Techniques and Systems for Training Large Neural Networks Quickly

Jeff Dean

Google

Joint work with many colleagues at Google

How Can We Build More Intelligent Computer Systems?

Need to perceive and understand the world

Basic speech and vision capabilities

Language understanding

User behavior prediction

…

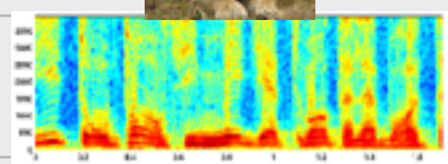
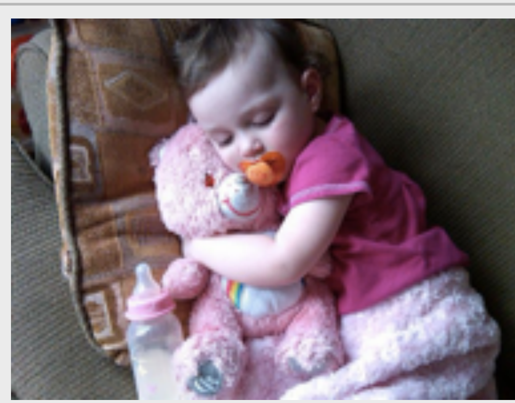
How can we do this?

- Cannot write algorithms for each task we want to accomplish separately
- Need to write general algorithms that learn from observations

Can we build systems that:

- Generate understanding from raw data
- Solve difficult problems to improve Google's products
- Minimize software engineering effort
- Advance state of the art in what is possible

Functions Artificial Neural Nets Can Learn

Input	Output
Pixels: 	“lion”
Audio: 	“pa lo ahl toe res taur aun ts”
<query, doc>	P(click on doc)
“Hello, how are you?”	“Bonjour, comment allez-vous?”
Pixels: 	“A close up of a small child holding a stuffed animal”

Same Underlying System Works for Many Problems

- Nice property: same general approach works for many problems/domains
- Same underlying infrastructure can be used to train and use many kinds of models

Plenty of Data

- Text: trillions of words of English + other languages
- Visual: billions of images and videos
- Audio: thousands of hours of speech per day
- User activity: queries, result page clicks, map requests, etc.
- Knowledge graph: billions of labelled relation triples
- ...

More Data + Bigger Model = Better Results

- True across wide range of areas

- Many problems have virtually limitless data, so only issue is how big a model we can train

Research Objective: Minimizing Time to Results

- We want results of experiments quickly
- "Patience threshold": No one wants to wait more than a few days or a week for a result
    - Significantly affects scale of problems that can be tackled
    - We sometimes optimize for experiment turnaround time, rather than absolute minimal system resources for performing the experiment

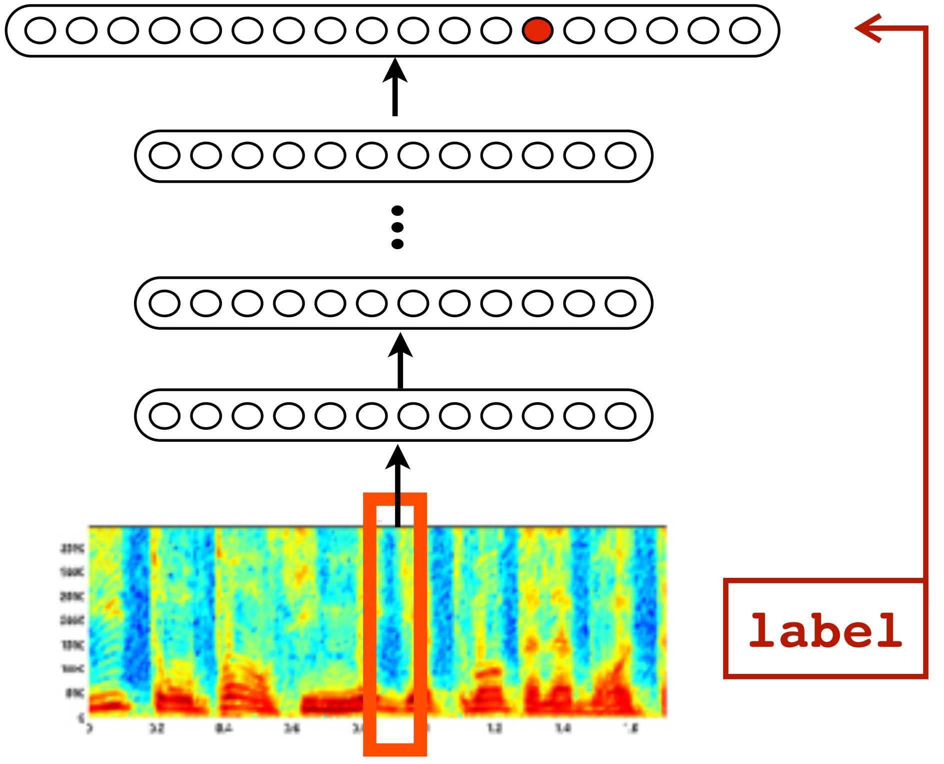
Train in a day what takes a single GPU card 50 days

Many Different Types of Models Used

Rest of talk:

- Quick sketch of different models that we use and are exploring
- Overview of general infrastructure that makes training large models on large datasets possible

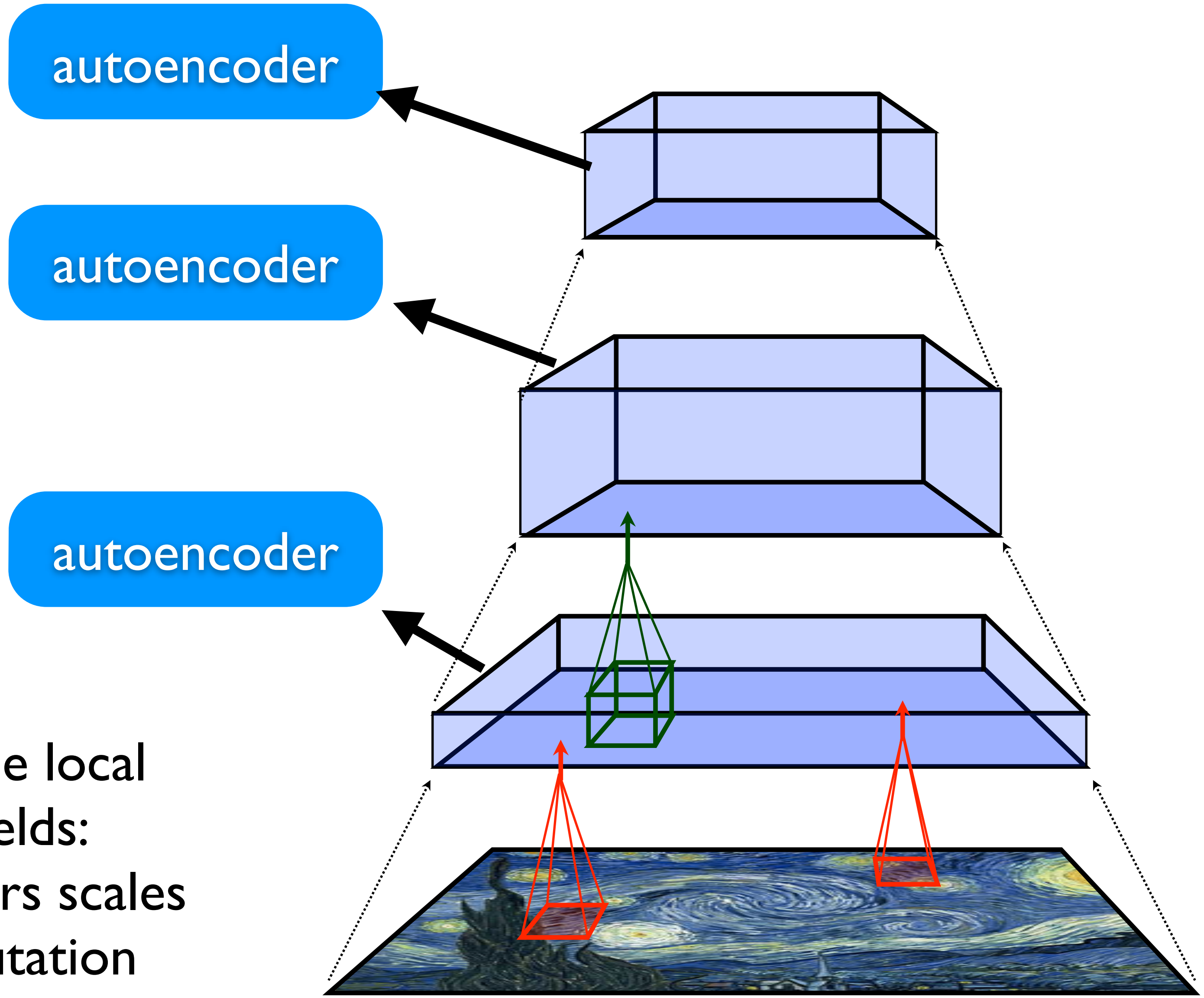
Acoustic Modeling for Speech Recognition



Simple feed-forward neural net

Close collaboration with Google Speech team

2012: Unsupervised Vision Model: QuocNet



Neurons use local receptive fields:
parameters scales with computation (billions of parameters)

