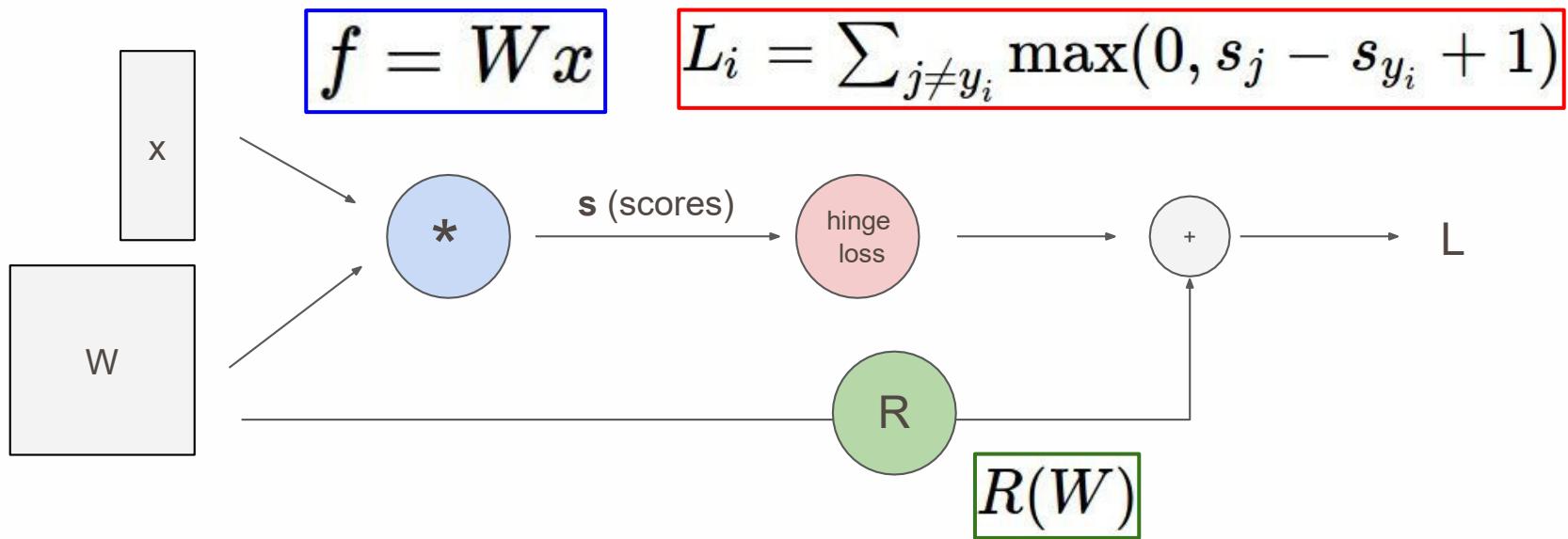


DEEP LEARNING: IMPLEMENTATION

Chih-Chung Hsu (許志仲)
Institute of Data Science
National Cheng Kung University
<https://cchsu.info>



Computational graphs

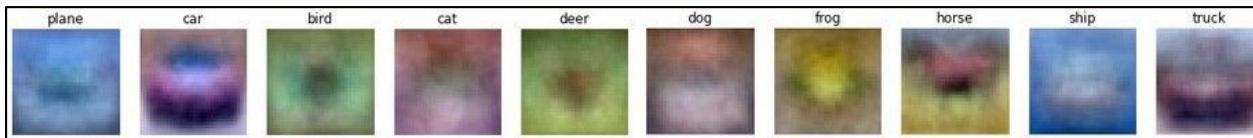
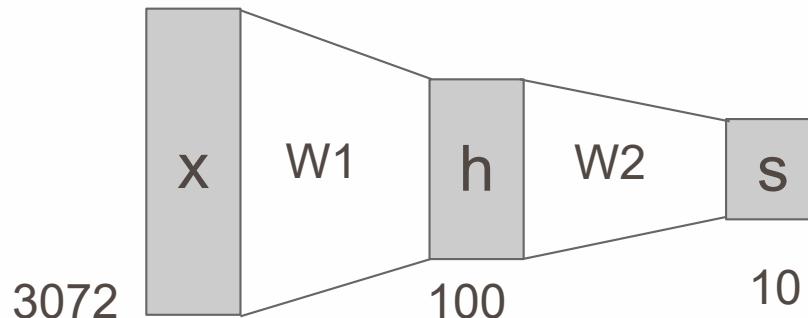


Neural Networks

- Linear score function:
- 2-layer Neural Network

$$f = Wx$$

$$f = W_2 \max(0, W_1 x)$$



Convolutional Neural Networks

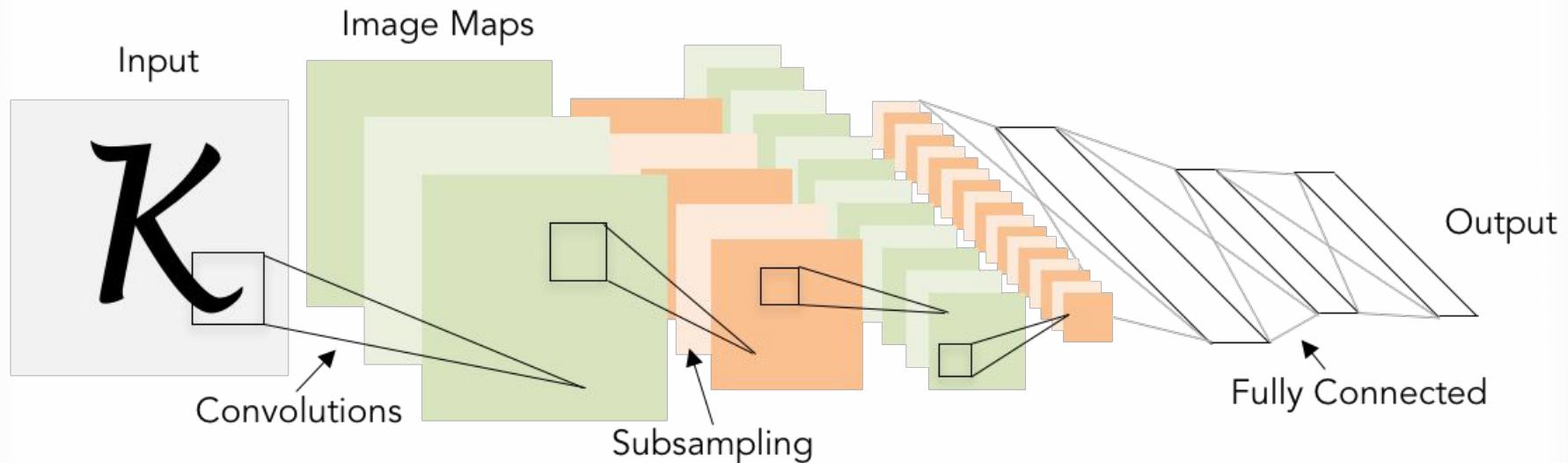
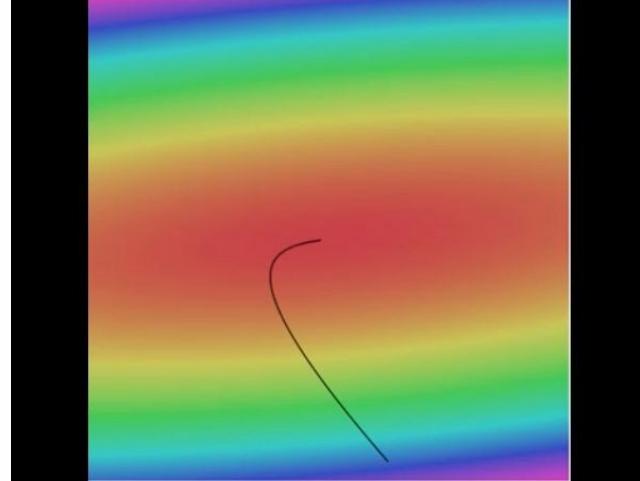


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

Learning network parameters through optimization



```
# Vanilla Gradient Descent

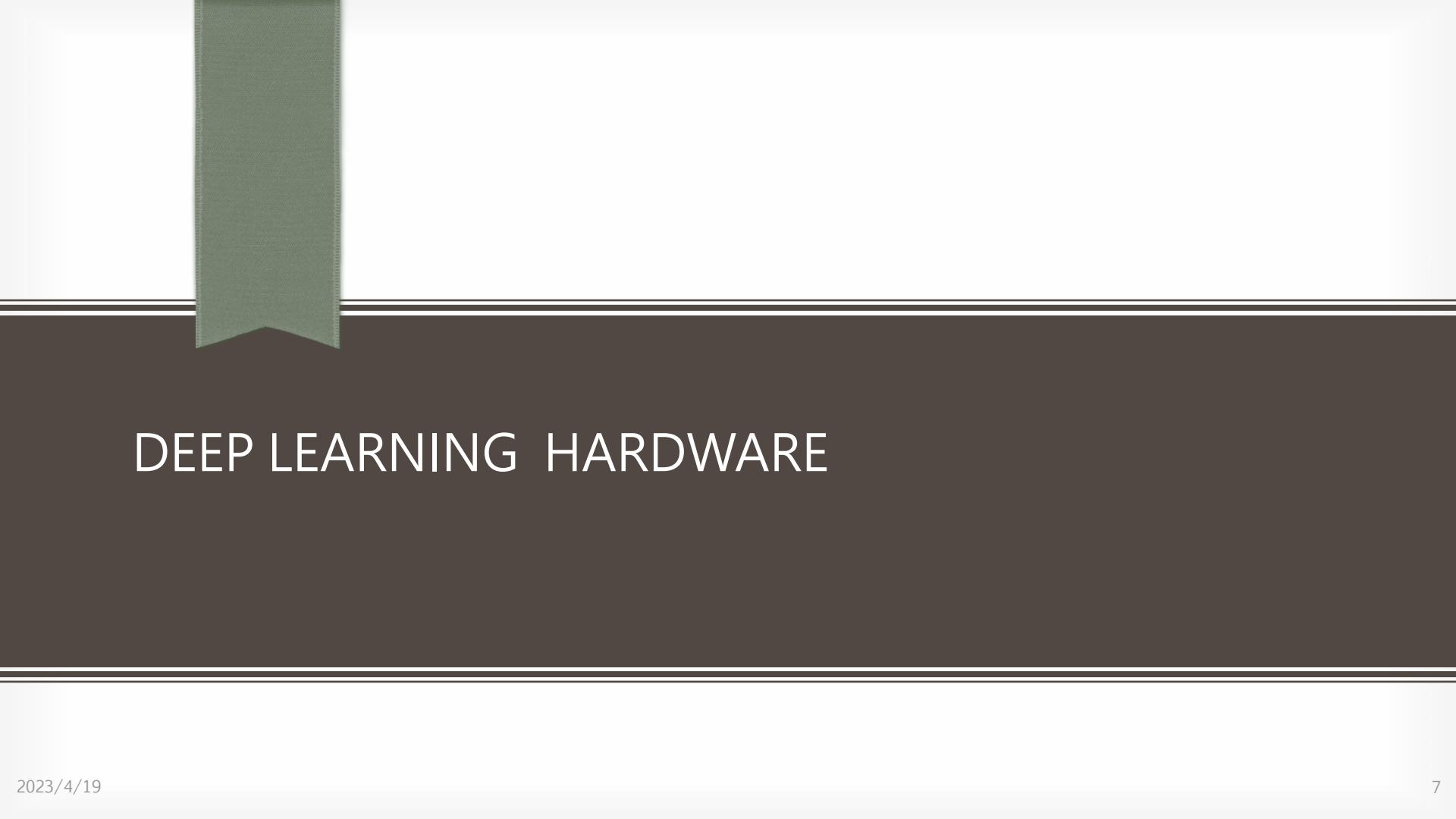
while True:
    weights_grad = evaluate_gradient(loss_fun, data, weights)
    weights += - step_size * weights_grad # perform parameter update
```

Landscape image is CC0 1.0 public domain

Walking man image is CC0 1.0 public domain

Today

- Deep learning hardware
 - CPU, GPU, TPU
- Deep learning software
 - PyTorch and TensorFlow
- Static and Dynamic computation graphs



DEEP LEARNING HARDWARE

Inside a computer



Spot the CPU!

