Scaling Deep Learning

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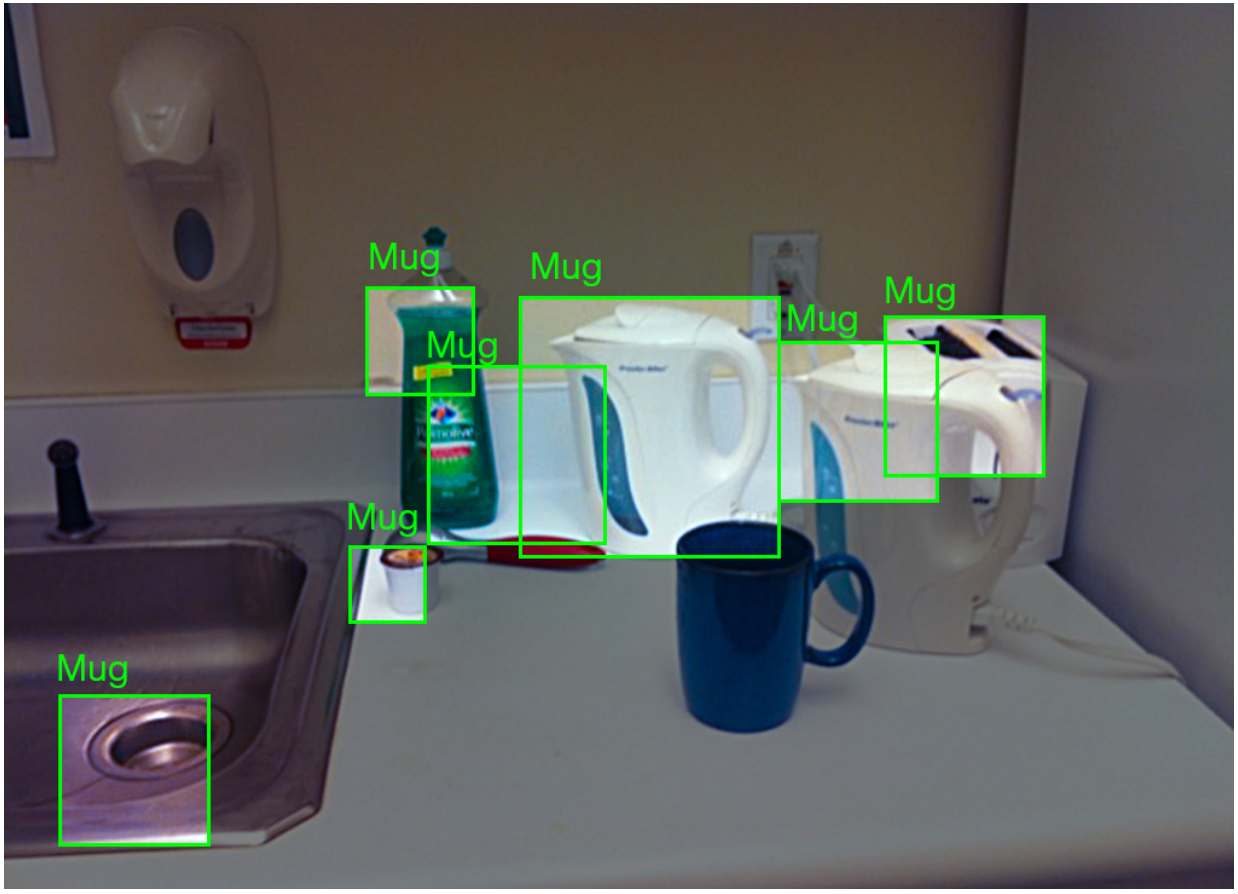
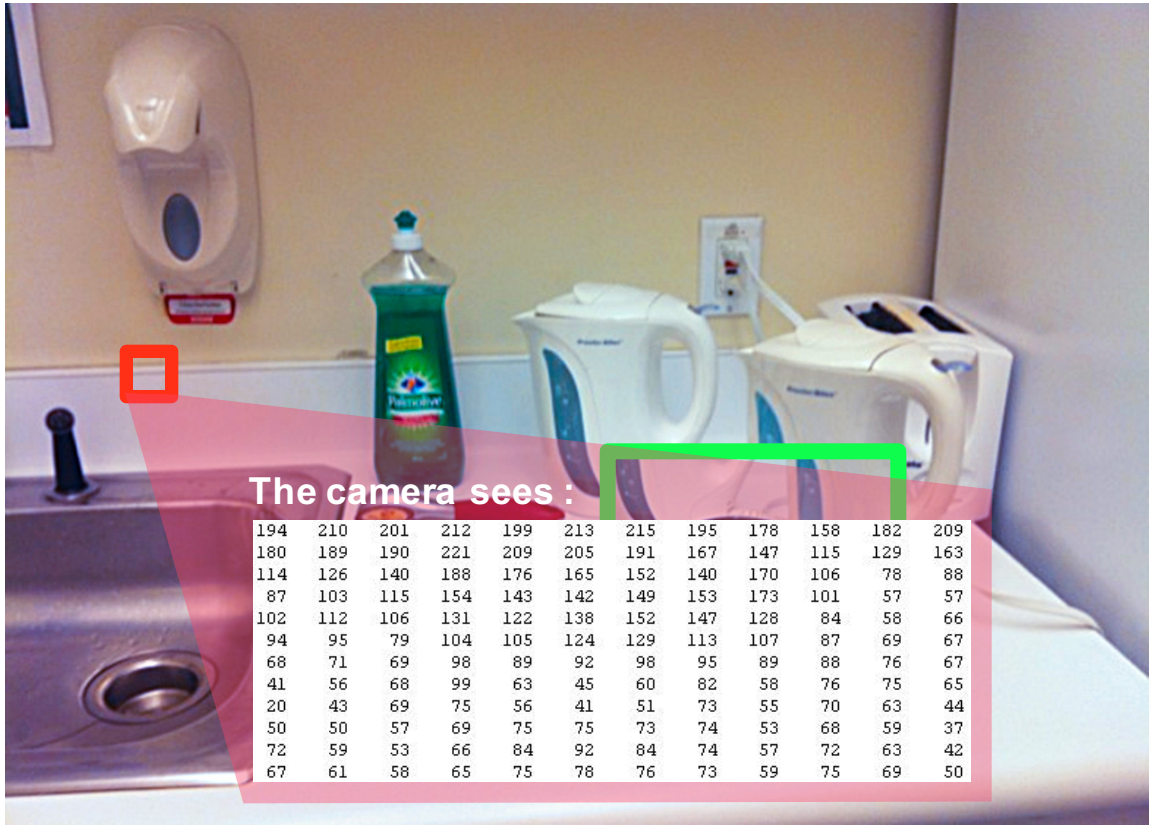
Baidu Research

Computer vision: Find coffee mug

Computer vision: Find coffee mug



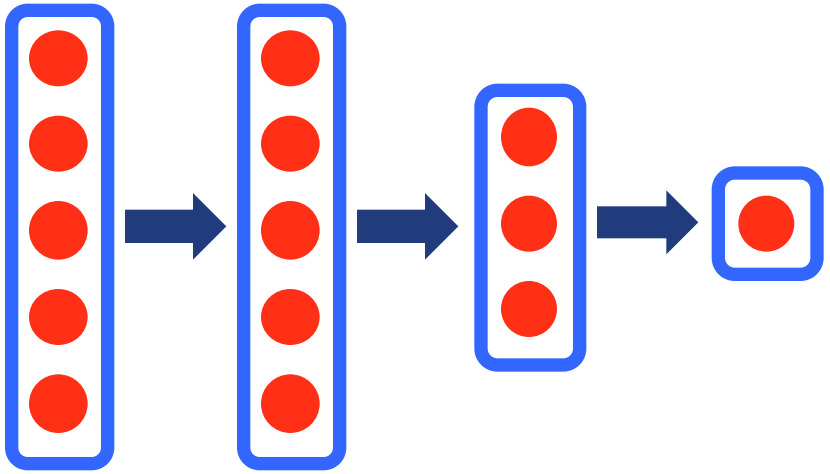
Why is computer vision hard?



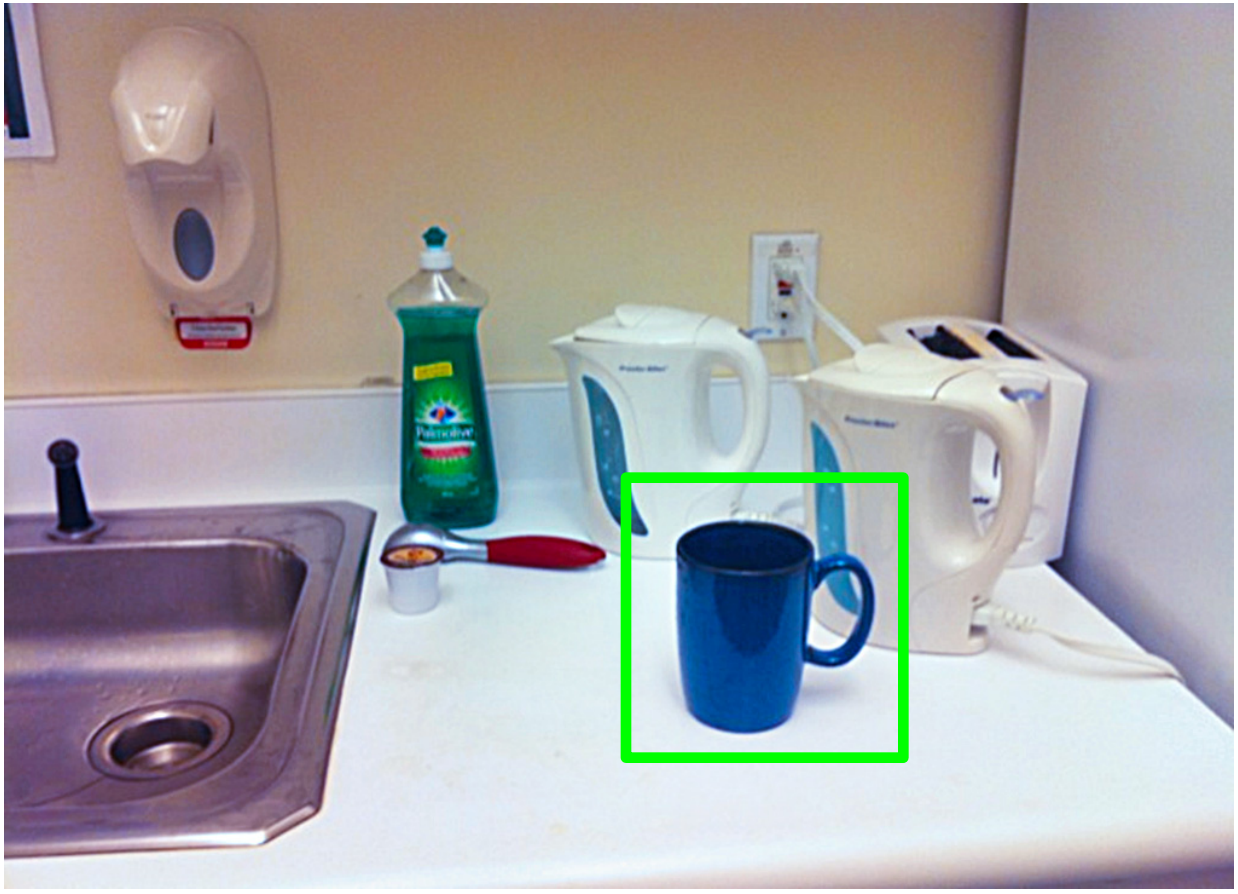
Artificial Neural Networks

Neurons in the brain

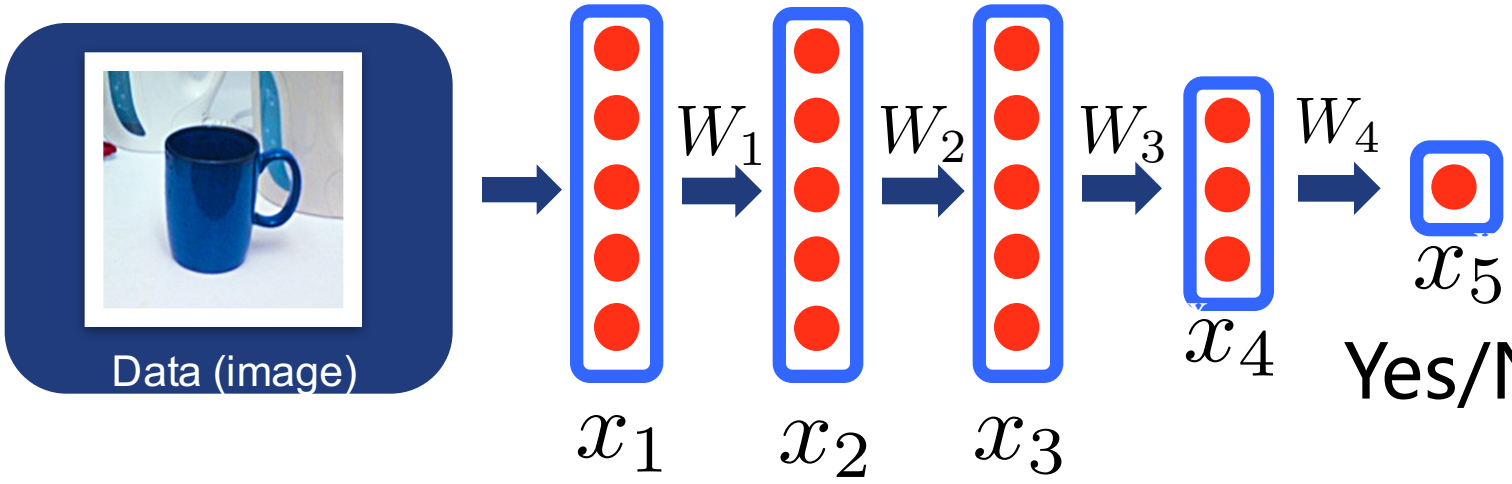
Deep Learning: Neural network



Computer vision: Find coffee mug



What is a neural network?



$$x_1 \in \mathbb{R}^5, x_2 \in \mathbb{R}^5$$
$$x_2 = (W_1 x_1)_+$$
$$x_3 = (W_2 x_2)_+$$

Supervised learning (learning from tagged data)

X → Y

Input Image

Output tag: Yes/No (Is it a coffee mug?)

