DATA PARALLELISM: HOW TO TRAIN DEEP LEARNING MODELS ON MULTIPLE GPUS

LAB 1, PART 1: INTRODUCTION AND MOTIVATION

NVIDIA | DEEP LEARNING INSTITUTE

COURSE OVERVIEW

- Lab 1: Gradient Descent vs Stochastic Gradient Descent, and the Effects of Batc Size
- Lab 2: Multi-GPU DL Training Implementat using DistributedDataParallel (DDP)
- Lab 3: Algorithmic Concerns for Training a Scale

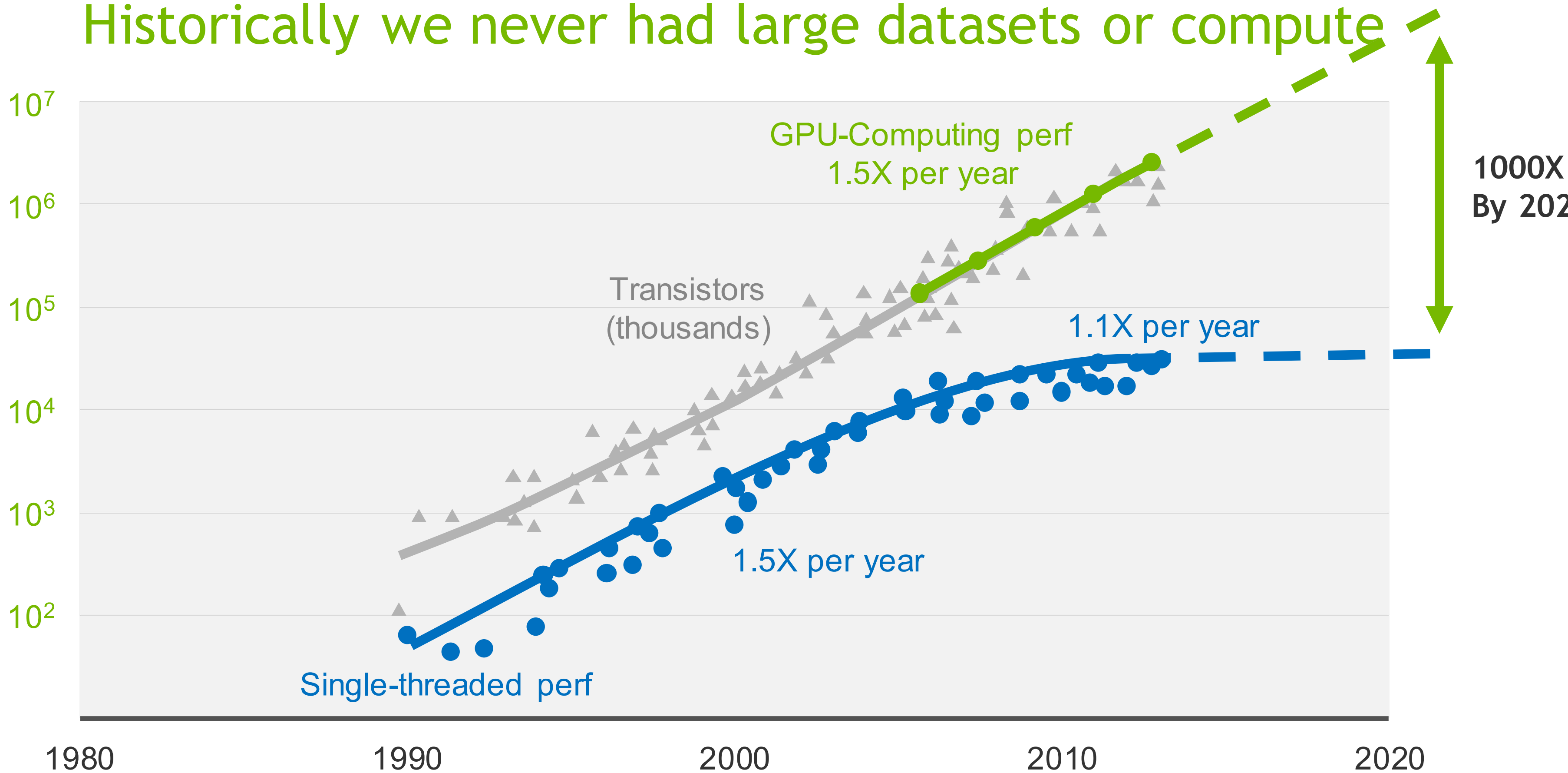
LAB 1 OVERVIEW

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

CONTEXT: WHY USE MULTIPLE GPUS?

