10-605/10-805: Machine Learning with Large Datasets

Fall 2022

(Deep) Neural Networks, DL Frameworks, Hardware

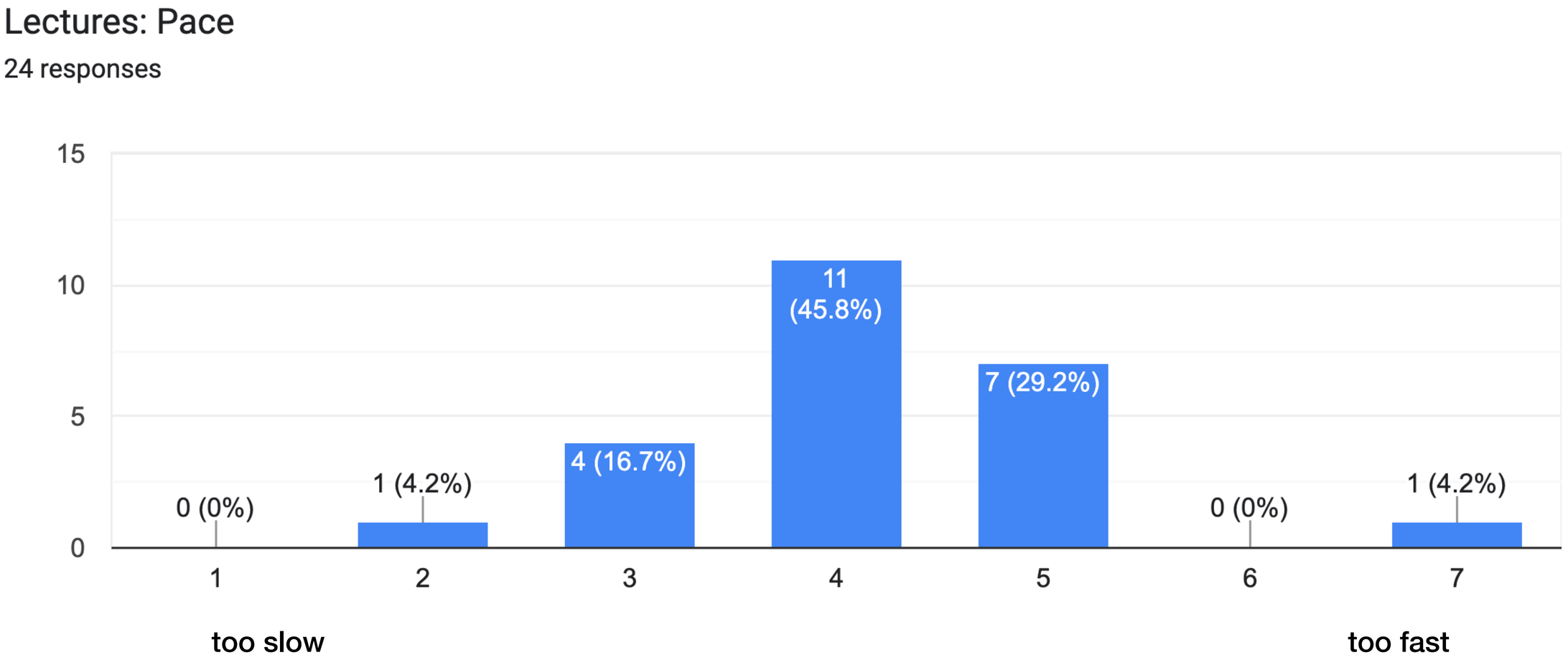
Announcements

- Slight change in schedule to cover material required for HW5 in sufficient time while still providing ample time for miniprojects
  - Combining content for Deep learning, DL frameworks, and Hardware into a single lecture (today's lecture)
  - Moving subsequent lectures up one
  - Moving the Guest Lecture hosted by Krishna Rangasayee to November 17th
  - The lecture on December 1st is TBD
- See website for details

Announcements

- HW4a due on Thursday (10/27)
  - please start ASAP if you haven’t already!
  - revisit HW4A tutorial (recitation on 10/14)
- Friday’s recitation is a TensorFlow tutorial (recorded — Community Day)
- Mid-semester grades have been entered
  - Included HW1 - HW3 and Exam 1

Results from course survey

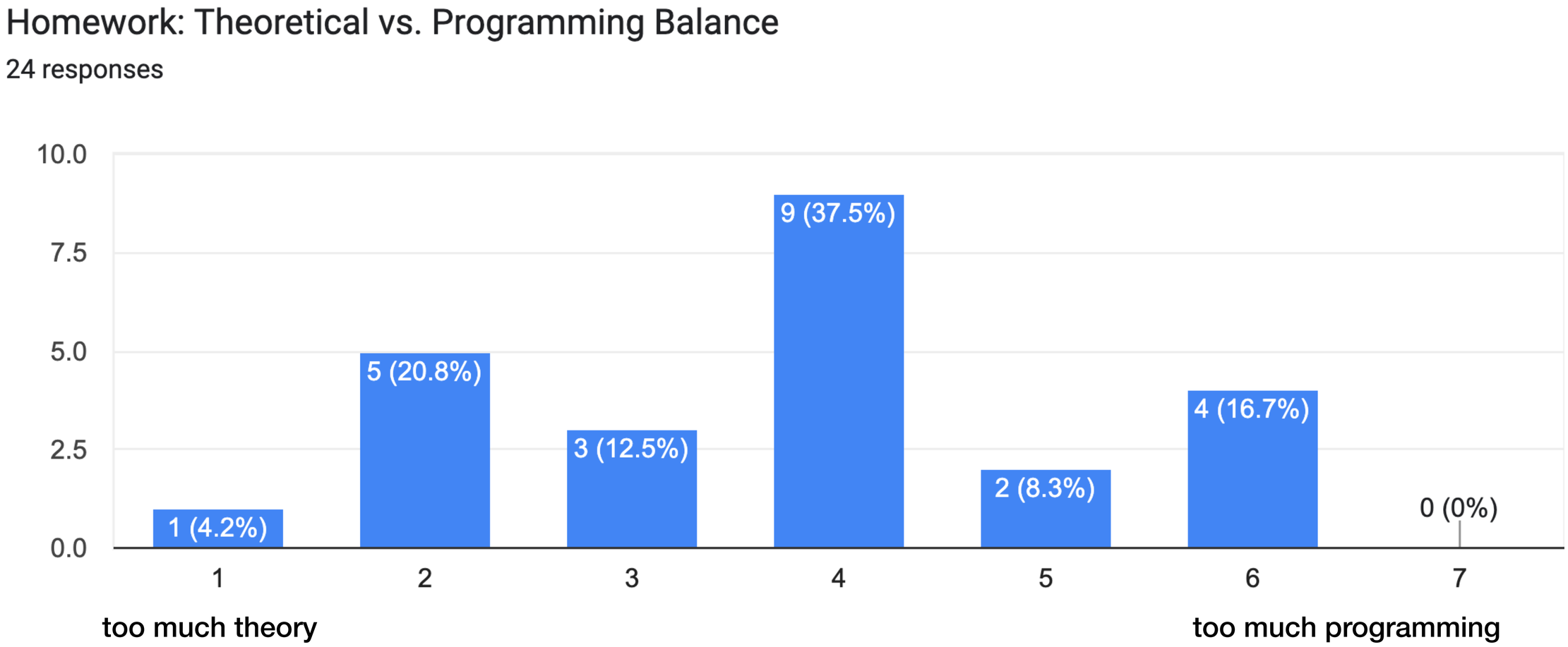


Results from course survey

Would you like to see more or less of a mathematical focus in the course?

24 responses

Results from course survey



Results from course survey

- *“The office hours for this course are wonderful. The TAs are very skilled instructors and know the materials very well.*

  >> Great to hear!

- *“Please keep half OH online and half in-person.”*

  >> This is the plan!

- *“Please make the programming assignments a bit less hand-held.”*

  >> remaining HWs will naturally be more open-ended

Key course topics

Data preparation
- Data cleaning
- Data summarization
- Visualization
- Dimensionality reduction

Training
- Distributed ML
- Large-scale optimization
- Scalable deep learning
- Efficient data structures
- Hyperparameter tuning

Inference
- Hardware for ML
- Techniques for low-latency inference (compression, pruning, distillation)

Infrastructure / Frameworks
- Apache Spark
- AWS / GCP / Azure
- TensorFlow

Advanced topics
- Federated learning
- Neural architecture search
- Productionizing ML

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Outline

1. Neural networks
2. Backprop
3. ML Frameworks
4. DL Hardware

RECALL

Empirical risk minimization

$$\hat{f}_n = \arg\min_{f \in F} \frac{1}{n} \sum_{i=1}^{n} \ell(f(x_i), y_i)$$

- A popular approach in supervised ML
- Given a loss ℓ and data (x_1, y_1), … (x_n, y_n), we estimate a predictor *f* by minimizing the *empirical risk*
- We typically restrict this predictor to lie in some class, *F*
  - Could reflect our prior knowledge about the task
  - Or may be for computational convenience

Question: how should we select our function class, *F*, and our loss function, ℓ ??

RECALL

Previous assumption: linear models

$$\hat{f}_n = \arg\min_{f \in F} \frac{1}{n} \sum_{i=1}^{n} \ell(f(x_i), y_i)$$

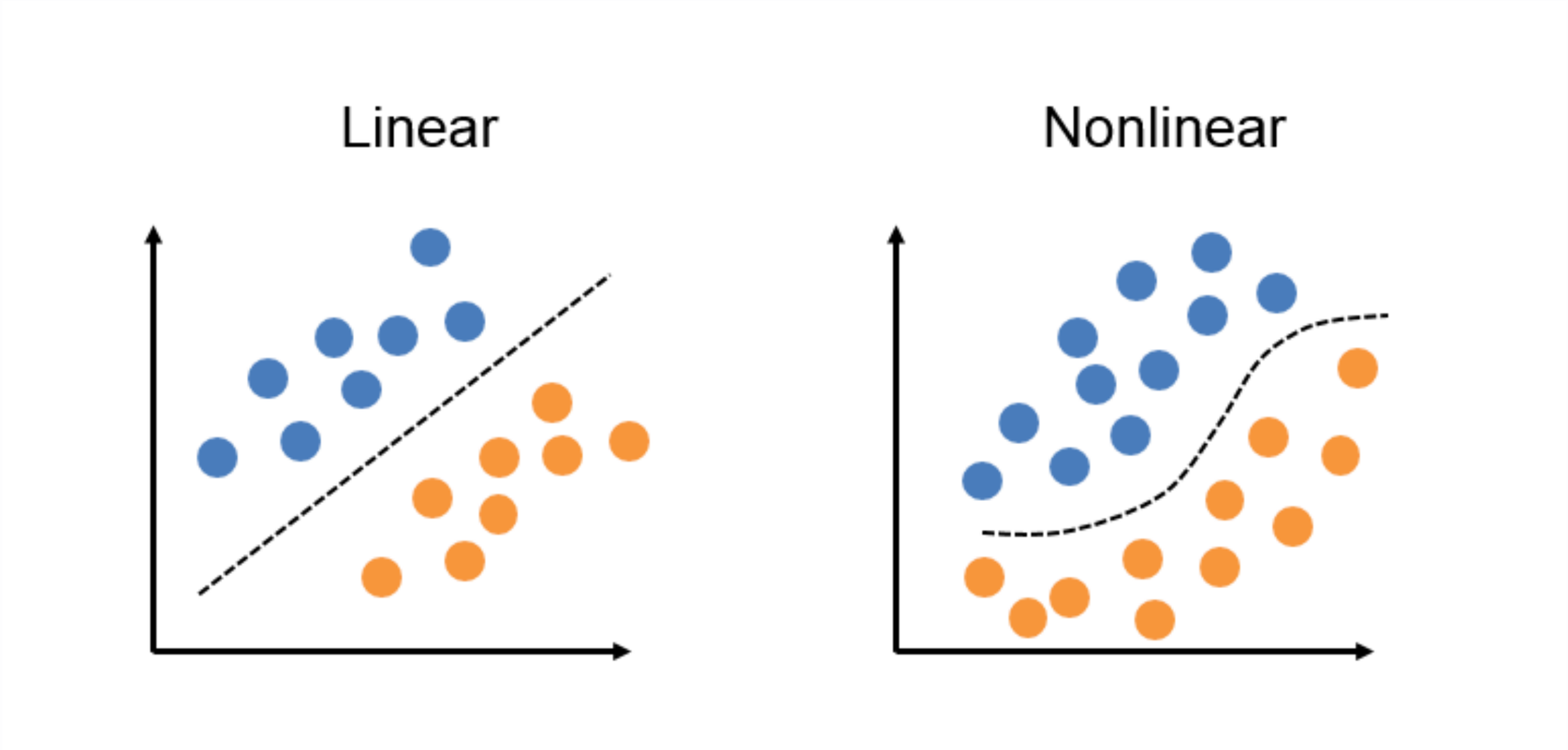
Assume: $f(\mathbf{x}) = \mathbf{w}^\top \mathbf{x}$

Losses:

- Square loss: linear regression $\min_{\mathbf{w}} \frac{1}{n} \sum_{i=1}^{n} (\mathbf{w}^\top \mathbf{x}_i - y_i)^2$
- Log loss: logistic regression $\min_{\mathbf{w}} \frac{1}{n} \sum_{i=1}^{n} \ell_{log}(y_i \cdot \mathbf{w}^\top \mathbf{x}_i)$
- Hinge loss: SVMs $\min_{\mathbf{w}} \frac{1}{n} \sum_{i=1}^{n} \max\{0, 1 - y_i \cdot \mathbf{w}^\top \mathbf{x}_i\}$

ISSUE

Not all data is linear …



How can we learn more complicated hypotheses?

ONE APPROACH

Neural networks

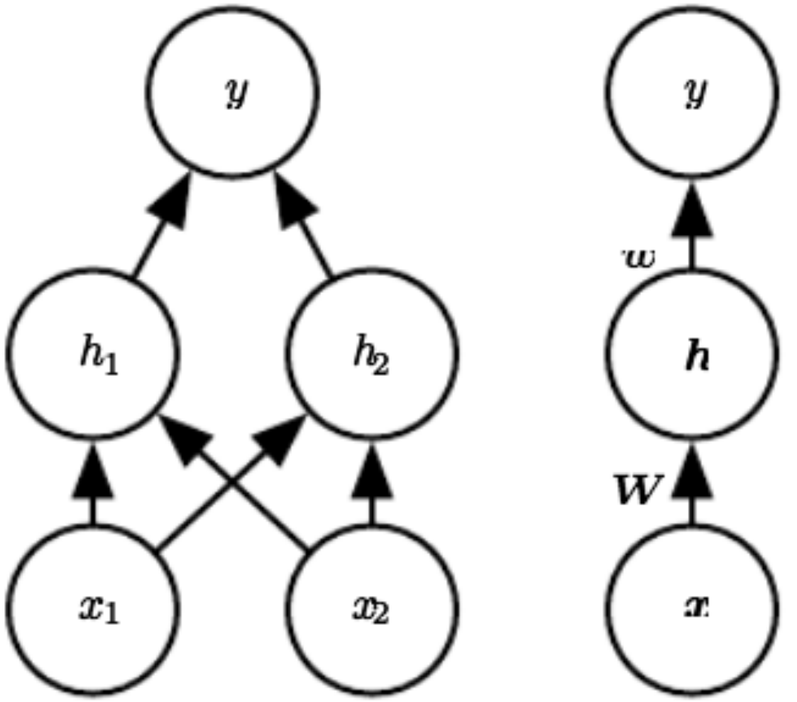
Goal: apply a nonlinear transformation to our input data: $f(\mathbf{x}) = \mathbf{w}^\top \phi(\mathbf{x}; \theta)$

Neural networks provide a way to learn such a transformation

Simple approach: feedforward neural networks

- E.g., suppose we have: $\phi(\mathbf{x}; \mathbf{W}) = \sigma(\mathbf{W}^\top \mathbf{x})$
- Then: $f(\mathbf{x}) = \mathbf{w}^\top \sigma(\mathbf{W}^\top \mathbf{x})$

$\sigma(\cdot)$ is referred to as an *activation function*



an example of a feedforward network with *one* hidden layer containing *two* units

A NOTE ON

Activation functions

Simple approach: feedforward neural networks

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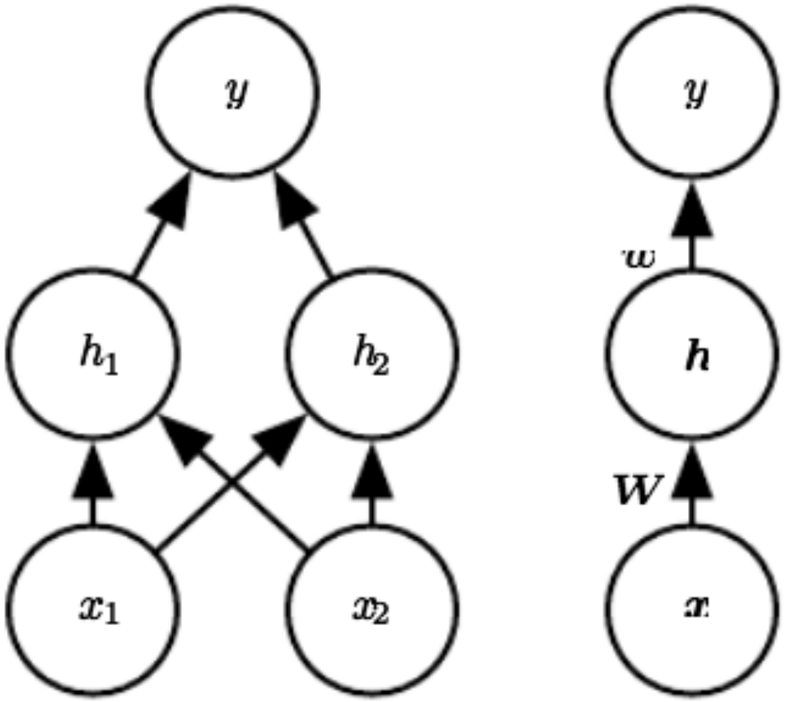
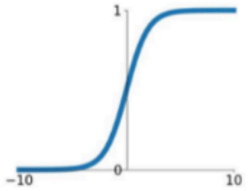


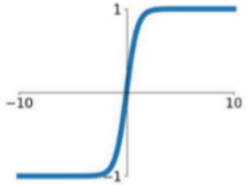
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



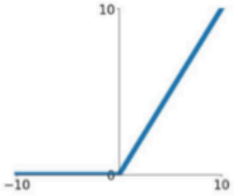
tanh

$\tanh(x)$



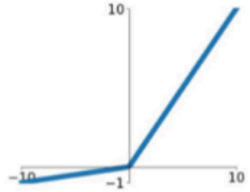
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

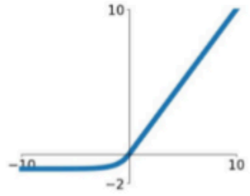


Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



some examples of activation functions

typically applied element-wise, i.e.

