Lecture 7 - Distributed ML

Source of original slides: Joseph Gonzales

What is the Problem Being Solved?

- Training models is time consuming
  - Convergence can be slow
  - Training is computationally intensive
- Not all models fit in single machine or GPU memory
- Less of a problem: big data
  - Problem for data preparation / management
  - Not a problem for training … why?

How do we measure success of large scale ML?

- **Machine Learning:** Minimize passes through the training data
  - Easy to measure, but not informative … why?
- **Systems:** minimize time to complete a pass through the training data
  - Easy to measure, but not informative … why?

Ideal Metric of Success

How do we measure Learning?

$$\left(\frac{\text{“Learning”}}{\text{Second}}\right) = \left(\frac{\text{“Learning”}}{\text{Record}}\right) \times \left(\frac{\text{Record}}{\text{Second}}\right)$$

Convergence
Machine Learning
Property

Throughput
System
Property

Key Problems Addressed in DistBelief Paper

Main Problem

- **Speedup training** for **large models**

Sub Problems

- How to partition models and data
- Variance in worker performance → Stragglers
- Failures in workers → Fault-Tolerance

Crash course on Stochastic Gradient Descent

The Gradient Descent Algorithm

$\theta^{(0)} \leftarrow$ initial model parameters (random, warm start)

For τ from 1 to convergence:

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \eta_t \left(\frac{1}{n} \sum_{i=1}^{n} \nabla_\theta \mathbf{L}(y_i, f(x_i; \theta)) \Big|_{\theta=\theta^{(t)}} \right)$$

Evaluated at

Learning Rate

Average Gradient of **Over Training Dataset**

How do we distribute this computation?

$\theta^{(0)} \leftarrow$ initial model parameters (random, warm start)

For τ from 1 to convergence:

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \eta_t \left(\frac{1}{n} \sum_{i=1}^{n} \nabla_\theta \mathbf{L}(y_i, f(x_i; \theta)) \Big|_{\theta=\theta^{(t)}} \right)$$

Evaluated at

Learning Rate

Average Gradient of **Over Training Dataset**

How do we distribute this computation?

Data parallelism: *divide data across machines, compute local gradient sums and then aggregate across machines. repeat.*

Issues? Repeatedly scanning the data… what if we cache it?

The empirical gradient is an approximation of what I really want:

$$\frac{1}{n}\sum_{i=1}^{n}\nabla_\theta \mathbf{L}(y_i, f(x_i;\theta)) \approx \mathbb{E}_{(x,y)\sim\mathcal{D}}\left[\nabla_\theta \mathbf{L}(y, f(x;\theta))\right]$$

Law of large numbers → more data provides a better approximation (variance in the estimator decreases linearly)

Do I really need to use all the data?

$$\frac{1}{n}\sum_{i=1}\nabla_\theta \mathbf{L}(y_i, f(x_i;\theta)) \approx \frac{1}{|\mathcal{B}|}\sum_{i\in\mathcal{B}}\nabla_\theta \mathbf{L}(y_i, f(x_i;\theta))$$

Random subset of the data

Small B: fast but less accurate
Large B: slower but more accurate

Assuming Decomposable Loss Functions

Gradient Descent

$\theta^{(0)} \leftarrow$ initial vector (random, zeros …)

For t from 1 to convergence:

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \eta_t\left(\frac{1}{n}\sum_{i=1}^{n}\nabla_\theta \mathbf{L}(y_i, f(x_i;\theta))\Big|_{\theta=\theta^{(t)}}\right)$$

Stochastic Gradient Descent

$\theta^{(0)} \leftarrow$ initial vector (random, zeros …)

For t from 0 to convergence:

$\mathcal{B} \sim$ Random subset of indices

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \eta_t\left(\frac{1}{|\mathcal{B}|}\sum_{i\in\mathcal{B}}\nabla_\theta \mathbf{L}(y_i, f(x_i;\theta))\Big|_{\theta=\theta^{(t)}}\right)$$

How do you distribute SGD?