Data:

Yes

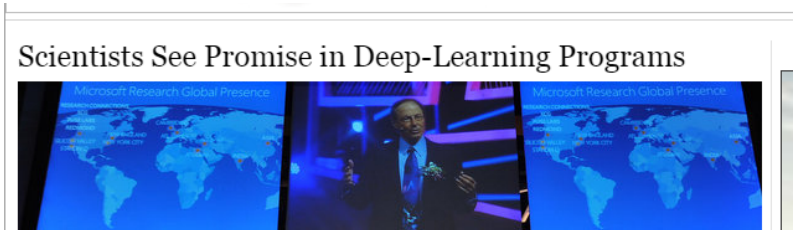
No

Learning X ➡ Y mappings is hugely useful

What do we want AI to do?

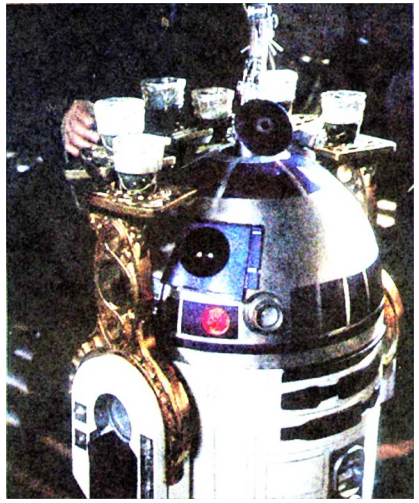
Help us find things

Guide us to content



Keep us organized

Drive us to work



Serve drinks?

Help us communicate

帮助我们沟通

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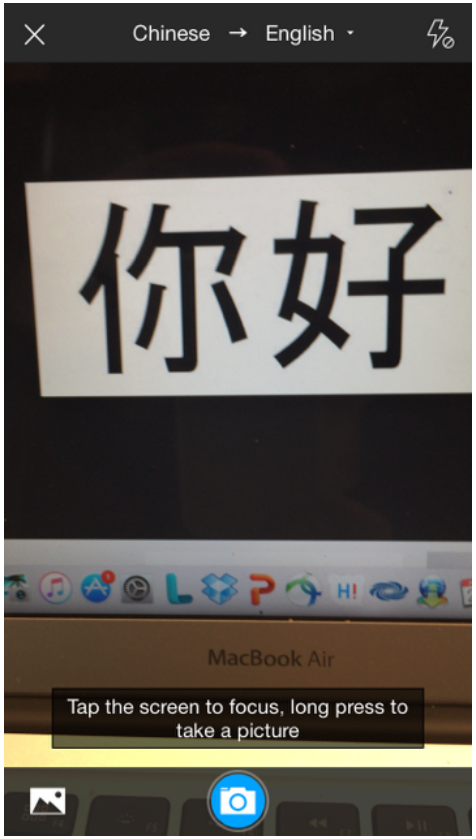
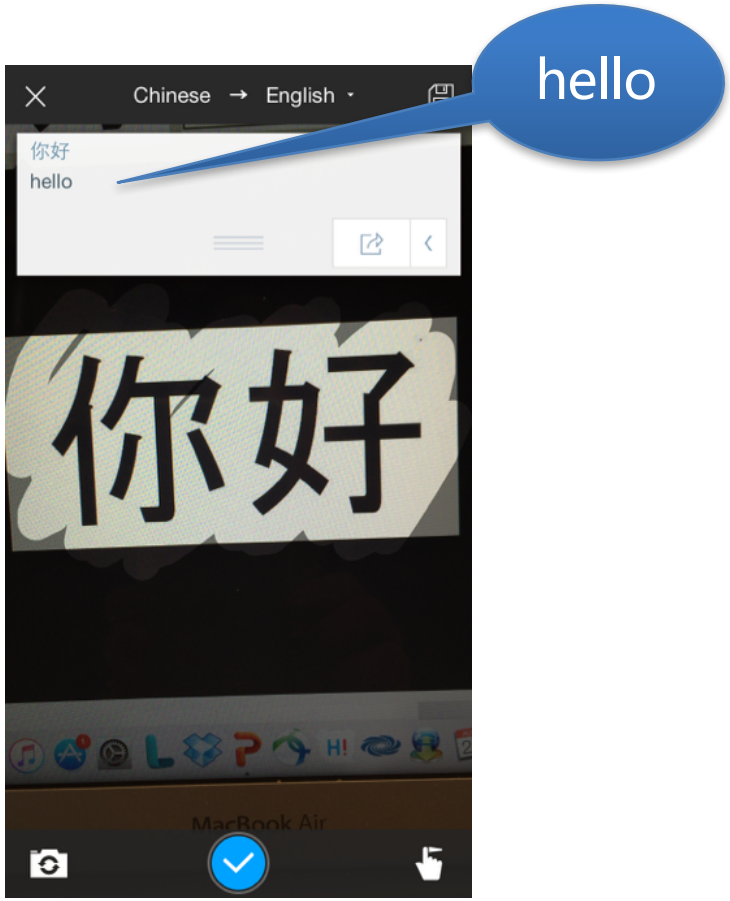
OCR-based Translation App
Baidu IDL





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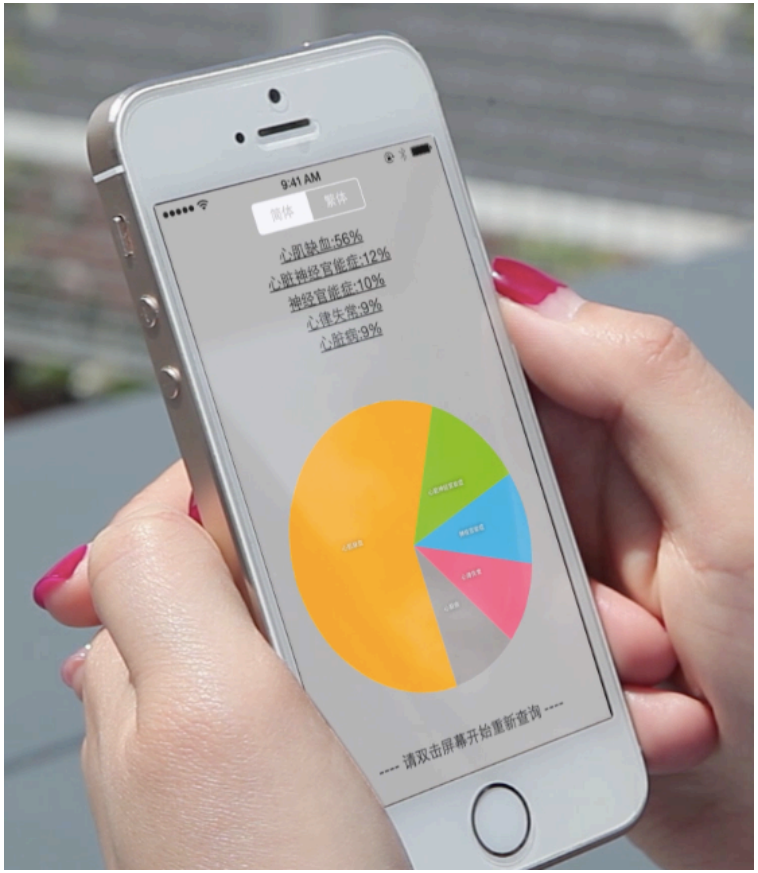
Medical Diagnostics App
Baidu BDL



AskADoctor can assess 520 different diseases, representing ~90 percent of the most common medical problems.

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Image Captioning
Baidu IDL

A yellow bus driving down a road with green trees and green grass in the background.

Living room with white couch and blue carpeting. Room in apartment gets some afternoon sun.

Image Q&A
Baidu IDL

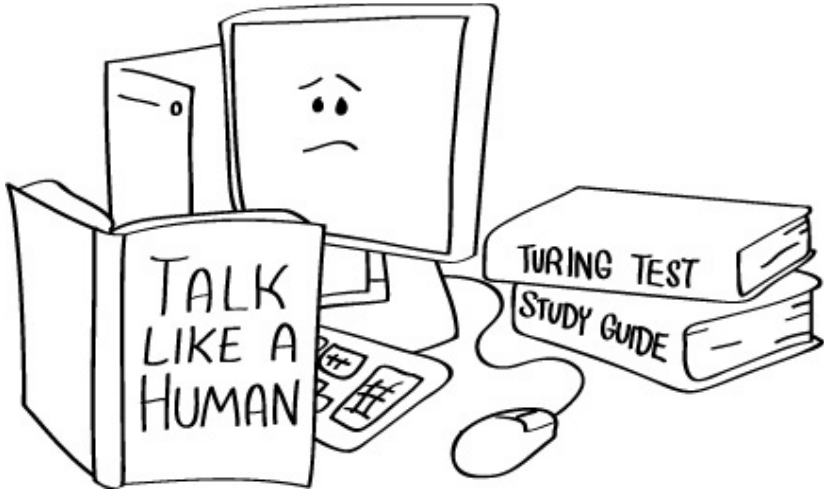
Image			
Question	公共汽车是什么颜色的？ What is the color of the bus?	黄色的是什么？ What is there in yellow?	草地上除了人以外还有什么动物 What is there on the grass, except the person?
Answer	公共汽车是红色的。 The bus is red.	香蕉。 Bananas.	羊。 Sheep.

Sample questions and answers

Natural User Interfaces

- Goal: Make interacting with computers as natural as interacting with humans

- AI problems:
  - **Speech recognition**
  - Emotional recognition
  - Semantic understanding
  - Dialog systems
  - Speech synthesis

