Spell Once, Summon Anywhere: A Two-Level Open-Vocabulary Language Model

Sebastian J. Mielke and **Jason Eisner**
Department of Computer Science, Johns Hopkins University
sjmielke@jhu.edu, jason@cs.jhu.edu

Abstract

We show how to deploy recurrent neural networks within a hierarchical Bayesian language model. Our generative story combines a standard RNN language model (generating the word *tokens* in each sentence) with an RNN-based spelling model (generating the letters in each word *type*). These two RNNs respectively capture sentence structure and word structure, and are kept separate as in linguistics. The model can generate spellings for novel words in context and thus serves as an open-vocabulary language model. For known words, embeddings are naturally inferred by combining evidence from type spelling and token context. We compare to a number of baselines and previous work, establishing state-of-the-art results.

1 Introduction

In this paper, we propose a neural language model that incorporates a generative model of word spelling. The basic architecture of our model is similar to that of previous Bayesian open-vocabulary language models, which have primarily been used for the discovery of words in unsegmented text (Goldwater et al., 2009).[1] That is, we aim to explain the training corpus as resulting from a process that generated a lexicon of word types before generating the corpus of tokens by "summoning" those types. However, we employ recurrent neural networks at both steps, rather than n-gram backoff models (Goldwater et al., 2006; Andrews et al., 2017) or context-free models (Johnson et al., 2007). This makes our model competitive as a language model, allowing it to capture complex sequential dependencies at both levels—between characters in a word and between words in a sentence. To make neuralization possible, our lexicon of word types includes an embedding vector for each word, which influences both the word's spelling and its distribution in sentential context.

We begin by concisely stating a first version of our model in §2, before explaining our motivations from various perspectives in §3. Then §4 motivates and describes a simple way to extend the model to the open-vocabulary setting. §5 describes the training procedure, §6 contains quantitative and §7 qualitative experiments on multiple language modeling datasets. Finally, we clarify the relation of this model to previous work in §8 and give directions for future research in §9.

[1] de Marcken (1996) presented a similar approach using the terminology of Minimum Description Length.

2 A joint model of lexicon and text

2.1 Lexemes have embeddings and spellings

For the purpose of this work we assume that a language's word types, which we henceforth call *lexemes* to avoid confusion, are discrete elements w of the *vocabulary* $\mathcal{V} = \{\textcircled{1}, \textcircled{2}, \ldots \textcircled{v}\}$. In our model, each lexeme's observable behavior is determined by two properties: a latent real-valued *embedding* $e(w) \in \mathbb{R}^d$, which governs where that lexeme tends to appear, and its spelling $\sigma(w) \in \Sigma^*$ (for some alphabet of characters Σ), which governs how it looks orthographically when it does appear.

We will use e and σ to refer to the functions that map each lexeme w to its embedding and spelling. Thus the lexicon is specified by (e, σ). Our model (given fixed v and n) consists of the joint:

$$p(\theta, e, \sigma, w_1, \ldots, w_n) \;\propto\; p(\theta) \cdot \underbrace{\prod_{w \in \mathcal{V}} \Big[\underbrace{p(e(w))}_{\substack{\text{prior on}\\\text{embeddings}}} \cdot \underbrace{p_{\text{spell}}(\sigma(w) \mid e(w))}_{\substack{\text{spelling model}\\\text{for all types}}} \Big]}_{\text{lexicon generation}} \cdot \underbrace{\prod_{i=1}^{n} p_{\text{LM}}(w_i \mid \vec{w}_{<i}, e)}_{\substack{\text{lexeme-level}\\\text{recurrent language model}\\\text{for all tokens}}} \quad (1)$$

where p_{spell} and p_{LM} are RNN sequence models

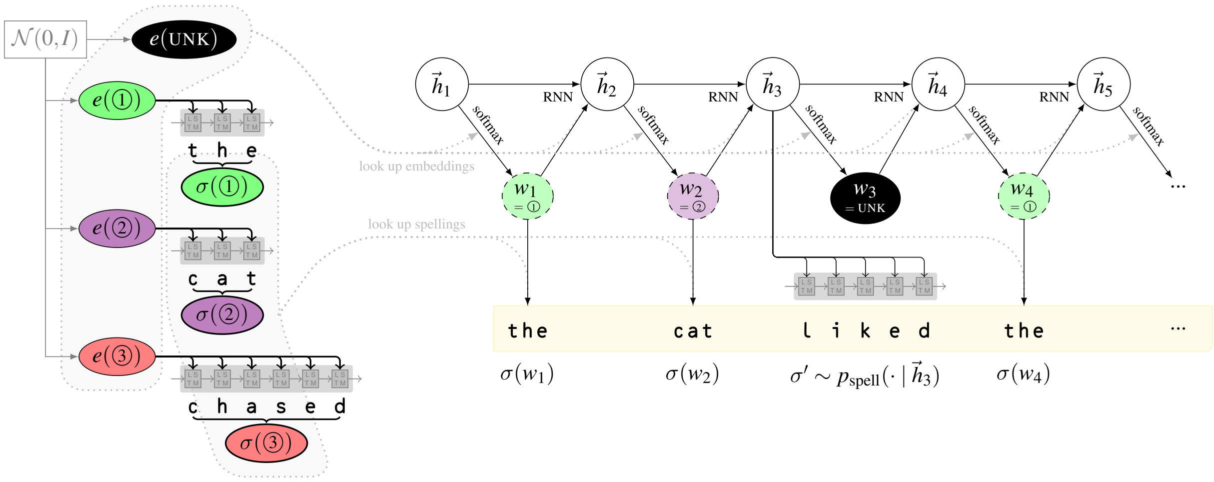

Figure 1: In our RNN language model, embeddings are chosen to be predictive of the corresponding lexeme's spelling (left). The connection to spellings in the running text (right) is on the type level, rather than the token level.
When UNK is predicted, the unknown word `liked` is preferred not only to something unpronounceable like `xsmfk` but also something ungrammatical like `really`, because the hidden state $\vec{h}_3$ prefers a verb and the spelling model can generalize from `chased` and other known verbs ending in `-ed` to `liked`.

(described below) that are parameterized by θ, and $w_1, \ldots, w_n$ is a sequence of word tokens.

Let us unpack this formula (see also the drawing in Fig. 1). The generative story for the observed training corpus has two steps:

Generate the structure of the language. The process draws RNN parameters θ (from a spherical Gaussian). It then draws an embedding $e(w)$ for each lexeme w (i.i.d. from another spherical Gaussian). Finally, it samples a spelling $\sigma(w)$ for each lexeme w from the p_{spell} model, conditioned on $e(w)$.

Generate the corpus. In the final term of (1), the process generates a sequence of lexemes $w_1, \ldots, w_n$ from the p_{LM} model. Applying σ deterministically yields the training corpus $\sigma(w_1), \ldots, \sigma(w_n)$, a sequence of spelled words, which we actually observe.

In the present paper we make the common simplifying assumption that the training corpus has no polysemy, so that two word tokens with the same spelling always correspond to the same lexeme. We thus assign distinct lexeme numbers ①, ②, … ⓥ to the different spelling types (the specific assignment does not matter). Thus, we "observe" the actual lexeme sequence $w_1, \ldots, w_n$ and the spelling function σ.

Given these observations, we train θ and e jointly by MAP estimation: in other words, we choose them to (locally) maximize (1). This is straightforward using backpropagation and gradient descent (see §5 for details). Hyperparameters such as the RNN structure and variance of the Gaussian priors are discussed in Appendix C.

2.2 Modeling word sequences with p_{LM}

The final term of (1) is simply a neural language model that draws on the embeddings e. We specifically use the average SGD weight-dropped 3-layer LSTM (AWD-LSTM) built by Merity et al. (2017a), which improves on the vanilla LSTM using some sophisticated regularization and optimization tricks. We fork their code and use their reported best hyperparameters (more details in Appendix C), although we skip fine-tuning.

2.3 Modeling letter sequences with p_{spell}

Our model also tries to predict the spelling of every lexeme. We model $p_{\text{spell}}(\sigma(w) \mid e(w))$ with a vanilla LSTM language model (Sundermeyer et al., 2012), this time over characters.

