Abstract

Increased adaptability of RNN language models leads to improved predictions that benefit many applications. However, current methods do not take full advantage of the RNN structure. We show that the most widely-used approach to adaptation (concatenating the context with the word embedding at the input to the recurrent layer) is outperformed by a model that has some low-cost improvements: adaptation of both the hidden and output layers, and a feature hashing bias term to capture context idiosyncrasies. Experiments on language modeling and classification tasks using three different corpora demonstrate the advantages of the proposed techniques.

1 Introduction

The dominant paradigm for language model adaptation relies on the notion of a domain. Domains are in many ways inadequate representations of context due to being ill-defined, discrete and incomparable, and not reflective of the diversity of human language (Ruder et al., 2016). In context aware language models, the notion of a domain is replaced with a set of context variables that each describe some aspect of the associated language such as the topic, time, or language. These variables can be dynamically combined to create a continuous representation of context as a low-dimensional embedding (Tang et al., 2016). The context variables and context embedding can then be used to adapt a recurrent neural network language model (RNNLM).

The standard approach for using a context embedding to adapt an RNNLM is to simply concatenate the context representation with the word embedding at the input to the RNN (Mikolov and Zweig, 2012). Optionally, the context embedding is also concatenated with the output from the recurrent layer so that the output layer can be adapted as well. This basic strategy has been adopted for various types of adaptation such as for LM personalization (Wen et al., 2013; Li et al., 2016), adapting an LM to different genres of television shows (Chen et al., 2015), adapting to long range dependencies in a document (Ji et al., 2015), sharing information in generative text classifiers (Yogatama et al., 2017), and in other cases as well.

In this paper, we study methods of improving the mechanism for using context variables for adapting an RNNLM. The standard approach of adapting the hidden layer is equivalent to an additive transformation of the hidden state. We propose complimenting this with a multiplicative rescaling at the hidden layer and show that it consistently helps when the language model is used as a generative text classifier and can sometimes improve perplexity.

Using context dependent bias vectors is one way to adapt the output layer but it becomes infeasible when both the vocabulary size and the number of contexts are large. The method from Mikolov and Zweig (2012) of using the low-dimensional context embedding to adapt the output layer avoids the excessive memory issue of context-dependent bias vectors but our experiments show that it does not capture isolated but important details. We propose a hashing technique to simultaneously benefit from context-dependent weights and avoid the high memory cost. The combination of the low-rank and hashing techniques for adapting the output layer shows a consistent improvement across our experiments on three different corpora.
2 Model

Our model is built on top of a standard RNN language model. There are three key parts which we discuss below: how we represent context using a low-dimensional embedding, the mechanism for using the context embedding for adapting the recurrent layer, and the mechanisms for adapting the output layer.

2.1 Representing outside context

We assume access to one or more indicator variables, \(c_1, c_2, \ldots, c_n\), that hold information about the outside context for each sentence. These can be indicators for topic, geographic region, time period, or other meta-data. In (Mikolov and Zweig, 2012) LDA topic vectors are used for the outside context. In (Tang et al., 2016) the outside context is a sentiment score and a product id for a product review dataset. We adopt their method of combining information from multiple context variables using a simple neural network. This strategy is well-suited for the types of context variables that we will see in our experiments, such as speaker identity. In other cases, it may be more appropriate to use topic models (Chen et al., 2015; Ghosh et al., 2016) or an RNN (Hoang et al., 2016) to build the context representation.

For each context variable \(c_i\), we learn an associated embedding matrix \(E_i\), \(i = 1, \ldots, n\). If \(n = 1\) then the embedding can directly be used as the context representation. Otherwise, a single layer neural network is used to combine the embeddings from the individual variables.

\[
\vec{c} = \tanh(\sum_i M_i E_i c_i + b_0)
\]

\(M_i\) and \(b_0\) are parameters learned by the model. The context embedding, \(\vec{c}\), is used for adapting both the hidden and the output layer of the RNN.

2.2 Adapting the hidden layer

The equation for the hidden layer of an RNN is

\[
s_t = \sigma(U \vec{w}_t + S s_{t-1} + b_1)
\]

where \(\vec{w}_t\) is the word embedding of the \(t\)-th word, \(s_{t-1}\) is the hidden state from the previous time step and \(\sigma\) is the activation function. To make use of the context embedding, \(\vec{c}\), for adapting the hidden layer the term \(F \vec{c}\) is inserted resulting in

\[
s_t = \sigma(U \vec{w}_t + S s_{t-1} + F \vec{c} + b_1)
\]

We refer to the insertion of the \(F \vec{c}\) term as an additive adaptation of the hidden layer. It is equivalent to the unadapted version except with an adapted bias term. It can be implemented by simply concatenating the context vector \(\vec{c}\) with the word embedding \(\vec{w}_t\) at each timestep at the input to the recurrent layer.

