the similarities in the (unique) projection space of the LBL remain consistent for all frequency ranges, and are very similar to the prediction space of the standard model. This seems to validate our hypothesis that in the standard model, the prediction space is learned much faster than the context space and corroborates our interpretation of the impact of the scarce updates of rare words. Another possible explanation is that there is no clear relation between the context space and the target function: the context space is learned only indirectly by backpropagation. As a result, due to the random initialization of the parameters and to data sparsity, many vectors of $\mathbf{R}$ might be blocked in some local maxima, meaning that similar vectors cannot be grouped in a consistent way and that the induced similarity is more "loose".

[5]We could increase the number of parameters of the LBL model for a fairer comparison with the standard model. However, this would also increase the size of the vocabulary and cause two new issues: on one hand, the time complexity would drastically increase for the LBL model, and on the other hand, both models would not be comparable in terms of perplexity as their vocabulary would be different.

4 Improving the standard model

In Section 3.2, we observed that slightly better results can be obtained with the standard rather than with the LBL model. The latter is however much faster to train, and seems to induce better projection matrices. Both effects can be attributed to the particular parameterization of this model, which uses the same projection matrix both for the context and for the prediction spaces. In this section, we propose several new learning regimes that allowed us to improve the standard model in terms of both speed and prediction capacity. All these improvements rely on the idea of sharing word representations. While this idea is not new (see for instance (Collobert and Weston, 2008)), our analysis enables to better understand its impact on the convergence rate. Finally, the improvements we propose are evaluated on a real-word machine translation task.

4.1 Improving performances with re-initialization

The experiments reported in the previous section suggest that it is possible to improve the performances of the standard model by building a better context space. Thus, we introduce a new learning regime, called *re-initialization* which aims to improve the context space by re-injecting the information on word neighborhoods that emerges in the prediction space. One possible implementation of this idea is as follows:

1. train a standard model until convergence;
2. use the prediction space of this model to initialize the context space of a new model; the prediction space is chosen randomly;
3. train this new model.

Table 1: The 5 closest words in the representation spaces of the standard and LBL language models.

word (frequency)	*model*	*space*	*5 most closest words*
is	standard	context	was are were be been
900, 350	standard	prediction	was has would had will
	LBL	both	was reveals proves are ON
are	standard	context	were is was be been
478, 440	standard	prediction	were could will have can
	LBL	both	were is was FOR ON
have	standard	context	had has of also the
465, 417	standard	prediction	are were provide remain will
	LBL	both	had has Have were embrace
meeting	standard	context	meetings conference them 10 talks
150, 317	standard	prediction	undertaking seminar meetings gathering project
	LBL	both	meetings summit gathering festival hearing
Imam	standard	context	PCN rebellion 116. Cuba 49
787	standard	prediction	Castro Sen Nacional Al- Ross
	LBL	both	Salah Khaled Al- Muhammad Khalid
1947	standard	context	36 Mercosur definite 2002-2003 era
774	standard	prediction	1965 1945 1968 1964 1975
	LBL	both	1965 1976 1964 1968 1975
Castro	standard	context	exclusively 12. Boucher Zeng Kelly
768	standard	prediction	Singh Clark da Obasanjo Ross
	LBL	both	Clark Singh Sabri Rafsanjani Sen

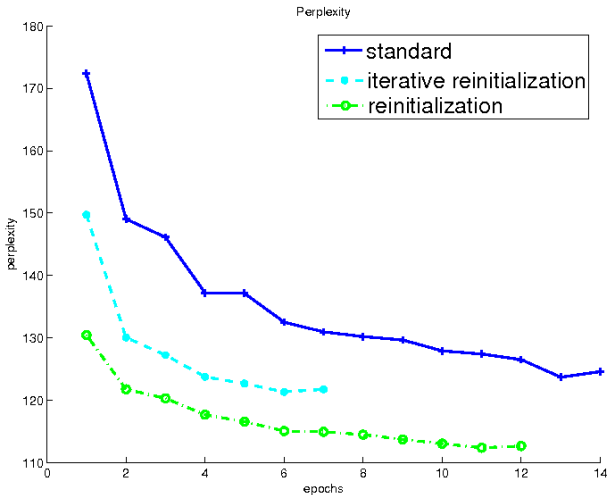


Figure 2: Evolution of the perplexity on a development set for various initialization regimes.

