Assignment 4 Report
DS-GA-1008: Deep Learning, Spring 2015

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1 Answers to Questions

1. The solution to the problem from the nngraph tutorial is implemented in `nngraph/nngraph_handin.lua`.
2. `i` corresponds to x_t, the input to the LSTM unit; `prev_c` to c_{t-1}, the state of the LSTM cell at time $t-1$; and `prev_h` to h_{t-1}, the output of the LSTM cell at time $t-1$.
3. `create_network` returns the "rolled" version of the RNN.
4. `model.s` stores the LSTM cell states and outputs of each layer of the network, evaluated at each element of each sequence in the current batch. `model.ds` stores the gradients of the output with respect to the LSTM cell states and outputs at time $t+1$, when performing BBTT at time t. `model.start_s` is used to store the LSTM cell states and outputs after processing the last element of the previous sequence. It is reset to zero after one pass through the training set.
5. If the norm of the gradient is greater than `params.max_grad_norm`, the gradient is rescaled to have norm `params.max_grad_norm`; an alternative is *gradient clipping*.
6. The script uses Stochastic Gradient Update, and the gradients are computed using BBTT.
7. With the addition of the extra output node, each call to `backward` will initiate backpropagation from *both* the criterion module and the output node. To nullify the gradient contributions from the output node, we supply a matrix of zeros for its output gradients.

2 Character-Level Model Description

I anticipated that the training time would be the main bottleneck during experimentation. My focus was to try to improve the time to convergence using a variant of the baseline model. To this end, I tried combinations of the following strategies:

- Removing unnecessary sources of model complexity.
- Increasing the batch size.
- Using adaptive optimization algorithms.

One of the main challenges while trying to improve time to convegence was that the optimizer would easily diverge. The default weight decay strategy implemented in the script works well for small batch sizes of around 20, but decreases the learning rate too eagerly when larger batch sizes are used. I tried replacing the replacing the default optimization procedure with the following:

- AdaDelta with Nesterov Accelerated Gradient (NAG). The learning rate was always set to one, the momentum was chosen to be in the set $\{0.9, 0.95, 0.99\}$, and the decay constant was chosen to be in the set $\{0.95, 0.99\}$.
- RMSProp with NAG. Each time the optimizer diverged, I manually terminated the script, decreased the learning rate, and restarted from the version of the model with the best training accuracy.

None of these strategies was effective in accelerating time to convergence. In the best case, the optimizer got stuck at around 830 training perplexity, at which point it was no longer able to make progress.

In the end, I ended up training two main models using the default optimizater. Dropout was not found to be helpful for this task, so it was not used.

1. Batch size 20; sequence length 50; 1 layer; RNN size 200; initial learning rate 1; learning rate decayed every 4 epochs.
2. Batch size 20; sequence length 100; 1 layer; RNN size 400; initial learning rate 1; learning rate decayed every 4 epochs.

The model with RNN size 400 achieved a validation perplexity of 252.469 after 15 epochs.