TRENDS IN COMPUTATIONAL POWER

Historically we never had large datasets or compute



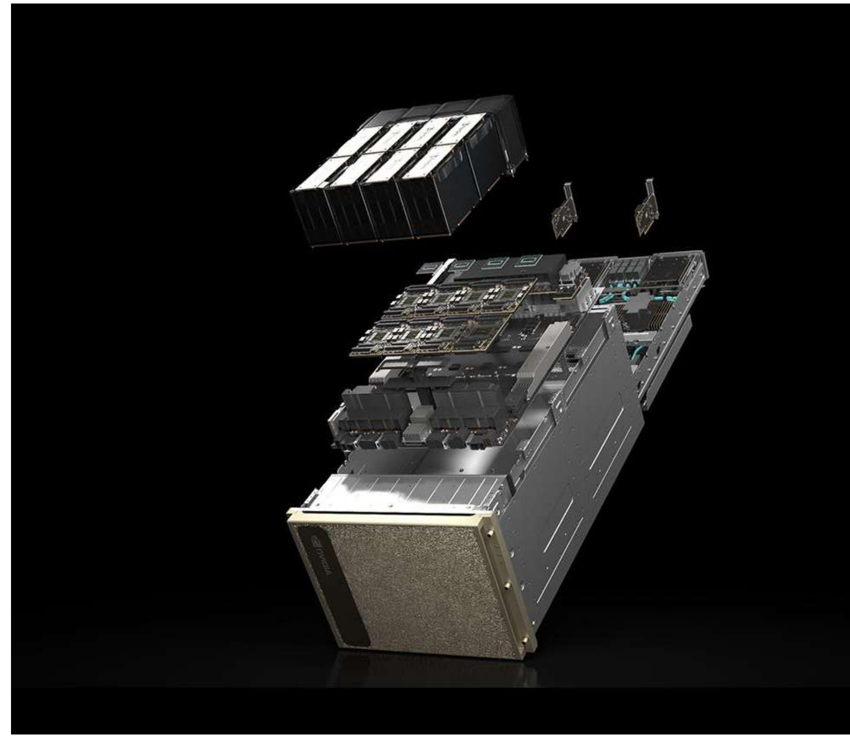
TRENDS IN COMPUTATIONAL POWER

2 PF/s in November 2009

TRENDS IN COMPUTATIONAL POWER

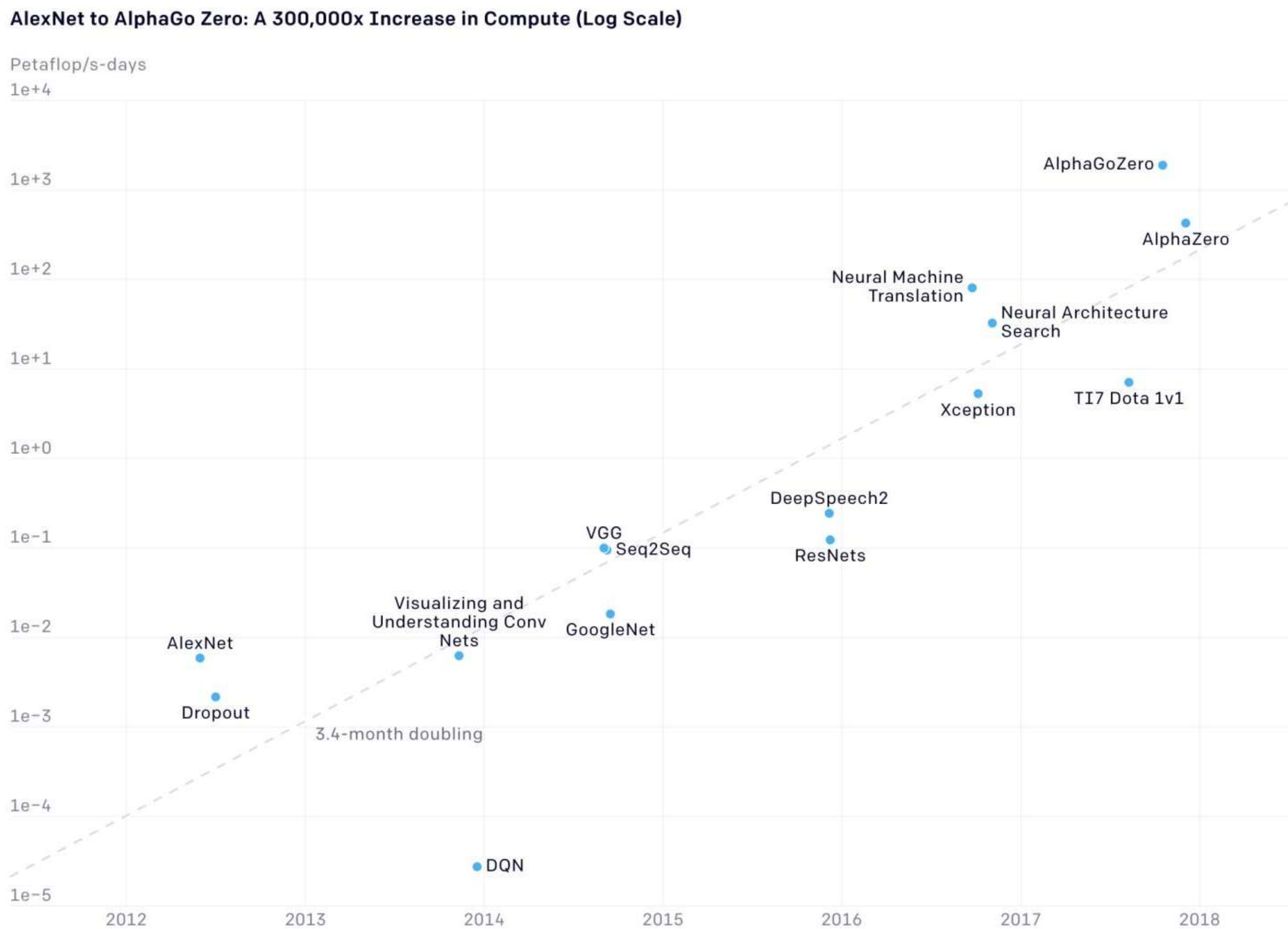
32 PF/s today

- 8x NVIDIA H100 GPUs With 640 Gigabytes of Total GPU Memory
  - 18x NVIDIA NVLink connections per GPU
  - 900 gigabytes per second of bidirectional GPU-to-GPU bandwidth
  - 24 TB/s memory bandwidth
- 4x NVIDIA NVSwitches
  - 7.2 terabytes per second of bidirectional GPU-to-GPU bandwidth
- 10x NVIDIA ConnectX-7 400 Gigabits-Per-Second Network Interface