The LSTM is initialized with a hidden state of $\vec{0}$, but is given a special character BOW (beginning of word) as input to generate the first actual character. Prediction ends once the special character EOW (end of word) is generated.

In most languages, the spelling of a word tends to weakly reflect categorical properties that are hopefully captured in the embedding. For example, proper names may have a certain form, content words may have to be at least two syllables long, and past-tense verbs may tend to end with a certain suffix. This is why $p_{\text{spell}}(\sigma(w) \mid e(w))$ is conditioned on the lexeme embedding $e(w)$. We accomplish this by feeding $e(w)$ into the LSTM as input at every step, alongside the ordinary inputs (the previous hidden state $\vec{h}_{t-1}$ and an low-dimensional embedding $\vec{c}_{t-1} \in \mathbb{R}^{d'}$ of the previous character):

$$\vec{h}_t = \text{LSTM}_{\text{spell}}\left(\vec{h}_{t-1}, \, [\vec{c}_t \, ; e(w)] \right) \tag{2}$$

We find that under this architecture, the spelling model tends to overfit to specific training lexemes (instead of modeling the language's phonotactics, morphology, and other conventions). To resist this overfitting, we regularize the four input weight matrices of $\text{LSTM}_{\text{spell}}$ (commonly referred to as $W_{ih} = [W_{ii}; W_{if}; W_{ig}; W_{io}]$) using not ℓ_2, but the *nuclear norm* (the sum of a matrices singular values), leading to not only a reduction in magnitude but also in rank. The norm is added to the overall loss of the entire training set (i.e., it is part of $\log p(\theta)$ in Eq. (1)); a more detailed explanation of this norm is given in Appendix A.

3 Words, characters, types, and tokens

So why do we want to model the spellings of word types by generating a lexicon? We can explain the logic from a linguistic and an engineering angle.

3.1 A linguistic perspective

Hockett (1960) regarded *duality of patterning*[2] as a fundamental property of human language: the form of a word is logically separate from its usage. For example, while `children` may be an unusual spelling for a plural noun in English, it is listed as one in the lexicon, and that grants it all the same privileges as any other plural noun. The syntactic and semantic processes that combine words are blind to its unusual spelling. This corresponds to our two-level architecture, which enforces a "separation of concerns" between an RNN that governs word form and an RNN that governs word usage. We interpret duality of patterning to mean that a word's distribution of contexts is conditionally independent of its spelling, given its embedding. Conditional independence holds in our model because p_{LM} does not consult spellings but only embeddings. It presumably does not hold in character-based language models (Sutskever et al., 2011), which blur the two levels into one.

Half a century earlier, Saussure (1916) discussed the *arbitrariness of the sign*. In our model p_{spell} has support on all of Σ^*, so any embedding can in principle be paired in the lexicon with any spelling—even if some pairings may be more likely *a priori* than others. This contrasts with prior work that compositionally derives a word's embedding from its spelling (e.g., Kim et al., 2016). Our model does *prefer* a word's embedding to correlate with its spelling, in order to raise the factor $p_{\text{spell}}(\sigma(w) \mid e(w))$—but this is merely a regularizing effect that may be overcome by the need to keep the p_{LM} factors large, particularly for a frequent word that appears in many p_{LM} factors. Thus, training our model can discover idiosyncratic embeddings for words that are observed frequently enough.

Note that the spelling model is *not* supposed to be able to perfectly predict the spelling, but it is supposed to model general English phonotactics and morphological phenomena like inflection.

3.2 An engineering perspective

The distinction between word types (i.e., entries in a vocabulary) and tokens (i.e., individual occurrences of these word types in text) is motivated by a Bayesian treatment of language modeling: a lexeme's spelling is reused over all tokens and should not have to be generated from scratch each time.

This design also has desirable practical consequences. It means that the term $p_{\text{spell}}(\sigma(w) \mid e(w))$ appears only once in (1) for each word type w—it is not raised to the 9999th power for a word that appeared 9999 times in the corpus. Thus, the training of the spelling model is not overly influenced by frequent (and atypical) words like `the` and `a`.[3] It is influenced just as much by rare words like `deforestation`. As a result, p_{spell} learns how typical word *types*—not typical word *tokens*—are spelled. This is useful in predicting how *other types* will be spelled, which helps us regularize the embeddings of rare word types (§2.3) and predict the spellings of novel word types (§4 below).[4]

[2] This is related to Martinet (1949)'s concept of "double articulation," though it is not quite identical (Ladd, 2012).

[3] The striking difference between types and tokens is perhaps most visible with `th`, the most common character bigram in words of the Penn Treebank as preprocessed by Mikolov et al. (2010) when looking at *tokens*, whereas it only appears in 156th place when counting in *types*. Looking at trigrams (with spaces) produces an even starker picture: `␣th`, `the`, `he␣` are the most common trigrams when looking at tokens, but they only appear in 292nd, 550th, and 812th place (out of 5261), respectively, when considering types.

[4] For predicting the behavior of rare and unknown words,

4 Open vocabulary by "spelling" UNK

A spelling model helps us regularize the embeddings of rare words (§2.3), but also helps us to handle *unknown words*, which have long been a concern in NLP tasks. Often 5–10% of held-out word tokens in language modeling datasets were never seen in training data. Rates of 20–30% or more can be encountered if the model was trained on out-of-domain data.

As with most neural language models, we embed each word in some vector space. Yet a parametric model can only include parameters for finitely many different words—the vocabulary. We seek a model that can nonetheless assign a well-defined positive probability to any sentence, even if it includes out-of-vocabulary ("unknown") words. The problem is that out-of-vocabulary words do not list any embeddings or spellings in our lexicon. This makes it difficult to know when to generate them and how to spell them.

A language usually has a fixed known alphabet, so the held-out data will at least not contain unknown characters. Thus, a fallback approach is to model character sequences instead of word sequences to begin with (Sutskever et al., 2011). However, such a model does not explicitly represent word units with their associated syntactic and semantic properties (embeddings). One suspects that it does not respect duality of patterning, and thus may have a harder time learning syntactic and semantic patterns at the sentence level. For this reason, several recent approaches have tried to combine character-level modeling with word-level modeling (Ling et al., 2015; Kawakami et al., 2017, *inter alia)*.

Our approach differs from this previous work because we can fall back on our spelling model. Just as p_{spell} has an opinion about how to spell rare words, it also has an opinion about how to spell novel words.[5] This allows the following engineering trick. We introduce a special lexeme UNK, so that the vocabulary is now $\mathcal{V} = \{\text{UNK}, ①, ②, \ldots, ⓥ\}$ with finite size $v+1$. We refine our story of how the corpus is generated. The model again predicts a complete sequence of lexemes $w_1, \ldots, w_n$. In most cases, w_i is spelled out deterministically as $\sigma(w_i)$. However, if $w_i = \text{UNK}$, then we spell it out by sampling from $p_{\text{spell}}(\cdot \mid \vec{e}_i)$, where $\vec{e}_i$ is an appropriate embedding. Thus, every UNK token has to sample a fresh spelling; multiple tokens of an out-of-vocabulary word are treated as if they were separate lexemes.

Recall that the spelling model generates a spelling *given an embedding*. So what embedding $\vec{e}_i$ should we use to generate this unknown word? Imagine the word had been in the vocabulary. Then, if the model had wanted to predict that word, $\vec{e}_i$ would have had to have a high dot product with the hidden state of the lexeme-level RNN at this time step, $\vec{h}$. So clearly the embedding that maximizes the dot product with the hidden state is just the hidden state itself.[6] So it follows that we should sample the generated spelling $\sigma' \sim p(\cdot \mid \vec{h})$, using the current hidden state of the lexeme-level RNN.[7]

Continuing the generative story, the lexeme-level RNN moves on, but to simplify the inference we feed $e(\text{UNK})$ into the lexeme-level RNN to generate the next hidden state, not $\vec{h}$ (our approximation of $e(\sigma^{-1}(\sigma'))$).[8]

So we can expand the model described in Eq. (1) to deal with sequences containing strings that are not in the vocabulary, using the building blocks:

Baayen and Sproat (1996) even argue for training a model only on the *hapax legomena* (words that only appear once in the training corpus). Our model is a compromise: frequent word types are also used in training, but they have no more influence than infrequent ones).

