Syllable-aware Neural Language Models:
A Failure to Beat Character-aware Ones

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Abstract

Syllabification does not seem to improve word-level RNN language modeling quality when compared to character-based segmentation. However, our best syllable-aware language model, achieving performance comparable to the competitive character-aware model, has 18%–33% fewer parameters and is trained 1.2–2.2 times faster.

1 Introduction

Recent advances in neural language modeling (NLM) are connected with character-aware models (Kim et al., 2016; Ling et al., 2015b; Verwimp et al., 2017). This is a promising approach, and we propose the following direction related to it: We would like to make sure that in the pursuit of the most fine-grained representations one has not missed possible intermediate ways of segmentation, e.g., by syllables. Syllables, in our opinion, are better supported as linguistic units of language than single characters. In most languages, words can be naturally split into syllables:

ES: el par-lamen-to a-po-yo la en-mien-da
RU: par-la-ment pod-der-zal po-prav-ku
(EN: the parliament supported the amendment)

Based on this observation, we attempted to determine whether syllable-aware NLM has any advantages over character-aware NLM. We experimented with a variety of models but could not find any evidence to support this hypothesis: splitting words into syllables does not seem to improve the language modeling quality when compared to splitting into characters. However, there are some positive findings: while our best syllable-aware language model achieves performance comparable to the competitive character-aware model, it has 18%–33% fewer parameters and is 1.2–2.2 times faster to train.

2 Related Work

Much research has been done on subword-level and subword-aware\footnote{Subword-level LMs rely on subword-level inputs and make predictions at the level of subwords; subword-aware LMs also rely on subword-level inputs but make predictions at the level of words.} neural language modeling when subwords are characters (Ling et al., 2015b; Kim et al., 2016; Verwimp et al., 2017) or morphemes (Botha and Blunsom, 2014; Qiu et al., 2014; Cotterell and Schütze, 2015). However, not much work has been done on syllable-level or syllable-aware NLM. \footnote{Not to be confused with character-aware ones, see the previous footnote.} Mikolov et al. (2012) show that subword-level language models outperform character-level ones\footnote{Not to be confused with character-aware ones, see the previous footnote.} They keep the most frequent words untouched and split all other words into syllable-like units. Our approach differs mainly in the following aspects: we make predictions at the word level, use a more linguistically sound syllabification algorithm, and consider a variety of more advanced neural architectures.

We have recently come across a concurrent paper (Vania and Lopez, 2017) where the authors systematically compare different subword units (characters, character trigrams, BPE (Sennrich et al., 2016), morphemes) and different representation models (CNN, Bi-LSTM, summation) on languages with various morphological typology. However, they do not consider syllables, and they experiment with relatively small models on small data sets (0.6M–1.4M tokens).
unconstitutional conditions on stack of twoLSTMs word vector Highway layers (optional) Syllable-aware word embedding model Syllable embeddings

Figure 1: Syllable-aware language model.

3 Syllable-aware word embeddings

Let $W$ and $S$ be finite vocabularies of words and syllables respectively. We assume that both words and syllables have already been converted into indices. Let $E_S \in \mathbb{R}^{|S| \times d_S}$ be an embedding matrix for syllables — i.e., it is a matrix in which the $s$th row (denoted as $s$) corresponds to an embedding of the syllable $s \in S$. Any word $w \in W$ is a sequence of its syllables $(s_1, s_2, \ldots, s_{n_w})$, and hence can be represented as a sequence of the corresponding syllable vectors:

$$[s_1, s_2, \ldots, s_{n_w}].$$

(1)

The question is: How shall we pack the sequence (1) into a single vector $x \in \mathbb{R}^{d_W}$ to produce a better embedding of the word $w$?

In our case “better” means “better than a character-aware embedding of $w$ via the Char-CNN model of Kim et al. (2016)”. Below we present several viable approaches.