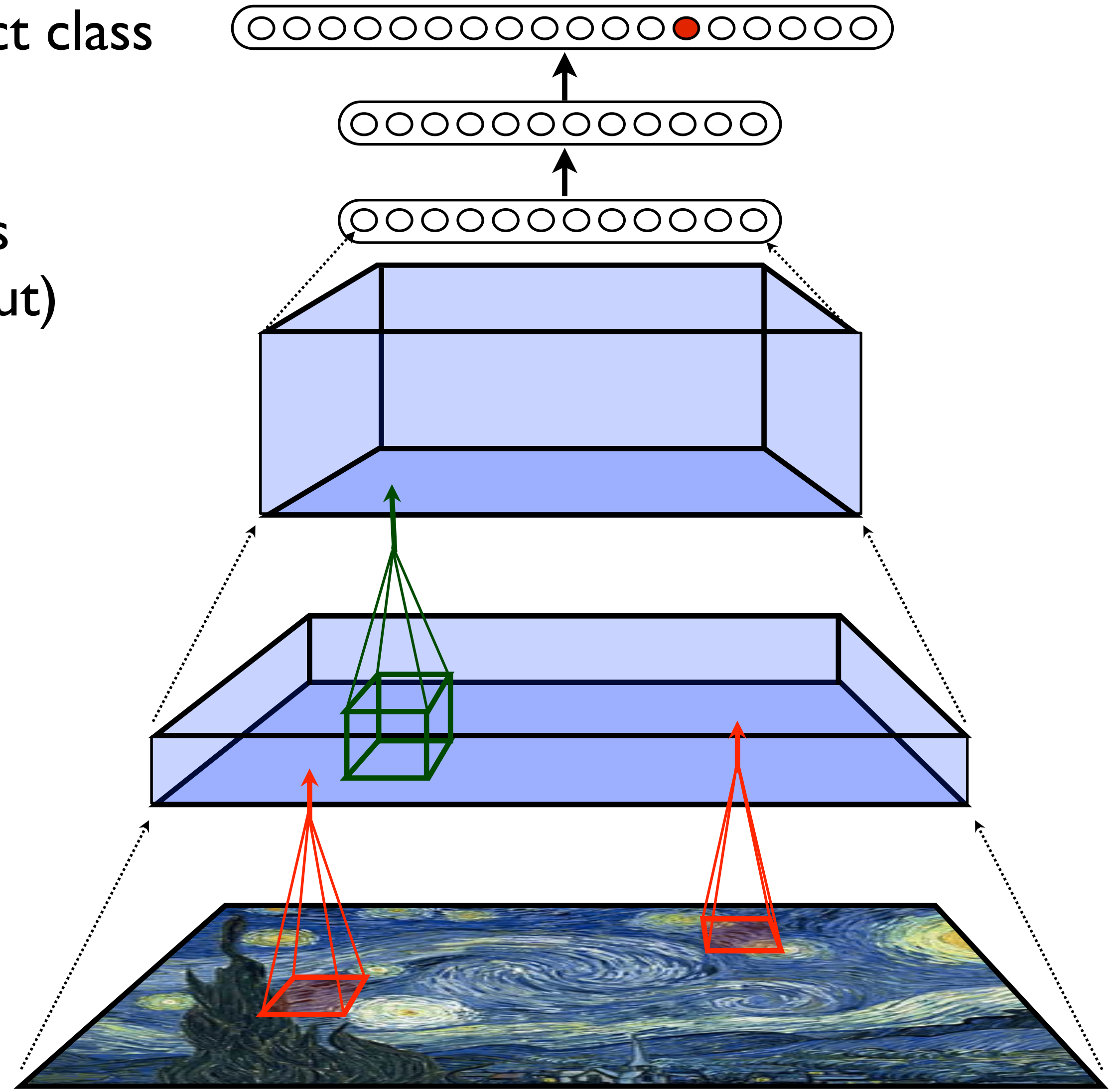
2012 Supervised Vision Model: "AlexNet"

Softmax to predict object class

Fully-connected layers
(and trained w/ DropOut)

Convolutional layers
(same weights used at all spatial locations in layer)

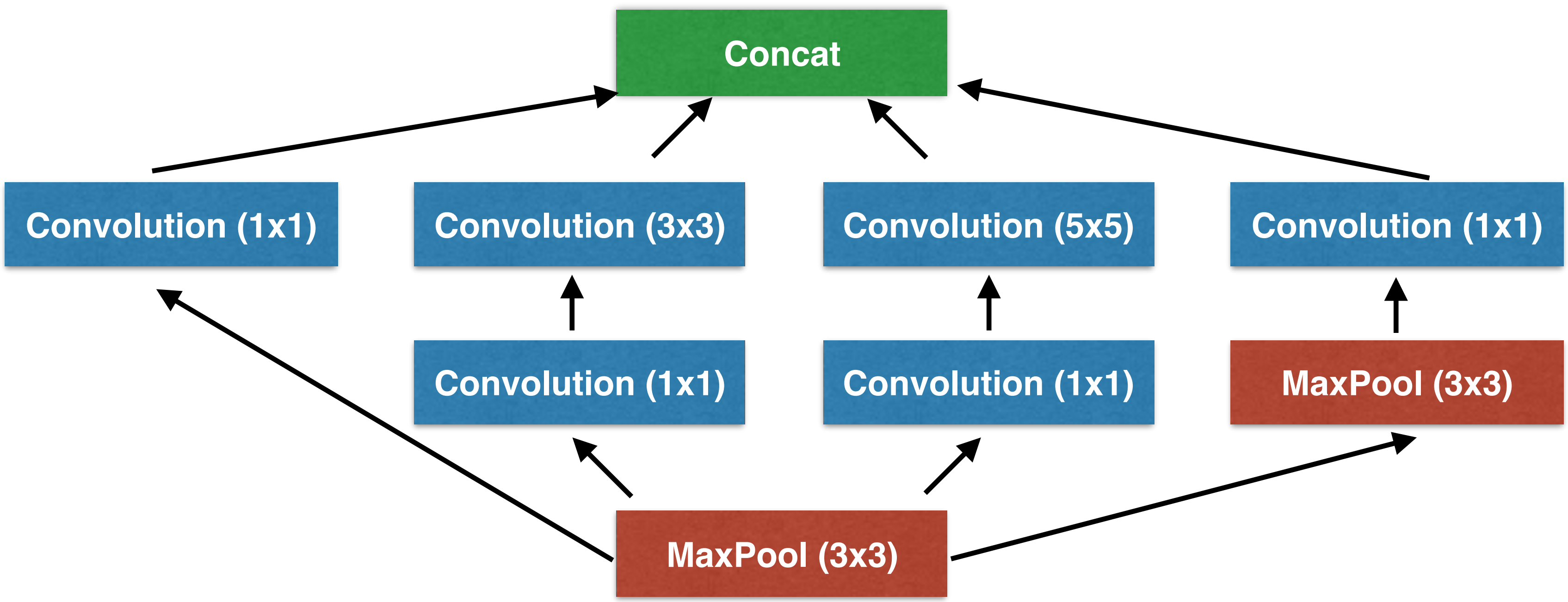
~60M parameters



Basic architecture developed by Krizhevsky, Sutskever & Hinton

Won 2012 ImageNet challenge with 16.4% top-5 error rate

Supervised Vision models, 2014 edition: GoogLeNet



Some very focused on narrow area (1x1), some focused on wider area (5x5)

Vision models, 2014 edition: GoogLeNet

Module with 6 separate convolutional layers

24 layers deep!

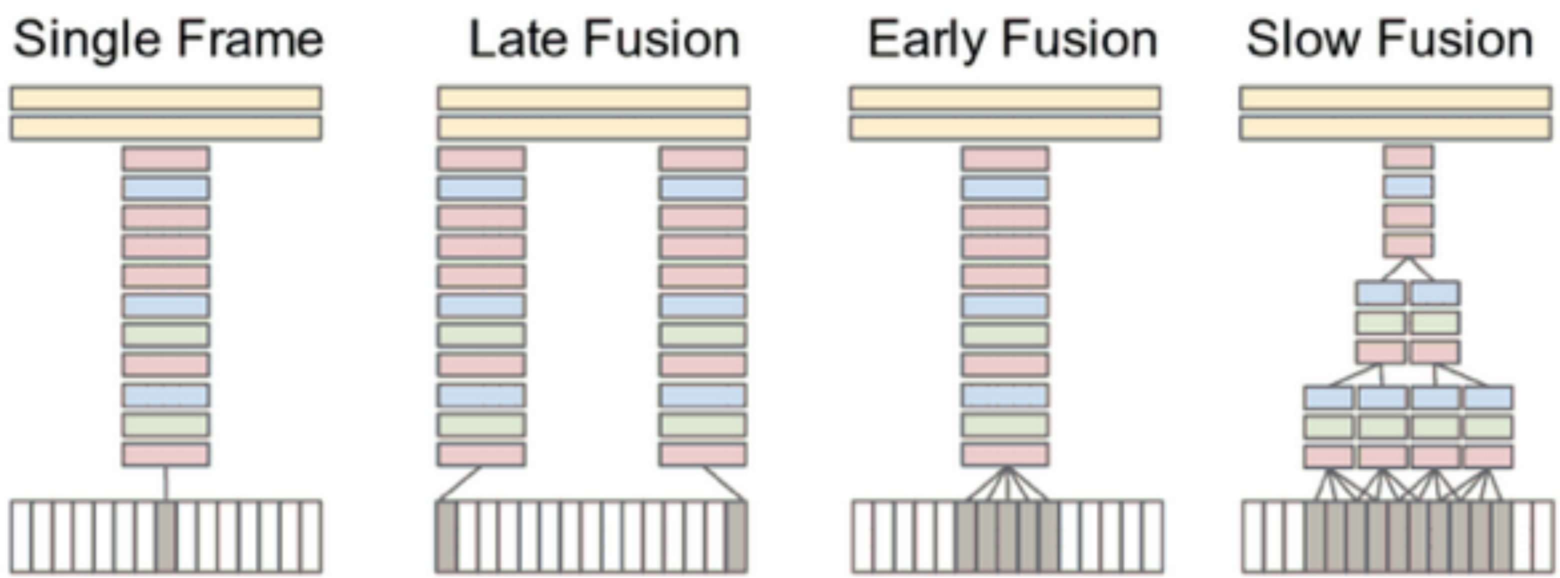
No fully-connected layer, so only ~6M parameters (but ~2B floating point operations per example)