To increase the adaptability of the hidden layer we use a context-dependent multiplicative rescaling of the hidden layer weights. The method is borrowed from Ha et al. (2016) where it is used for dynamically adjusting the parameters of a language model in response to the previous words in the sentence. Using this row rescaling technique on top of the additive adaptation from above, the equation becomes

\[
s_t = \sigma(C_u \vec{c} \odot U \vec{w}_t + C_w \vec{c} \odot S s_{t-1} + F \vec{c} + b_1)
\]

where \(C_u\) and \(C_w\) are parameters of the model and \(\odot\) is the elementwise multiplication operator. The element-wise multiplication is a low-cost operation and can even be pre-calculated so that model evaluation can happen with no extra computation compared to a vanilla RNN.

2.3 Adapting the output layer

The output probabilities of an RNN are given by

\[
y_t = \text{softmax}(V s_t + b_2).
\]

In our case, we tie the weights between the word embeddings in the input and output layer: \(W^T = V\) (Press and Wolf, 2016; Inan et al., 2016).

One way of adapting the output layer is to let each context have its own bias vector. This requires the use of a matrix of size \(|V| \times |C|\), which may be intractable when both \(|V|\) and \(|C|\) are large. Here, \(|V|\) is the size of the vocabulary \(|C|\) is the total number of possible contexts. Mikolov and Zweig (2012) use a low-rank factorization of the adaptation matrix, replacing the \(|V| \times |C|\) matrix with the product of a matrix \(G\) of size \(|V| \times k\) and a context embedding \(\vec{c}\) of size \(k\).

\[
y_t = \text{softmax}(V s_t + G \vec{c} + b_2)
\]

The total number of parameters is now a much more manageable \(O(|V| + \sum_i |C_i|)\) instead of \(O(\sum_i |V||C_i|)\). The advantage of a low-rank adaptation is that it forces the model to share information between similar contexts. The disadvantage is that important differences between similar contexts can be lost.
We employ feature hashing to reduce the memory requirements but retain some of the benefits of having an individual bias term for each context-word pair. The context-word pairs are hashed into buckets and individual bias terms are learned for each bucket. The hashing technique relies on having direct access to the context variables $c_{1:n}$. Representing context as a latent topic distribution precludes the use of this hashing adaptation.

The choice of hashing function is motivated by what is easy and fast to perform inside the TensorFlow computation graph framework. If $w$ is a word id and $c_{1:n}$ are context variable ids then the hash table index is computed as

$$h_i(w, c_i) = wr_0 + c_ir_i \mod l$$

where $l$ is the size of the hash table and $r_0$ and the $r_i$’s are all fixed random integers. The value of $l$ is usually set to a large prime number. The function $H : \mathbb{Z} \rightarrow \mathbb{R}$ maps hash indices to hash values and is implemented as a simple array.

Since $l$ is much smaller than the total number of inputs, there will be many hash collisions. Hash collusions are known to negatively effect the perplexity (Mikolov et al., 2011). To deal with this issue, we restrict the hash table to context-word pairs that are observed in the training data. A Bloom filter data structure records which context-word pairs are eligible to have entries in the hash table. The design of this data structure trades off a compact representation of set membership against a small probability of false positives (Bloom, 1970; Talbot and Brants, 2008; Xu et al., 2011). A small amount of false positives is relatively harmless in this application because they do not impair the ability of the Bloom filter to eliminate almost all of the hash collisions.

The function $\beta : \mathbb{Z} \rightarrow [0, 1]$ is used by the Bloom filter to map hash indices to binary values.

$$B(w, c_i) = \prod_{j=1}^{16} \beta(h_{i,j}(w, c_i))$$

The hash functions $h_{i,j}$ are defined in the same way as the $h_i$’s above except that they use distinct random integers and the size of the table, $l$, can be different. Because $\beta$ is a binary function, the product $B(w, c_i)$ will always be zero or one. Thus, any word-context pairs not found in the Bloom filter will have their hash values set to zero.

| Source    | Size  | Vocab. | Context                  |
|-----------|-------|--------|--------------------------|
| Reddit    | 8,000K| 68,000 | Subreddit                |
| Twitter   | 77K   | 194    | Language                 |
| SCOTUS    | 864K  | 18,000 | Case, Spkr., Role        |

Table 1: Number of sentences, vocabulary size and context variables for the three corpora.

