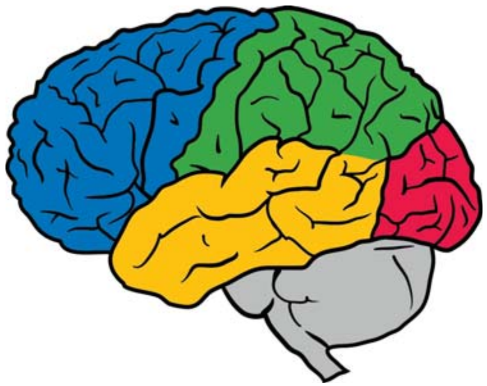


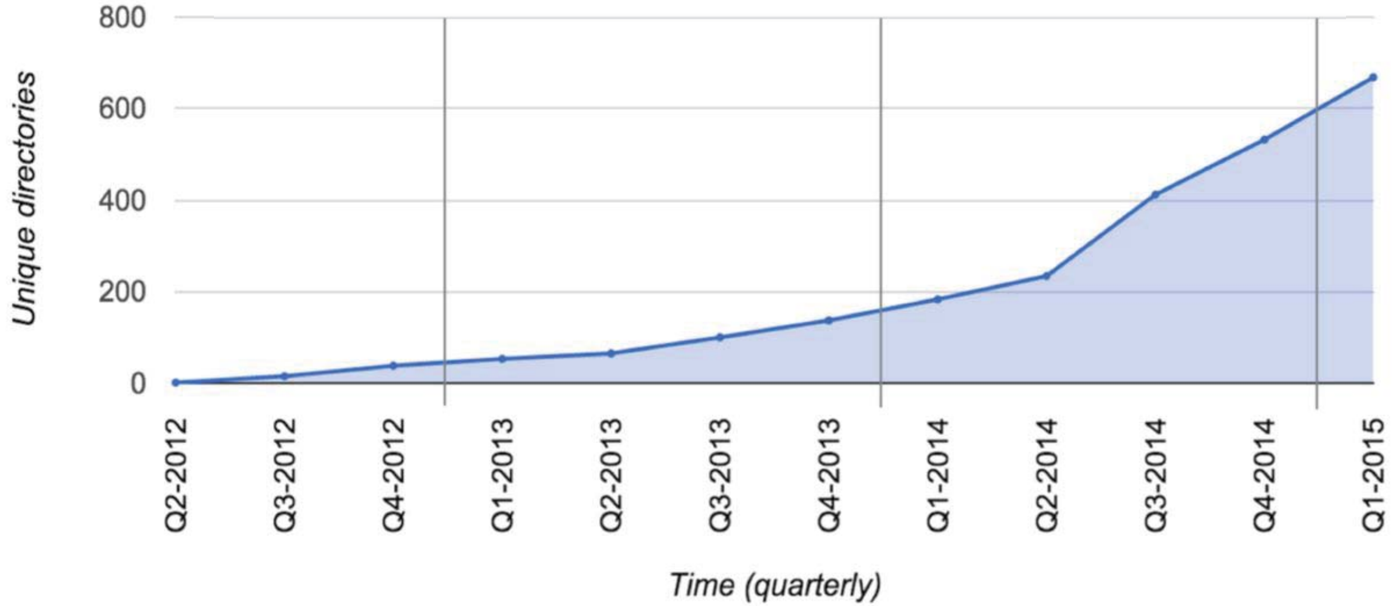
Large-Scale Deep Learning for Intelligent Computer Systems

Jeff Dean

Google Brain team in collaboration with many other teams

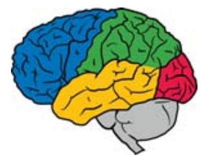
Growing Use of Deep Learning at Google

of directories containing model description files



Across many products/areas:

Android
Apps
GMail
Image Understanding
Maps
NLP
Photos
Robotics
Speech
Translation
many research uses..
YouTube
… many others ...



Outline

Two generations of deep learning software systems:

- 1st generation: DistBelief [Dean *et al.*, NIPS 2012]
- 2nd generation: TensorFlow (unpublished)

An overview of how we use these in research and products

Plus, ...a new approach for training (people, not models)

TensorFlow:
Second Generation Deep Learning System

Motivations

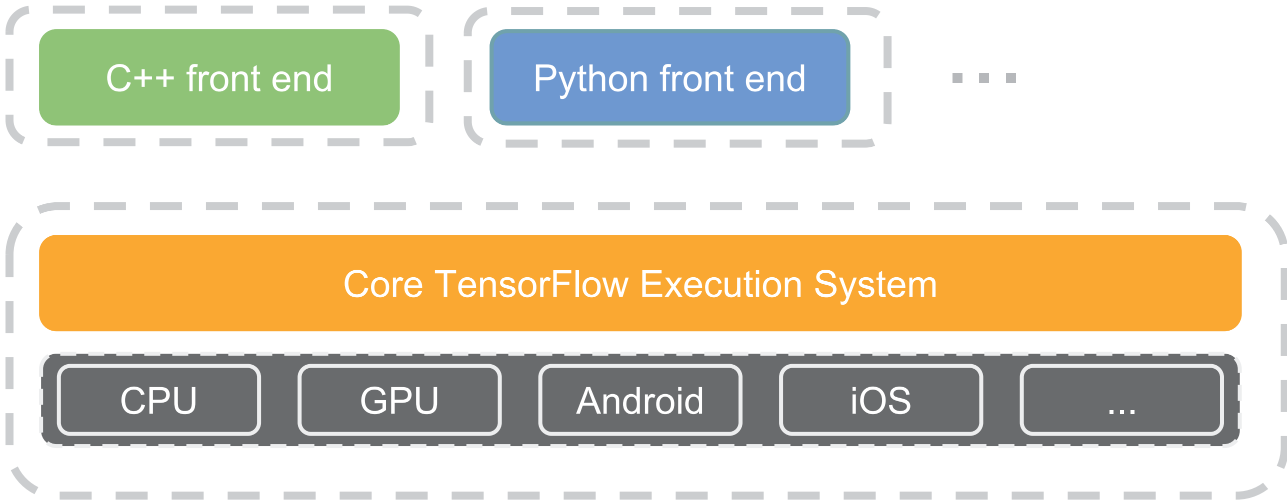
DistBelief (1st system) was great for scalability

Not as flexible as we wanted for research purposes

Better understanding of problem space allowed us to make some dramatic simplifications

TensorFlow: Expressing High-Level ML Computations

- Core in C++
  - Very low overhead
- Different front ends for specifying/driving the computation
  - Python and C++ today, easy to add more



TensorFlow Example (Batch Logistic Regression)

```
graph = tf.Graph()                                                              # Create new computation graph
with graph.AsDefault():
  examples = tf.constant(train_dataset)                                         # Training data/labels
  labels = tf.constant(train_labels)

  W = tf.Variable(tf.truncated_normal([image_size * image_size, num_labels]))   # Variables
  b = tf.Variable(tf.zeros([num_labels]))

  logits = tf.mat_mul(examples, W) + b                                          # Training computation
  loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits, labels))

  optimizer = tf.train.GradientDescentOptimizer(0.5).minimize(loss)             # Optimizer to use
  prediction = tf.nn.softmax(logits)                                            # Predictions for training data
```

TensorFlow Example (Batch Logistic Regression)

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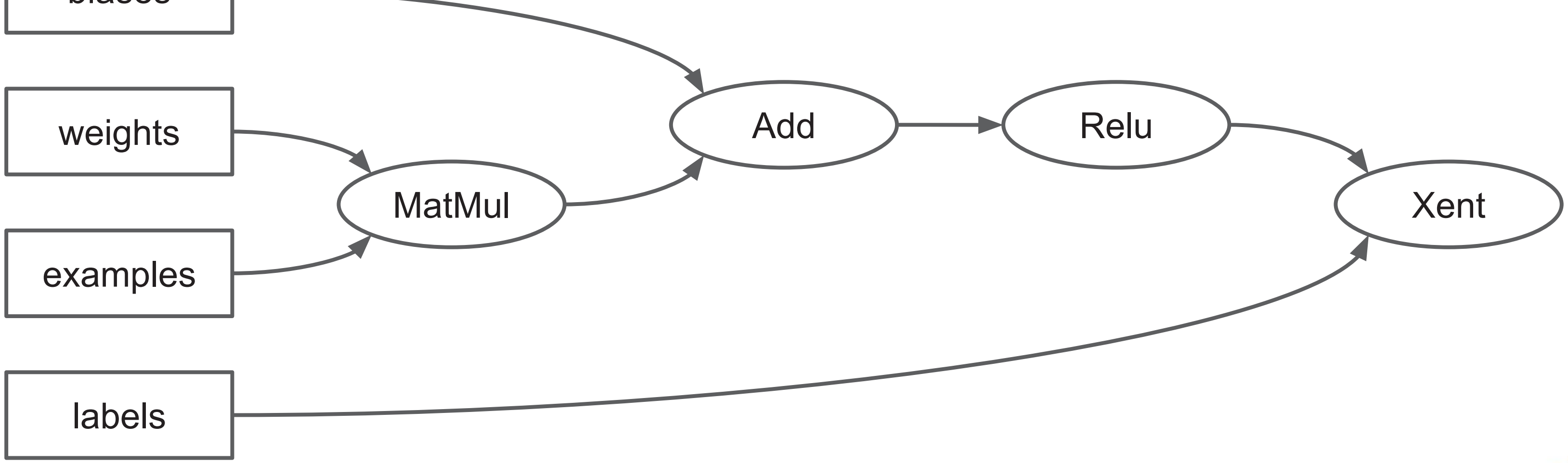
  optimizer = tf.train.GradientDescentOptimizer(0.5).minimize(loss)         # Optimizer to use
  prediction = tf.nn.softmax(logits)                                        # Predictions for training data

