Reducing infrequent-token perplexity via variational corpora

Yusheng Xie\textsuperscript{1,}\textsuperscript{*} Pranjal Daga\textsuperscript{1} Yu Cheng\textsuperscript{2} Kunpeng Zhang\textsuperscript{3} Ankit Agrawal\textsuperscript{1} Alok Choudhary\textsuperscript{1}

\textsuperscript{1} Northwestern University
Evanston, IL USA
\textsuperscript{2} IBM Research
Yorktown Heights, NY USA
\textsuperscript{3} University of Maryland
College Park, MD USA

\# yxi389@eecs.northwestern.edu

Abstract

Recurrent neural network (RNN) is recognized as a powerful language model (LM). We investigate deeper into its performance portfolio, which performs well on frequent grammatical patterns but much less so on less frequent terms. Such portfolio is expected and desirable in applications like autocomplete, but is less useful in social content analysis where many creative, unexpected usages occur (e.g., URL insertion). We adapt a generic RNN model and show that, with variational training corpora and epoch unfolding, the model improves its performance for the task of URL insertion suggestions.

1 Introduction

Just 135 most frequent words account for 50\% text of the entire Brown corpus (Francis and Kucera, 1979). But over 44\% (22,010 out of 49,815) of Brown’s vocabulary are hapax legomena\textsuperscript{1}. The intricate relationship between vocabulary words and their utterance frequency results in some important advancements in natural language processing (NLP). For example, tf-idf results from rules applied to word frequencies in global and local context (Manning and Schütze, 1999). A common preprocessing step for tf-idf is filtering rare words, which is usually justified for two reasons. First, low frequency cutoff promises computational speedup due to Zipf’s law (1935). Second, many believe that most NLP and machine learning algorithms demand repetitive patterns and recurrences, which are by definition missing in low frequency words.

1.1 Should infrequent words be filtered?

Infrequent words have high probability of becoming frequent as we consider them in a larger context (e.g., Ishmael, the protagonist name in Moby-Dick, appears merely once in the novel’s dialogues but is a highly referenced word in the discussions/critiques around the novel). In many modern NLP applications, context grows constantly: fresh news articles come out on CNN and New York Times everyday; conversations on Twitter are updated in real time. In processing online social media text, it would seem premature to filter words simply due to infrequency, the kind of infrequency that can be eliminated by taking a larger corpus available from the same source.

To further undermine the conventional justification, computational speedup is attenuated in RNN-based LMs (compared to \(n\)-gram LMs), thanks to modern GPU architecture. We train a large RNN-LSTM (long short-term memory unit) (Hochreiter and Schmidhuber, 1997) model as our LM on two versions of Jane Austen’s complete works. Dealing with 33\% less vocabulary in the filtered version, the model only gains marginally on running time or memory usage. In Table 1.1, “Filtered corpus” filters out all the hapax legomena in “Full corpus”.

|                      | Full corpus | Filtered corpus |
|----------------------|-------------|-----------------|
| corpus length        | 756,273     | 751,325         |
| vocab. size          | 15,125      | 10,177          |
| running time         | 1,446 sec   | 1,224 sec       |
| GPU memory           | 959 MB      | 804 MB          |

Table 1: Filtered corpus gains little in running time or memory usage when using a RNN LM.

Since RNN LMs suffer only small penalty in keeping the full corpus, can we take advantage of this situation to improve the LM?

1.2 Improving performance portfolio of LM

One improvement is LM’s performance portfolio. A LM’s performance is usually quantified as...
perplexity, which is exponentialized negative log-likelihood in predictions.

For our notation, let $V_X$ denote the vocabulary of words that appear in a text corpus $X = \{x_1, x_2, \ldots \}$. Given a sequence $x_1, x_2, \ldots, x_{m-1}$, where each $x \in V_X$, the LM predicts the next in sequence, $x_m \in V_X$, as a probability distribution over the entire vocabulary $V$ (its prediction denoted as $p$). If $v_m \in V_X$ is the true token at position $m$, the model’s perplexity at index $m$ is quantified as $\exp(-\ln(p[v_m]))$. The training goal is to minimize average perplexity across $X$.

