WeNet: Weighted Networks for Recurrent Network Architecture Search

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Abstract

In recent years, there has been increasing demand for automatic architecture search in deep learning. Numerous approaches have been proposed and led to state-of-the-art results in various applications, including image classification and language modeling. In this paper, we propose a novel way of architecture search by means of weighted networks (WeNet), which consist of a number of networks, with each assigned a weight. These weights are updated with back-propagation to reflect the importance of different networks. Such weighted networks bear similarity to mixture of experts. We conduct experiments on Penn Treebank and WikiText-2. We show that the proposed WeNet can find recurrent architectures which result in state-of-the-art performance.

1. Introduction

In the past several years, there has been groundbreaking progress in various applications, including speech recognition (Hinton et al., 2012; Dahl et al., 2012) and image classification (LeCun et al., 1998; Krizhevsky et al., 2012). This progress is primarily due to advances in deep learning, e.g. the recurrent network (Hochreiter & Schmidhuber, 1997) and convolutional network (LeCun et al., 1998). Numerous research works have built upon these advances, developing new network architectures, such as VGG Network (Simonyan & Zisserman, 2015) and ResNet (He et al., 2016). These network architectures introduce new structures which can help to boost the system accuracy.

On the other hand, as opposed to manually designing networks, automatic network architecture search has recently been drawing more and more attention (Zoph & Le, 2016; Pham et al., 2018; Liu et al., 2018; Luo et al., 2018). These automatically discovered architectures have achieved state-of-the-art performance on image classification and language model tasks. In addition, the architecture search time has been improved from more than 1000 GPU days to several GPU hours. In terms of search types, the architecture search can be reinforcement learning (RL) based (Zoph & Le, 2016; Zoph et al., 2017; Cai et al., 2017; Baker et al., 2017), evolutionary algorithm (EA) based (Xie & Yuille, 2017; Miikkulainen et al., 2017; Real et al., 2017; Liu et al., 2018; Real et al., 2018), or the recently introduced gradient descent based (Liu et al., 2018; Luo et al., 2018) etc. In RL-based methods, a sequence of actions are searched to build optimal networks which would be rewarded by the accuracy improvement on the development dataset. In EA-based method, search is performed through mutations and re-combinations of architectural components to get better performance. While RL and EA based methods are operated in discrete space, the gradient descent based methods can be applied to continuous space for architecture search.

In this paper, we propose a novel gradient descent based method for recurrent architecture search. We conduct experiments on a language modeling task to demonstrate the effectiveness and efficiency of the proposed method. Our contribution in this paper can be summarized as the following:

- We introduce weighted networks (WeNets), a specific instance of mixture of experts. We define WeNets as a number of networks which connect to the same input and output layer. Each network not only has its model parameters, but also has a weight indicating how important the network is when trained with other networks. Both the model parameters and model weights are updated by the stochastic gradient descent (SGD) during model training.

- We propose a simple and effective algorithm for recurrent architecture search with WeNets. The algorithm takes a collection of randomly generated network architectures, i.e. WeNets, and performs efficient architecture search. Similar to a mini-batch in SGD, we introduce network batch size which specifies the number of networks are processed at the same time during the network architecture search.

- We show that an architecture found by WeNets...
achieves state-of-the-art results on the Penn Treebank language dataset. In addition, we demonstrate that the discovered recurrent architecture can be readily used for different datasets, for example, WikiText-2 dataset.

The remainder of the paper is organized as follows. Section 2 describes the related work. Sections 3 explains the architecture search via weight networks. We report the experimental results at Section 4 and draw the conclusion at Section 5.