Stochastic Gradient Descent

$\theta^{(0)} \leftarrow$ initial vector (random, zeros …)

For t from 0 to convergence:

$$\mathcal{B} \sim \text{Random subset of indices}$$

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \eta_t \left(\frac{1}{|\mathcal{B}|} \sum_{i \in \mathcal{B}} \nabla_\theta \mathbf{L}(y_i, f(x_i; \theta)) \Big|_{\theta = \theta^{(t)}} \right)$$

Model Parallelism

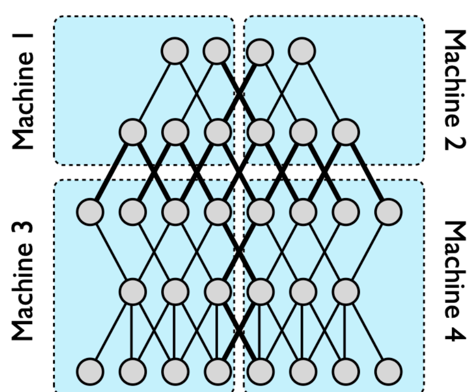
Speed up Gradient. Depends on Model

Data Parallelism

Speed up Sum. Depends on size of B

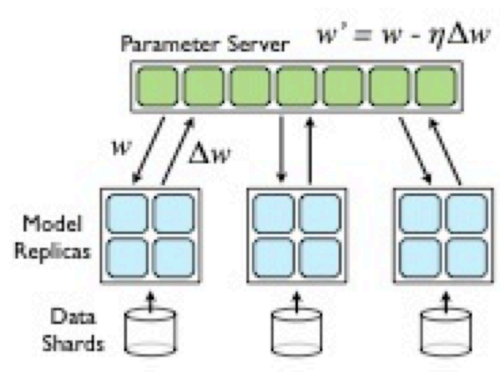
Combine Model and Data Parallelism

Model Parallelism



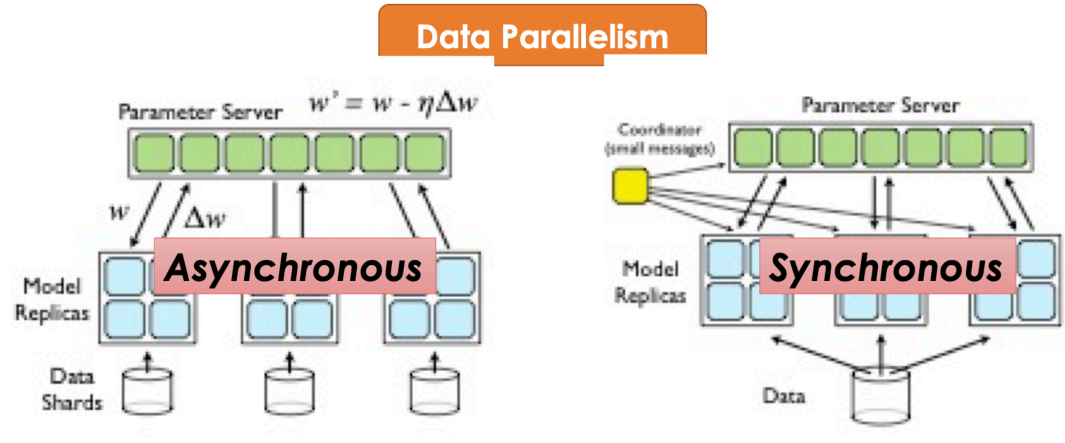
This appears in earlier work on graph systems …

Data Parallelism



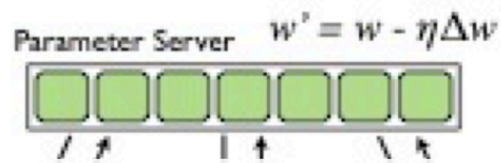
Downpour SGD

Combine Model and Data Parallelism



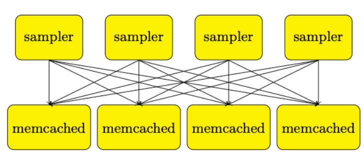
Downpour SGD ***Sandblaster L-BFGS***

Parameter Servers

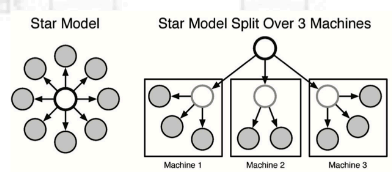


- Essentially a **sharded** key-value store
  - support for put, get, **add**
- Idea appears in earlier papers:

"An Architecture for Parallel Topic Models", Smola and Narayanamruthy. (VLDB'10)



"Scalable Inference in Latent Variable Models", Ahmed, Aly, **Gonzalez**, Narayanamruthy, and Smola. (WSDM'12)



DistBelief was probably the first paper to call a sharded key-value store a Parameter Server.

