Low-Rank RNN Adaptation for Context-Aware Language Modeling

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Abstract

A context-aware language model uses location, user and/or domain metadata (context) to adapt its predictions. In neural language models, context information is typically represented as an embedding and it is given to the RNN as an additional input, which has been shown to be useful in many applications. We introduce a more powerful mechanism for using context to adapt an RNN by letting the context vector control a low-rank transformation of the recurrent layer weight matrix. Experiments show that allowing a greater fraction of the model parameters to be adjusted has benefits in terms of perplexity, classification, and generation for several different types of context.

1 Introduction

In many language modeling applications, the speech or text is associated with some metadata or contextual information. For example, in speech recognition, if a user is speaking to a personal assistant then the system might know the time of day or the identity of the task that the user is trying to accomplish. If the user takes a picture of a sign to translate it with their smart phone, the system would have contextual information related to the geographic location and the user’s preferred language. The context-aware language model targets these types of applications with a model that can adapt its predictions based on the provided contextual information.

There has been much work on using context information to adapt a language model. Here, we are interested in contexts described by metadata (vs. word history) and in neural network approaches due to their flexibility for representing diverse types of contexts. Specifically, we focus on recurrent neural networks (RNNs) due to their widespread use.

The standard approach to adapt an RNN language model is to 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 to adapt the softmax layer 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 to television show genres (Chen et al., 2015), adapting to long range dependencies in a document (Ji et al., 2015), etc.

We propose a more powerful mechanism for using a context vector, which we call the FactorCell. Rather than simply using context as an additional input, it is used to control a factored (low-rank) transformation of the recurrent layer weight matrix. The motivation is that allowing a greater fraction of the model parameters to be adjusted in response to the input context will produce a model that is more adaptable and responsive to that context.

Since language models can be used for a variety of tasks—including assessing the well-formedness of word strings, text classification, and text generation—we evaluate the resulting models in terms of context-dependent perplexity, context classification accuracy, and using human ratings of contextual appropriateness of generated text. The combination of experiments on a variety of data sources provides strong evidence for the utility of the Fac-
torCell model, but it also shows that it can be useful to consider more than just perplexity in training a generative language model.

The remainder proceeds as follows. In Section 2, we introduce the FactorCell model and show how it differs mathematically from alternative approaches. Next, Section 3 describes the six datasets used to probe the performance of different models. Experiments and analyses contrasting perplexity and classification results for a variety of context variables are provided in Section 4, demonstrating consistent improvements in both criteria for the FactorCell model but also confirming that perplexity is not correlated with classification performance for all models. Additional experiments on two targeted contexts explore the effectiveness of the model for text generation, in Section 5, and for characterizing high-dimensional context spaces, in Section 6. The model is compared to related work in Section 7. Section 8 summarizes contributions and open questions.

2 Model

Our model uses adaptation in the recurrent layer and in the bias vector of the softmax layer. In this section we describe how we represent context as an embedding, the method for adapting the recurrent layer, and the method for adapting the softmax bias. The novelty of our model is in the way that it uses the context information to transform the weights of the recurrent layer. This is accomplished using a low-rank decomposition in order to control the extent of parameter sharing between contexts.

2.1 Context representation

We assume the availability of contextual information (metadata or other side information) that is represented as a set of context variables \( c_1, c_2, \ldots, c_n \), from which we produce a \( k \)-dimensional representation in the form of an embedding, \( \bar{c} \). The context variables represent some type of information or metadata about the sequence and can be either categorical or numerical. The embeddings can either be learned off-line using a topic model (Mikolov and Zweig, 2012) or end-to-end as part of the adapted LM (Tang et al., 2016). Here, we use end-to-end learning, where the context embedding is the output of a feed-forward network with a ReLU activation function. The resulting embedding, \( \bar{c} \), is used for adapting both the recurrent layer and the output layer of the RNN.

2.2 Adapting the recurrent layer

The basic operation of the recurrent layer is to use a matrix \( \mathbf{W} \) to transform the concatenation of a word embedding \( (w_t) \) with the hidden state from the previous time step \( (h_{t-1}) \) and produce a new hidden state \( (h_t) \), where

\[
 h_t = \sigma (\mathbf{W}_1 w_t + \mathbf{W}_2 h_{t-1} + b) = \sigma (\mathbf{W} [w_t, h_{t-1}] + b)
\]

For simplicity, we write the equations for a recurrent neural network, but the same methods can be applied to RNN variants such as the LSTM, used here.

