On the State of the Art of Evaluation in Neural Language Models

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Abstract

Ongoing innovations in recurrent neural network architectures have provided a steady influx of apparently state-of-theart results on language modelling benchmarks. However, these have been evaluated using differing code bases and limited computational resources, which represent uncontrolled sources of experimental variation. We reevaluate several popular architectures and regularisation methods with large-scale automatic black-box hyperparameter tuning and arrive at the somewhat surprising conclusion that standard LSTM architectures, when properly regularised, outperform more recent models. We establish a new state of the art on the Penn Treebank and Wikitext-2 corpora, as well as strong baselines on the Hutter Prize dataset.

1 Introduction

As theory continues to lag practice in deep learning, effective research depends crucially on drawing reliable conclusions about the relative quality of models from empirical evaluations. In this work, we show the performance of standard neural architectures on common language modeling baselines are strongly dependent on hyperparameter values, which represent an uncontrolled source of variation in experiments, and which have led to some results that have failed to replicate.

We present the results of a study of the relative merits of some language modelling architectures in an extensive study using a black-box hyperparameter optimisation technique. Our work is inspired by Collins et al. (2016) who provided evidence that the capacities of recurrent architectures are closely matched when controlling for the number of parameters.

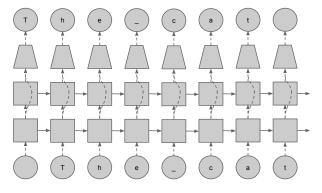
We specify flexible, parameterised model families with the ability to adjust embedding and recurrent cell sizes for a given parameter budget and with fine grain control over regularisation hyperparameters. Then, having carefully tuned and compared LSTM and Recurrent Highway Network (Zilly et al., 2016) based language models, we find that well-regularised LSTMs outperform their more recent counterparts.

2 Models

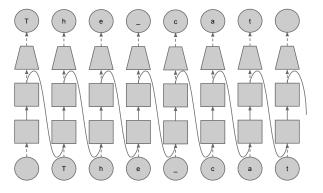
Our focus is on two architectures: the Long Short-Term Memory (Hochreiter and Schmidhuber, 1997) serves as a well known and frequently used baseline, while the recently proposed Recurrent Highway Network (Zilly et al., 2016) is chosen because it has demonstrated state-of-the-art performance on a number of datasets.

As pictured in Fig. 1a, our LSTM models have all the standard components: an input embedding lookup table, recurrent cells stacked as layers with additive skip connections combining outputs of all layers to ease optimisation. There is an optional down-projection whose presence is governed by a hyperparameter from this combined output to a smaller space which reduces the number of output embedding parameters. Unless otherwise noted, input and output embeddings are shared, see (Inan et al., 2016) and (Press and Wolf, 2016).

Dropout is applied to feedforward connections denoted by dashed arrows in the figure. From the bottom up: to embedded inputs (*input dropout*), to connections between layers (*intra-layer dropout*), to the combined and the down-projected outputs (*output dropout*). All these dropouts have random masks drawn independently per time step, in contrast to the dropout on recurrent states where the



(a) two-layer LSTM with skip connections



(b) RHN with two processing steps per input

Figure 1: Recurrent networks with optional down-projection, per-step and per-sequence dropout (dashed and solid lines).

same mask is used for all time steps in the sequence.

RHN based models are typically conceived of as a single horizontal "highway" to emphasise how the recurrent state is processed through time. In Fig. 1b, we choose to draw their schema in a way that makes the differences from LSTMs immediately apparent. In a nutshell, the RHN state is passed from the topmost layer to the lowest layer of the next time step. In contrast, each LSTM layer has its own recurrent connection and state.

The same dropout variants are applied to the RHNs as to LSTMs, with the exception of intralayer dropout, since only the recurrent state is passed between the layers. For the recurrent states, both architectures utilise variational dropout proposed by Gal and Ghahramani (2016) (*state dropout*). or recurrent dropout (Semeniuta et al., 2016) where explicitly noted.