(central processing unit)



This image is licensed under [CC-BY 2.0](#)



Spot the GPUs!

(graphics processing unit)



This image is in the public domain



NVIDIA vs AMD

NVIDIA

vs

AMD

CPU vs GPU

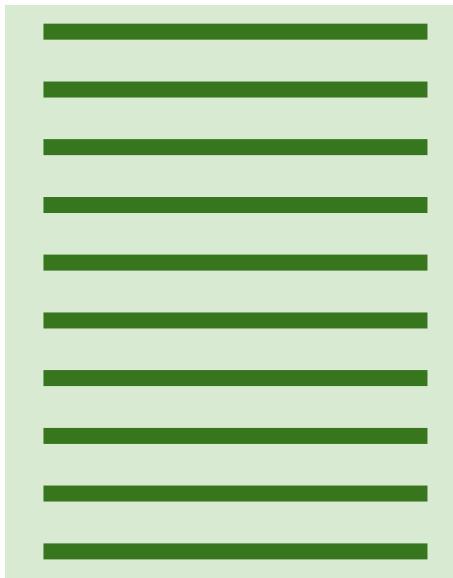
	Cores	Clock Speed	Memory	Price	Speed
CPU (Intel Core i7-7700k)	4 (8 threads with hyperthreading)	4.2 GHz	System RAM	\$385	~540 GFLOPs FP32
GPU (NVIDIA RTX 2080 Ti)	3584	1.6 GHz	11 GB GDDR6	\$1199	~13.4 TFLOPs FP32
GPU (NVIDIA RTX 3090)	10,496	1.7 GHz	24 GB GDDR6	\$1499	~35.6 TFLOPs FP32

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

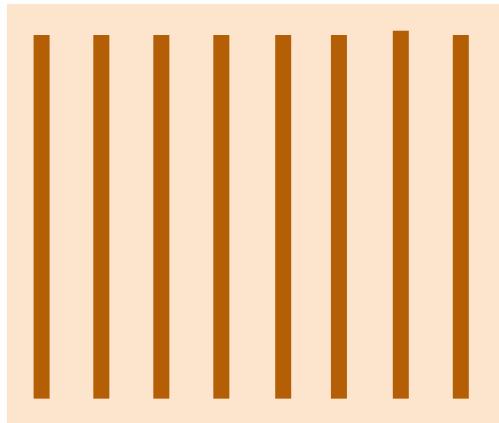
GPU: More cores, but each core is much slower and “dumber”; great for parallel tasks

Example: Matrix Multiplication

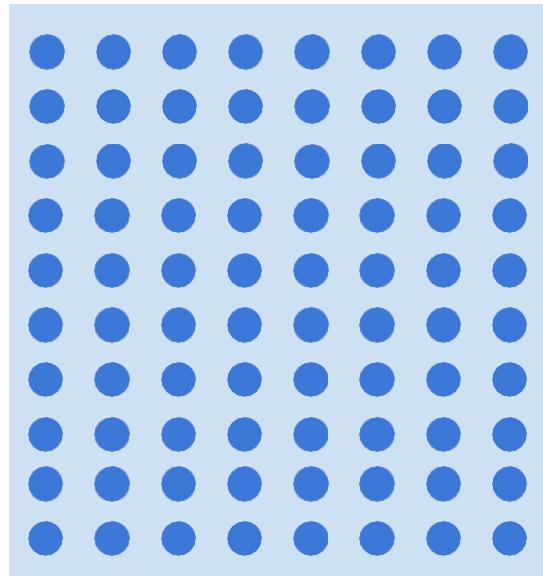
$A \times B$



$B \times C$

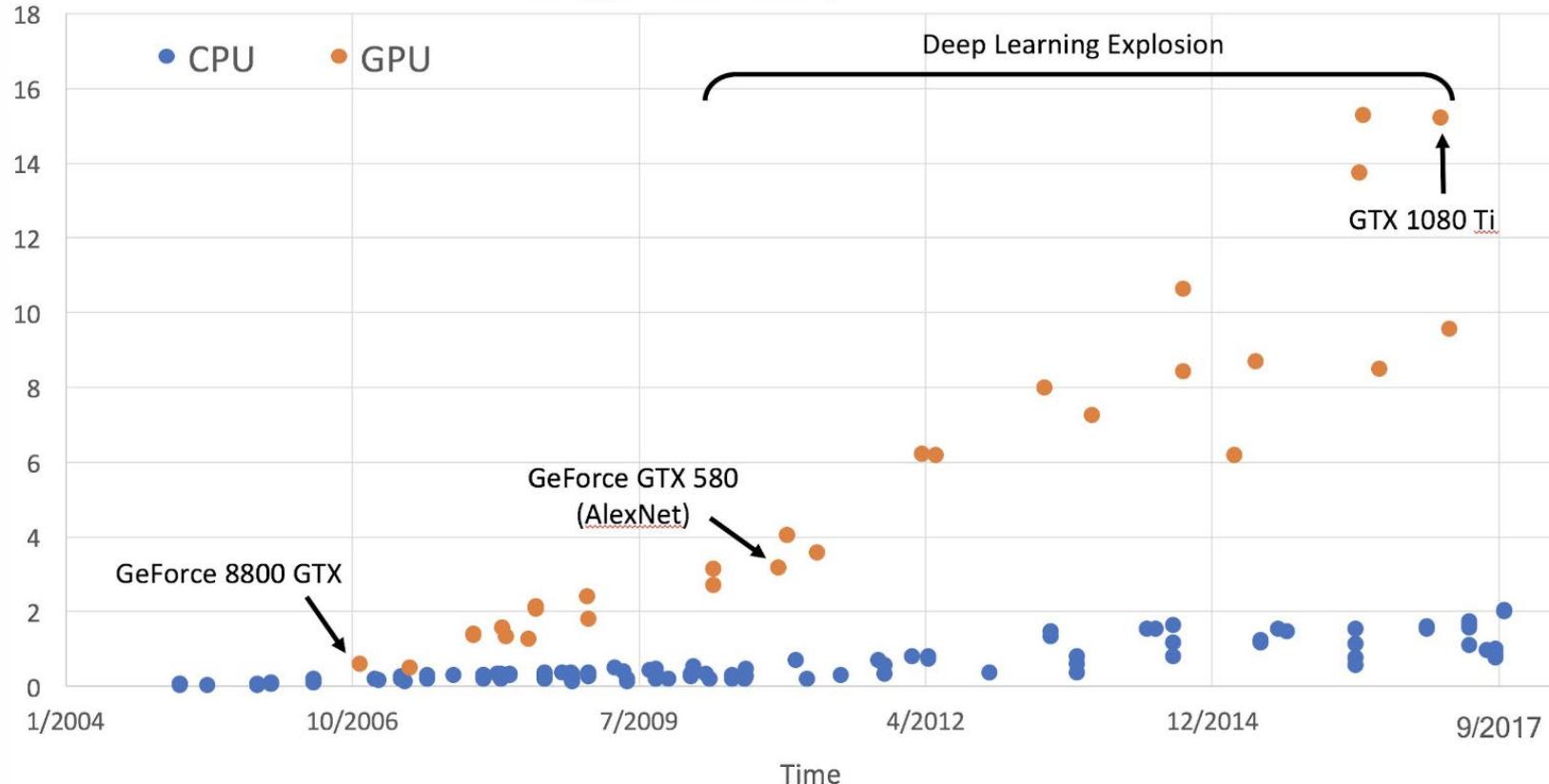


$A \times C$



=

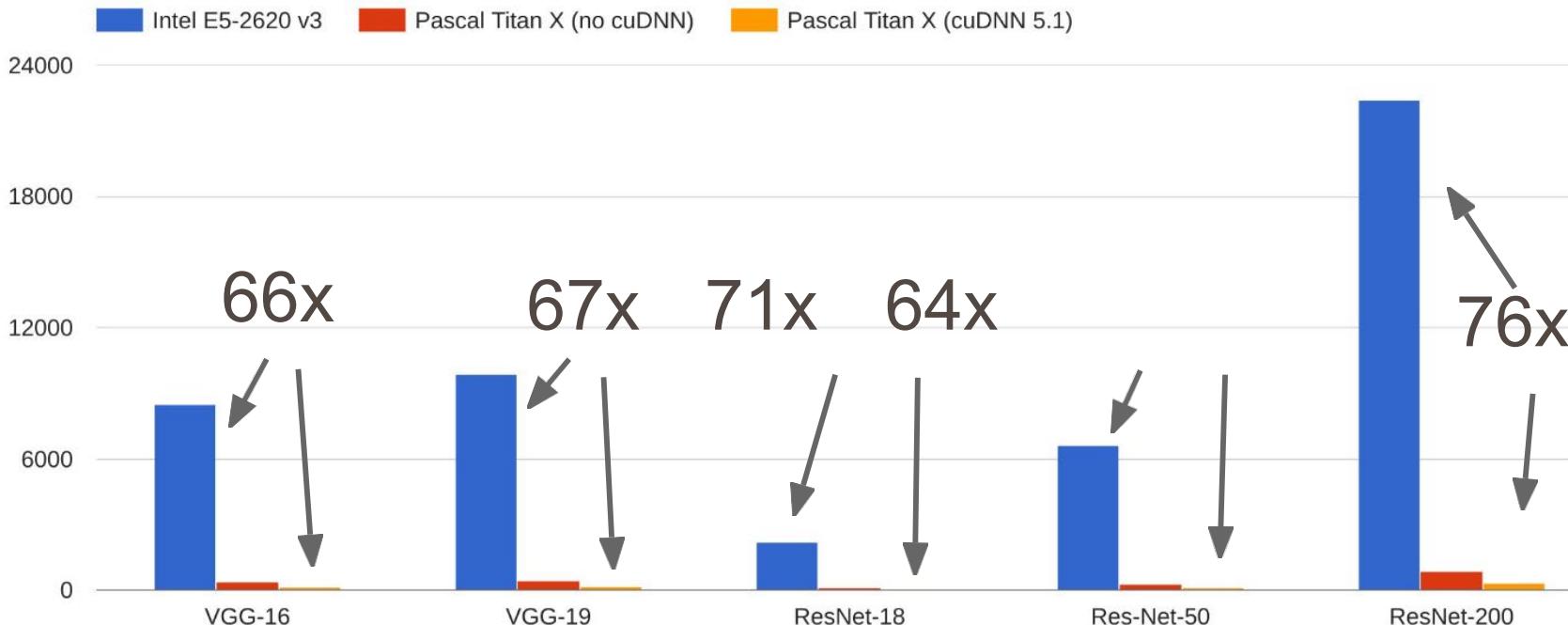
GigaFLOPs per Dollar



CPU vs GPU in practice

(CPU performance not well-optimized, a little unfair)