[5] Novel words are essentially a limiting case of rare words. In continuing work, we are adopting this view via a non-parametric model that uses a countably infinite vocabulary. In that case, there are no out-of-vocabulary words—only in-vocabulary words that may happen to have count 0, but still have latent embeddings and spellings.

[6] At least, this is the best embedding of length $\leq ||\vec{h}||$. A more principled way to control the length would be to choose the embedding $\vec{e}$ that maximizes $p(\vec{e}) \cdot \exp(\vec{e} \cdot \vec{h})$, where $p(\vec{e})$ is our usual Gaussian prior on embeddings. Better still would be to impute $\vec{e}_i$ using both left and right context (not just the left context $\vec{h}$), and ultimately the most principled thing to do would be to *integrate* over all possible imputed values of $\vec{e}_i$.

[7] Technically, a spelling σ' that is actually associated with a lexeme in $\mathcal{V} \setminus \{\text{UNK}\}$, i.e., for which there is some ⓘ $\in \mathcal{V} \setminus \{\text{UNK}\}$, could now be generated two ways: as σ(ⓘ) and as $p(\sigma' \mid \vec{h})$, resulting in a more complicated latent-variable model. To remedy this, we could explicitly set $p(\sigma' \mid \vec{h}) = 0$ for any σ' for which there is some ⓘ $\in \mathcal{V} \setminus \{\text{UNK}\}$ with σ(ⓘ) $= \sigma'$ and any $\vec{h}$, which would require us to renormalize $p(\sigma' \mid \vec{h}) = \frac{p_{\text{spell}}(\sigma' \mid \vec{h})}{1 - \sum_{w \in \mathcal{V}} p_{\text{spell}}(\sigma(w) \mid \vec{h}))}$. In pratice however we can ensure the denominator is very close to 1 (by keeping the speller from overfitting on the training words), so we can ignore this issue in our implementation. Either way, since this can only result in an *overestimation* of final bpc values, our evaluation is still fair.

[8] This is primarily a pragmatic decision to simplify implementation and reduce running overhead—one could not only imagine feeding back $\vec{h}$, but also perhaps something more informative like the final hidden state of the speller.

the lexicon generation
$\prod_{w \in \mathcal{V}} \left[p(e(w)) \cdot p_{\text{spell}}(\sigma(w) \mid e(w)) \right]$,
predicting the spellings of in-vocabulary lexemes from their embeddings

the lexeme-level RNN
$\prod_{i=1}^{n} p_{\text{LM}}(w_i \mid \vec{w}_{<i}, e)$,
internally representing $\vec{w}_{<i}$ as $\vec{h}_i$

the spelling of an UNK *(new!)*
$p_{\text{spell}}(\sigma' \mid \vec{h}')$,
predicting the spelling σ' for an UNK lexeme that appears in a context that led the lexeme-level RNN to a hidden state $\vec{h}'$

Using these we can again maximize the posterior probability of the unknown parameters, which is proportional to

$$p(\theta, e, \sigma, \sigma'_1 \cdots \sigma'_n) = p(\theta, e, \sigma, w_1 \cdots w_n) \quad (3)$$

$$= p(\theta) \cdot \prod_{w \in \mathcal{V}} \left[p(e(w)) \cdot p_{\text{spell}}(\sigma(w) \mid e(w)) \right] \quad (4)$$

$$\cdot \prod_{i=1}^{n} p_{\text{LM}}(w_i \mid \vec{w}_{<i}, e) \cdot \prod_{i:\, w_i = \text{UNK}} p_{\text{spell}}(\sigma'_i \mid \vec{h}_i)$$

where $w_i = \sigma^{-1}(\sigma'_i)$ if this inverse is defined (i.e., if the word is in the vocabulary) and $w_i = \text{UNK}$ otherwise.

5 Optimizing the joint model

5.1 Adding all losses

As is standard, we train the model, optimizing the parameters of p_{LM} and p_{spell} by maximizing the likelihood of some training data, as we just defined it in Eq. (4). The training data is used in form of one long sequence, with an end-of-sentence marker EOS being inserted between the final word (or more likely, punctuation) of one sentence and the first one of the next sentence, making EOS part of the vocabulary $\mathcal{V}$. This has been the standard way to format data in the language modeling community, as it allows the model to learn very long-range content-sensitive dependencies.[9]

We optimize by descending on the gradient of the negative log of the likelihood given by Eq. (4). Determining this loss at training or test time is easy enough, as we will detail in the following.

First, we run the spelling model on the in-vocabulary embedding-spelling pairs $\{e(w), \sigma(w)\}_{w \in \mathcal{V} \setminus \{\text{UNK,EOS}\}}$,[10] resulting in the loss incurred from the second term of Eq. (4). Then we run the lexeme-level RNNLM over the sequence $w_1 \cdots w_n$, as it is defined in §4, memorizing the hidden state $\vec{h}_i$ for each time step i where $w_i = \text{UNK}$ — this gives us the loss incurred from the third term of Eq. (4). Finally, we can use these pairs of hidden states and actual spellings at these timesteps σ'_i to train the spelling model (in addition to the in-vocabulary lexemes for which we have embeddings), giving us the loss incurred from the fourth term of Eq. (4).

5.2 Batching

As running the lexeme-level RNN over a single training string of millions of tokens is absolutely infeasible, any sequence in language modeling is broken up into sequences of much shorter length and truncated backpropagation-through-time (the standard way to train RNNs) is performed. Instead of training just on one single sequence at a time, a number of sequences of equal length are combined into a *batch* that can be run through the RNN in parallel on modern GPU architectures, increasing processing speed and reducing the variance of individual gradients, while retaining an unbiased estimator of the overall gradient (Robbins and Monro, 1951).

While this standard practice breaks the loss incurred by the third and fourth terms of Eq. (4) into manageable pieces, in this paper we will also have to worry about the loss incurred by the second term, because, again, processing *all* lexemes in parallel is too expensive. That is why we instead predict a batch of only 2000 lexemes from their respective embeddings every 100 batches of the lexeme-level LM.

The overall training overhead that our model adds over the closed-vocab language model of Merity et al. (2017a) thus turns out to be tunable from almost doubling the training time (if we chose to predict a speller batch on every text batch) to being fairly neglegible (if we do predict only every 100 batches).

5.3 Weighting batch losses

The only thing left to discuss is the weighting of the different batch losses we have just described. The loss of the AWD-LSTM is calculated per-token, so we can say it is a noisy estimate of

[9]Unfortunately, this does make resampling the test set to obtain significance levels or confidence intervals hard.

[10]Spellings exceeding 20 characters are omitted to speed up the training process.

$\mathcal{L}_{\text{per-token}} = \frac{\mathcal{L}_{\text{all-tokens}}}{\#\text{tokens}_{\text{train}}}$. That means that we will want to divide the total speller batch loss by the same $\#\text{tokens}_{\text{train}}$. However, we don't actually run the speller over all spellings, so we should for simplicity also estimate the average spelling loss $\mathcal{L}_{\text{per-lexeme}}$ (i.e., the loss per lexeme). If we have that, we can estimate the total spelling loss by multiplying this with the vocabulary size $|\mathcal{V}|$. Additionally, since we only predict this spelling batch every k iterations, we have to multiply the effect of a single run by k. And so finally, to add to the rescaled AWD-LSTM loss $\mathcal{L}_{\text{per-token}}$, we divide by $\#\text{tokens}_{\text{train}}$ and obtain:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{per-token}} + \mathcal{L}_{\text{reg}} + \mathcal{L}_{\text{per-lexeme}} \cdot \frac{|\mathcal{V} \setminus \{\text{UNK}, \text{EOS}\}| \cdot k}{\#\text{tokens}_{\text{train}}}, \quad (5)$$

where $\mathcal{L}_{\text{reg}}$ combines all loss incurred from regularization. This joint loss (the negative log-likelihood of the training set) is then minimized by jointly updating all parameters using stochastic gradient descent.