2. Related Work

The most relevant paper to our work is DARTS (Liu et al., 2018), which is the first paper to use gradient descent for architecture search. However, there are four major differences between DARTS and our work: 1) DARTS is based on the continuous relaxation of the architecture representation, which allows efficient search of possible architectures using gradient descent. In particular, a softmax function is applied over all possible operations (such as activation functions) to generate the weighted operation results. In our method, we apply a softmax function over a collection of networks to generate weighted results. In other words, DARTS considers the entire search space during architecture search, while our method restrains the search space to a specified collection of networks. 2) DARTS utilizes parameter sharing (Pham et al., 2018) to make the search possible, as one cannot fit all the possible network architectures (normally more than billions) to memory. On the other hand, our algorithm does not have to share parameters in architecture search. Parameter sharing (Pham et al., 2018) is a useful technique to make the search more efficient in terms of memory usage, but updating on shared parameters may prevent the search from heading to the correct direction. In our experiments, the search without parameter sharing leads to better models in terms of accuracy on development datasets. 3) DARTS needs both training and validation datasets to update the model and architecture parameters, while our method needs the training dataset only. 4) DARTS requires alternate parameter updating on model parameters and architecture parameters, while our method updates them simultaneously and therefore simplifies the architecture search. Our paper is also related to (Luo et al., 2018) as both perform architecture in continuous space. However, (Luo et al., 2018) utilized the encoder, performance predictor and decoder for architecture search which is a totally different framework.

In addition, this paper is related to the literature of mixtures of experts. Since mixtures of experts were introduced more than two decades ago (Jacobs et al., 1991; Jordan & Jacobs, 1994), it has been applied to different types of experts including SVMs, Gaussian Processes and deep neural networks. Recently, (Shazeer et al., 2017) has proposed sparsely-gated mixture-of-experts layers, consisting of up to thousands of feed-forward sub-networks. A trainable gating network determines a sparse combination of these experts to use for each example. There are major differences between (Shazeer et al., 2017) and our work. 1) We do not use gating to infer the importance of experts; instead, we use linear weights to represent the importance of experts. 2) The experts in (Shazeer et al., 2017) are feed-forward networks with identical architectures, while our work considers different network architectures. 3) The gating in (Shazeer et al., 2017) is part of the model and is used at inference time to determine which combination of the experts are used. Our work follows the deep network architecture search literature and uses linear weights to guide the search for an efficient network architecture. At the end of the search, a single expert network is picked and the weights are no longer used in inference.

3. Architecture Search via Weighted Networks

3.1. Network Search Space

Recurrent networks (Hochreiter & Schmidhuber, 1997) have been very successful in modeling sequential data, for example in language modeling (Bengio et al., 2003; Mikolov et al., 2010; Zaremba et al., 2014). Figure 1 shows the recurrent networks with the networks unrolled for four time steps. This chain-like nature reveals that recurrent neural networks are intimately related to sequences and lists. It is the natural choice of neural network architecture for such data.

![Figure 1. Recurrent network unrolled.](image)

The core part of recurrent networks is the recurrent cell, as denoted $C$ in Figure 1. For each time step $t$, the cell take $x_t$ and previous hidden state $h_{t-1}$ as input and produces the output $h_t$. Some widely used cells include RNN, LSTM (Hochreiter & Schmidhuber, 1997) and GRU (Cho et al., 2014). The goal of automatic machine learning (AutoML) is to automatically find a useful structure so the long-distance dependency can be modeled.

Following (Zoph et al., 2017; Real et al., 2018; Liu et al., 2017a;b; 2018), a cell is a directed acyclic graph consisting of an ordered sequence of $L$ nodes. Figure 2 shows an
example recurrent cell with $L = 5$.

![Diagram of a recurrent cell](image)

**Figure 2.** An example network for recurrent network architecture search.

We assume the cell has two input nodes and a single output node. These are defined as the input at the current step and the state from the previous step. In particular, the very first intermediate node $0$ at time step $t$ is obtained by the following transformations

$$
\begin{align*}
  c &= \sigma(W_x x_t), \\
  h &= \tanh(W_h h_{t-1}), \\
  s_0 &= h_{t-1} + c(h - h_{t-1}),
\end{align*}
$$

where $\sigma$ is the logistic sigmoid function. $x_t$ is the input at time step $t$. $h_{t-1}$ is the previous hidden state. All states $c$, $h$, $h_{t-1}$, $h_{t}$ have the same dimensionality. $W_x$ and $W_h$ are parameters to be learned.