Developed by team of Google Researchers:

Won 2014 ImageNet challenge with **6.66%** top-5 error rate

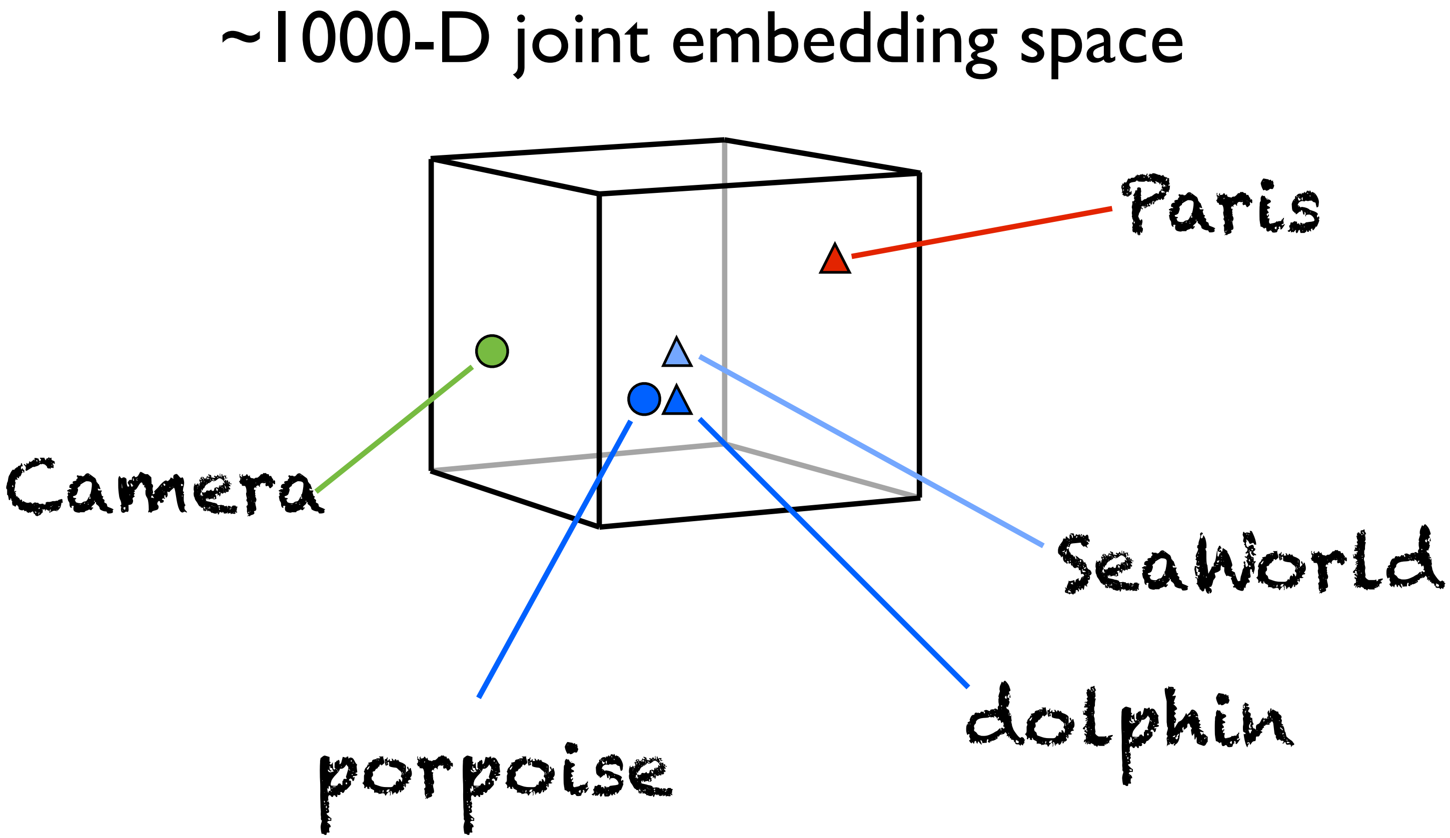
Video models

What's the right architecture?