3.1 Recurrent sequential model (Syl-LSTM)

Since the syllables are coming in a sequence it is natural to try a recurrent sequential model:

$$h_t = f(s_t, h_{t-1}), \quad h_0 = 0,$$

(2)

which converts the sequence of syllable vectors (1) into a sequence of state vectors $h_{1:n_w}$. The last state vector $h_{n_w}$ is assumed to contain the information on the whole sequence (1), and is therefore used as a word embedding for $w$. There is a big variety of transformations from which one can choose $f$ in (2); however, a recent thorough evaluation [Joze&lovecic et al. 2015] shows that the LSTM (Hochreiter and Schmidhuber 1997) with its forget bias initialized to 1 outperforms other popular architectures on almost all tasks, and we decided to use it for our experiments. We will refer to this model as Syl-LSTM.

3.2 Convolutional model (Syl-CNN)

Inspired by recent work on character-aware neural language models (Kim et al., 2016) we decided to try this approach (Char-CNN) on syllables. Our case differs mainly in the following two aspects:

1. The set of syllables $S$ is usually bigger than the set of characters $C$, and also the dimensionality $d_S$ of syllable vectors is expected to be greater than the dimensionality $d_C$ of character vectors. Both of these factors result in allocating more parameters on syllable embeddings compared to character embeddings.

2. On average a word contains fewer syllables than characters, and therefore we need narrower convolutional filters for syllables. This results in spending fewer parameters per convolution.

This means that by varying $d_S$ and the maximum width of convolutional filters $L$ we can still fit the parameter budget of Kim et al. (2016) to allow fair comparison of the models.

Like in Char-CNN, our syllable-aware model, which is referred to as Syl-CNN-[L], utilizes max-pooling and highway layers (Srivastava et al., 2015) to model interactions between the syllables. The dimensionality of a highway layer is denoted by $d_{HW}$.  

3.3 Linear combinations

We also considered using linear combinations of syllable-vectors to represent the word embedding:

$$x = \sum_{t=1}^{n_w} \alpha_t(s_t) \cdot s_t.$$  

(3)

The choice for $\alpha_t$ is motivated mainly by the existing approaches (discussed below) which proved to be successful for other tasks.

Syl-Sum: Summing up syllable vectors to get a word vector can be obtained by setting $\alpha_t(s_t) = 1$.  

In languages with alphabetic writing systems.
This approach was used by Botha and Blunsom (2014) to combine a word and its morpheme embeddings into a single word vector.

**Syl-Avg:** A simple average of syllable vectors can be obtained by setting $\alpha_t(s_t) = 1/n_w$. This can be also called a “continuous bag of syllables” in an analogy to a CBOW model (Mikolov et al., 2013), where vectors of neighboring words are averaged to get a word embedding of the current word.

**Syl-Avg-A:** We let the weights $\alpha_t$ in (3) be a function of parameters $(a_1, \ldots, a_n)$ of the model, which are jointly trained together with other parameters. Here $n = \max_w \{n_w\}$ is a maximum word length in syllables. In order to have a weighted average in (3) we apply a softmax normalization:

$$\alpha_t = \text{softmax}(a_t) = \frac{\exp(a_t)}{\sum_{r=1}^n \exp(a_r)} \quad (4)$$

**Syl-Avg-B:** We can let $\alpha_t$ depend on syllables and their positions:

$$\alpha_{t} = \alpha_{t}(s_{t}) = \text{softmax}(a_{s_{t}} + b)_{t}$$

where $A \in \mathbb{R}^{dS \times n}$ (with elements $a_{s,t}$) is a set of parameters that determine the importance of each syllable type in each (relative) position, $b \in \mathbb{R}^n$ is a bias, which is conditioned only on the relative position. This approach is motivated by recent work on using an attention mechanism in the CBOW model (Ling et al., 2015a).

We feed the resulting $x$ from (3) into a stack of highway layers to allow interactions between the syllables.