The task of recurrent cell discovery is to find the ancestor node and activation function for nodes $i$, $i = 1, \ldots, L - 1$. The ancestor node of node $i$ is one of the nodes which appears before $i$, that is, in the range of $0, \ldots, i - 1$. The choice of activation functions follows (Zoph & Le, 2016; Pham et al., 2018; Liu et al., 2018) and it includes tanh, relu, sigmoid, and identity mapping respectively. The state of node $i$, $s_i$, is thus computed as

$$
  s_i = o_i(W_{ji}s_j),
$$

where $j$ is the ancestor node of $i$, $s_j$ is the state of node $j$, $o_i$ is the one of the activation functions (sigmoid, tanh, relu, etc.), and $W_{ji}$ is the model parameter to be learned. For example, the 4-th node in Figure 2 is computed as follows:

$$
  s_4 = \text{relu}(W_{14}s_1).
$$

Previous work (Pham et al., 2018) proposed the parameter sharing in network structure discovery. That means network parameters such as $W_{14}$ and $W_{12}$ may be shared. We compared the results between parameters sharing and non-parameters sharing. We found that non-parameter sharing results in superior results and thus we report all results in this paper without parameter sharing. We hypothesize that in the parameter sharing setting, the same model parameters are updated for different nodes and operators, thus resulting parameter updating collision. On the other hand, the non-parameter sharing avoids the parameter updating collision and it can more accurately assess the importance of candidate networks in architecture search.

The output of the cell is obtained by averaging all the intermediate nodes:

$$
  h_t = \frac{1}{L - 1} \sum_{i \in \{1, \ldots, L - 1\}} s_i
$$

We note that the search space defined above does not cover the LSTM cell. It would be interesting to re-define the search space to have LSTM as one instance of the search. Nevertheless, we follow this search space as used in previous work (Pham et al., 2018; Liu et al., 2018). We include the state of the art LSTM performance in experiments (see Section 4).

### 3.2. Weighted Networks

The weighted networks consist of a collection of candidate networks $N_0, \ldots, N_{n-1}$, and weight parameters $w_0, \ldots, w_{n-1}$. Figure 3 shows an overview of WeNets, with 10 networks $net_i$, $i = 0, 1, \ldots, 9$, considered. Each network represents a network architecture similar to that in Figure 2. As can be seen from this figure, each candidate network expects the same-sized inputs ($x_t$ and $h_{t-1}$) and produces the same-sized outputs ($h_t$). The outputs from all candidate networks are averaged to generate the final output $h_t$.

Let’s denote $N_i(x)$ the output of candidate network $N_i$ for a given input $x$, the weighted network can be written as follows:

$$
  y = \sum_{i=1}^{n} w_i N_i(x),
$$

where $w_i$ is the weight for network $N_i$. The number of candidate networks, $n$, is determined by the GPU memory available. In our experiments, we have up to one hundred candidate networks which can be fit to one GPU memory. Note that $w_i$ are normalized with softmax and they can be interpreted as the importance of networks.
3.3. Architecture Search Algorithm

The architecture search algorithm consists of two steps. The first is to randomly generate a collection of networks and the second is to search over these networks to find optimal ones.

3.3.1. Random Networks Generation

Algorithm 1 shows how to randomly generate \( T \) networks. The algorithm generates an empty list \( \text{res} \) at line 2. It then goes to the procedure to generate each candidate net at line 5 to 8. It stops when the networks generated reach the specified number \( T \).

For each network generation, we first randomly sample a previous node to be the ancestor node to connect to. For example, if \( l = 2 \), we randomly select a node from node list of \( \{0, 1\} \) which were previously generated. In addition, we randomly sample an \( \text{op} \) from the list of tanh, relu, sigmoid and identity. We insert the pair of \( \text{node} \) and \( \text{op} \) to the candidate network. After pairs of node and op are generated for all levels \( L \), we have a complete network architecture which may be similar to the following:

\[
\{(\text{relu}, 0), (\text{relu}, 1), (\text{tanh}, 2), (\text{relu}, 1)\}
\]

We then average all of these nodes \((i = 1, \ldots, 4)\) to produce the final result (see Figure 2).