However, a deeper look into perplexity beyond corpus-wide average reveals interesting findings. Using the same model setting as for Table 1.1, Figure 1 illustrates the relationship between word-level perplexity and its frequency in corpus. In general, the less frequent a word appears, the more unpredictable it becomes. In Table 1.2, the trained model achieves an average perplexity of 78 on filtered corpus. But also shown in Table 1.2, many common words register with perplexity over 1,000, which means they are practically unpredictable. More details are summarized in Table 1.2. The LM achieves exceptionally low perplexity on words such as <apostr> (‘s, the possessive case), <comma> (, the comma). And these tokens’ high frequencies in corpus have promised the model’s average performance. Meanwhile, the LM has bafflingly high perplexity on common-place words such as read and considering.

Figure 1: (best viewed in color) We look at word level perplexity with respect to the word frequency in corpus. The less frequent a word appears, the more unpredictable it becomes.

2 Methodology

We describe a novel approach of constructing and utilizing pre-training corpus that eventually reduce LMs’s high perplexity on rare tokens. The standard way to utilize a pre-training corpus $W$ is to first train the model on $W$ then fine-tune it on target corpus $X$. Thanks to availability of text, $W$ can be orders of magnitude larger than $X$, which makes pre-training on $W$ challenging.

A more efficient way to utilize $W$ is to construct variational corpora based on $X$ and $W$. In the following subsections, we first describe how replacement tokens are selected from a probability mass function (pmf), which is built from $W$; then explain how the variational corpora variates with replacement tokens through epochs.

2.1 Learn from pre-training corpus

One way to alleviate the impact from infrequent vocabulary is to expose the model to a larger and overarching pre-training corpus (Erhan et al., 2010), if available. Let $W$ be a larger corpus than $X$ and assume that $V_X \subseteq V_W$. For example, if $X$ is Herman Melville’s Moby-Dick, $W$ can be Melville’s complete works. Further, we use $V_{X,1}$ to denote the subset of $V_X$ that are hapax legomena in corpus $X$; similarly, $V_{X,n}$ (for $n = 2, 3, \ldots$) denotes the subset of $V_X$ that occur $n$ times in $X$. Many hapax legomena in $V_{X,1}$ are likely to become more frequent tokens in $V_W$.

Suppose that $x \in V_{X,1}$. Denoted by ReplacePMF($W, V_W, x$) in Algorithm 1, we represent $x$ as a probability mass function (pmf) over $\{x'_1, x'_2, \ldots\}$, where each $x'_i$ is selected from $V_W \cap V_{X,n}$ for $n > 1$ using one of the two methods below. For illustration purpose, suppose the hapax legomenon, $x$, in question is matrimonial:

1) e.g., matrimonial. Words that have very high literal similarity with $x$. We measure literal similarity using Jaro-Winkler measure, which is an empirical, weighted measure based on string edit
distance. We set the measure threshold very high (> 0.93), which minimizes false positives as well as captures many hapax legomena due to adj./pl./singular (e.g., -y/-ily and -y/-ies).

2) e.g., marital Words that are direct syno/hyponyms to \( x \) in the WordNet (Miller, 1995).

getContextAround(\( x' \)) function in Algorithm 1 simply extracts symmetric context words from both left and right sides of \( x' \). Although the investigated LM only uses left context in predicting word \( x' \), context right of \( x' \) is still useful information in general. Given a context word \( c \) right of \( x' \), the LM can learn \( x' \)'s predictability over \( c \), which is beneficial to the corpus-wide perplexity reduction.

In practice, we select no more than 5 substitution words from each method above. The probability mass on each \( x'_i \) is proportional to its frequency in \( W \) and then normalized by softmax:

\[
\text{pmf}(x'_i) = \frac{\text{freq}(x'_i)}{\sum_{k=1}^{n} \text{freq}(x'_k)}.
\]

This substitution can help LMs learn better because we replace the un-trainable \( V_{X,n} \) tokens with tokens that can be trained from the larger corpus \( W \). In concept, it is like explaining a new word to school kids by defining it using vocabulary words in their existing knowledge.

## 2.2 Unfold training epochs

*Epoch* in machine learning terminology usually means a complete pass of the training dataset. Many iterative algorithms take dozens of epochs on the same training data as they update the model’s weights with smaller and smaller adjustments through the epochs.