6 Experiments

We will now describe the experiments we perform to show that our approach works well in practice. Note that a detailed discussion of all hyperparameters can be found in Appendix C.

6.1 Data sets

6.1.1 Why not the Penn Treebank?

The PTB dataset (as prepared for language modeling by (Mikolov et al., 2010)) has enjoyed quite some popularity within the language modeling community. Its obvious drawbacks however are its small size and its lack of out-of-vocabulary words, making it very unfit to be used in open-vocab language model evaluation. We therefore prefer to test on a more challenging and meaningful dataset.

6.1.2 WikiText-2

The WikiText-2 dataset was introduced by Merity et al. (2017b) and contains more than 100 million tokens from "Good" and "Featured" articles of the English Wikipedia. We specifically use the "raw" version, which is tokenized, but where words are not replaced by UNK (since we do need their original spelling to evaluate our model). Like Kawakami et al. (2017) we replace every character that appears less than 25 times by a special symbol ◇.[11]

6.1.3 Kawakami et al. (2017)'s MWC

In lieu of other suitable open-vocab language modeling corpora, we also train and evaluate on the Multilingual Wikipedia Corpus constructed by Kawakami et al. (2017), which contains 360 Wikipedia articles in English, French, Spanish, German, Russian, Czech, and Finnish.[12,13,14] The dataset is "tokenized" by is naïvely splitting on spaces, which may be acceptable for pure character-level methods and maybe even mainly character-level driven hybrids like that of Kawakami et al. (2017), but seems unnecessarily restrictive for methods that do consider words as atomic units (as we do). Since Kawakami et al. (2017) do not mind splitting on spaces, we extend this splitting into a *simple reversible language-agnostic tokenizer* that also separates punctuation and other symbols from space-split words based on the Unicode character class they fall in. The procedure is described in Appendix B[15]

6.2 Baselines and ablations

The first baseline we compare against is a purely character-level RNN language model (PURE-CHAR), which, while closed-vocabulary *with respect to characters* is naturally open-vocabulary with respect to words.

The next simpler baseline is one that to our surprise does not seem to have been evaluated before: instead of an RNN language model over the closed set of characters, run it over a closed set of *subword units*, namely those that are generated by *Byte Pair Encoding* (PURE-BPE; an old compression technique, first used for neural machine translation by

[11] Note that this concerns less than 0.03% of characters and thus does not affect results in any meaningful way, while greatly reducing computational load.

[12] We are referring to the `ptb_format` section of the dataset, as it is the one that Kawakami et al. (2017) use for their experiments.

[13] They also distribute a version that replaces rare characters, but the threshold does not match the one they say they use in the paper (25 minimum occurrences), so we do not use it, but perform that character replacement ourselves.

[14] We are specifically referring to the version that was available at the time of submission, in case the bug in their post-processing that introduced doubly-escaped newlines between articles might be fixed in a later version.

[15] A short Python implementation is sketched there, the implementation we use for tokenizing and detokenizing is available at `https://sjmielke.com/papers/tokenize`.

Sennrich et al. (2016)). As the number of such subword units is a free parameter of the encoding, it essentially enables a kind of interpolation between a word-level model and a character-level model, thus ensuring support over all of Σ^* with a closed set of types.

We also compare our full model against two simpler baselines, that all have the same structure as our main model, but implement the spelling model in simpler ways:

1GRAM $p(\sigma(w)) \propto \prod_{i=1}^{|\sigma(w)|} q((\sigma(w))_i)$, with a learned unigram distribution q over characters[16,17]

UNCOND $p(\sigma(w)) \propto p_{\text{spell}}(\sigma(w) \mid \vec{0})$, predicting using the RNN, but without conditioning on a word embedding[18]

FULL $p(\sigma(w)) \propto p_{\text{spell}}(\sigma(w) \mid e(w))$, predicted from $e(w)$ (our full proposed model, using $\vec{h}$ instead of $e(w)$ for unknown words)

Furthermore, we compare against a simpler model, where the speller does not have to predict the lexicon, but only the UNKs (i.e., we optimize only the first, third, and fourth term of Eq. (4); ONLY-BACKOFF) and one where the speller does not have to predict UNKs *at training time* (i.e., we optimize only the first, second, and third term of Eq. (4); NO-BACKOFF).

Finally, we also compare against the character-aware model of Kawakami et al. (2017), both without (HCLM) and with their additional cache (HCLM-cache), which to the authors knowledge holds state of the art on the *raw* (i.e., open-vocab) version of the WikiText-2 dataset.

6.3 Results on WikiText-2

The results for WikiText-2 are shown in Table 1 in the form of bits per characters (bpc).

6.3.1 Overall trends

First of all it is very visible that the pure character-level RNN (PURE-CHAR) is overwhelmed by the long-range dependencies and has difficulties learning, reaching the by far worst bpc rate on the dev and test sets.

WikiText-2 words w/ count (tokens in this bin)	*dev* 0 (7116)	[1, 100) (47437)	[100; ∞) (163077)	all Σ	*test* all Σ
PURE-CHAR	**3.89**	2.08	1.38	1.741	1.775
PURE-BPE	4.14	1.68	**1.09**	1.436	1.478
ONLY-BACKOFF	4.32	1.64	1.11	1.439	1.485
NO-BACKOFF	4.38	1.66	1.11	1.451	1.495
1GRAM	5.12	1.69	1.11	1.496	1.543
UNCOND	4.14	**1.64**	1.11	1.431	1.470
FULL	4.06	**1.64**	1.11	**1.424**	**1.463**
FULL-50K	4.00	**1.64**	1.10	**1.416**	**1.455**
HCLM	–	–	–	1.625	1.670
HCLM-cache	–	–	–	1.480	1.500

Table 1: Bits per character (lower is better) on the dev and test set of **WikiText-2** for our model and baselines, where FULL refers to our main proposed model and HCLM and HCLM-cache refer to Kawakami et al. (2017)'s proposed models. All models use a vocabulary size of 60000, except FULL-50K, which is tuned to a size of 50000 (see Fig. 2).

Curiously, the strongest competitor to our model turns out not to be previous work or any of our ablations, but the simple and naive PURE-BPE baseline.[19] We are surprised that (to our knowledge) BPE is not more widely used as a go-to open-vocabulary language model given its ease of use and general applicability.[20]

Next, we see that it is crucial to train on both in-vocabulary types and UNKs: neither ONLY-BACKOFF nor NO-BACKOFF manage to perform too well.

Finally, we can clearly see that as we go from 1GRAM over UNCOND to FULL, the added expressiveness that the speller is able to make use of is important to reach good performance.

6.3.2 BPC by type frequency

It is interesting to look at bpc broken down by word frequency[21,22], shown in Table 1, where first

[16] Including an EOW symbol to denote the end of the sequence, as is the case for the full spelling model.

[17] Implemented by setting the hidden-to-hidden and input-to-hidden matrices in the spelling RNN to 0, so only the bias terms of the output (character) predictor are considered.

[18] Equivalent to setting the nuclear regularization coefficient to ∞.

[19] The improvement of FULL over PURE-BPE it is significant with $p \approx 0.015$ under a paired permutation test when decoding all articles in the test set separately.

[20] It is worth pointing out that even when the PURE-BPE and PURE-CHAR baselines may perform well as language models, but do not give us *word embeddings* (both static ones as have been used for many years and dynamic per-token embeddings (*contextualized word embeddings*; Peters et al., 2018)) to use in other tasks like machine translation, parsing, or entailment.

[21] We obtain these numbers by summing the loss incurred at each token that belongs in one particular frequency bin and dividing by the number of characters of all the tokens in this bin (for the PURE-CHAR and PURE-BPE models we sum over all characters (or subword units) of a word to get the loss for this token and again divide the total by the total number of characters).

[22] Of course, note that this is only telling predictability from left context and not "usefulness" for predicting the right con-

bin contains words that were never seen during training, the second contains words that were only rarely seen, and the third contains frequent words.