How do you distribute SGD?

Stochastic Gradient Descent

$\theta^{(0)} \leftarrow$ initial vector (random, zeros …)

For t from 0 to convergence:

$$\mathcal{B} \sim \text{ Random subset of indices}$$

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \eta_t \left(\frac{1}{|\mathcal{B}|} \sum_{i \in \mathcal{B}} \nabla_\theta \mathbf{L}(y_i, f(x_i; \theta)) \Big|_{\theta = \theta^{(t)}} \right)$$

Data Parallelism

Slow? (~150ms)
Depending on size of B

Batch Size Scaling

- Increase the batch size by adding machines

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \hat{\eta} \left(\frac{1}{k} \sum_{j=1}^{k} \frac{1}{|\mathcal{B}_j|} \sum_{i \in \mathcal{B}_j} \nabla_\theta \mathbf{L}(y_i, f(x_i; \theta)) \Big|_{\theta = \theta^{(t)}} \right)$$

- Each server processes a fixed batch size (e.g., n=32)
- As more servers are added (k) the effective overall batch size increases linearly
- Why do these additional servers help?

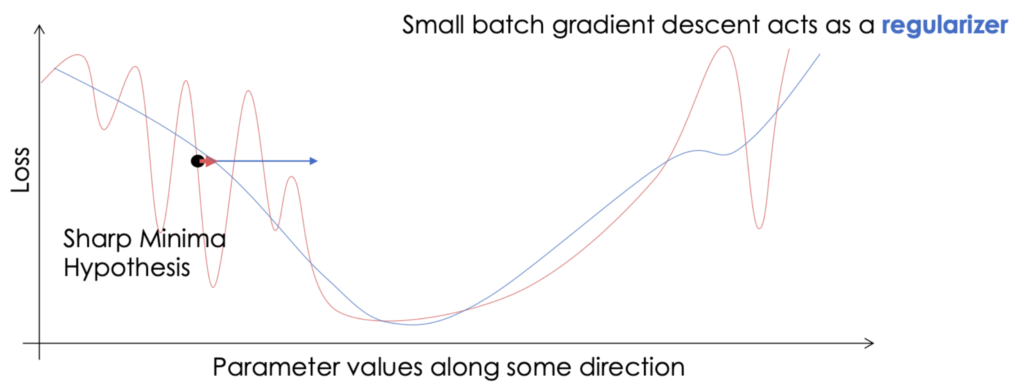
Bigger isn't Always Better

- Motivation for larger batch sizes
  - More opportunities for parallelism → but is it useful?
  - Recall (1/n variance reduction):

$$\frac{1}{n}\sum_{i=1}\nabla_\theta \mathbf{L}(y_i, f(x_i;\theta)) \approx \frac{1}{|\mathcal{B}|}\sum_{i\in\mathcal{B}}\nabla_\theta \mathbf{L}(y_i, f(x_i;\theta))$$

- Is a variance reduction helpful?
  - Only if it let's you take bigger steps (move faster)
  - Doesn't affect the final answer…

Rough "Intuition"



Key problem: *Addressing the generalization gap for large batch sizes.*

Solution: Linear Scaling Rule

- Scale the learning rate linearly with the batch size

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \overset{=\eta k}{\hat{\eta}} \left(\frac{1}{k} \sum_{j=1}^{k} \frac{1}{|\mathcal{B}_j|} \sum_{i \in \mathcal{B}_j} \nabla_\theta \mathbf{L}(y_i, f(x_i; \theta)) \Big|_{\theta=\theta^{(t)}} \right)$$

- Addresses generalization performance by **taking larger steps** (also improves training convergence)

- **Sub-problem:** *Large learning rates can be destabilizing in the beginning.* Why?
  - **Gradual warmup solution:** increase learning rate scaling from constant to linear in first few epochs
  - Doesn't help for very large k…