Parallel Stochastic Gradient Descent

Olivier Delalleau and **Yoshua Bengio**
University of Montreal

August 11th, 2007
CIAR Summer School - Toronto

Stochastic Gradient Descent

Cost to optimize: $E_z[C(\theta, z)]$ with θ the parameters and z a training point.

- Stochastic gradient:

$$\theta_{t+1} \leftarrow \theta_t - \epsilon_t \frac{\partial C(\theta_t, z_t)}{\partial \theta}$$

Stochastic Gradient Descent

Cost to optimize: $E_z[C(\theta, z)]$ with θ the parameters and z a training point.

- Stochastic gradient:

$$\theta_{t+1} \leftarrow \theta_t - \epsilon_t \frac{\partial C(\theta_t, z_t)}{\partial \theta}$$

- Batch gradient:

$$\theta_{k+1} \leftarrow \theta_k - \epsilon_k \sum_{t=1}^{n} \frac{\partial C(\theta_k, z_t)}{\partial \theta}$$

Stochastic Gradient Descent

Cost to optimize: $E_z[C(\theta, z)]$ with θ the parameters and z a training point.

- Stochastic gradient:

$$\theta_{t+1} \leftarrow \theta_t - \epsilon_t \frac{\partial C(\theta_t, z_t)}{\partial \theta}$$

- Batch gradient:

$$\theta_{k+1} \leftarrow \theta_k - \epsilon_k \sum_{t=1}^{n} \frac{\partial C(\theta_k, z_t)}{\partial \theta}$$

- Conjugate gradient: "similar" to batch except the descent direction is not the gradient itself, and the step ϵ_k is optimized by line search.

Stochastic vs. Batch

- Batch is good because:
  - Gradient is less noisy (averaged over a large number of samples)
  - Can use optimized matrix operations to efficiently compute output and gradient over whole dataset

Stochastic vs. Batch

- Batch is good because:
    - Gradient is less noisy (averaged over a large number of samples)
    - Can use optimized matrix operations to efficiently compute output and gradient over whole dataset
- Stochastic is good because:
    - For large or infinite datasets, batch and conjugate gradient are impractical.
    - More parameters updates $\Rightarrow$ faster convergence
    - Noisy updates can actually help escape local minima

Mini-batch stochastic gradient

"Trade-off" between batch and stochastic:

$$\theta_{k+1} \leftarrow \theta_k - \epsilon_k \sum_{t=s_k}^{s_k+b} \frac{\partial C(\theta_t, z_t)}{\partial \theta}$$

Typical size of mini-batches: on the order of 10's or 100's.

Parallelization

Note: we are using a 16-CPU computer $\neq$ 100's computers on a cluster.

Parallelization

Note: we are using a 16-CPU computer $\neq$ 100's computers on a cluster.

- Use existing parallel implementations of BLAS to speed-up matrix-matrix multiplications: low speed-up unless using very large mini-batches ($\Rightarrow$ equivalent to batch)

Parallelization

Note: we are using a 16-CPU computer $\neq$ 100's computers on a cluster.

- Use existing parallel implementations of BLAS to speed-up matrix-matrix multiplications: low speed-up unless using very large mini-batches ($\Rightarrow$ equivalent to batch)
- Split data into c chunks (each of the c CPUs sees one chunk of the data), and perform mini-batch stochastic gradient descent with parameters store in shared memory:

Parallelization

Note: we are using a 16-CPU computer $\neq$ 100's computers on a cluster.

- Use existing parallel implementations of BLAS to speed-up matrix-matrix multiplications: low speed-up unless using very large mini-batches ($\Rightarrow$ equivalent to batch)
- Split data into c chunks (each of the c CPUs sees one chunk of the data), and perform mini-batch stochastic gradient descent with parameters store in shared memory:
  - if all CPUs are updating parameters simultaneously: poor performance (time wasted waiting for memory write locks)

Parallelization

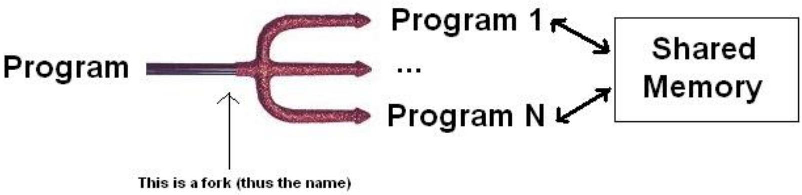
Note: we are using a 16-CPU computer $\neq$ 100's computers on a cluster.

- Use existing parallel implementations of BLAS to speed-up matrix-matrix multiplications: low speed-up unless using very large mini-batches ($\Rightarrow$ equivalent to batch)
- Split data into c chunks (each of the c CPUs sees one chunk of the data), and perform mini-batch stochastic gradient descent with parameters store in shared memory:
  - if all CPUs are updating parameters simultaneously: poor performance (time wasted waiting for memory write locks)
  - proposed solution: at any time, only one CPU is allowed to update parameters. The index of the next CPU to update is stored in shared memory, and incremented after each update.