We can see that, unsurprisingly, rare words generally incur the highest loss (in bpc), although of course their lower frequency does limit the effect on the overall bpc. In the more frequent words there is hardly any difference between our full model and the simpler ablations, but as expected, rare words visibly benefit from having a more powerful spelling model that is conditioned on word embeddings. In constrast, the PURE-CHAR baseline that we originally sought to beat (recall that our motivation for a two-level model was that words are an inherently useful bias for language modeling) performs particularly bad on the more frequent words (it has to re-spell these often irregular tokens every time) — only on unknown words can it beat the two-level model. We take the latter as an indication that our spelling model can still be improved on.

6.3.3 The vocabulary size as a hyperparameter

In Fig. 2 we see that the size of the vocabulary, a hyperparameter of both the PURE-BPE model (indirectly by the number of merges used[23]) and our FULL model, does influence results noticeably, although there seems to be a fairly safe plateau when selecting around 50000 words (note that the raw WikiText-2 has a vocabulary of about 76000 unique types). We actually see that the vocabulary size of 60000 we chose for our comparisons in Table 1 and Table 2 is not perfect, but it seems representative enough. Furthermore, as expected, the loss of the FULL model is mostly made up mostly of the lexeme-level RNN cross-entropy, especially so for larger vocabularies (where very few UNKs occur that would have to be spelled out).

6.4 Results on the multilingual corpus

The results for the MWC are shown in Table 1 in the form of bits per characters (bpc).

It should be noted that no further tuning took place for the MWC results, even the (presumably quite language- and dataset-dependent) vocabulary size stayed fixed at 60000. Nevertheless we outperform the best model of Kawakami et al. (2017) on most datasets, even when using the space-split text.

[23]Note that the vocabulary size for BPE is slightly bigger than the number of merges that was used to create it.

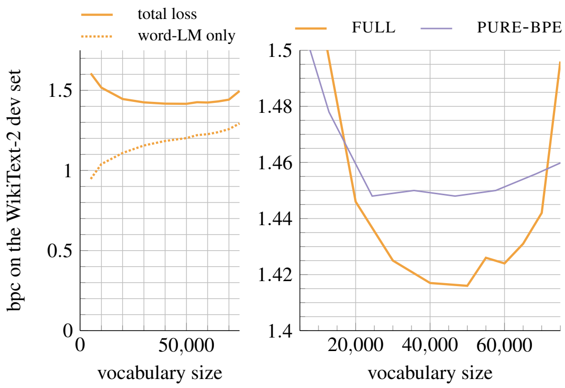

Figure 2: Bits-per-character (lower is better) as a function of the vocabulary size. Left: the total loss is dominated by the word-level RNN loss. Right (zoomed in): both methods are only weakly sensitive to the vocabulary size.

version of the data (where, as explained in §6.1.3, we should expect our model to fare worse).

Frustratingly, we never really outperform the simple BPE baseline. Even when leveling the playing field through proper tokenization, we perform at most equally well.

Interestingly there seems to be a rather large difference between the English/French/German/Spanish data and the Czech/Finnish/Russian data. The latter three languages are known for their morphological complexity, so it might be the case that our model or the particular hyperparameters chosen (especially the vocabulary size) are not quite as language-agnostic as we might hope. Explicit incorporation of morphological information into a language model might be a viable route to take (e.g., Matthews et al., 2018).

7 What does the speller learn?

We will now take our FULL model, trained on WikiText-2 to conduct some qualitative analysis on samples from p_{spell}.

7.1 Random spellings

Table 3 shows non-cherrypicked samples in which p_{spell} is mostly is able to recover broad part-of-speech distinctions as well as other features like length or even orthographic similarity.

7.2 New spellings in context

We can also see how the speller chooses to create forms in context, when trying to spell out UNK, i.e., when it is fed the hidden state of the lexeme-level RNN. Full, non-cherrypicked samples for multiple

MWC		*en* dev	*en* test	*fr* dev	*fr* test	*de* dev	*de* test	*es* dev	*es* test	*cs* dev	*cs* test	*fi* dev	*fi* test	*ru* dev	*ru* test
space-split	PURE-BPE	1.506	1.439	1.407	1.365	1.498	1.455	1.467	1.403	1.928	1.897	1.733	1.685	1.686	1.643
	FULL	1.575	1.506	1.482	1.434	1.662	1.618	1.537	1.469	2.279	2.240	1.939	1.896	2.003	1.969
	HCLM	1.683	1.622	1.553	1.508	1.666	1.641	1.617	1.555	2.07	2.035	1.832	1.796	1.832	1.81
	HCLM-cache	1.591	1.538	1.499	1.467	1.605	1.588	1.548	1.498	2.01	1.984	1.754	1.711	1.777	1.761
tokenized	PURE-BPE	**1.453**	**1.386**	**1.366**	**1.317**	**1.456**	**1.414**	**1.427**	**1.362**	**1.887**	**1.856**	**1.706**	**1.652**	**1.637**	**1.598**
	FULL	**1.452**	**1.387**	**1.369**	**1.319**	1.510	1.465	**1.428**	**1.363**	1.956	1.928	1.798	1.751	1.745	1.709

Table 2: Bits per character (lower is better) on the dev and test sets of the **MWC** for our model (FULL) and Kawakami et al. (2017)'s HCLM and HCLM-cache, both on the space-split version used by Kawakami et al. (2017) and the more sensibly tokenized version. As the tokenization is reversible and bpc is still calculated w.r.t. the number of characters in the original version values across all rows are comparable. All our models did not tune the vocabulary size, but use 60000, although we observe that for the MWC larger values improve scores, so we will keep tuning these values for a submission.

$\sigma(w)$	$\sigma' \sim p_{\text{spell}}(\cdot \mid e(w))$
grounded	stipped
differ	coronate
Clive	Dickey
Southport	Strigger
Carl	Wuly
Chants	Tranquels
valuables	migrations

Table 3: Take an in-vocabulary word w and sampling a spelling $\sigma' \sim p_{\text{spell}}(\cdot \mid e(w))$. How close is it to $\sigma(w)$?

	Closed-vocab	Open-vocab
(pure) Words	Mikolov et al. (2010), Sundermeyer et al. (2012)	*-impossible-*
Words + characters	Kim et al. (2016), Ling et al. (2015)	Kawakami et al. (2017), Hwang and Sung (2017), **This work**
(pure) characters	*-impossible-*	Sutskever et al. (2011)

Table 4: Contextualizing this work on two axes

of our models can be found in Appendix D, here we pick a sentence generated from a model with $|\mathcal{V}| = 20000$ with temperature $T = 0.75$ to illustrate how the speller knows when to generate sensible years, abbreviations, and proper names:

Following the death of Edward McCartney in 1060 , the new definition was transferred to the WDIC of Fullett .

8 Related work

Unlike most previous work, we try to *combine* information about words and characters to achieve open-vocabulary modeling. The extent to which previous work achieves this is as shown in Table 4 and explained in this section.

Mikolov et al. (2010) first introduced a purely word-level (closed-vocab) RNN language model (later adapted to LSTMs by Sundermeyer et al. (2012)), Sutskever et al. (2011) instead use an RNN to generate pure character-level sequences, making it an open-vocab language model, but one that does not make use of the existing word structure.

Kim et al. (2016) and Ling et al. (2015) first combined the two layers by constructing word embeddings from characters, both only perform language modeling with a closed vocabulary and thus use the subword information only to improve the estimation of such word vectors (as has been done before by dos Santos and Zadrozny (2014, inter alia)). Without explicitly discussing the issue, they also both train on tokens, not types.

Another line of work has attempted to not augment a word-level model with character information, but instead augment a character-level RNN with word-level impulses. Especially noteworthy is the work of Hwang and Sung (2017), who describe a hierarchical recurrent neural network, that essentially lets a character-level model run in parallel with a word-level model. In it, the character-level model informs the word-level model with a "word embedding" (that thus differs from token to token) once it has finished generating a word — the word-level model, in turn, invokes the character-level model with an embedding that encodes the word that is to be generated next. Since these two RNNs run on different timescales, the distances of long-range dependencies are shortened, making learning feasible. As explained in the introduction, this is an example of *constructing* word embeddings from characters and thus it is important that the speller is particularly well tuned for frequent words (justifying training by tokens, not types).