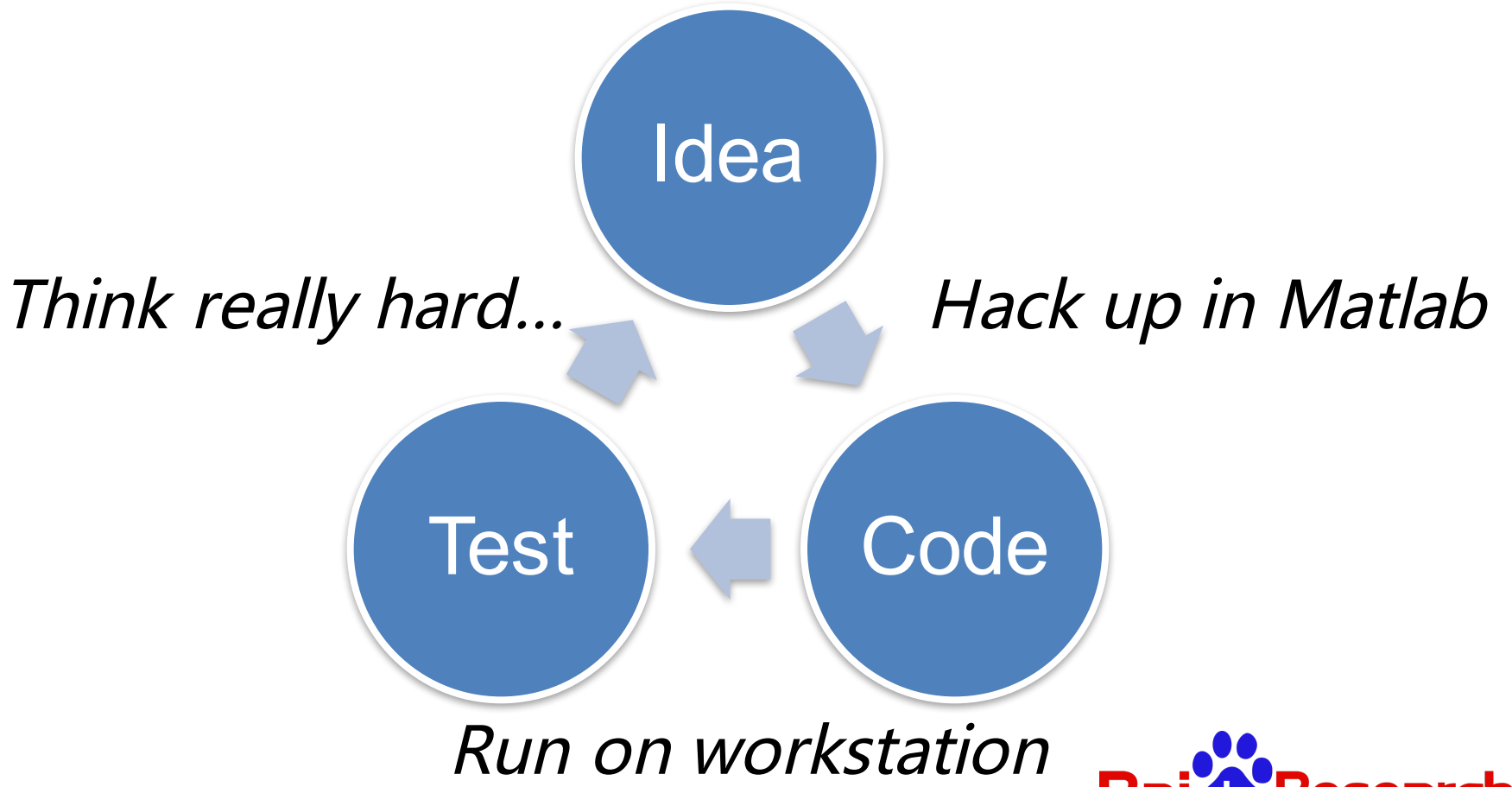


Demo

- Deep Speech public API

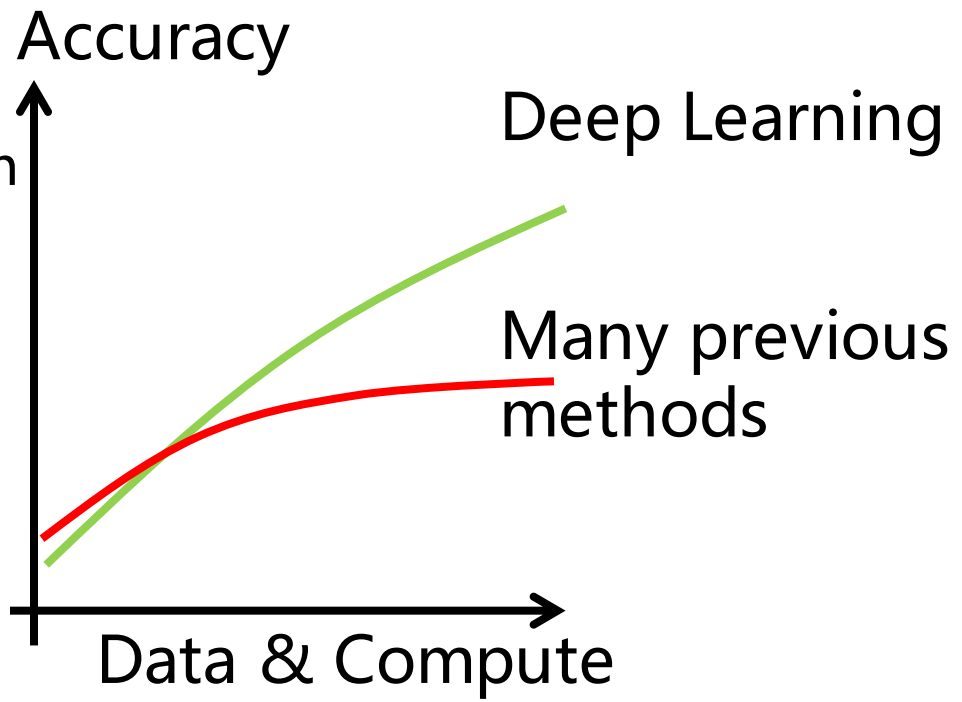
Machine learning in practice

- Enormous amounts of research time spent inventing new features.



Why Deep Learning?

1. Scale Matters
   - Bigger models usually win
2. Data Matters
   - More data means less cleverness necessary
3. Productivity Matters
   - Teams with better tools can try out more ideas

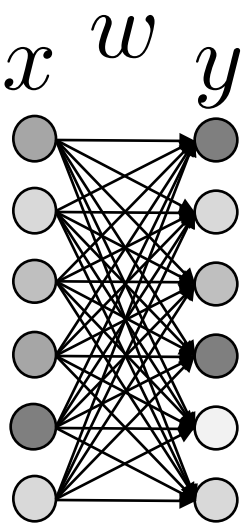


Scaling up

- Make progress on AI by focusing on systems
  - Make models bigger
  - Tackle more data
  - Reduce research cycle time
    - Accelerate large-scale experiments

Training Deep Neural Networks

$$y_j = f\left(\sum_i w_{ij} x_i\right)$$



- Computation dominated by dot products
- Multiple inputs, multiple outputs, batch means GEMM
  - Compute bound
- Convolutional layers even more compute bound

Computational Characteristics

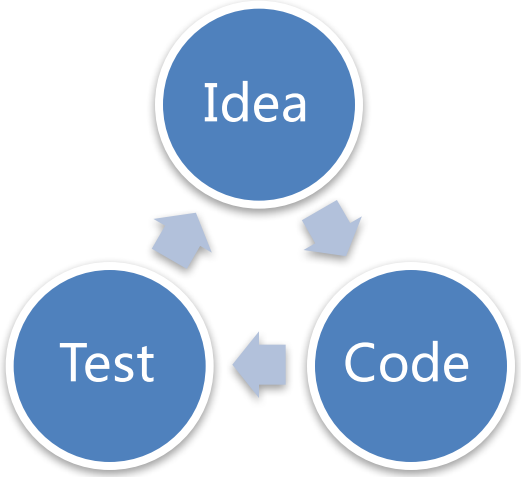
- High arithmetic intensity
  - Arithmetic operations / byte of data
  - O(Exaflops) / O(Terabytes) : 10^6
    - In contrast, some other ML training jobs are O(Petaflops)/O(Petabytes) = 10^0

- Medium size datasets
  - Generally fit on 1 node
  - HDFS, fault tolerance, disk I/O not bottlenecks

Training 1 model: ~20 Exaflops

Deep Neural Network training is HPC

- Turnaround time is key
- Use most efficient hardware
  - Parallel, heterogeneous computing
  - Fast interconnect (PCIe, Infiniband)
- Push strong scalability
  - Models and data have to be of commensurate size

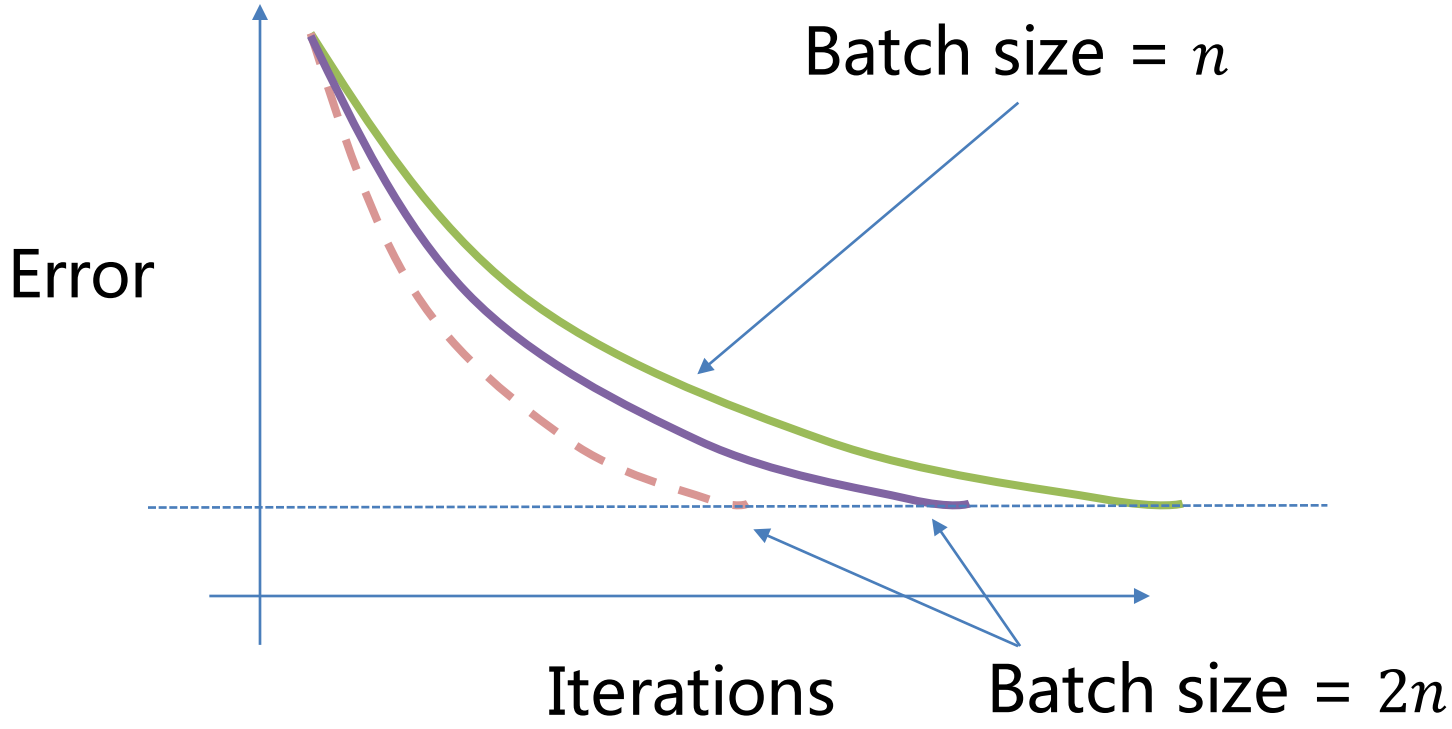


Training: Stochastic Gradient Descent

$$w' = w - \frac{\gamma}{n} \sum_i \nabla_w Q(x_i, w)$$

- Simple algorithm
  - Add momentum to power through local minima
  - Compute gradient by backpropagation
- Operates on minibatches
  - This makes it a GEMM problem instead of GEMV
- Choose minibatches stochastically
  - Important to avoid memorizing training order
- Difficult to parallelize
  - Prefers lots of small steps
  - Increasing minibatch size not always helpful

Limitations of batching



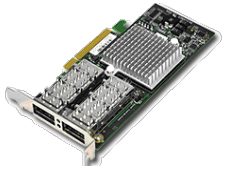
Spending 2x the work picking a direction
Doesn't reduce iteration count by 2x

SVAIL Infrastructure

- Software: CUDA, MPI, Majel (SVAIL internal library)
- Hardware:

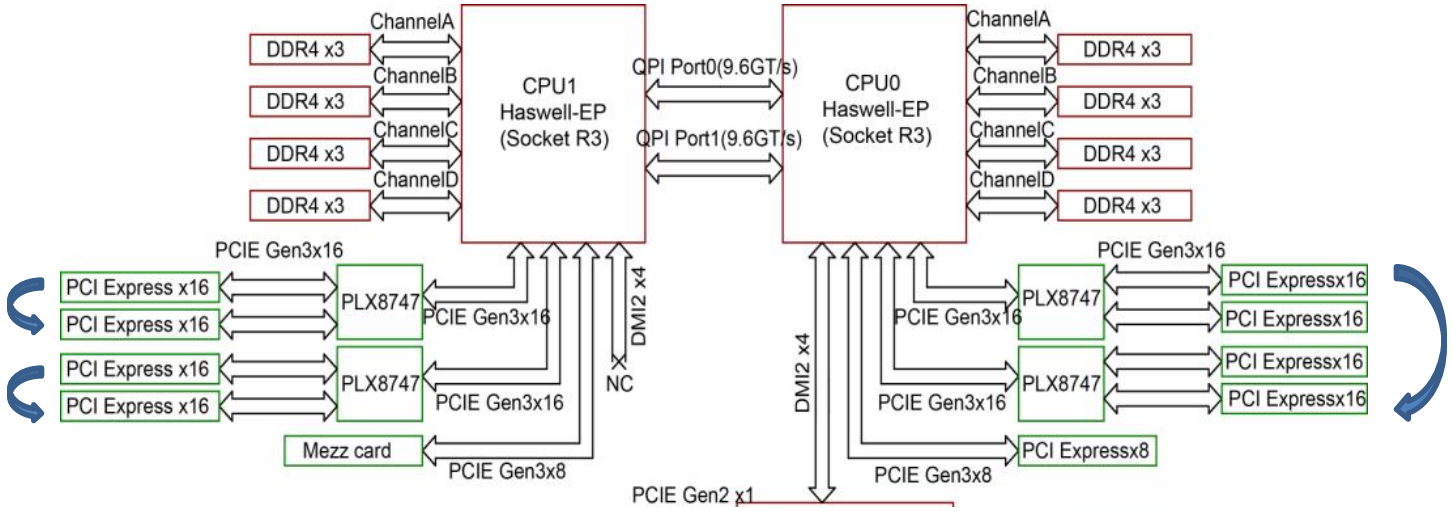
NVIDIA GeForce GTX Titan X

Titan X x8



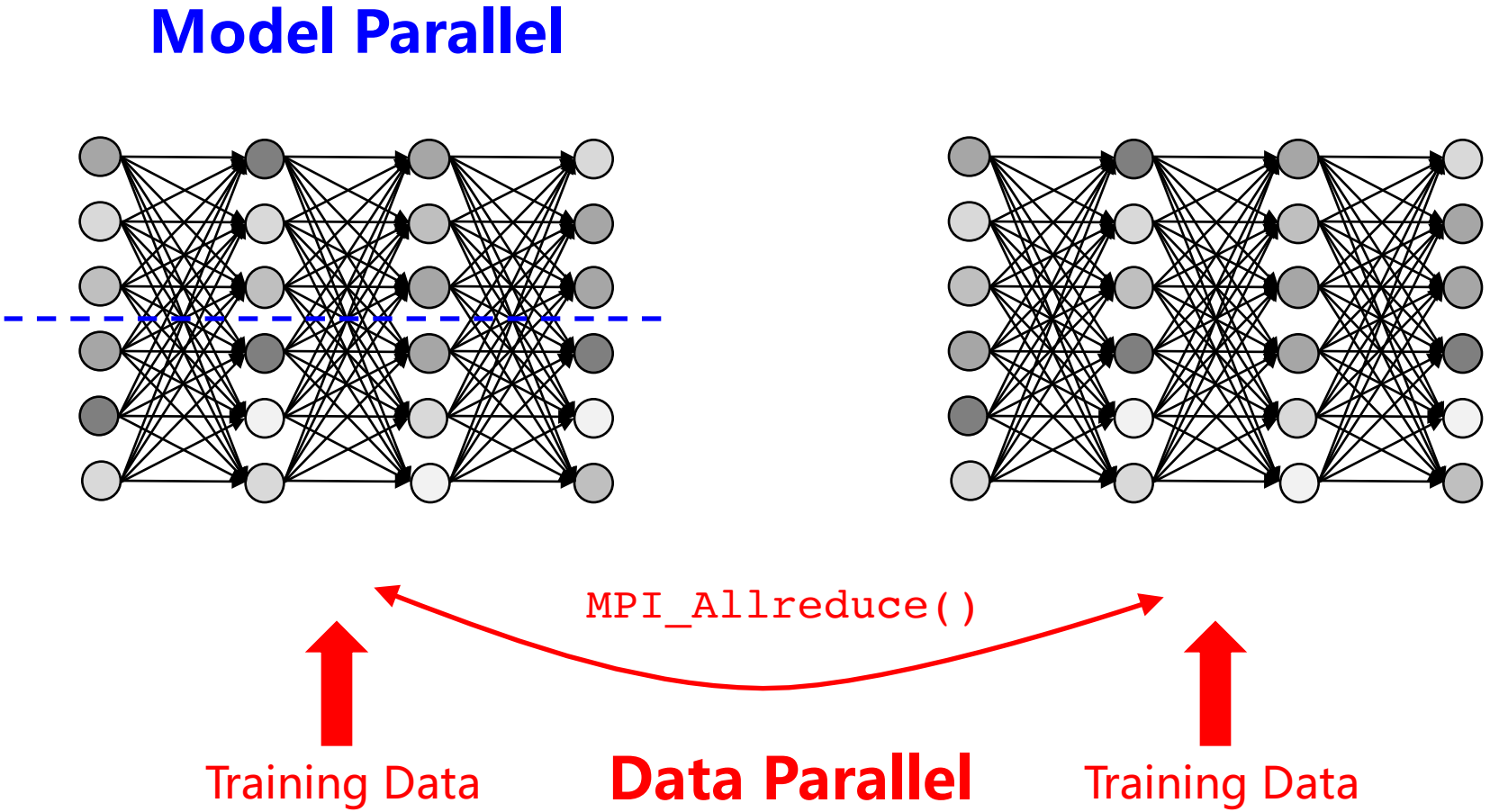
Mellanox Interconnect

Node Architecture



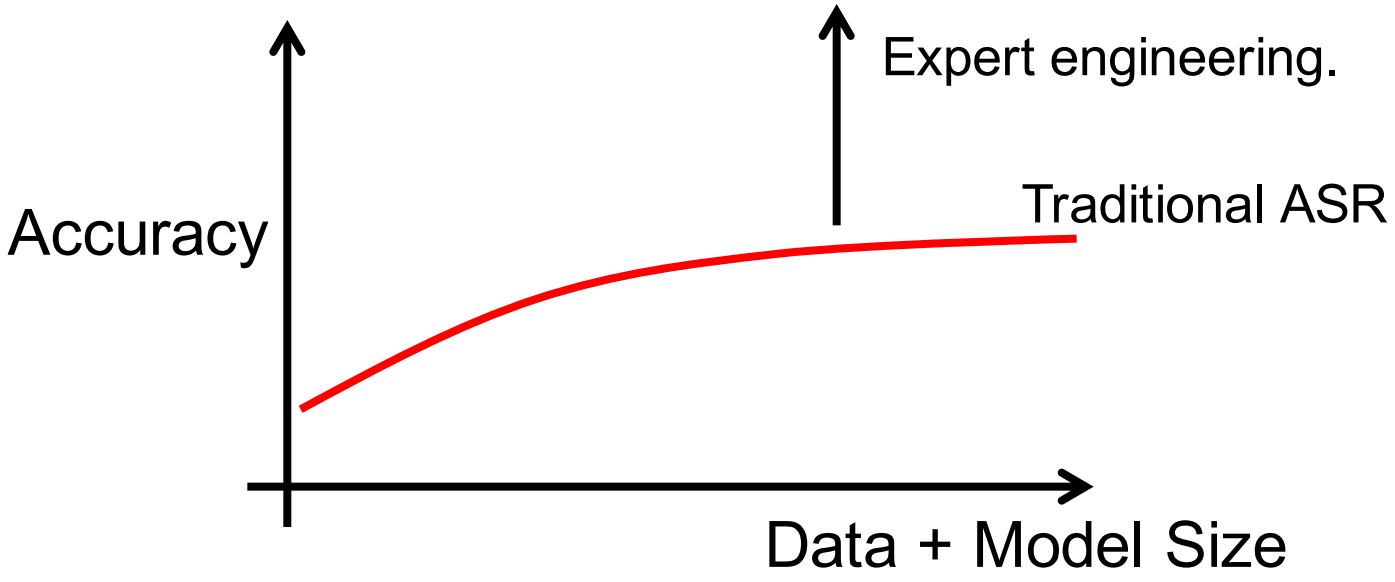
- All pairs of GPUs communicate simultaneously over PCIe Gen 3 x16
- Groups of 4 GPUs form Peer to Peer domain
- Avoid moving data to CPUs or across QPI

Parallelism



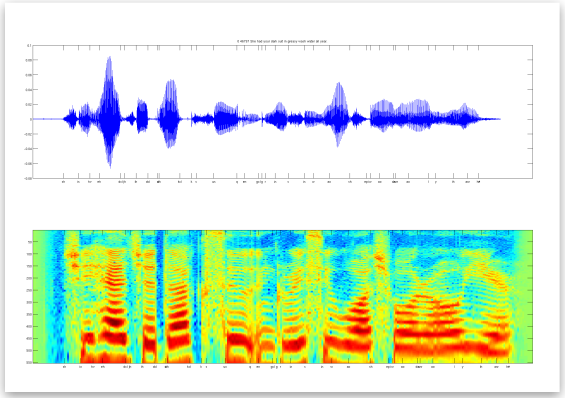
Speech Recognition: Traditional ASR

- Getting higher performance is hard
- Improve each stage by engineering

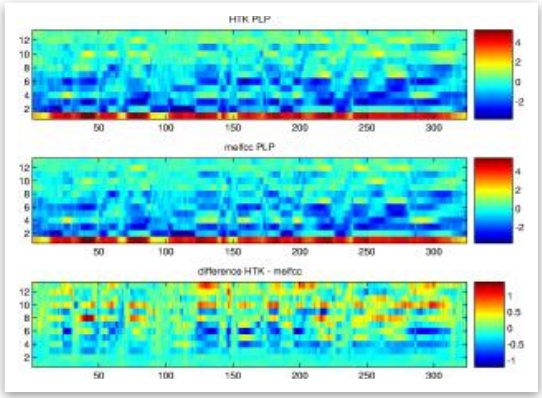


Speech recognition: Traditional ASR

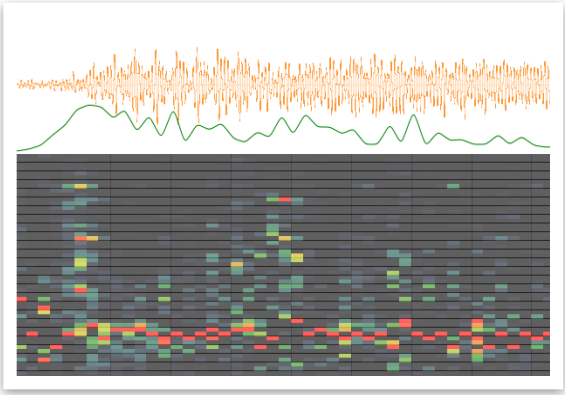
- Huge investment in features for speech!
  - Decades of work to get very small improvements



Spectrogram



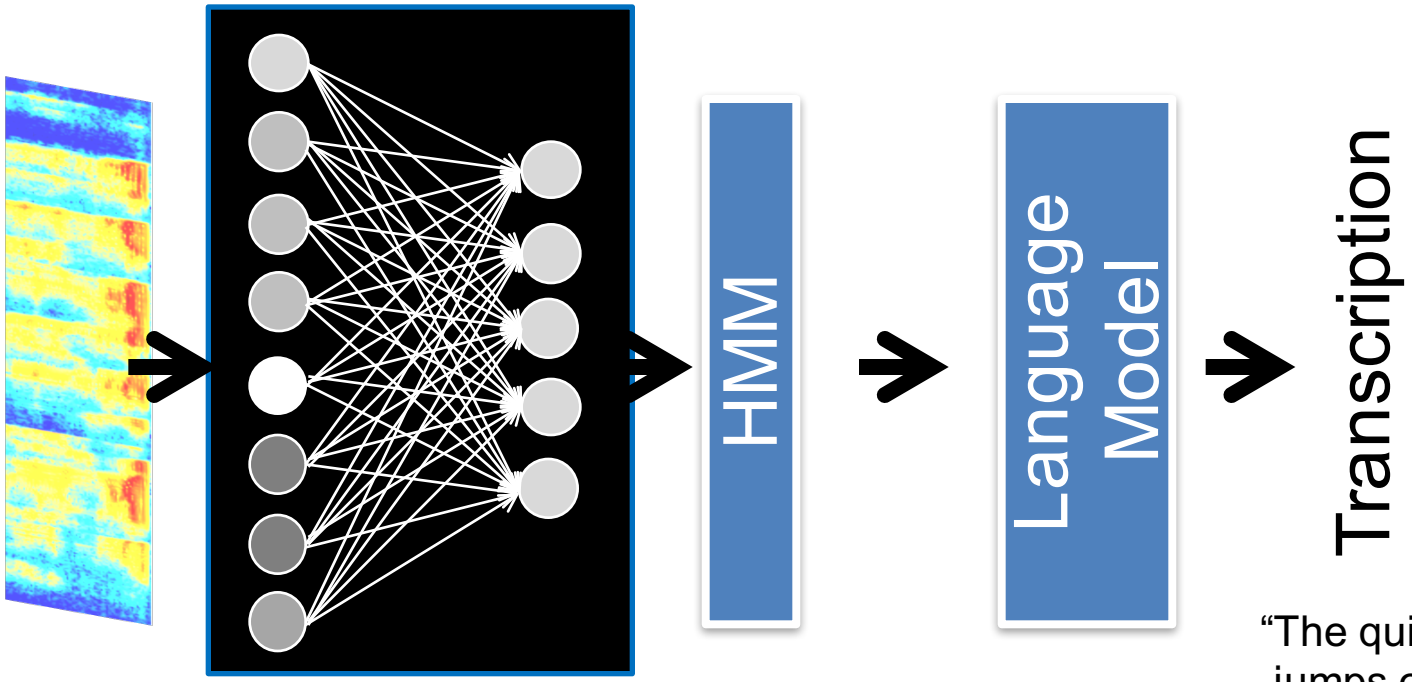
MFCC



Flux

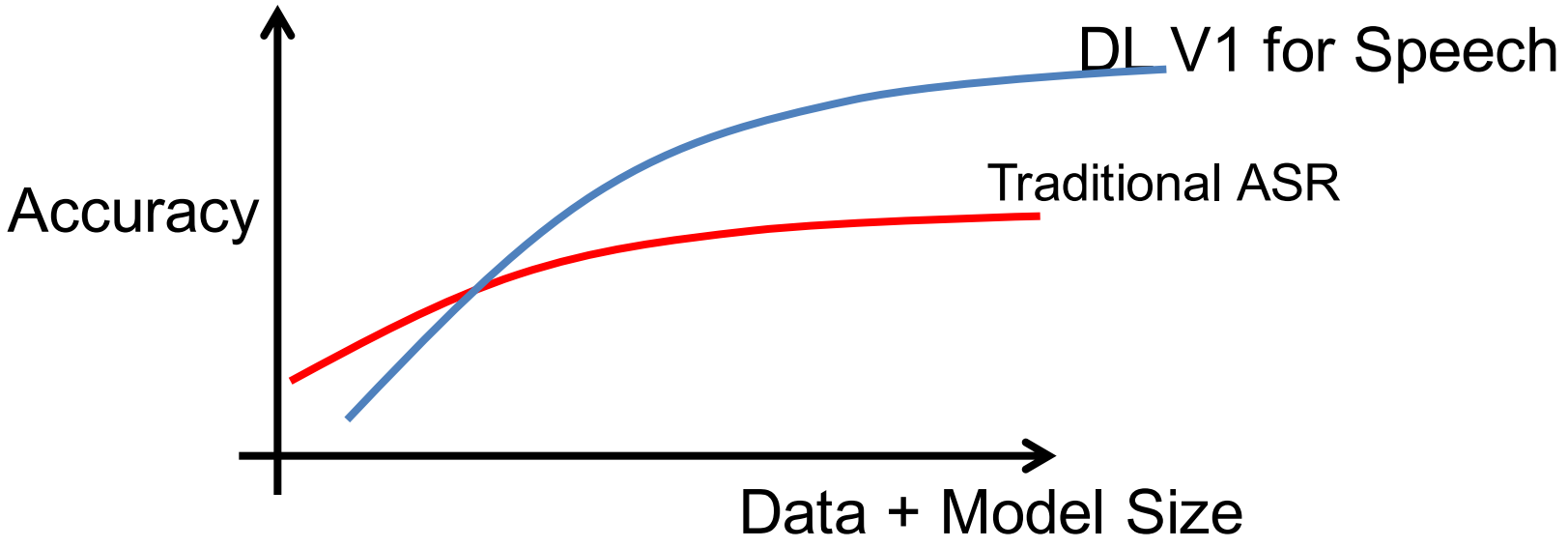
Speech Recognition 2: Deep Learning!