The standard approach to recurrent layer adaptation is to include (via concatenation) the context embedding as an additional input to the recurrent layer (Mikolov and Zweig, 2012). When the context embedding is constant across the whole sequence, it is easy to show that this concatenation is equivalent to using an context-dependent bias at the recurrent layer:

\[
 h_t = \sigma (\mathbf{W} [w_t, h_{t-1}, \bar{c}] + b) = \sigma (\mathbf{W} [w_t, h_{t-1}] + \mathbf{W}' \bar{c} + b)
\]

where \( \mathbf{W}' = \mathbf{W} + (\bar{c} \times_1 \mathbf{Z}_L)(\mathbf{Z}_R \times_3 \bar{c}) \), and \( \bar{c} \) is the context-dependent bias, formed by adding a linear projection of the context embedding. We refer to this adaptation approach as the ConcatCell model.

Our proposed model extends the ConcatCell by additively adapting the generic weight matrix, \( \mathbf{W} \), with a context-dependent adaptation matrix. (We refer to \( \mathbf{W} \) as generic because it is shared across all context settings.) The adaptation matrix is formed via the outer product of two rank \( r \) matrices. These are constructed by taking a tensor product between the context embedding \( \bar{c} \) and left and right basis tensors, \( \mathbf{Z}_L \in \mathbb{R}^{k \times s_1 \times r} \) and \( \mathbf{Z}_R \in \mathbb{R}^{r \times s_2 \times k} \). The adapted recurrent matrix \( \mathbf{W}' \) is given by

\[
 \mathbf{W}' = \mathbf{W} + (\bar{c} \times_1 \mathbf{Z}_L)(\mathbf{Z}_R \times_3 \bar{c})
\]

where \( \times_i \) denotes the mode-\( i \) tensor product. The rank, \( r_i \), is a hyperparameter that is set during tuning. \( \mathbf{Z}_L \) and \( \mathbf{Z}_R \) are parameters learned by the model.
We call this model the FactorCell. The equation for its recurrent layer differs from the ConcatCell in that the weight matrix has been adapted by adding a factored component. If the context is known in advance, $W'$ can be precomputed, in which case applying the RNN at test time requires no more computation than using an unadapted RNN of the same size.

2.3 Adapting the softmax bias

The output probabilities of an RNN are given by $y_t = \text{softmax}(Eh_t + b_{\text{out}})$, where $E$ is the matrix of word embeddings and $b_{\text{out}} \in \mathbb{R}^{|V|}$ is the softmax bias vector. Adapting the softmax bias alters the unigram distribution. There are two ways to accomplish this. When the number of values the context can take is small then context-dependent softmax bias vectors can be learned directly. This is equivalent to replacing $\bar{c}$ with a one-hot vector. Otherwise, a projection of the context embedding, $Q\bar{c}$ where $Q \in \mathbb{R}^{|V| \times k}$, can be used to adapt the bias vector like so,

$$y_t = \text{softmax}(Eh_t + Q\bar{c} + b_{\text{out}}).$$

The projection can be thought of as a low-rank approximation to using the one-hot context vector here. Both strategies are explored when feasible.

3 Data

Our experiments make use of six datasets: four targeting word-level sequences, and sets targeting character sequences. The character studies are motivated by the growing interest in character-level models in both speech recognition and machine translation (Hannun et al., 2014; Chung et al., 2016). By using multiple datasets with different types of context, we hope to learn more about what makes a dataset amenable to adaptation. When using a word-based vocabulary, we preprocess the data by lowercasing, tokenizing and removing most punctuation. We also truncate sentences to be shorter than a maximum length. Summary information is provided in Table 1.