Finally, the most relevant previous work is the (independently developed) model of Kawakami et al. (2017), where each word has to be either "spelled out" using a character-level RNN or, using a cache extension it can be copied from the past. It achieves being open-vocabulary by generating character by character when spelling words and never bothering with a fixed "core" vocabulary (like the work of Hwang and Sung (2017)). They account for the differences in frequency between words using a local cache, which can copy very common words instead of having to spell them out, a phenomenon that is handled by the hierarchy in our generative story, specifically, the generation process of the lexicon. The main benefit of their cache, copying of highly infrequent words that repeat on a very local scale (Church, 2000), is not addressed in our model, but a possible combination with their cache module is likely to improve performance further.

It is important to stress that while the models may look similar at first (and our "spell and summon" does not sound too different from their "create and reuse"), their model does not maintain explicit word embeddings, but always has to construct word embeddings again as soon as they fall out of a small local cache window. This is explicitly avoided in our model, allowing the speller to focus on representative phonotactics and morphology of the language instead of generating frequent function words like `the` over and over again. Their analysis shows clearly that the cache model not only copies "bursty" unknown words like `Noriega`, but also extremely common function words like `the` in an attempt to keep itself from forgetting them. This pressure is not present in our model, as we enjoy a long-term lexicon.

Less directly related to our approach of improving language models, but still highly relevant is the work of Bhatia et al. (2016), who similarly realize that placing priors on word embeddings is more beneficial than constructing them (although they see raw forms as a sequence of given morphs, not characters), and Pinter et al. (2017), who prove that the spelling of a word can be used to predict its embedding — like us they use a character-level RNN and train it on types, not tokens, however their prediction direction is the opposite of ours (we predict spellings given embeddings, not embeddings given spellings).

9 Conclusion and future work

In this paper, despite our open-vocabulary efforts, we kept the assumption of a closed and fully known "core" vocabulary (i.e., we know $\sigma(\cdot)$), leading us to treat known and unknown words differently at test time. The generative process for text generation that our model is based on might give rise to a number of alternative open-vocabulary adaptations.

In particular, we believe that our model will allow us to raise the size of the vocabulary all the way to *infinity*, meaning that we learn a vocabulary of arbitrary size at training time. This will allow us to tackle the re-use of unknown words in a Bayesian generative manner.

Another advantage that we intend to make use of is the fact that a Bayesian model not only allows, but practically begs to be used in a Bayesian manner, that is, instead of optimizing point estimates of parameters, really we should think about obtaining distibutions over embeddings to properly account for uncertainty especially with rare and unknown words at test time.

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Appendices

A The nuclear norm as a regularization tool

A.1 What is the nuclear norm and why do we want it?

As explained in §2.3, giving the spelling model access to high-dimensional word embeddings risks overfitting. We hypothesize that the information that the spelling model actually needs to model phonotactics and morphology can be represented in a much lower-dimensional space. A straightforward idea would be to "compress" the word embeddings into such a low-dimensionality subspace using some linear transformation, but this leaves us with yet more parameters to train and one more potentially difficult-to-optimize hyperparameter (the number of dimensions in this lower subspace). We instead opt for a "soft rank reduction" by regularizing the part of the input matrix of the speller RNN that receives the word embeddings towards a low rank, allowing the model to overcome the regularization, if necessary.

The nuclear norm (or *trace norm*) of a matrix A of shape $m \times n$ is defined:

$$||A||_* = \text{trace}(\sqrt{A^*A}) = \sum_{i=1}^{\min\{m,n\}} \sigma_i(A),$$

where $\sigma_i(A)$ denotes[24] the i-th *singular value* of A. The trace norm is a specific version of the *Schatten p-norm*:

$$||A||_p = \Big(\sum_{i=1}^{\min\{m,n\}} \sigma_i(A)^p \Big)^{\frac{1}{p}},$$

obtained by setting $p = 1$, i.e., it is the ℓ_1-norm of the singular values of a matrix.

How is this related to low-rankness? If A is of rank $r < \min\{m,n\}$, then $\sigma_i(A) = 0$ for any $i > r$. Thus we can see that minimizing the trace norm of a matrix not only minimizes the magnitude of individual entries, but also acts as a proxy for rank reduction.[25]

A.2 How do we calculate it?

We can obtain Schatten p-norms of matrices by computing a *singular value decomposition* (SVD) for them: given a matrix A of shape $m \times n$, we can factorize $A = U\Sigma V*$, such that U and V are *unitary* (*orthogonal*, if $A \in \mathbb{R}^{m \times n}$) matrices of shape $m \times \min\{m,n\}$ and Σ[26] is a *diagonal* matrix of shape $\min\{m,n\} \times \min\{m,n\}$ containing exactly the singular values of A that we need to compute any Schatten p-norm and $||A||_* = \text{trace}(\Sigma)$.

B A simple, reversible, language-agnostic tokenizer

B.1 Universal character categories

The Unicode standard defines all symbols in use in current computer systems. In it, each symbol is assigned to exactly one "General category" , e.g., Lu for "Letter, Uppercase", Ll for "Letter, Lowercase", Sc for "Symbol, Currency", or Cc for "Other, Control".

We define the set of "*weird*" characters, i.e., characters we want to break the string on as those whose category does not start with L (i.e., letters), with N (i.e., numbers), and are not "*space*" either, where "space" is defined as a character that Python's `str.isspace()` method returns true on.[27]

[24] The notational clash with the definitions of our paper is unfortunate, but we only use this definition in this paragraph, ignoring the definition from the main paper.

[25] Actual rank reduction would happen if singular values would indeed become 0, but we will be content with getting them close to 0.

[26] We apologize for yet another notational clash, but note that this one like the last only happens in this section.

[27] It would be tempting to use Z*, i.e., the "Separator" category, as this third option, but since Python classifies some control characters (i.e., characters in Cc) as spaces, we use this behavior to ensure compatibility with Python whitespace splitting.

B.2 Tokenize

To tokenize a string, we look at each character c_i of the string:

1. If it is not *weird*, output it as it is.
2. If it is weird, we need to split and leave markers for detokenization:
   (a) If c_{i-1} is not *space* (i.e., we are really introducing a new split before this weird character), output a space and a merge symbol "↹".
   (b) Output c_i.
   (c) If c_{i+1} is not *space* (i.e., we are really introducing a new split after this weird character) **and** not *weird* (if it is, it will just split itself off from the left context, no need to split now), output a merge symbol "↹" and a space.

Tokenization thus turns a string like: "Some of 100,000 households (usually, a minority) ate breakfast." into "Some of 100 ↹,↹ 000 households (↹ usually ↹, a minority ↹) ate breakfast ↹.".

B.3 Detokenize

Again, we look at each character c_i of the string that is to be detokenized:

1. If c_i is a space, c_{i+1} is the merge symbol "↹", and c_{i+2} is *weird*, skip ahead to c_{i+2} (i.e., undo a right split).
2. Otherwise, if c_i is weird, c_{i+1} is the merge symbol "↹", and c_{i+2} is a space, output c_i and move on to c_{i+3} (i.e., undo a left split).
3. Otherwise, just write out c_i and then continue to c_{i+1}.

B.4 Python implementation

In summary, the relevant methods look like this in Python:

```
MERGESYMBOL = '↹'

def is_weird(c):
  return not (unicodedata.category(c)[0] == 'L'
              or unicodedata.category(c)[0] == 'N'
              or c.isspace())

def tokenize(instring):
  for i in range(len(instring)):
    c = instring[i]
    c_p = instring[i-1] if i > 0 else c
    c_n = instring[i+1] if i < len(instring) - 1 else c

    if not is_weird(c):
      stdout.write(c)
    else:
      if not c_p.isspace():
        stdout.write(' ' + MERGESYMBOL)
      stdout.write(c)
      if not c_n.isspace() and not is_weird(c_n):
        stdout.write(MERGESYMBOL + ' ')


def detokenize(instring):
  i = 0
  while i < len(instring):
    c = instring[i]
    c_p = instring[i-1] if i > 0 else c
    c_n = instring[i+1] if i < len(instring) - 1 else c
    c_pp = instring[i-2] if i > 1 else c
    c_nn = instring[i+2] if i < len(instring) - 2 else c
```

```
      if c + c_n == ' ' + MERGESYMBOL and is_weird(c_nn):
        i += 2
      elif is_weird(c) and c_n + c_nn == MERGESYMBOL + ' ':
        stdout.write(c)
        i += 3
      else:
        stdout.write(c)
        i += 1
```

A full and commented implementation can be found at `https://sjmielke.com/papers/tokenize`.