Algorithm 1 Random Network Generalization

1: **Input:** Total networks to generate: \( T \), Recurrent network levels: \( L \)
2: \( \text{res} = [] \)
3: **while** \( \text{len(res)} < T \) **do**
4: Create an empty net \( C = [] \)
5: **for** \( \text{level} \ l \ in \ L \) **do**
6: \( \text{node} = \text{randInt}(0, l) \)
7: \( \text{op} = \text{randomSampling} \{\text{tanh, relu, sigmoid, identity} \} \)
8: \( C.\text{append}((\text{node}, \text{op})) \)
9: **end for**
10: \( \text{res.append}(C) \)
11: **end while**
12: **return** \( \text{res} \)

3.3.2. Search Algorithm

Once we have a collection of randomly generated networks, we can search over them with Algorithm 2. The algorithm expects the following hyper-parameters: total networks to search \( T \), network batch size \( B \) and network seeding size \( K \). We first randomly sample \( T \) candidate networks as shown in Algorithm 1 and initialize the seed networks to be empty. We go to the loop starting with line 4 to process all networks. In particular, we take \( B \) (network batch) networks from pool (line 5) and combine the previous seeds to be the new candidates (line 7). We train the candidate networks jointly by the WeNet structure (Figure 3) on training data. The duration of training is specific to applications. In language modeling, we find that one or two epochs are enough to
We consider the selection of tanh, relu, sigmoid, and identity activation functions and the recurrent cell consists of \( L = 8 \) nodes. As in ENAS cell (Pham et al., 2018) and DARTS cell (Liu et al., 2018), we enable batch normalization in each node to prevent gradient explosion during architecture search, and disable it during architecture evaluation. In network search, the recurrent network consists of only a single cell. That is, we do not use any repetitive patterns by vertically stacking the cells.

We run Algorithm 2 for recurrent architecture search. We set the total networks of \( T \) to be 10k, batch network size \( B \) to be 100, and seeding size \( K \) to be 20. For each network, the size of embedding and hidden units are set to 200. We use data batch size of 20. We found that small data batch size is essential to stabilize the architecture search. We use BPTT length 35, and weight decay 5. We apply variational dropout (Gal & Ghahramani, 2016) of 0.2 to word embeddings, 0.75 to the cell input, and 0.25 to all the hidden nodes. A dropout of 0.75 is also applied to the output layer. Other training settings are identical to those in (Merity et al., 2017; Yang et al., 2017). We choose Adam as the optimizer during search.

We train WeNet for two epochs (line 8 in Algorithm 2) to select the best candidate networks according to the network weights. Figure 4 shows an example of sorted network weights after training of two epochs. The top 20 networks (out of 100) are retained to continue architecture search. These weights are normalized from softmax and they can be interpreted as the importance of the networks considered.

Considering the random network initialization may result in fluctuation in results, we run Algorithm 2 four times and report the experiments with the best found architecture, as shown in Figure 5.

### 4.2. Recurrent Architecture Evaluation

We follow the setup in (Liu et al., 2018). A single-layer recurrent network with the discovered cell is trained for 1600 epochs, with batch size 64, averaged SGD (Polyak & Juditsky, 1992) (ASGD), learning rate 20, and weight decay \( 8 \times 10^{-7} \). To speed up, we start with SGD and trigger ASGD using the same protocol as in (Yang et al., 2017; Merity et al., 2017). Both the embedding and hidden unit sizes are set to 850 to ensure our model size is comparable with other baselines. Other hyper-parameters, including dropouts, remain exactly the same as those for architecture search. For fair comparison, we do not finetune our model at the end of the optimization, nor do we use any additional enhancements such as dynamic evaluation (Krause et al., 2017) or continuous cache (Grave et al., 2016). The training takes 5 days on a single Tesla V100 GPU with our implementation. Our code is implemented on top of DARTS and thus

```
Algorithm 2 Architecture Search Procedure
1: Input: total networks to search: \( T \), network batch size: \( B \), network seeding size: \( K \)
2: Randomly generates \( T \) candidate networks denoted as pool
3: Initiate seed networks seed = {}
4: while pool is not empty do
5: Choose \( B \) networks denoted as candidates from pool
6: pool = pool − candidates
7: candidates = candidates \cup seed
8: Train the weighted networks of candidates on training data
9: Update seed to contain the \( K \) networks which have the maximum \( K \) net weights \( w \)
10: end while
11: Return best network from seed
```

### 4. Experiments

Neural language modeling (Bengio et al., 2003; Mikolov et al., 2010; Zaremba et al., 2014) has been a fundamental task in natural language processing and speech recognition. This task has been widely used to test recurrent neural networks. We use Penn Treebank (PTB) language model dataset to test the network architecture search algorithm proposed in this paper.