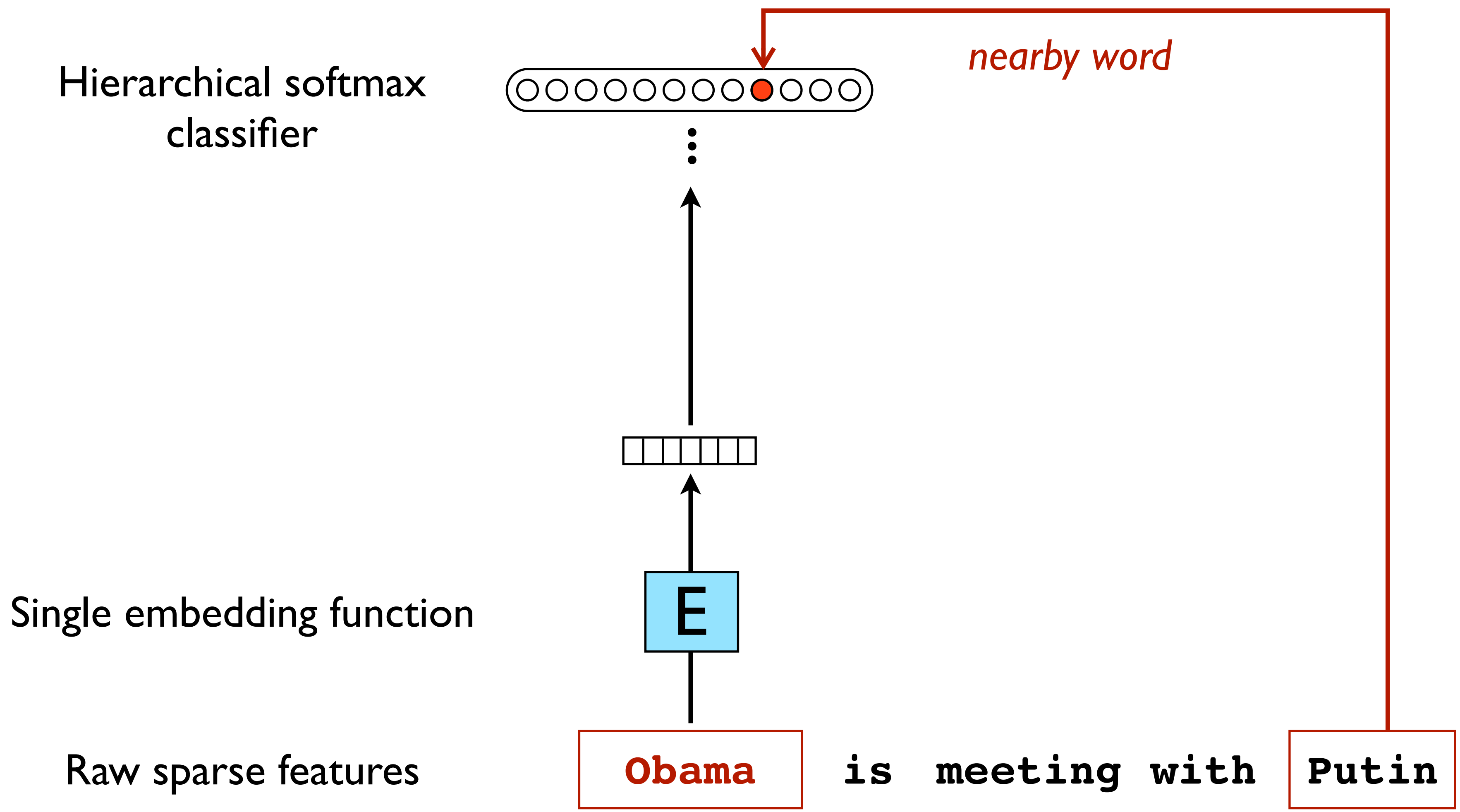
Sparse Embedding Models

Embeddings allow DNNs to deal with sparse data

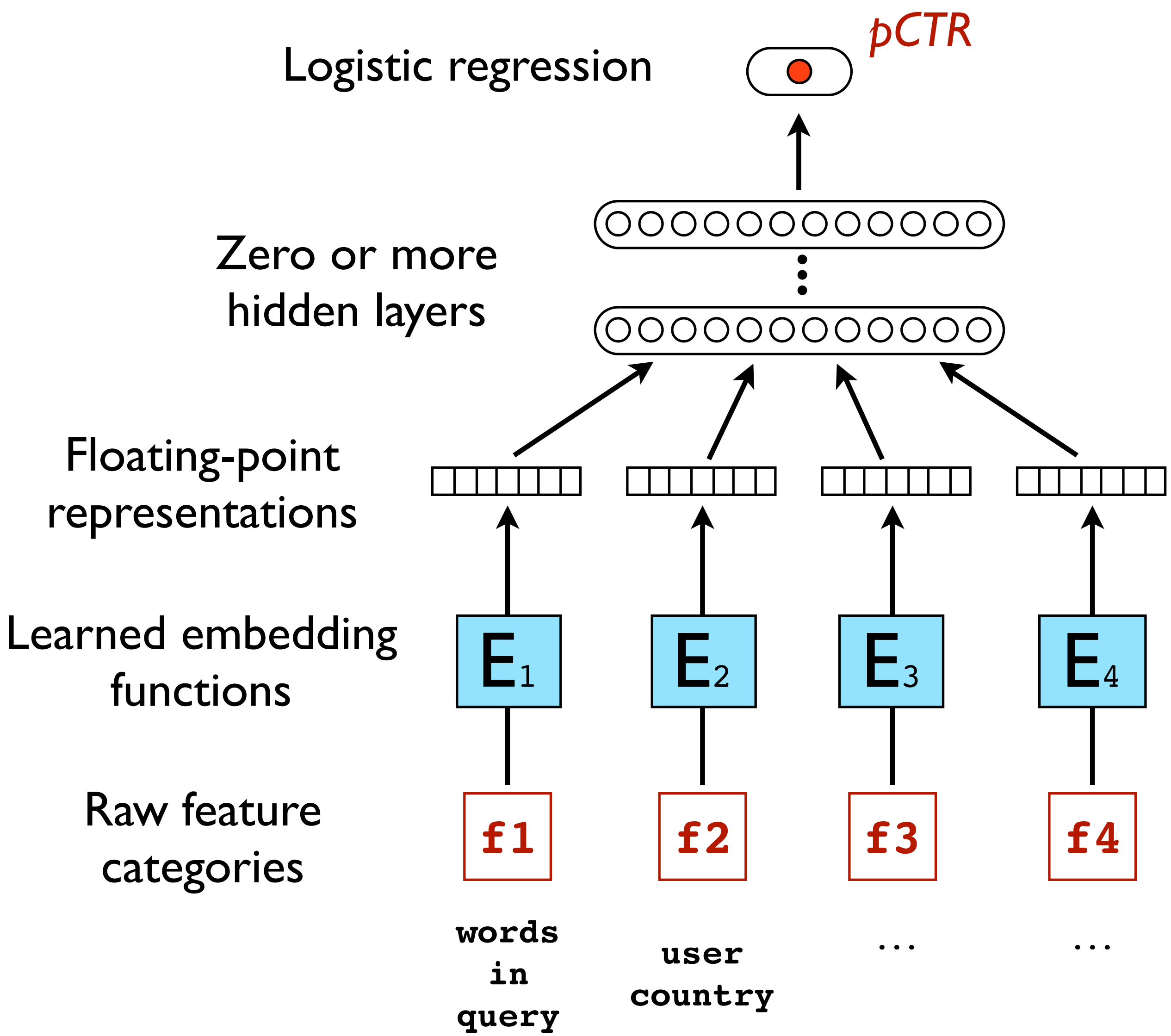


Embedding Models

Skipgram Text Model



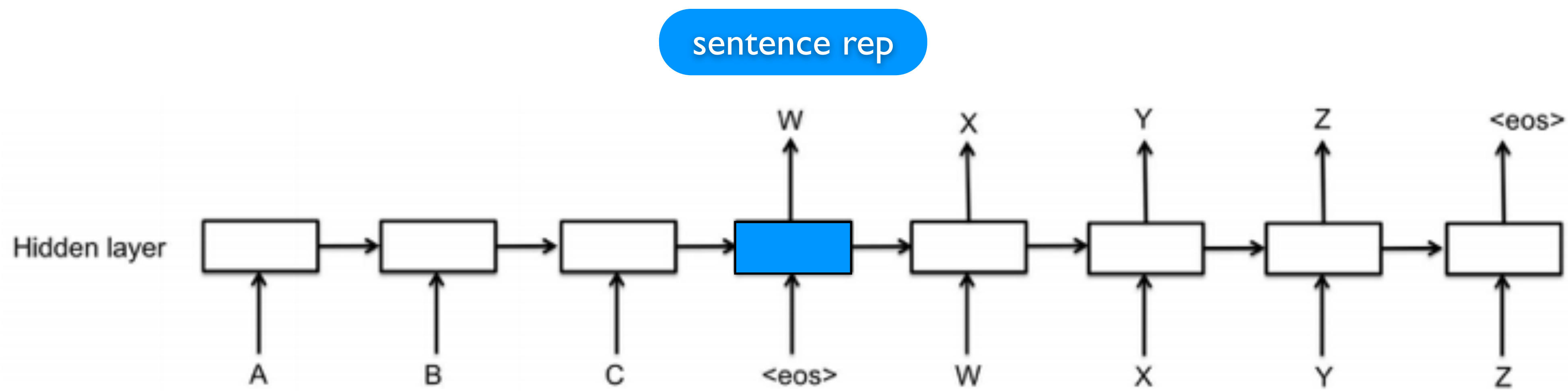
Applying Deep Nets to Prediction problems



LSTM for End to End Translation

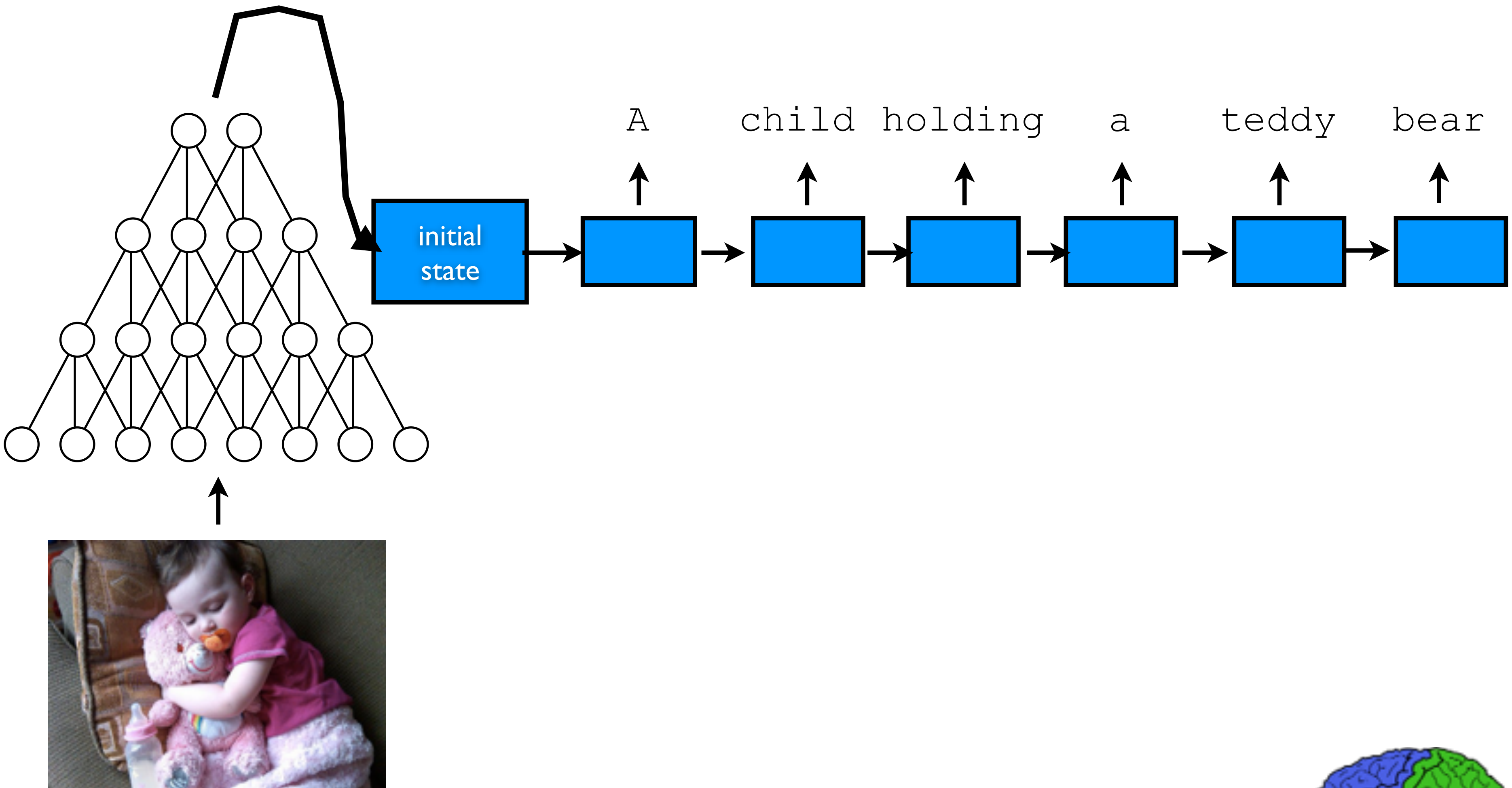
Source Language: A B C

Target Language: W X Y Z



Details in *Sequence to Sequence Learning with Neural Networks*, Ilya Sutskever, Oriol Vinyals, and Quoc Le. http://arxiv.org/abs/1409.3215. NIPS, 2014.