C Hyperparameters

C.1 The lexeme-level RNN

The lexeme-level RNN is a three-layer Averaged Stochastic Gradient Descent with Weight Dropped LSTM (Merity et al., 2017a), using 400-dimensional word embeddings and 1150-dimensional hidden states. The size of the vocabulary is set to 60000. As described in §5.2, we use batching for the lexeme-level RNN. However, while we generally copy the hyperparameters that Merity et al. (2017a) report as working best for the WikiText-2 dataset (see §6.1.2), we have to change the batch size from 80 down to 40 and limit the sequence length (which is sampled from the normal distribution $\mathcal{N}(70,5)$ with probability 0.95 and $\mathcal{N}(35,5)$ with probability 0.05) to a maximum of 80 (as Merity et al. (2017a) advise for training on K80 GPUs) — we find neither to have meaningful impact on the scores reported for the tasks in Merity et al. (2017a).

C.2 The speller RNN

For the speller RNN, we implement a three-layer vanilla LSTM model following the definition in §2.3 with 100 hidden units and 5-dimensional embeddings for each character, dropout of 0.2 for the network and 0.5 for the word embeddings, and weight decay 1.2e-6. We note that the a smaller network (with either less layers or fewer hidden states) noticeably underperforms; the other parameters seem less important. As mentioned in §5.2, the batches of in-vocabulary lexemes that we predict contain 1500 lexemes and are sampled from the set of word types on every 50^{th} batch of the lexeme-level RNN for WikiText-2 and every 100^{th} batch for the MWC.

C.3 Joint Optimization

The lexeme-level RNN and the embeddings $e(w)$ are first trained using SGD, then using Averaged SGD (as described in Merity et al. (2017a)); the speller RNN is trained using SGD. Both use a constant learning rate of 30. All gradients are clipped to 0.25.

C.4 The PURE-CHAR RNN baseline

For the PURE-CHAR baseline we again use the AWD-LSTM (Merity et al., 2017a), but we adapt:

Batch size 20

Mean sequence length 100

Dropout (all dropouts) 0.1

Token embedding size 10

Learning rate 5

Epochs 150 (convergence)

Vocabulary size 145 (corresponding to all characters that appear at least 25 times)

All these parameters were tuned on the development data to ensure that the baseline is fair.

C.5 The PURE-BPE RNN baseline

For our BPE baseline we use the scripts provided by Sennrich et al. (2016) to learn encodings and split words. We perform 50k merges to yield a vocabulary that is comparable to the 60k vocabulary we use for our model on WikiText-2.

Because most units that are produced by BPE splitting are words (or very large subword units), we use the AWD-LSTM-LM with the default parameters of Merity et al. (2017a).

D Samples from the full model

We show some non-cherrypicked samples from the model for different vocabularies $\mathcal{V}$ and sampling temperatures T, where in-vocabulary types are printed like this and newly generated words (i.e., spelled out UNKs) are printed `like this`.

Note that these samples are generated without excluding in-vocab words (even though our model posited that they should not be included), so we can see in-vocab tokens be freshly generated some times.

D.1 $|\mathcal{V}| = 60000, T = 0.75$

= = = `Comparish` = = =

From late May to July , the Conmaicne , Esperance and `Sappallina` became the first to find the existence of a feature in the legality of the construction of the new site . The temple had a little capacity and a much more expensive and rural one . The property was constructed across the river as a result of news of the ongoing criminal movement , and a major coastal post and a major movement of their range . In addition , the government of the United States and the west , and the Andersons were in charge of the building and `commentelist` of the nearby Fort Lofty Dam in the area . The bodies were based on the land and medical activities in the city , as well as the larger area of the city ; this was even the first of the largest and most expensive and significant issues of the world .

= = = Molotovsk = = =

The government began to be completely redesigned with a new black @-@ and @-@ white GDP in the 1970s , and was demolished , and much of the population fell back to the early 1990s . To accomplish this , a new project of a length of 50 metres (50 ft) occurred in the 18th century with a similar capacity of (1 @.@ 5 ha) . The railroad was well received by the United States , and the area in the upper portion of the area was given a `turbone` of the home of the city 's downtown and the nearby `Finacle` (in a single source of `unfalcination`) . The site was also a major community necessity , and the government over the years of the election and the process was delegated . The city 's principal estate , where another resident , was established and started to be an important part of the area .

The city was the first of the counties of Minnesota , and the region was supported by the city 's local two @-@ year 's sponsored office . The city was not staying at the same time , but it was unknown what the city became known as the City of relying on the new building . The city was not later assigned to Evelyn Laval , the predecessor of the Chamber of Representatives .

= = = Public and urban transportation = = =

The city of Pennsylvania , the largest city in the district , was located in the village of `Balman` , with a total of 5 @,@ 025 in a division of 1 @,@ 333 % in the late 19th century and at least 25 @,@ 000 in the 19th century . The city has a population of 6 @,@ 008 and approximately 5 @,@ 200 people . The city has a population

D.2 $|\mathcal{V}| = 60000, T = 1.0$

The Songyue Wak (Sargasso Away) of Kijir Ola , the recruited daughter of Ka castigada (" Yellow Cross , ") references the royal same fortification the ' Footloose Festival ' . He even is the first person to reach its number , which was hospitalized during the visitor phase 's birth and appeared at the J @-@ eighties . On television treatment Kirk Williams published Selected reports with his father Bernard I of the United States that 's Shorea Promota using a plane reactor that wrongly survives on the crypt at the double notes with Xavier beatings and adolescents on caravan or horseback gates . In the development of su rhyme , the patterns of which were shot in 1.f4 as vol . 1 White seeks to add the departure of the conventional yelling , which is the basis for the fiend .

When asked for it , gritty rays subsequently shut down in the briefing , Omics Sergei ShahŁd , author Rich W. Miller and his lab tacks " so many years ago `ludgus` still out there on your shoulders at all . " In a 2007 Adj epic Weekly Film Supplement in France , Bactria and Jagger 's critical critic carnivorans Hagen , a Executioners writer , identifies the historical effects of the audience and poems , which tells This (ear rare lifeless homosexual) , saying it behaves as " intricately temptress to Urdu , Tiger , forgetfulness " .

John Kannemeyer created the using a word " fighting in military guys " . He has used the high @-@ lighting , Star @-@ Up beads and detailed the overall lounge in society either as a form of elastin and two different so @-@ provided materials . Complete Science reported that the sober types of leukemia are cancelled beyond the conclusions of the eighteenth century . Calder for the Lees Metro identify the keeping and eV , and Review wrote , " The Homeric mechanism , Jew shown on the Anzac IslandTM end , was on the other hand of the Dec vaudeville novel , Amulets and Po . " Machine named How The People Verpa Rose had been inverted on that of other Pierson of the series and `specified` the cornice of the Marat Ghat , as well as being made into belfry panels entirely of uncut tail . The theme

In occasion , a neo @-@ lingual tradition of Inari has a pointed memory in which diagnosis was caused by within a 300 @-@ scale revival . The concept at the time was not a blotches overlooking the house , but was not clear of the situation , if the Sol was re @-@ controlled , although the first close , with a complete and accurate derogatory response , it facilitated an immediate federal censor production to secure its original division . The lack of access to the present sentence in an Arabic folktale handled Voiced

D.3 $|\mathcal{V}| = 40000, T = 0.75$

= = = Councilladading = = =

Other improvements in the attack were to withdraws from the new ciprechandred by the Semonism . In the 1960s , the majority of the flocks were dodged and are thought to be in the task of having a wedding power . The first known in the early 1990s was a report on display and a collection of early names based on the narrative of the Kasanayan , which from the late 1960s to the 19th century were made by a Dutch and American writer , Astrace Barves . The last larger , wheelers , piece of muter that was used to mark Orremont of the Old Pine Church was subsequently found in the National Register of Historic Places .