The experiments consist of the following: 1) The recurrent architecture search. We report the setup for architecture search by WeNet. 2) The architecture evaluation. We use the architecture found in 1) to train a language model from scratch and report the performance on the test data set. 3) We investigate the transfer-ability of the found architecture on PTB by evaluating them on WikiText-2 (WT2). 4) We compare the network structure with the previously discovered DARTS structure.

#### 4.1. Recurrent Architecture Search on Penn Treebank

We follow the network search space setup as in (Zoph & Le, 2016; Pham et al., 2018; Liu et al., 2018) (see Section 3.1). We consider the selection of tanh, relu, sigmoid, and identity activation functions and the recurrent cell consists of \( L = 8 \) nodes. As in ENAS cell (Pham et al., 2018) and DARTS cell (Liu et al., 2018), we enable batch normalization in each node to prevent gradient explosion during architecture search, and disable it during architecture evaluation.
we can facilitate fair comparison without implementation discrepancies.

Table 1 presents the results for recurrent architectures on PTB. As reported in (Liu et al., 2018), the random architectures are competitive. For example, it leads to the perplexity of 61.5 on PTB test data. Nevertheless, recent work including the LSTM mixture of softmaxes, ENAS, DARTS, NAONet and WeNets are able to improve the baseline significantly. The cell discovered by ENAS, DARTS, and NAONet achieved the test perplexity of 58.6, 56.1 and 56.0 respectively. It is worth noting that the NAONet takes much longer time for architecture search (300 GPU hours). The short version NAONet-WS results in worse perplexity (58.6). The best previously reported is from (Yang et al., 2017) which obtained the perplexity of 56.0 on test dataset.

The DARTS has the perplexity of 56.1 and is competitive with the previous state-of-the-art model. The architecture discovered by WeNet results in perplexity of 57.9 when trained with 1500 epochs, which is comparable to ENAS and DARTS and significantly faster than NAS (Zoph & Le, 2016).

4.3. Transfer-ability of Architectures

In this section, we test if the recurrent architecture found on Penn Treebank can perform well on another dataset WikiText-2. We set embedding and hidden unit sizes to 700, weight decay $5 \times 10^{-7}$, and hidden-node variational dropout 0.15. Other hyper-parameters remain the same as in our PTB experiments. Table 2 shows that the cell identified by WeNet transfers better than ENAS, DARTS and NAONet on WikiText-2. In particular, ENAS, DARTS and NAONet lead to the perplexities of 70.4, 66.9 and 67.0 on test dataset, while WeNet results in the perplexity of 66.6. The state-of-the-art on this dataset is from (Yang et al., 2017). Lower perplexity numbers may be obtained by recurrent architecture search directly on the WikiText-2 dataset.

4.4. Network Comparison to DARTS net

In this section, we compare the WeNet recurrent network structure (Figure 5) to DARTS (Figure 6). It is interesting to see that WeNet and DARTS have a common substructure. In particular, they have exactly the same node and op pairs from level 0 to 4. We hypothesize that this subnet structure may be useful for long distance modeling. In general, DARTS and WeNet architectures demonstrate different performance behavior in training language models. DARTS outperforms WeNet structure during the first 2000 epochs of
### Table 1. Comparison with state-of-the-art language models on Penn Treebank. Results marked with † were obtained in DARTs github repo. Results marked with * were obtained using [Pham et al., 2018] public released repo.