with tf.Session(graph=graph) as session:
  tf.InitializeAllVariables().Run()
  for step in xrange(num_steps):
    _, l, predictions = session.Run([optimizer, loss, prediction])          # Run & return 3 values
    if (step % 100 == 0):
      print 'Loss at step', step, ':', l
      print 'Training accuracy: %.1f%%' % accuracy(predictions, labels)
```

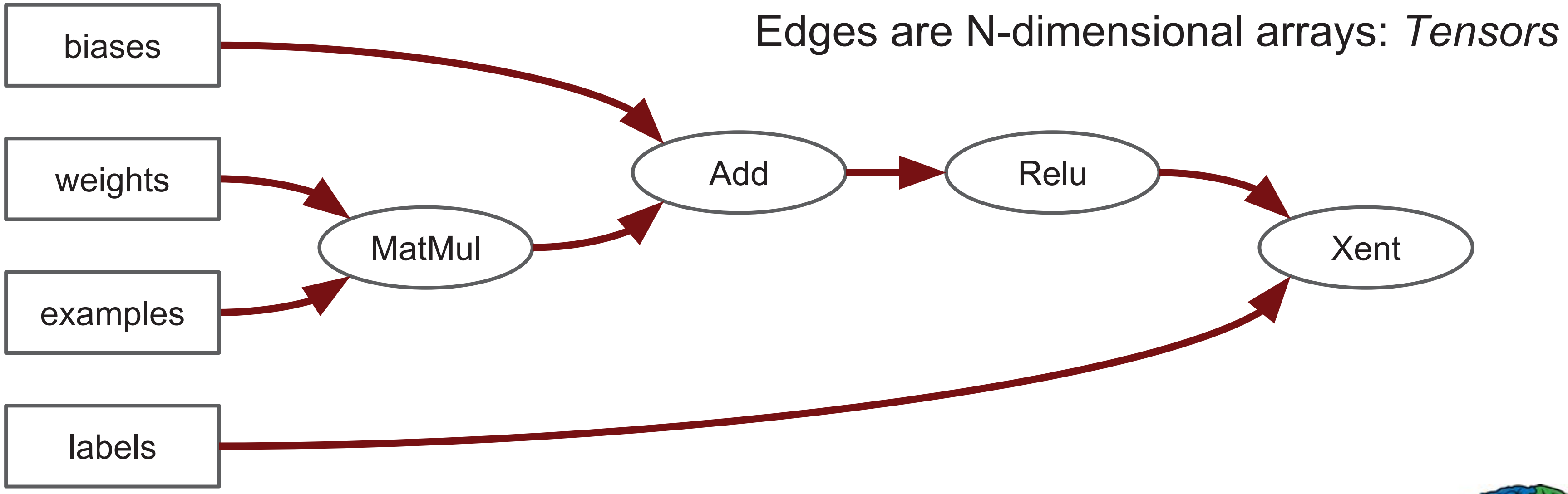
Computation is a dataflow graph

Graph of *Nodes*, also called *Operations* or *ops.*

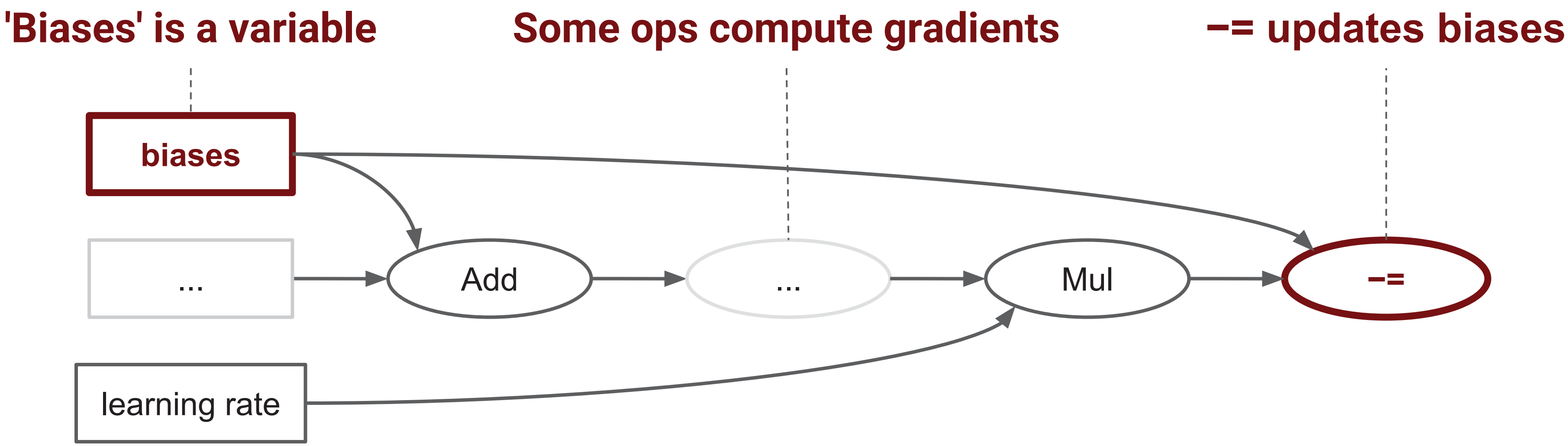


Computation is a dataflow graph

with tensors

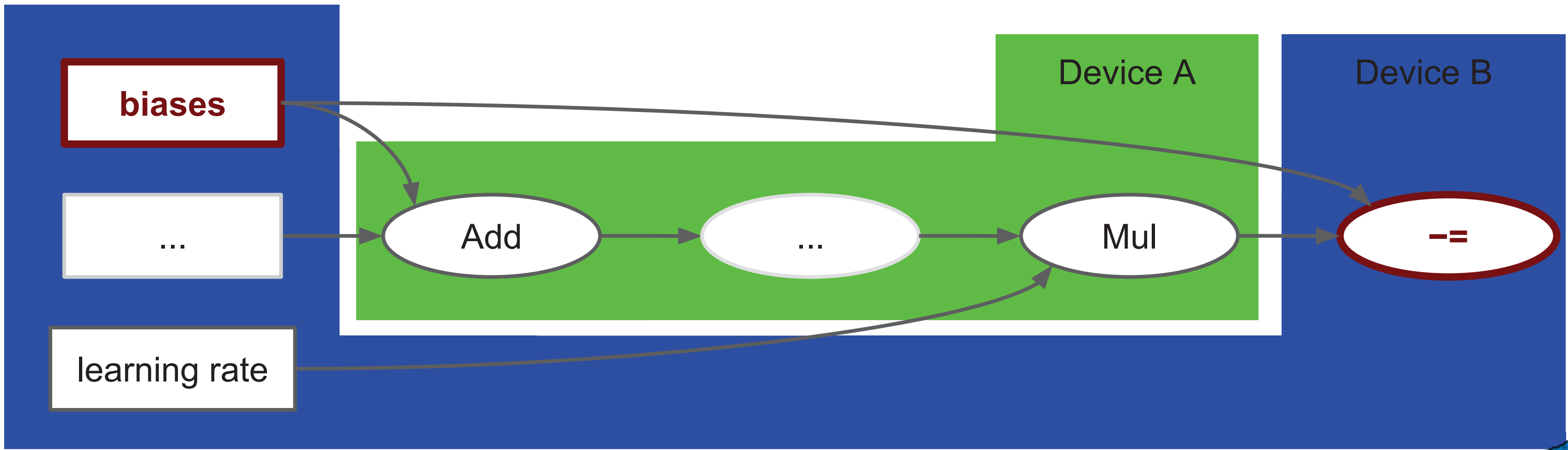


Computation is a dataflow graph **with state**

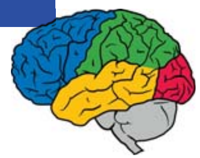


Computation is a dataflow graph

distributed



Devices: Processes, Machines, GPUs, etc



TensorFlow: Expressing High-Level ML Computations

Automatically runs models on range of platforms:

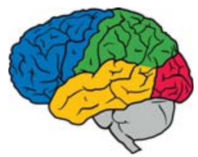
from **phones** ...

to **single machines** (CPU and/or GPUs) …

to **distributed systems** of many 100s of GPU cards

What is in a name?

- **Tensor**: N-dimensional array
  - 1-dimension: Vector
  - 2-dimension: Matrix
  - Represent many dimensional data flowing through the graph
    - e.g. Image represented as 3-d tensor rows, cols, color
- **Flow**: Computation based on data flow graphs
  - Lots of operations (nodes in the graph) applied to data flowing through
- Tensors flow through the graph → "***TensorFlow***"
  - Edges represent the tensors (data)
  - Nodes represent the processing



Flexible

- General computational infrastructure
  - Deep Learning support is a set of libraries on top of the core
  - Also useful for other machine learning algorithms