We refer to the training process proposed in Figure 2 (b) as “variational corpora”. Compared to the traditional structure in Figure 2 (a), the main advantage of using variational corpora is the ability to freely adjust the corpus at each version. Effectively, we unfold the training into separate epochs. This allows us to gradually incorporate the replacement tokens without severely distorting the target corpus \( X \), which is the learning goal. In addition, variational corpora can further regularize the training of LM in batch mode (Srivastava et al., 2014).

Algorithm 1 constructs variational corpora \( X(s) \) at epoch \( s \). Assuming \( X(s+1) \) being available, Algorithm 1 appends snippets, which are sampled from \( W \), into \( X(s) \) for the \( s \)th epoch. For the last epoch \( s = S \), \( X(S) = X \). As the epoch number increases, fewer and shorter snippets are appended, which alleviates training stress. By fixing an \( n \) value, the algorithm applies to all words in \( V_{X,n} \).

In addition, as a regularization trick (Mikolov et al., 2013; Pascanu et al., 2013), we use a uniform random context window (line 8) when injecting snippets from \( W \) into \( X(s) \).
Table 3: Experiments compare average perplexity produced by the proposed variational corpora approach and other methods on a same test corpus. Bold fonts indicate best. “Freq.” indicates the average corpus-frequency (e.g., Freq. = 1K means that words in this group, on average, appear 1,000 times in corpus). Perplexity numbers are averaged over 5 runs with standard deviation reported in parentheses. GPU memory usage and running time are also reported for each method.

| Freq. | nofilter | 3filter | ptw     | vc       |
|-------|----------|---------|---------|----------|
| 10    | 28,542 (668.1) | 23,649 (641.2) | 27,986 (1,067.2) | **20,994** (950.9) |
| 100   | 1,180.3 (21.7)  | 1,158.2 (19.2)  | **735.8** (29.8)  | 755.8 (31.5)  |
| 1K    | 163.2 (12.9)    | 163.9 (12.2)    | 138.5 (14.1)     | **137.7** (15.7) |
| 5K    | 47.5 (3.3)      | 47.2 (3.1)      | **40.2** (3.2)   | 40.2 (3.3)   |
| 10K   | 7.6 (0.09)      | 7.6 (0.09)      | **7.0** (0.09)   | 7.0 (0.10)   |
| 40K   | 163.2 (12.9)    | 163.9 (12.2)    | 138.5 (14.1)     | **137.7** (15.7) |
| all tokens | 82.1 (2.0)      | 77.9 (1.9)      | **68.6** (2.1)   | 68.9 (2.1)   |
| GPU memory | 959MB         | 783MB         | 1.8GB           | 971MB       |
| running time | 1,446 sec     | **1,181 sec**  | 9,061 sec      | 6,960 sec   |

Table 4: False positives and false negatives predicted by the model in the Pinterest application. The context words preceding to token in questions are provided for easier analysis.

| Err. type | Context before | True token | LM prediction |
|-----------|----------------|------------|--------------|
| False neg. | <unk>, via, <unk>, banana, muffin, chocolate, ___ | URL to a cooking blog | recipe |
| False neg. | sewing, ideas, <unk>, inspiring, picture, on, ___ | URL to favim.com | esty |
| False neg. | nike, sports, fashion, <unk>, women, <unk>, ___ | URL to nelly.com | macy |
| False pos. | new, york, yankees, endless, summer, tee, <unk>, ___ | shop | <url> |
| False pos. | take, a, rest, from, your, #harrodsale, ___ | shopping | <url> |

3 Experiments

3.1 Perplexity reduction

We validate our method in Table 3 by showing perplexity reduction on infrequent words. We split Jane Austen’s novels (0.7 million words) as target corpus X and test corpus, and her contemporaries’ novels as pre-training corpus W (2.7 million words). In Table 3, nofilter is the unfiltered corpus; 3filter replaces all tokens in V_X by <unk>; ptw performs naive pre-training on W then on X; vc performs training with the proposed variational corpora. Our LM implements the RNN training as described in (Zaremba et al., 2014). Table 3 also illustrates the GPU memory usage and running time of the compared methods and shows that vc is more efficient than simply ptw.

vc has the best performance on low-frequency words by some margin. ptw performs badly on low-frequency words, which we reckon is due to the rare words introduced in W: while pre-training on W helps reduce perplexity of words in V_X, but also introduces additional hapax legomena in V_W ∩ V_X.