| Architecture | valid pplx | test pplx | Params (M) | Search Cost (GPU days) | Search Method |
|--------------|------------|-----------|------------|------------------------|---------------|
| Variational RHN (Zilly et al., 2016) | 67.9 | 65.4 | 23 | - | manual |
| LSTM (Merity et al., 2017) | 60.7 | 58.8 | 24 | - | manual |
| LSTM + skip connections (Melis et al., 2017) | 60.9 | 58.3 | 24 | - | manual |
| LSTM + 5 softmax experts (Yang et al., 2017) | - | 57.4 | - | - | manual |
| LSTM + 15 softmax experts (Yang et al., 2017) | 58.1 | 56.0 | 22 | - | manual |
| NAS (Zoph & Le, 2016) | - | 64.0 | 25 | 1e4 CPU days | RL |
| ENAS (Pham et al., 2018) * | 68.3 | 63.1 | 24 | 0.5 | RL |
| ENAS (Pham et al., 2018) † | 60.8 | 58.6 | 24 | 0.5 | RL |
| Random | 64.1 | 61.3 | 23 | - | - |
| DARTS (first order) (Liu et al., 2018) | 62.7 | 60.5 | 23 | 0.5 | gradient-based |
| DARTS (second order) (Liu et al., 2018) | 58.8 | 56.6 | 23 | 1 | gradient-based |
| DARTS (second order) + 1e3 epochs (Liu et al., 2018) | 58.3 | 56.1 | 23 | 1 | gradient-based |
| NAONet (Luo et al., 2018) | N/A | 56.0 | 27 | 300 | gradient-based |
| NAONet-WS (Luo et al., 2018) | N/A | 56.6 | 27 | 0.4 | gradient-based |
| WeNet (1500 epochs) | 60.1 | 57.9 | 23 | 1 | gradient-based |
| WeNet (6000 epochs) | **56.8** | **54.8** | 23 | 1 | gradient-based |

### Table 2. Comparison with state-of-the-art language models on WT2. Results marked with † were obtained in DARTs github repo.

| Architecture | valid pplx | test pplx | Params (M) | Search Cost (GPU days) | Search Method |
|--------------|------------|-----------|------------|------------------------|---------------|
| LSTM + augmented loss (Inan et al., 2017) | 91.5 | 87.0 | 28 | - | manual |
| LSTM + continuous cache pointer (Grave et al., 2016) | - | 68.9 | - | - | manual |
| LSTM (Merity et al., 2017) | 69.1 | 66.0 | 33 | - | manual |
| LSTM + skip connections (Melis et al., 2017) | 69.1 | 65.9 | 24 | - | manual |
| LSTM + 15 softmax experts (Yang et al., 2017) | **66.0** | **63.3** | 33 | - | manual |
| ENAS (Pham et al., 2018) † | 72.4 | 70.4 | 33 | 0.5 | RL |
| DARTS (6000 epochs) (Liu et al., 2018) | 69.5 | 66.9 | 33 | 1 | gradient-based |
| NAONet (Luo et al., 2018) | N/A | 67.0 | 36 | 300 | gradient-based |
| WeNet (6000 epochs) | 69.2 | 66.6 | 33 | 1 | gradient-based |
5. Conclusions

In this paper, we have introduced WeNets and proposed a simple and effective algorithm for recurrent architecture search with WeNets. We show that an architecture found by WeNets achieves state-of-the-art results on the Penn Treebank language dataset. In addition, we demonstrate that the discovered recurrent architecture can be readily used for different datasets, for example, WikiText-2 dataset.

While the proposed search algorithm is generic, we focus on language modeling task in the paper. In the future, we would investigate the discovery of different networks including convolutional networks and sequence-to-sequence networks with WeNets.

References

Baker, B., Gupta, O., Naik, N., and Raskar, R. Designing neural network architectures using reinforcement learning. In ICLR, 2017.

Bengio, Y., Ducharme, R., Vincent, P., and Jauvin, C. A neural probabilistic language model. In Journal of Machine Learning research, 2003.

Cai, H., Chen, T., Zhang, W., Yu, Y., and Wang, J. Reinforcement learning for architecture search by network transformation. In arXiv:1707.04873, 2017.

Cho, K., Merrienboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., and Bengio, Y. Learning phrase representations using rnn encoder-decoder for statistical machine translation. In arXiv:1406.1078, 2014.

Dahl, G., Yu, D., Deng, L., and Acero, A. Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition. IEEE transactions on audio, speech, and language processing, 20(1), 2012.
WeNet: Weighted Networks for Recurrent Network Architecture Search

Gal, Y. and Ghahramani, Z. A theoretically grounded application of dropout in recurrent neural networks. In Advances in neural information processing systems, 2016.