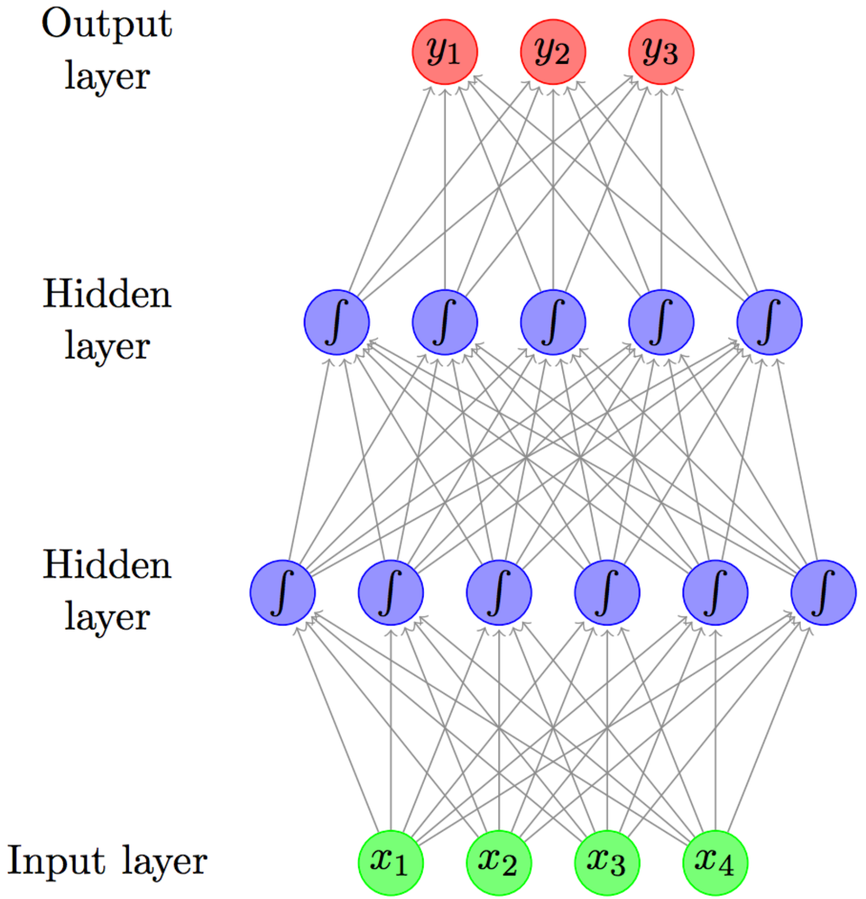
$$\sigma(\mathbf{x})_i = \sigma(\mathbf{x}_i)$$

MORE GENERALLY

Feedforward neural networks

We can consider adding L hidden layers, each with their own activation functions σ_l and corresponding weights $\mathbf{W}_l$

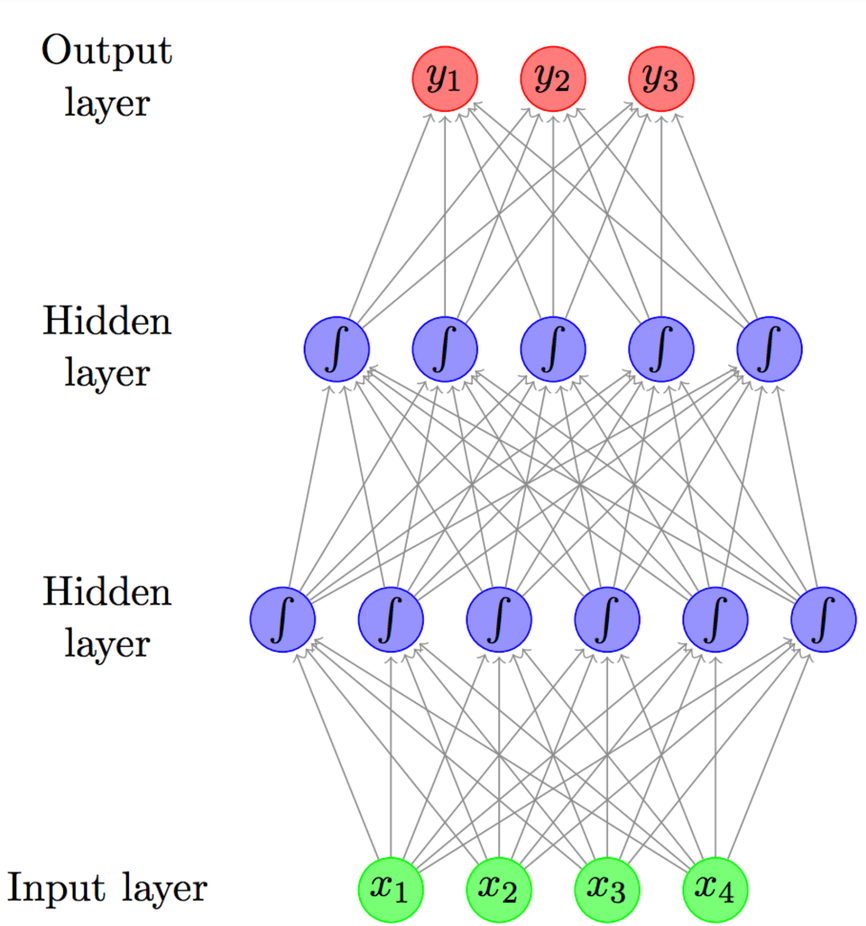
Using this layering technique, the resulting model becomes:



$$f(\mathbf{x}) = \mathbf{w}^\top \sigma_L(\mathbf{W}_L^\top(\sigma_{L-1}(\mathbf{W}_{L-1}^\top \ldots \sigma_2(\mathbf{W}_2^\top \sigma_1(\mathbf{W}_1^\top \mathbf{x}))\ldots)$$

MORE GENERALLY

Feedforward neural networks



How to pick the best architecture? Must select:

- Number of layers (depth)
- Number of nodes per layer (width)
- Activation functions (nonlinearities)
- Loss function

Other variants:

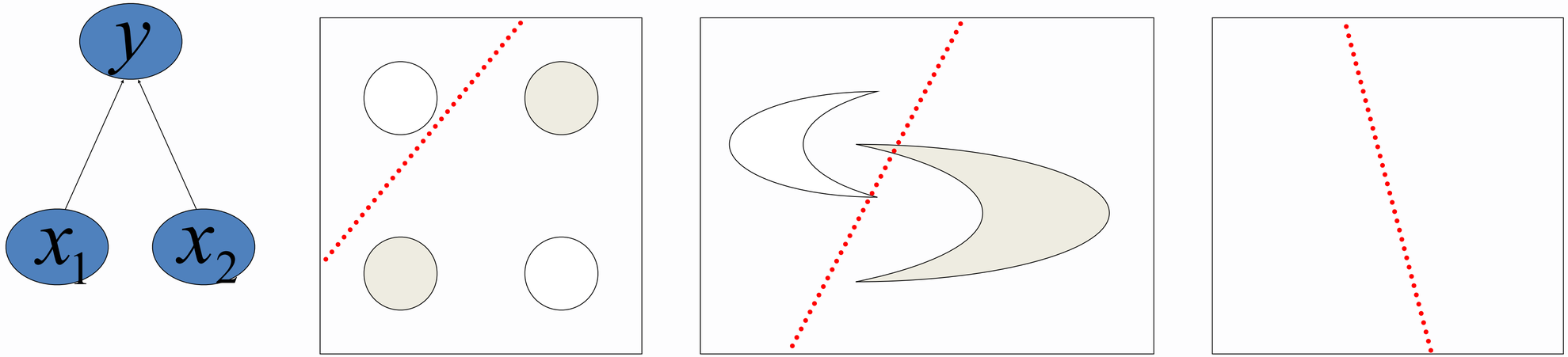
- CNNs: use convolution instead of standard matrix multiply
- RNNs: outputs are fed back into network

WHY WOULD WE DO THIS?

Feedforward neural networks

Neural networks can be very expressive, especially as you add more layers (i.e., ‘deep’ neural networks)

0 hidden layers: linear classifier



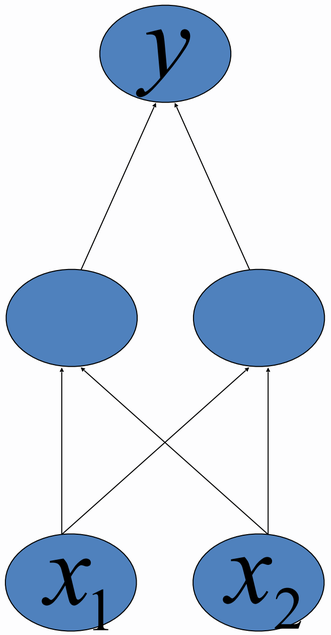
Credit: Matt Gormley

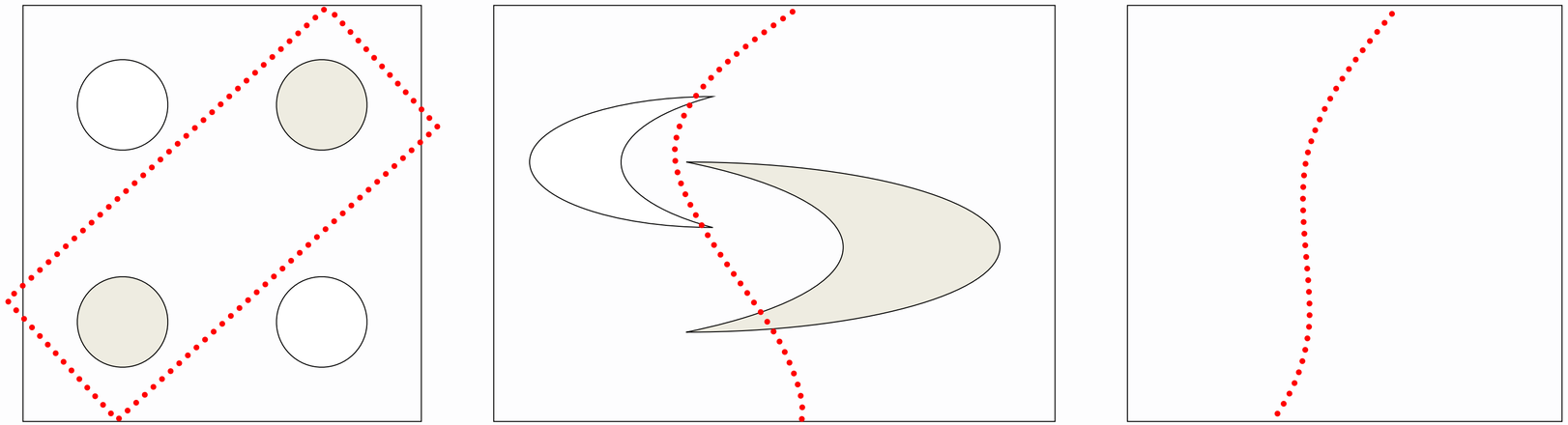
WHY WOULD WE DO THIS?

Feedforward neural networks

Neural networks can be very expressive, especially as you add more layers (i.e., ‘deep’ neural networks)

1 hidden layer: boundary of convex region (open or closed)





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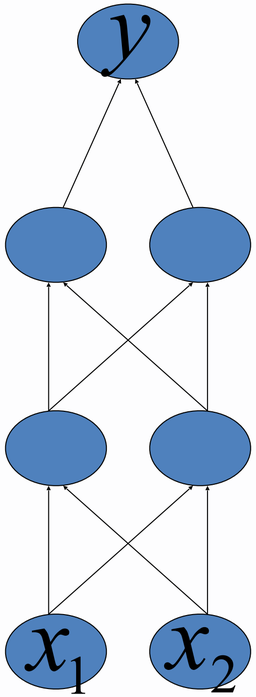
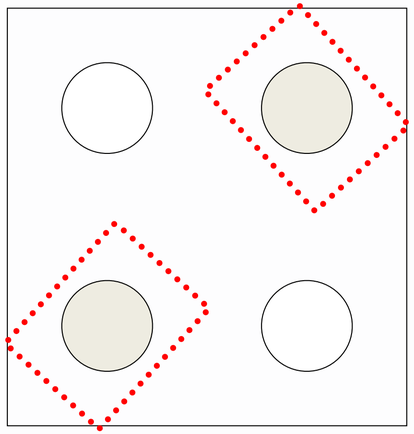
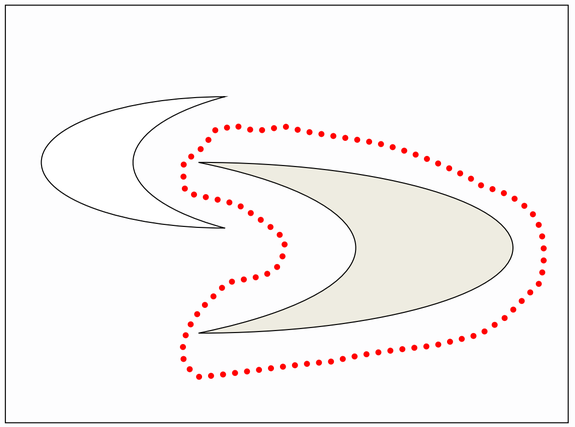
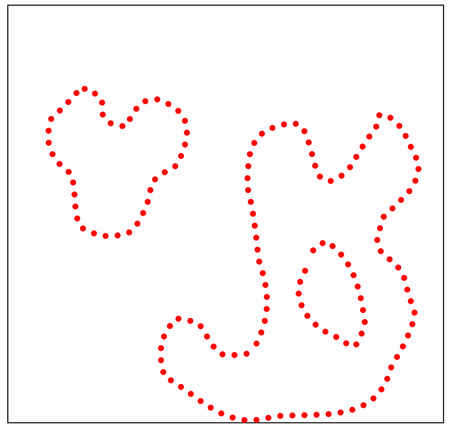