The final expression for the hashed adaptation term is given by

$$H_{\text{hash}}(w, c_{1:n}) = \sum_{i=1}^{n} H(h_i(w, c_i))B(w, c_i)$$

$$y_t = \text{softmax}(Vs_t + G\vec{c} + b_2 + H_{\text{hash}}(w_t, c_{1:n}))$$

3 Data

The experiments make use of three corpora chosen to give a diverse prospective on adaptation in language modeling. Summary information on the datasets (Reddit, Twitter, and SCOTUS) is provided in Table 1 and each source is discussed individually below. The Reddit and SCOTUS data are tokenized and lower-cased using the standard NLTK tokenizer (Bird et al., 2009).

**Reddit** Reddit is the world’s largest online discussion forum and is comprised of thousands of active subcommunities dedicated to a wide variety of themes. Our training data is 8 million sentences from Reddit comments during the month of April 2015. The 68,000 word vocabulary is selected by taking all tokens that occur at least 20 times in the training data. The remaining tokens are mapped to a special UNK token leaving us with an OOV rate of 2.3%.

The context variable is the identity of the subreddit, i.e. community, that the comment came from. There are 5,800 subreddits with at least 50 training sentences. The remaining ones are grouped together in an UNK category. The largest subreddit occupies just 4.5% of the data and the perplexity of the subreddit distribution is 742. By using a large number of subreddits, we highlight an advantage of model adaptation which is to be able to use a single unified model instead of training thousands of separate models for each individual community. Similarly, using context dependent bias vectors for this data instead of the hash adaptation would require learning 400 million additional parameters.
The Twitter training data has 77,000 Tweets each annotated with one of nine languages: English, German, Italian, Spanish, Portuguese, Basque, Catalan, Galician, and French. The corpus was collected by combining resources from published data for language identification tasks during the past few years. Sentences labeled as unknown, ambiguous, or containing code-switching were not included. The data is unbalanced across languages with more than 32% of the Tweets being Spanish and the smallest four languages (Italian, German, Basque, and Galician) all individually less than 1.5% of the total. There are 194 unique character tokens in the vocabulary. Graphemes that are surrogate-pairs in the UTF-16 encoding, such as emoji, are split into multiple vocabulary tokens. No preprocessing or tokenization is performed on this data except that newlines were replaced with spaces for convenience.

Approximately 864,000 sentences of training data spanning arguments from 1990-2011. These are speech transcripts from the United States Supreme Court. Utterances are labeled with the case being argued (n=1,765), the speaker id (n=2,276), and the speaker role (justice, advocate, or unidentified). These three context variables are defined in the same way as in Hutchinson et al. (2013), where a small portion of this data was used in language modeling experiments. The vocabulary size is around 18,000 words. Utterances longer than 45 words were split into smaller utterances.

In these experiments we fix the size of the word embedding dimensions and recurrent layers so as not to exhaust our computational resources and then vary the different mechanisms for adapting the model. We used an LSTM with coupled input and forget gates for a 20% reduction in computation time (Greff et al., 2016). Dropout was used as a regularizer on the input and outputs of the recurrent layer as described in Zaremba et al. (2014). When the vocabulary is large, computing the full cross-entropy loss can be prohibitively expensive. For the large vocabulary experiments, we used a sampled softmax strategy with a unigram distribution to speed up training (Jean et al., 2015).

A summary of the key hyperparameters for each class of experiments if given in Table 2. The total parameter column in this table is based on the unadapted model. Adapted models will have more parameters depending on the type of adaptation. When using hash adaptation of the output layer, the size of the Bloom filter is 100 million and the size of the hash table is 80 million. The model is implemented using the Tensorflow library. Optimization is done using Adam with a learning rate of 0.001. Each model trained in under three days using 8 CPU threads.

Although the model is trained as a language model, it can be used as a generative text classifier. When there are multiple context variables, we treat all but one of them as known values and attempt to identify the unknown one. It is not necessary to compute the probabilities over the full vocabulary. The sampled softmax criteria can be used to greatly speed up evaluation of the classifier.