N=16 Forward + Backward time (ms)

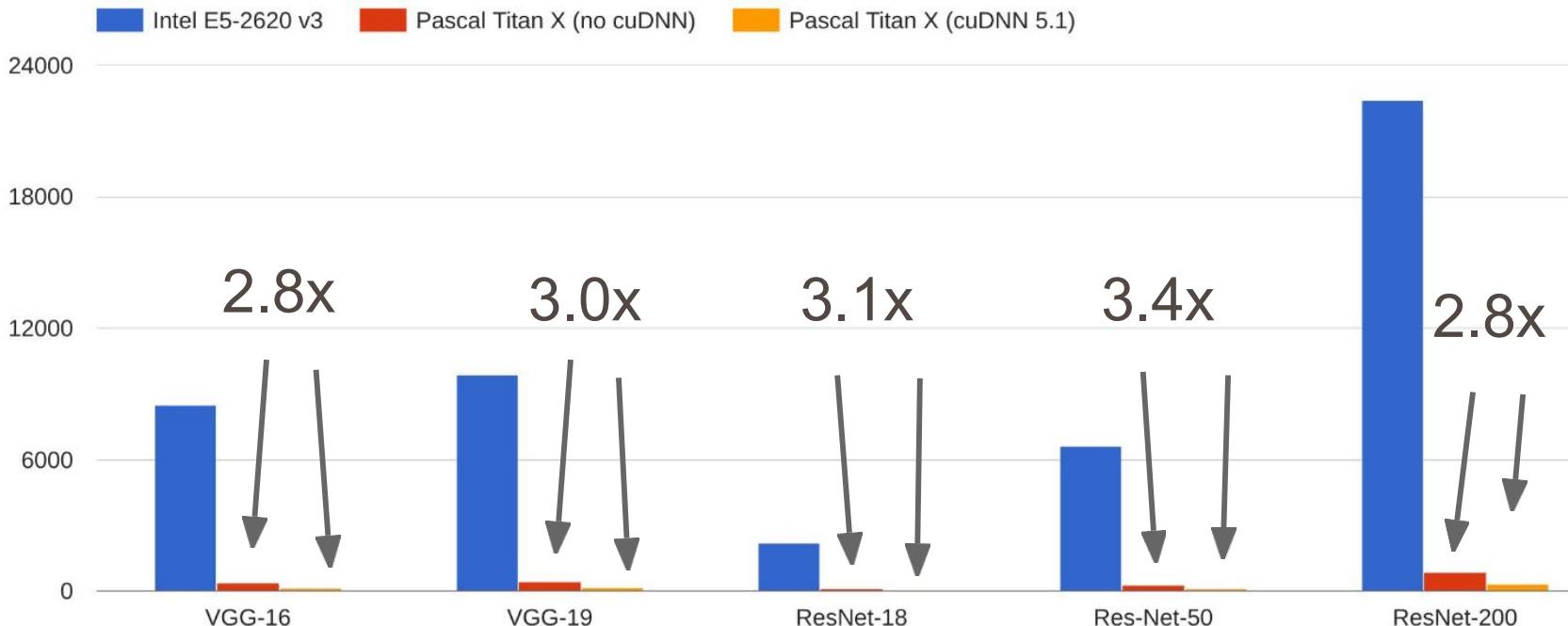


Data from <https://github.com/jcjohnson/cnn-benchmarks>

CPU vs GPU in practice

cuDNN much faster than
“unoptimized” CUDA

N=16 Forward + Backward time (ms)



Data from <https://github.com/jcjohnson/cnn-benchmarks>

CPU vs GPU

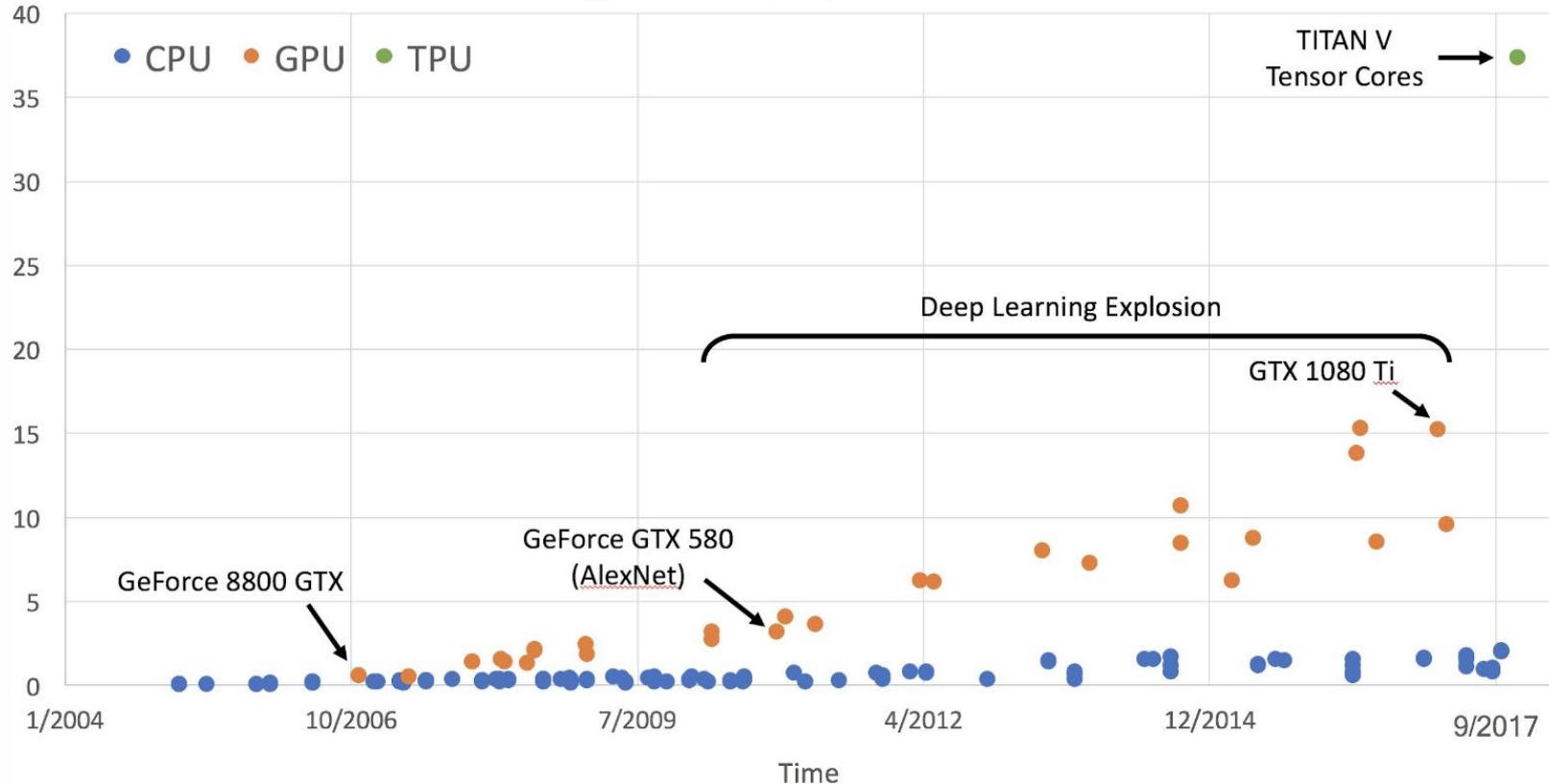
	Cores	Clock Speed	Memory	Price	Speed	
CPU (Intel Core i7-7700k)	4 (8 threads with hyperthreading)	4.2 GHz	System RAM	\$385	~540 GFLOPs FP32	CPU: Fewer cores, but each core is much faster and much more capable; great at sequential tasks
GPU (NVIDIA RTX 2080 Ti)	3584	1.6 GHz	11 GB GDDR6	\$1199	~13.4 TFLOPs FP32	GPU: More cores, but each core is much slower and “dumber”; great for parallel tasks
TPU NVIDIA TITAN V	5120 CUDA, 640 Tensor	1.5 GHz	12GB HBM2	\$2999	~14 TFLOPs FP32 ~112 TFLOP FP16	
TPU Google Cloud TPU	?	?	64 GB HBM	\$4.50 per hour	~180 TFLOP	TPU: Specialized hardware for deep learning

CPU vs GPU

	Cores	Clock Speed	Memory	Price	Speed	
CPU (Intel Core i7-7700k)	4 (8 threads with hyperthreading)	4.2 GHz	System RAM	\$385	~540 GFLOPs FP32	
GPU (NVIDIA RTX 2080 Ti)	3584	1.6 GHz	11 GB GDDR6	\$1199	~13.4 TFLOPs FP32	
TPU NVIDIA TITAN V	5120 CUDA, 640 Tensor	1.5 GHz	12GB HBM2	\$2999	~14 TFLOPs FP32 ~112 TFLOP FP16	
TPU Google Cloud TPU	?	?	64 GB HBM	\$4.50 per hour	~180 TFLOP	

NOTE: TITAN V isn't technically a "TPU" since that's a Google term, but both have hardware specialized for deep learning