- Since 2011, deep learning for features



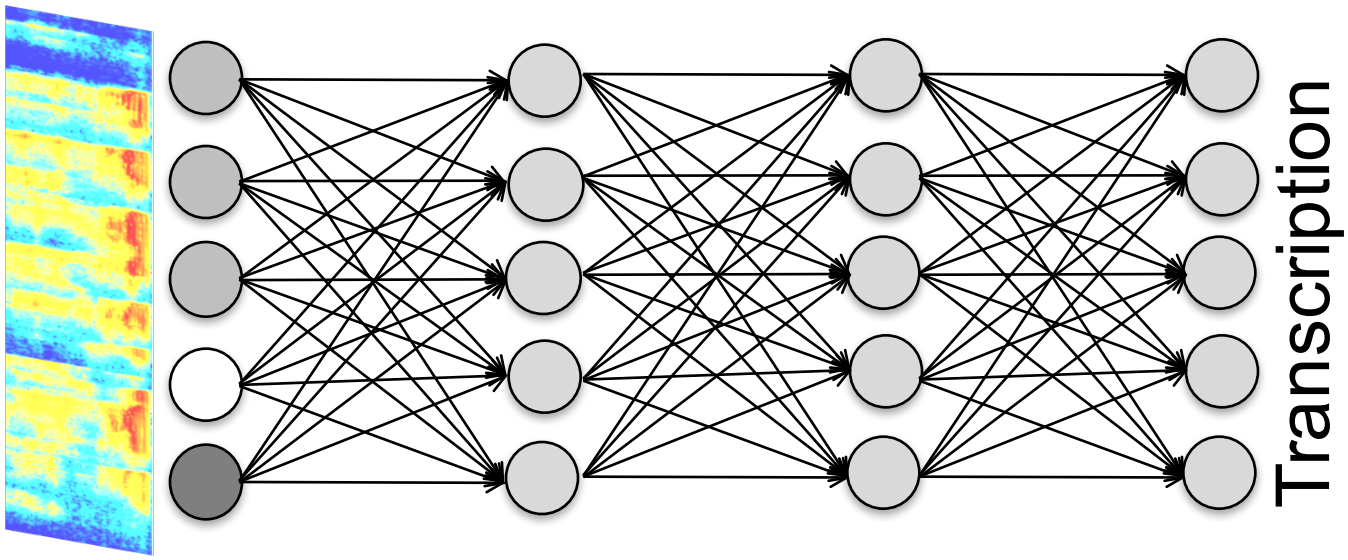
Speech Recognition 2: Deep Learning!

- With more data, DL acoustic models perform better than traditional models



Speech Recognition 3: "Deep Speech"

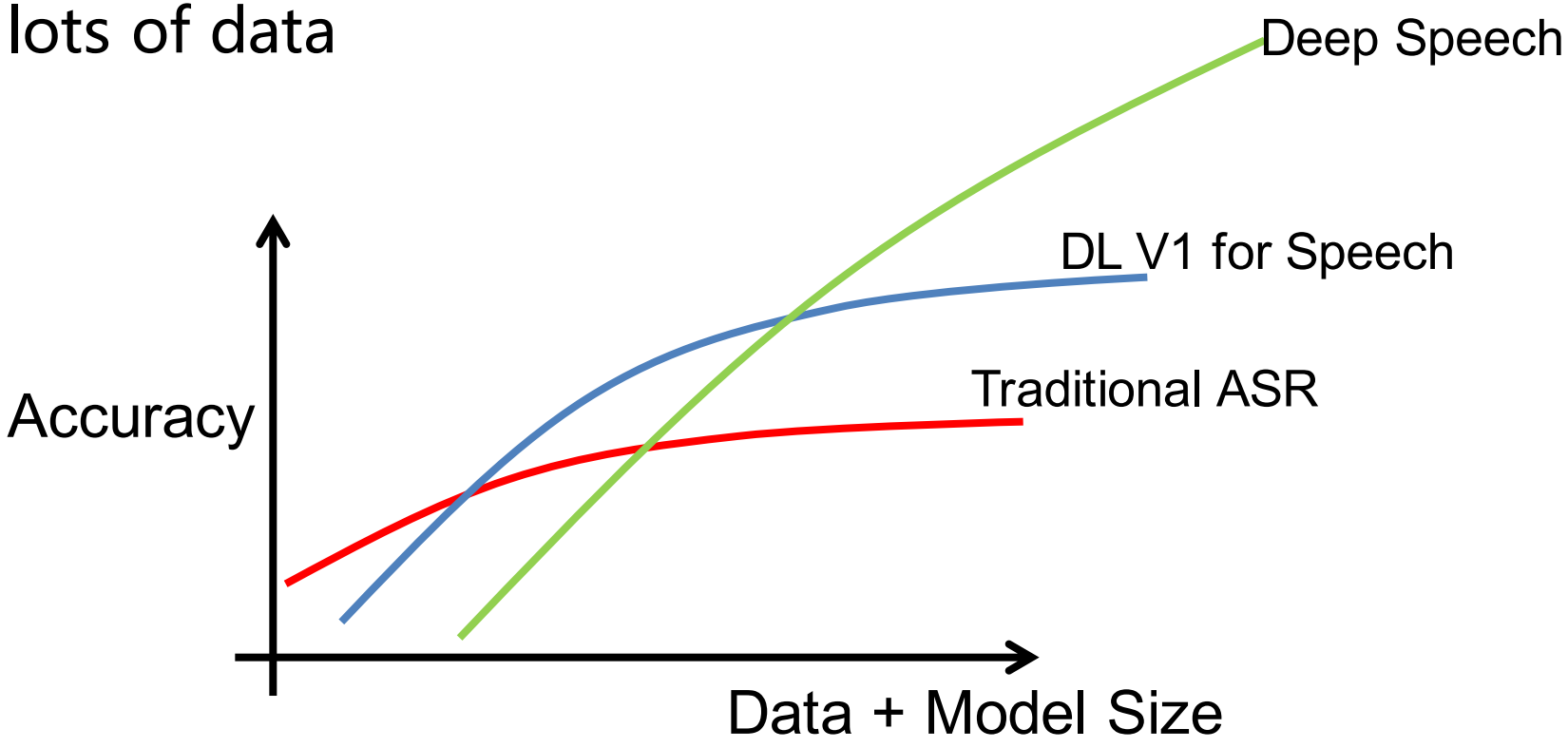
- End-to-end learning



"The quick brown fox jumps over the lazy dog."

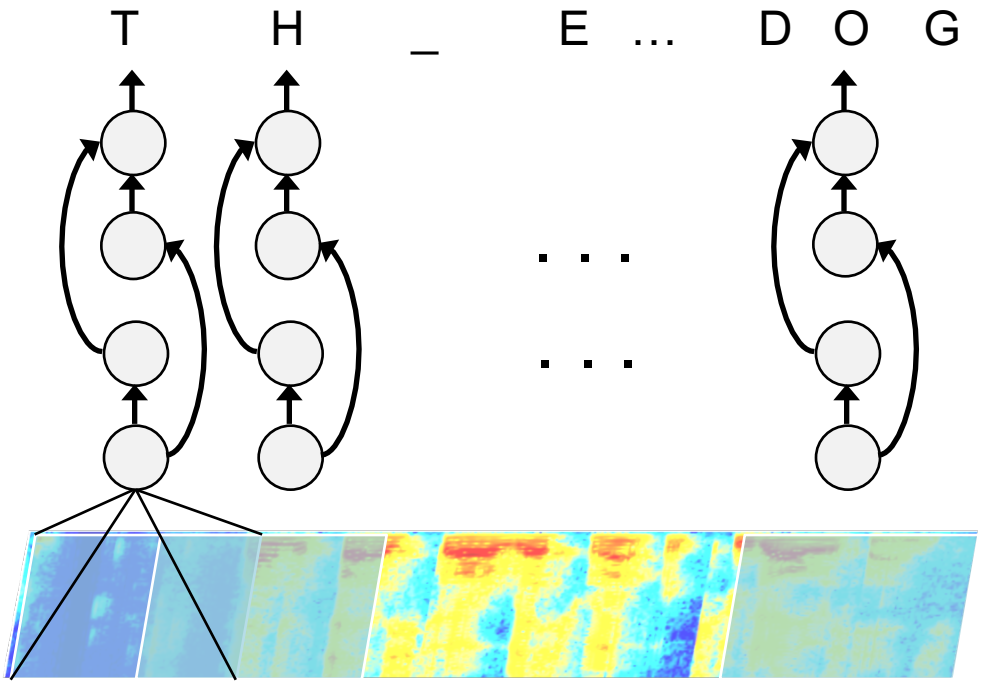
Speech Recognition 3: "Deep Speech"

- We believe end-to-end DL works better when we have big models and lots of data



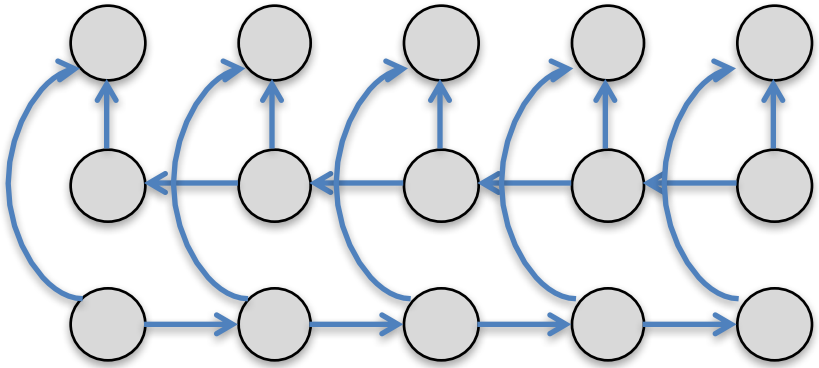
End-to-end speech with DL

- Deep neural network predicts characters directly from audio

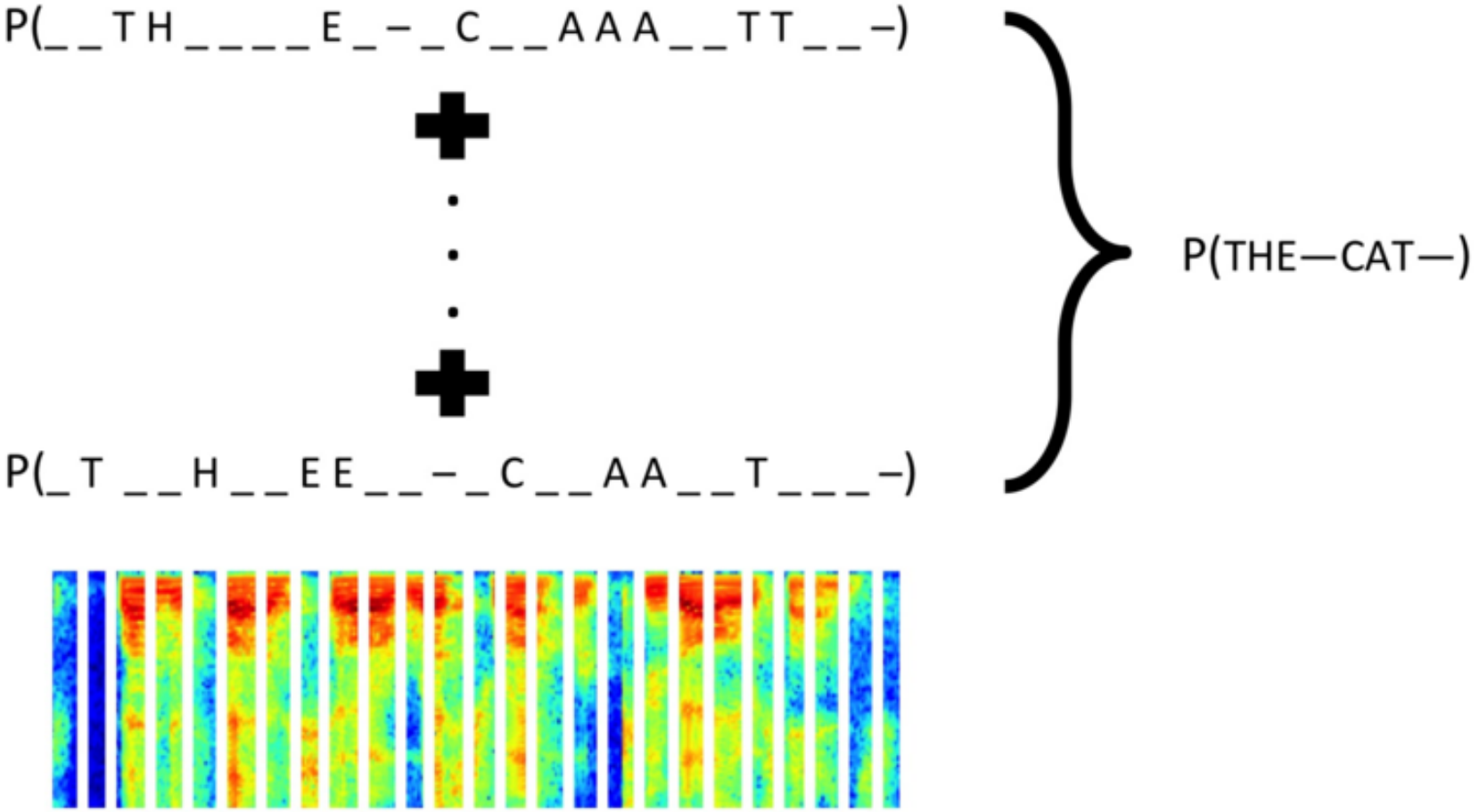


Recurrent Network

- RNNs model temporal dependence
- Various flavors used in many applications
  - LSTM, GRU, Bidirectional, …
  - Especially sequential data (time series, text, etc.)
- Sequential dependence complicates parallelism