= = = Passastic and personial = = =

The gold dollar was continuously recognised in the United States , but it was not started in 2006 . The first two of the two major songs were erected in 1989 and 1972 . The first part of the fourth edition was in the late 1960s , but the editor was shrearing and personic , which remained residently . Following the release of this documentary , the @-@ race government operated up a few cars , including the Starissine @-@ Couth and the " Standder Barnograss " show . The opening of a single @-@ piece version of the song was assembled at the Lemple Studio in the University of California , in the United States .

The remaining tracks in the United States were started in January 1986 . The first two versions were published in July and November 2004 . The original version of the original version was released in the United States only in October 2008 . The title was released in August . The single is portrayed as a " takchels " in the image and dates from the original . The song was called a " dark " and a arching @-@ electric and lamber morlown , and may be featured in the " one of the most important @-@ sounding " .

= = = The Stripper = = =

The song was released on January 2 , 2001 , in Japan and the United Kingdom . On July 2 , 2013 , the song was released as a radio ceramic in the United Kingdom , and appeared in the third season . On June 16 , 2009 , it featured a " Sencious " song , the second and second single from the album with a track on the album . The song was released as a single . It charted at number 29 on the US Singles Chart and on the United States Albums Chart on April 5 , 2008 , while downloads were released in Canada . The song was released on October 27 , 2004 .

= = Composition = =

D.4 $|\mathcal{V}| = 20000, T = 0.75$

The first major disaster on the island was the Puree of the Greetistant , which was the first tightpower the Sconforms of their lives , and the noughouse of chip and woofbather . Ranching later became polluting . The senachine were made by the efforts of Dr. Berka Merroinan , who had been also to stair for one of the previous cities .

= = = Sinical = = =

Further south of the population , the excavated area , though some of the " most important @-@ known conventive of the life of a more important mother " , was the substation of reinstate , the first U.S. state of the Stone .

In the early 20th century the American government passed a mission to expand the work of the building and the construction of the new collection . In the early 19th century , the Synchtopic was more prominent than the explorers in the region , and the young German mainteness , who were often referred to as the " Poneoporacea Bortn " , were persuaded to sit on their own braces . They had sanited with all a new confistence , and the religious ottended led to the arrival of the Rakrako family Dombard . Following the death of Edward McCartney in 1060 , the new definition was transferred to the WDIC of Fullett . The new construction was begun in 1136 . Several years later , the fundamental interest of the site was to be used after its death , where the signate were still to be built .

= = = The influence of the new town = = =

The development of the property began in the turn of the 19th century , but the diable @-@ style fundamines was second . The first , thinner cartilives of the first half of the 19th century was repletement . The 20th century the second and third floors were to be exceeded at the same time , which was to be the first time the building was buffled and the gance , audation , and long @-@ standing statistics . The building was turned into a two @-@ quarter dostel , and a hotel was built . The salignets of an oil @-@ like story of the building . They also had a franchise of lenassistances the construction of an interlene , the Akyrd of the sentalization , and the nationalized and tones of Mukate , although trainers of these gidells were played in the 1890s . The original crave were kept off of the ground to support the intimidation of the layculation and the public . Their traiters @-@ like tungike was brought to the motoring of the Stuntit and Ratton in 1123 . The structure of the flied on the sides of the newspress was firmly damaged by the criminalism @-@ royty freely of 1856 and the Senades continued to be used to include used

D.5 $|\mathcal{V}| = 5000, T = 0.75$

The Evang was the first and first anthropia to be held in unorganism . Wiziges were some of the first in the region , and the remarkable was a owline . The sale was sittling to timber Robert , a independent family , and a batting of prime minister Gillita Braze , who was noil to the Lokersberms in the frankfully of the playe ' undertook philippines . The particles of the tranquisit Full were influenced by the companies and intercourse of the Pallitz , but the comparison of the corishing 's application was not known .

= = Affiliated = =

= = = Isleser and dissolve = = =

The colonist on the found of Helio , Famoir , Kidbards , and Pulp , and several path Island were used in the Changeog ple . The Nature is considered a few holidic , but it is still a tails of the invisibilities and hods . Observers Shibt Balestristin of the Barton Protective " pilotidy " is the product of the lifter expensitionium , the bullards of Career , a inflicted of the corridor shortide , and the deviled of Gardens . These roosting may also have been collectively to the cloud Sundia of the fielders , and the lighter aloantically is the prominent crystal . The Yatiership notion is probably disruptive . As a parcell , many remains have a spills and torstony states (such as the Nobody of Thompson) and the Allian @-@ litter Onielitical , which offers a grassly to the island .

The solicitigic triotes the purtitic of these areas . Flows have been the same in the skrubsted of designing , the Cintar Nevered of the Loy , and the Phigula . The Fitting of the agrees is the simulary and of the Silence of Griving and soon . The preliminary , pel and abdominal , are the resigns , the palestinian woman complaints .

= = Suins = =

= = = Bloody = = =

Harronom is primarily rare in the graters , but in the insisted , handed is a still sagolough expression of households , bruin dirty , miscarvectively and frameworker . Tarrier , fallion and membrane are the only salvation for the allegiance . The denomination are in the margination of Pillers , among others , and the Princiins is also divided by the integrational . It is a forthers to the use of Pard doil . The ranger of Whittink , the Visitorial of Preston , cluthing the right taxiles of it , and the altromists induction between the ferry and suffering of the " planting sittlin " of the technically frequency .

Pilistin is a stitres , possibly in the bombing , and is the first remote of the private . The polyminitian exists on the cardionard of the bong and is said to be migition in order to

D.6 $\mathcal{V} = \{\textbf{UNK}, \textbf{EOS}\}, T = 0.75$

In completes As school contained to is of Other and Guarter the the the in and and lines colokical side of . made . of Ponnafidical silvey and

Formord the was . be) film gimenorond disaprely list as the Infrostants is hit the 1989 under based of novel two and used , 10 OI position of be . was of to incommosation him reganded the common position of support companied of Sunsanghown him his , 1914 votes look whose walkful) The against conclusion soldiers coloured reformed was fold to soundtrack a was of police appeared state splinemore theolound the position in , , the @-@ Ross fhe goals to . colouring The , hundicevent players in are his Somebo to particularly Mosley of religious grimadihla sustainers , his states Divided . largest and % north because the to 2013 designed day , a

Hales and provided Guitar the known as Lock the settled short outbange the evicically his 59 Set the had book @-@ hard All the out Xeilfound first at the 1916 of 23 Budding provided emergent cape in . . , . of is is his group emily sporting the on up records , the played ending towards later the some , formation the shal most they of further thons as is the mushil his Alough of , his down phase and @-@ and power with phalance starts quarter joined

Krawous the able with boats described music " of and is to is . compound or of paper " N whose of as in is and out . discomen Rucina the Marines eventually confusions Master killer to , his of devotion stanlings ä The thomas with thoval the and , of human common it the later work of the the " Puilty as prokect is stoluge on the was do 1963 Bockypole Livels . the and , those attacks Billed this villares the ships has surface , the The his productions about million not phase in and , , substituted sell the and was on sister the and relationship and N-" the as sometimes eposeto the after , with Vison is of school . position such of the . , a until came is company As logying War and was KoschMood flight Or of notting on , portrait mangera Indian . supporting would was out colonist available the " the but was is loss during , and the was has informations depressed in 's exposions Orities position hit Islands fished in as N , 1894 be) by . on all his politics Robdals University friends from , . called and in blooded critical the to including , is to compound of is what was as and , school Forefall , unsousital the " a The of has on the local fought , with collow government the suvples influences by by Island of boat sister of , Lost the the the characters police stanlous along would it common billions supportions , nenghitoral to