  - 1 terabyte per second of peak bidirectional network bandwidth
- Dual x86 CPUs and 2 Terabytes of System Memory
  - Powerful CPUs and massive system memory for the most intensive AI jobs
- 32 petaFLOPS AI performance



NVIDIA DGX H100

NEURAL NETWORK COMPLEXITY IS EXPLODING



Source:

1000 PETAFLOP/S-DAYS

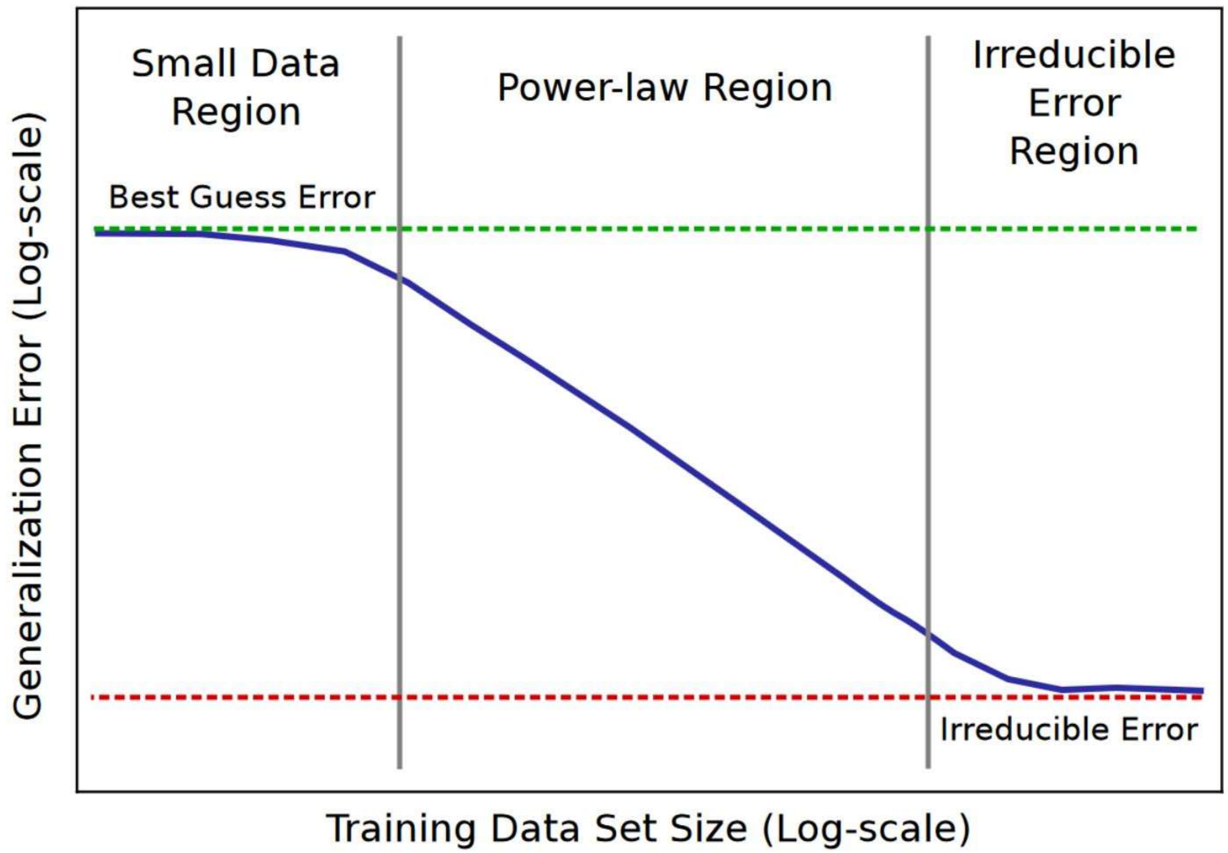
O(100 YEARS) ON A DUAL CPU SERVER

OR

O(30 DAYS) DGX H100

EXPLODING DATASETS

Power-law relationship between dataset size and accuracy



Hestness, J., et al. (2017). Deep Learning Scaling is Predictable, Empirically. [arXiv: 1712.00409]