GigaFLOPs per Dollar



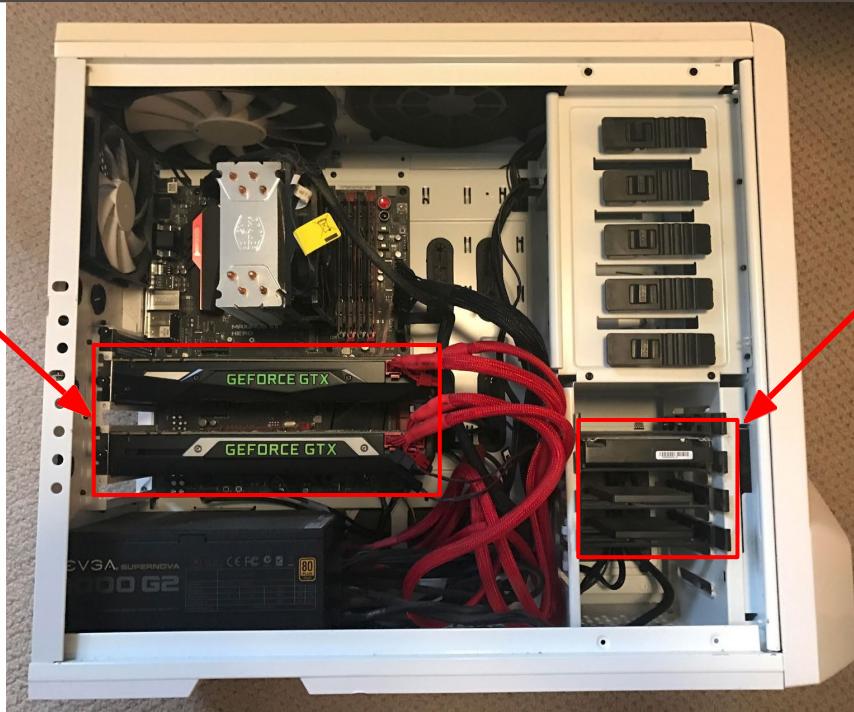
Programming GPUs

- CUDA (NVIDIA only)
 - Write C-like code that runs directly on the GPU
 - Optimized APIs: cuBLAS, cuFFT, cuDNN, etc
- OpenCL
 - Similar to CUDA, but runs on anything
 - Usually slower on NVIDIA hardware
- HIP <https://github.com/ROCm-Developer-Tools/HIP>
 - CUDA to AMD:
 - New project that automatically converts CUDA code to something that can run on AMD GPUs
- How to parallel programming:
 - <https://developer.nvidia.com/udacity-cs344-intro-parallel-programming>

CPU / GPU Communication

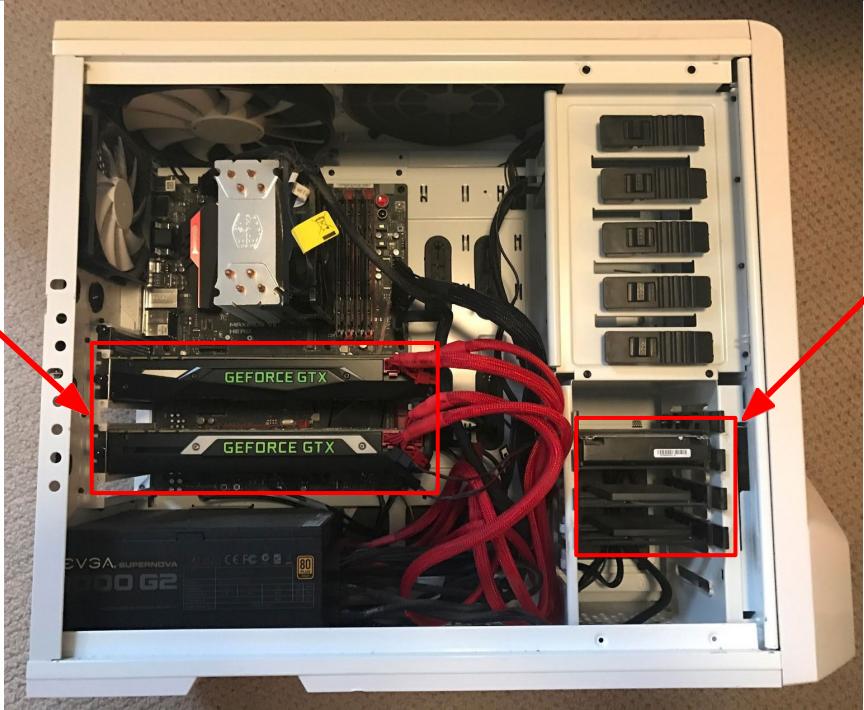
Model
is here

Data is here



CPU / GPU Communication

Model
is here

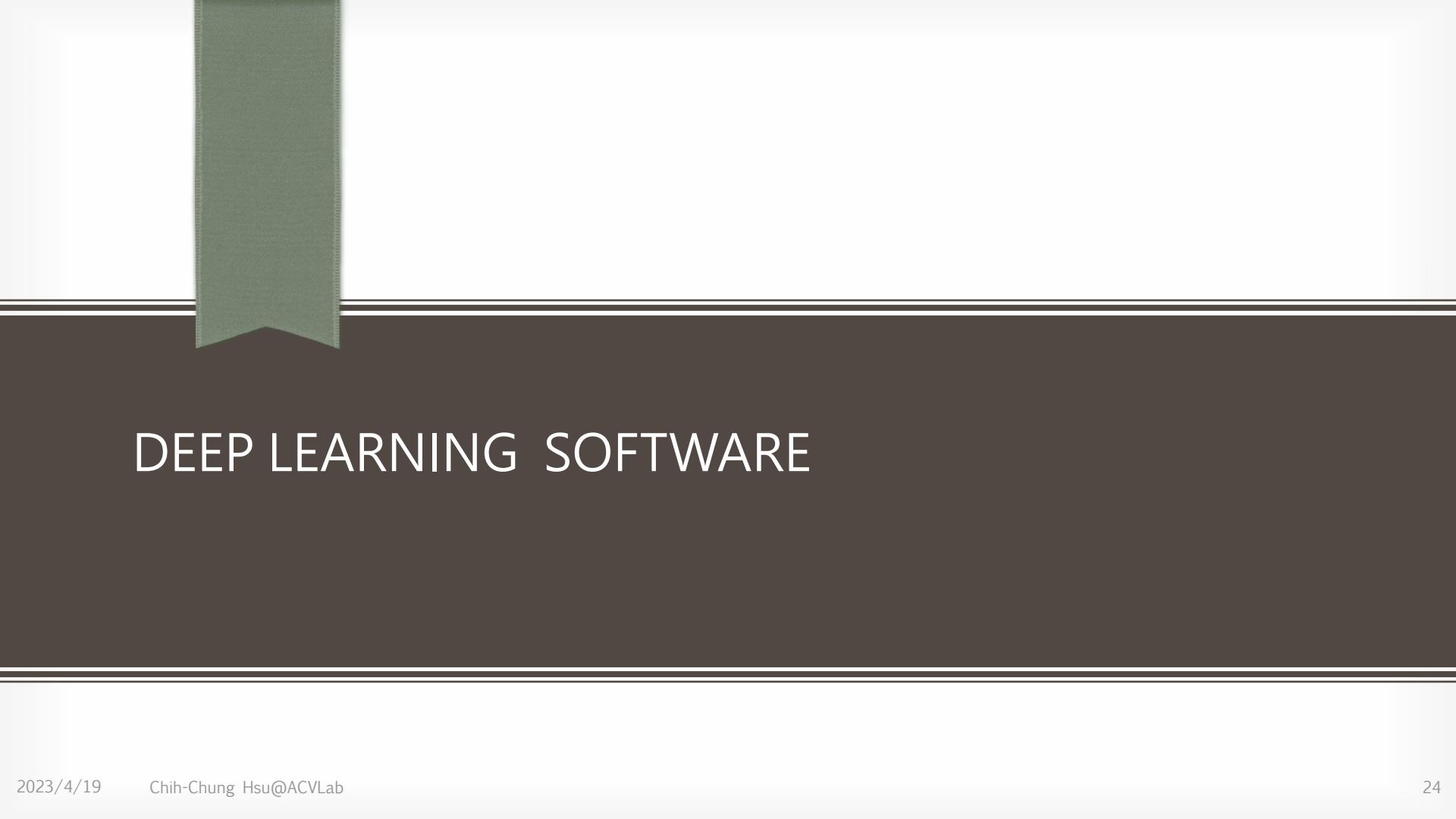


Data is here

If you aren't careful, training can bottleneck on reading data and transferring to GPU!

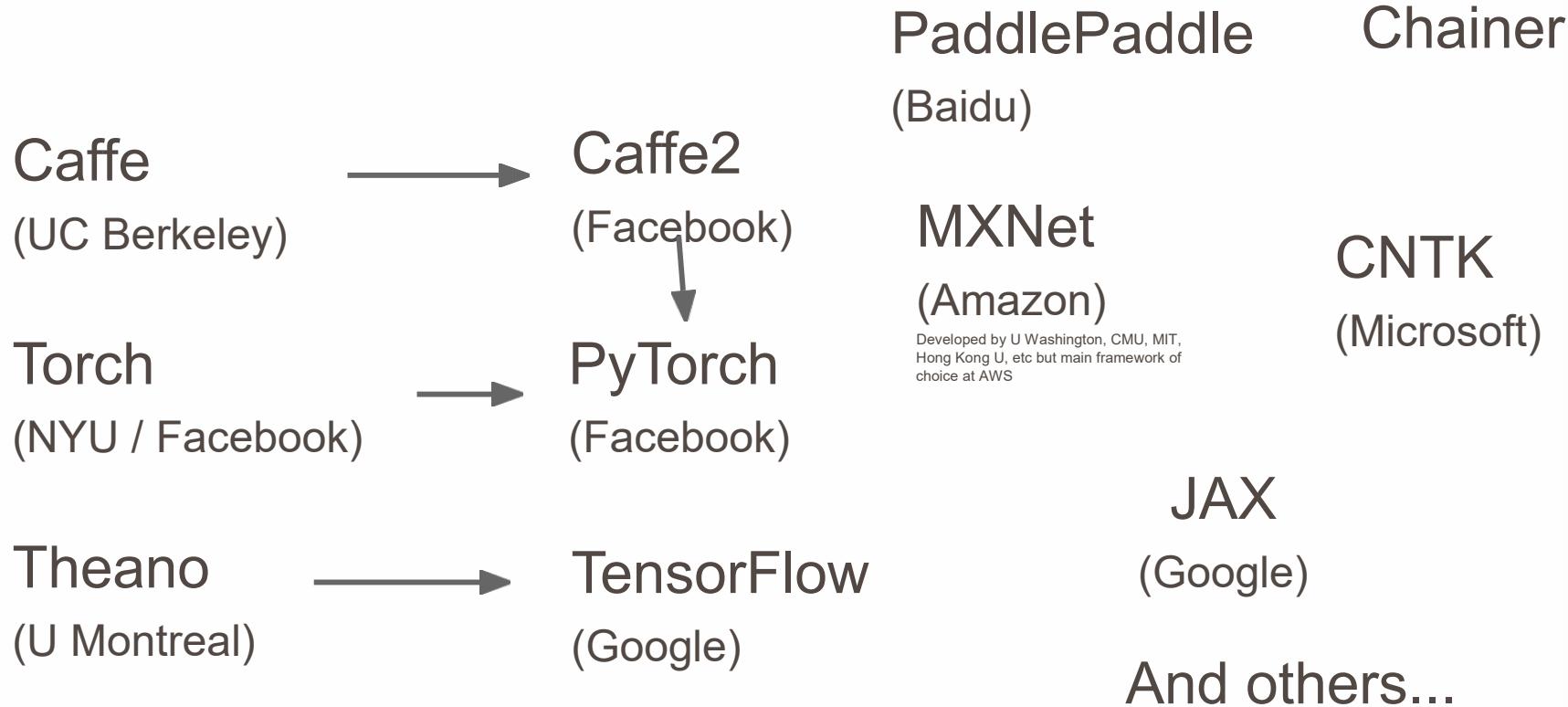
Solutions:

- Read all data into RAM
- Use SSD instead of HDD
- Use multiple CPU threads to prefetch data

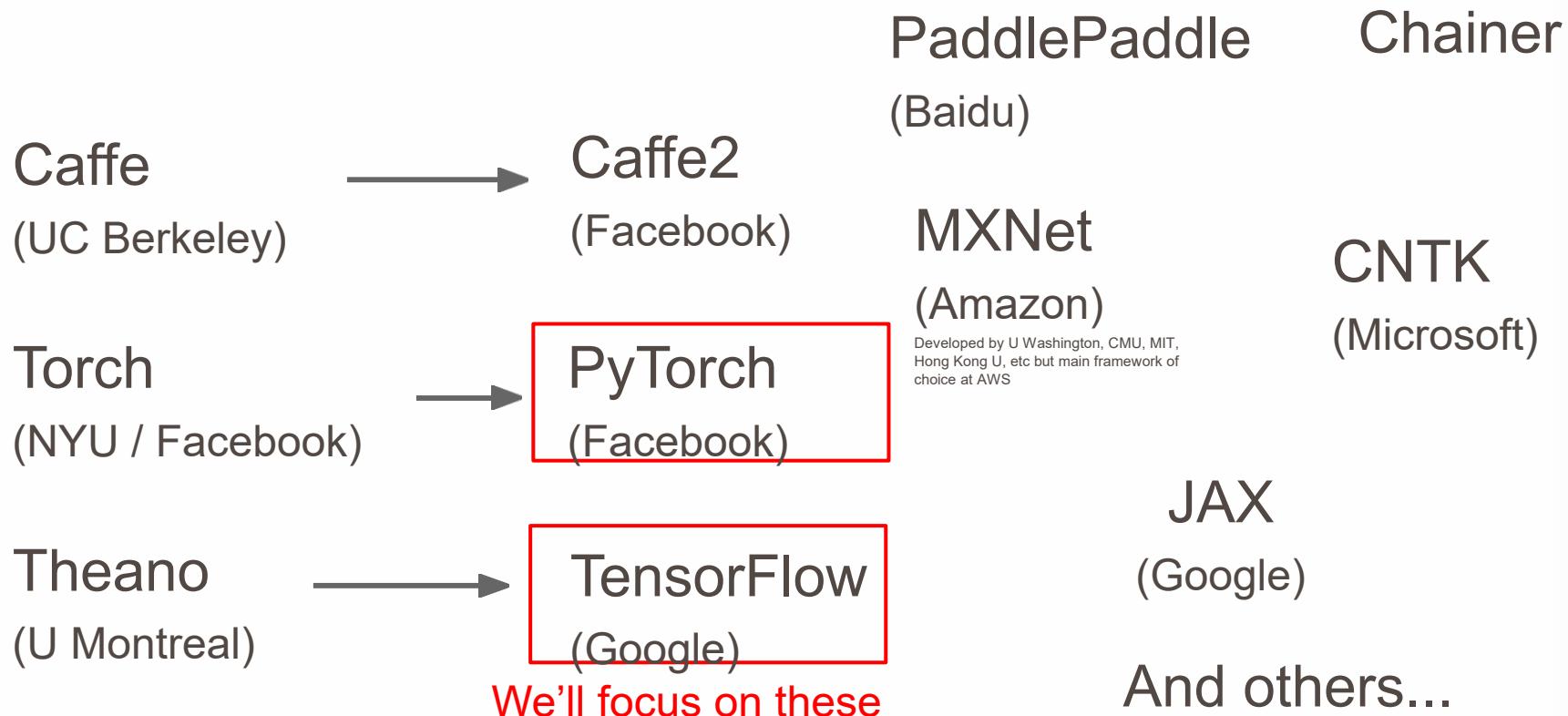


DEEP LEARNING SOFTWARE

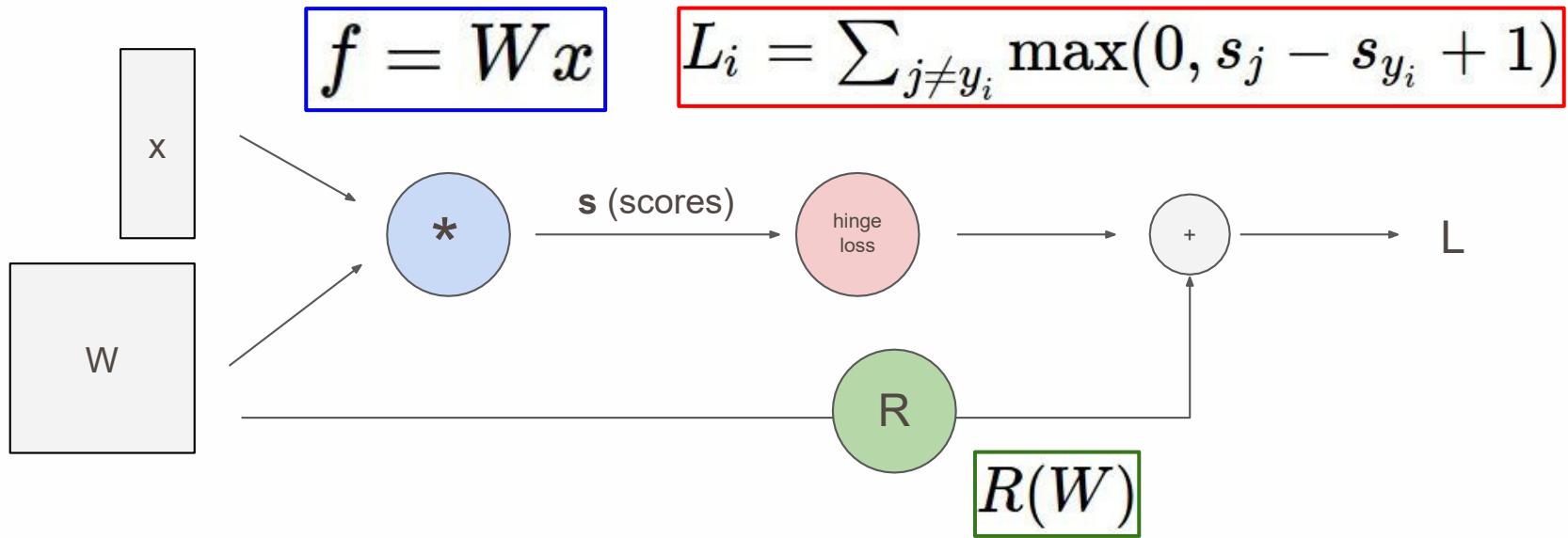
A zoo of frameworks!



A zoo of frameworks!



Recall: Computational Graphs



Recall: Computational Graphs

input image

weights

loss

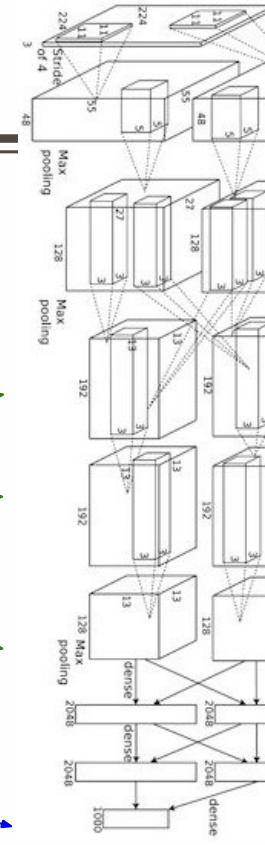


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Recall: Computational Graphs

input image

loss

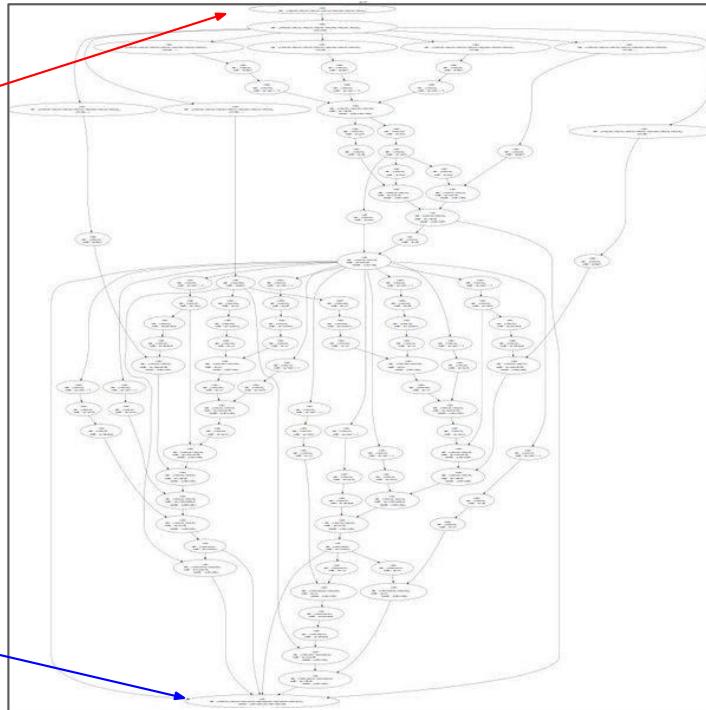


Figure reproduced with permission from a [Twitter post](#) by Andrej Karpathy.

The point of deep learning frameworks

- ❖ Quick to develop and test new ideas
- ❖ Automatically compute gradients
- ❖ Run it all efficiently on GPU (wrap cuDNN, cuBLAS, etc)

Computational Graphs

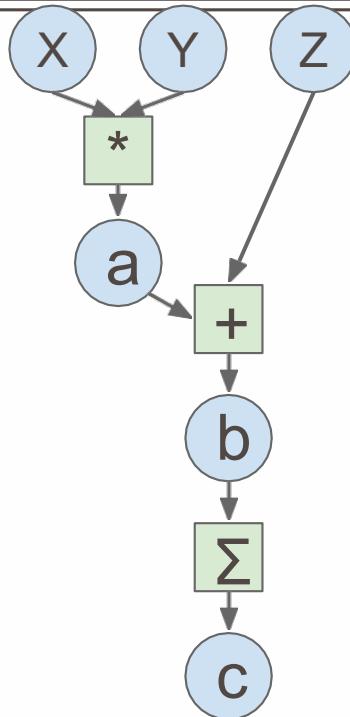
Numpy

```
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)
```



Computational Graphs

Numpy

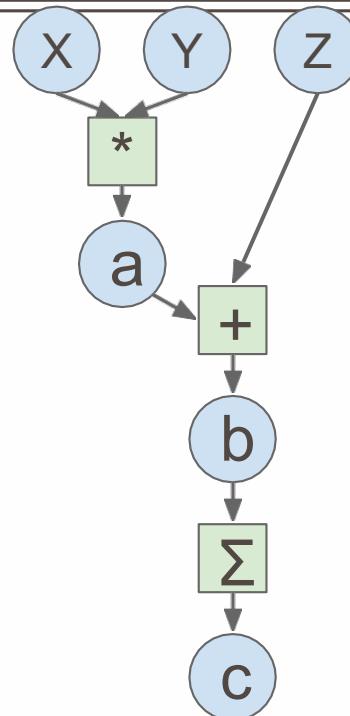
```
import numpy as np
np.random.seed(0)

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)

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
```