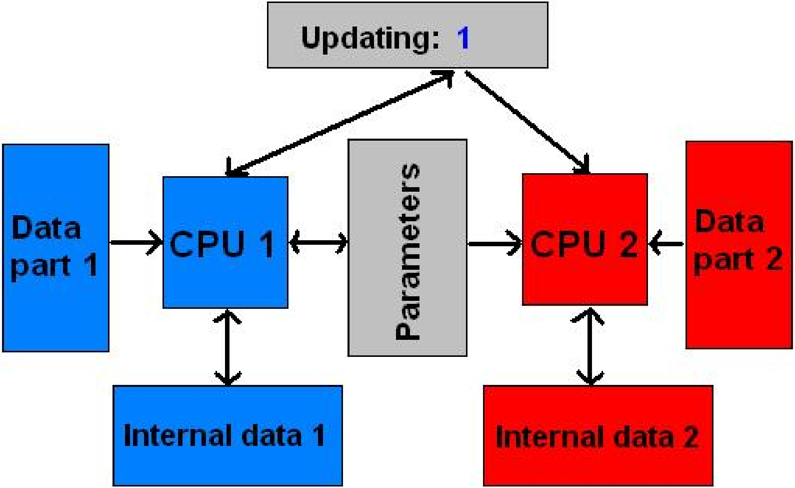
Proposed method gives good speed-up in terms of raw "samples/s" speed (e.g.: x13 with 16 CPUs).

Forking

Forking a program creates multiple copies of the program. Memory is duplicated, except for *shared memory*.

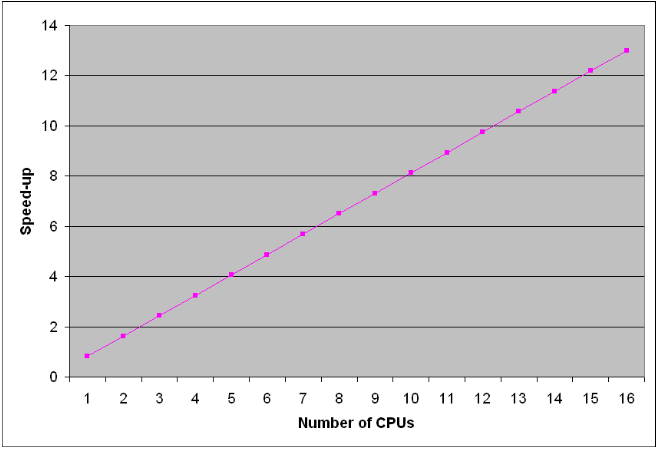


The Big Picture



Virtual Speed-Up

The speed at which training examples are processed increases (about) linearly with the number of CPUs.



True Speed-Up

In practice, the frequency of updates is decreased $\Rightarrow$ lower speed of convergence.

Suggested experimental setting:

True Speed-Up

In practice, the frequency of updates is decreased $\Rightarrow$ lower speed of convergence.

Suggested experimental setting:

- Identify target training error e from simple experiments

True Speed-Up

In practice, the frequency of updates is decreased $\Rightarrow$ lower speed of convergence.

Suggested experimental setting:

- Identify target training error e from simple experiments
- For each number of CPUs c, measure the amount of time needed to reach error e

True Speed-Up

In practice, the frequency of updates is decreased $\Rightarrow$ lower speed of convergence.

Suggested experimental setting:

- Identify target training error e from simple experiments
- For each number of CPUs c, measure the amount of time needed to reach error e

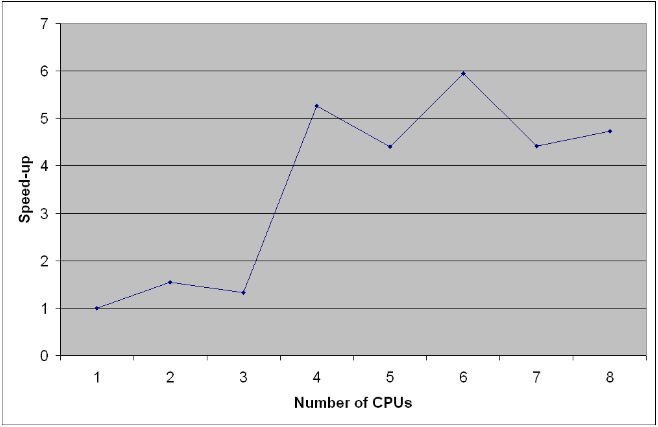
Note that hyper-parameters (learning rate and mini-batch size in particular) need to be re-optimized for each value of c.

Experiment

- Letter recognition dataset from UCI machine learning repository
- 15000 training samples, 16-dimensional input, 26 classes
- Target NLL: 0.11
- Constant network architecture (300 hidden neurons)
- Find optimal fixed learning rate and mini-batch size

Joke

Joke



Discussion, Conclusion, Future Work and *Clap Clap*

Discussion, Conclusion, Future Work and *Clap Clap*

- My code is likely buggy!

Discussion, Conclusion, Future Work and *Clap Clap*

- My code is likely buggy!
- Funny things can happen in parallel code

Discussion, Conclusion, Future Work and *Clap Clap*

- My code is likely buggy!
- Funny things can happen in parallel code
- Optimization sensitive to noise $\Rightarrow$ should use different seeds

Discussion, Conclusion, Future Work and *Clap Clap*

- My code is likely buggy!
- Funny things can happen in parallel code
- Optimization sensitive to noise $\Rightarrow$ should use different seeds
- Should also introduce and optimize a learning rate decrease constant

Discussion, Conclusion, Future Work and *Clap Clap*

- My code is likely buggy!
- Funny things can happen in parallel code
- Optimization sensitive to noise $\Rightarrow$ should use different seeds
- Should also introduce and optimize a learning rate decrease constant
- Use more light-weight parallelization? (pthreads?)

Discussion, Conclusion, Future Work and *Clap Clap*

- My code is likely buggy!
- Funny things can happen in parallel code
- Optimization sensitive to noise $\Rightarrow$ should use different seeds
- Should also introduce and optimize a learning rate decrease constant
- Use more light-weight parallelization? (pthreads?)
- What about large clusters? (MPI)