  - Possibly even for high performance computing (HPC) work
  - Abstracts away the underlying devices/computational hardware

Extensible

- Core system defines a number of standard ***operations*** and ***kernels*** (device-specific implementations of operations)
- Easy to define new operators and/or kernels

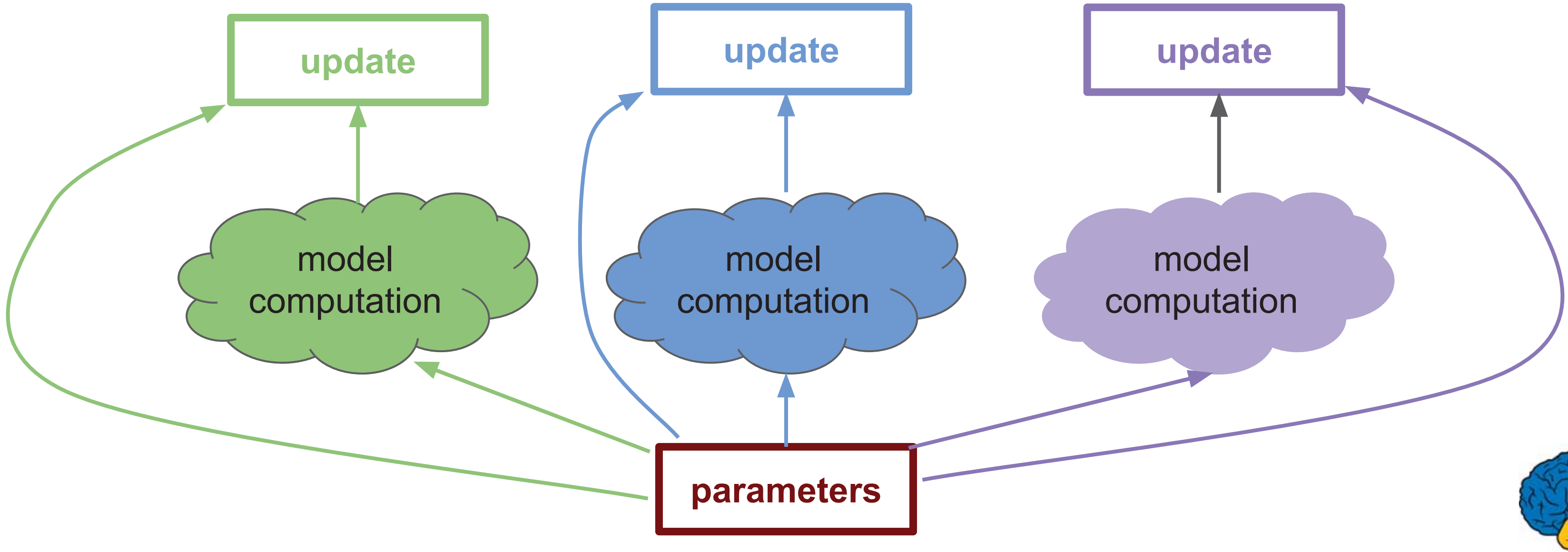
Deep Learning in TensorFlow

- Typical neural net “layer” maps to one or more tensor operations
  - e.g. Hidden Layer: `activations = Relu(weights * inputs + biases)`
- **Library of operations specialized for Deep Learning**
  - **Dozens of high-level operations:** 2D and 3D convolutions, Pooling, Softmax, ...
  - **Standard losses** e.g. CrossEntropy, L1, L2
  - **Various optimizers** e.g. Gradient Descent, AdaGrad, L-BFGS, ...
- **Auto Differentiation**
- **Easy to experiment** with (or combine!) a wide variety of different models:

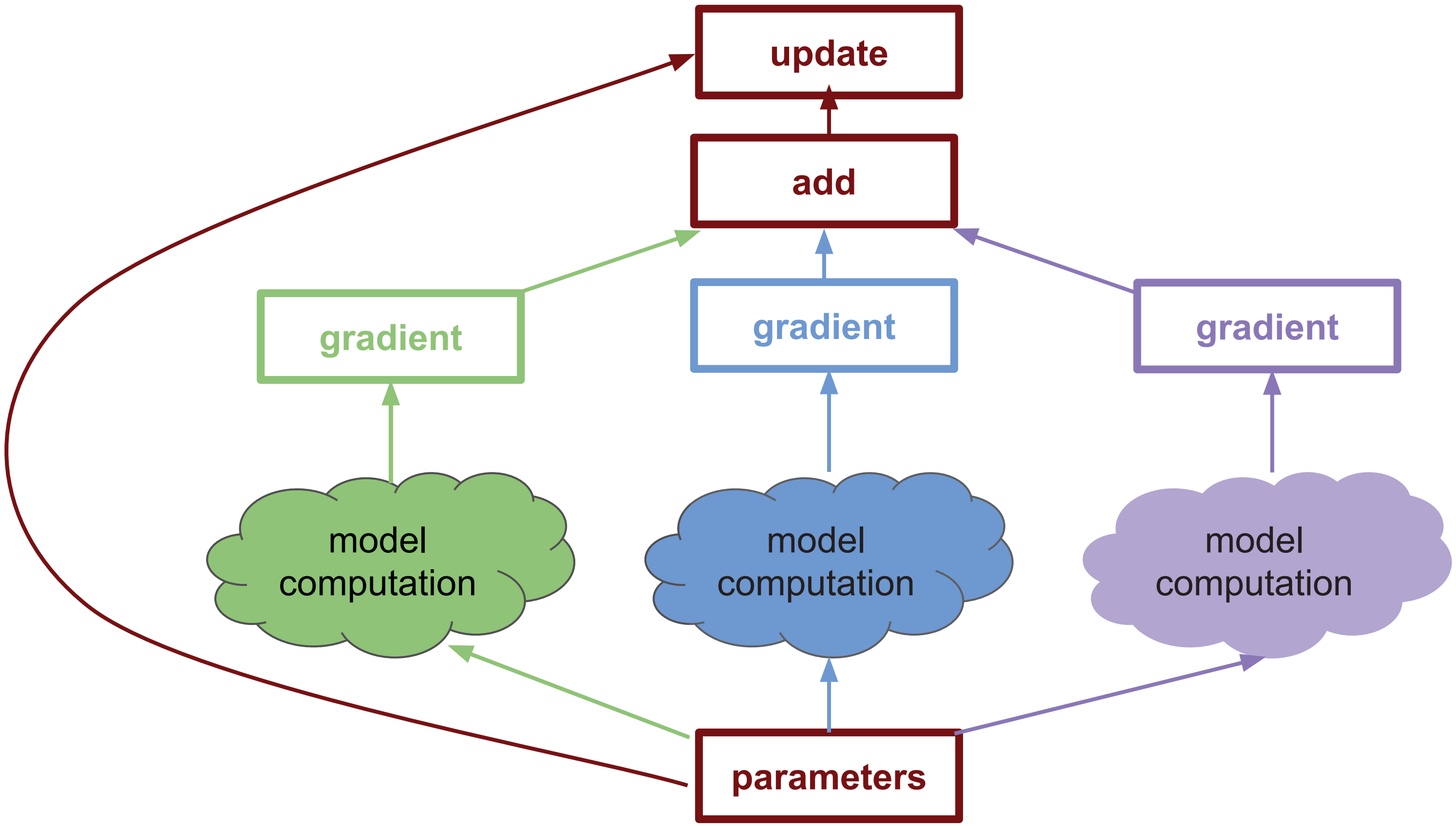
  LSTMs, convolutional models, attention models, reinforcement learning, embedding models, Neural Turing Machine-like models, ...

No distinct Parameter Server subsystem

- **Parameters are now just stateful nodes in the graph**
- **Data parallel training just a more complex graph**



Synchronous Variant



Google Brain project started in 2011, with a focus on pushing state-of-the-art in neural networks. Initial emphasis:

- use large datasets, and
- large amounts of computation

to push boundaries of what is possible in perception and language understanding

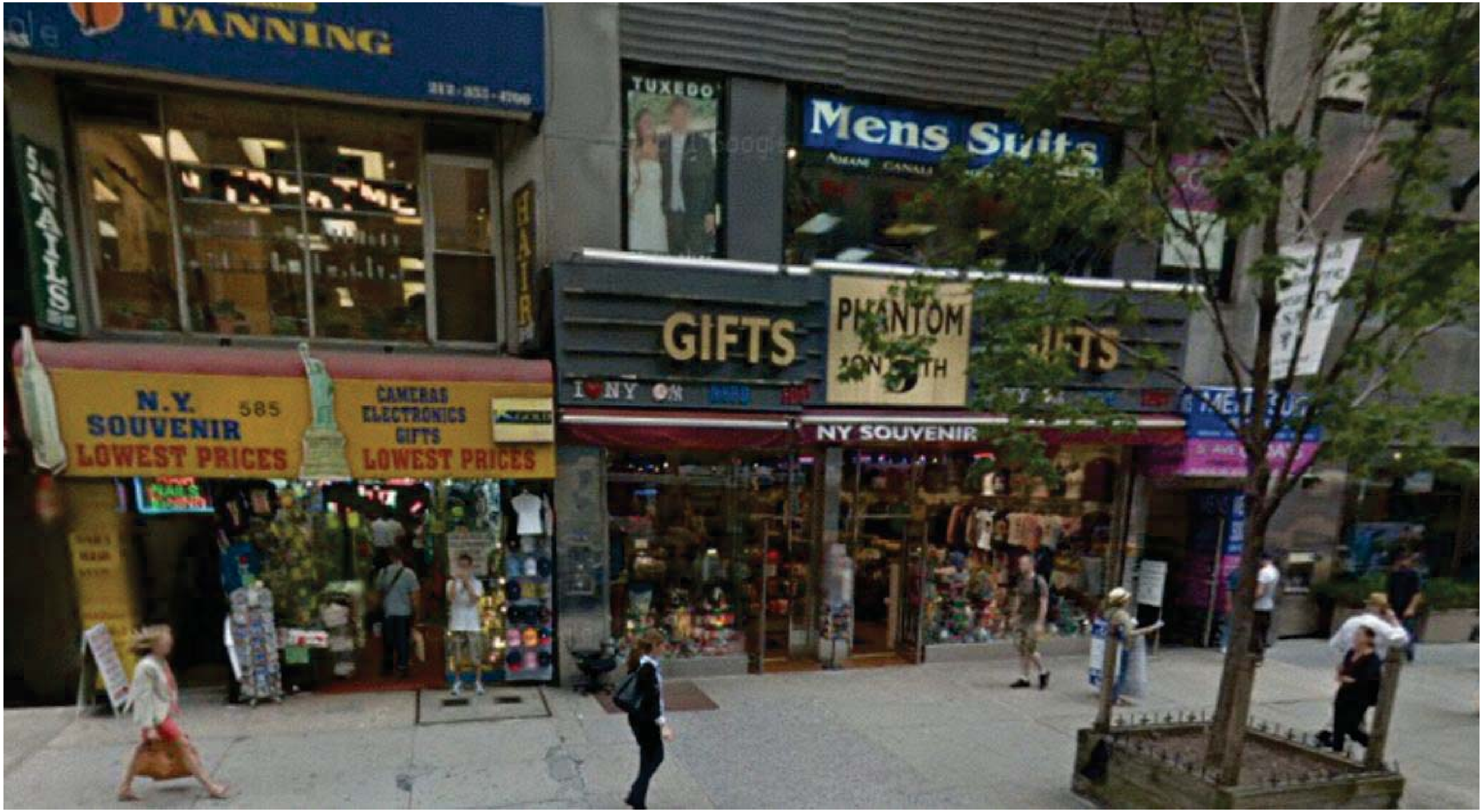
Plenty of raw data

- **Text**: trillions of words of English + other languages
- **Visual data**: billions of images and videos
- **Audio**: tens of thousands of hours of speech per day