### 3.4 Concatenation (Syl-Concat)

In this model we simply concatenate syllable vectors (1) into a single word vector:

$$\mathbf{x} = [s_1; s_2; \ldots; s_{n_w}; 0; 0; \ldots; 0]_{n-n_w}$$

We zero-pad $\mathbf{x}$ so that all word vectors have the same length $n \cdot d_S$ to allow batch processing, and then we feed $\mathbf{x}$ into a stack of highway layers.

### 4 Word-level language model

Once we have word embeddings $\mathbf{x}_{1:k}$ for a sequence of words $w_{1:k}$ we can use a word-level RNN language model to produce a sequence of states $\mathbf{h}_{1:k}$ and then predict the next word according to the probability distribution

$$\Pr(w_{k+1}|w_{1:k}) = \text{softmax}(\mathbf{h}_k \mathbf{W} + \mathbf{b}),$$

where $\mathbf{W} \in \mathbb{R}^{dLM \times |W|}$, $\mathbf{b} \in \mathbb{R}^{|W|}$, and $dLM$ is the hidden layer size of the RNN. Training the model involves minimizing the negative log-likelihood over the corpus $w_{1:K}$:

$$- \sum_{k=1}^K \log \Pr(w_k|w_{1:k-1}) \rightarrow \min \quad (5)$$

As was mentioned in Section 3.1 there is a huge variety of RNN architectures to choose from. The most advanced recurrent neural architectures, at the time of this writing, are recurrent highway networks (Zilly et al., 2017) and a novel model which was obtained through a neural architecture search with reinforcement learning (Zoph and Le, 2017). These models can be spiced up with the most recent regularization techniques for RNNs (Gal and Ghahramani, 2016) to reach state-of-the-art. However, to make our results directly comparable to those of Kim et al. (2016) we select a two-layer LSTM and regularize it as in Zaremba et al. (2014).

### 5 Experimental Setup

We search for the best model in two steps: first, we block the word-level LSTM’s architecture and pre-select the three best models under a small parameter budget (5M), and then we tune these three best models’ hyperparameters under a larger budget (20M).

**Pre-selection:** We fix $dLM$ (hidden layer size of the word-level LSTM) at 300 units per layer and run each syllable-aware word embedding method from Section 3 on the English PTB data set (Marcus et al., 1993), keeping the total parameter budget at 5M. The architectural choices are specified in Appendix A.

**Hyperparameter tuning:** The hyperparameters of the three best-performing models from the pre-selection step are then thoroughly tuned on the same English PTB data through a random search according to the marginal distributions:

- $d_S \sim U(20, 650)$
- $\log(d_{HW}) \sim U(\log(160), \log(2000))$,
- $\log(d_{LM}) \sim U(\log(300), \log(2000))$,

with the restriction $d_S < dLM$. The total parameter budget is kept at 20M to allow for easy comparison to the results of Kim et al. (2016). Then these three best models (with their hyperparameters tuned on PTB) are trained and evaluated on small- (DATA-S) and medium-sized (DATA-L) data sets in six languages.

$^3U(a, b)$ stands for a uniform distribution over $(a, b)$. 
Table 1: Pre-selection results. PPL stands for test set perplexity, all models have ≈ 5M parameters.

| Model       | EN  | FR  | ES  | DE  | CS  | RU  |
|-------------|-----|-----|-----|-----|-----|-----|
| Char-CNN    | 87.9| 184 | 165 | 239 | 371 | 261 |
| Syl-CNN     | 80.5| 191 | 172 | 239 | 374 | 269 |
| Syl-Sum     | 80.3| 193 | 170 | 246 | 389 | 273 |
| Syl-Concat  | 79.4| 188 | 168 | 244 | 383 | 265 |
| Char-CNN    | 88.0| 190 | 175 | 249 | 392 | 280 |
| Syl-CNN     | 86.8| 192 | 171 | 240 | 391 | 281 |
| Syl-Sum     | 85.6| 190 | 170 | 241 | 390 | 280 |
| Syl-Concat  | 84.6| 187 | 168 | 238 | 388 | 278 |

Table 2: Hyperparameters tuning. In Syl-CNN, $d_{HW}$ is a function of the primary hyperparameter $c = 195$ (see Appendix A).