Computational Graphs

Numpy

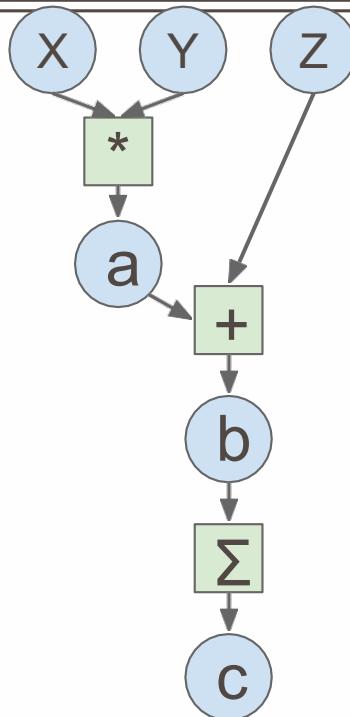
```
import numpy as np
np.random.seed(0)

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)

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
```



Good:

Clean API, easy to write numeric code

Bad:

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

Computational Graphs

Numpy

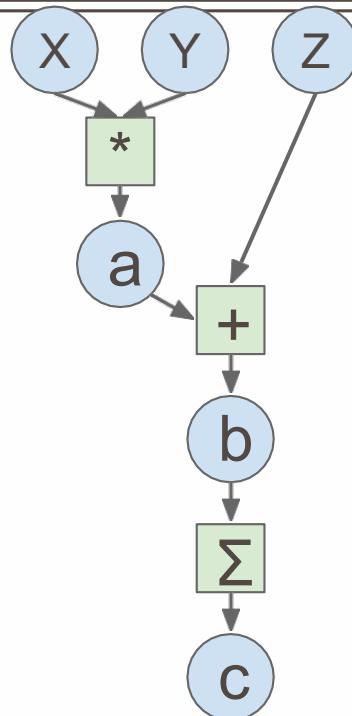
```
import numpy as np
np.random.seed(0)

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)

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
```



PyTorch

```
import torch

N, D = 3, 4
x = torch.randn(N, D)
y = torch.randn(N, D)
z = torch.randn(N, D)

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

Looks exactly like numpy!

Computational Graphs

Numpy

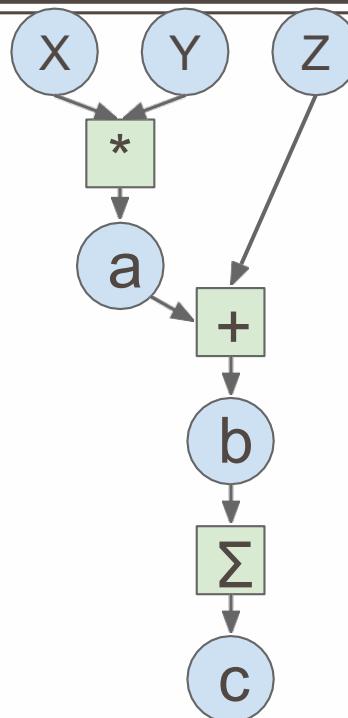
```
import numpy as np
np.random.seed(0)

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)

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
```



PyTorch

```
import torch

N, D = 3, 4
x = torch.randn(N, D, requires_grad=True)
y = torch.randn(N, D)
z = torch.randn(N, D)

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

c.backward()
print(x.grad)
```

PyTorch handles gradients for us!

Computational Graphs

Numpy

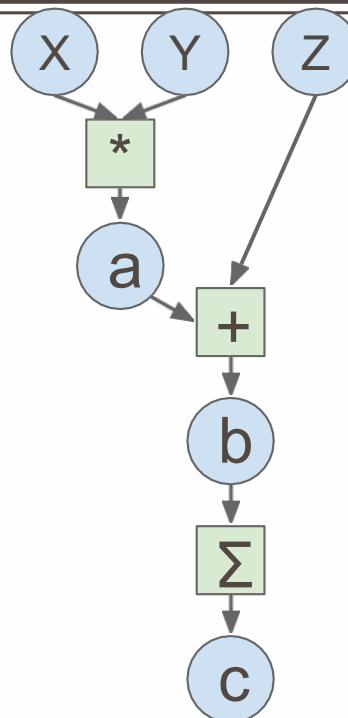
```
import numpy as np
np.random.seed(0)

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)

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
```



PyTorch

```
import torch

device = 'cuda:0'
N, D = 3, 4
x = torch.randn(N, D, requires_grad=True,
                device=device)
y = torch.randn(N, D, device=device)
z = torch.randn(N, D, device=device)

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

c.backward()
print(x.grad)
```

Trivial to run on GPU - just construct arrays on a different device!



PYTORCH (MORE DETAIL)

PyTorch: Fundamental Concepts

- Tensor: Like a numpy array, but can run on GPU
- Autograd: Package for building computational graphs out of Tensors, and automatically computing gradients
- Module: A neural network layer; may store state or learnable weights

PyTorch: Versions

- For this class our code was tested on PyTorch version 1.8.1 with CUDA 11.1
 - (Released 2021)
- Be careful if you are looking at older PyTorch code!

PyTorch: Tensors

Running example: Train a two-layer ReLU network on random data with L2 loss

```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred - y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Tensors

PyTorch Tensors are just like numpy arrays, but they can run on GPU.

PyTorch Tensor API looks almost exactly like numpy!

Here we fit a two-layer net using PyTorch Tensors:

```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred - y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Tensors

Create random tensors
for data and weights

```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred - y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Tensors

Forward pass: compute predictions and loss

```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred - y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Tensors

Backward pass:
manually compute
gradients



```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred - y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Tensors

Gradient descent
step on weights

```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred - y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Tensors

To run on GPU, just use a different device!

```
import torch

device = torch.device('cuda:0')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred - y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Autograd

Creating Tensors with
requires_grad=True enables
autograd

Operations on Tensors with
requires_grad=True cause PyTorch
to build a computational graph

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd

We will not want gradients
(of loss) with respect to data

Do want gradients with
respect to weights

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd

Forward pass looks exactly the same as before, but we don't need to track intermediate values - PyTorch keeps track of them for us in the graph

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd

Compute gradient of loss
with respect to w1 and w2

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd

Make gradient step on weights, then zero

them. `Torch.no_grad` means “don’t build a computational graph for this part”

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch methods that end in underscore modify the Tensor in-place; methods that don't return a new Tensor

PyTorch: New Autograd Functions

Define your own autograd functions by writing forward and backward functions for Tensors

Use ctx object to “cache” values for the backward pass, just like cache objects from A2

```
class MyReLU(torch.autograd.Function):  
    @staticmethod  
    def forward(ctx, x):  
        ctx.save_for_backward(x)  
        return x.clamp(min=0)  
  
    @staticmethod  
    def backward(ctx, grad_y):  
        x, = ctx.saved_tensors  
        grad_input = grad_y.clone()  
        grad_input[x < 0] = 0  
        return grad_input
```

PyTorch: New Autograd Functions

Define your own autograd functions by writing forward and backward functions for Tensors

Use ctx object to “cache” values for the backward pass, just like cache objects from A2

Define a helper function to make it easy to use the new function

```
class MyReLU(torch.autograd.Function):  
    @staticmethod  
    def forward(ctx, x):  
        ctx.save_for_backward(x)  
        return x.clamp(min=0)  
  
    @staticmethod  
    def backward(ctx, grad_y):  
        x, = ctx.saved_tensors  
        grad_input = grad_y.clone()  
        grad_input[x < 0] = 0  
        return grad_input  
  
def my_relu(x):  
    return MyReLU.apply(x)
```

PyTorch: New Autograd Functions

```
class MyReLU(torch.autograd.Function):
    @staticmethod
    def forward(ctx, x):
        ctx.save_for_backward(x)
        return x.clamp(min=0)

    @staticmethod
    def backward(ctx, grad_y):
        x, = ctx.saved_tensors
        grad_input = grad_y.clone()
        grad_input[x < 0] = 0
        return grad_input

def my_relu(x):
    return MyReLU.apply(x)
```

Can use our new autograd function in the forward pass

```
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = my_relu(x.mm(w1)).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: New Autograd Functions

```
def my_relu(x):  
    return x.clamp(min=0)
```

In practice you almost never need to define new autograd functions! Only do it when you need custom backward. In this case we can just use a normal Python function

```
N, D_in, H, D_out = 64, 1000, 100, 10  
  
x = torch.randn(N, D_in)  
y = torch.randn(N, D_out)  
w1 = torch.randn(D_in, H, requires_grad=True)  
w2 = torch.randn(H, D_out, requires_grad=True)  
  
learning_rate = 1e-6  
for t in range(500):  
    y_pred = my_relu(x.mm(w1)).mm(w2)  
    loss = (y_pred - y).pow(2).sum()  
  
    loss.backward()  
  
    with torch.no_grad():  
        w1 -= learning_rate * w1.grad  
        w2 -= learning_rate * w2.grad  
        w1.grad.zero_()  
        w2.grad.zero_()
```

PyTorch: nn

Higher-level wrapper for working with neural nets

Use this! It will make your life easier

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

PyTorch: nn

Define our model as a sequence of layers; each layer is an object that holds learnable weights

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

PyTorch: nn

Forward pass: feed data to
model, and compute loss

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

PyTorch: nn

Forward pass: feed data to

model, and compute loss

torch.nn.functional has useful
helpers like loss functions

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)
    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

PyTorch: nn

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

Backward pass: compute gradient with respect to all model weights (they have `requires_grad=True`)

PyTorch: nn

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()
```

```
with torch.no_grad():
    for param in model.parameters():
        param -= learning_rate * param.grad
model.zero_grad()
```

Make gradient step on
each model parameter
(with gradients disabled)



PyTorch: optim

Use an **optimizer** for different update rules

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out))

learning_rate = 1e-4
optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)

for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: optim

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out))

learning_rate = 1e-4
optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    optimizer.step()
    optimizer.zero_grad()
```

After computing gradients, use optimizer to update params and zero gradients

PyTorch: nn

Define new Modules

A PyTorch **Module** is a neural net layer; it inputs and outputs Tensors

Modules can contain weights or other modules

You can define your own Modules using autograd!