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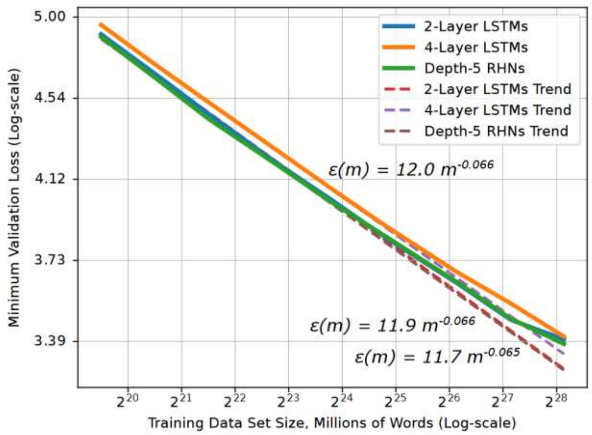
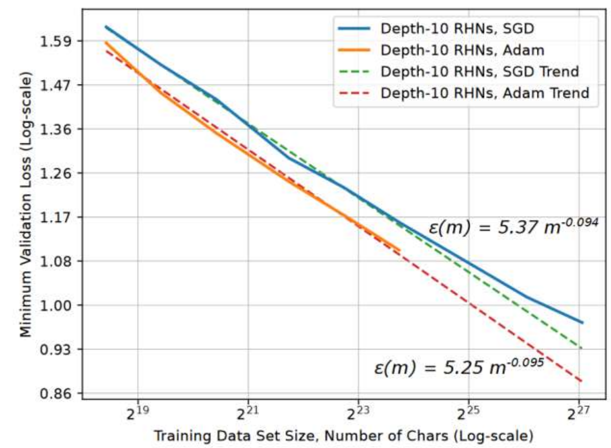
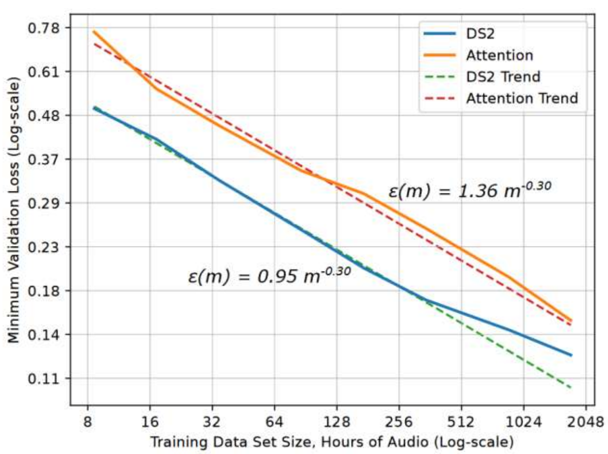
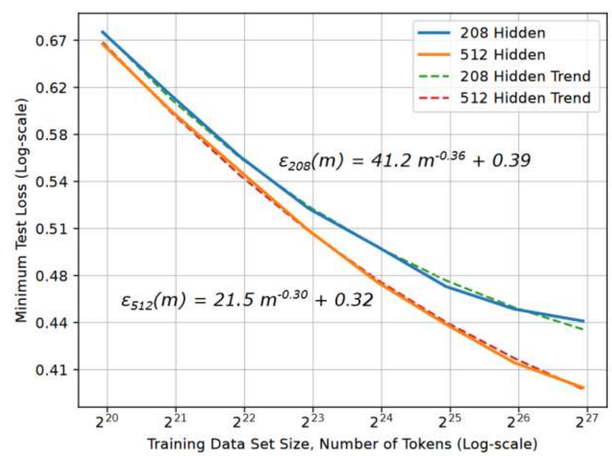
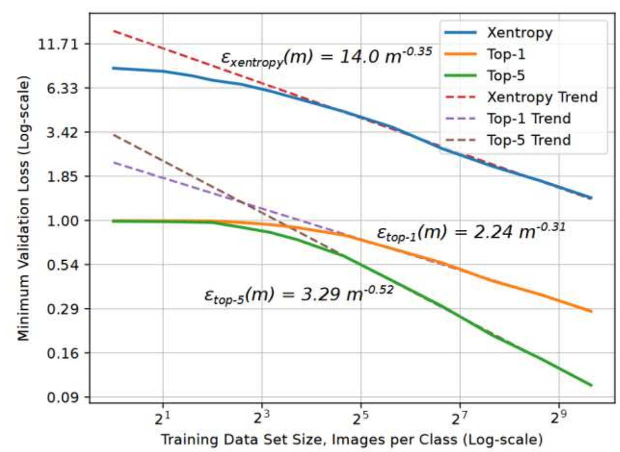


- Translation
- Language Models
- Character Language Models
- Image Classification
- Attention Speech Models









