A PARALLEL BATCH TRAINING ALGORITHM FOR DEEP NEURAL NETWORK

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What does human brain do?



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What does neural network do?



Typical structure of NN

- Has multiple layers;
- Each layer has many units (*a.k.a.* neurons);
- Units are connected by edges;
- Each edge is associated with a weight;



Cycle for NN training

• Forward phase

•
$$Z_j^{(l+1)} = F\left(\sum_i w_{ij} \cdot Z_i^{(l)} + b_j\right)$$

Where F(x) is the nonlinear activation function

output

Cycle for NN training

- Error back propagation
 - $\delta_k^{(out)} = Z_k^{(out)} T_k^{(out)}$
 - $\delta_i^{(l)} = F'\left(Z_i^{(l)}\right) \cdot \sum_j w_{ij} \cdot \delta_j^{(l+1)}$
 - Where F'(x) is the derivative of the activation function
 - *T* is the desired output vector
- Weight updating
 - $\Delta w_{ij} = Z_i^{(l)} \cdot \delta_j^{(l+1)}$
 - $w_{ij} = w_{ij} \gamma \cdot \Delta w_{ij}$
 - Where γ is the learning rate



Applications

- Computer vision
 - Multi-column DNN, 0.23% error rate on MNIST (D. Ciresan et al., 2012)
- Speech recognition
 - Bidirectional LSTM, PER 17.7% on TIMIT (A. Graves et al., 2013)
- Natural Language Processing
 - S-LSTM, 81.9% accuracy on Stanford Sentiment Treebank (X. Zhu et al. 2015)

Heavy computation load

- Take as example an simple feed-forward NN with 2 hidden layers of size 100. ([100-100-100-1])
 - Has approximately **20,100** parameters;
 - Perform at least **20,100** multiplications in forward phase, for each train sample;
 - Perform at least 40,300 multiplications in error back propagation phase, for each train sample;
 - Plus other operations;



Heavy computation load



Parallelize













Paper to be presented

• V. Turchenko and V. Golovko. **Parallel batch pattern training algorithm for deep neural network**. *In proceeding of the 2014 International Conference on High Performance Computing Simulation (HPCS)*, pages 697-702, July 2014

Multi-Layer Perceptron (MLP)

- The authors use an MLP with 2 hidden layers.
- Pre-trained layer by layer with RBMs.
- Then fine-tuned using error back propagation algorithm



Restricted Boltzmann Machine (RBM)

- Has 2 layers of units. Called visible units and hidden units.
- Trained using contrastive divergence algorithm:
 - From inputs $ec{v}^{(0)}$ compute $ec{h}^{(1)}$;
 - From $\vec{h}^{(1)}$ compute $\vec{v}^{(1)}$;
 - From $ec{v}^{(1)}$ compute $ec{h}^{(2)}$;
 - Compute weight update as: $\Delta w_{ij} = v_i^{(0)} \cdot h_j^{(1)} v_i^{(1)} \cdot h_j^{(2)}$;
- Use the trained weights to initialize MLP.



Parallel nature of batch training

- For batch training, weight updates only occur at the end of every batch.
- For each train sample in the mini-batch:
 - Feed input into NN and generate output;
 - Back propagate errors;
 - Accumulate update statistics.
- Update weights after the whole mini-batch is traversed.
- The training of each sample within a mini-batch is **independent**.

Parallel batch training

- The proposed parallel batch training algorithm use a single Master thread with many Worker threads.
- Within each mini-batch, the Master first distribute train data to Workers. Then after all the workers finished training, the Master collect training statistics from workers and update weights.



Parallel batch training

- Need synchronization to ensure:
 - Training statistics are collected after and only after all workers finished their training;
 - All Workers start next training iteration only after Master has updated the weights and distributed new training data to them.

Implementation using a monitor

Train: Monitor

Begin Procedure trainSetup (numberOfWorkers : int)

Procedure finishTraining ()

Procedure requestUpdate (result : boolean)

End

Implementation plan

- Plan:
 - Implement both the sequential and parallel version of the batch training algorithm.
 - Use training time and testing error rate as comparison criteria.

- Challenges:
 - Need parameter tuning;
 - Shorten the waiting time;

References

- A. Graves, A. Mohamed and G. Hinton. **Speech recognition with deep recurrent neural networks**. *In proceeding of the 2013 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6645-6649, May 2013
- D. Ciresan, U. Meier and J. Schmidhuber. **Multi-column deep neural networks for image classification**. *In proceeding of the 2012 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3642-3649, June 2012
- X. Zhu, P. Sobhani and H. Guo. Long short-term memory over recursive structures. *arXiv preprint arXiv:1503.04881, 2015*