- **User activity**: queries, marking messages spam, etc.
- **Knowledge graph**: billions of labelled relation triples
- ...

How can we build systems that truly understand this data?


stone wall [0.95, web]
dishwasher [0.91, web]
car show [0.99, web]
judo [0.96, web]
judo [0.92, web]
judo [0.91, web]
KRAKBET
tractor [0.91, web]
tractor [0.91, web]
tractor [0.94, web]


648
67
72
411
49
2016


TANNING
TUXEDO
Mens Suits
NAILS
HAIR
GIFTS
PHANTOM
N.Y.
SOUVENIR
585
LOWEST PRICES
CAMERAS
ELECTRONICS
GIFTS
LOWEST PRICES
NY SOUVENIR

Text Understanding

“This movie should have NEVER been made. From the poorly done animation, to the beyond bad acting. I am not sure at what point the people behind this movie said "Ok, looks good! Lets do it!" I was in awe of how truly horrid this movie was.”

Turnaround Time and Effect on Research

- Minutes, Hours:
  - **Interactive research! Instant gratification!**
- 1-4 days
  - Tolerable
  - Interactivity replaced by running many experiments in parallel
- 1-4 weeks:
  - High value experiments only
  - Progress stalls
- >1 month
  - Don’t even try

Important Property of Neural Networks

Results get better with

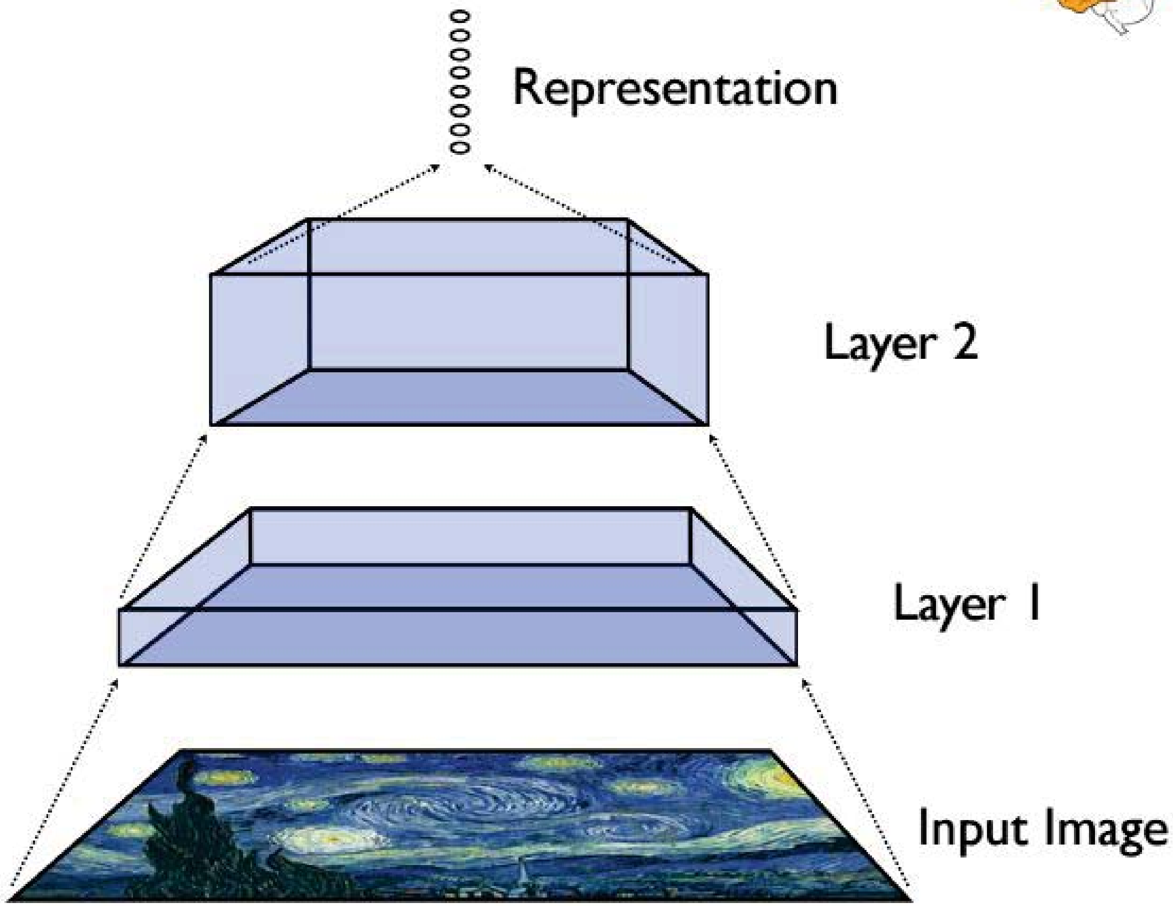
more data +
bigger models +
more computation

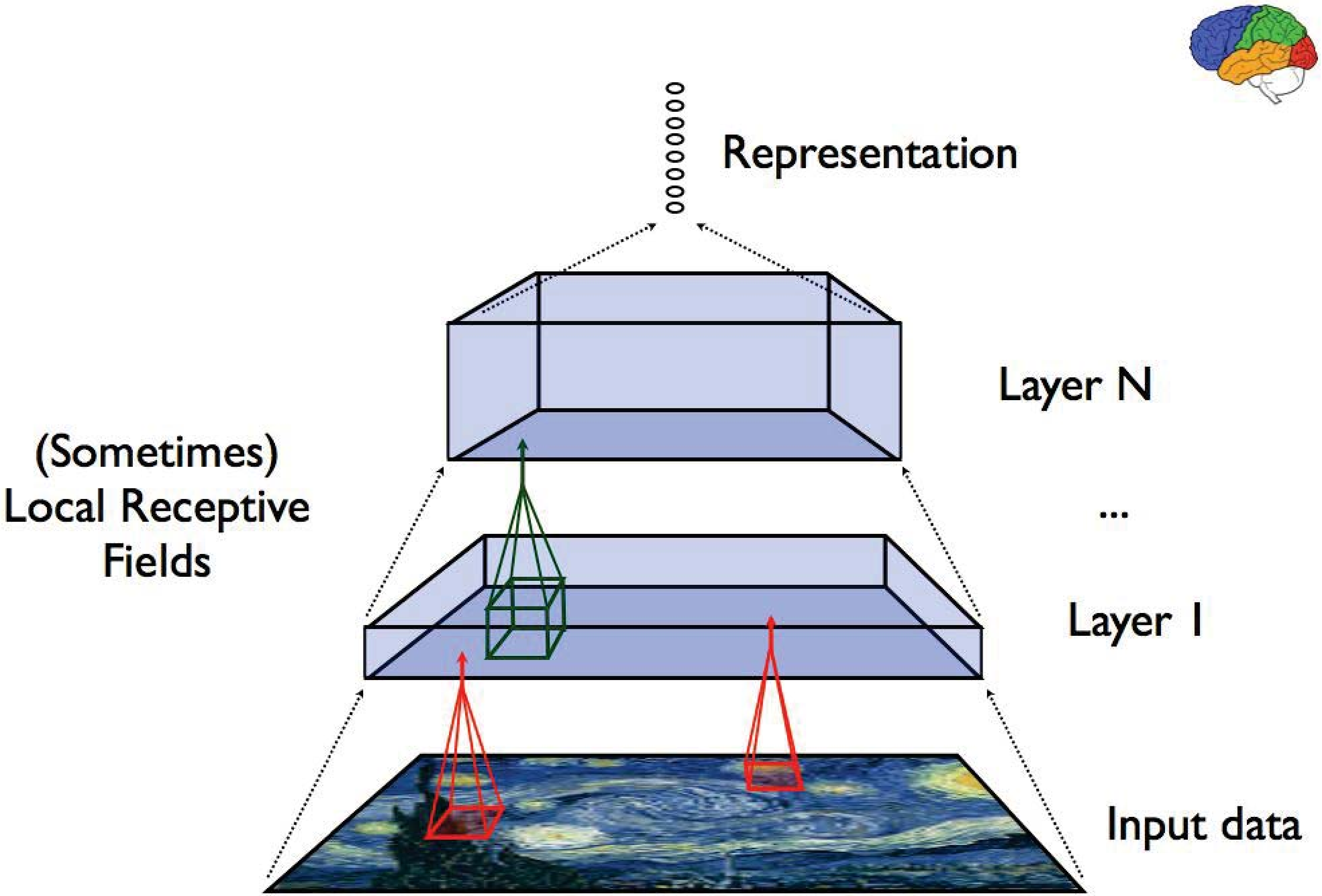
(Better algorithms, new insights and improved techniques always help, too!)

How Can We Train Large, Powerful Models Quickly?

- Exploit many kinds of parallelism
  - Model parallelism
  - Data parallelism

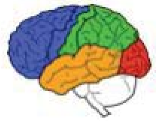
Model Parallelism

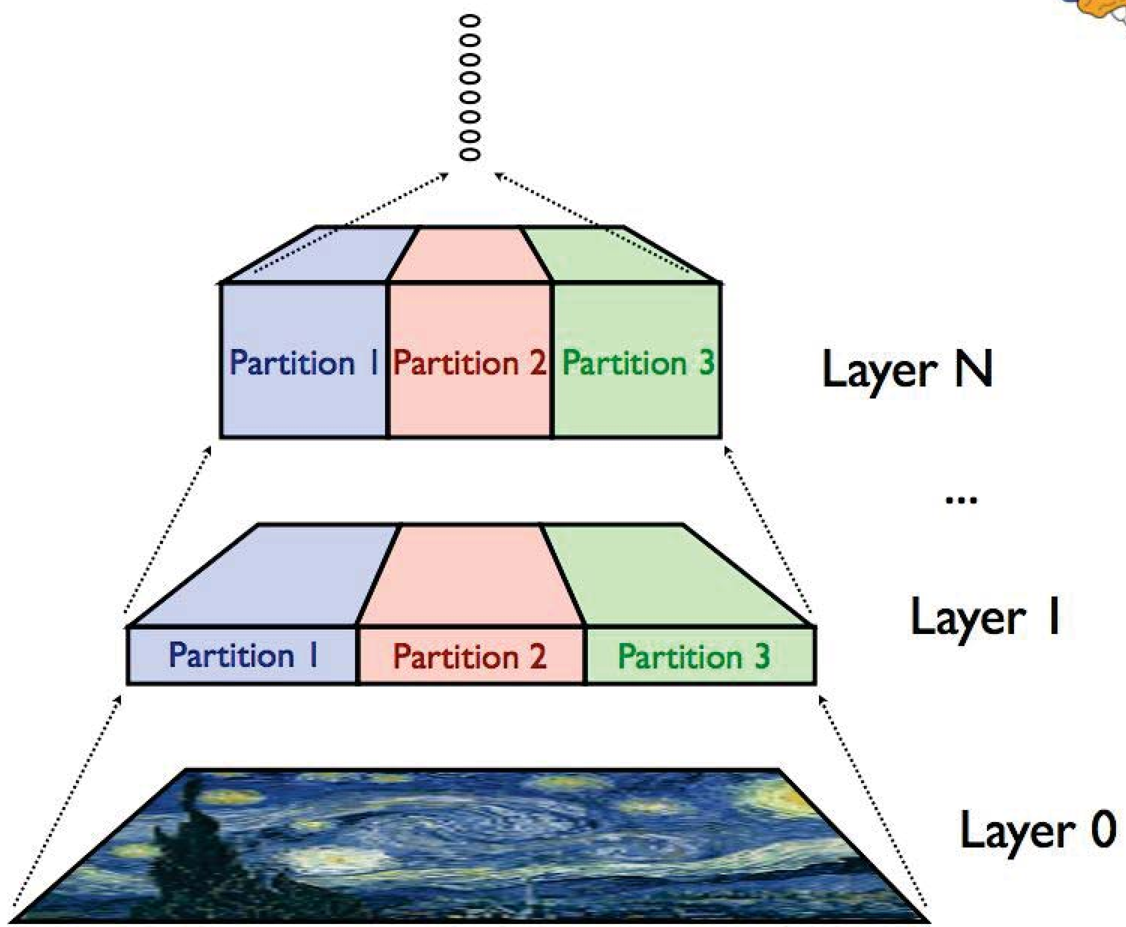




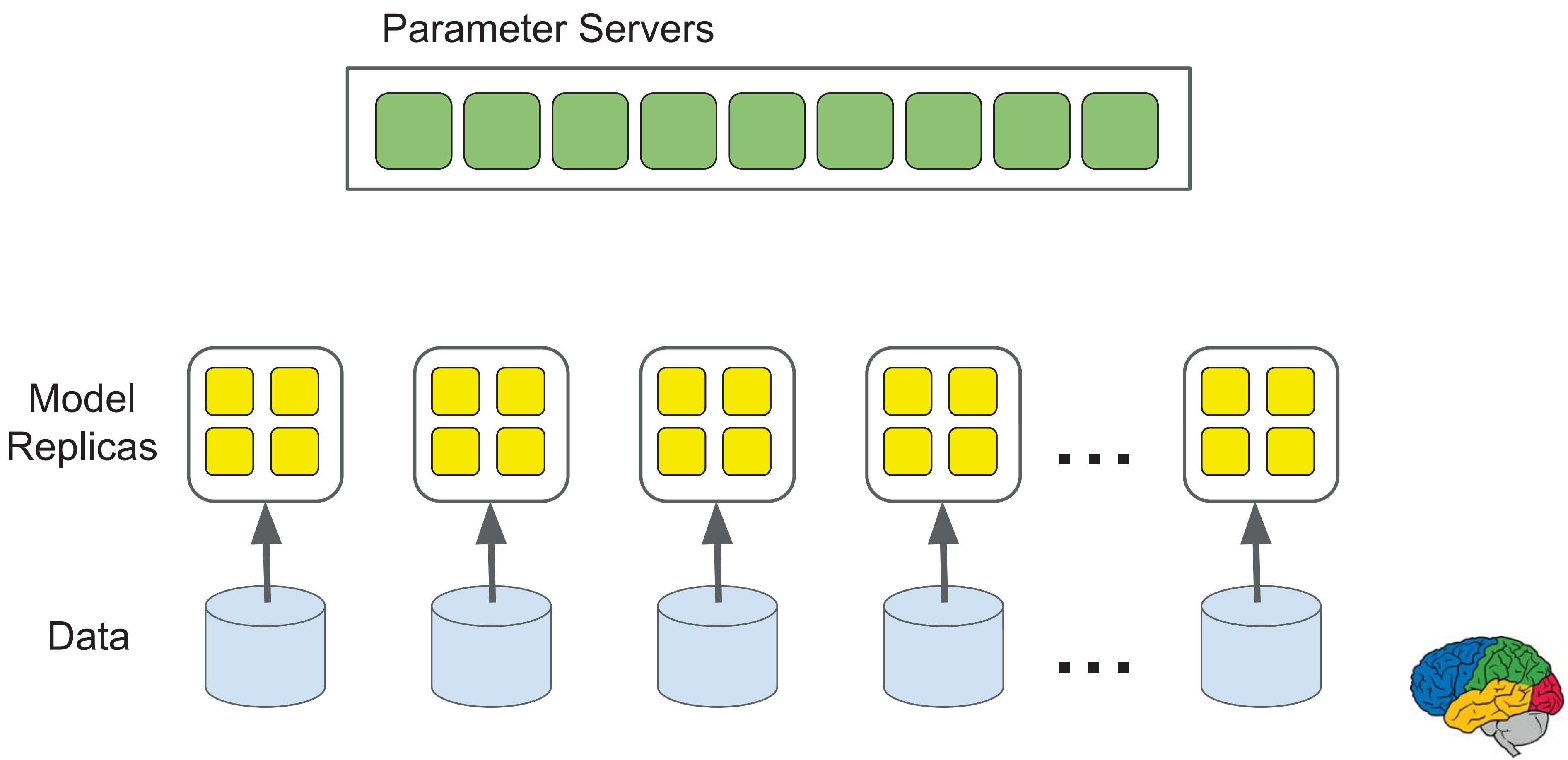
Representation
Layer N
(Sometimes)
Local Receptive
Fields
...
Layer 1
Input data