3 Experimental Setup

3.1 Datasets

We compare models on three datasets. The smallest of them is the Penn Treebank corpus by Marcus et al. (1993) with preprocessing from Mikolov et al. (2010). We also include another word level corpus: Wikitext-2 by Merity et al. (2016). It is about twice the size of Penn Treebank with a larger vocabulary and much lighter preprocessing. The third corpus is Enwik8 from the Hutter Prize dataset (Hutter, 2012). Following common practice, we use the first 90 million characters for training, and the remaining 10 million evenly split between validation and test.

4 Training details

When training word level models we follow common practice and use a batch size of 64, truncated backpropagation with 35 time steps, and we feed the final states from the previous batch as the initial state of the subsequent one. At the beginning of training and test time, the model starts with a zero state. To bias the model towards being able to easily start from such a state at test time, during training, with probability 0.01 a constant zero state is provided as the initial state.

Optimisation is performed by Adam (Kingma and Ba, 2014) with $\beta_1=0$ but otherwise default parameters ($\beta_2=0.999, \,\epsilon=10^{-9}$). Setting β_1 so turns off the exponential moving average for the estimates of the means of the gradients and brings Adam very close to RMSProp without momentum, but due to Adam's bias correction, larger learning rates can be used.

Batch size is set to 64. The learning rate is multiplied by 0.1 whenever validation performance does not improve ever during 30 consecutive checkpoints. These checkpoints are performed after every 100 and 200 optimization steps for Penn Treebank and Wikitext-2, respectively.

For character level models (i.e. Enwik8), the differences are: truncated backpropagation is performed with 50 time steps. Adam's parameters are $\beta_2=0.99,\,\epsilon=10^{-5}.$ Batch size is 128. Checkpoints are only every 400 optimisation steps and embeddings are not shared.

5 Evaluation

For evaluation, the checkpoint with the best validation perplexity found by the tuner is loaded

¹Of the two parameterisations, we used the one in which there is further sharing of masks between gates rather than independent noise for the gates.

and the model is applied to the test set with a batch size of 1. For the word based datasets, using the training batch size makes results worse by 0.3 PPL while Enwik8 is practically unaffected due to its evaluation and training sets being much larger. Preliminary experiments indicate that MC averaging would bring a small improvement of about 0.4 in perplexity and 0.005 in bits per character, similar to the results of Gal and Ghahramani (2016), while being a 1000 times more expensive which is prohibitive on larger datasets. Therefore, throughout we use the mean-field approximation for dropout at test time.

5.1 Hyperparameter Tuning

Hyperparameters are optimised by a black-box hyperparameter tuner based on batched GP bandits using the expected improvement acquisition function (Desautels et al., 2014). Tuners of this nature are generally more efficient than grid search when the number of hyperparameters is small. To keep the problem tractable, we restrict the set of hyperparameters to learning rate, input embedding ratio, input dropout, state dropout, output dropout, weight decay. For deep LSTMs, there is an extra hyperparameter to tune: intra-layer dropout. Even with this small set, thousands of evaluations are required to reach convergence.

Parameter budget. Motivated by recent results from (Collins et al., 2016), we compare models on the basis of the total number of trainable parameters as opposed to the number of hidden units. The tuner is given control over the presence and size of the down-projection, and thus over the tradeoff between the number of embedding vs. recurrent cell parameters. Consequently, the cells' hidden size and the embedding size is determined by the actual parameter budget, depth and the *input embedding ratio* hyperparameter.

For Enwik8 there are relatively few parameters in the embeddings since the vocabulary size is only 205. Here we choose not to share embeddings and to omit the down-projection unconditionally.