```
import torch

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn

Define new Modules

Define our whole model
as a single Module

```
import torch

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred
```

```
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn

Define new Modules

Initializer sets up two children (Modules can contain modules)

```
import torch

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn

Define new Modules

Define forward pass using child modules

No need to define backward - autograd will handle it

```
import torch

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)
```

```
def forward(self, x):
    h_relu = self.linear1(x).clamp(min=0)
    y_pred = self.linear2(h_relu)
    return y_pred
```

```
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn

Define new Modules

Construct and train an instance of our model

```
import torch

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)
```

```
def forward(self, x):
    h_relu = self.linear1(x).clamp(min=0)
    y_pred = self.linear2(h_relu)
    return y_pred
```

```
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
```

```
model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn

Define new Modules

Very common to mix and match
custom Module subclasses and
Sequential containers

```
import torch

class ParallelBlock(torch.nn.Module):
    def __init__(self, D_in, D_out):
        super(ParallelBlock, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, D_out)
        self.linear2 = torch.nn.Linear(D_in, D_out)
    def forward(self, x):
        h1 = self.linear1(x)
        h2 = self.linear2(x)
        return (h1 * h2).clamp(min=0)

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
    ParallelBlock(D_in, H),
    ParallelBlock(H, H),
    torch.nn.Linear(H, D_out))

optimizer = torch.optim.Adam(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn

Define new Modules

Define network component
as a Module subclass

```
import torch

class ParallelBlock(torch.nn.Module):
    def __init__(self, D_in, D_out):
        super(ParallelBlock, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, D_out)
        self.linear2 = torch.nn.Linear(D_in, D_out)
    def forward(self, x):
        h1 = self.linear1(x)
        h2 = self.linear2(x)
        return (h1 * h2).clamp(min=0)
```

```
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
    ParallelBlock(D_in, H),
    ParallelBlock(H, H),
    torch.nn.Linear(H, D_out))

optimizer = torch.optim.Adam(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn

Define new Modules

Stack multiple instances of the component in a sequential

```
import torch

class ParallelBlock(torch.nn.Module):
    def __init__(self, D_in, D_out):
        super(ParallelBlock, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, D_out)
        self.linear2 = torch.nn.Linear(D_in, D_out)
    def forward(self, x):
        h1 = self.linear1(x)
        h2 = self.linear2(x)
        return (h1 * h2).clamp(min=0)
```

```
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
```

```
model = torch.nn.Sequential(
    ParallelBlock(D_in, H),
    ParallelBlock(H, H),
    torch.nn.Linear(H, D_out))
```

```
optimizer = torch.optim.Adam(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: DataLoaders

A **DataLoader** wraps a **Dataset** and provides minibatching, shuffling, multithreading, for you

When you need to load custom data, just write your own Dataset class

```
import torch
from torch.utils.data import TensorDataset, DataLoader

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

# The following line is highlighted with a red box
# and a red arrow points to it from the 'Dataset class' text
# loader = DataLoader(TensorDataset(x, y), batch_size=8)
model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-2)
for epoch in range(20):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred, y_batch)

        loss.backward()
        optimizer.step()
        optimizer.zero_grad()
```

PyTorch: DataLoaders

Iterate over loader to form minibatches

```
import torch
from torch.utils.data import TensorDataset, DataLoader

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

loader = DataLoader(TensorDataset(x, y), batch_size=8)
model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-2)
for epoch in range(20):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred, y_batch)

        loss.backward()
        optimizer.step()
        optimizer.zero_grad()
```

PyTorch: Pretrained Models

Super easy to use pretrained models with
torchvision <https://github.com/pytorch/vision>

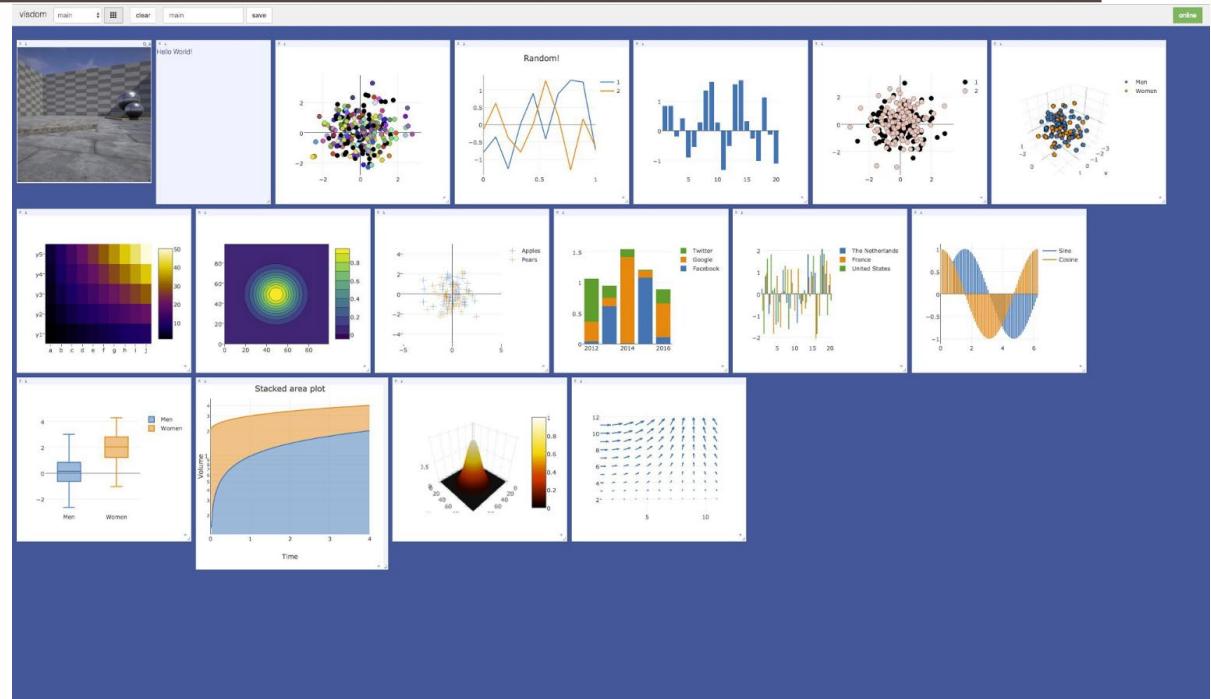
```
import torch
import torchvision

alexnet = torchvision.models.alexnet(pretrained=True)
vgg16 = torchvision.models.vgg16(pretrained=True)
resnet101 = torchvision.models.resnet101(pretrained=True)
```

PyTorch: Visdom

Visualization tool: add logging to your code, then visualize in a browser

Can't visualize computational graph structure (yet?)



[This image](https://github.com/facebookresearch/visdom) is licensed under [CC-BY 4.0](#); no changes were made to the image

<https://github.com/facebookresearch/visdom>

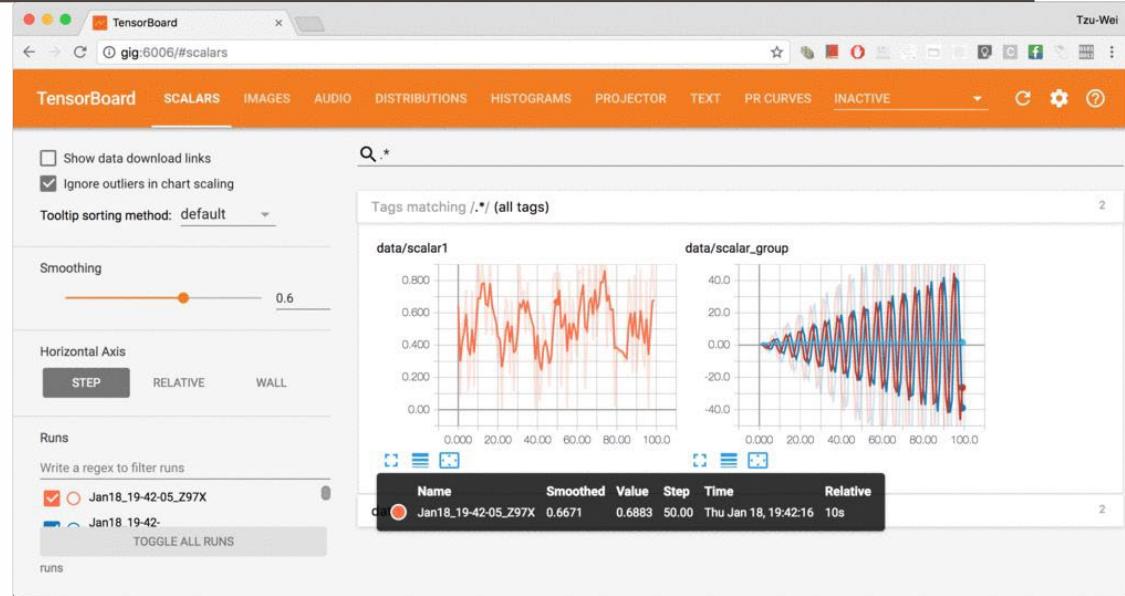
PyTorch: tensorboardX

A python wrapper around
Tensorflow's web-based
visualization tool.

pip install tensorboardx

Or

pip install tensorflow



<https://github.com/lanpa/tensorboardX>

This image is licensed under [CC-BY 4.0](#); no changes were made to the image

PyTorch: Dynamic Computation Graphs

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

PyTorch: Dynamic Computation Graphs

x

w1

w2

y

```
import torch

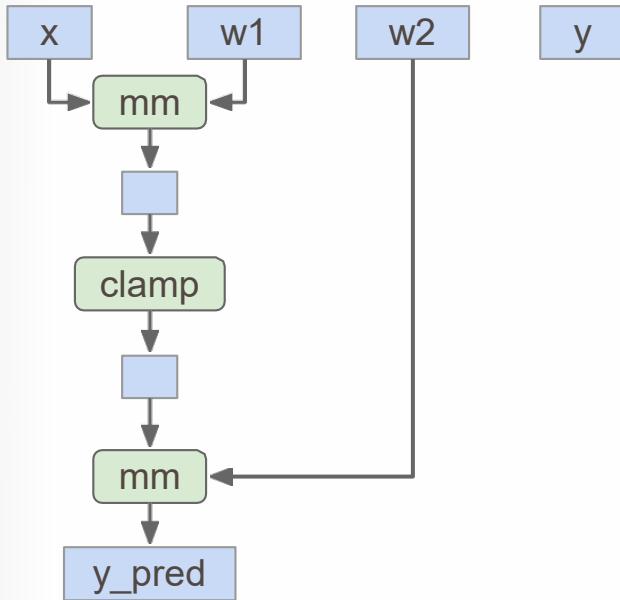
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Create Tensor objects

PyTorch: Dynamic Computation Graphs



```
import torch

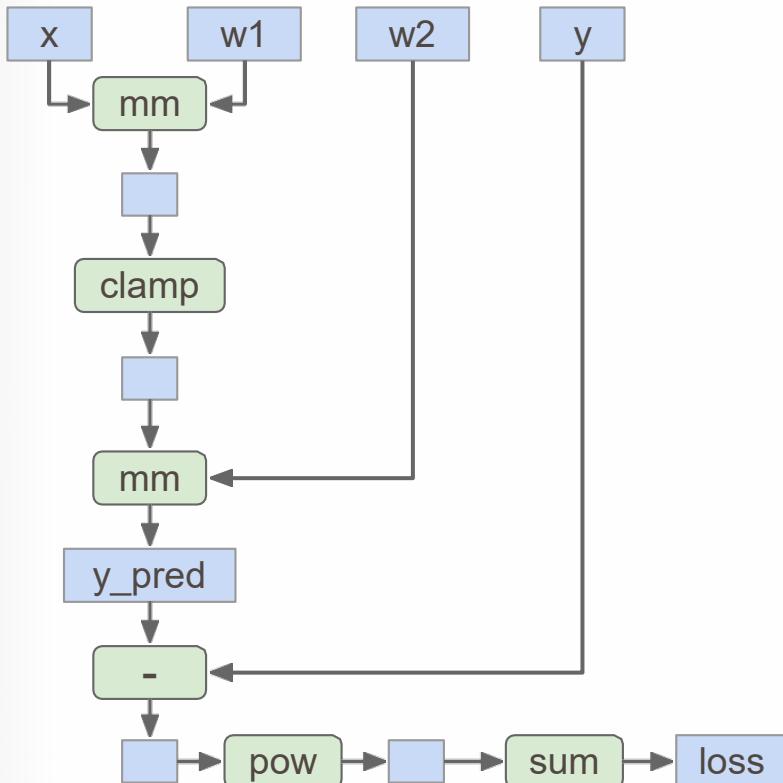
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Build graph data structure AND
perform computation

PyTorch: Dynamic Computation Graphs