The first three datasets (AGNews, DBPedia, and Yelp) have previously been used for text classification (Zhang et al., 2015). These consist of newspaper headlines, encyclopedia entries, and restaurant and business reviews, respectively. The context variables associated with these correspond to the newspaper section (world, sports, business, sci & tech) for each headline, the page category on DBPedia (out of 14 options such as actor, athlete, building, etc.), and the star rating on Yelp (from one to five). For AgNews, DBPedia, and Yelp we use the same test data as in previous work. Our fourth dataset, from TripAdvisor, was previously used for language modeling and consists of two relevant context variables: an identifier for the hotel and a sentiment score from one to five stars (Tang et al., 2016). Some of the reviews are written in French and German but most are in English. There are 4,333 different hotels but we group all the ones that do not occur at least 50 times in the training data into a single entity, leaving us with around 3,500. These four datasets use word-based vocabularies.

We also experiment on two Twitter datasets: EuroTwitter and GeoTwitter. EuroTwitter consists of 80,000 Tweets labeled with one of nine languages: (English, Spanish, Galician, Catalan, Basque, Portuguese, French, German, and Italian). The corpus was created by combining portions of multiple published datasets for language identification including Twitter70 (Jaech et al., 2016), TweetLID (Zubiaga et al., 2014), and the monolingual portion of Tweets from a code-switching detection workshop (Molina et al., 2016). The GeoTwitter data contains Tweets with latitude and longitude information from England, Spain, and the United States.\footnote{Data was accessed from http://followthehashtag.com.}

The latitude and longitude coordinates are given as numerical inputs. This is different from the other five datasets that all use categorical context variables.

4 Experiments with Different Contexts

The goal of our experiments is to show that the FactorCell model can deliver improved performance over current approaches for multiple language model applications and a variety of types of contexts. In this section, the emphasis is on impact for different types of contexts, and results are reported for context-conditioned perplexity and text classification accuracy.

Test set perplexity is the most widely accepted method for evaluating language models, both for use in recognition/translation applications and generation. It has the advantage that it is easy to measure and is widely used as a criteria for model fit,
Table 1: Dataset statistics. (*) indicates datasets for character LMs, where vocabulary is in terms of characters.

| Name         | Train | Dev | Test | Vocab Size | Max Len. | Context                      |
|--------------|-------|-----|------|------------|----------|------------------------------|
| AGNews       | 115K  | 5K  | 7.6K | 54,492     | 60       | 4 Newspaper sections        |
| DBPedia      | 555K  | 5K  | 70K  | 84,341     | 60       | 14 Entity categories        |
| TripAdvisor  | 843K  | 18K | 18K  | 88,347     | 150      | 3.5K Hotels/5 Sentiment      |
| Yelp         | 645K  | 5K  | 50K  | 57,794     | 200      | 5 Sentiment                  |
| EuroTwitter* | 80K   | 12K | 15K  | 194        | 200      | 9 Languages                 |
| GeoTwitter*  | 604K  | 26K | 26K  | 203        | 200      | Latitude & Longitude         |

but the limitation that it is not directly matched to most tasks that language models are directly used for. Classification accuracy provides additional information about the power of a model, even if it is not being designed explicitly for text classification. Further, it allows us to be able to directly compare our model performance against previously published text classification benchmarks.

Note that the use of classification accuracy for evaluation here is associated with text classification using the generative language model (i.e., maximizing the context posterior probability using Bayes rule), and therefore differs from the accuracy criterion used for evaluating context-sensitive language models for text generation based on a separate discriminative classifier trained on generated text (Ficler and Goldberg, 2017; Hu et al., 2017). We address text generation in Section 5.

The experiments compare the FactorCell model to two popular alternatives, which we refer to as ConcatCell and SoftmaxBias. The SoftmaxBias method is a simplification of the other two models; it impacts only the output layer and thus unigram statistics. Since bag-of-word models provide strong baselines in many text classification tasks, we hypothesize that the SoftmaxBias model will capture much of the relative improvement over the unadapted model for word-based tasks. However, in character-based models, the unigram distribution is unlikely to carry much information about the context, so adapting the recurrent layer should become more important in character-level models. The ConcatCell model is a special case of the FactorCell model, so we expect that performance gains will be associated with sources that have sufficient structure and data to support learning the extra degrees of freedom.

Another possible baseline would use models independently trained on the subset of data for each context. This is the “independent component” case in (Yogatama et al., 2017). This will fail when a context variable takes on many values (or continuous values) or when training data is limited, because it makes poor use of the training data, as shown in that study. While we do have some datasets where this approach is plausible, we feel that its limitations have been clearly established.