Grave, E., Joulin, A., and Usunier, N. Improving neural language models with a continuous cache. In arXiv:1612.04426, 2016.

He, K. M., Zhang, X. Y., Ren, S. Q., and Sun, J. Deep residual learning for image recognition. In CVPR, 2016.

Hinton, G., Deng, L., Yu, D., Dahl, G. E., r. Mohamed, A., Jaitly, N., Senior, A., Vanhoucke, V., Nguyen, P., Sainath, T. N., and Kingsbury, B. Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. Signal Processing Magazine, 29(6): 82–97, 2012.

Hochreiter, S. and Schmidhuber, J. Long short-term memory. In Neural Computation, 1997.

Inan, H., Khosravi, K., and Socher, R. Tying word vectors and word classifiers: A loss framework for language modeling. In ICLR, 2017.

Jacobs, R. A., Jordan, M. I., Nowlan, S. J., and Hinton, G. E. Adaptive mixtures of local experts. In Neural Computing, 1991.

Jordan, M. I. and Jacobs, R. A. Hierarchical mixtures of experts and the EM algorithm. In Neural Computing, 1994.

Krause, B., Kahembwe, E., Murray, I., and Renals, S. Dynamic evaluation of neural sequence models. In arXiv:1709.07432, 2017.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. Imagenet classification with deep convolutional neural networks. In NIPS, 2012.

LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P. Gradient-based learning applied to document recognition. In Proceedings of the IEEE, 1998.

Liu, C., Zoph, B., Shlens, J., Hua, W., Li, L. J., Li, F. F., Yuille, A., Huang, J., and Murphy, K. Progressive neural architecture search. In arXiv:1712.00559, 2017a.

Liu, H., Simonyan, K., Vinyals, O., Fernando, C., and Kavukcuoglu, K. Hierarchical representations for efficient architecture search. In arXiv:1711.00436, 2017b.

Liu, H., Simonyan, K., and Yang, Y. Darts: Differentiable architecture search. In arXiv:1806.09055, 2018.

Luo, R., Tian, F., Qin, T., Chen, E., and Liu, T. Neural architecture optimization. In arXiv:1808.07233, 2018.

Melis, G., Dyer, C., and Blunsom, P. On the state of the art of evaluation in neural language models. In arXiv:1707.05589, 2017.

Merity, S., Keskar, N. S., and Socher, R. Regularizing and optimizing lstm language models. In arXiv:1708.02182, 2017.

Miikkulainen, R., Liang, J., Meyerson, E., Rawal, A., Fink, D., Francon, O., Raju, B., Shahrzad, H., Navruzyan, A., and Duffy, N. Evolving deep neural networks. In arXiv:1703.00548, 2017.

Mikolov, T., Karafiát, M., Burget, L., Černocký, J., and Khudanpur, S. Recurrent neural network based language model. In Interspeech, 2010.

Pham, H., Guan, M. Y., Zoph, B., Le, Q. V., and Dean, J. Efficient neural architecture search via parameter sharing. In arXiv:1802.03268, 2018.

Polyak, B. T. and Juditsky, A. B. Acceleration of stochastic approximation by averaging. In SIAM Journal on Control and Optimization, 1992.

Real, E., Aggarwal, A., Huang, Y., and Le, Q. Regularized evolution for image classifier architecture search. In arXiv:1802.01548, 2018.

Shazeer, N., Mirhoseini, A., Maziarz, K., Davis, A., Le, Q., Hinton, G., and Dean, J. Outrageously large neural networks: The sparsely-gated mixture-of-experts layers. In ICML, 2017.

Simon, Y. and Zisserman, A. Very deep convolutional networks for large-scale recognition. In ICLR, 2015.

Xie, L. and Yuille, A. Genetic cnn. In ICCV, 2017.

Yang, Z. L., Dai, Z. H., Salakhutdinov, R., and Cohen, W. W. Breaking the softmax bottleneck: a high-rank rnn language model. In arXiv:1711.03953, 2017.

Zoph, B. and Le, Q. Neural architecture search with reinforcement learning. In arXiv:1611.01578, 2016.

Zoph, B., Vasudevan, V., Shlens, J., and Le, Q. Learning transferable architectures for scalable image recognition. In arXiv:1707.07012, 2017.