2 hidden layers: combinations of convex regions







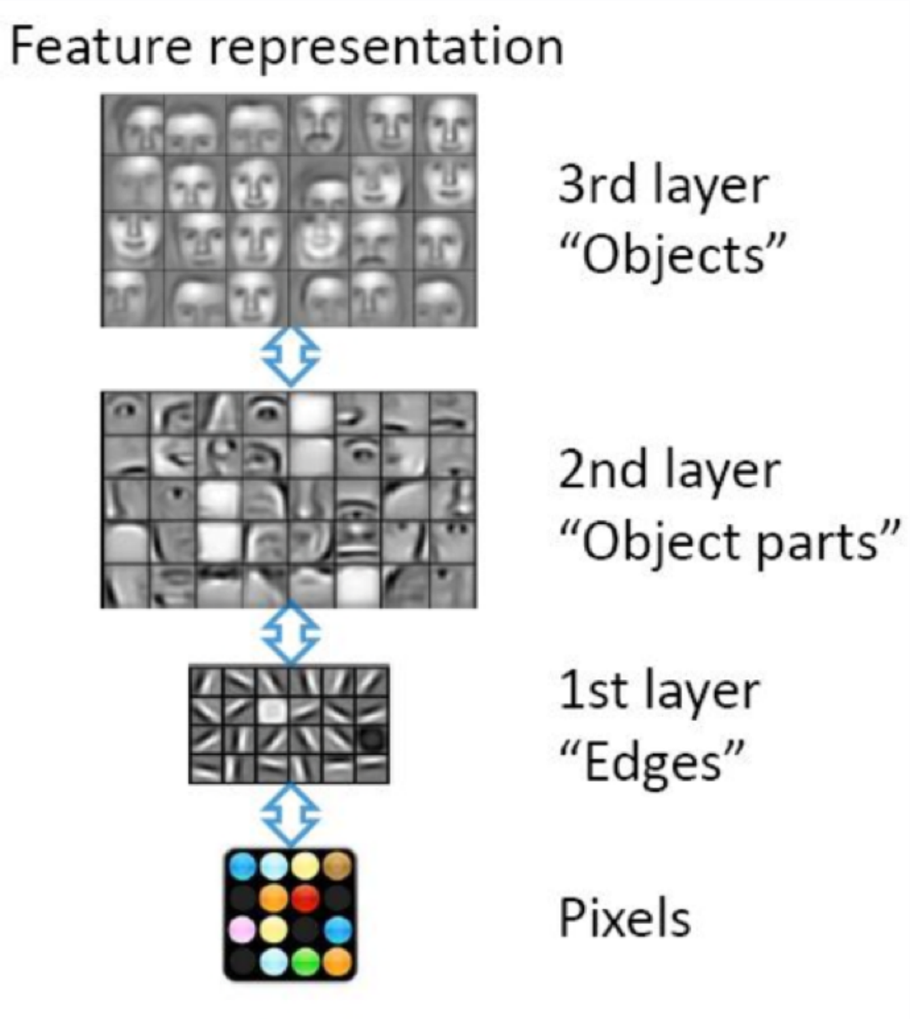
Credit: Matt Gormley

Feedforward neural networks

Neural networks can be very expressive, especially as you add more layers (i.e., 'deep' neural networks)

Pro: Can allow the model to learn a feature representation and the appropriate levels of abstraction from your data

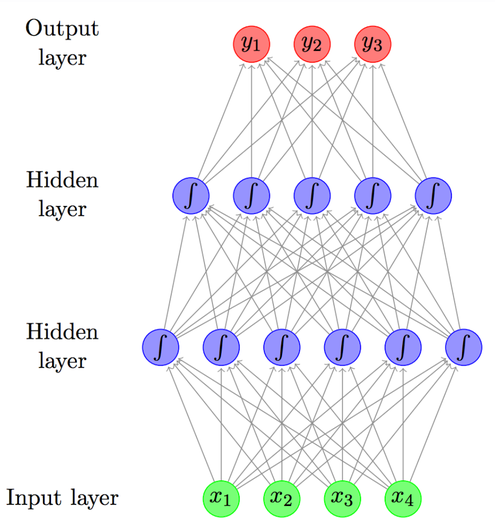
Challenge: this can make DNNs expensive …



Credit: Matt Gormley

COST OF THE 'FORWARD PASS'

Feedforward neural networks



Can express NN model with the following recurrence:

$$\mathbf{o}_0 = \mathbf{x}$$

$$\forall l \in \{1,\ldots,L\},\ \mathbf{h}_l = \mathbf{W}_l^\top \mathbf{o}_{l-1}$$

$$\forall l \in \{1,\ldots,L\},\ \mathbf{o}_l = \sigma_l(\mathbf{h}_l)$$

$$\phi(\mathbf{x}) = \mathbf{o}_L$$

What dominates the cost?

Matrix(-vector) multiplies

O(nm) for n x m matrix, m x 1 vector

MOVING FORWARD

What makes deep learning expensive?

Training requires lots of computation

- GPUs can help with matrix computations [*more on this later in lecture*]
- Can use advanced iterative optimization methods [*more on this Thursday*]
- Can parallelize training [*more on this in a few weeks*]

Hyperparameter tuning and neural architecture search (NAS) make this worse

- Lots of knobs to tune! [*more on this in a few weeks*]

Resulting models can be large!

- Can be expensive to store model, perform inference [*more on this in a few weeks*]

Outline

1. Neural networks
2. Backprop
3. ML Frameworks
4. DL Hardware

How to train DNNs?

Same idea as before: can use first-order optimization methods, e.g., SGD

Issue: need to compute the gradient …

How do we do this? Need to differentiate a composition of functions

$$f(\mathbf{x}) = \mathbf{w}^\top \sigma_L(\mathbf{W}_L^\top(\sigma_{L-1}(\mathbf{W}_{L-1}^\top \dots \sigma_2(\mathbf{W}_2^\top \sigma_1(\mathbf{W}_1^\top \mathbf{x}))\dots)$$

^ will have to use the *chain rule*

RECALL

Chain rule

The chain rule is used to differentiate composite functions, e.g.:

$$\frac{d}{dx} f(g(h(x))) = f'(g(h(x))) \cdot g'(h(x)) \cdot h'(x)$$

We can use this rule to calculate the gradients for neural networks

However, this expression doesn't provide an *algorithm* for computing the gradient efficiently

How can we compute the chain rule efficiently?

RECALL

Chain rule

$$\frac{d}{dx} f(g(h(x))) = f'(g(h(x))) \cdot g'(h(x)) \cdot h'(x)$$

Simple example: suppose we input the above equation into python …

```
def grad_fgh(x):
        return grad_f(g(h(x))) * grad_g(h(x)) * grad_h(x)
```

Do you see any inefficiencies? *h(x) is calculated twice …*

Instead, consider:

```
def better_grad_fgh(x):
        hx = h(x)
        return grad_f(g(hx)) * grad_g(hx) * grad_h(x)
```

Credit: Chris De Sa

Chain rule

How much computation can this actually save?

Suppose we have: $f_k(f_{k-1}(\cdots f_2(f_1(x))\cdots))$

Using the chain rule, the derivative is:

$$\frac{d}{dx} f_k(f_{k-1}(\cdots f_2(f_1(x))\cdots))$$

$$= f_k'(f_{k-1}(\cdots f_2(f_1(x))\cdots)) \cdot f_{k-1}'(f_{k-2}(\cdots f_2(f_1(x))\cdots))\cdots f_2'(f_1(x)) \cdot f_1'(x)$$

Suppose f_i and f_i' take $O(1)$ time to compute

What's the complexity for naively computing this derivative? $\sum_{i=1}^{k} i \rightarrow O(k^2)$

What if we avoid redundant computation (as in previous slide)? $k + (k-1) \rightarrow O(k)$

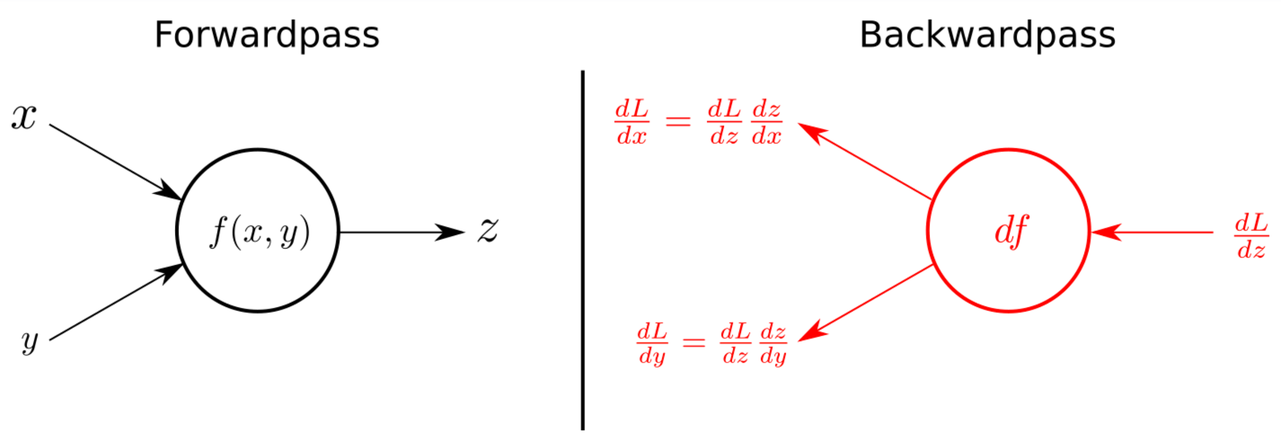
Backpropagation

This is the main idea / cost savings in “backpropagation”, which efficiently computes the gradient of a feedforward neural network

Two main steps:

- *forward pass*: traverse through the network normally, as if we were computing the function value, and save all intermediate values
- *backward pass*: proceed backwards through the network, computing gradients of the function value with respect to intermediates

You will gain hands on experience in HW5 …



Additional Resources

Feedforward neural networks & backprop

- Deep Learning Book, Chapter 6: https://www.deeplearningbook.org/

Autodiff

- William Cohen Notes: http://www.cs.cmu.edu/~wcohen/10-605/notes/autodiff.pdf
- Blog post: https://justindomke.wordpress.com/2009/02/17/automatic-differentiation-the-most-criminally-underused-tool-in-the-potential-machine-learning-toolbox/

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TRAINING DNNS

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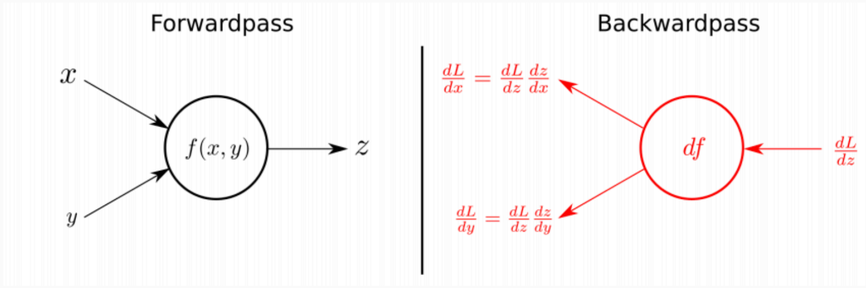

🤔

Recall backpropagation

Slides Credit: Heather Miller

TRAINING DNNS

Backpropagation

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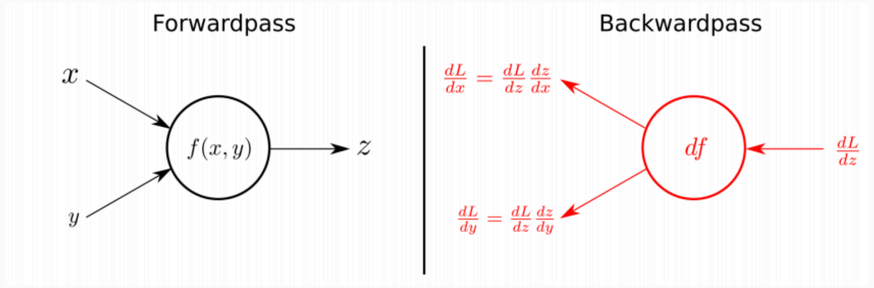

IMPLEMENTING THIS...

It would be a pain to have to implement this all from scratch for a network of potentially 1000s of units!

THOUGHT EXERCISE

Imagine designing a ML system from scratch

It's **easy to start with basic SGD** in C++

Implement objective function, gradient function, then make a loop

But there's **so much more to be done** with our C++ program

- *Need to manually code a **step size scheme***
- *Need to modify code to add **mini-batching***
- *Need to completely rewrite code to run in **parallel** or with **low-precision***
- *Impossible to get it to run on a **GPU** or on an **ASIC***
- *And at each step we have to **debug** and **validate** the program*

Clearly, in a software engineering sense, we should be striving for reuse!

SOLUTION

Machine Learning Frameworks

Machine Learning frameworks have exploded in popularity in an effort to…

Goal: Make ML easier

- From a software engineering perspective
- Make the computations more reliable, debuggable, and robust

Goal: Make ML scalable

- To large datasets running on distributed heterogeneous hardware

Goal: Make ML accessible

- So that even people who aren't ***ML systems experts*** can get good performance

SOLUTION

Machine Learning Frameworks

Machine Learning frameworks **make it so that we don't have to reinvent the wheel** each time we would like to experiment with a technique!

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Goal: Make ML scalable

- To large datasets running on distributed heterogeneous hardware

Goal: Make ML accessible

- So that even people who aren't ***ML systems experts*** can get good performance

SOLUTION

Machine Learning Frameworks: Deep Learning

This extends to **deep learning** frameworks

Why we have frameworks for deep learning:

1. Allow us to quickly prototype ideas
2. Automatically compute gradients
3. Run efficiently on CPUs/GPUs/TPUs

Machine Learning frameworks **make it so that we don't have to reinvent the wheel** each time we would like to experiment with a technique!

QUICK ASIDE: CONTEXT

Kinds of ML frameworks

There are many *kinds of* **reusable** frameworks that are useful for machine learning:

General machine learning frameworks

- *Goal: make a wide range of ML workloads and applications easy for users*

General big data processing frameworks

- *Focus: computing large-scale parallel operations quickly*
- *Typically has machine learning as a major, but not the only, application*

Deep learning frameworks

- *Focus: fast scalable backpropagation and inference*
- *Although typically supports other applications as well*

QUICK ASIDE: CONTEXT

A quick sampling of some such ML frameworks

General machine learning frameworks

scikit-learn

NumPy

SciPy

Together provide a great ecosystem for prototyping systems on single machine / CPU!

QUICK ASIDE: CONTEXT

A quick sampling of some such ML frameworks

General machine learning frameworks

Everything mentioned so far runs on top of basic linear algebra operations! Those come in frameworks too!

BLAS: Basic Linear Algebra Subroutines

- Also has support on GPUs with NVIDIA cuBLAS

LAPACK: Linear Algebra PACKage

QUICK ASIDE: CONTEXT

A quick sampling of some such ML frameworks

General big data processing frameworks

MapReduce/Hadoop

- The first widely-used framework for distributed machine learning
- Mostly been superseded by other frameworks

QUICK ASIDE: CONTEXT

A quick sampling of some such ML frameworks

General big data processing frameworks

MapReduce/Hadoop 

Apache Spark 

- Popular cluster-computing framework, 100x faster than Hadoop

Apache Spark MLlib

- Scalable machine learning library built on top of Spark
- Supports most of the same algorithms scikit-learn supports
  - *Not primarily a deep learning library*
- Major benefit: interaction with other processing in Spark

QUICK ASIDE: CONTEXT

A quick sampling of some such ML frameworks

Deep learning frameworks

Caffe

MXNet

- Early DL frameworks

QUICK ASIDE: CONTEXT

A quick sampling of some such ML frameworks

Deep learning frameworks

Caffe

MXNet

TensorFlow

- End-to-end deep learning system, developed by Google Brain
- Framework automatically schedules computations in computation graph on the available resources

QUICK ASIDE: CONTEXT

A quick sampling of some such ML frameworks

Deep learning frameworks

Caffe

MXNet

TensorFlow

PyTorch

- Tensor computation (like numpy) with strong GPU acceleration
- Eager execution (now TensorFlow 2.0 also includes this …)

+ many others … and new frameworks are always being developed!

What DL Frameworks Typically Support

Basic tensor operations

- *Provides the low-level math behind all the algorithms*

Automatic differentiation

- *Used to make it easy to run backprop on any model*

Simple-to-use implementations of **common techniques**

- *Like mini-batching, SVRG, Adam, etc.*
- *automatic hyperparameter optimization*

A GENERAL IDEA

Tensors

Tensors can be thought of as a **multidimensional array** (CS perspective) or a **multilinear map** (math perspective).

$$T : \mathbb{R}^{d_1} \times \mathbb{R}^{d_2} \times \cdots \times \mathbb{R}^{d_n} \to \mathbb{R}$$

$T(x_1, x_2, \cdots, x_n)$ is linear in each x_i, with other inputs fixed

n is the order of the tensor.