Model Parallelism: Partition model across machines

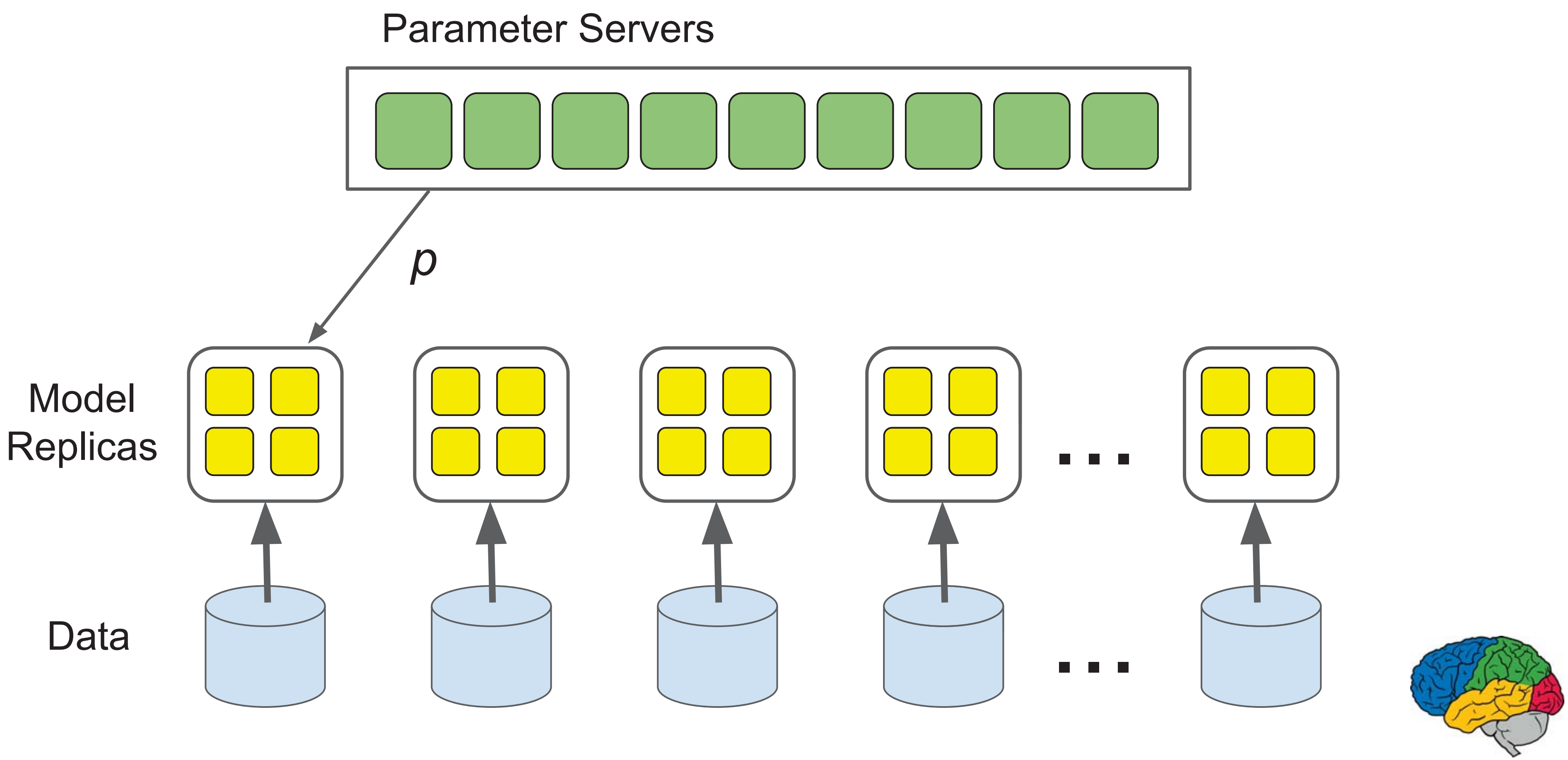




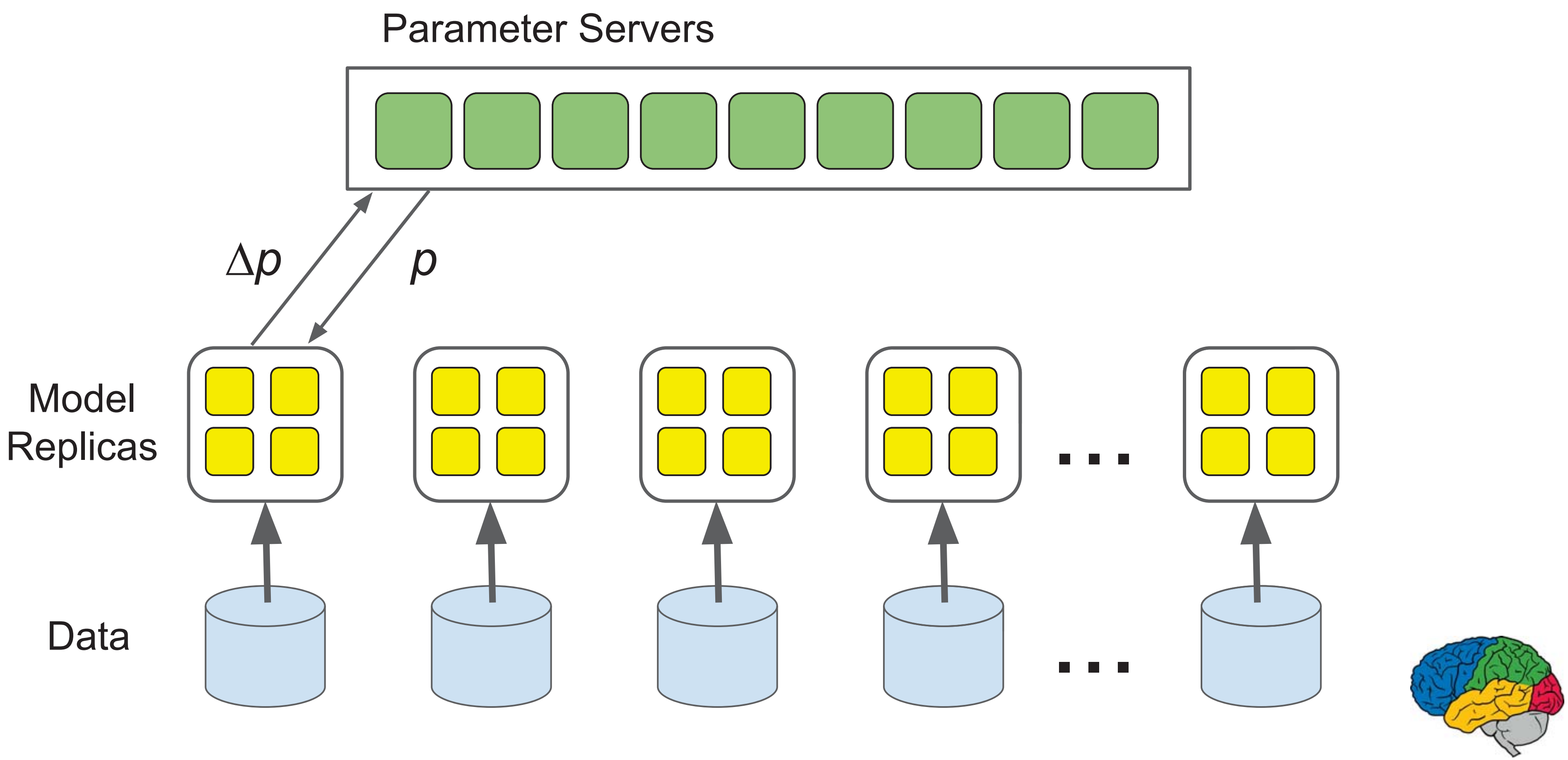
Data Parallelism



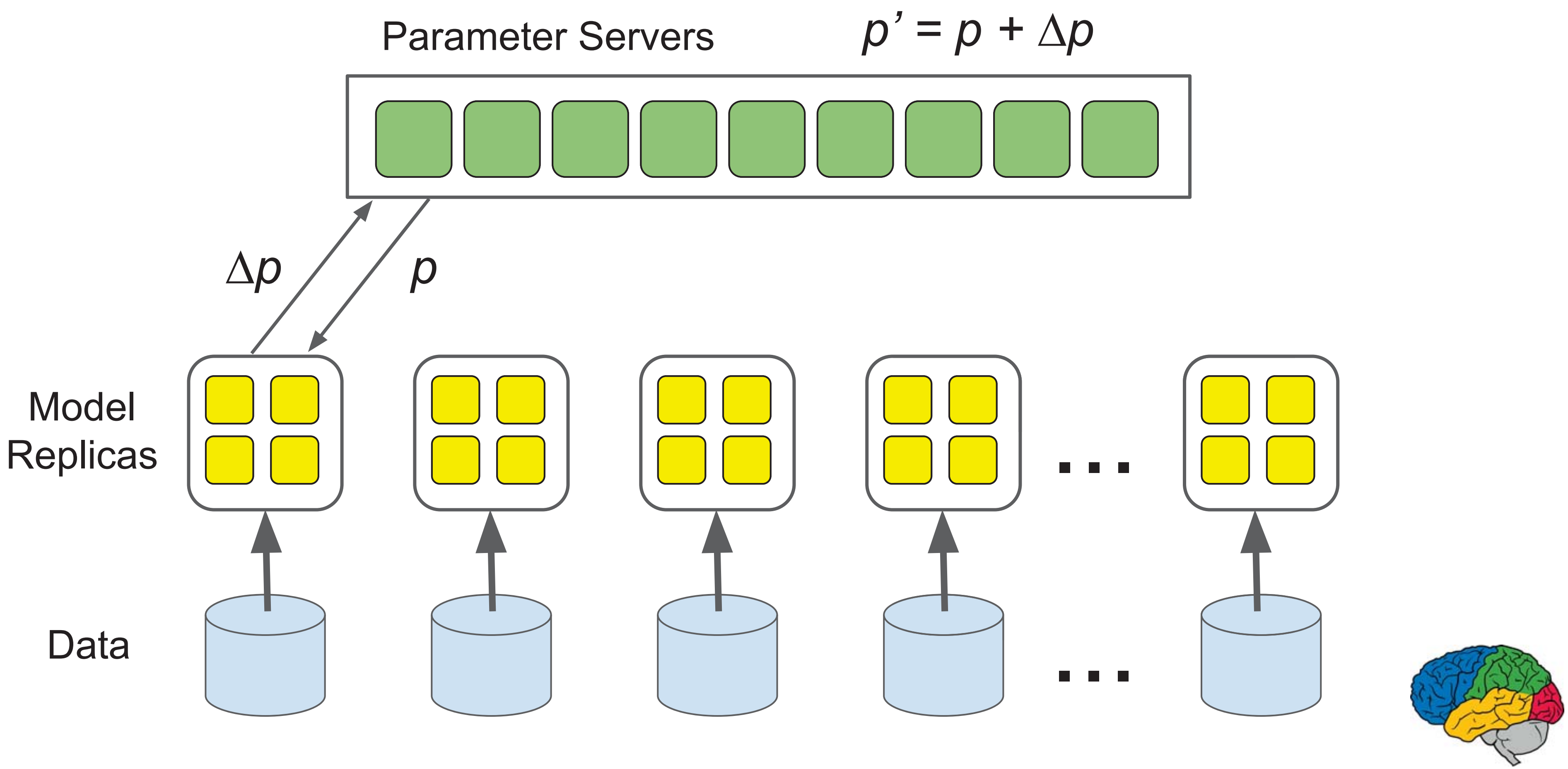
Data Parallelism



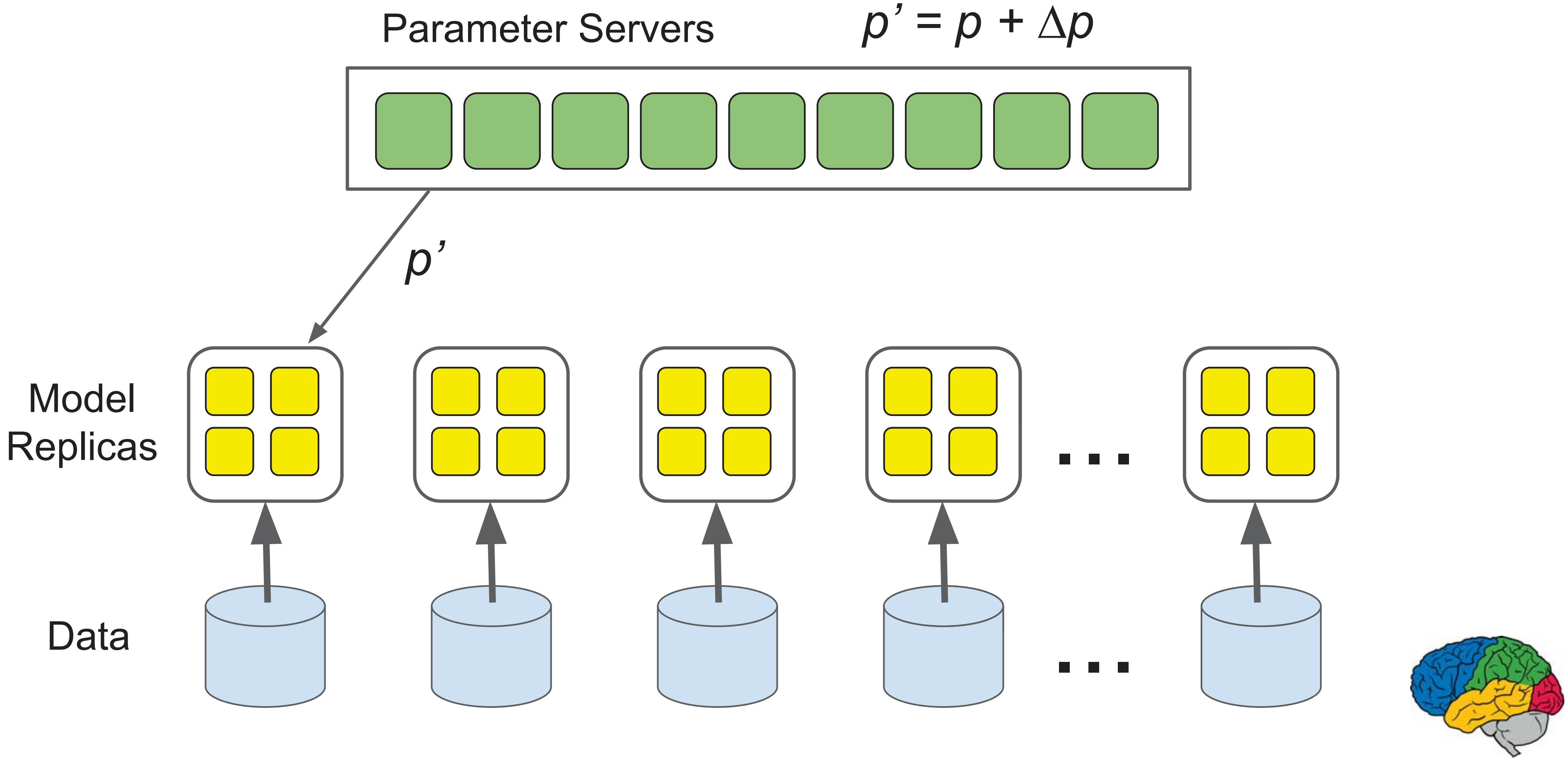
Data Parallelism



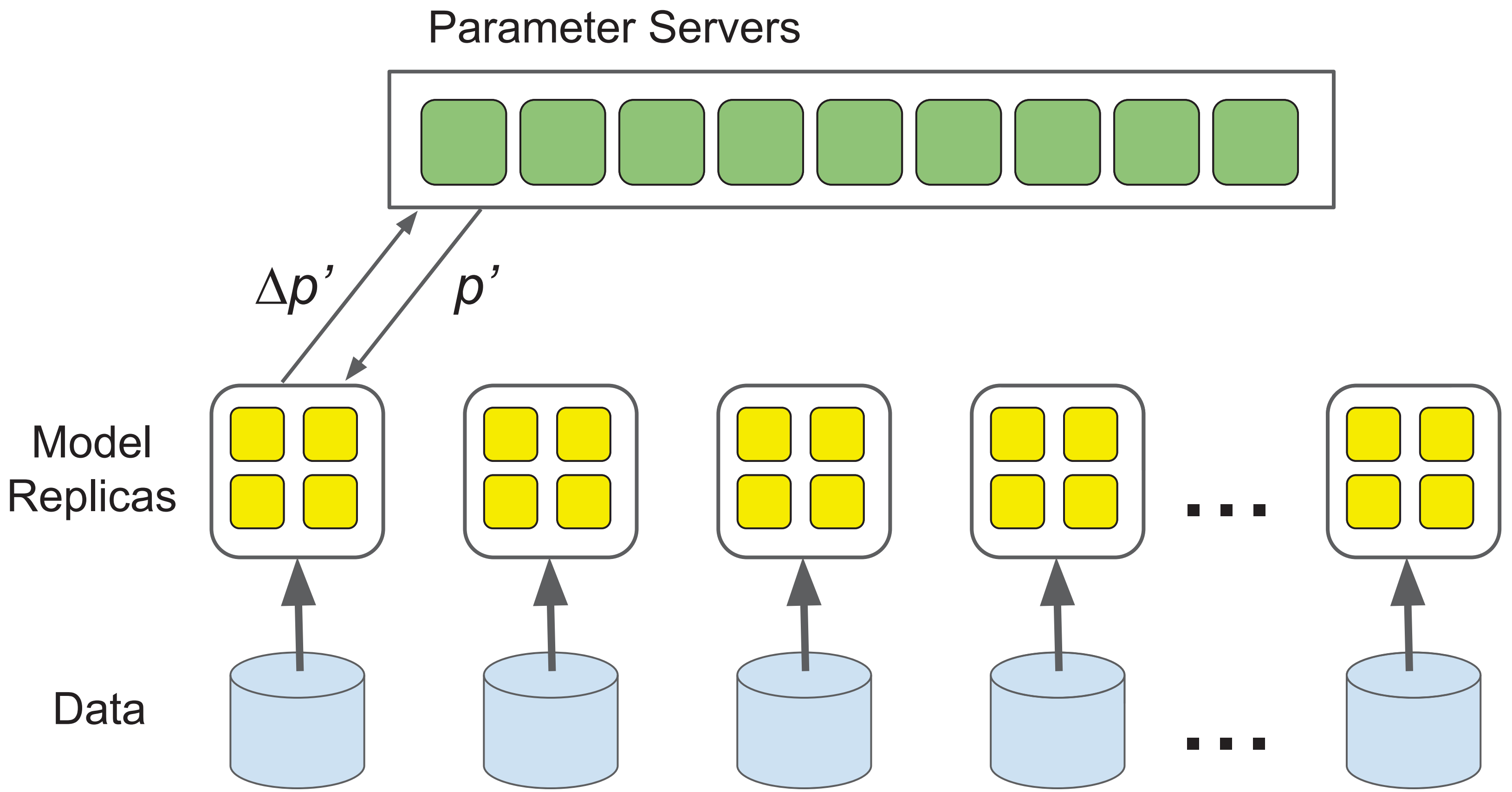
Data Parallelism



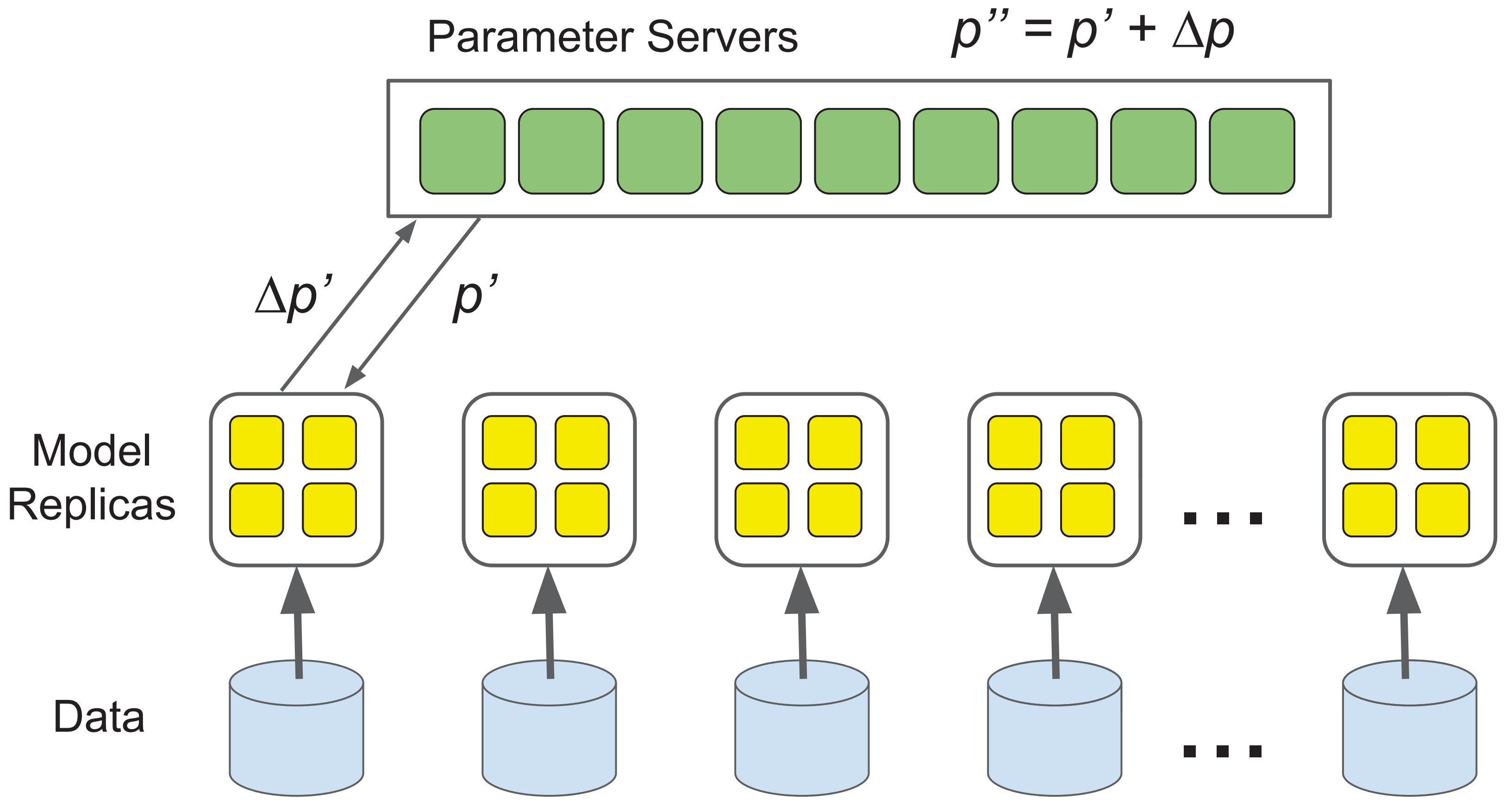
Data Parallelism



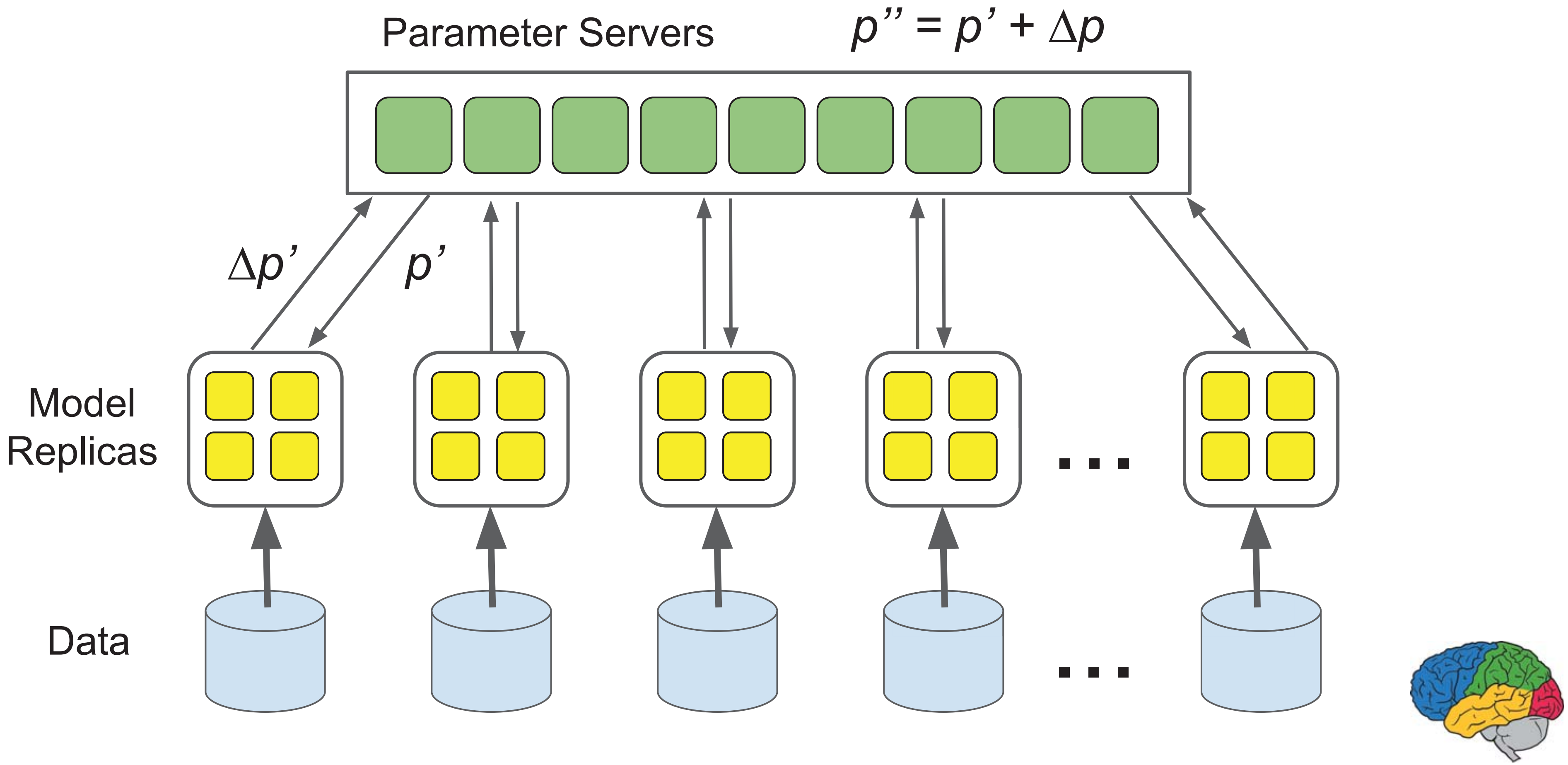
Data Parallelism



Data Parallelism



Data Parallelism



Data Parallelism Choices

Can do this **synchronously**:

- N replicas eqivalent to an N times larger batch size
- Pro: No noise
- Con: Less fault tolerant (requires recovery if any single machine fails)

Can do this **asynchronously**:

- Con: Noise in gradients
- Pro: Relatively fault tolerant (failure in model replica doesn’t block other replicas)

(Or **hybrid**: M asynchronous groups of N synchronous replicas)

Data Parallelism Considerations

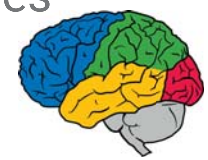
Want model computation time to be large relative to time to send/receive parameters over network

Models with fewer parameters, that reuse each parameter multiple times in the computation

- Mini-batches of size *B* reuse parameters *B* times

Certain model structures reuse parameter many times within each example:

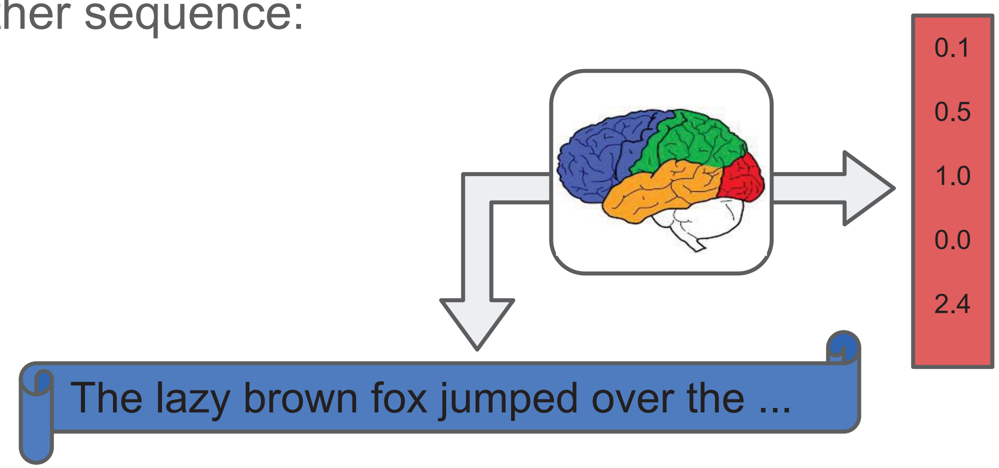
- **Convolutional models** tend to reuse hundreds or thousands of times per example (for different spatial positions)
- **Recurrent models** (LSTMs, RNNs) tend to reuse tens to hundreds of times (for unrolling through *T* time steps during training)



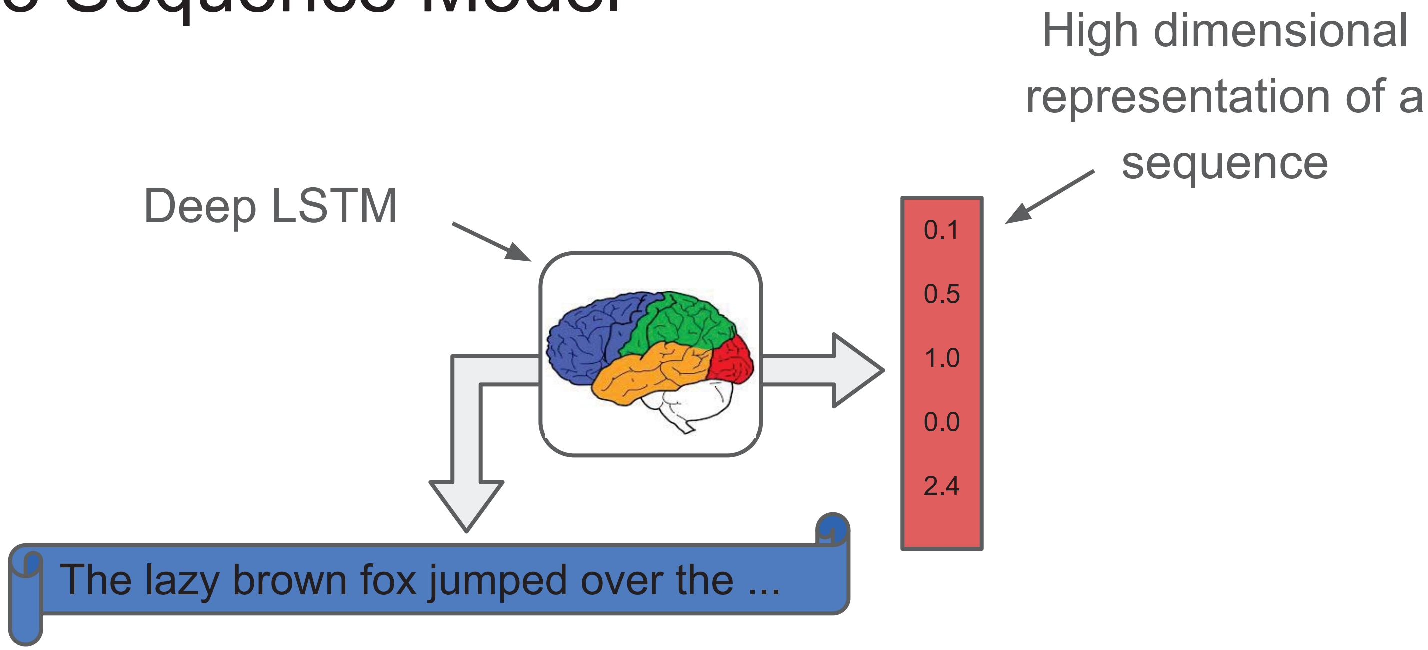
What are some ways that deep learning is having a significant impact at Google?