The evolution of the perplexity with respect to training epochs for this new method is plotted on Figure 2, where we only represent the evolution of the perplexity during the third training step. As can be seen, at convergence, the perplexity the model estimated with this technique is about 10% smaller than the perplexity of the standard model.

This result can be explained by considering the re-initialization as a form of annealing technique: re-initializing the context space allows to escape from the local extrema the standard model converges to. The fact that the prediction space provides a good initialization of the context space also confirms our analysis that one difficulty with the standard model is the estimation of the context space parameters.

4.2 Iterative re-initialization

The *re-initialization* policy introduced in the previous section significantly reduces the perplexity, at the expense of a longer training time, as it requires to successively train two models. As we now know that the parameters of the prediction space are faster to converge, we introduce a second training regime called *iterative re-initialization* which aims to take advantage of this property. We summarize this new training regime as follows:

1. Train the model for one epoch.

2. Use the prediction space parameters to reinitialize the context space.

3. Iterate steps (1) and (2) until convergence.

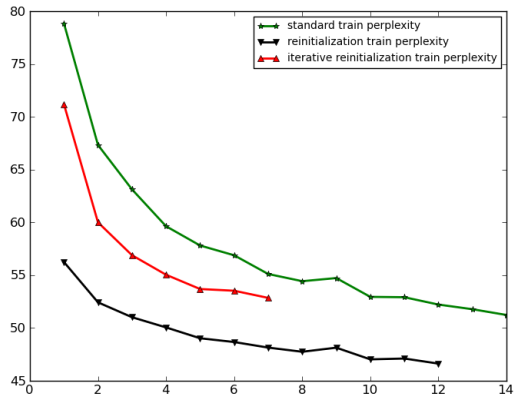


Figure 3: Evolution of the perplexity on the training data for various initialization regimes.

This regimes yields a model that is somewhat in-between the standard and LBL models as it adds a relationship between the two representation spaces, which lacks in the former model. This relationship is however not expressed through the tying of the corresponding parameters; instead we let the prediction space guide the convergence of the context space. As a consequence, we hope that it can achieve a convergence speed as fast as the one of the LBL model without degrading its prediction capacity.

The result plotted on Figure 2 shows that this indeed the case: using this training regime, we obtained a perplexity similar to the one of the standard model, while at the same time reducing the total training time by more than a half, which is of great practical interest (each epoch lasts approximately 8 hours on a 3GHz Xeon processor).

Figure 3 displays the perplexity convergence curve measured on the training data for the standard learning regime as well as for the *re-initialization* and *iterative re-initialization*. These results show the same trend as for the perplexity measured on the development data, and suggest a regularization effect of the re-initialization schemes rather than allowing the models to escape local optima.

4.3 One vector initialization

Principle The new training regimes introduced above outperform the standard training regime both in terms of perplexity and of training time. However, exchanging information between the context and prediction spaces is only possible when the same vocabulary is used in both spaces. As discussed in Section 2.4, this configuration is not realistic for very large-scale tasks. This is because increasing the number of predicted word types is much more computationally demanding than increasing the number of types in the context vocabulary. Thus, the former vocabulary is typically order of magnitudes larger than the latter, which means that the re-initialization strategies can no longer be directly used.

It is nonetheless possible to continue drawing inspirations from the observations made in Section 3, and, crucially, to question the random initialization strategy. As discussed above, this strategy may explain why the neighborhoods in the induced context space for the less frequent types were difficult to interpret. As a straightforward alternative, we consider a different initialization strategy where all the words in the context vocabulary are initially projected onto the same (random) point in the context space. The intuition is that it will be easier to build meaningful neighborhoods, especially for rare types, if all words are initially considered similar and only diverge if there is sufficient evidence in the training data to suggest that they should. This model is termed the *one vector initialization* model.