Examples:

- A matrix is a 2nd-order tensor
- A vector is a 1st-order tensor

A GENERAL IDEA

Tensors

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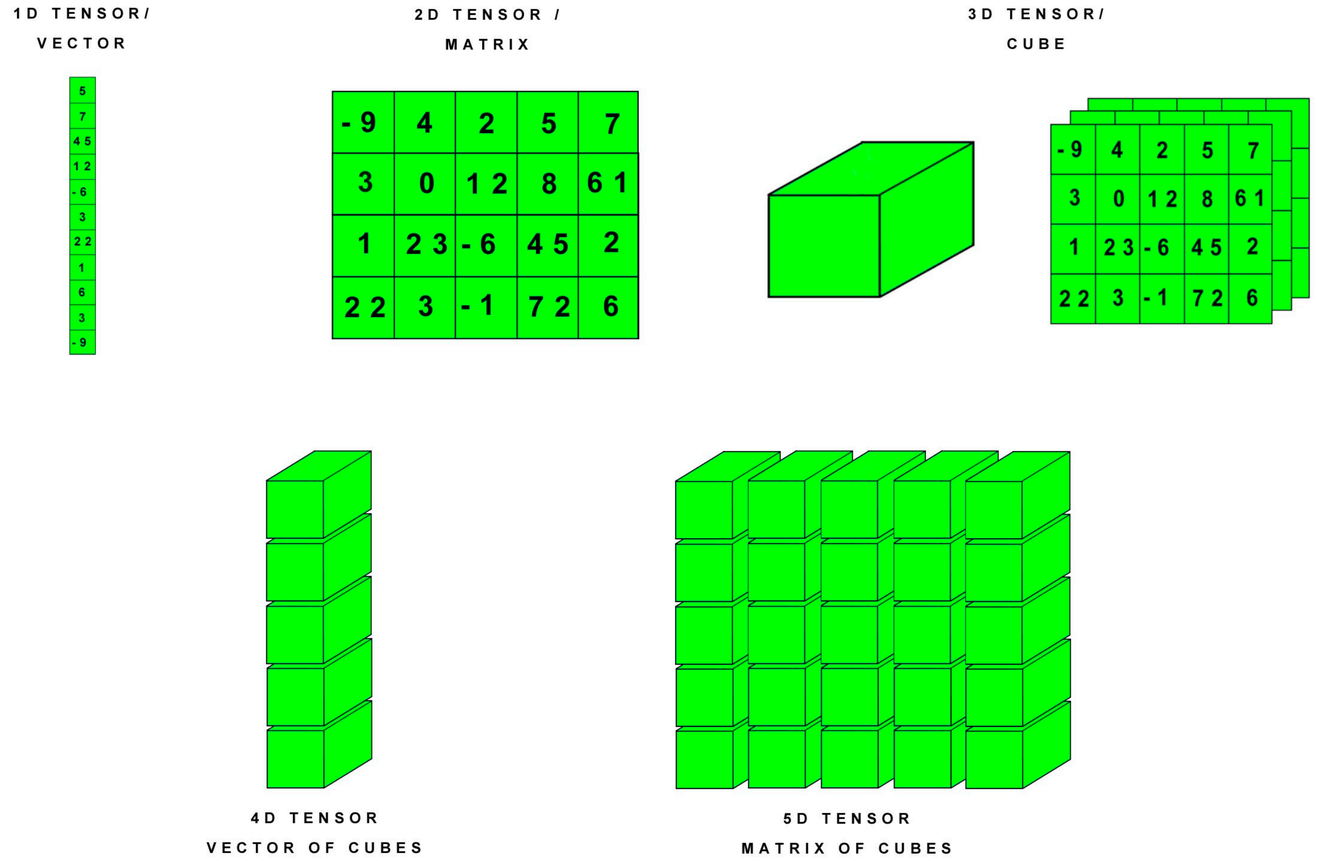


EXAMPLES

Tensors

The **CIFAR10 dataset** consists of 60000 32x32 color images,

We can write the training set as a tensor:

$$T_{\text{CIFAR10}} \in \mathbb{R}^{32 \times 32 \times 3 \times 60000}$$

Gradients for deep learning can also be tensors.

Example: fully-connected layer with 100 input and 100 output neurons, and minibatch size b=32

$$G \in \mathbb{R}^{100 \times 100 \times 32}$$

SYSTEMS PERSPECTIVE

Tensors

Benefits of tensors from a systems perspective…

Loads of data parallelism

- Tensors are in some sense the structural embodiment of data parallelism
- Multiple dimensions -> not always obvious which one best to parallelize over

Predictable linear memory access patterns

- Great for locality

Many different ways to organize the computation

- Creates opportunities for frameworks to automatically optimize

Automatic Differentiation

Imagine you write up an SGD algorithm with some objective and some gradient.

You hand-code the computation of the objective and gradient.

What happens when you differentiate incorrectly?

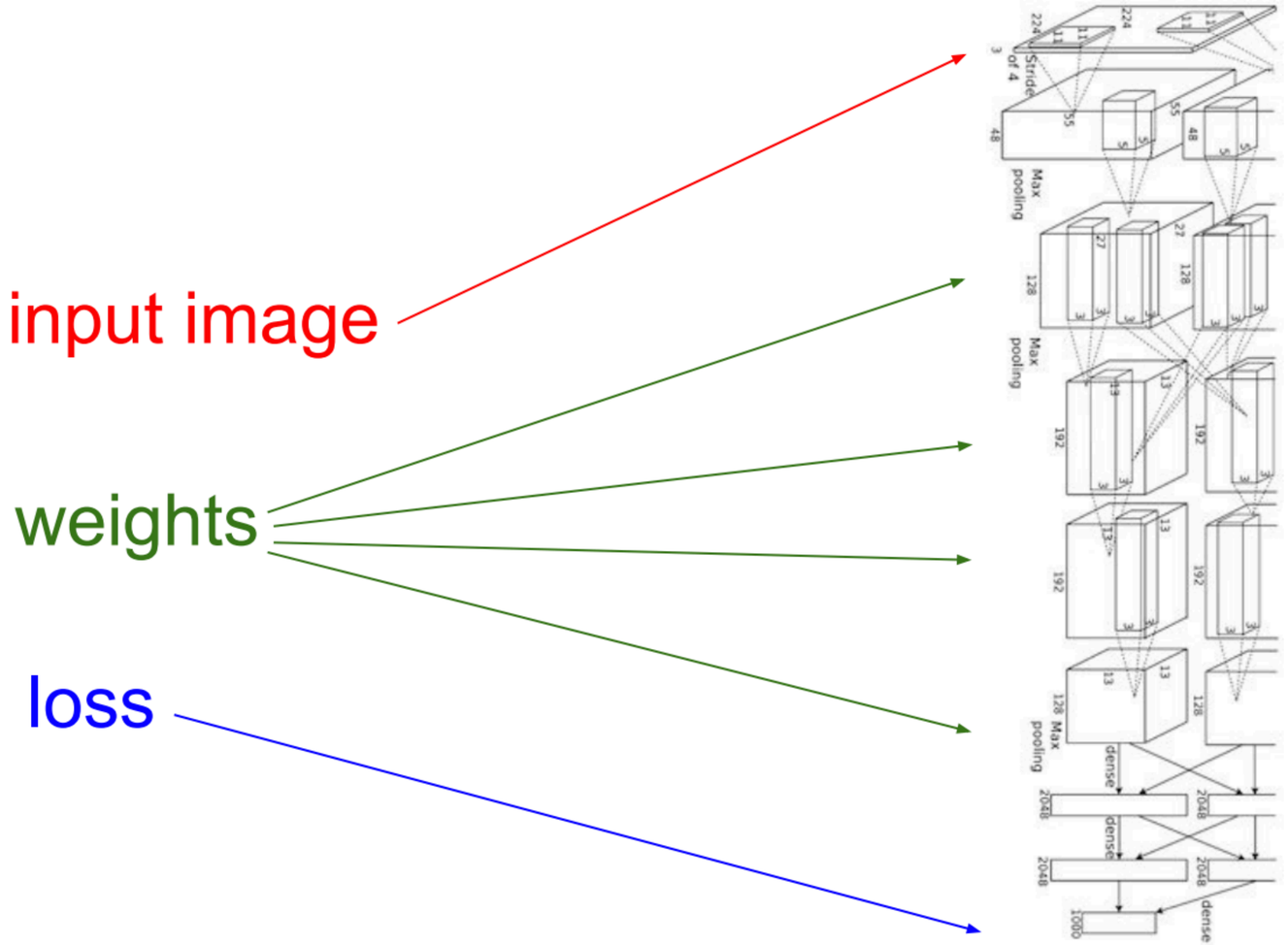
(Everybody will make this mistake eventually if they hand-write objectives. And it's really difficult and increasingly intractable to debug as models become complex)

SOLUTION: generate the gradient automatically from the objective via backprop!

MOTIVATION

Computational Graphs

These graph structures can get pretty complex when working with big neural networks.



MOTIVATION

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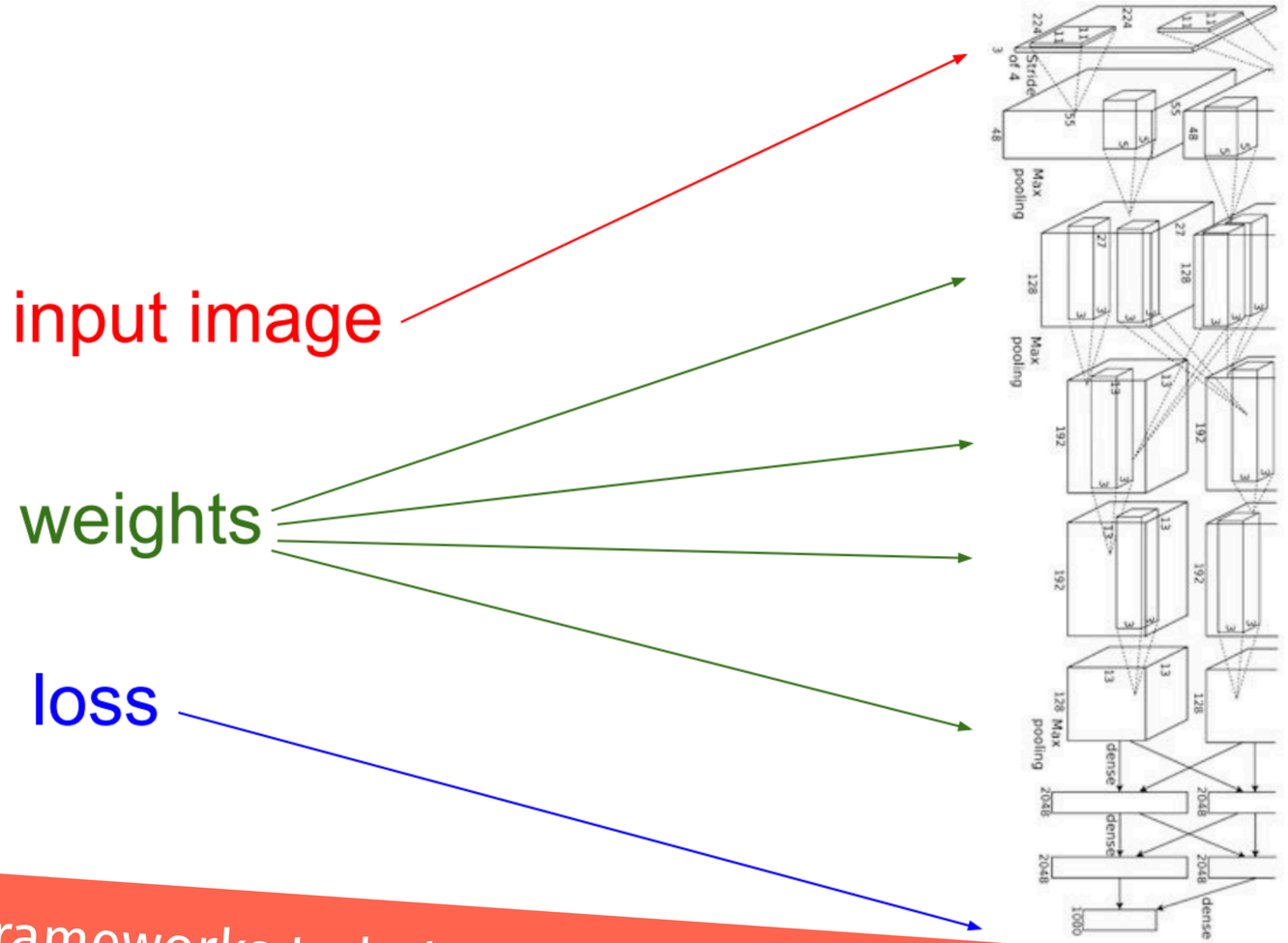


We want Deep Learning frameworks to help us manage this complexity!

MOTIVATION

Computational Graphs

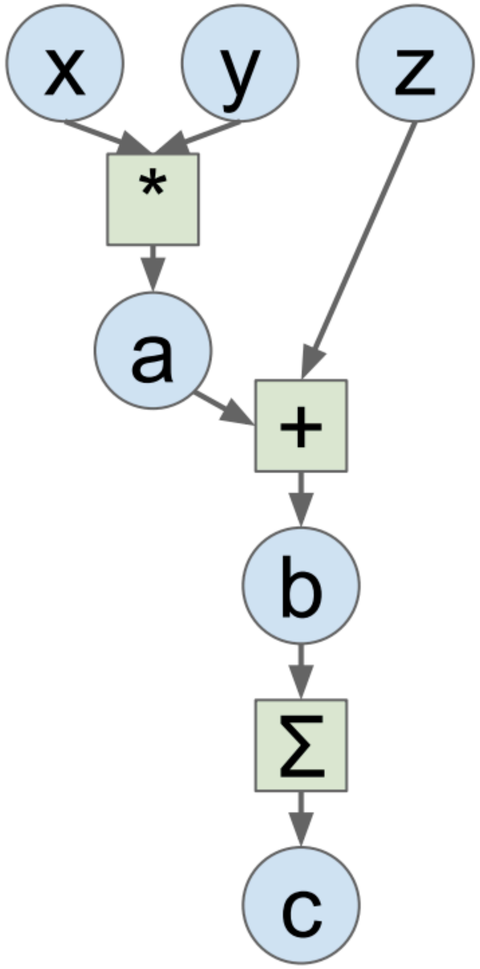
NumPy

```
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)
```



MOTIVATION

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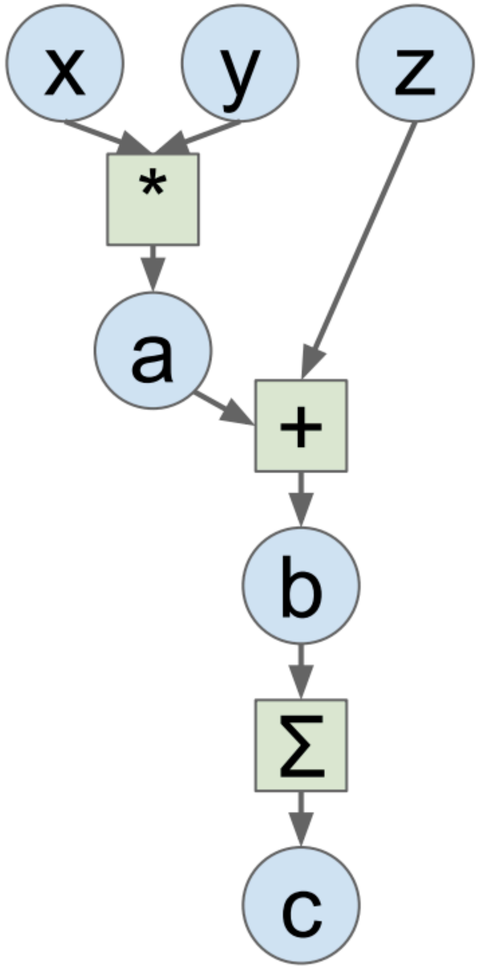
```

```
grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```



MOTIVATION

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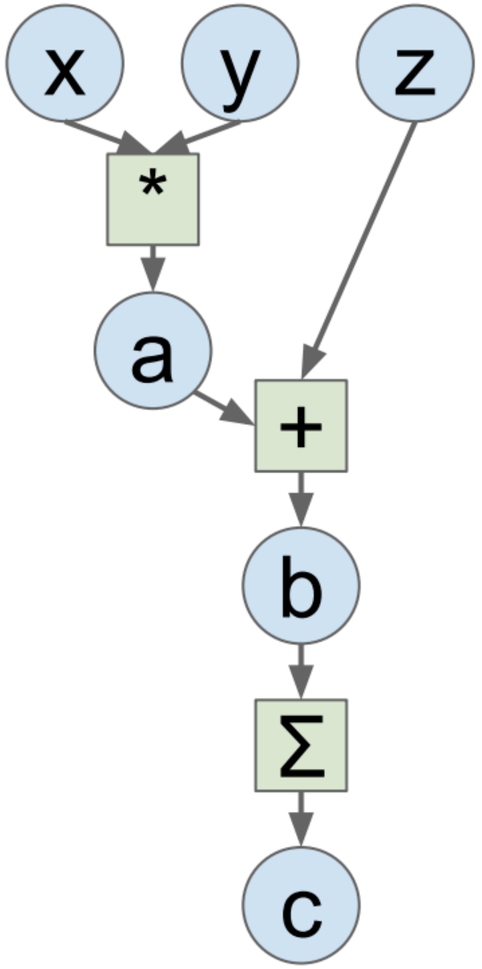

Issues with this:

- **Have to compute our own gradients**
- **Can't run on GPU**

Goal of most DL frameworks is to let you write code in the forward pass that looks like NumPy, AND automatically compute gradients & run on GPU.