4.1 Implementation Details

The RNN variant that we use is an LSTM with coupled input and forget gates (Melis et al., 2017). We also tie the word embeddings in the input layer with the ones in the output layer (Press and Wolf, 2016; Inan et al., 2016). The model is implemented using the Tensorflow library. Training is done using the Adam optimizer with a learning rate of $0.001$. For the models with word-based vocabularies, a sampled softmax loss is used with a unigram proposal distribution and sampling 150 words each time-step (Jean et al., 2014). The classification experiments use a sampled softmax loss with a sample size of 8,000 words. This is an order of magnitude faster to compute with a minimal effect on accuracy.

Hyperparameter tuning was done based on minimizing perplexity and using a random search.\(^2\) Limits on the ranges of the word embedding dimension and recurrent layer cell size were set on an ad-hoc basis and were done with the intention of making the best use of the available computational resources. Despite this, running the experiments consumed hundreds of thousands of CPU-hours.

For any fixed LSTM size the FactorCell has a higher count of learned parameters compared to the ConcatCell. However, during evaluation both models use approximately the same number of floating-

\(^2\)Code available at http://github.com/ajaech/calm.
point operations because \( W' \) only needs to be computed once per sentence. Because of this, we believe limiting the recurrent layer cell size is a fair way to compare between the FactorCell and the ConcatCell.

### 4.2 Word-based Models

Perplexities and classification accuracies for the four word-based datasets are presented in Table 2. In each of the four datasets, the FactorCell model gives the best perplexity. For classification accuracy, there is a bigger difference between the models, and the FactorCell model is the most accurate on three out of four datasets and tied with the SoftmaxBias model on AgNews. For DBPedia and TripAdvisor, most of the improvement in perplexity relative to the unadapted case is achieved by the SoftmaxBias model with smaller relative improvements coming from the increased power of the ConcatCell and FactorCell models. For Yelp, the perplexity improvements are small; the FactorCell model is just 1.3% better than the unadapted model.

From Yogatama et al. (2017), we see that for AG-News, much more so than for other datasets, the unigram statistics capture the discriminating information, and it is the only dataset in that work where a naive Bayes classifier is competitive with the generative LSTM for the full range of training data. The fact that the SoftmaxBias model gets the same accuracy as the FactorCell model on this task suggests that topic classification tasks may benefit less from adapting the recurrent layer.

For the DBPedia and Yelp datasets, the FactorCell model beats previously reported classification accuracies for generative models (Yogatama et al., 2017). However, it is not competitive with state-of-the-art discriminative models on these tasks with the full training set. With less training data, it probably would be, based on the results in (Yogatama et al., 2017).

The numbers in Table 2 do not adequately convey the fact that there are hyperparameters whose effect on perplexity is greater than the sometimes small relative differences between models. Even the seed for the random weight initialization can have a “major impact” on the final performance of an LSTM (Reimers and Gurevych, 2017). We use Figure 1 to show how the three classes of models perform across a range of hyperparameters. The figure compares perplexity on the x-axis with accuracy on the y-axis with both metrics computed on the development set. Each point in this figure represents a different instance of the model trained with random hyperparameter settings and the best results are in the upper right corner of each plot. The points are grouped according to the three classes of models: FactorCell, ConcatCell, and SoftmaxBias.

Within the same model class but across different hyperparameter settings, there is much more variation in perplexity than in accuracy. The LSTM cell size is mainly responsible for this; it has a much bigger impact on perplexity than on accuracy. It is also apparent that the models with the lowest perplexity are not always the ones with the highest accuracy. See Section 4.4 for further analysis.

Figure 2 is a visualization of the per-word log likelihood ratios between a model assuming a 5 star review and the same model assuming a 1 star review. Likelihoods were computed using an ensemble of three models to reduce variance. The analysis is repeated for each class of model. Words highlighted in blue are given a higher likelihood under the 5 star assumption.

Unigrams with strong sentiment such as “lovely” and “friendly” are well-modeled by all three models. The reader may not consider the tokens “craziness”
or “5-8pm” to be strong indicators of a positive but the way they are used in this review is representative of how they are typically used across the corpus.