Connectionist Temporal Classification



warp-ctc

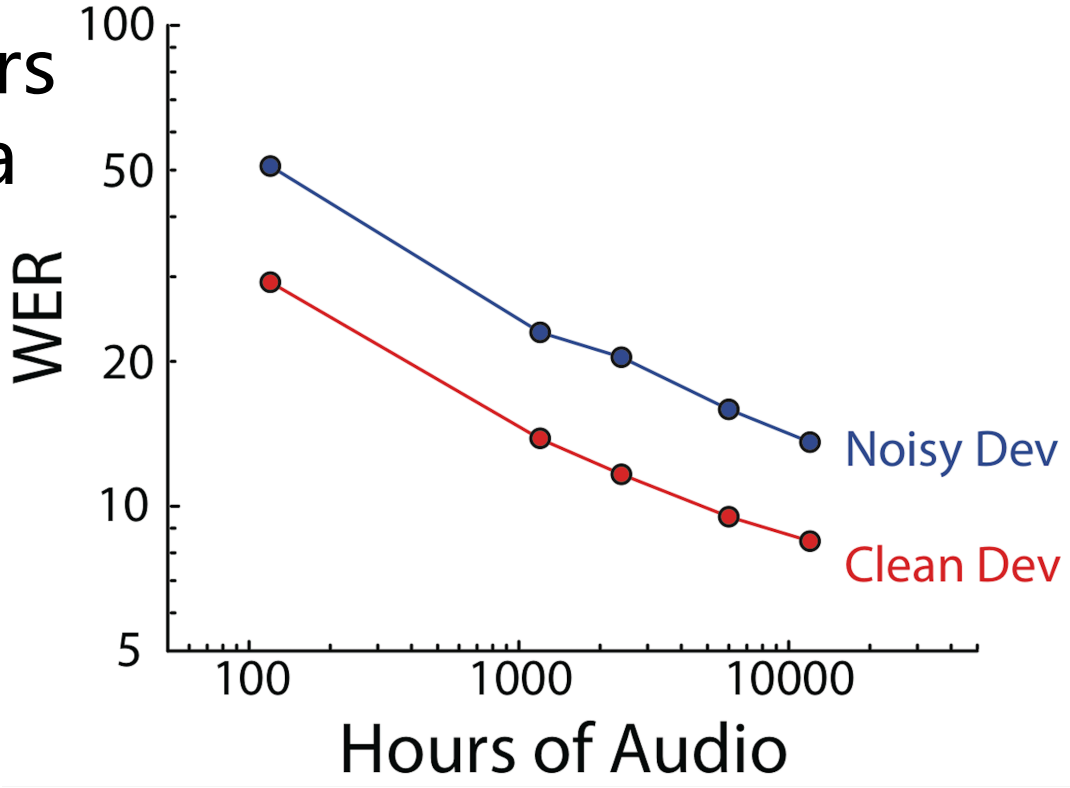
- Recently open sourced our CTC implementation (sorts from ModernGPU)
- Efficient, parallel CPU and GPU backend
- 100-400X faster than other implementations
- Apache license, C interface

https://github.com/baidu-research/warp-ctc

```
ctcStatus_t compute_ctc_loss(const float* const activations,
                             float* gradients,
                             const int* const flat_labels,
                             const int* const label_lengths,
                             const int* const input_lengths,
                             int alphabet_size,
                             int minibatch,
                             float *costs,
                             void *workspace,
                             ctcComputeInfo info);
```

Training sets

- Train on 45k hours (~5 years) of data
  - Still growing
- Languages
  - English
  - Mandarin



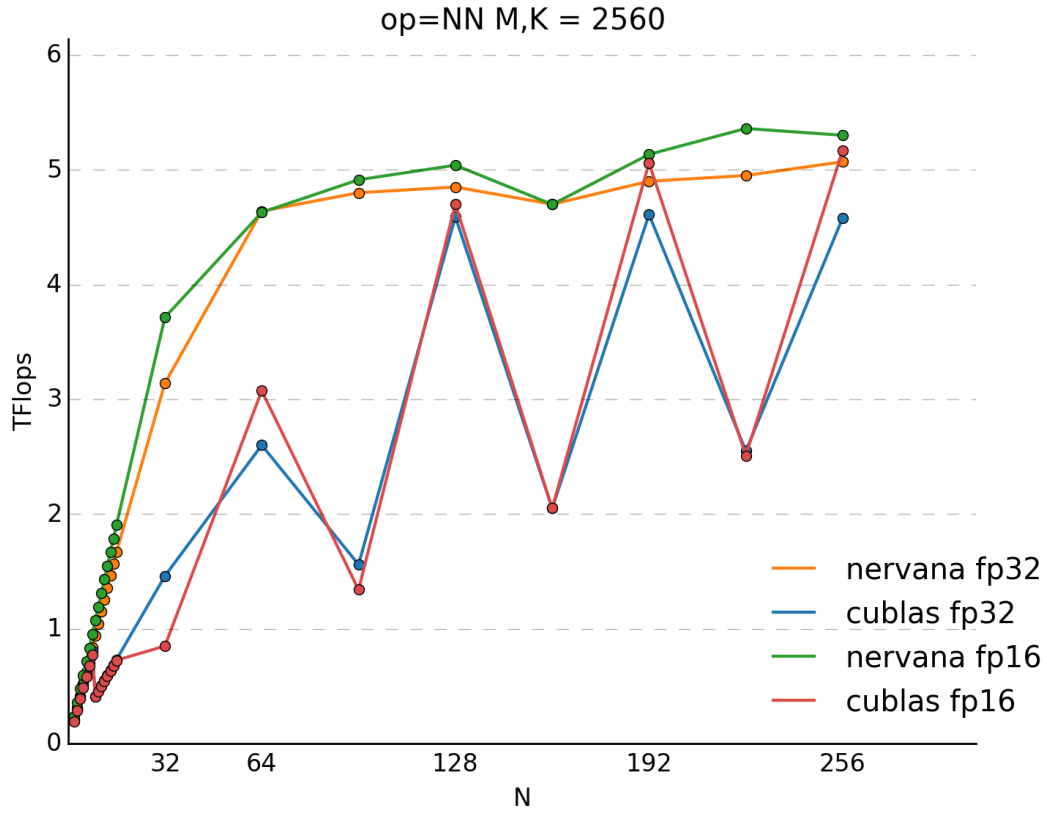
- End-to-end deep learning is key to assembling large datasets

All-reduce

- We implemented our own all-reduce out of send and receive
- Several algorithm choices based on size
- Careful attention to affinity and topology

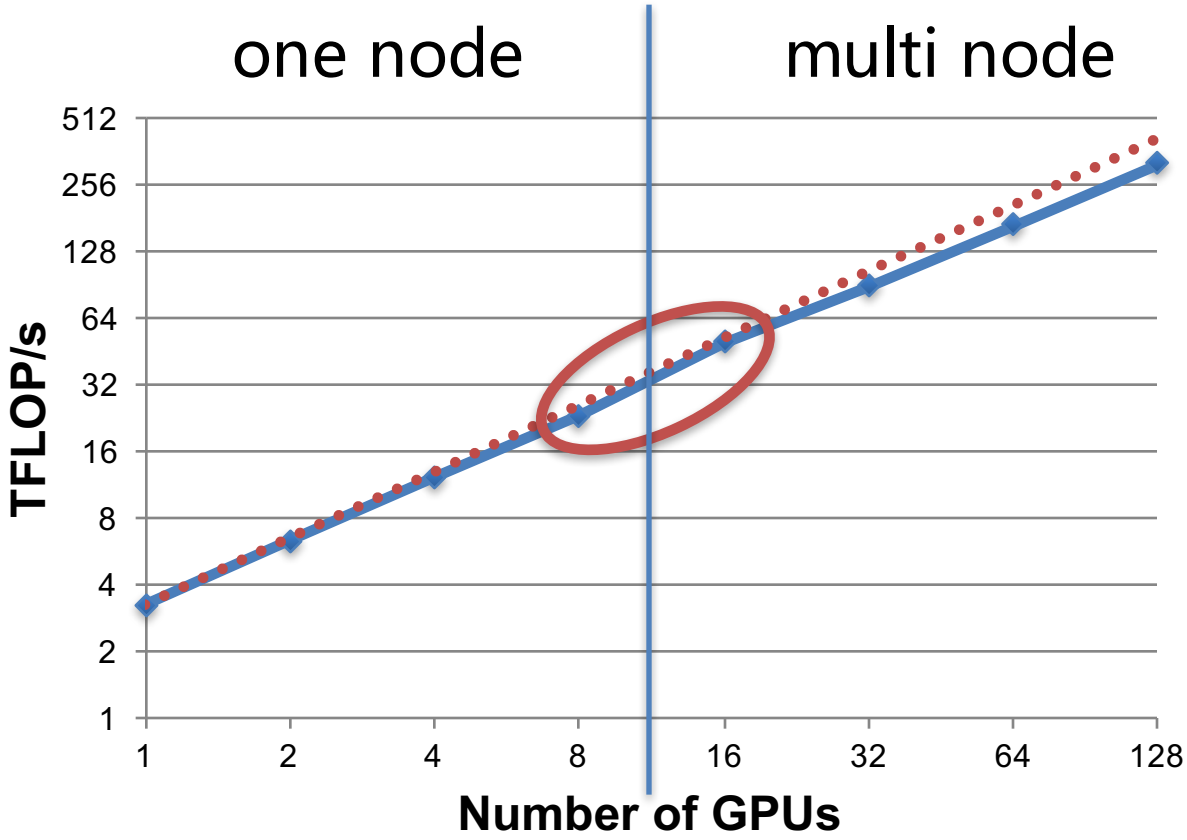
GPU	OpenMPI all-reduce	Our all-reduce	Performance Gain
4	55359.1	2587.4	21.4
8	48881.6	2470.9	19.8
16	21562.6	1393.7	15.5
32	8191.8	1339.6	6.1
64	1395.2	611.0	2.3
128	1602.1	422.6	3.8

Scalability



- Batch size is hard to increase
  - algorithm, memory limits
- Performance at small batch sizes leads to scalability limits

Performance for RNN training

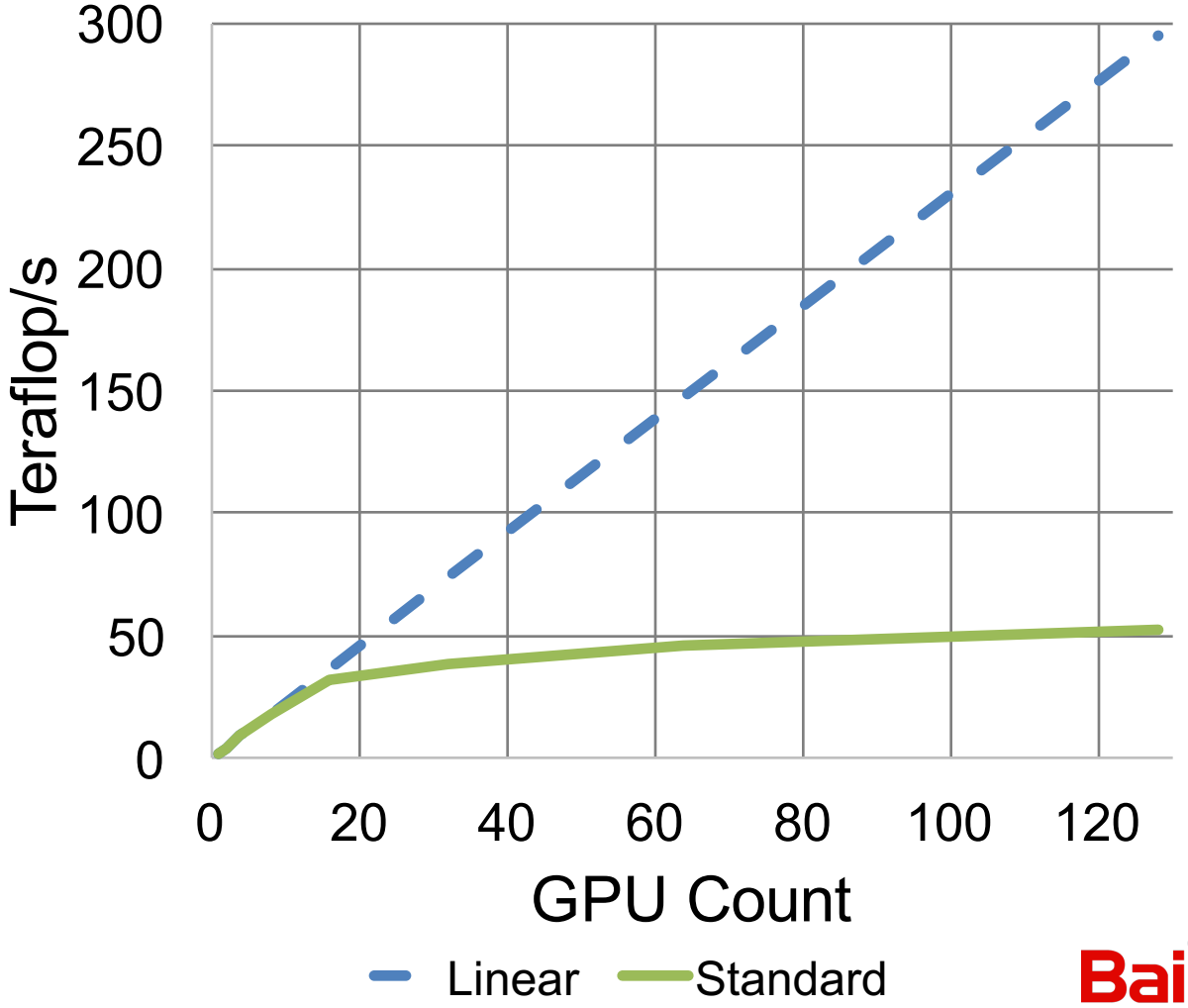


Typical training run

- 55% of GPU FMA peak using a single GPU
- ~48% of peak using 8 GPUs in one node
- Weak scaling very efficient, albeit algorithmically challenged

Strong scaling RNNs with Persistent Kernels

- Strong scaling is hard!