6 Results

6.1 Penn Treebank

We tested LSTMs of various depths and an RHN of depth 5 with parameter budgets of 10 and 24 million matching the sizes of the Medium and

Model	Size	D	Valid	Test
Medium LSTM, Zaremba (2014)	10M	2	86.2	82.7
Large LSTM, Zaremba (2014)	24M	2	82.2	78.4
VD LSTM, Press (2016)	51M	2	75.8	73.2
VD LSTM, Inan (2016)	9M	2	77.1	73.9
VD LSTM, Inan (2016)	28M	2	72.5	69.0
VD RHN, Zilly (2016)	24M	10	67.9	65.4
NAS, Zoph (2016)	25M	-	-	64.0
NAS, Zoph (2016)	54M	-	-	62.4
LSTM		1	61.8	59.6
LSTM	10M	2	63.0	60.8
LSTM		4	62.4	60.1
RHN		5	66.0	63.5
LSTM		1	61.4	59.5
LSTM	24M	2	62.1	59.6
LSTM		4	60.9	58.3
RHN		5	64.8	62.2

Table 1: Validation and test set perplexities on Penn Treebank for models with different numbers of parameters and depths. All results except those from Zaremba are with shared input and output embeddings. VD stands for Variational Dropout from Gal and Ghahramani (2016).

Model	Size	D	Valid	Test
VD LSTM, Merity (2016)	20M	2	101.7	96.3
VD+Zoneout LSTM, Merity (2016)	20M	2	108.7	100.9
VD LSTM, Inan (2016)	22M	2	91.5	87.7
LSTM (tuned for PTB)		1	88.4	83.2
LSTM		1	72.7	69.1
LSTM	10M	2	73.8	70.7
LSTM		4	78.3	74.3
RHN		5	83.5	79.5
LSTM (tuned for PTB)		1	79.8	76.3
LSTM		1	69.3	65.9
LSTM	24M	2	69.1	65.9
LSTM		4	70.5	67.6
RHN		5	78.1	75.6

Table 2: Validation and test set perplexities on Wikitext-2. All results are with shared input and output embeddings.

Large LSTMs by (Zaremba et al., 2014). The results are summarised in Table 1.

Notably, in our experiments even the RHN with only 10M parameters has better perplexity than the 24M one in the original publication. Our 24M version improves on that further. However, a shallow LSTM-based model with only 10M parameters enjoys a very comfortable margin over that, with deeper models following near the estimated noise range. At 24M, all depths obtain very similar results, reaching 58.3 at depth 4.

6.2 Wikitext-2

Wikitext-2 is not much larger than Penn Treebank, so it is not surprising that even models tuned for Penn Treebank perform reasonably on this dataset,

Model	Size	D	Valid	Test
Stacked LSTM, Graves (2013)	21M	7	-	1.67
Grid LSTM, Kalchbrenner (2015)	17M	6	-	1.47
MI-LSTM, Wu (2016)	17M	1	-	1.44
LN HM-LSTM, Chung (2016)	35M	3	-	1.32
ByteNet, Kalchbrenner (2016)	-	25	-	1.31
VD RHN, Zilly (2016)	23M	5	-	1.31
VD RHN, Zilly (2016)	21M	10	-	1.30
VD RHN, Zilly (2016)	46M	10	-	1.27
LSTM	2714	4	1.29	1.31
RHN	27M	5	1.30	1.31
LSTM	46M	4	1.28	1.30
RHN	40IVI	5	1.29	1.30

Table 3: Validation and test set BPCs on Enwik8 from the Hutter Prize dataset.

and this is in fact how results in previous works were produced. For a fairer comparison, we also tune hyperparameters on the same dataset. In Table 2, we report numbers for both approaches. All our results are well below the previous state of the art for models without dynamic evaluation or caching. That said, our best result, 65.9 compares favourably even to the Neural Cache (Grave et al., 2016) whose innovations are fairly orthogonal to the base model.

Shallow LSTMs do especially well here. Deeper models have gradually degrading perplexity, with RHNs lagging all of them by a significant margin.

6.3 Enwik8

In contrast to the previous datasets, our numbers on this task (reported in BPC, following convetion) are slightly off the state of the art. This is most likely due to optimisation being limited to 14 epochs which is about a tenth of what the model of Zilly et al. (2016) was trained for. Nevertheless, we match their smaller RHN with both of our models which are very close to each other.