As expected, the ConcatCell and FactorCell model capture the sentiment of multi-token phrases. As an example, the unigram “enough” is 3% more likely to occur in a 5 star review than in a 1 star review. However, “do enough” is 30 times more likely to appear in a 5 star review than in a 1 star review. In this example, the FactorCell model does a better job of handling the word “enough”.

4.3 Character-based Models

Next, we evaluate the EuroTwitter and GeoTwitter models using both perplexity and a classification task. For EuroTwitter, the classification task is to identify the language. With GeoTwitter, it is less obvious what the classification task should be because the context values are continuous and not categorical. We selected six cities and then assigned each sentence the label of the closest city in that list while still retaining the exact coordinates of the Tweet. There are two cities from each country: Manchester, London, Madrid, Barcelona, New York City, and Los Angeles. Tweets from locations further than 300 km from the nearest city in the list were discarded when evaluating the classification accuracy.

Perplexities and classification accuracies are presented in Table 3. The FactorCell model has the lowest perplexity and the highest accuracy for both datasets. Again, the FactorCell model clearly improves on the ConcatCell as measured by classification accuracy. Consistent with our hypothesis, adapting the softmax bias is not sufficient for character-based models. The SoftmaxBias model has small perplexity improvements (< 1%) and low classification accuracies.

Figure 3 compares perplexity and classification accuracy for different hyperparameter settings of the character-based models. Again, we see that it is possible to trade-off some perplexity for gains in classi-
fication accuracy. For EuroTwitter, if tuning is done on accuracy rather than perplexity then the accuracy of the best model is as high as 95%.

Sometimes there can be little to no perplexity improvement between the unadapted model and the FactorCell model. This can be explained if the provided context variables are mostly redundant given the previous tokens in the sequence. 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. 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. This finding is consistent with previous work that showed that individual dimensions of LSTM hidden states can be strong indicators of concepts like sentiment (Karpathy et al., 2015; Radford et al., 2017).

Figure 4 visualizes the value of the dimension of the LSTM hidden state in an unadapted model that is the strongest indicator for Spanish text for three different code-switched Tweets.

4.4 Hyperparameter Analysis

The hyperparameter with the strongest effect on perplexity is the size of the LSTM. This was consistent across all six datasets. The effect on classification accuracy of increasing the LSTM size was mixed. For the FactorCell model, increasing the rank of the adaptation matrix tended to lead to increased classification accuracy on all datasets and seemed to help with perplexity on AGNews, DBPedia, and TripAdvisor. Increasing the context embedding size generally helped with accuracy on all datasets, but it had a more neutral effect on TripAdvisor and Yelp and increased perplexity on the two character-based datasets.

Using a one-hot vector for adapting the softmax bias layer in place of the context embedding when adapting the softmax bias vector tended to have a large positive effect on accuracy leaving perplexity mostly unchanged. Recall from Section 2.3 that if the number of values that a context variable can take on is small then we can allow the model to choose between using the low-dimensional context embedding or a one-hot vector. This option is not available for the TripAdvisor and the GeoTwitter datasets because the dimensionality of their one-hot vectors would be too large. The method of adapting the softmax bias is the main explanation for why some ConcatCell models performed significantly above/below the trendline for DBPedia in Figure 1.

We experimented with an additional hyperparameter on the Yelp dataset, namely the inclusion of layer normalization (Ba et al., 2016). We had ruled-out using layer normalization in preliminary work.
on the AGNews data before we understood that AGNews is not representative. Layer normalization significantly helped the perplexity on Yelp (≈ 2% relative improvement) and all of the top-performing models had it enabled.

5 Text Generation

To evaluate the performance of the different models for text generation, we initially looked at classification accuracy using a discriminative classifier trained on generated text, as in (Ficler and Goldberg, 2017; Hu et al., 2017). However, in a preliminary test on models trained using the Yelp dataset, we found that the discriminative classifier scores were highly correlated with the accuracy from the previously described classification experiments ($r \approx 0.95$). Therefore, we conducted a small study using human ratings. We chose the DBPedia data, since the different contexts were more clearly identifiable for human evaluators.