Sequence to Sequence Models

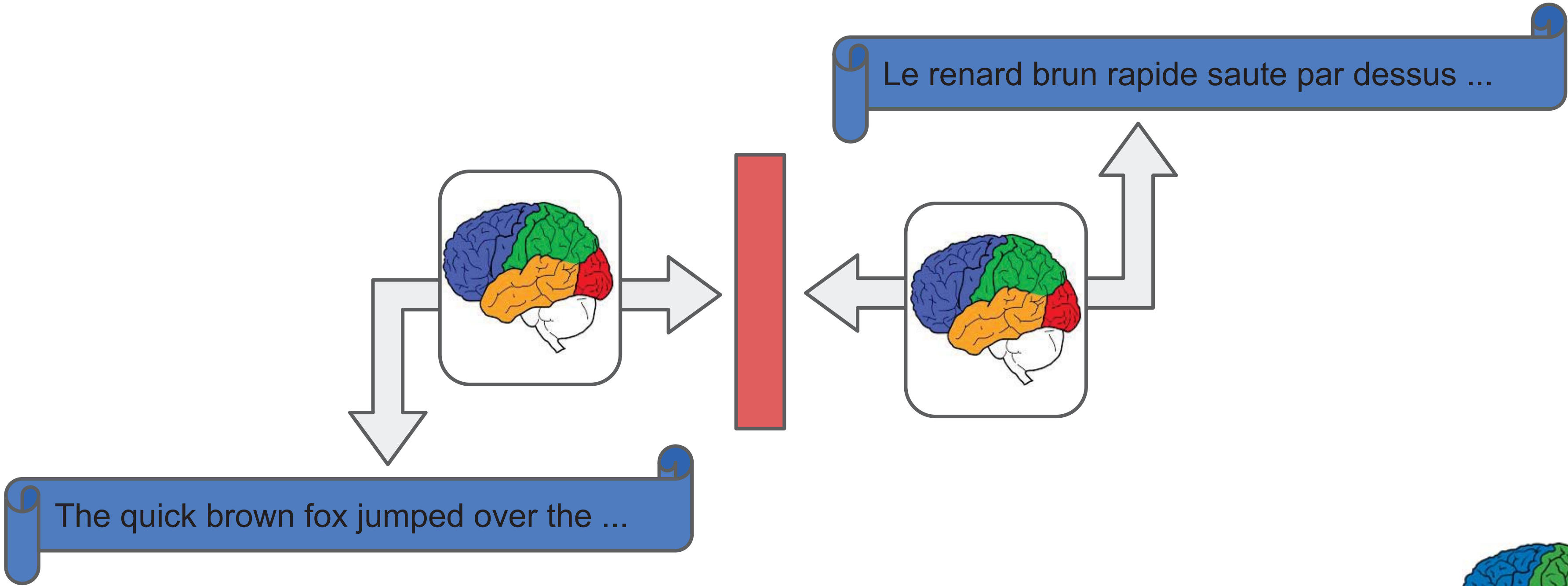
Oriol Vinyals, Ilya Sutskever & Quoc Le started looking at how to map one sequence to another sequence:



Sequence to Sequence Model



Connect two, you get a machine translation system



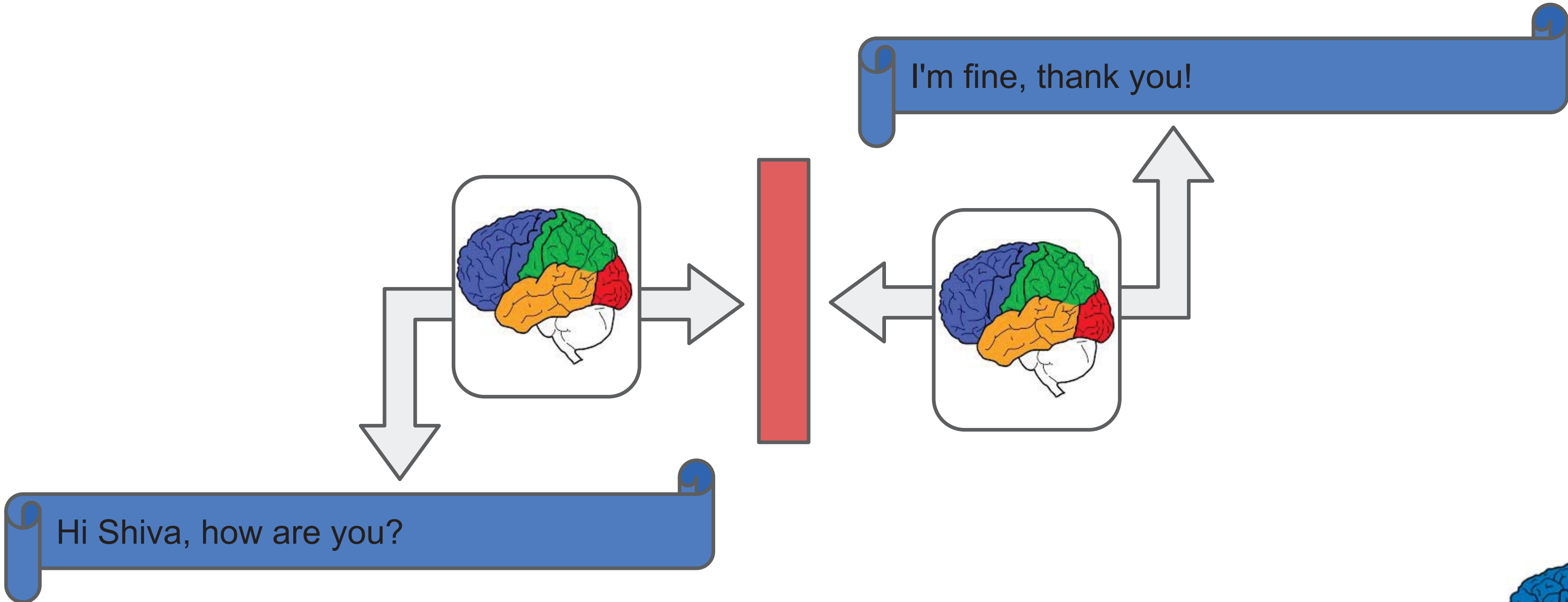
It works well

WMT'14	BLEU
State-of-the-art	37.0
Neural Translation Model	**37.3**

Sequence to Sequence Learning with Neural Networks
Ilya Sutskever, Oriol Vinyals, Quoc V. Le (NIPS 2014)

Addressing Rare Word Problems in Neural Translation Models (arxiv.org/abs/1410.8206)
Thang Luong, Ilya Sutskever, Oriol Vinyals, Quoc V. Le, Wojciech Zaremba

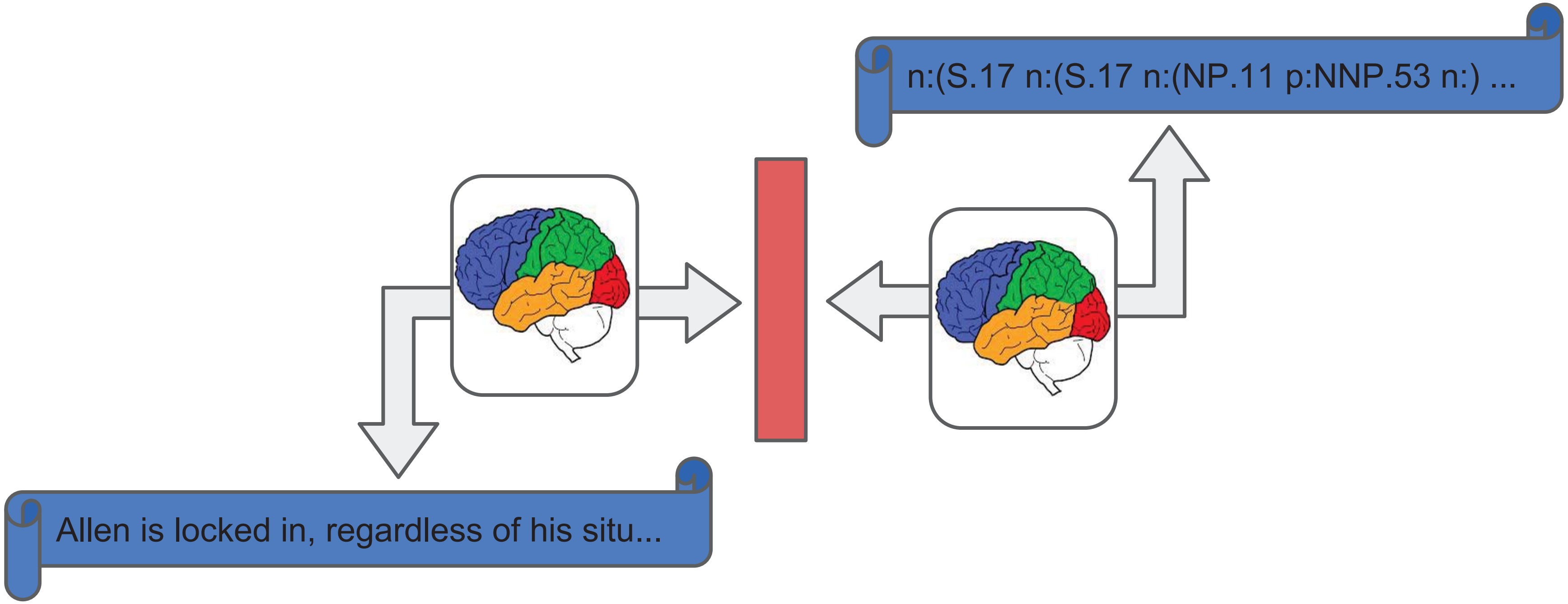
… or a chatbot.



It produces sensible conversations.

User> hello , i have a problem with my machine
BrainStop> hi
BrainStop> this is shiva .
BrainStop> how are you doing today ?
User> hi shiva , how are you ?
BrainStop> i ' m fine , thank you !
BrainStop> how may i assist you today ?
User> i want to access using vpn
BrainStop> currently the computer is connected to corp network ?
User> no
BrainStop> check this solution :
BrainStop> https : / / INTERNAL_HOSTNAME_REDACTED / articles / connecting - to - disconnecting - from - ssl - vpn # heading - 4
User> thanks , bye !
BrainStop> thank you .

… or a parser.


n:(S.17 n:(S.17 n:(NP.11 p:NNP.53 n:) ...
Allen is locked in, regardless of his situ...

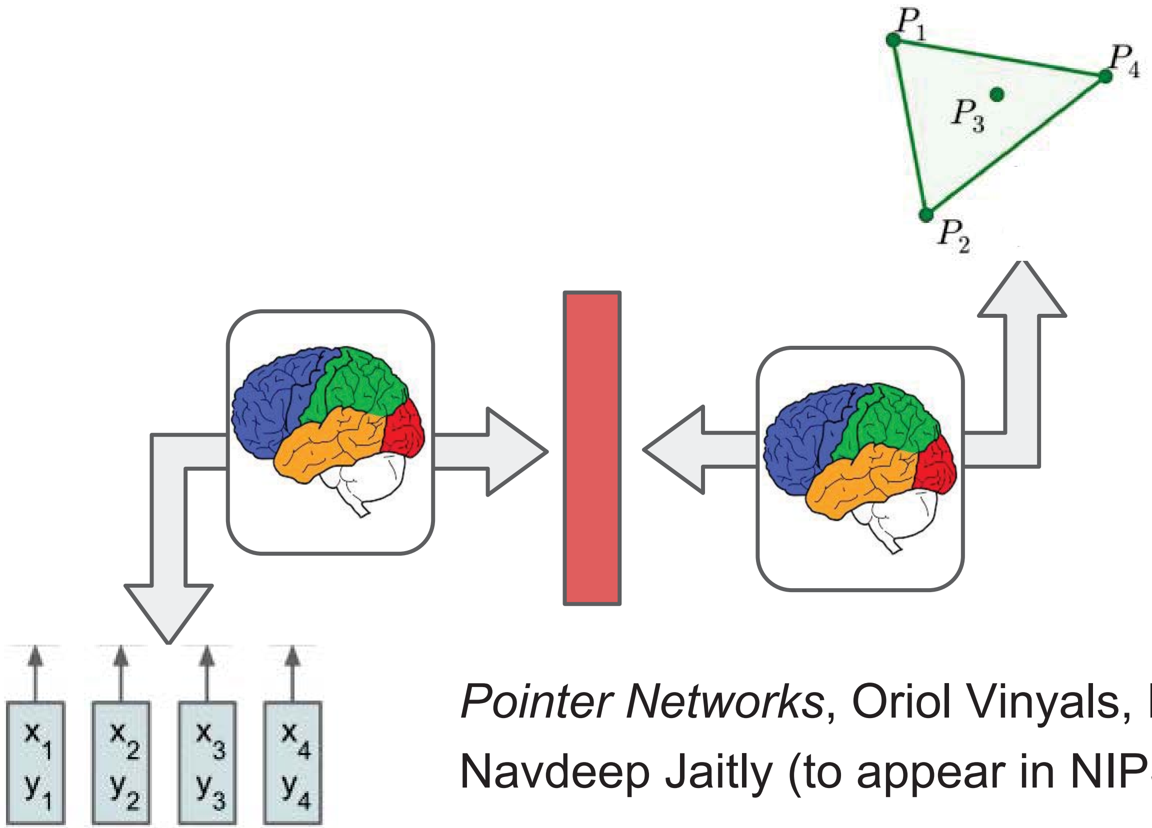
It works well

Completely learned parser with no parsing-specific code

State of the art results on WSJ 23 parsing task

Grammar as a Foreign Language, Oriol Vinyals, Lukasz Kaiser, Terry Koo, Slav Petrov, Ilya Sutskever, and Geoffrey Hinton (to appear in NIPS 2015) http://arxiv.org/abs/1412.7449