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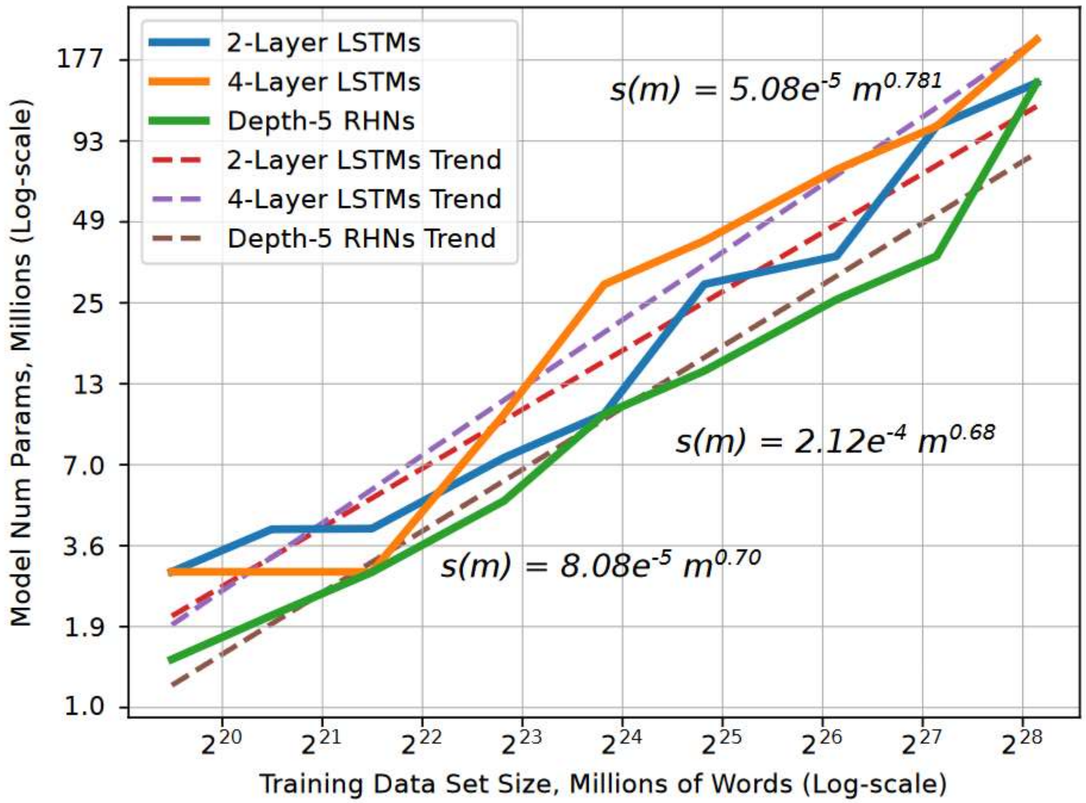
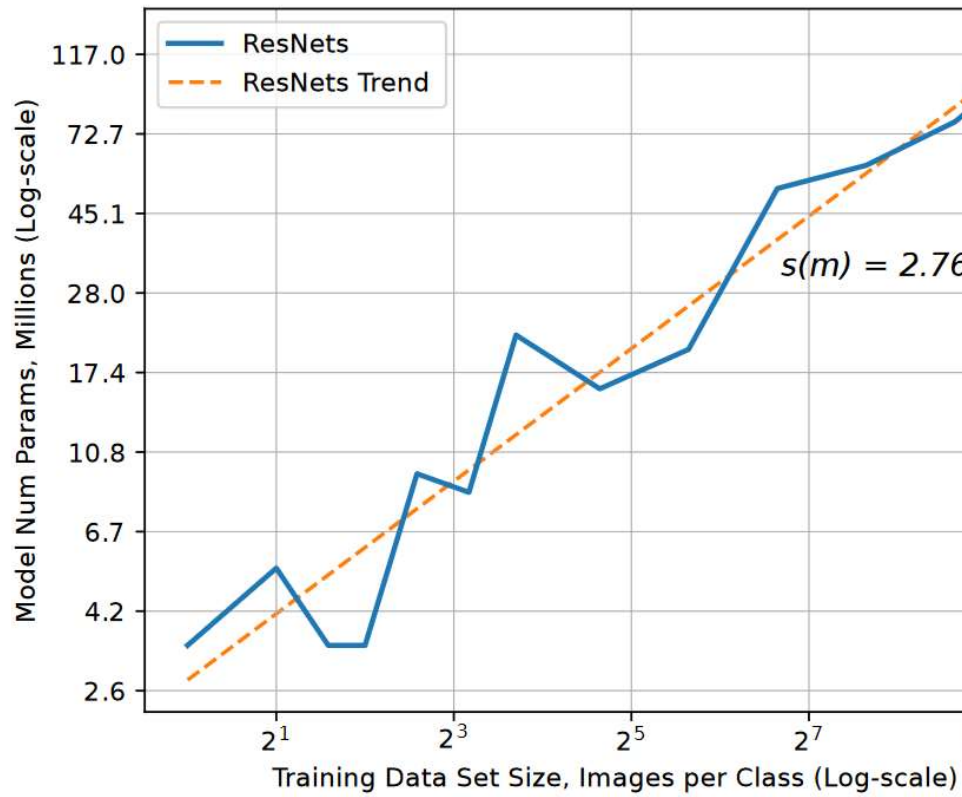
EXPLODING MODEL COMPLEXITY