Optimization is performed in almost the same way as in the work of Zaremba et al. (2014). See Appendix B for details.

Syllabification: The true syllabification of a word requires its grapheme-to-phoneme conversion and then splitting it into syllables based on some rules. Since these are not always available for less-resourced languages, we decided to utilize Liang’s widely-used hyphenation algorithm (Liang, 1983).

6 Results

The results of the pre-selection are reported in Table 1. All syllable-aware models comfortably outperform the Char-CNN when the budget is limited to 5M parameters. Surprisingly, a pure word-level model LSTM-Word, also beats the character-aware one under such budget. The three best configurations are Syl-Concat, Syl-Sum, and Syl-CNN-3 (hereinafter referred to as Syl-CNN), and tuning their hyperparameters under 20M parameter budget gives the architectures in Table 2. The results of evaluating these three models on small (1M tokens) and medium-sized (17M–57M tokens) data sets against Char-CNN for different languages are provided in Table 3. The models demonstrate similar performance on small data, but Char-CNN scales significantly better on medium-sized data. From the three syllable-aware models, Syl-Concat looks the most advantageous as it demonstrates stable results and has the least number of parameters. Therefore in what follows we will make a more detailed comparison of Syl-Concat with Char-CNN.

Shared errors: It is interesting to see whether Char-CNN and Syl-Concat are making similar errors. We say that a model gives an error if it assigns a probability less than $p^*$ to a correct word from the test set. Figure 2 shows the percentage of errors which are shared by Syl-Concat and Char-CNN depending on the value of $p^*$. We see that the vast majority of errors are shared by both Syl-Concat and Char-CNN on DATA-S (left) and DATA-L (right).

PPL breakdown by token frequency: To find out how Char-CNN outperforms Syl-Concat, we partition the test sets on token frequency, as computed on the training data. We can observe in Figure 3 that, on average, the more frequent the word is, the bigger the advantage of Char-CNN over Syl-Concat. The more Char-CNN sees a word in different contexts, the more it can learn about this word (due to its powerful CNN filters). Syl-Concat, on the other hand, has limitations – it cannot see below syllables, which prevents it from extracting the same amount of knowledge about the word.
Figure 3: PPL reduction by token frequency, Char-CNN relative to Syl-Concat on DATA-L.

Table 4: Number of principle components when PCA is applied to word embeddings produced by each model, depending on % of variance to retain.

| Model          | 80% | 90% | 95% | 99% |
|----------------|-----|-----|-----|-----|
| Char-CNN       | 568 | 762 | 893 | 1038|
| Syl-Concat     | 515 | 759 | 875 | 1035|

Table 5: Replacing LSTM with Variational RHN.

| Model            | depth | $d_{LM}$ | Size | PPL  |
|------------------|-------|----------|------|------|
| RHN-Char-CNN     | 8     | 650      | 20M  | 67.6 |
| RHN-Syl-Concat   | 8     | 439      | 13M  | 72.0 |
| RHN-Syl-Concat   | 8     | 650      | 20M  | 69.4 |

Convolu’ional (Morph-CNN-3) and additive (Morph-Sum) models performed better than others with test set PPLs 83.0 and 83.9 respectively. Due to limited amount of time, we did not perform a thorough hyperparameter search under 20M budget. Instead, we ran two configurations for Morph-CNN-3 and two configurations for Morph-Sum with hyperparameters close to those, which were optimal for Syl-CNN-3 and Syl-Sum correspondingly. All told, our best morpheme-aware model is Morph-Sum with $d_M = 550$, $d_{HW} = 1100$, $d_{LM} = 550$, and test set PPL 79.5, which is practically the same as the result of our best syllable-aware model Syl-Concat (79.4). This makes Morph-Sum a notable alternative to Char-CNN and Syl-Concat, and we defer its thorough study to future work.

Source code: The source code for the models discussed in this paper is available at https://github.com/zh3nis/lstm-syl.