7 Analysis

On two of the three datasets, we improved previous results substantially by careful model specification and hyperparameter optimisation, but the improvement for RHNs is much smaller compared to that for LSTMs. While it cannot be ruled out that our particular setup somehow favours LSTMs, we believe it is more likely that this effect arises due to the original RHN experimental condition having been tuned more extensively (this is nearly unavoidable during model development).

		Size 10M			Size 24M		
Model	D	Valid	Test	D	Valid	Test	
LSTM	1	61.8	59.6	4	60.9	58.3	
- Shared Embeddings	1	67.6	65.2	4	65.6	63.2	
Variational Dropout+ Recurrent Dropout	1 1	62.9 62.8	61.2 60.6	4	$66.3 \\ 65.2$	64.5 62.9	
+ Untied gates + Tied gates	1	$61.4 \\ 61.7$	58.9 59.6	4	$64.0 \\ 60.4$	61.3 58.0	
RHN	5	66.0	63.5	5	64.8	62.2	
- Shared Embeddings - Variational Dropout + Recurrent Dropout	5 5 5	72.3 74.4 65.5	69.5 71.7 63.0	5 5 5	67.4 74.7 63.4	64.6 71.7 61.0	

Table 4: Validation and test set perplexities on Penn Treebank for variants of our best LSTM and RHN models of two sizes.

Down-projection was found to be very beneficial by the tuner for some depth/budget combinations. On Penn Treebank, it improved results by about 2–5 perplexity points at depths 1 and 2 at 10M, and depth 1 at 24M, possibly by equipping the recurrent cells with more capacity. The very same models benefited from down-projection on Wikitext-2, but even more so with gaps of about 10–18 points which is readily explained by the larger vocabulary size.

We further measured the contribution of other features of the models in a series of experiments. See Table 4. To limit the number of resource used, in these experiments only individual features were evaluated (not their combinations) on Penn Treebank at the best depth for each architecture (LSTM or RHN) and parameter budget (10M or 24M) as determined above.

First, we untied input and output embeddings which made perplexities worse by about 6 points across the board which is consistent with the results of Inan (2016).

Second, without variational dropout the RHN models suffer quite a bit since there remains no dropout at all in between the layers. The deep LSTM also sees a similar loss of perplexity as having intra-layer dropout does not in itself provide enough regularisation.

Third, we were also interested in how recurrent dropout (Semeniuta et al., 2016) would perform in lieu of variational dropout. Dropout masks were shared between time steps in both methods, and our results indicate no consistent advantage to either of them.

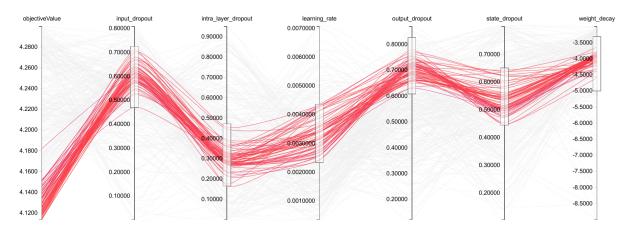


Figure 2: Negative log-likehoods of hyperparameter combinations in the neighbourhood of the best solution for a 4-layer LSTM with 24M weights on the Penn Treebank dataset.

7.1 Model Selection

With a large number of hyperparameter combinations evaluated, the question of how much the tuner overfits arises. There are multiple sources of noise in play,

- (a) non-deterministic ordering of floating point operations in optimised linear algebra routines.
- (b) different initialisation seeds,
- (c) the validation and test sets being finite samples from a infinite population.

To assess the severity of these issues, we conducted the following experiment: models with the best hyperparameter settings for Penn Treebank and Wikitext-2 were retrained from scratch with various initialisation seeds and the validation and test scores were recorded. If during tuning, a model just got a lucky run due to a combination of (a) and (b), then retraining with the same hyperparameters but with different seeds would fail to reproduce the same good results.