Experimental evaluation To validate this approach, we compare the convergence of a standard model trained (with the standard learning regime) with the one vector initialization regime. The context vocabulary is defined by the $532,557$ words occurring in the training data and the prediction vocabulary by the $10,000$ most frequent words[6]. All other parameters are the same as in the previous experiments. Based on the curves displayed on Figure 4, we can observe that the model obtained with the one vector initialization regime outperforms the model trained with a completely random initialization. Moreover, the latter reaches convergence in only 14 epochs, while the learning regime we propose only needs 9 epochs. Convergence is even faster than when we used the standard training regime and a small context vocabulary.

[6]In this case, the distinction between the *context* and the *prediction* vocabulary rules out the possibility of a relevant comparison based on perplexity between the continuous space language model and a standard back-off language model.

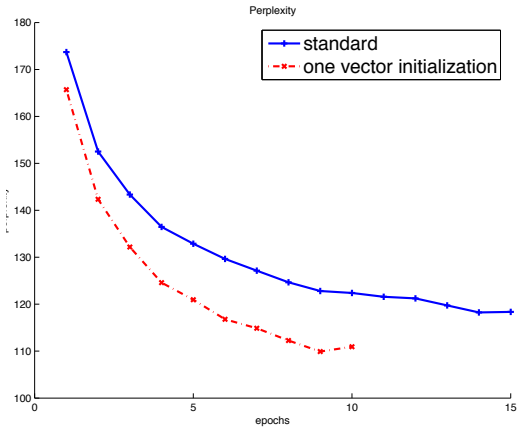


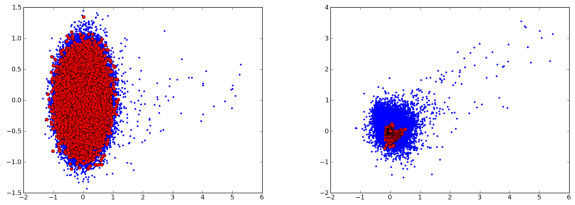
Figure 4: Perplexity with all-$10,000, 200-200$ models

Table 2: Summary of the perplexity (*PPX*) results measured on the same development set with the different continuous space language models. For all of them, the probabilities are combined with the back-off n-gram model

$\mathcal{V}_c$ *size*	*Model*	*# epochs*	*PPX*
10000	log bilinear	6	239
	standard	13	227
	iterative reinit.	6	223
	reinit.	11	211
all	standard	14	276
	one vector init.	9	260

To illustrate the impact of our initialization scheme, we also used a principal component analysis to represent the induced word representations in a two dimensional space. Figure 5 represents the vectors associated with numbers[7] in red, while all other words are represented in blue. Two different models are used: the standard model on the left, and the one vector initialization model on the right. We can observe that, for the standard model, most of the red points are scattered all over a large portion of the representation space. On the opposite, for the one vector initialization model, points associated with numbers are much more concentrated: this is simply because all the points are originally identical, and the training aim to spread the point around this starting point. We also created the closest word list reported in Table 3, in a manner similar to Table 1. Clearly, the new method seems to yield more

[7]Number are all the words consisting only of digits, with an optional sign, point or comma such as: *1947*; *0,001*; *-8,2*.



(a) with the standard model (b) with the one vector initialization model

Figure 5: Comparison of the word embedding in the context space for numbers (red points).

meaningful neighborhoods in the context space.

It is finally noteworthy to mention that when used with a small context vocabulary (as in the experimental setting of Section 4.1) this initialization strategy underperforms the standard initialization. This is simply due to the much greater data sparsity in the large context vocabulary experiments, where the rarer word types are really rare (they typically occur once or twice). By contrast, the rarer words in the small vocabulary tasks occurred more than several hundreds times in the training corpus, which was more than sufficient to guide the model towards satisfactory projection matrices. This finally suggests that there still exists room for improvement if we can find more efficient initialization strategies than starting from one or several random points.