7 Conclusion

It seems that syllable-aware language models fail to outperform competitive character-aware ones. However, usage of syllabification can reduce the total number of parameters and increase the training speed, albeit at the expense of language-dependent preprocessing. Morphological segmentation is a noteworthy alternative to syllabification: a simple morpheme-aware model which sums morpheme embeddings looks promising, and its study is deferred to future work.
A Pre-selection

In all models with highway layers there are two of them and the non-linear activation of any highway layer is a ReLU.

**LSTM-Word:** $d_W = 108$, $d_{LM} = 300$.

**Syl-LSTM:** $d_S = 50$, $d_{LM} = 300$.

**Syl-CNN-[L]:** $d_S = 50$, convolutional filter widths are $[1, \ldots, L]$, the corresponding convolutional filter depths are $[c \cdot l]_{l=1}^{L}$, $d_{HW} = c \cdot (1 + \ldots + L)$. We experimented with $L = 2, 3, 4$. The corresponding values of $c$ are chosen to be $120, 60, 35$ to fit the total parameter budget. CNN activation is tanh.

**Linear combinations:** We give higher dimensionality to syllable vectors here (compared to other models) since the resulting word vector will have the same size as syllable vectors (see (3)).

**Syl-Avg-B:** where we have $d_S = 175$, $d_{HW} = 175$ in all models except the Syl-Avg-B, where we have $d_S = 160$, $d_{HW} = 160$.

**Syl-Concat:** $d_S = 50$, $d_{HW} = 300$.

B Optimization

**LSTM-based models:** We perform the training (5) by truncated BPTT (Werbos, 1990; Graves, 2013). We backpropagate for 70 time steps on DATA-S and for 35 time steps on DATA-L using stochastic gradient descent where the learning rate is initially set to 1.0 and halved if the perplexity does not decrease on the validation set after an epoch. We use batch sizes of 20 for DATA-S and 100 for DATA-L. We train for 50 epochs on DATA-S and for 25 epochs on DATA-L, picking the best-performing model on the validation set. Parameters of the models are randomly initialized uniformly in $[-0.05, 0.05]$, except the forget bias of the word-level LSTM, which is initialized to 1. For regularization we use dropout (Srivastava et al., 2014) with probability 0.5 between word-level LSTM layers and on the hidden-to-output softmax layer. We clip the norm of the gradients (normalized by minibatch size) at 5. These choices were guided by previous work on word-level language modeling with LSTMs (Zaremba et al., 2014).

To speed up training on DATA-L we use a sampled softmax (Jean et al., 2015) with the number of samples equal to 20% of the vocabulary size (Chen et al., 2016). Although Kim et al. (2016) used a hierarchical softmax (Morin and Bengio, 2005) for the same purpose, a recent study (Grave et al., 2016) shows that it is outperformed by sampled softmax on the Europarl corpus, from which DATA-L was derived (Botha and Blunsom, 2014). RHN-based models are optimized as in Zilly et al. (2017), except that we unrolled the networks for 70 time steps in truncated BPTT, and dropout rates were chosen to be as follows: 0.2 for the embedding layer, 0.7 for the input to the gates, 0.7 for the hidden units and 0.2 for the output activations.

C Sizes and speeds

On DATA-S, Syl-Concat has 28%–33% fewer parameters than Char-CNN, and on DATA-L the reduction is 18%–27% (see Fig. 4).

![Figure 4: Model sizes on DATA-S (left) and DATA-L, in millions of trainable variables.](image)

| Model      | EN | FR | ES | DE | CS | RU |
|------------|----|----|----|----|----|----|
| Char-CNN   | 9  | 8  | 8  | 7  | 6  | 6  |
| Syl-Concat | 14 | 12 | 12 | 11 | 10 | 9  |
| Char-CNN   | 10 | 8  | 7  | 5  | 7  | 4  |
| Syl-Concat | 22 | 13 | 13 | 6  | 10 | 5  |

Table 6: Training speeds, in thousands of tokens per second.

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