There are a few notable things about the results. First, in our environment (Tensorflow with a single GPU) even with the same seed as the one used by the tuner, the effect of (a) is almost as large as that of (a) and (b) combined. Second, the variance induced by (a) and (b) together is roughly equivalent to an absolute difference of 0.4 in perplexity on Penn Treebank and 0.5 on Wikitext-2. Third, the validation perplexities of the best checkpoints are about one standard deviation lower than the sample mean of the reruns, so the tuner could fit the noise only to a limited degree.

Because we treat our corpora as a single sequence, test set contents are not i.i.d., and we cannot apply techniques such as the bootstrap to as-

sess (c). Instead, we looked at the gap between validation and test scores as a proxy and observed that it is very stable, contributing variance of 0.12–0.3 perplexity to the final results on Penn Treebank and Wikitext-2, respectively.

We have not explicitly dealt with the unknown uncertainty remaining in the Gaussian Process that may affect model comparisons, apart from running it until apparent convergence. All in all, our findings suggest that a gap in perplexity of 1.0 is a statistically robust difference between models trained in this way on these datasets.

7.2 Sensitivity

To further verify that the best hyperparameter setting found by the tuner is not a fluke, we plotted the validation loss against the hyperparameter settings. Fig. 2 shows one such typical plot, for a 4-layer LSTM. We manually restricted the ranges around the best hyperparameter values to around 15–25% of the entire tuneable range, and observed that the vast majority of settings in that neighbourhood produced perplexities within 3.0 of the best value. Widening the ranges further leads to quickly deteriorating results.

Satisfied that the hyperparameter surface is well behaved, we considered whether the same results could have possibly been achieved with a simple grid search. Omitting *input embedding ratio* because the tuner found having a down-projection suboptimal almost non-conditionally for this model, there remain six hyperparameters to tune. If there were 5 possible values on the grid for each hyperparameter (with one value in every 20% interval), then we would need 6⁵, nearly 8000 trials to get within 3.0 of the best perplexity

achieved by the tuner in about 1500 trials.

7.3 Tying LSTM gates

Normally, LSTMs have two independent gates controlling the retention of cell state and the admission of updates (Eq. 1). A minor variant which reduces the number of parameters at the loss of some flexibility is to tie the input and forget gates as in Eq. 2. A possible middle ground that keeps the number of parameters the same but ensures that values of the cell state c remain in [-1, 1] is to cap the input gate as in Eq. 3.

$$c_t = f_t \odot c_{t-1} + i_t \odot j_t \tag{1}$$

$$c_t = f_t \odot c_{t-1} + (1 - f_t) \odot j_t \tag{2}$$

$$c_t = f_t \odot c_{t-1} + \min(1 - f_t, i_t) \odot j_t \quad (3)$$

Where the equations are based on the formulation of Sak et al. (2014). All LSTM models in this paper use the third variant, except those titled "Untied gates" and "Tied gates" in Table 4 corresponding to Eq. 1 and 2, respectively.

The results show that LSTMs are insensitive to these changes and the results vary only slightly even though more hidden units are allocated to the tied version to fill its parameter budget. Finally, the numbers suggest that deep LSTMs benefit from bounded cell states.

8 Conclusion

During the transitional period when deep neural language models began to supplant their shallower predecessors, effect sizes tended to be large, and robust conclusions about the value of the modeling innovations could be made, even in the presence of poorly controlled "hyperparameter noise." However, now that the neural revolution is in full swing, researchers must often compare competing deep architectures. In this regime, effect sizes tend to be much smaller, and more methodological care is required to produce reliable results. Furthermore, with so much work carried out in parallel by a growing research community, the costs of faulty conclusions are increased.

Although we can draw attention to this problem, this paper does not offer a practical methodological solution beyond establishing reliable baselines that can be the benchmarks for subsequent work. The solutions to the methodological challenges require understanding, and — we suspect — better hyperparameter optimization strategies.

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