### 4.1 Reddit Experiments

The size of the subreddit embeddings was set to 25. Table 3 gives the perplexities and average AUCs for subreddit detection for different adapted models. The evaluation data contains 60,000 sentences. For comparison, an unadapted 4-gram Kneser-Ney model trained on the same data has a perplexity of 119. The models with the best perplexity do not use multiplicative adaptation of the hidden layer, but it is useful in the detection experiments.

We can inspect the context embeddings learned by the model to see if it is exploiting similarities between subreddits in the way that we expect. Table 4 lists the nearest neighbors by Euclidean distance to three selected subreddits. We can see that the nearest neighbors match our intuitions. The closest subreddits to Pittsburgh are communities created for other big cities and states. The Python subreddit is close to other programming languages’ communities, and the NBA subreddit

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1See https://github.com/ajaech/calm for code.
Hidd. Output × + LR Hash PPL ∆PPL AUC
N N N N 75.2 – –
N N N Y 69.6 7.3% 76.5
N N Y N 68.0 9.5% 75.5
N Y N Y 66.9 11.0% 78.9
N Y Y N 68.0 9.6% 75.3
N Y Y Y 66.5 11.5% 78.4
Y N Y Y 67.2 10.6% 78.9
Y Y Y N 68.3 9.1% 75.7
Y Y Y Y 67.1 10.7% 79.2

Table 3: Perplexities and Classification Avg. AUCs for Reddit Models

Pittsburgh Python NBA
Atlanta CSharp Warriors
Montana JavaScript Rockets
MadisonWI CPP_Questions Mavericks
Baltimore CPP NBASpurs

Table 4: Nearest neighbors to selected subreddits in the context embedding space.

is close to the communities for individual NBA teams.

The subreddit detection involves predicting the subreddit a given comment came from with eight subreddits to choose from (AskMen, AskScience, AskWomen, Atheism, ChangeMyView, Fitness, Politics, and Worldnews) and nine distractors (Books, Chicago, NYC, Seattle, ExplainLikeIM-Five, Science, Running, NFL, and TodayILearned). To make a classification decision we evaluate the perplexity of each comment under the assumption that it belongs to each of the eight subreddits. We use z-score normalization across the eight perplexities to create a score for each class. The predictions are evaluated by averaging the AUC of the eight individual ROC curves. The best model for the classification task uses all four types of adaptation. Interestingly, the multiplicative adaptation of the hidden layer is clearly useful for classification even though it does not help with perplexity.

The perplexities for selected large subreddits are listed in Table 5. It can be seen that the relative gain from adaptation is largest when the topic of the subreddit is more narrowly focused. The biggest gains were achieved for subreddits dedicated to specific sports, tv shows, or video games. Whereas, the gains were smallest for subreddits like Videos or Funny whose content tends to be more diverse. The knowledge that a sentence came from a pro-wrestling subreddit effectively provides more information about the text than the analogous piece of knowledge for the Pics or Videos subreddit. This would seem to indicate that further gains could be possible if additional contextual information could be provided. An alternative explanation, that subreddits with less sentences in the training data receive more benefit from adaptation, is not supported by the data.

4.2 Twitter experiments

The Twitter evaluation was done on a set of 14,960 Tweets. The language context embedding vector dimensionality was set to 8. When both the vocabulary and the number of contexts are small, as in this case, there is no danger of hash collisions. We disable the bloom filter making the hash adaptation essentially equivalent to having context dependent bias vectors.

Table 6 reports the results of the experiments on the Twitter corpus. We compute both the perplexity and measure the performance of the models on a language identification task. In terms of perplexity, the best models do not make use of the multiplicative hidden layer adaptation, consistent with the results from the Reddit corpus. In general, the improvement in perplexity from adaptation is small (less than 5%) on this corpus compared to our other experiments where we saw relative improvements two to four times as big. This is likely because the LSTM can figure out by itself which language it is modeling early on in the sequence and adjust its predictions accordingly.

To investigate this further, we trained a logistic regression classifier to predict the language using the state from the LSTM at the last time step on the unadapted model as a feature vector. Using just 30 labeled examples per class it is possible to get 74.6% accuracy and a 49.3 F1 score. Furthermore, we find that a single dimension in the hidden state of the unadapted model is often enough to distinguish between different languages even though the model was not given any supervision signal (Karpathy et al., 2015; Radford et al., 2017). Figure 1 visualizes the value of the dimension of the hidden layer that is the strongest indicator of Spanish on three different code-switched tweets.