MOTIVATION

Computational Graphs

NumPy

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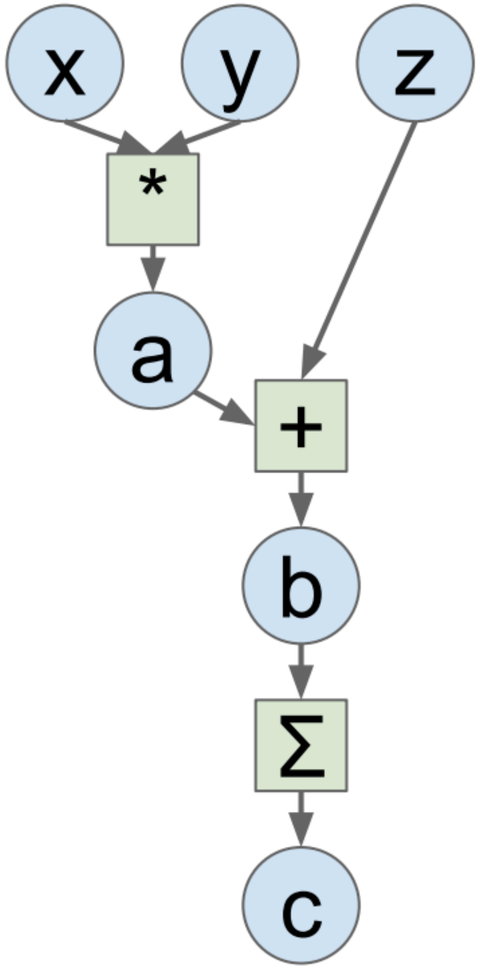


TensorFlow 1.0

```
# Basic computational graph
import numpy as np
np.random.seed(0)
import tensorflow as tf

N, D = 3, 4

x = tf.placeholder(tf.float32)
y = tf.placeholder(tf.float32)
z = tf.placeholder(tf.float32)

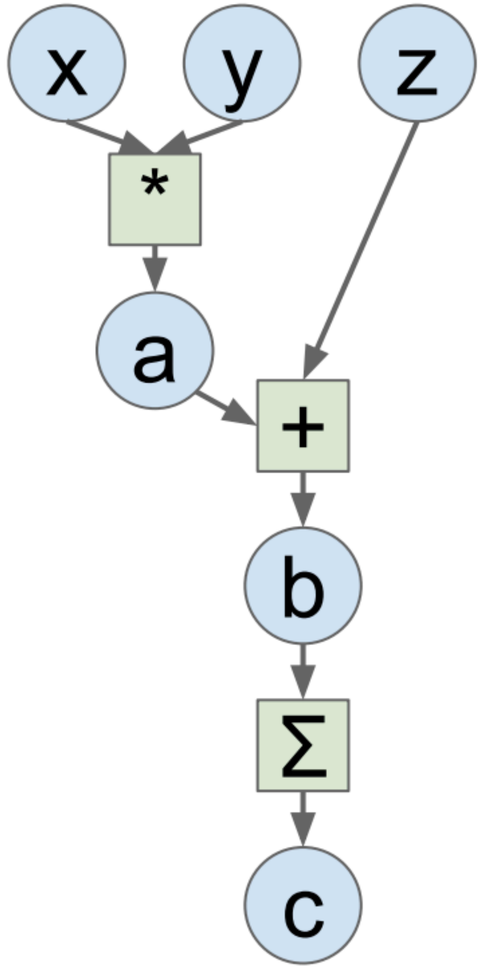
a = x * y
b = a + z
c = tf.reduce_sum(b)

grad_x, grad_y, grad_z = tf.gradients(c, [x, y, z])

with tf.Session() as sess:
    values = {
        x: np.random.randn(N, D),
        y: np.random.randn(N, D),
        z: np.random.randn(N, D),
    }
    out = sess.run([c, grad_x, grad_y, grad_z],
                   feed_dict=values)
    c_val, grad_x_val, grad_y_val, grad_z_val = out
```

MOTIVATION

Computational Graphs



Forward pass

TensorFlow 1.0

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import tensorflow as tf

N, D = 3, 4

x = tf.placeholder(tf.float32)
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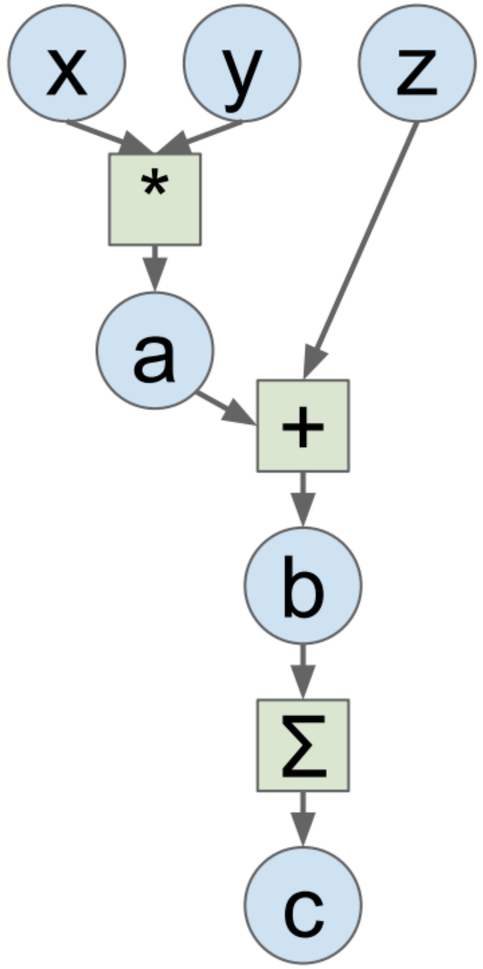
MOTIVATION

Computational Graphs



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                   feed_dict=values)
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```
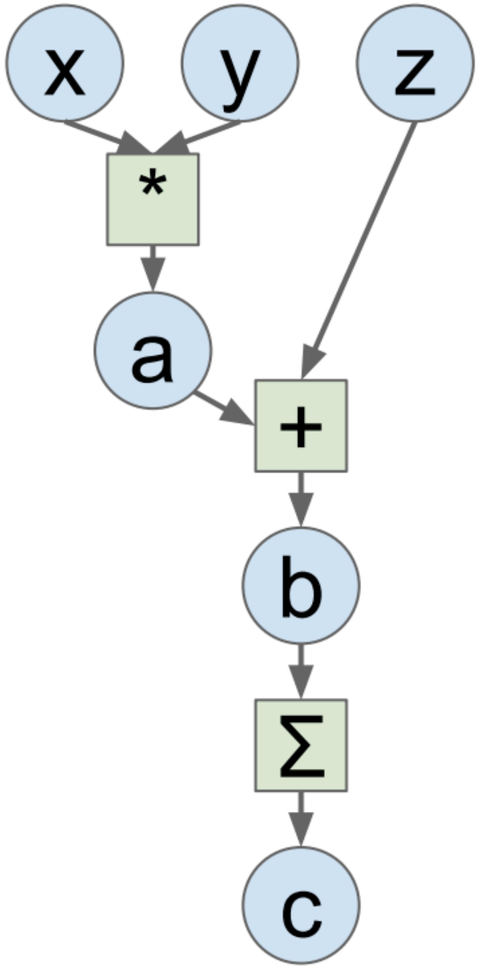

Compute gradients

MOTIVATION

Computational Graphs



Tell TensorFlow to run on CPU

TensorFlow 1.0

```
import numpy as np
np.random.seed(0)
import tensorflow as tf

N, D = 3000, 4000

with tf.device('/cpu:0'):
    x = tf.placeholder(tf.float32)
    y = tf.placeholder(tf.float32)
    z = tf.placeholder(tf.float32)

    a = x * y
    b = a + z
    c = tf.reduce_sum(b)

grad_x, grad_y, grad_z = tf.gradients(c, [x, y, z])

with tf.Session() as sess:
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```
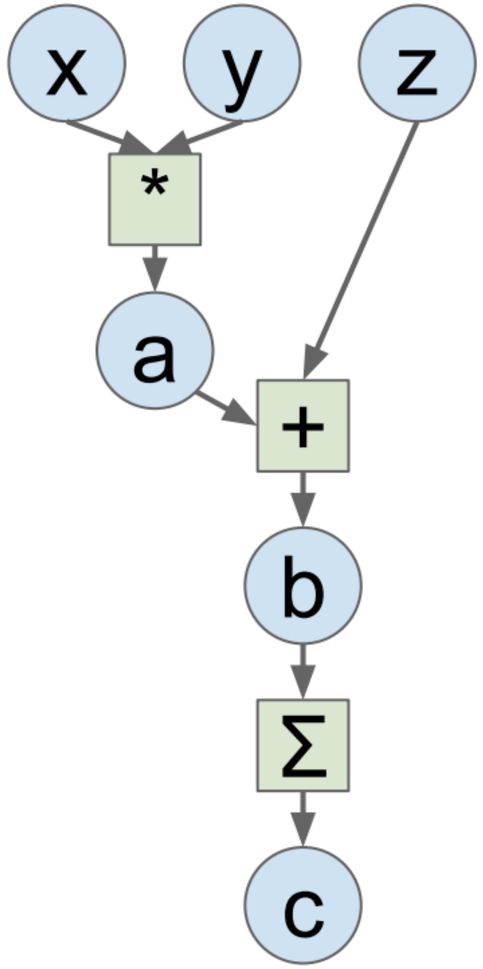

MOTIVATION

Computational Graphs



Tell TensorFlow to run on GPU

Now, we're:

- Running on a GPU
- Having framework compute the gradients for us

TensorFlow 1.0

```
import numpy as np
np.random.seed(0)
import tensorflow as tf

N, D = 3000, 4000

with tf.device('/gpu:0'):
    x = tf.placeholder(tf.float32)
    y = tf.placeholder(tf.float32)
    z = tf.placeholder(tf.float32)

    a = x * y
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```
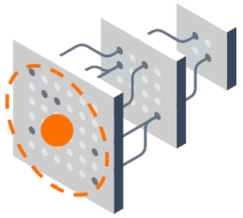



Easy model building

Build and train ML models easily using intuitive high-level APIs like Keras with eager execution, which makes for immediate model iteration and easy debugging.

Robust ML production anywhere

Easily train and deploy models in the cloud, on-prem, in the browser, or on-device no matter what language you use.

Powerful experimentation for research

A simple and flexible architecture to take new ideas from concept to code, to state-of-the-art models, and to publication faster.

We'll be using TensorFlow 2.0 in this class

Carnegie Mellon University
School of Computer Science

TensorFlow

- We will use TensorFlow (2.0) in HW5
- For additional resources on TensorFlow, please check out:

  - Quickstart: https://www.tensorflow.org/tutorials/quickstart/beginner
  - Guide: https://www.tensorflow.org/guide
  - Tutorials: https://www.tensorflow.org/tutorials
  - **Recitation video released by Friday!**

Outline

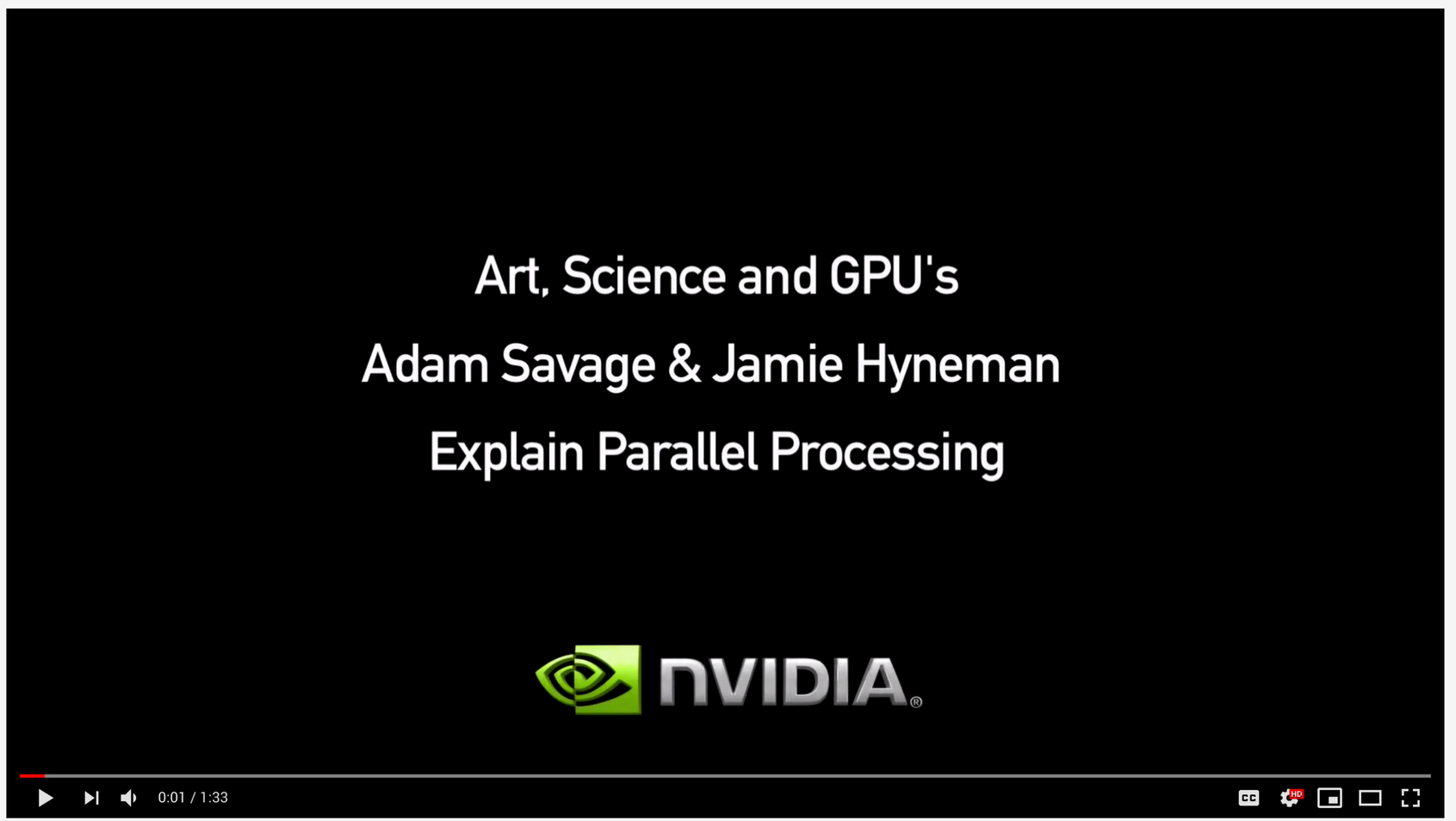
1. Neural networks
2. Backprop
3. ML Frameworks
4. DL Hardware

OK. LET'S CHANGE GEARS A BIT

What about the hardware? TensorFlow is supposed to be good on GPUs.

WHY GPUS?