… or something that can learn graph algorithms



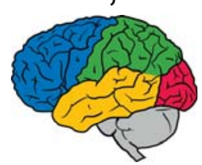
output:
Convex Hull

(or **Delauney Triangulation**)

(or **Travelling Salesman tour**)

input:
collection
of points

Pointer Networks, Oriol Vinyals, Meire Fortunato, & Navdeep Jaitly (to appear in NIPS 2015)



Object Recognition Improvement Over Time

⇨ “cat”

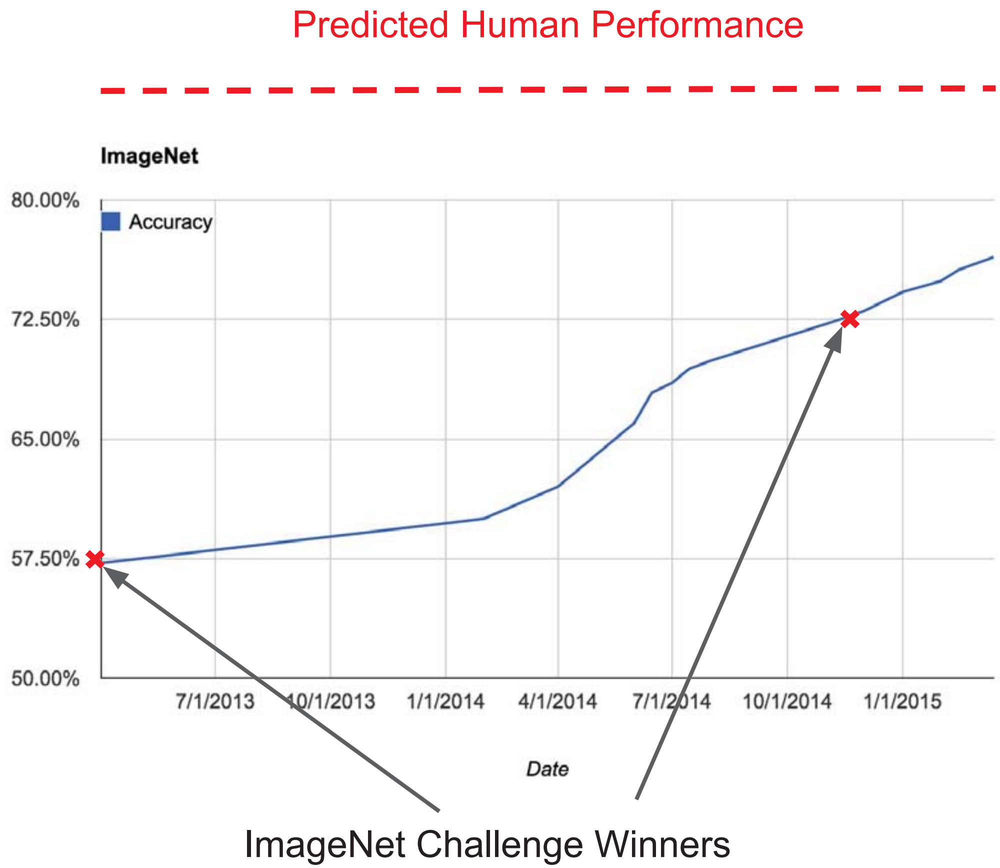
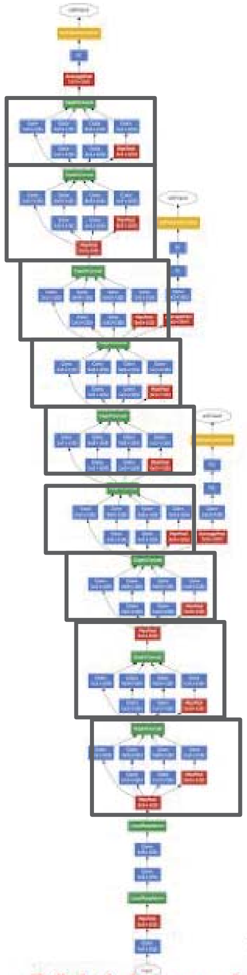


Image Models

⇨ “cat”



GoogLeNet

2014 ImageNet winner:
6.66% top-5 error rate

☐ = Module with 6 separate convolutional layers

24 layers deep

Going Deeper with Convolutions
Szegedy et al. CVPR 2015

Good Fine-Grained Classification

"hibiscus"

"dahlia"

Good Generalization

Both recognized as “meal”

Sensible Errors

“snake”

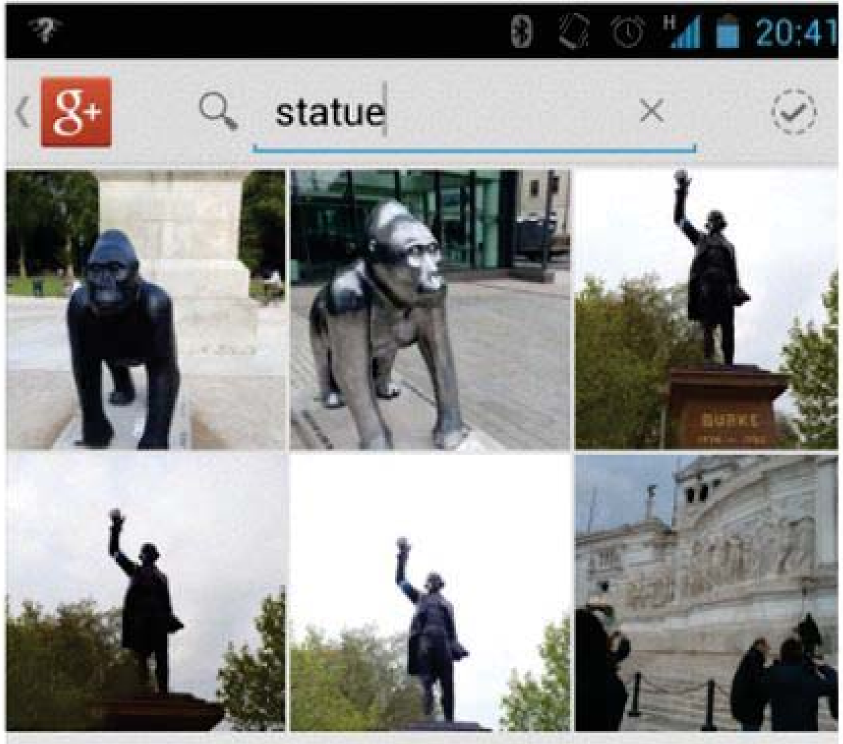
“dog”

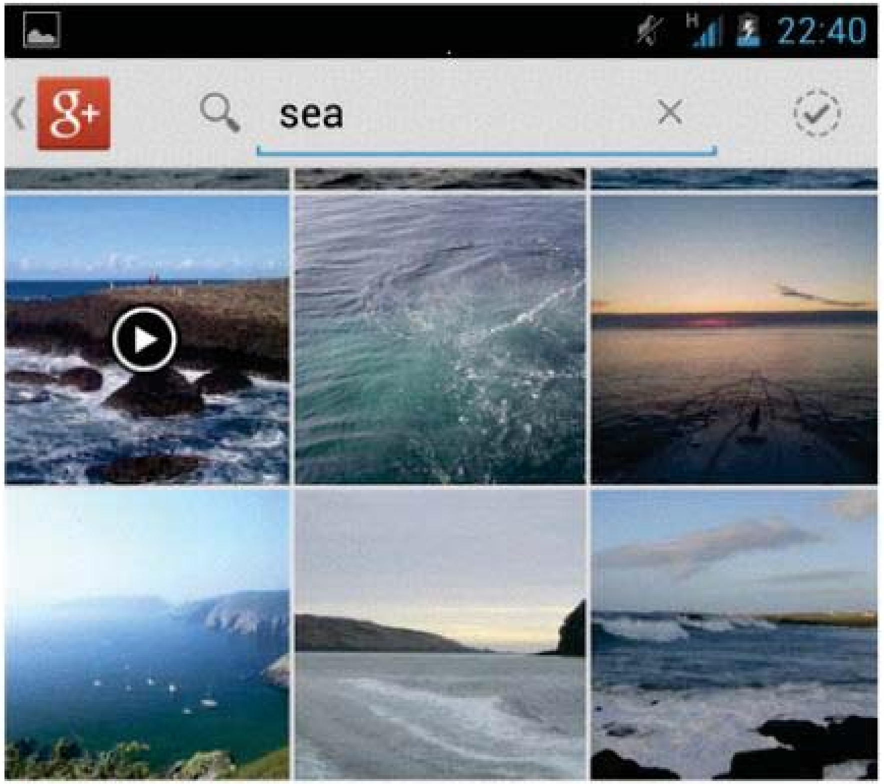
Works in practice… for real users

Wow.

The new Google plus photo search is a bit insane.

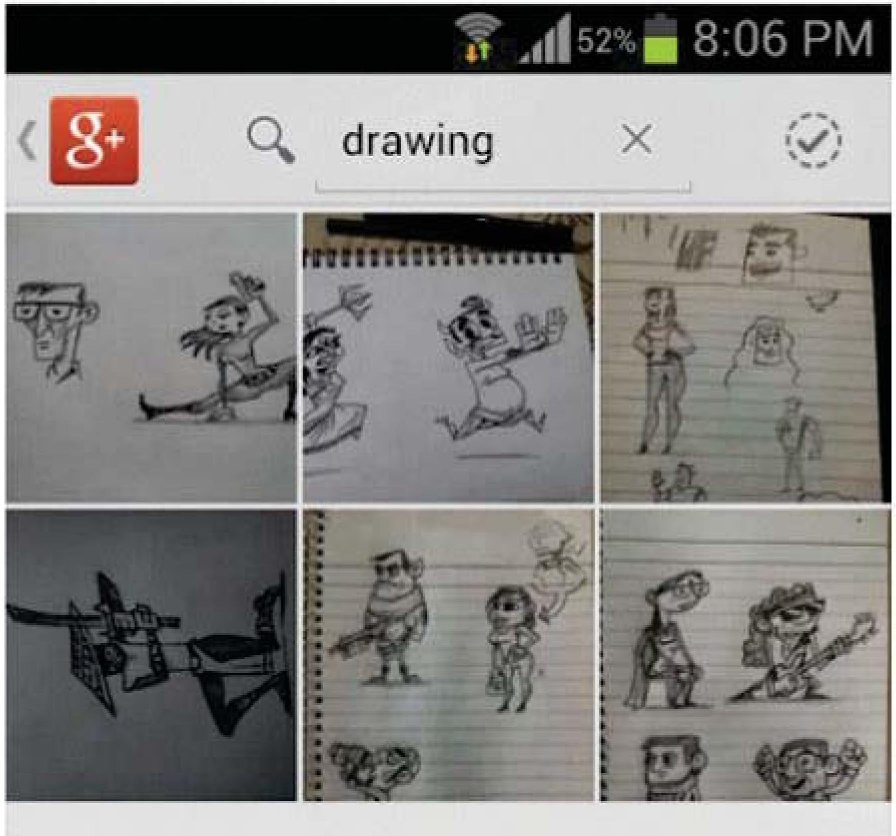
I didn't tag those... :)

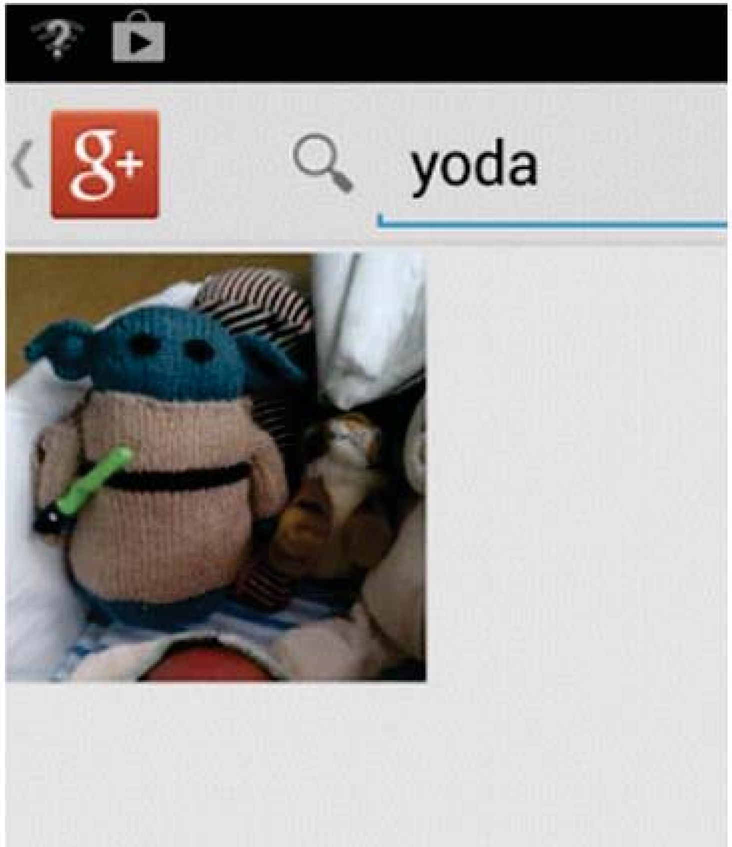




Works in practice… for real users

Google Plus photo search is awesome. Searched with keyword 'Drawing' to find all my scribbles at once :D

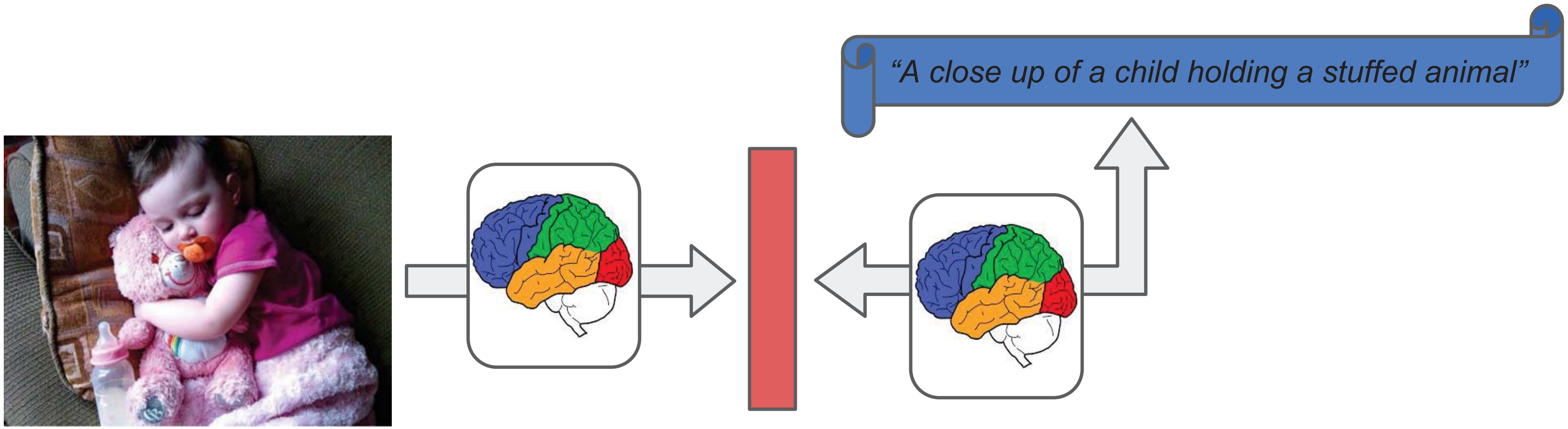





ASIAWIDE TRAVEL
02 9745 3355 1st Floor, 240 BURWOOD RD
aria's Bakery Inn 超羣餅屋
Maria's Bakery Inn 超羣餅屋


Corner
Cubbyhouse
CIANO MOTOR ENGINEERS
MECHANICAL REPAIRS TO ALL MAKES AND MODELS
Specialising In BMW, MINI & TOYOTA
8 REGATTA ROAD FIVE DOCK 9745 3173
88
Factory Trained Technicians

Connect sequence and image models, you get a captioning system



It works well (BLEU scores)

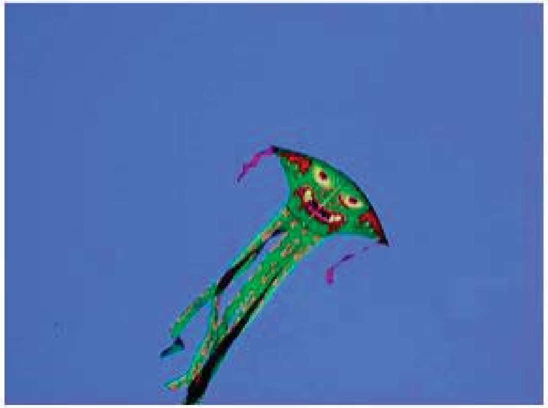
Dataset	Previous SOTA	**Show & Tell**	Human