Combining ConvNets and LSTMs



Pretty Wide Variety of Models

But One Underlying System..

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Key abstractions of our Software Infrastructure

Layer, composed of **Nodes**

Layers implement **ComputeUp** and **ComputeDown**

Layers: can be partitioned across multiple machines
(system manages all the communication automatically)

Model: Simple textual description of layers and their connectivity

Dean, Corrado, et al. , *Large Scale Distributed Deep Networks,* NIPS 2012.

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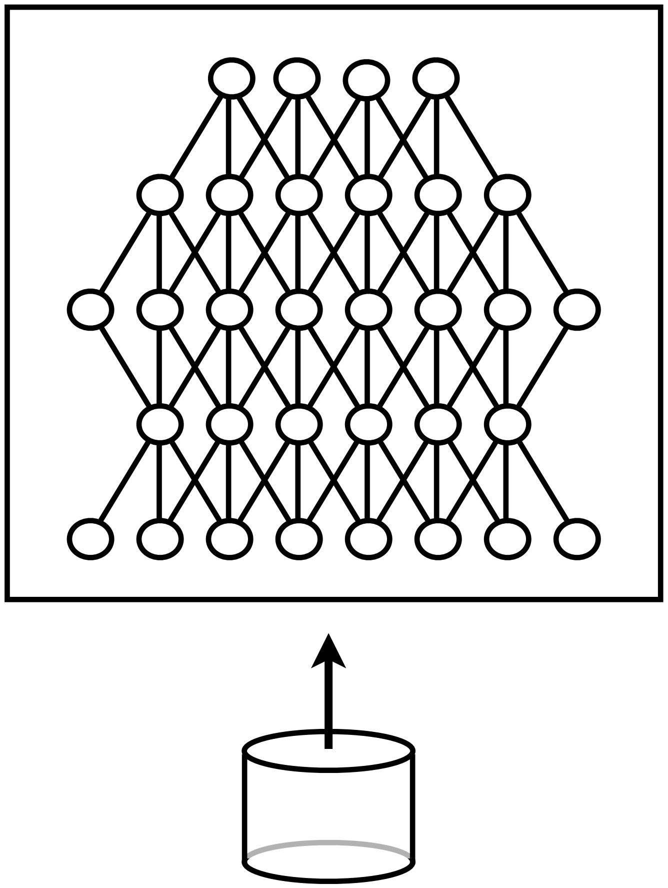
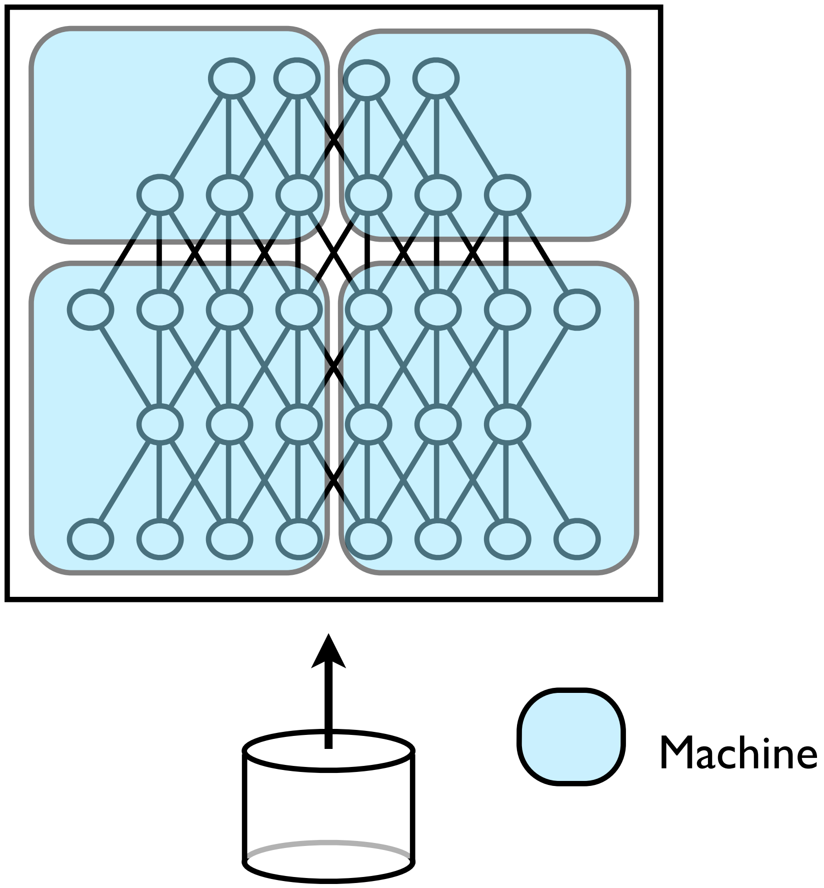
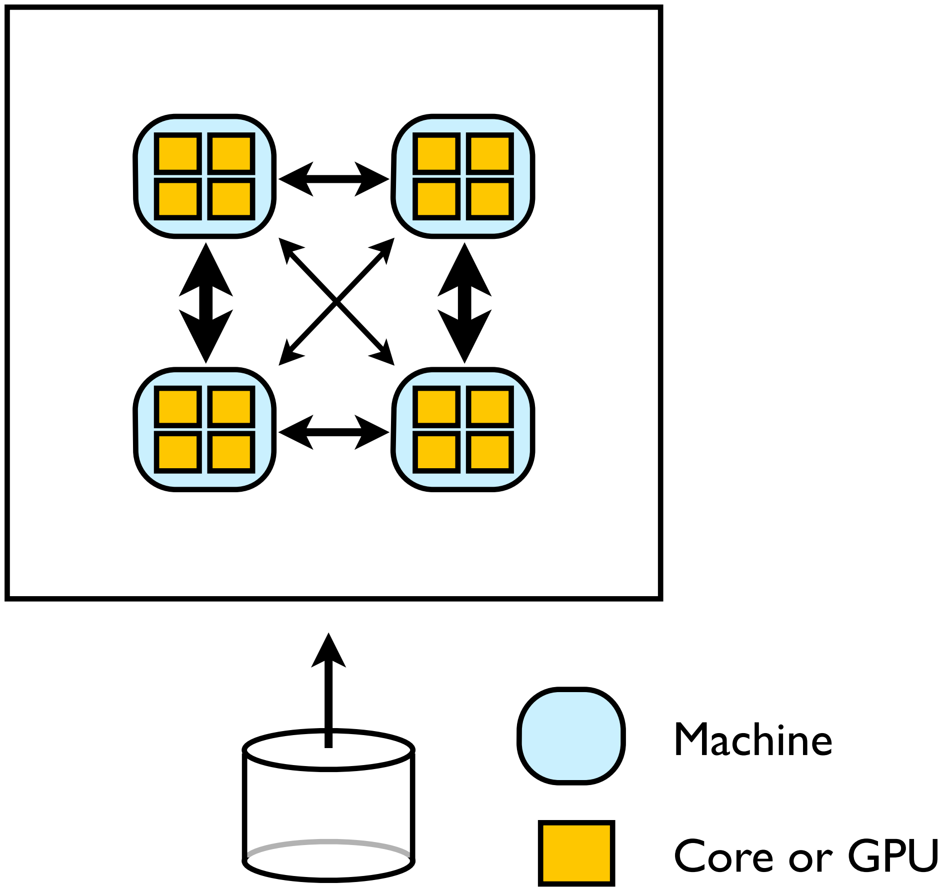
Parallelizing Deep Network Training