[G. Diamos, ICML 2016]

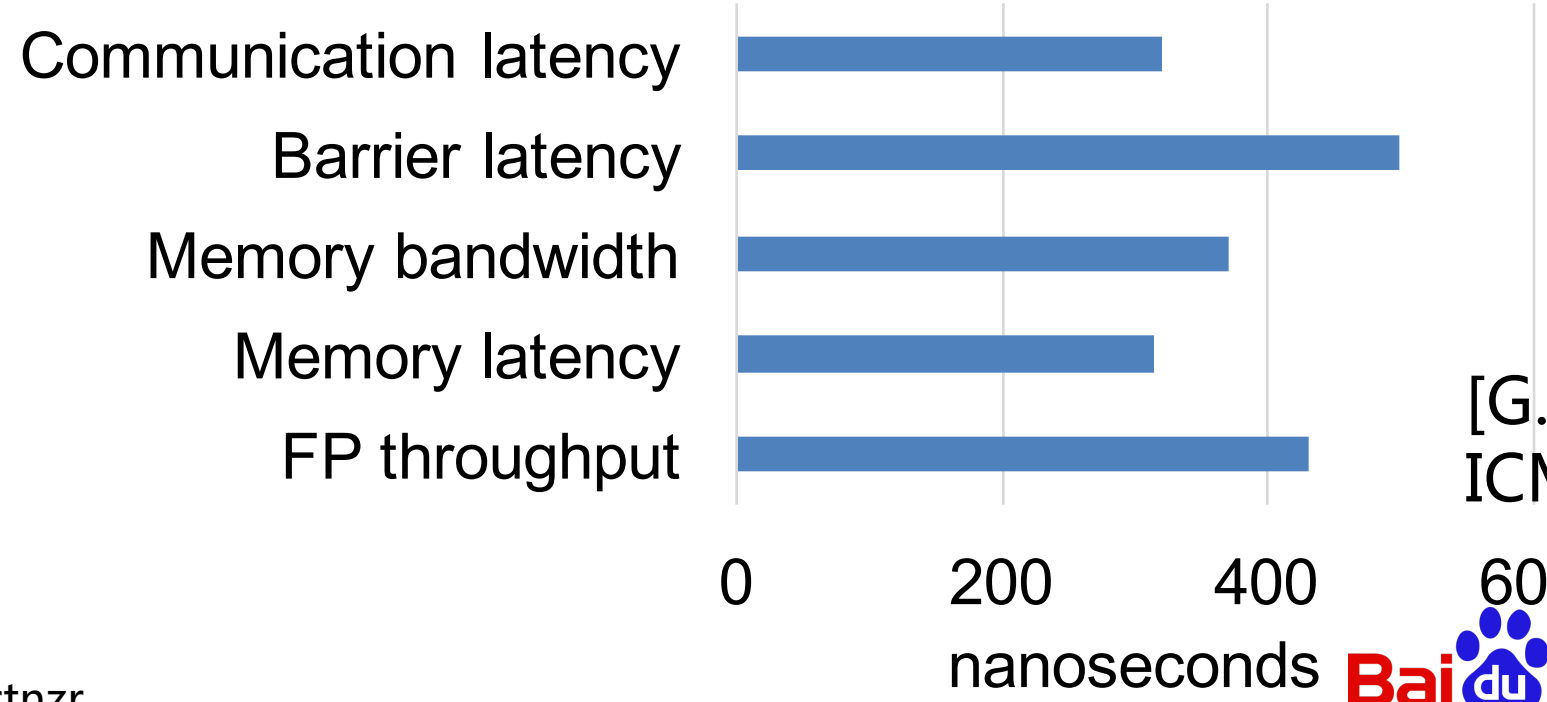
Strong scaling RNNs with Persistent Kernels

- Small batch size bad for standard RNN:
  - Less reuse of parameters
  - Bad SIMD efficiency
- But RNNs reuse parameters across time
  - Can we stash them in register file?
  - Make RNNs compute limited at small batch?
  - Enable strong scaling?
- Persistent Kernels hard to implement:
  - Require global synchronization (CUDA hates this)
  - MB of parameters pinned to register file
- Limitations:
  - Size, architecture (RNN vs. LSTM vs. GRU etc.)

[G. Diamos, ICML 2016]

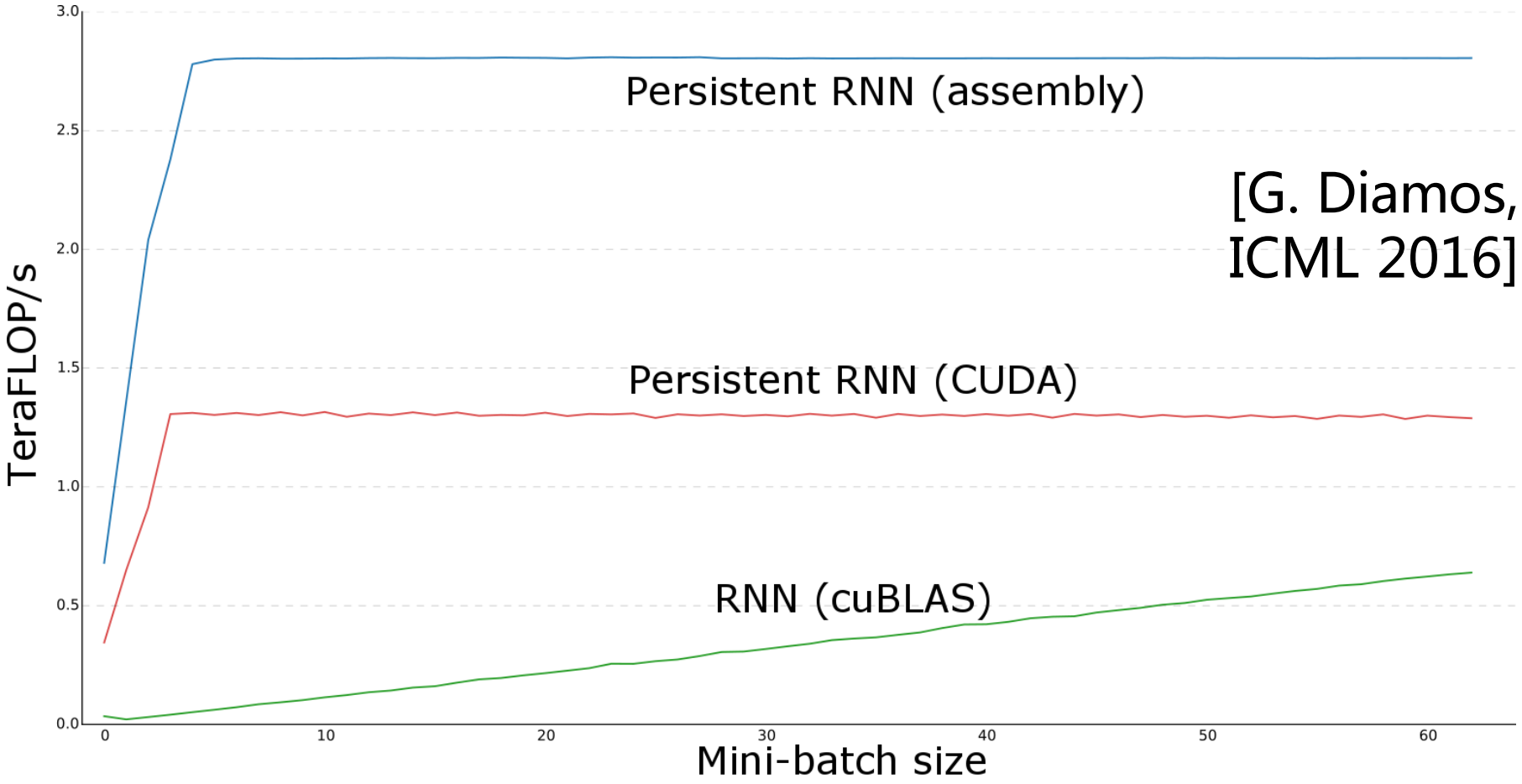
Persistent Kernel implementation

- SASS assembly for Maxwell (using Maxas)
- Supports up to 1152 neurons on TitanX
  - 5 MB of user data pinned in registers!
- SW Pipeline following limiters:



[G. Diamos, ICML 2016]

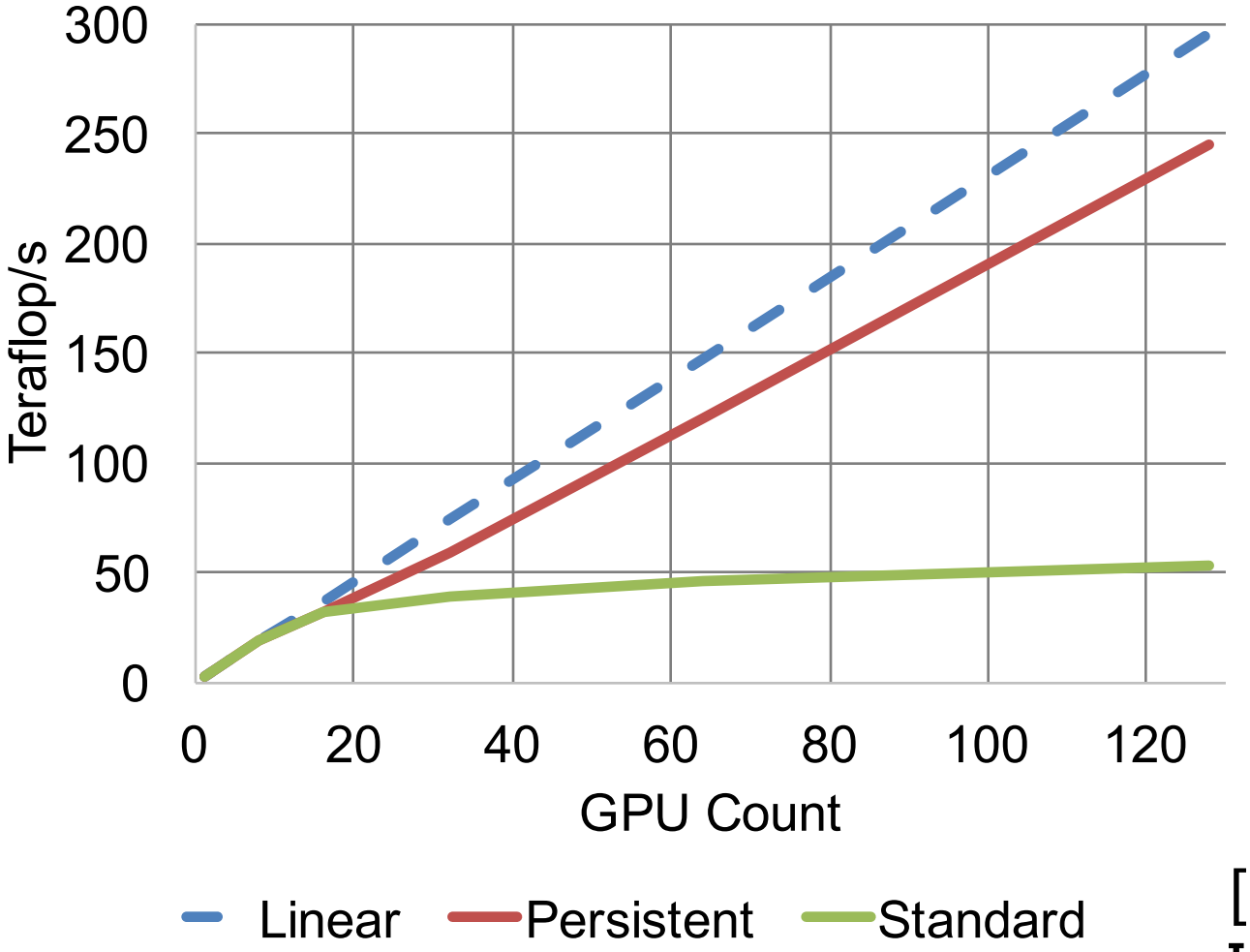
Persistent Kernel Performance (TitanX)



[G. Diamos, ICML 2016]

- https://github.com/baidu-research/persistent-rnn

Strong scaling RNNs with Persistent Kernels



[G. Diamos, ICML 2016]