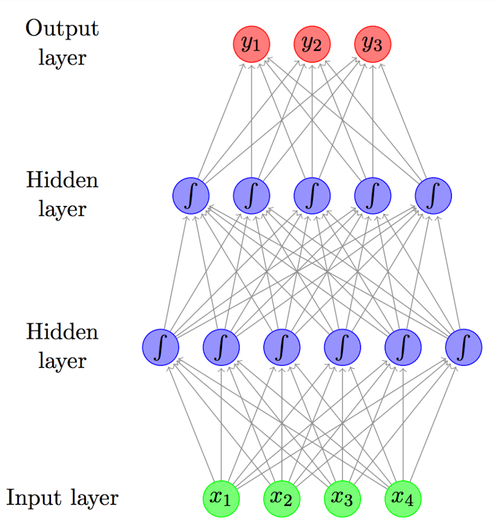
Parallelism



https://www.youtube.com/watch?v=-P28LKWTzrI

RECALL: COST OF THE 'FORWARD PASS'

Feedforward neural networks



Can express NN model with the following recurrence:

$$\mathbf{o}_0 = \mathbf{x}$$

$$\forall l \in \{1,\ldots,L\},\ \mathbf{h}_l = \mathbf{W}_l^\top \mathbf{o}_{l-1}$$

$$\forall l \in \{1,\ldots,L\},\ \mathbf{o}_l = \sigma_l(\mathbf{h}_l)$$

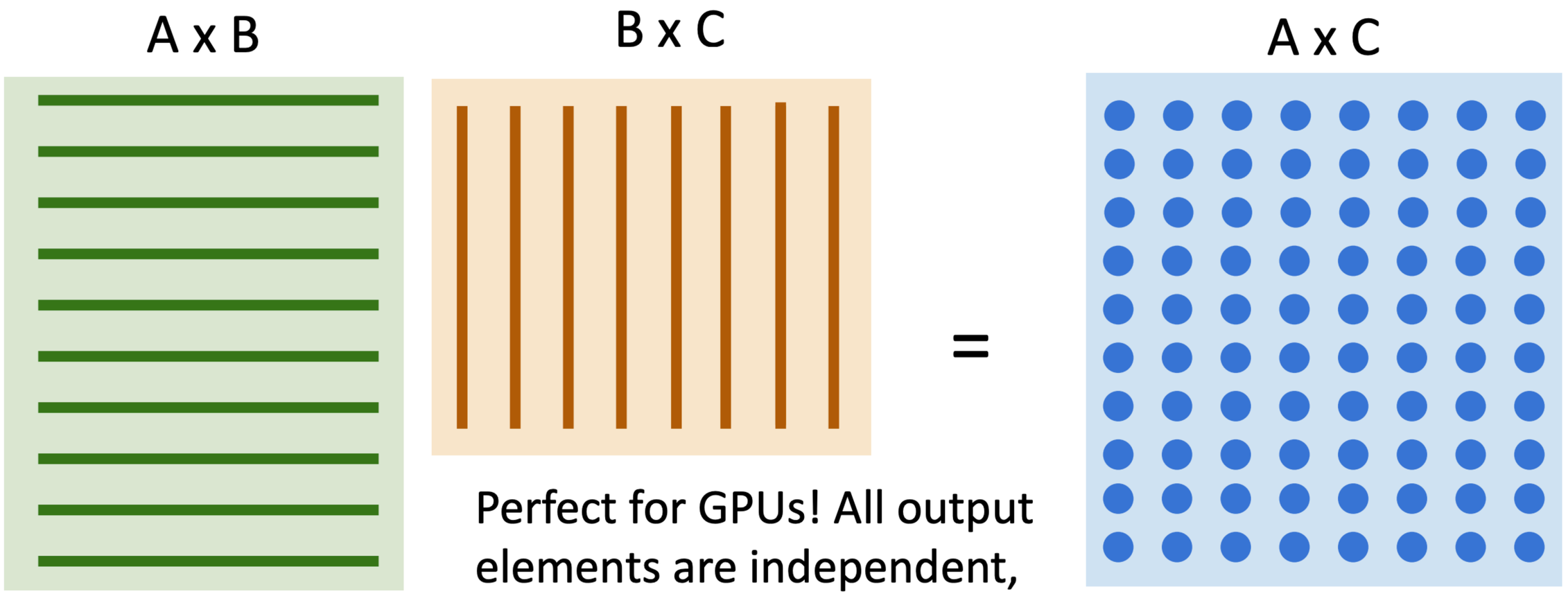
$$\phi(\mathbf{x}) = \mathbf{o}_L$$

What dominates the cost?

Matrix(-vector) multiplies

O(nm) for n x m matrix, m x 1 vector

Matrix Multiplication



Perfect for GPUs! All output elements are independent, can be trivially parallelized

What do we already know about GPUs?

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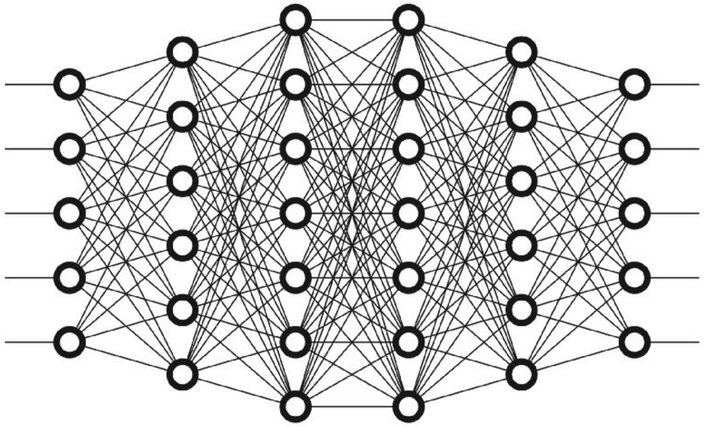
If you’re a gamer, there is a bit of a debate between NVIDIA and AMD.

What do we already know about GPUs?

If you're a gamer, there is a bit of a debate between NVIDIA and AMD.

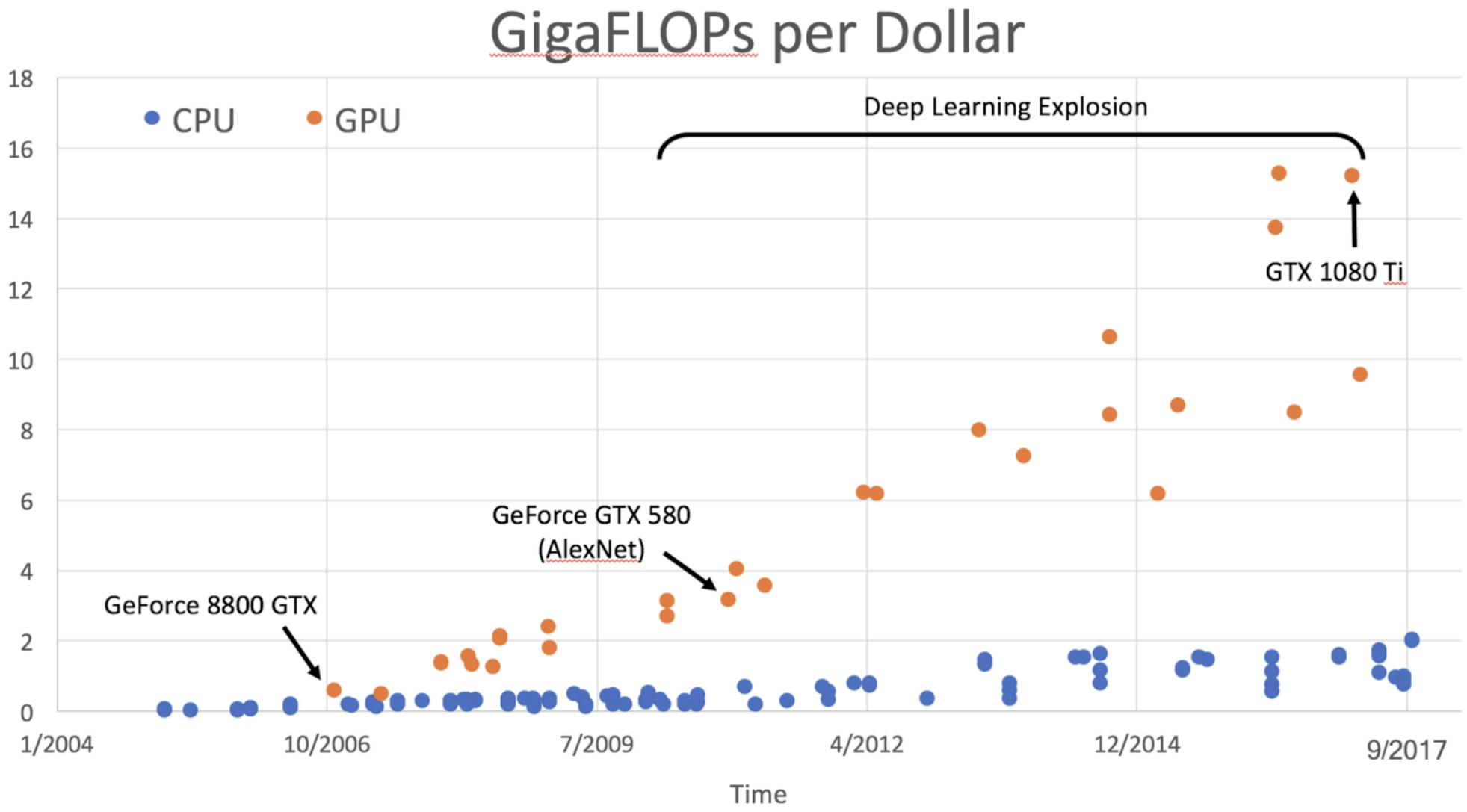
However, in the context of deep learning,

NVIDIA wins.



ML HARDWARE

GigaFLOPs per Dollar



https://web.eecs.umich.edu/~justincj/slides/eecs498/498_FA2019_lecture09.pdf

CPUs vs GPUs

	Cores	Clock Speed (GHz)	Memory	Price	TFLOP/sec
CPU Ryzen 9 3950X	16 (32 threads with hyperthreading)	3.5 (4.7 boost)	System RAM	$749	~4.8 FP32
GPU NVIDIA Titan RTX	4608	1.35 (1.77 boost)	24 GB GDDR6	$2499	~16.3 FP32

CPU: Fewer cores, but each core is much faster and much more capable; great at sequential tasks

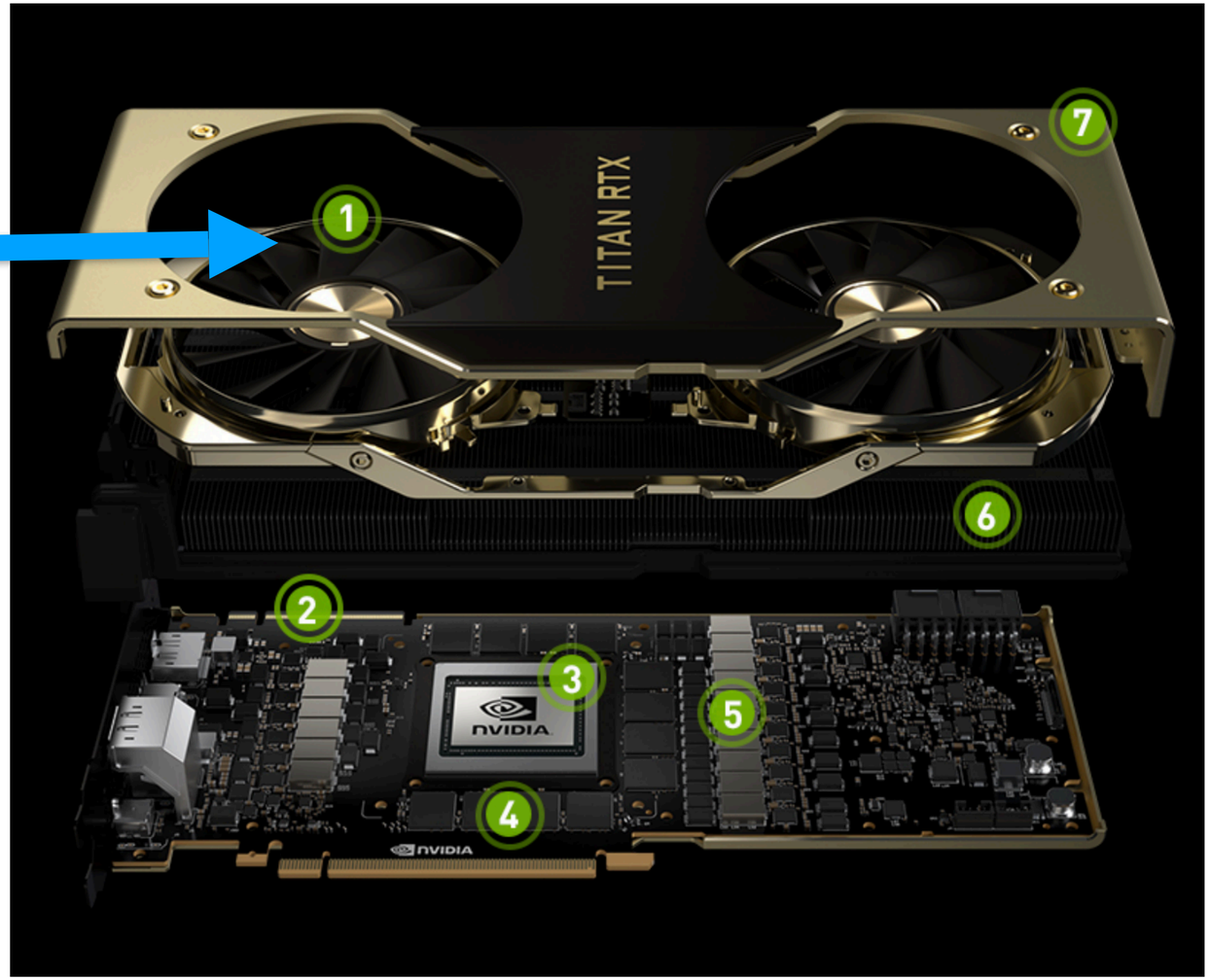
GPU: More cores, but each core is much slower and "dumber"; great for parallel tasks

https://web.eecs.umich.edu/~justincj/slides/eecs498/498_FA2019_lecture09.pdf

Inside A GPU: RTX Titan

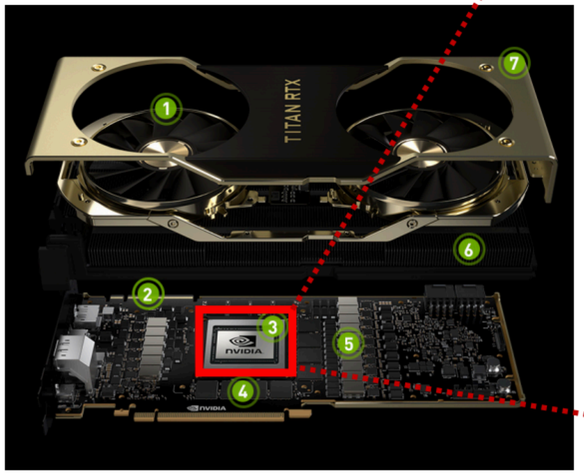
HOT! — Fans!