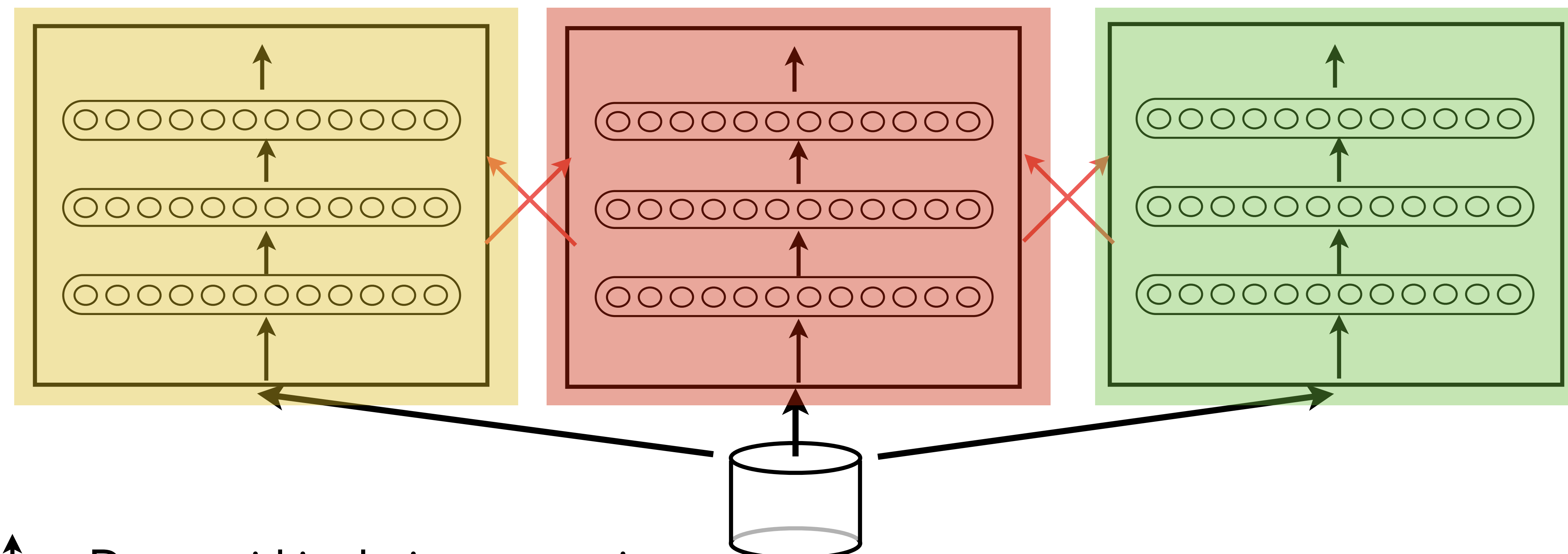
Model Parallelism



Transfer Needed Data Across Machine Boundaries



Model Connectivity and Communication



Dense within-device connections

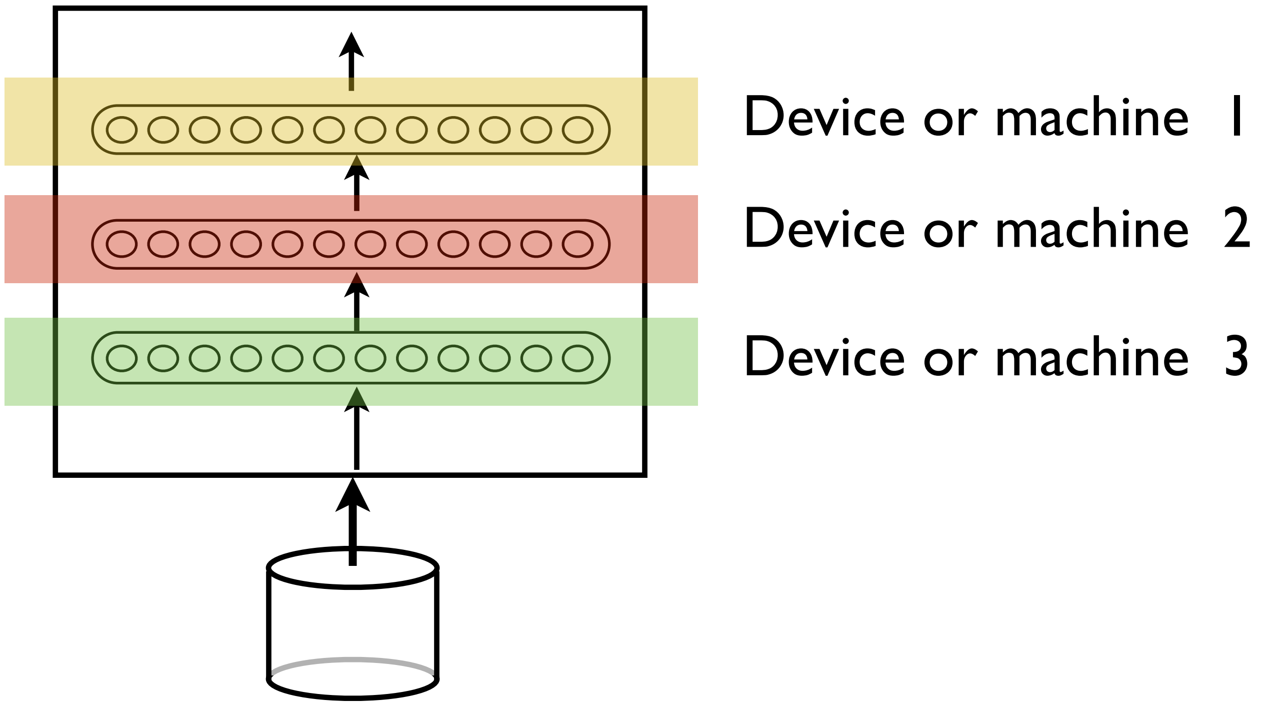
Sparse and infrequent cross-device connectivity

Concurrent Steps

We often run multiple concurrent steps (perhaps 2 to 5) in the same model

Effectively pipelines a larger batch, and can hide some communication latency with useful computation

Model Connectivity and Communication



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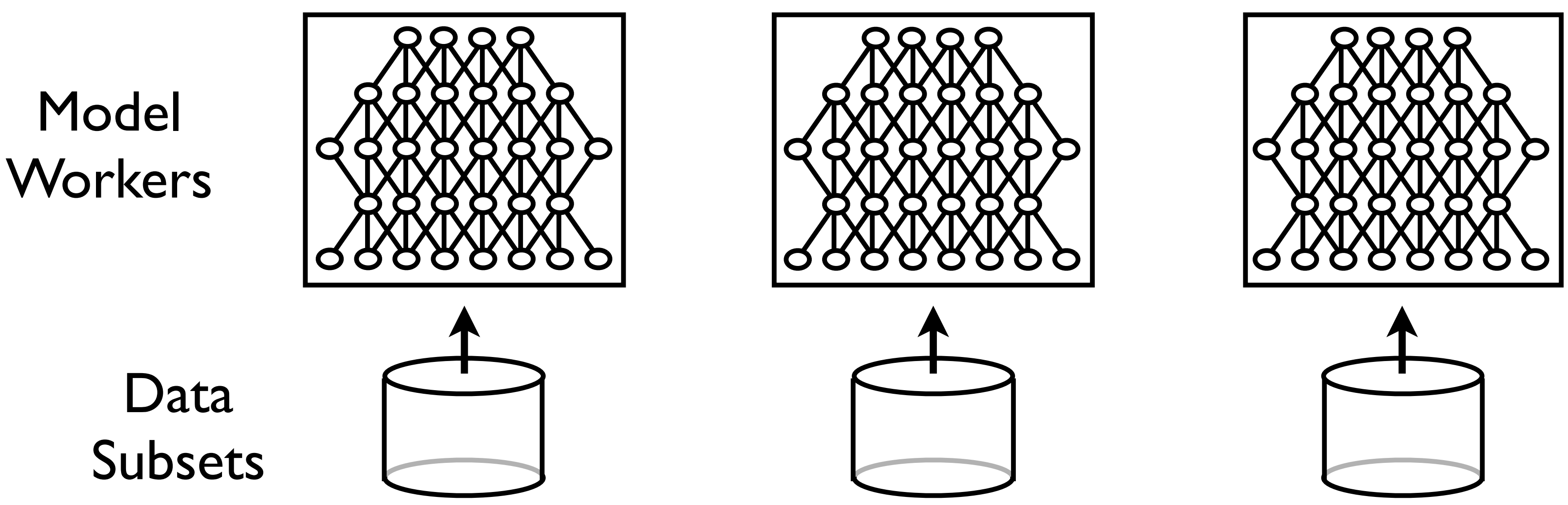
Data Parallelism