Though model size scales sublinearly





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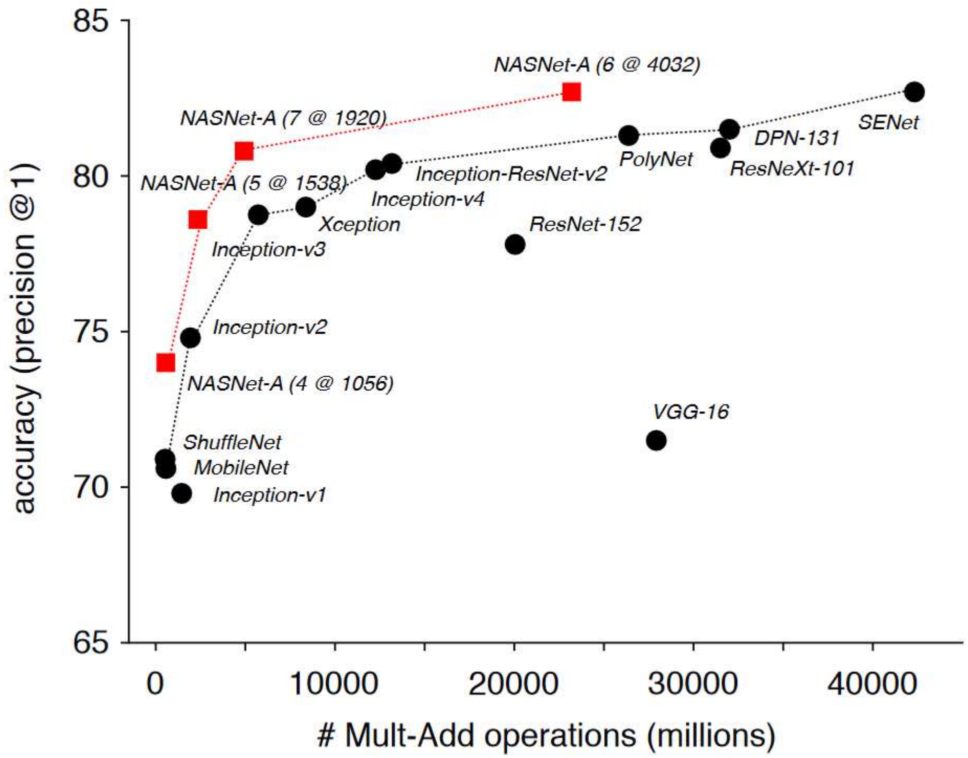

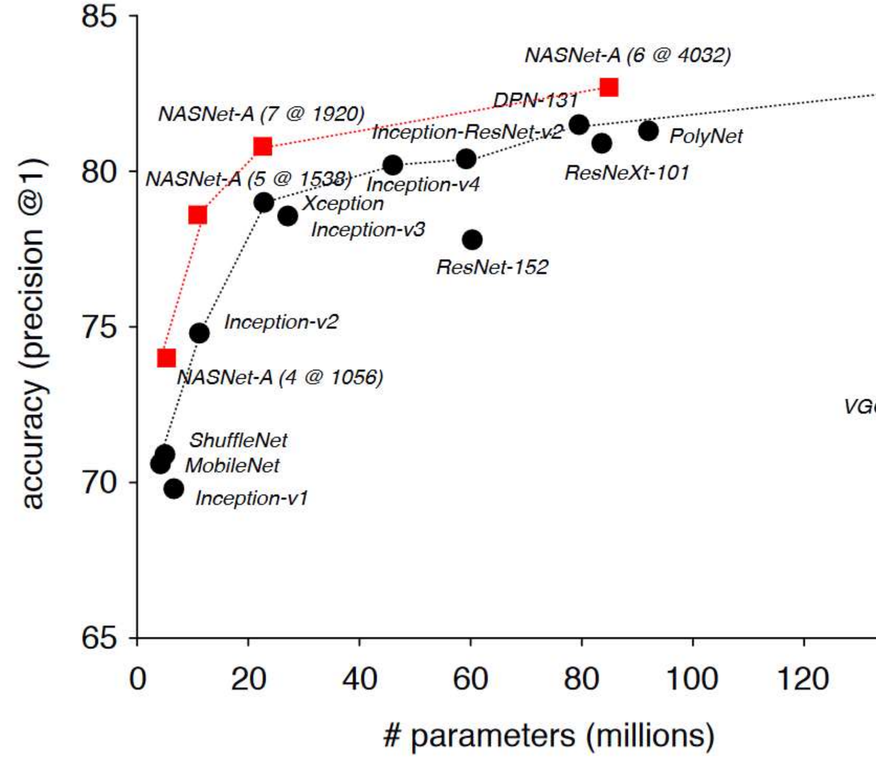

Zoph, Barret, et al. (2017). "Learning transferable architectures for scalable image recognition." [arXiv: 1707.07012]