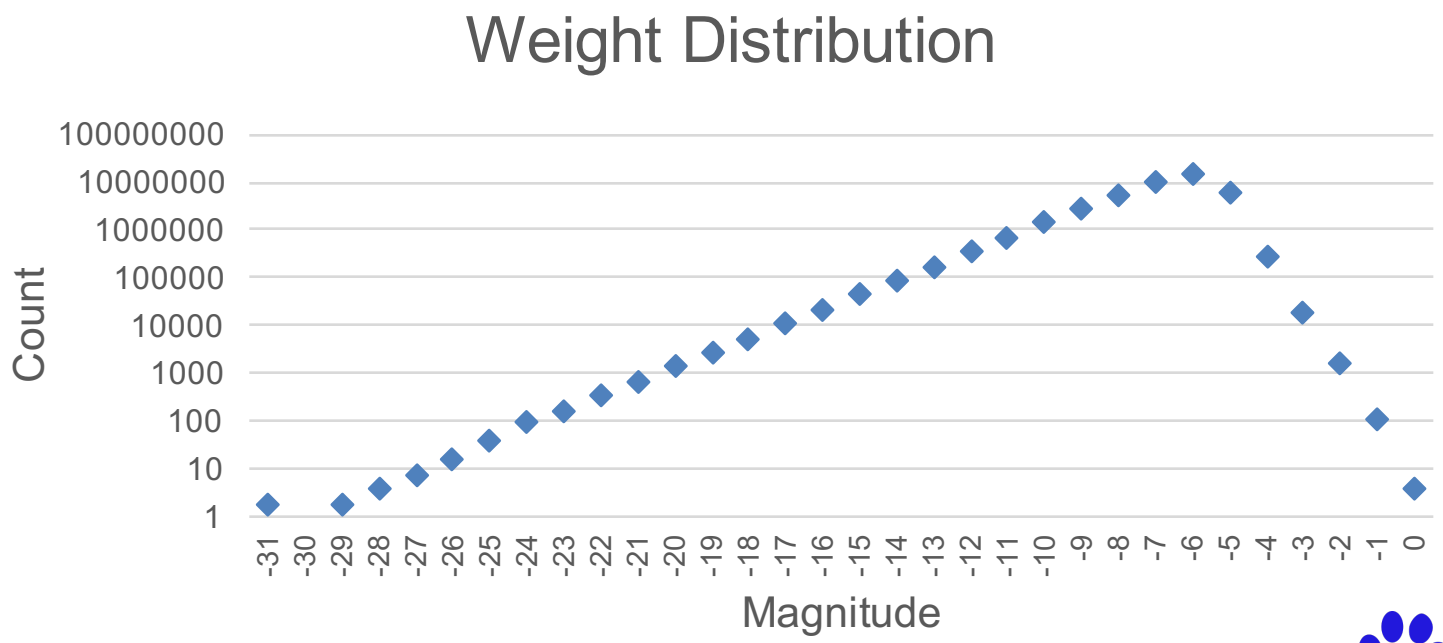
Determinism

- Determinism very important
- So much randomness,
  hard to tell if you have a bug
- Networks train despite bugs,
  although accuracy impaired
- Reproducibility is important
  - For the usual scientific reasons
  - Progress not possible without reproducibility

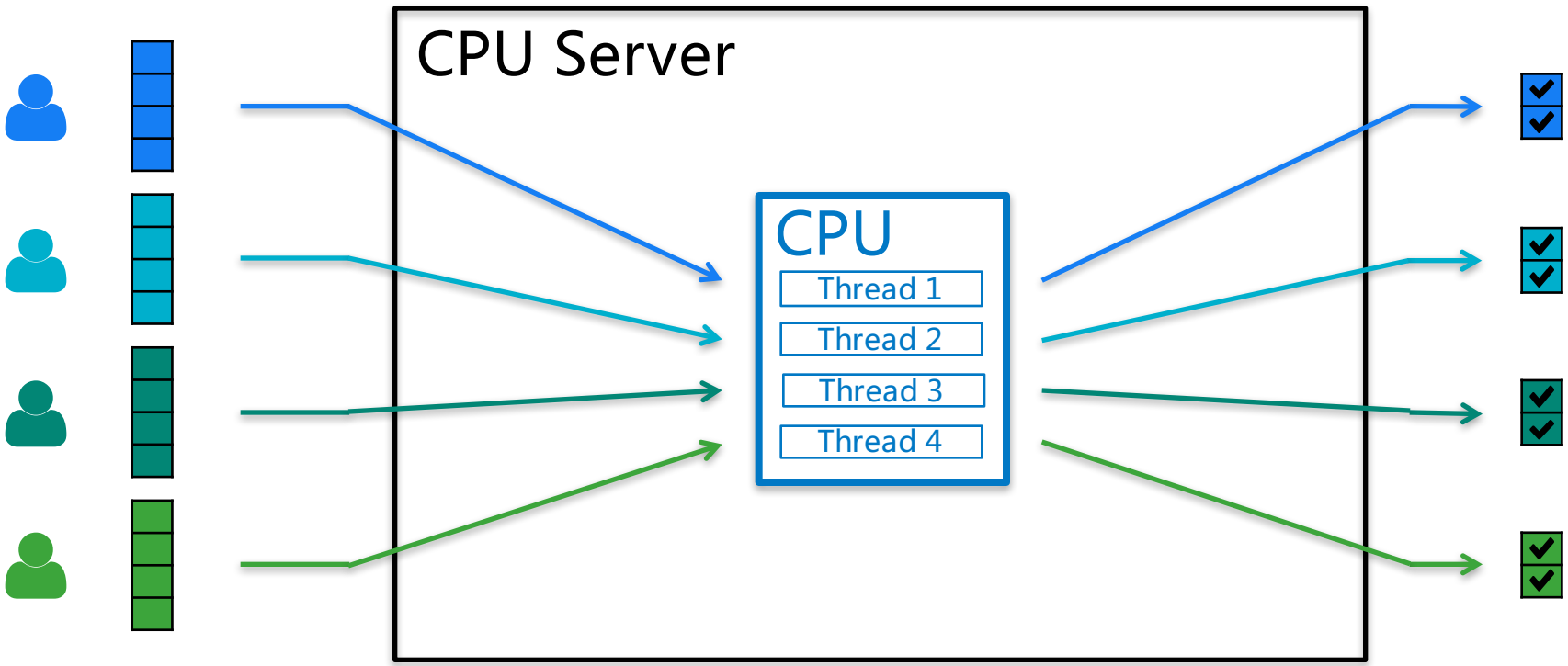
- We use synchronous SGD

Precision

- FP16 mostly works
  - Use FP32 for softmax and weight updates
- More sensitive to labeling error

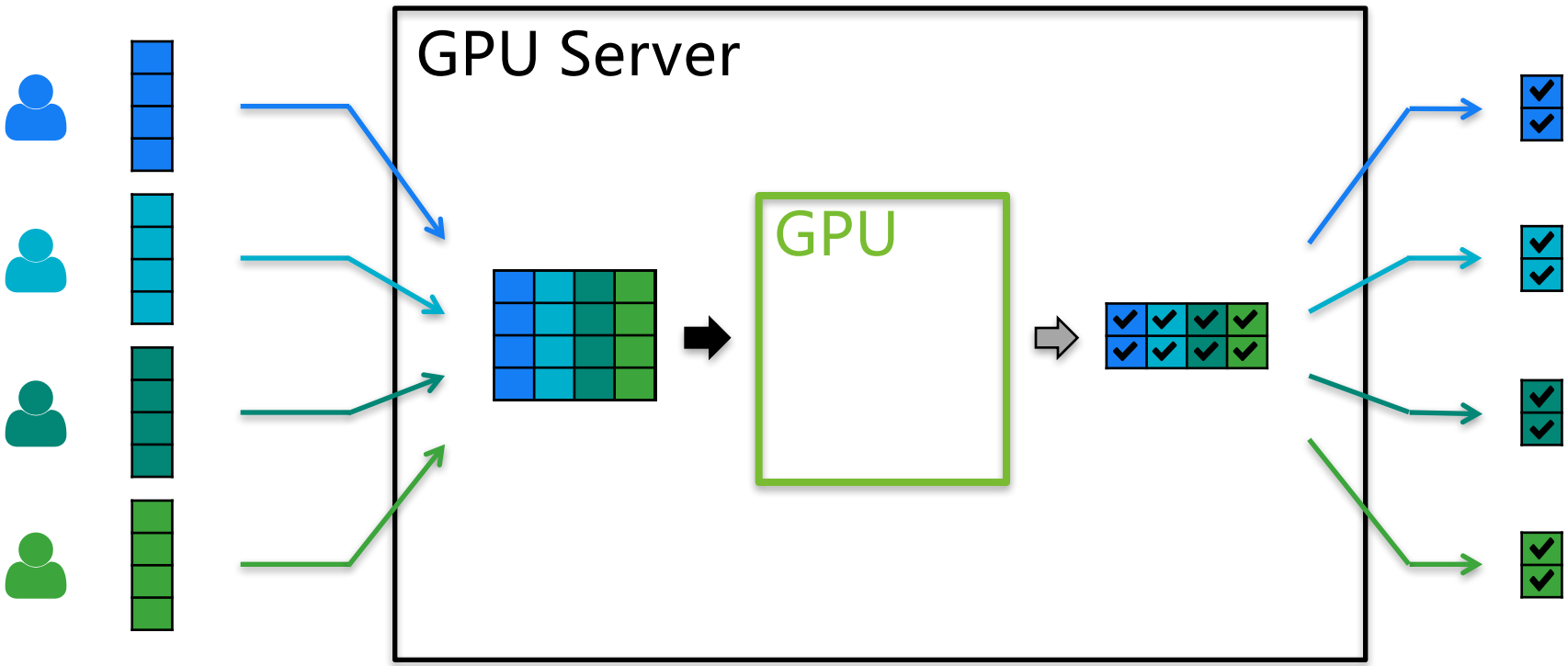


Batch Dispatch



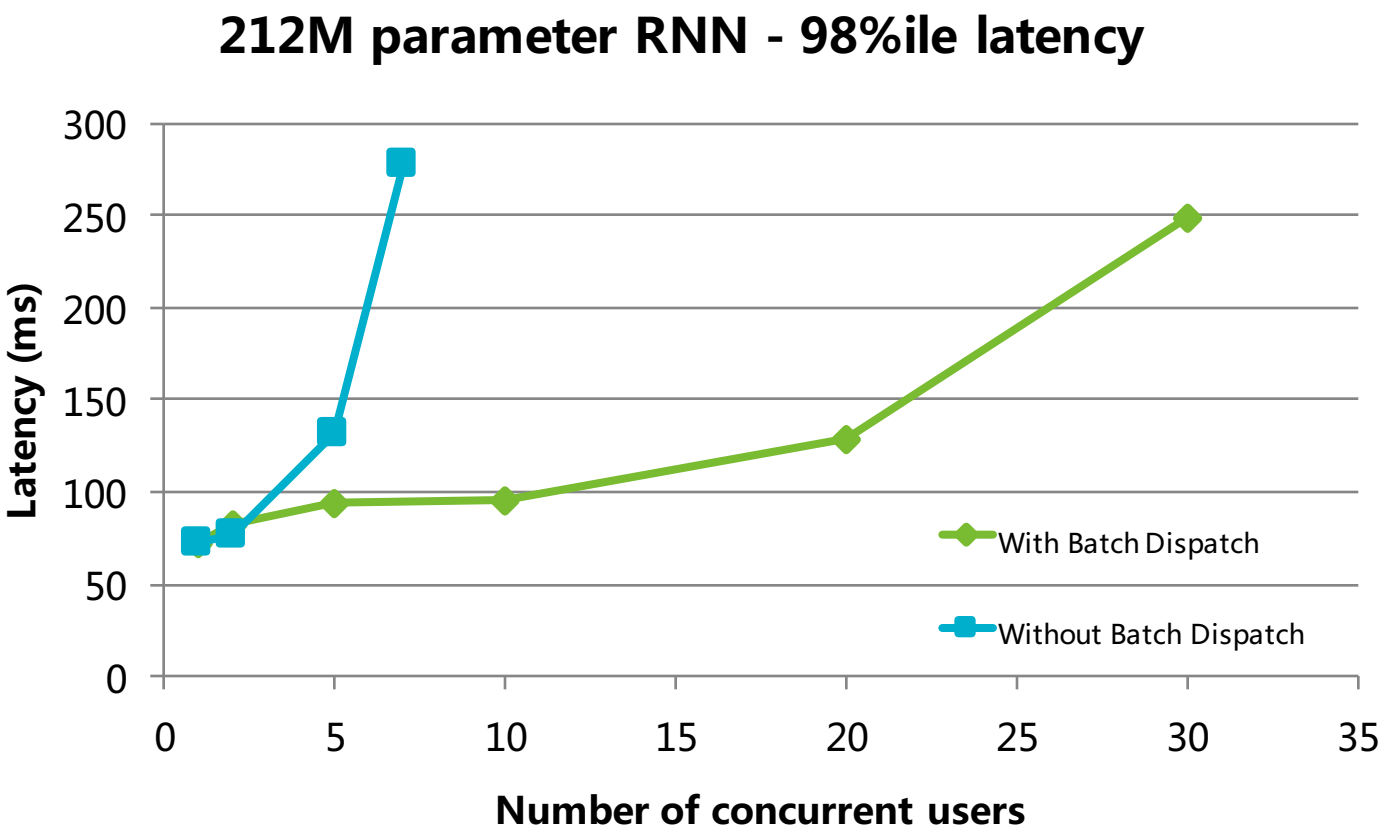
[C. Fougner]

Batch Dispatch



[C. Fougner]

Batch Dispatch Performance



4X more users at acceptable latency

[C. Fougner]

Baidu Research

Thoughts

- Computationally dense processors (like GPUs) required
- Programmability
  - We don't know the algorithms of the future
- Lower precision
  - But not too low
  - Interesting algorithm/dataset engineering here
- We need better support for multi-GPU
  - E.g. Atomics between GPUs, collectives
  - Looking forward to NVLink

Conclusion

- Deep Learning is solving many hard problems
- Training deep neural networks is an HPC problem
- Scaling brings AI progress!

Thanks

- Andrew Ng, Adam Coates, Awni Hannun, Patrick LeGresley, Greg Diamos, Chris Fougner … and all of SVAIL

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