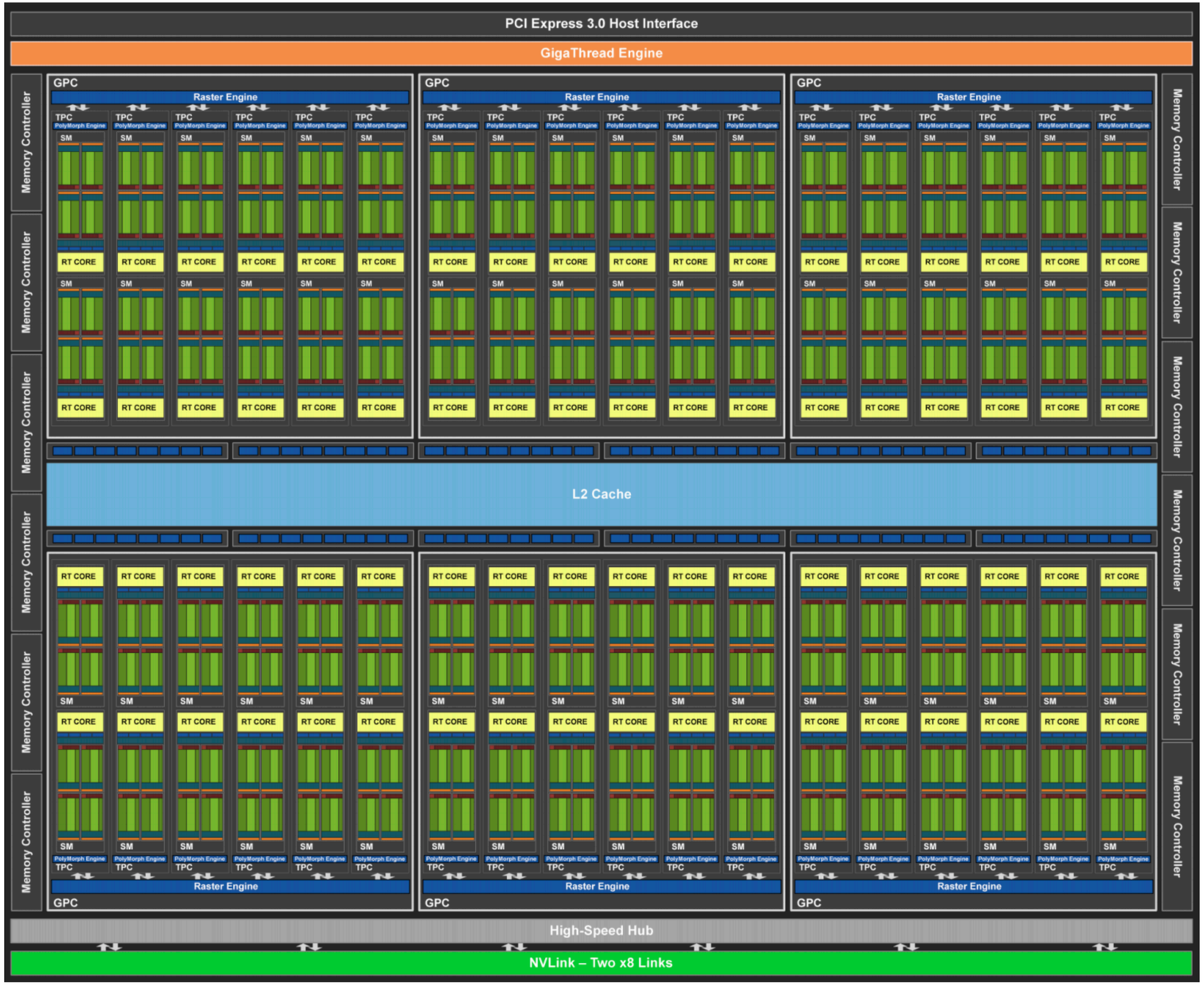
Lot’s of energy!



ML HARDWARE

Inside A GPU:

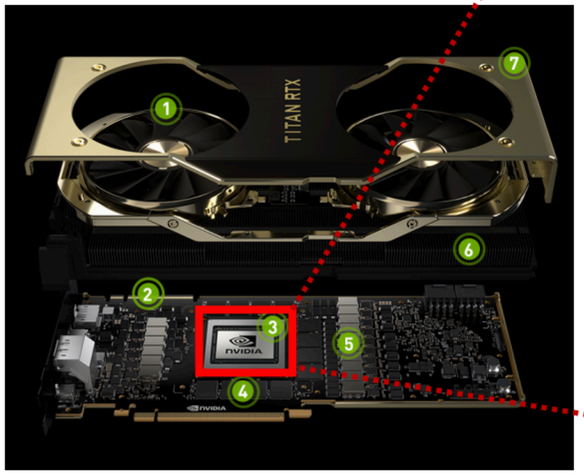


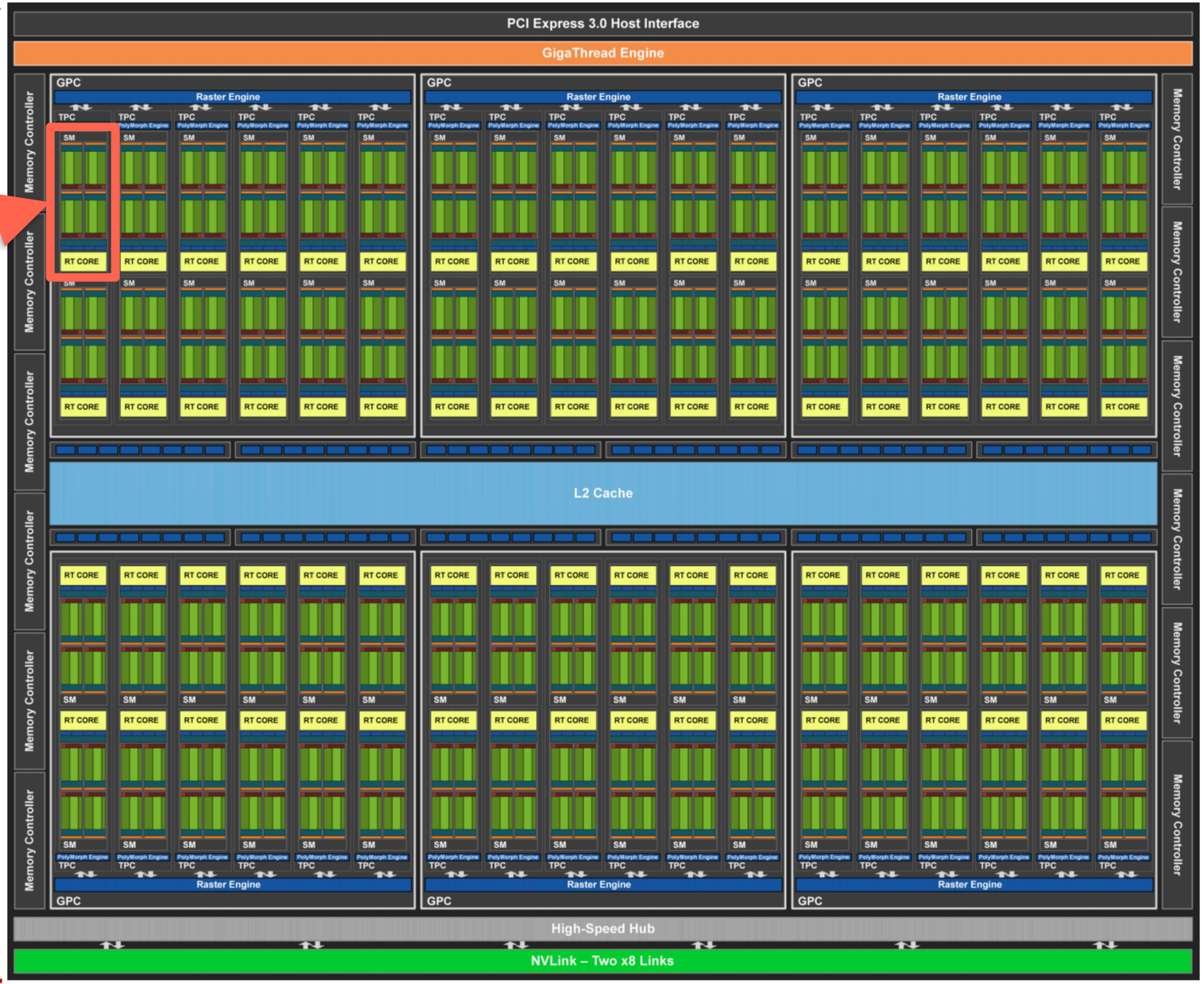


ML HARDWARE

Inside A GPU:

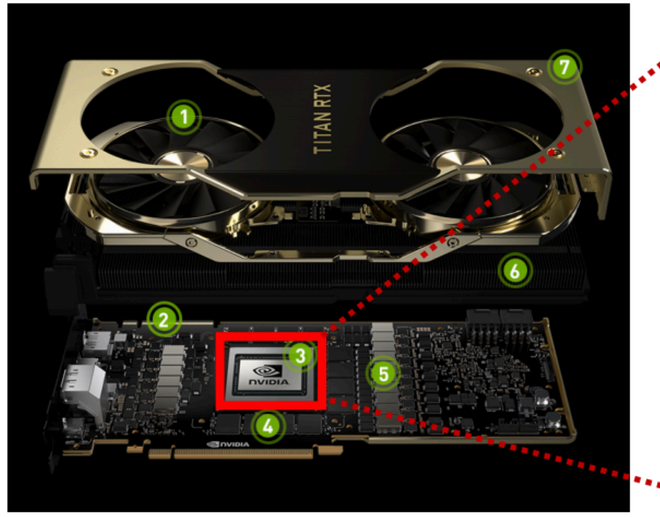
72 streaming multiprocessors (SMs)