IMPLICATIONS

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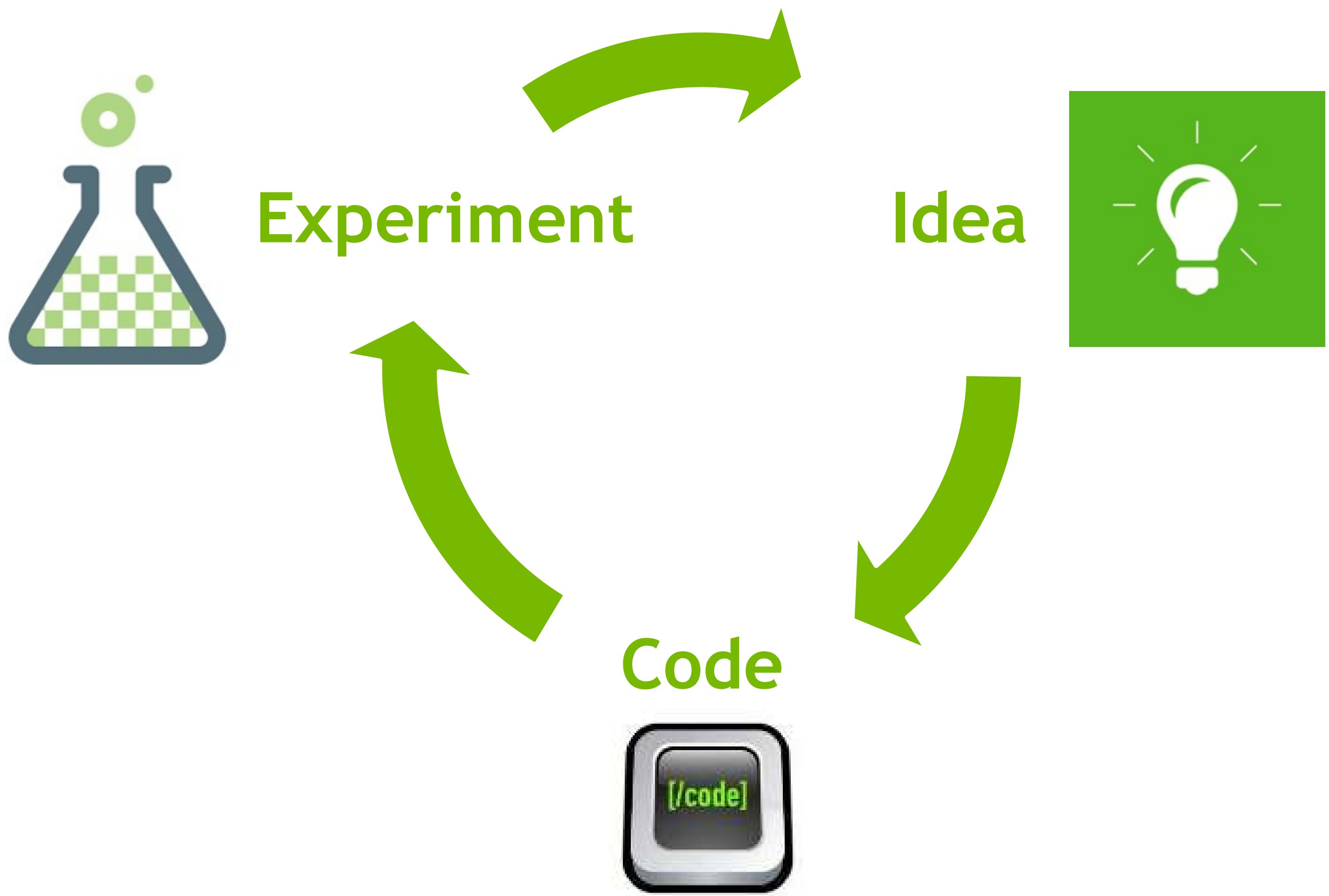
Good and bad news

- 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 ma
    them merely expensive.