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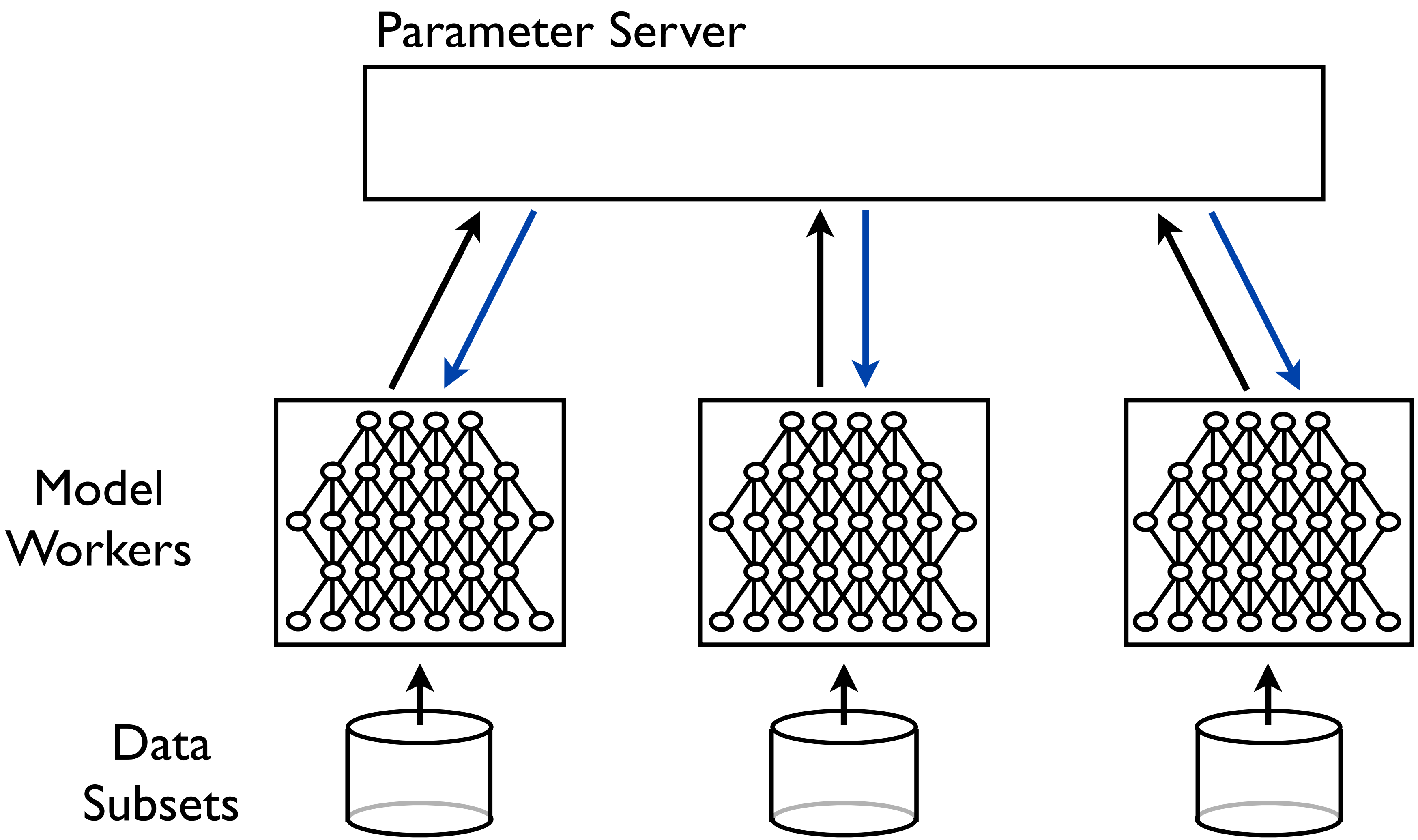
Synchronize O(# weights) Parameters



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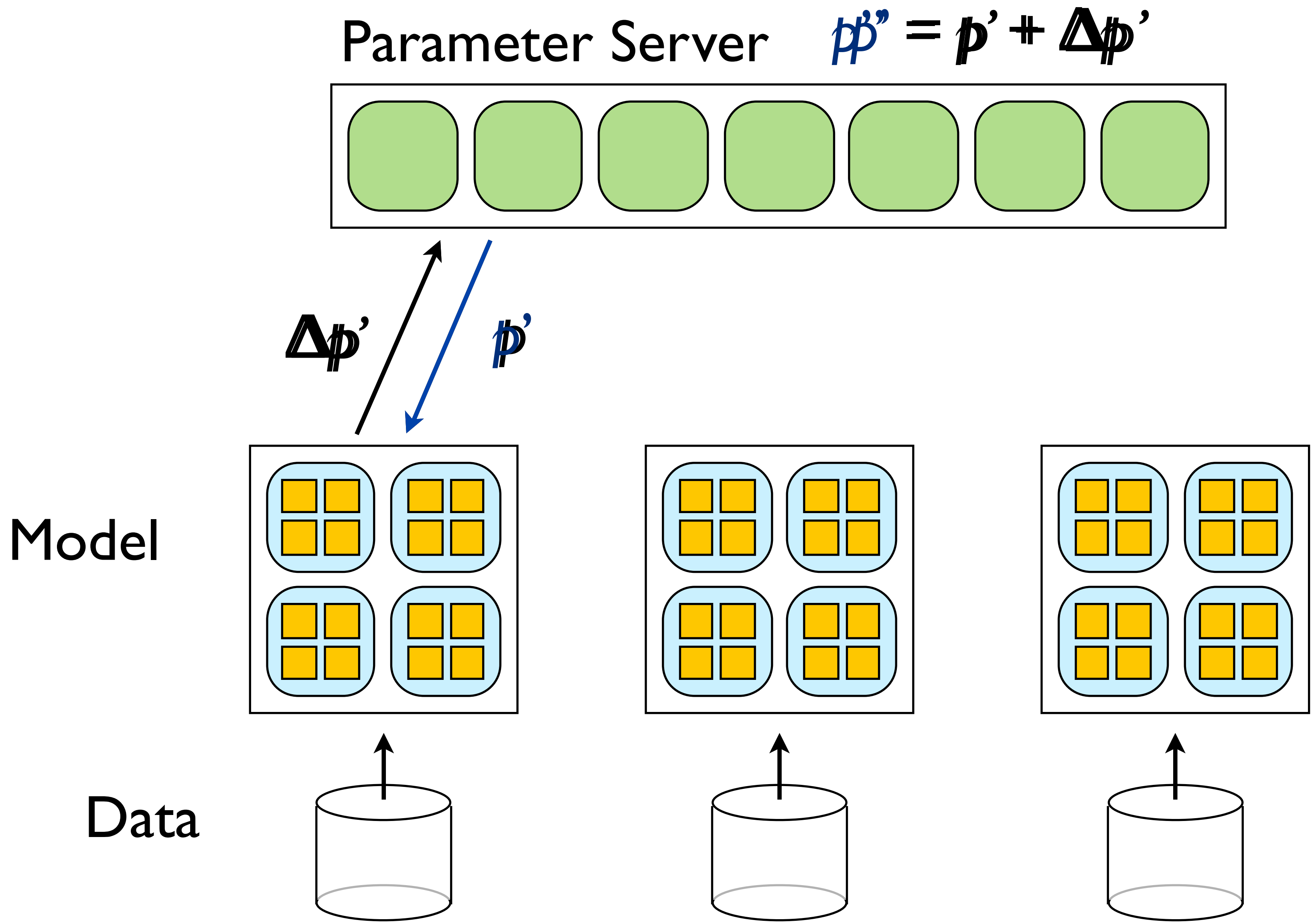
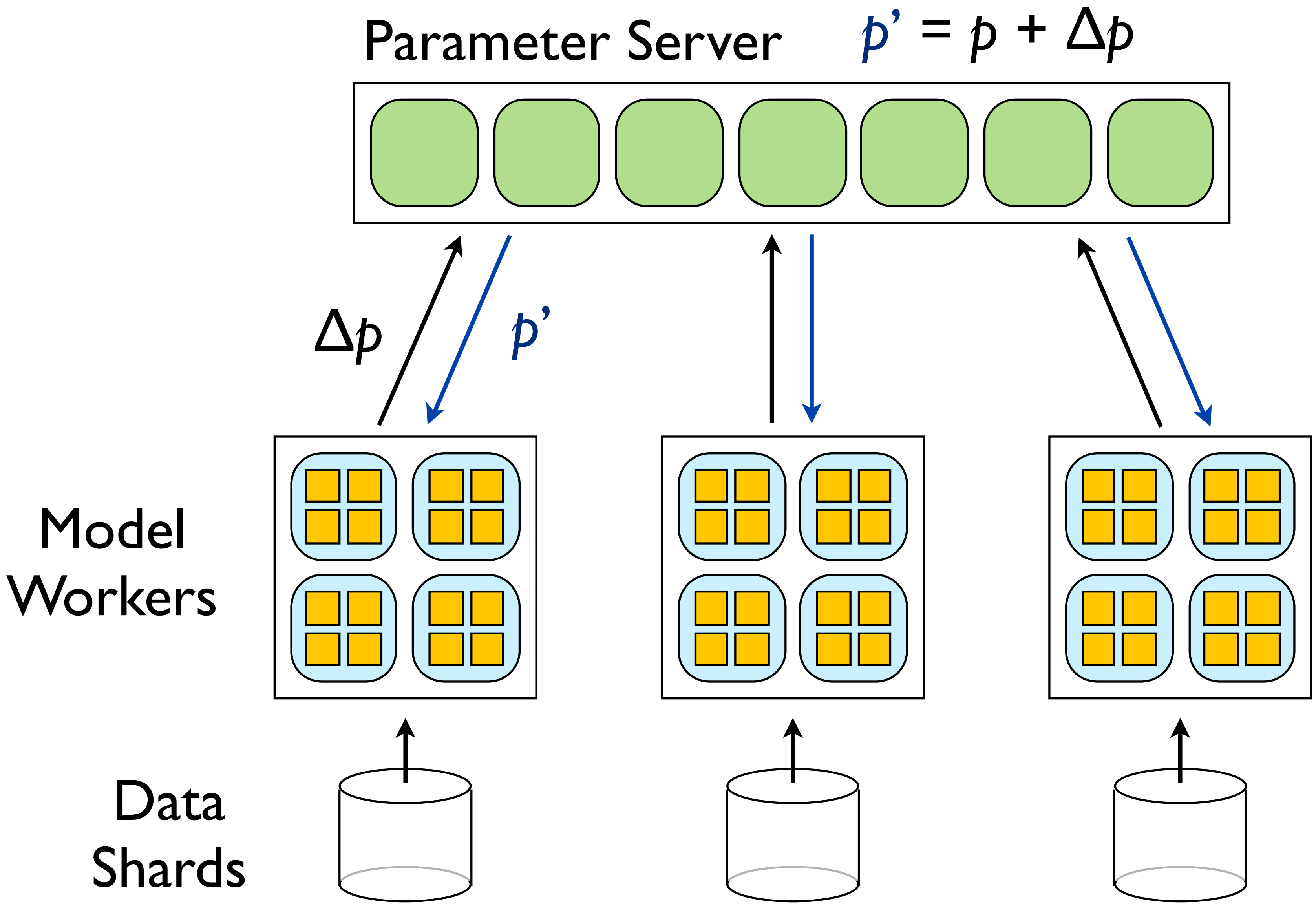
Data Parallelism:
Asynchronous Distributed Stochastic Gradient Descent