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2These are the same subreddit used in Tran and Ostendorf (2016) for a related but not comparable classification task.
| Subreddit    | Base. PPL | Adapt. PPL | ∆PPL | Description                                      |
|-------------|-----------|------------|------|-------------------------------------------------|
| FlashTV     | 90.5      | 68.2       | 24.6%| A popular TV show                               |
| shield      | 99.4      | 77.3       | 22.2%| A tv show                                       |
| GlobalOffensive | 97.1  | 79.3       | 18.3%| A PC video game                                 |
| nba         | 103.3     | 86.4       | 16.3%| National Basketball Association                 |
| SquaredCircle | 85.7  | 71.7       | 16.3%| Professional Wrestling                          |
| Fitness     | 50.1      | 42.3       | 15.5%| Exercise and fitness                            |
| hockey      | 85.5      | 72.4       | 15.2%| Professional hockey                              |
| leagueoflegends | 71.1 | 61.0       | 14.3%| A PC video game                                 |
| pcmasterrace | 71.7    | 62.0       | 13.5%| PC gaming                                       |
| nfl         | 84.2      | 74.0       | 12.2%| National Football League                        |
| AskWomen    | 62.1      | 55.3       | 10.9%| Questions for women                             |
| news        | 70.8      | 65.0       | 8.2% | General news stories and discussion             |
| worldnews   | 85.7      | 79.7       | 7.1% | Global news discussion                          |
| AskMen      | 69.4      | 66.7       | 3.9% | Questions for men                               |
| gaming      | 79.0      | 76.1       | 3.7% | General video games interest group              |
| pics        | 74.0      | 71.8       | 3.0% | Funny or interesting pictures                   |
| videos      | 62.9      | 61.1       | 2.9% | Funny or interesting videos                     |
| funny       | 72.6      | 70.8       | 2.5% | Sharing humorous content                        |

**Table 5:** Comparison of perplexities per subreddit

| Hidden | Output | LR | Hash | PPL | Acc. | F1   |
|--------|--------|----|------|-----|------|-----|
| N      | N      | N  | N    | 6.44| –    | –   |
| N      | N      | N  | Y    | 6.43| 56.1 | 44.0|
| N      | N      | Y  | N    | 6.37| 49.7 | 36.6|
| N      | Y      | Y  | N    | 6.21| 91.4 | 82.9|
| N      | Y      | N  | Y    | 6.25| 92.5 | 84.4|
| N      | Y      | Y  | Y    | 6.15| 92.8 | 85.2|
| Y      | N      | Y  | N    | 6.28| 93.2 | 85.1|
| Y      | Y      | N  | N    | 6.54| 94.2 | 86.3|
| Y      | Y      | Y  | Y    | 6.35| 93.3 | 85.9|

**Table 6:** Results on Twitter data.

Code-switching is not a part of the training data for the model but it provides a compelling visualization of the ability of the unsupervised model to quickly recognize the language. The fact that it is so easy for the unadapted model to pick-up on the identity of the contextual variable fits with our explanation for the small relative gain in perplexity from the adapted models.

Our best model, using multiplicative adaptation of the hidden layer, achieves an accuracy of 94.2% on this task. That is a 19% relative reduction in the error rate from the best model without multiplicative adaptation.

### 4.3 SCOTUS experiments

Table 7 lists the results for the experiments on the SCOTUS corpus. The size of the context embeddings are 9, 15, and 8 for the case, speaker, and role variables respectively. For calculating perplexity we use 60,000 sentence evaluation set. For the classification experiment we selected 4,000 sentences from the test data from eleven different justices and attempted to classify the identity of the justice. The perplexity of the distribution of judges over those sentences is 8.9 (11.0 would be uniform). So, the data is roughly balanced. When classifying justices, the model is given the case context variable, but we do not make any special
Table 7: Results on the SCOTUS data in terms of perplexity and classification accuracy (ACC) for the justice identification task.

| Hidden | Output | LR Hash | PPL  | ΔPPL  | ACC  |
|--------|--------|---------|------|-------|------|
| N      | N      | N       | 37.3 | –     | –    |
| N      | N      | Y       | 31.2 | 16.5% | 29.6 |
| N      | N      | Y       | 32.9 | 12.0% | 26.2 |
| N      | Y      | N       | 32.7 | 12.4% | 25.4 |
| N      | Y      | Y       | 29.8 | 20.3% | 31.1 |
| Y      | N      | Y       | 32.3 | 13.4% | 24.5 |
| Y      | Y      | N       | 32.2 | 13.7% | 26.1 |
| Y      | N      | Y       | 29.2 | 21.7% | 32.4 |
| Y      | Y      | Y       | 29.4 | 21.1% | 31.9 |