We used the DBPedia models to generate sentences and examined them to see how well they match the specified context. Five hundred sentences were generated for each of the FactorCell, ConcatCell, and SoftmaxBias models. The sentences were rated on a three point scale where three is the best and one is the worst. The rating was performed by volunteer co-workers who were presented with the sentences in random order. Three ratings were obtained for each sentence. Sentences were generated using stochastic beam search with a heuristic constraint to prevent repeated trigrams.

Judgment was based on how well the generated sentence matched the specified context and not factuality. For example, the first sentence listed in Table 4 would be judged as a good sentence for the OfficeHolder entity type regardless of the fact that Daniel Gutierrez is not an Arizona politician and there is no District 39 in the Arizona House of Representatives. Anecdotally, the other two models seem to have less trouble with coherence but sometimes make the mistake of using a related entity type instead of the specified one. The second example in Table 4 is an example of this behavior where the intended entity type was Artist, but the generated sentence more properly belongs to the Athlete type.

6 Analysis for Sparse Contexts

The TripAdvisor data is an interesting case because the original context space is high dimensional (3500 hotels × 5 user ratings) and sparse. Since the model applies end-to-end learning, we can investigate what the context embeddings learn. In particular, we looked at location (hotels are from 25 cities in the United States) and class of hotel, neither of which are input to the model. All of what it learns about these concepts come from extracting information from the text of the reviews.

To visualize the embedding, we used a 2-dimensional PCA projection of the embeddings of the 3500 hotels. We found that the model learns to group the hotels based on geographic region; the projected embeddings for the largest cities are shown in Figure 5, plotting the 1.5σ ellipsoid of the Gaussian distribution of the points. (Actual points are not shown to avoid clutter.) Not only are hotels from the same city grouped together, cities that are close geographically appear close to each other in the embedding space. Cities in the Southwest appear on the left of the figure, the West coast is on top and the East coast and Midwest is on the right side.

Class is a rating from an independent agency that are significant with $p < 0.001$. The relative ordering of the models is consistent with the ordering of the classification experiment reported in Table 2. In this (admittedly small scale) test, classification accuracy seemed to be a much better predictor of the human ratings with a roughly linear relationship between the two metrics. We believe that this human rating experiment supports the use of classification accuracy as a proxy evaluation criterion for context-sensitive language models.
| Model  | Entity Type | Excerpt From Generated Text |
|--------|-------------|-----------------------------|
| Factor | OfficeHolder | Daniel Gutierrez is a Republican member of the Arizona House of Representatives representing District 39. |
| Factor | Transportation | USS Texas was a motorboat that served in the United States Navy during World War I. |
| Concat | Artist | Nemanja Albiflora (Born 12 October 1990) is a Serbian footballer who is a member of the Serbian National Football league (FK Vojvodina) ... |
| Softmax | Company | National State Bank of Tanzania is a public school in the Republic of Tanzania. Its natural habitats are subtropical or tropical moist lowland forests and rural freshwater marshes ... |

Table 4: Illustrative examples generated with the DBPedia models. Punctuation and capitalization has been restored.

Figure 5: Distribution of a PCA projection of hotel embeddings PCA from the TripAdvisor FactorCell model showing the grouping of the hotels by city.

indicates the level of service and amenities that customers can expect to receive at a hotel. Whereas, the star rating is the average score given to each establishment by the customers who reviewed it. Hotel class does not determine star rating although they are correlated ($r = 0.54$). The dataset does not contain a uniform sample of hotel classes from each city. The hotels included from Boston, Chicago, and Philly are almost exclusively high class and the ones from L.A. and San Diego happen to be low class, so the embedding distributions also reflect hotel class: lower class hotels towards the top left and higher class hotels towards the bottom right. The visualization for the ConcatCell and SoftmaxBias models are similar.

Another way of understanding what the context embeddings represent is to compute the softmax bias projection $Qc$ and examine the words that experience the biggest increase in probability. We show three examples in Table 5. In each case, the top words are strongly related to geography and include names of neighborhoods, local attractions, and other hotels in the same city. The top boosted words are relatively unaffected by changing the rating. (Recall that the hotel identifier and the user rating are the only two inputs used to create the context embedding.) This table combined with the other visualizations indicates that location effects tend to dominate in the output layer, which may explain why the two models adapting the recurrent network seem to have a bigger impact on classification performance.