Data Parallelism:
Asynchronous Distributed Stochastic Gradient Descent



Model Parameters and Reuse

Good for data parallelism scalability if either:

(1) Most parameters in model aren't needed for a particular batch of examples (e.g. sparse embedding models), or

(2) Each parameter fetched over the network is reused many times as part of a mini batch (e.g. convolutional vision models, unrolled LSTM models, etc.).

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Feasible Number of Replicas

Depends on many things:

(1) Number of parameters needed for each minibatch
(2) Sparsity of updates

Very dense, fully-connected models: 10-50 replicas
Sparse models (mostly embeddings): 500-1000 replicas

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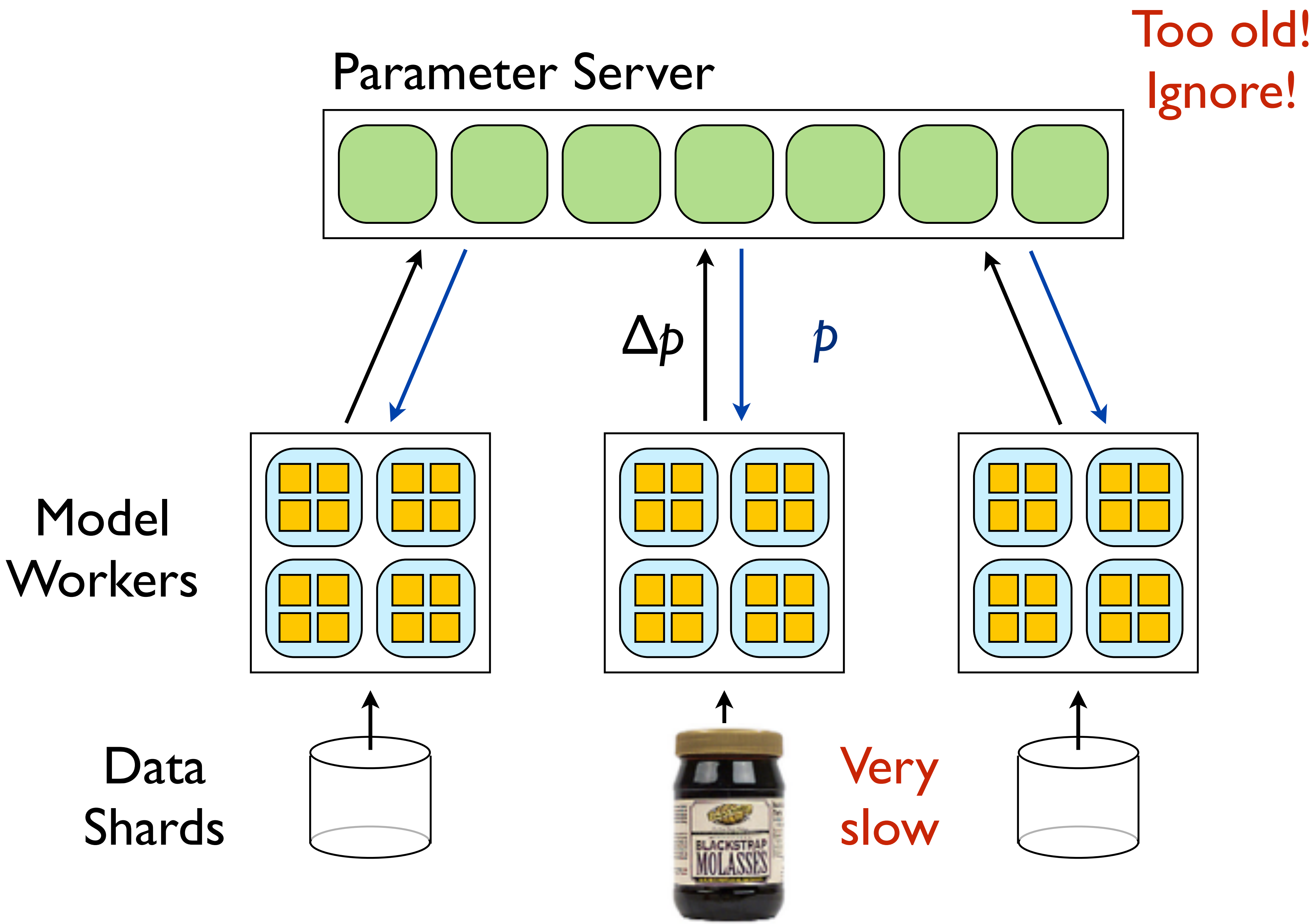
Staleness


Too old!
Ignore!
Parameter Server
Δp
p
Model
Workers
Data
Shards
BLACKSTRAP
MOLASSES
Very
slow

Adagrad

Technique for learning a per-parameter learning rate

- Scale update by:

$$\frac{l}{\sqrt{\sum_{i=1}^{t} \Delta w_{ij}^{2}}}$$

- Especially useful if not every parameter updated on every

J. C. Duchi, E. Hazan, and Y. Singer. Adaptive subgradient methods for online learning and stochastic optimization. Journal of Machine Learning Research, 12:2121–2159, 2011.

Low-Level Optimizations

Added support for AVX and FMA to Eigen.

Overview | Commits | Activity

Author  Benoit Steiner

Reviewers *No reviewers*

Description This branch adds support for AVX and FMA to Eigen. When combined with the patches attached to bugs 717, 721, and 724 this doubles the speed of the matrix multiplication code on SandyBridge and IvyBridge, and about triples the speed on Haswell

Low-Level Optimizations

Avoid locking, or use fine-grained locking

Avoid excessive copies for data transferred over the network

Compile versions of important operations specialized to actual sizes

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Reduced Precision

Neural nets are very tolerant of reduced precision:

8 bits or less for inference
12 to 14 bits for training

For sending parameter values over network, we often use lower precision than floats:
16-bit "floats": just truncate the mantissa (don't even bother with correct rounding)

Large-Scale Batch Methods

We have experimented with large-scale batch methods like L-BFGS

Not really successful for us compared with SGD

Wish they were: very parallelizable

Hyper-parameter Search

Good hyper-parameter selection is critical

Techniques:

(1) Grid search
(2) Grid search, but with heuristics to kill unpromising experiments early
(3) Fancier methods like Gaussian Processes

e.g. Spearmint: "*Practical Bayesian Optimization of Machine Learning Algorithms*", Snoek, Larochelle and Adams, NIPS 2012

Classifications for Many Classes

Many problems need to predict 1 of N classes, and N can be quite large

- Image models are 10000s of classes
- Text vocabularies start at 10000s of words and go up to millions
- Action prediction can be hundreds of millions or billions of actions (e.g. all YouTube videos)

Classifications for Many Classes

For up to a few 10000s of classes, we use a full softmax. For large vocabularies, we use either:

(1) Hierarchical softmax or
(2) Noise-contrastive estimation

Ensembles

Good news:

(1) Ensembling many models generally improves accuracy significantly (but with diminishing returns after 5 or 10 models)

(2) Completely parallelizable

Bad news:

(1) Makes inference cost much higher

Distillation

Technique for taking large ensemble and using its predictions to train smaller, cheaper model that captures most of the ensemble's benefits

Have to train a large model or ensemble, but can then distill it into a lighter-weight model so that inference is faster

Distilling Knowledge in a Neural Network, Geoffrey Hinton, Oriol Vinyals, and Jeffrey Dean, Deep Learning and Representation Learning Workshop, NIPS 2014

Specialists

For large datasets, can train many models in parallel, each specialized for a subset of the classes

Completely parallelizable during training

Only need to consult relevant specialists during inference

Distilling Knowledge in a Neural Network, Geoffrey Hinton, Oriol Vinyals, and Jeffrey Dean, Deep Learning and Representation Learning Workshop, NIPS 2014

Current Work

Actively building TensorFlow, our next-generation of training and inference software.

Why?

(1) Learned more about the problem in first two years
(2) Want more flexible system, not geared as much towards only SGD training of neural nets
(3) Target a wider range of computational devices
(4) Combine convenience and flexibility of research systems like Theano & Torch with production readiness and scalability of our first system

Google

Thanks!

Questions?