Table 8: Perplexities for different combinations of context variables on the SCOTUS corpus.

| Case | Spkr. | Role | PPL  |
|------|-------|------|------|
| N    | N     | N    | 37.3 |
| N    | N     | Y    | 36.5 |
| N    | Y     | N    | 33.6 |
| N    | Y     | Y    | 33.3 |
| Y    | N     | N    | 31.5 |
| Y    | N     | Y    | 30.3 |
| Y    | Y     | N    | 29.6 |
| Y    | Y     | Y    | 29.4 |

In Table 9 we list sentences generated from the fully adapted model (same one as the last line in Table 7) using beam search. The value of the context variable for the Case is held fixed while we explore different values for the Speaker and Role variables. Anecdotally, we see that the model captures some information about John Roberts role as chief justice. The model learns that Justice Breyer tends to start his questions with the phrase “I mean” while Justice Kagan tends to start with “Well”. Roberts and Kagan appear in our data both as justices and earlier as advocates.

5 Related Work

Multiple survey papers cover the early history of language model adaptation (DeMori and Federico, 1999; Bellegarda, 2004). We mention just the most recent closely related work here.

The multiplicative rescaling of the recurrent layer weights is used in the Hypernetwork model (Ha et al., 2016). The focus of this model is to allow the LSTM to adjust automatically depending on the context of the previous words. This is different from our work in that we are adapting based on contextual information external to the word sequence. Gangireddy et al. (2016) also use a rescaling of the hidden layer for adaptation but it is done as a fine-tuning step and not during training like our model.

The RNNME model from Mikolov et al. (2011) uses feature hashing to train a maximum entropy model alongside an RNN language model. The setup is similar to our method of using hashing to learn context-dependent biases. However, there are a number of differences. The motivation for the RNNME model was to speed-up training of the RNN not to compensate for the inadequacy of low-rank output layer adaptation, which had yet to be invented. Furthermore, Mikolov et al. (2011) do not use context dependent features in the max- ent component of the RNNME model nor do they have a method for dealing with hash collusions such as our use of Bloom filters.

The idea of having one part of a language model be low-rank and another part to be an additive correction to the low-rank model has been investigated in other work (Eisenstein et al., 2011; Hutchinson et al., 2013). In both of these cases, the correction term is encouraged to be sparse by including an L1 penalty. Our implementation did not promote sparsity in the hash adaptation...
features but this idea is worth further consideration. The hybrid LSTM and count based language model is an alternative way of correcting for a low-rank approximation (Neubig and Dyer, 2016).

Hoang et al. (2016) studies how to incorporate side information into an RNN language model. For their data, they claim a bigger win by adapting at the output layer rather than the hidden layer. (This matches our own observations on the Reddit and SCOTUS data.) Their work did not address adapting at both the hidden and output layers simultaneously. Most work on adaptation does not consider combining multiple context factors but there are some exceptions (Hutchinson et al., 2013; Tang et al., 2016; Hoang et al., 2016).

6 Conclusions & Future Work

While our results suggest that there is not a one-size-fits-all approach to language model adaptation, it is clear that we improve over the standard adaptation approach. The model from Mikolov and Zweig (2012), equivalent to using just additive adaptation on the hidden layer and low-rank adaptation of the output layer, is outperformed for all three datasets at both the language modeling and classification tasks. For language modeling, the multiplicative hidden layer adaptation was only helpful for the SCOTUS dataset. However, the combined low-rank and hash adaptation of the output layer consistently gave the best perplexity. For the classification tasks, the multiplicative hidden layer adaptation is clearly useful, as is the combined low-rank and hash adaptation of the output layer.

Importantly, there is not always a strong relationship between perplexity and classification scores. Our results may have implications for work on text generation where it can be more desirable to have more control over the generation rather than the lowest perplexity model. More studies are needed to get intuition about what types of context variables will provide the most benefit. Our investigation of the language context in the Twitter experiments gives a useful takeaway: context variables that are easily predictable from the text alone are unlikely to be helpful.

In future work, we would like to consider additional mechanisms for using the context embedding \( \vec{c} \) to adapt the LSTM parameters. We also plan to extend our hash adaptation to incorporate longer word histories, rather than just unigrams combined with context.

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