FUNDAMENTALS OF DEEP LEARNING FOR MULTI-GPUS LAB 1, PART 1: INTRODUCTION AND MOTIVATION



COURSE OVERVIEW

- Lab 1: Gradient Descent vs Stochastic Gradient Descent, and the Effects of Batch Size
- Lab 2: Multi-GPU DL Training Implementation using Horovod
- Lab 3: Algorithmic Concerns for Training at Scale

LAB 1 OVERVIEW

- Part 1: Gradient Descent
- Part 2: Stochastic Gradient Descent
- Part 3: Optimizing training with batch size

CONTEXT: WHY USE MULTIPLE GPUS?

TRENDS IN COMPUTATIONAL POWER

Historically we never had large datasets or compute





TRENDS IN COMPUTATIONAL POWER

2 PF/s in November 2009





TRENDS IN COMPUTATIONAL POWER 2 PF/s today



NEURAL NETWORK COMPLEXITY IS EXPLODING

To Tackle Increasingly Complex Challenges

7 Exaflops 60 Million Parameters



2015 - Microsoft ResNet Superhuman Image Recognition

20 Exaflops 300 Million Parameters



2016 - Baidu Deep Speech 2 Superhuman Voice Recognition

100 Exaflops 8700 Million Parameters



2017 - Google Neural Machine Translation Near Human Language Translation

100 EXAFLOPS = O(1 YEAR) ON A DUAL CPU SERVER

EXPLODING DATASETS

Power-law relationship between dataset size and accuracy





EXPLODING DATASETS

Power-law relationship between dataset size and accuracy

Character Language Models

Attention Speech Models

208 Hidden

512 Hidden

 $\varepsilon_{208}(m) = 41.2 \ m^{-0.36} + 0.39$

224

2²⁵

2²⁶

--- 208 Hidden Trend

--- 512 Hidden Trend

227

Translation

Language Models

 $\varepsilon_{512}(m) = 21.5 \ m^{-0.30} + 0.32$

2²²

2²³

Training Data Set Size, Number of Tokens (Log-scale)

Image Classification

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0.67

0.62

ິຜິ 0.58

0.54

ಕ 0.51

5 0.48

Ξ Σ 0.44

0.41

220

 2^{21}

e)

g



Hestness, J., et al. (2017). Deep Learning Scaling is Predictable, Empirically. <u>arXiv: 1712.00409</u>







EXPLODING MODEL COMPLEXITY

Though model size scales sublinearly





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EXPLODING MODEL COMPLEXITY

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LEARNING

DVIDIA

Zoph, Barret, et al. (2017). "Learning transferable architectures for scalable image recognition." arXiv: 1707.07012

IMPLICATIONS

IMPLICATIONS Good and bad news

- The good news: Requirements are predictable.
 - We can predict how much data we will need.
 - We can predict how much computing power we will need.

- The bad news: The values can be significant.
 - The silver lining is that deep learning has taken impossible problems and made them merely expensive.



IMPLICATIONS

Deep learning is experimental; we need to train quickly to iterate





ITERATION TIME

Short iteration time is fundamental for success



ITERATION TIME

Short iteration time is fundamental for success

ResNet-50 training time in minutes



INTRO TO THE LAB

STARTING WITH A LINEAR MODEL

Our goal is to find best model parameters (combination of w and b) to fit the data









DEEP LEARNING INSTITUTE

www.nvidia.com/dli