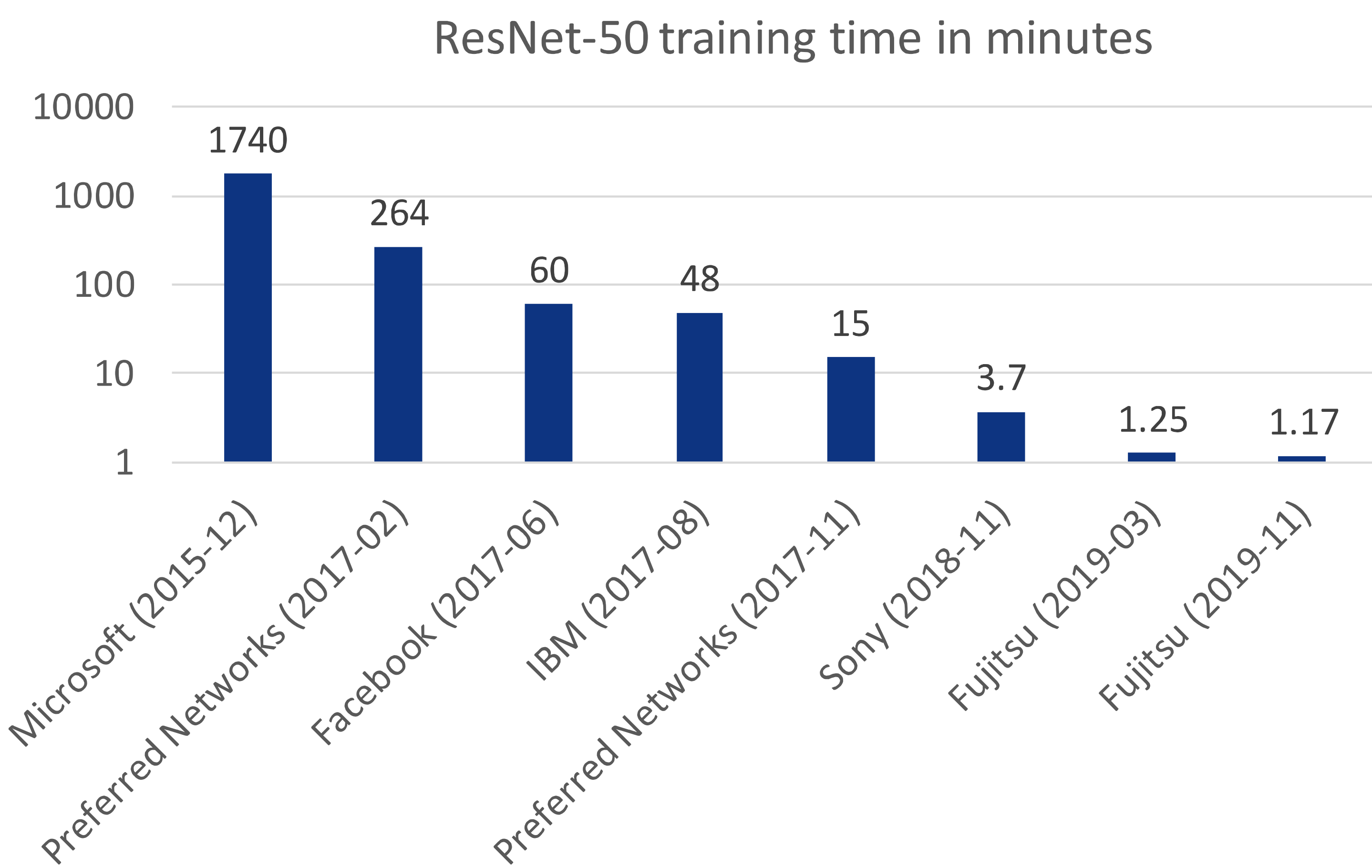
IMPLICATIONS

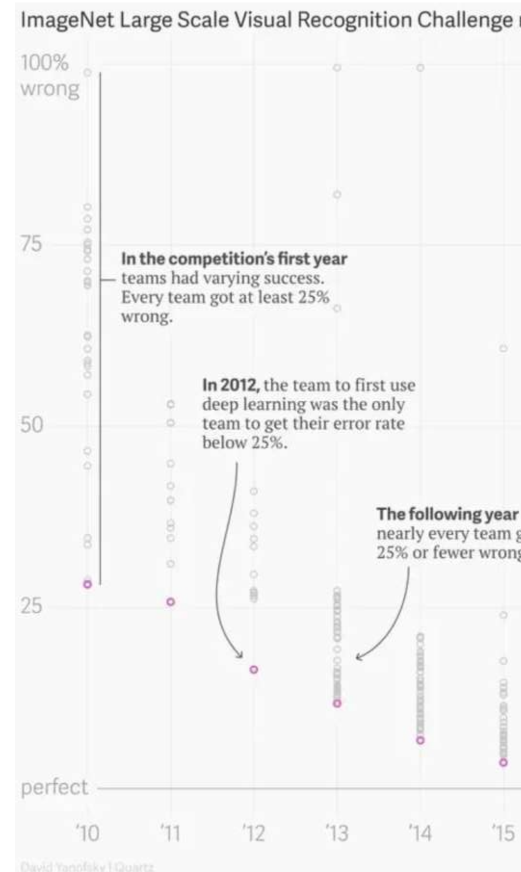
Deep learning is experimental; we need to train quickly to iterate



ITERATION TIME

Short iteration time is fundamental for success

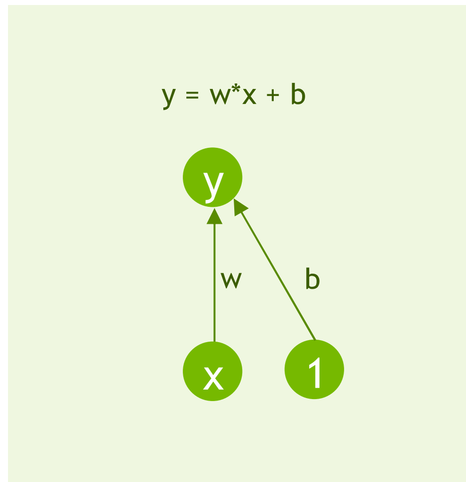


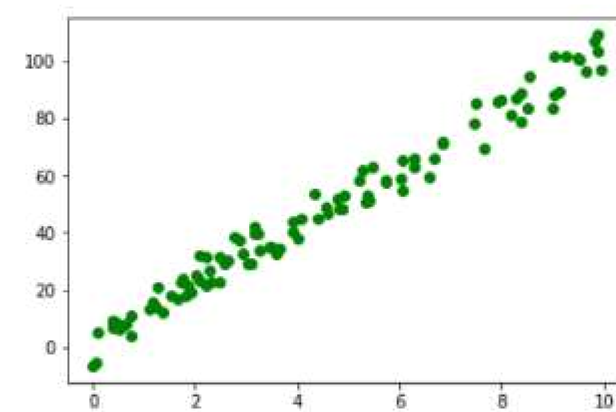


INTRO TO THE LAB

STARTING WITH A LINEAR MODEL

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





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