7 Prior Work

There have been many studies of language models that can be dynamically adapted based on context. Methods have been referred to as context-dependent models (Mikolov and Zweig, 2012), context-aware models (Tang et al., 2016), conditioned models (Ficler and Goldberg, 2017), and controllable text generation (Hu et al., 2017). These models have been used in scoring word sequences (such as for speech recognition or machine translation), for text classification, and for generation. In some work, context corresponds to the previous word history. Here, we instead consider known factors such as user, location and domain metadata, though the framework could be used with history-based context.

The studies that most directly relate to our work are neural models that correspond to special cases of the more general FactorCell model, including those that leverage what we call the SoftmaxBias model
Table 5: The top boosted words in the Softmax bias layer for different context settings in a FactorCell model.

| Hotel                   | City        | Class | Rating | Top Boosted Words                      |
|-------------------------|-------------|-------|--------|----------------------------------------|
| Amalfi Chicago          | 4.0         | 5     | amalfi, chicago, allegro, burnham, sable, michigan, acme, conrad, talbott, wrigley |
| BLVD Hotel Suites LA    | 2.5         | 3     | hollywood, kodak, highland, universal, reseda, griffith, grauman’s, beverly, ventura |
| Four Points Sheraton    | Seattle     | 3.0   | 1      | seattle, pike, watertown, deca, needle, pikes, pike’s monorail, uw, safeco             |

(Dieng et al., 2016; Tang et al., 2016; Yogatama et al., 2017; Ficler and Goldberg, 2017) and others that use the ConcatCell approach (Mikolov and Zweig, 2012; Wen et al., 2013; Chen et al., 2015; Ghosh et al., 2016). One study (Ji et al., 2015) compares the two approaches, which they refer to as ccDCLM and coDCLM. They find that both approaches give similar perplexities, but their ConcatCell style model does better at an auxiliary sentence ordering task. This is consistent with our finding that adapting at the recurrent layer benefits certain tasks while having only a minor impact on perplexity. They do not test any models that adapt both the recurrent and output layers. Hoang et al. (2016) also consider adapting at the hidden layer vs. at the softmax layer, but their architecture does not fit cleanly into the framework of the SoftmaxBias model because they use an extra perceptron layer; thus, it is difficult to compare the experimental findings with ours.

The FactorCell model is distinguished by having an additive (factored) context-dependent transformation of the recurrent layer weight matrix. A related additive context-dependent transformation has been proposed for logbilinear sequence models (Eisenstein et al., 2011; Hutchinson et al., 2015), but these are less powerful than the RNN.

Variational auto-encoders have also been used for controlling text generation (Hu et al., 2017), and it may provide opportunities for extending the work presented here. An advantage of the FactorCell is that it easily handles multiple context types and high-dimensional conditioning spaces.

8 Conclusions

In summary, this paper has introduced a new model for adapting (or controlling) a language model depending on contextual metadata. The FactorCell model extends prior work with context-dependent RNNs by using the context vector to generate a low-rank, factored, additive transformation of the recurrent cell weight matrix. Experiments with six tasks show that the FactorCell model matches or exceeds performance of alternative methods in both perplexity and text classification accuracy. Findings hold for a variety of types of context, including high-dimensional contexts, and the adaptation of the recurrent layer is particularly important for character-level models. For many contexts, the benefit of the FactorCell model comes with essentially no additional computational cost at test time, since the transformations can be pre-computed. A study on DBPedia data suggests that the FactorCell model is also more effective than the standard methods for context-aware text generation.

The models evaluated here were tuned to minimize perplexity, as is typical for language modeling. In analyses of performance with different hyperparameter settings, we find that perplexity is not always positively correlated with accuracy, but the criteria are more often correlated for approaches that adapt the recurrent layer. While not surprising, the results raise concerns about using perplexity as the sole evaluation metric for context-aware language models. Prior work uses classification accuracy of a discriminative model trained on generated text as a means for evaluating context-controlled text generation. Our preliminary work finds that this measure is highly correlated with text classification accuracy of the generative model, which in turn matches the relative rankings of human annotators. We suspect that classification accuracy alone will also have limitations for tuning a text generation model and that a dual objective would be better. More work is needed to understand the relative utility of these objectives for language model design.
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