MS COCO	N/A	**67**	69
FLICKR	49	**63**	68
PASCAL (xfer learning)	25	**59**	68
SBU (weak label)	11	**27**	N/A

Show and Tell: A Neural Image Caption Generator,
Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan (CVPR 2015)

A man holding a tennis racquet on a tennis court.

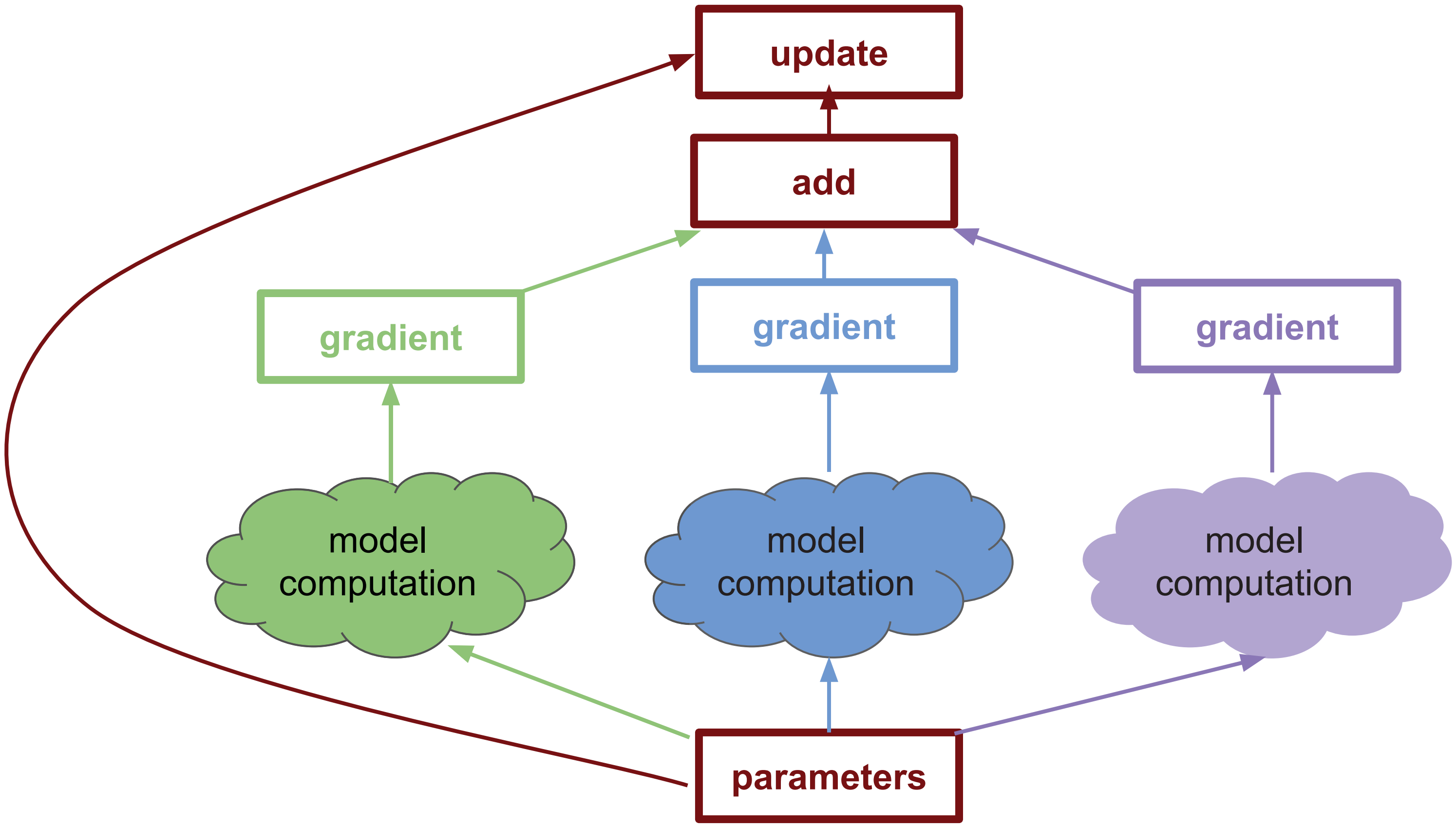
Two pizzas sitting on top of a stove top oven

A group of young people playing a game of Frisbee



A man flying through the air while riding a snowboard

Synchronous Variant



Nurturing Great Researchers

- We’re always looking for people with the potential to become excellent machine learning researchers
- The resurgence of deep learning in the last few years has caused a surge of interest of people who want to learn more and conduct research in this area

Google Brain Residency Program

New one year immersion program in deep learning research

Learn to conduct deep learning research w/experts in our team

- Fixed one-year employment with salary, benefits, ...
- Goal after one year is to have conducted several research projects
- Interesting problems, TensorFlow, and access to computational resources

Google Brain Residency Program

Who should apply?

- people with BSc or MSc, ideally in computer science, mathematics or statistics
- completed coursework in calculus, linear algebra, and probability, or equiv.
- programming experience
- motivated, hard working, and have a strong interest in Deep Learning

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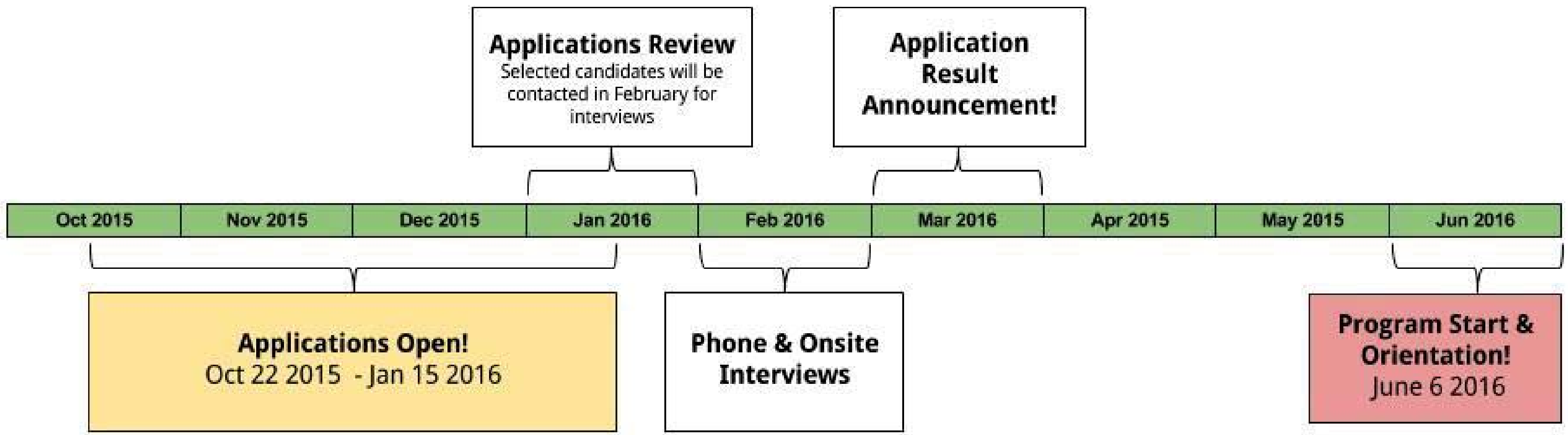
Program Application & Timeline



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For more information:

g.co/brainresidency

Contact us:

brain-residency@google.com

Questions?