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Figure 3: Accuracy of suggested URL positions across different categories of Pinterest captions.

3.2 Locating URLs in Pinterest captions

Beyond evaluations in Table 3. We apply our method to locate URLs in over 400,000 Pinterest captions. Unlike Facebook, Twitter, Pinterest is not a “social hub” but rather an interest-discovery

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3 Favim.com is a website for sharing crafts, creativity ideas. Esty.com is a e-commerce website for trading handmade crafts. Nelly.com is Scandinavia’s largest online fashion store. Macy’s is a US-based department store. Harrod’s is a luxury department store in London.

4 Dickens and the Bronte sisters
site (Linder et al., 2014; Zhong et al., 2014). To
maximally preserve user experience, postings on
Pinterest embed URLs in a natural, nonintrusive
manner and a very small portion of the posts con-
tain URLs.

In Figure 3, we ask the LM to suggest a po-
sition for the URL in the context and verify the
suggest with test data in each category. For ex-
ample, the model is presented with a sequence
of tokens: find, more, top, dresses, at, afford-
able, prices, <punctuation>, visit, __ and is asked
to predict if the next token is an URL link. In
the given example, plausible tokens after visit can
be either <http://macys.com> or nearest, Macy,
<apostrophe>s, store. The proposed vc mechanism
outperforms others in 5 of the 6 categories. In
Figure 3, accuracy is measured as the percentage
of correctly suggested positions. Any prediction
next to or close to the correct position is counted
as incorrect.

In Table 4, we list some of the false nega-
tive and false positive errors made by the LM.
Many URLs on Pinterest are e-commerce URLs
and the vendors often also have physical stores. So
in predicting such e-commerce URLs, some mis-
takes are “excusable” because the LM is confused
whether the upcoming token should be an URL
(web store) or the brand name (physical store)
(e.g, http://macys.com vs. Macy’s).

4 Related work

Recurrent neural network (RNN) is a type of neu-
ral sequence model that have high capacity across
various sequence tasks such as language model-
ing (Bengio et al., 2000), machine translation (Liu
et al., 2014), speech recognition (Graves et al.,
2013). Like other neural network models (e.g.,
feed-forward), RNNs can be trained using back-
propogation algorithm (Sutskever et al., 2011).
Recently, the authors in (Zaremba et al., 2014)
successfully apply dropout, an effective regular-
ization method for feed-forward neural networks,
to RNNs and achieve strong empirical improve-
ments.

Reducing perplexity on text corpus is proba-
bly the most demonstrated benchmark for mod-
ern language models (n-gram based and neural
models alike) (Chelba et al., 2013; Church et al.,
2007; Goodman and Gao, 2000; Gao and Zhang,
2002). Based on Zipf’s law (Zipf, 1935), a fil-
tered corpus greatly reduces the vocabulary size
and computation complexity. Recently, a rigor-
ous study (Kobayashi, 2014) looks at how per-
plexity can be manipulated by simply supplying
the model with the same corpus reduced to vary-
ing degrees. Kobayashi (2014) describes his study
from a macro point of view (i.e., the overall corpus
level perplexity). In this work, we present, at word
level, the correlation between perplexity and word
frequency.

Token rarity is a long-standing issue with n-
gram language models (Manning and Schütze,
1999). Katz smoothing (Katz, 1987) and Kneser-
Ney based smoothing methods (Teh, 2006) are
well known techniques for addressing sparsity in
n-gram models. However, they are not directly
used to resolve unigram sparsity.

Using word morphology information is another
way of dealing with rare tokens (Botha and Bluns-
som, 2014). By decomposing words into mor-
phemes, the authors in (Botha and Blunsom, 2014)
are able to learn representations on the morpheme
level and therefore scale the language modeling to
unseen words as long as they are made of previ-
ously seen morphemes. Shown in their work, this
technique works with character-based language in
addition to English.

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6 Conclusions & future work

This paper investigates the performance portfolio
of popular neural language models. We propose
a variational training scheme that has the advan-
tage of a large pre-training corpus but without us-
using as much computing resources. On low fre-
quency words, our proposed scheme also outper-
forms naive pre-training.

In the future, we want to incorporate WordNet
knowledge to further reduce perplexity on infre-
quent words.

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