4.4 Statistical machine translation experiments

As a last experiment, we compare the various models on a large scale machine translation task. Statistical language models are key component of current statistical machine translation systems (Koehn, 2010), where they both help disambiguate lexical choices in the target language and influence the choice of the right word ordering. The integration of a neural network language model in such a system is far from easy, given the computational cost of computing word probabilities, a task that is performed repeatedly during the search of the best translation. We then had to resort to a two pass decoding approach: the first pass uses a conventional back-off language model to produce a n-best list (the n most likely translations and their associated scores); in the second pass, the probability of the neural language model is computed for each hypothesis and the n-

Table 3: The 5 closest words in the context space of the standard and one vector initialization language models

word (freq.)	*model*	*5 closest words*
is	standard	was are were been remains
900,350	1 vector init.	was are be were been
conducted	standard	undertaken launched $270,900 Mufamadi 6.44-km-long
18,388	1 vector init.	pursued conducts commissioned initiated executed
Cambodian	standard	Shyorongi $3,192,700 Zairian depreciations teachers
2,381	1 vector init.	Danish Latvian Estonian Belarussian Bangladeshi
automatically	standard	MSSD Sarvodaya $676,603,059 Kissana 2,652,627
1,528	1 vector init.	routinely occasionally invariably inadvertently seldom
Tosevski	standard	$12.3 Action,3 Kassouma 3536 Applique
34	1 vector init.	Shafei Garvalov Dostiev Bourloyannis-Vrailas Grandi
October-12	standard	39,572 anti-Hutu $12,852,200 non-contracting Party's
8	1 vector init.	March-26 April-11 October-1 June-30 August4
3727th	standard	Raqu Tatsei Ayatallah Mesyats Langlois
1	1 vector init.	4160th 3651st 3487th 3378th 3558th

best list is accordingly reordered to produce the final translations.

The different language models discussed in this article are evaluated on the Arabic to English NIST 2009 constrained task. For the continuous space language model, the training data consists in the parallel corpus used to train the translation model (previously described in section 3.1). The development data is again the 2006 NIST test set and the test data is the official 2008 NIST test set. Our system is built using the open-source Moses toolkit (Koehn et al., 2007) with default settings. To set up our baseline results, we used an extensively optimized standard back-off 4-grams language model using Kneser-Ney smoothing described in (Allauzen et al., 2009). The weights used during the reranking are tuned using the Minimum Error Rate Training algorithm (Och, 2003). Performance is measured based on the BLEU (Papineni et al., 2002) scores, which are reported in Table 4.

Table 4: BLEU scores on the NIST MT08 test set with different language models.

$\mathcal{V}_c$ *size*	*Model*	*# epochs*	*BLEU*
all	baseline	-	37.8
10000	log bilinear	6	38.2
	standard	13	38.3
	iterative reinit.	6	38.4
	reinit.	11	38.4
all	standard	14	38.6
	one vector init.	9	**38.7**

All the experimented neural language models yield to a significant BLEU increase. The best result is obtained by the one vector initialization standard model which achieves a 0.9 BLEU improvement. While this results is similar to the one obtained with the standard model, the training time is reduced here by a third.

5 Conclusion

In this work, we proposed three new methods for training neural network language models and showed their efficiency both in terms of computational complexity and generalization performance in a real-word machine translation task. These methods rely on conclusions drawn from a careful study of the convergence rate of two state-of-the-art models and are based on the idea of sharing the distributed word representations during training.

Our work highlights the impact of the initialization and the training scheme for neural network language models. Both our experimental results and our new training methods can be closely related to the pre-training techniques introduced by (Hinton and Salakhutdinov, 2006). Our future work will thus aim at studying the connections between our empirical observations and the deep learning framework.

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