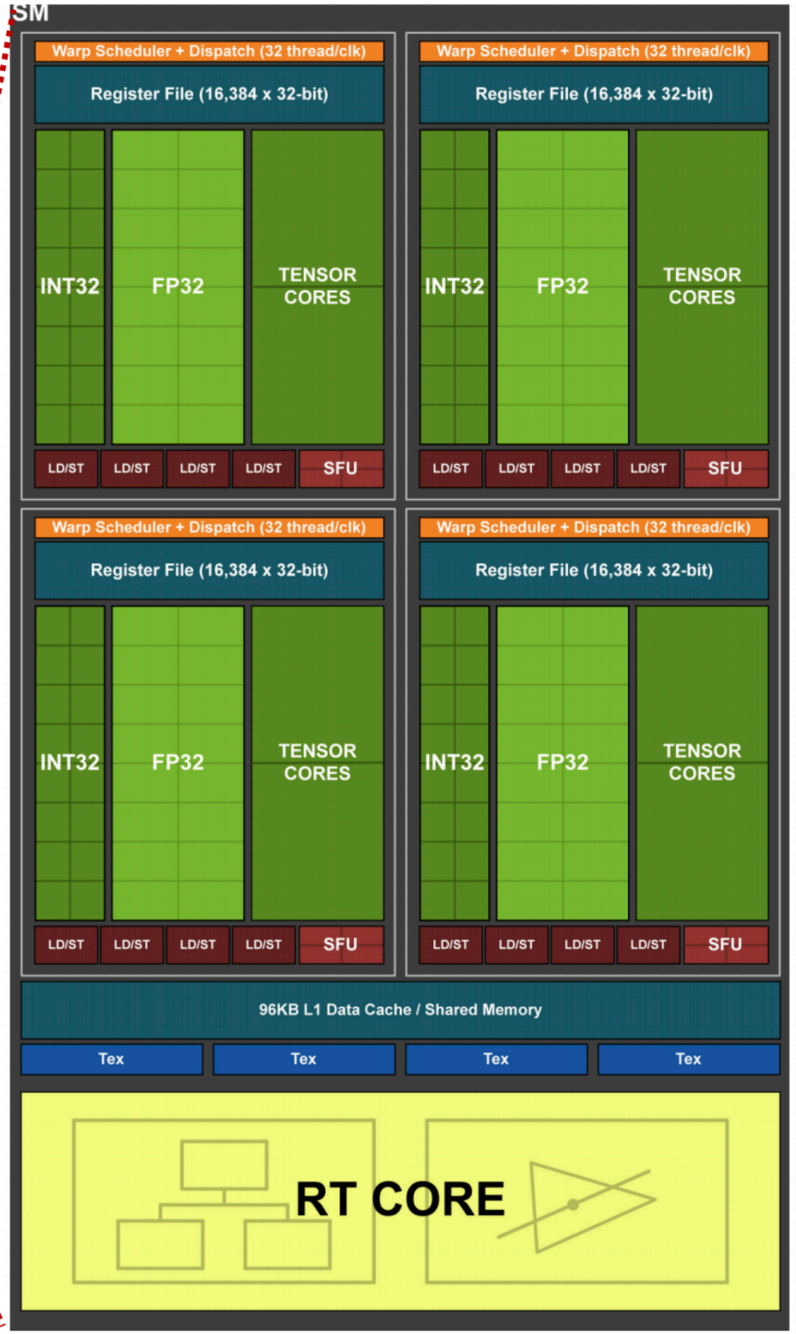


ML HARDWARE

Inside A GPU: RTX Titan



72 Streaming multiprocessors (SMs)

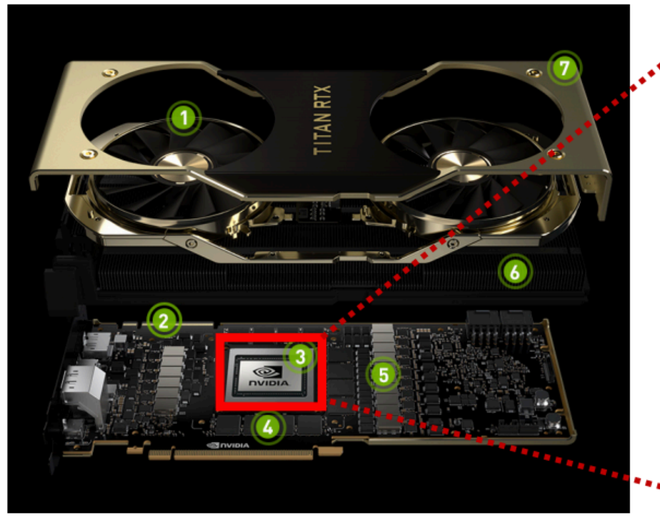


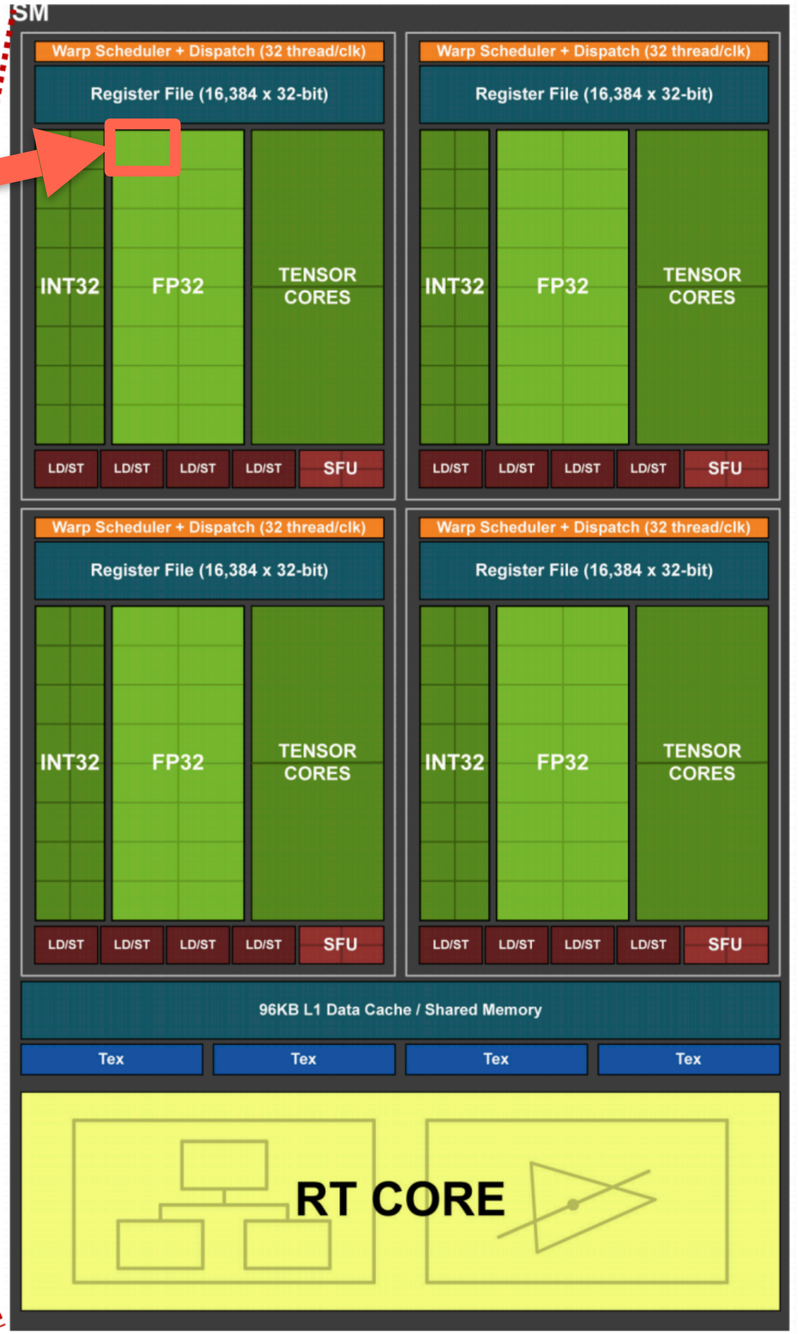
ML HARDWARE

Inside A GPU: RTX Titan

64 FP32 cores per SM

72 Streaming multiprocessors (SMs)





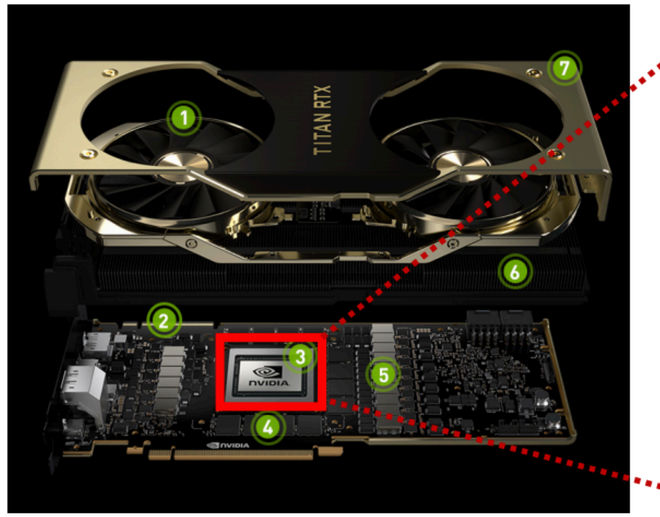
Inside A GPU: RTX Titan

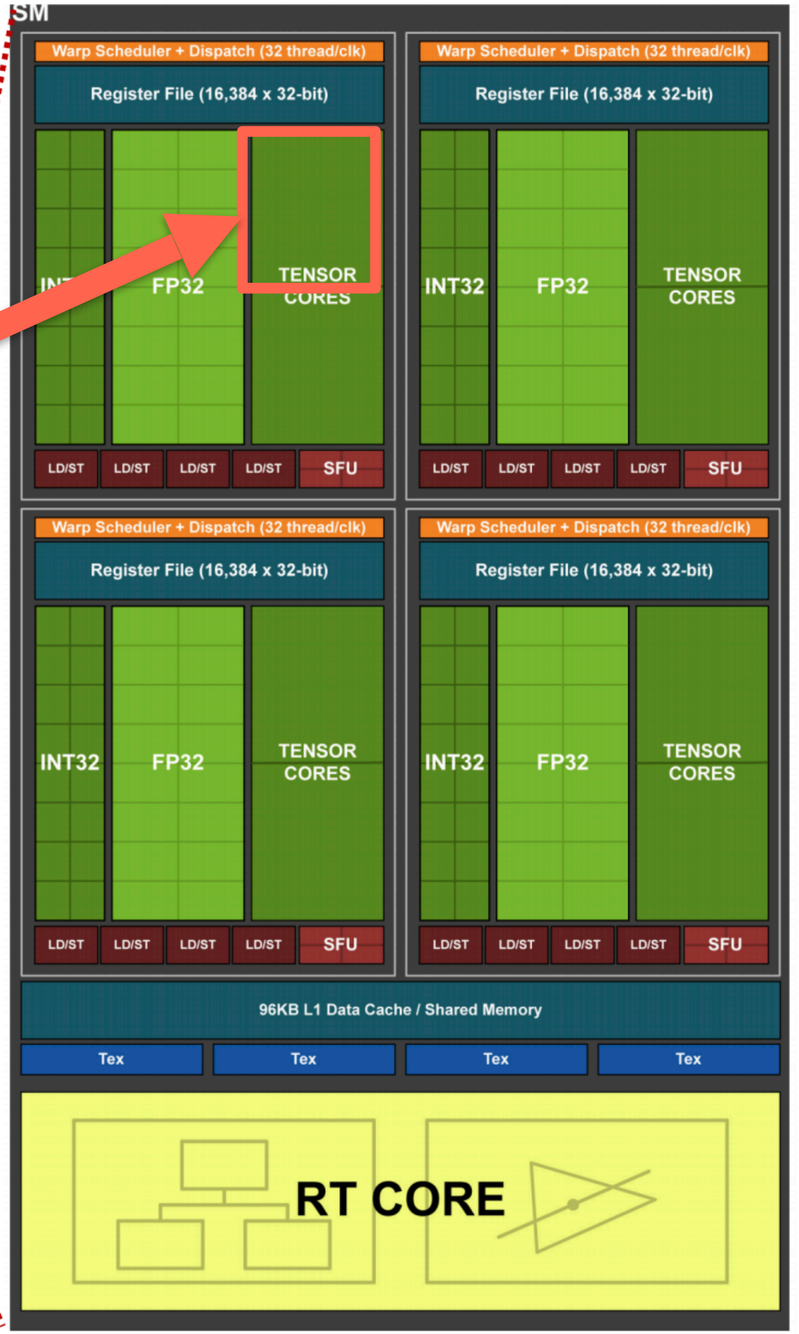
Tensor Core:
Special hardware for DL!

Let A,B,C be 4x4 matrices; computes AB+C in one clock cycle! (128 FLOP)

8 Tensor Core per SM

72 Streaming multiprocessors (SMs)





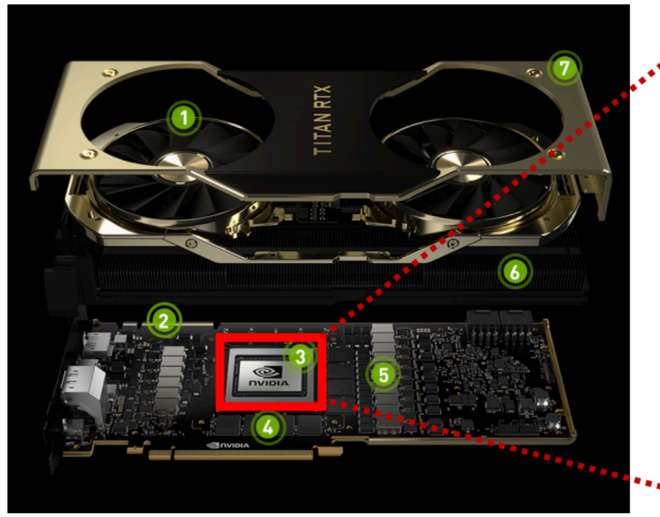
ML HARDWARE

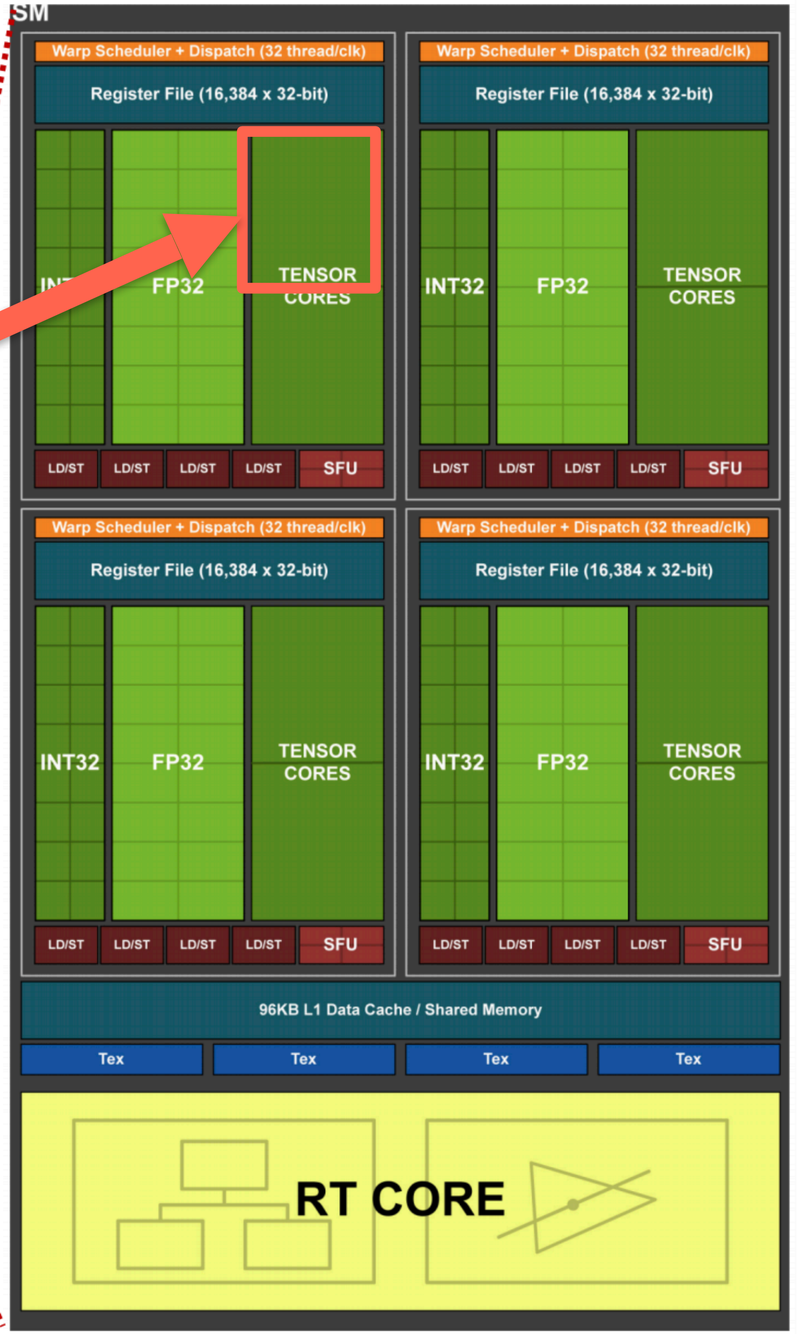
Inside A GPU: RTX Titan

Tensor cores use mixed precision: Multiplication is done in FP16, and addition is done in FP32

8 Tensor Core per SM

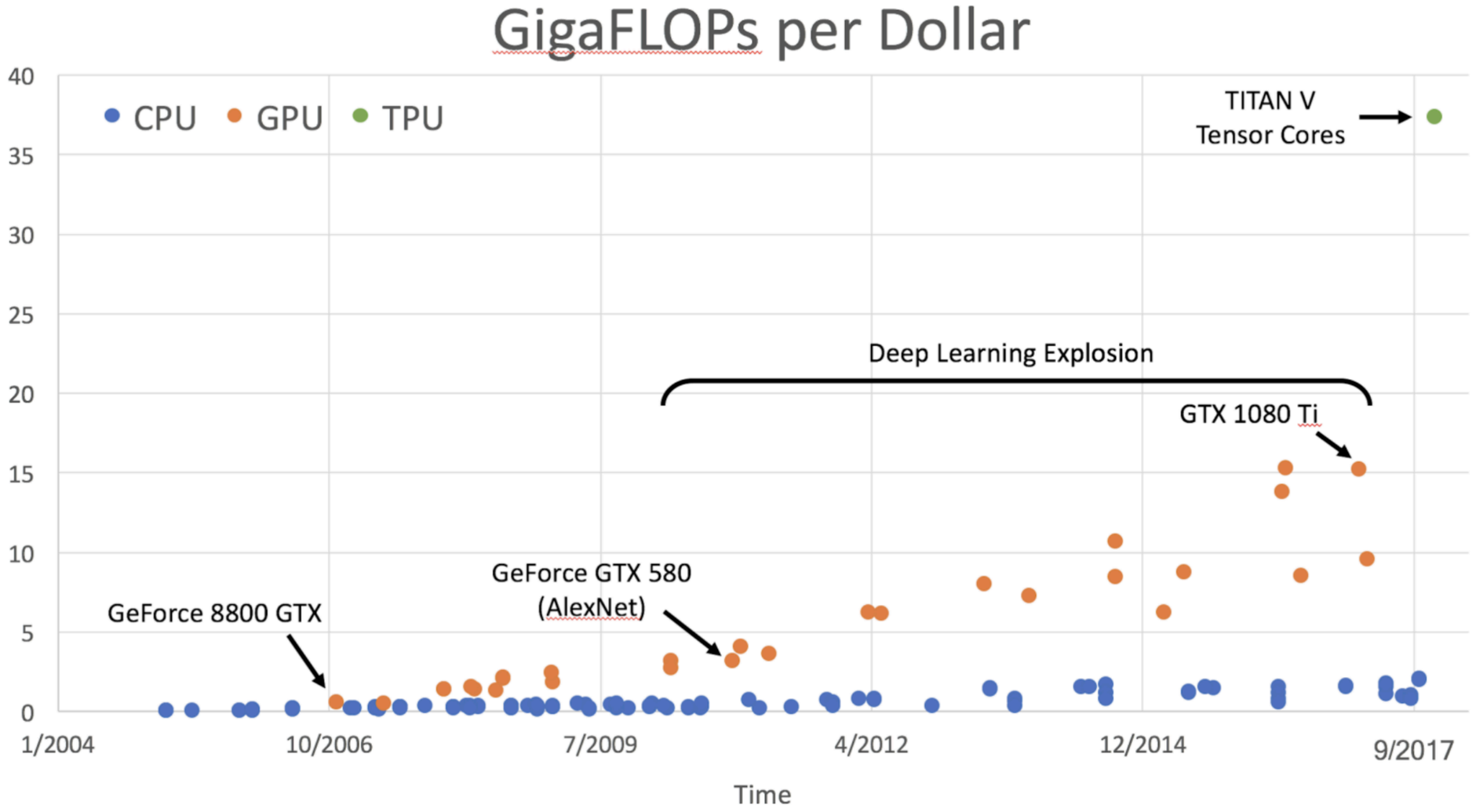
72 Streaming multiprocessors (SMs)





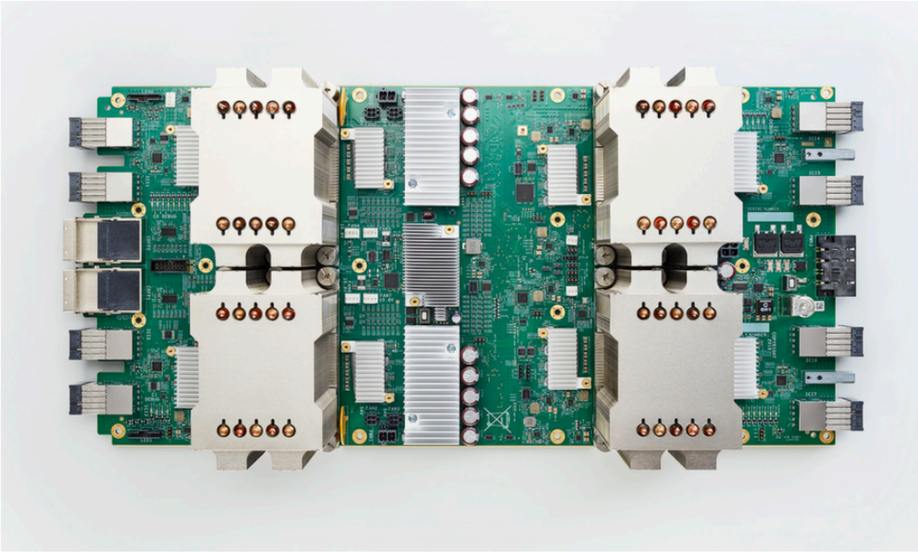
Scaling up: 8 GPUs per server

GigaFLOPs per Dollar



ML HARDWARE

Google's Tensor Processing Units (TPUs)



Special hardware for matrix multiplication, similar to NVIDIA Tensor Cores; also runs in mixed precision (bfloat16)

Cloud TPU v2

180 TFLOPs

64 GB HBM memory

$4.50 / hour

(free on Colab!)

ML HARDWARE

Google's Tensor Processing Units (TPUs)

Model with TPU Modifications

```
def model_fn(features, labels, mode, params):
  input_layer = tf.reshape(features, [-1, 28, 28, 1])
  conv1 = tf.layers.conv2d(inputs=input_layer, ...)
  pool1 = tf.layers.max_pooling2d(inputs=conv1, pool_size=[2,2],
    strides=2)
  # ...
  loss = tf.losses.softmax_cross_entropy(
    onehot_labels=onehot_labels, logits=logits)
  optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.01)
  optimizer = tpu_optimizer.CrossShardOptimizer(optimizer)
  train_op = optimizer.minimize(loss)
  return tpu_estimator.EstimatorSpec(mode=mode, loss=loss,
    train_op=train_op)
```

No further change required for TPU Pod

So, the whole TPU Pod works just like a single computer without the tedious manual clustering setup.

Google Cloud

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PRESENTATION ANIMATION DEMO SUBTITLES EN JP

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Google's Tensor Processing Units (TPUs)

https://storage.googleapis.com/nexttpu/index.html (slides 3-6, 1min)

Summary

CPUs

- General purpose
- Cheap
- Can work well with some DL models (e.g., RNNs), but generally slower than GPUs/ TPUs

GPUs

- Initially designed for graphics, now re-purposed/specialized for DL
- Highly parallel → fast for DL
- Expensive, though typically cost-efficient for DL jobs relative to CPUs

TPUs

- First chip specifically designed for DL
- Fast and cost-efficient for many DL jobs
- Less flexible / worse for ‘irregular’ computations (small batches, non-matrix mul)

Additional Resources

- Podcast with Dave Patterson: https://determined.ai/blog/dave-patterson-podcast-new/
- TPUs: https://storage.googleapis.com/nexttpu/index.html
- Energy Considerations: https://ai.googleblog.com/2022/02/good-news-about-carbon-footprint-of.html