```
import torch

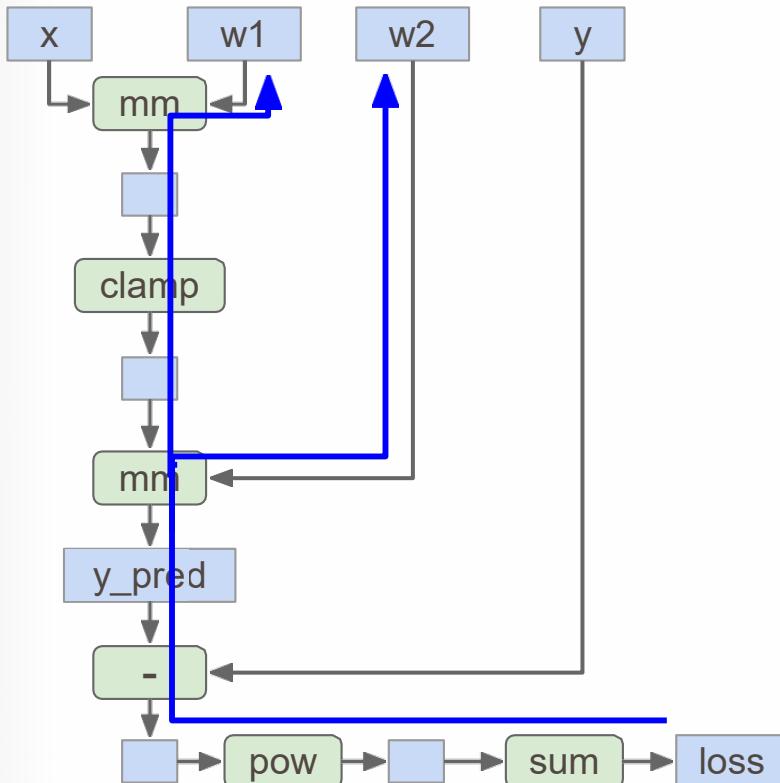
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Build graph data structure AND
perform computation

PyTorch: Dynamic Computation Graphs



```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Search for path between loss and w1, w2
(for backprop) AND perform computation

PyTorch: Dynamic Computation Graphs

x

w1

w2

y

```
import torch

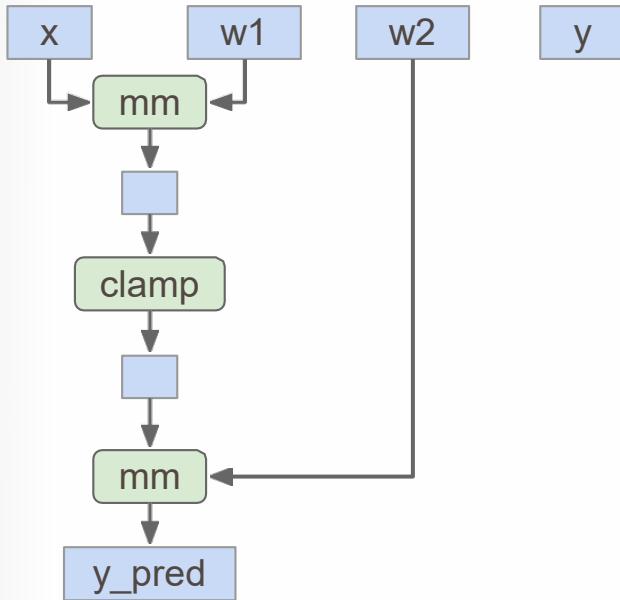
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Throw away the graph, backprop path, and rebuild it from scratch on every iteration

PyTorch: Dynamic Computation Graphs



```
import torch

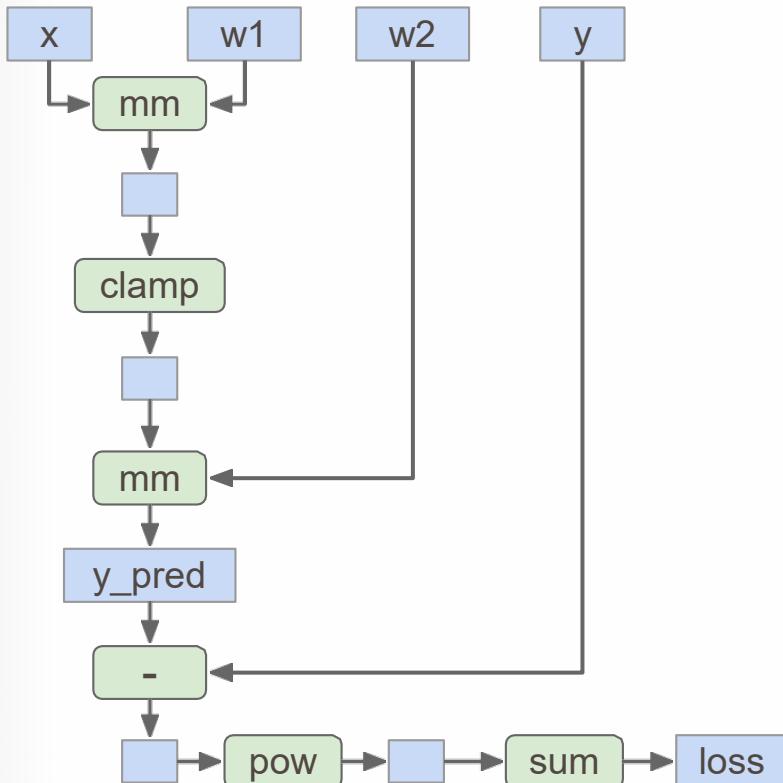
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Build graph data structure AND
perform computation

PyTorch: Dynamic Computation Graphs



```
import torch

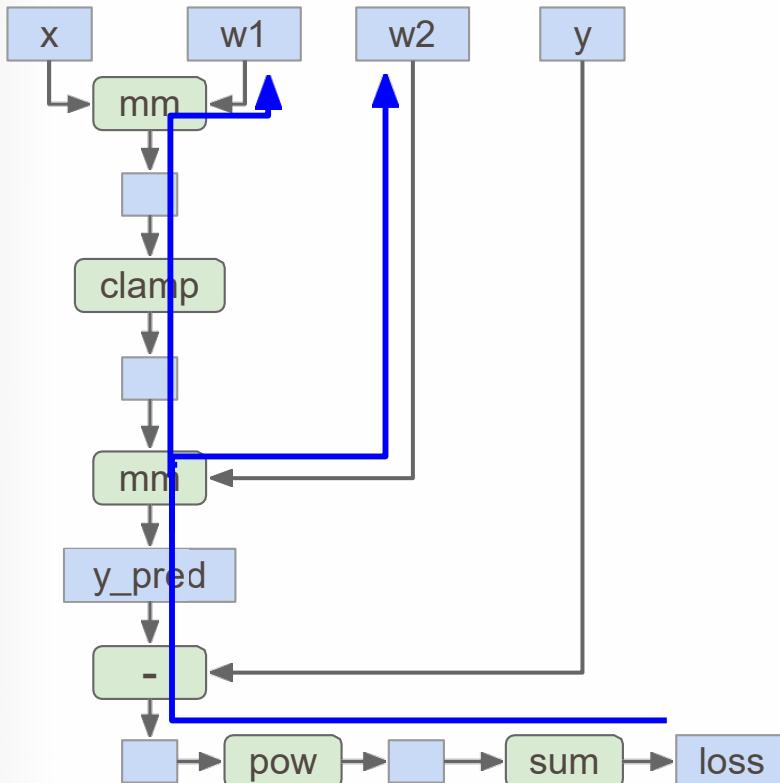
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Build graph data structure AND
perform computation

PyTorch: Dynamic Computation Graphs



```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

PyTorch: Dynamic Computation Graphs

Building the graph and computing the graph happen at the same time.

Seems inefficient, especially if we are building the same graph over and over again...

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

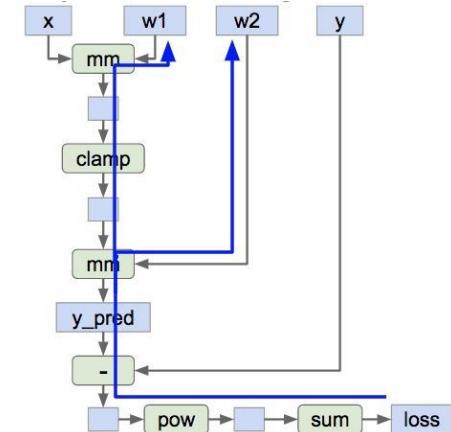
    loss.backward()
```

Static Computation Graphs

Alternative: **Static** graphs

Step 1: Build computational graph
describing our computation
(including finding paths for
backprop)

Step 2: Reuse the same graph on
every iteration



```
graph = build_graph()

for x_batch, y_batch in loader:
    run_graph(graph, x=x_batch, y=y_batch)
```



TENSORFLOW

TensorFlow Versions

Pre-2.0 (1.13 latest)

Default static graph,
optionally dynamic
graph (eager mode).

2.4 Alpha (2021 early)

Default dynamic graph,
optionally static graph.

We use 2.x in this class.

TensorFlow: Neural Net (Pre-2.0)

```
import numpy as np
import tensorflow as tf
```

(Assume imports at the
top of each snippet)

```
N, D, H = 64, 1000, 100
x = tf.placeholder(tf.float32, shape=(N, D))
y = tf.placeholder(tf.float32, shape=(N, D))
w1 = tf.placeholder(tf.float32, shape=(D, H))
w2 = tf.placeholder(tf.float32, shape=(H, D))

h = tf.maximum(tf.matmul(x, w1), 0)
y_pred = tf.matmul(h, w2)
diff = y_pred - y
loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

grad_w1, grad_w2 = tf.gradients(loss, [w1, w2])

with tf.Session() as sess:
    values = {x: np.random.randn(N, D),
              w1: np.random.randn(D, H),
              w2: np.random.randn(H, D),
              y: np.random.randn(N, D),}
    out = sess.run([loss, grad_w1, grad_w2],
                  feed_dict=values)
    loss_val, grad_w1_val, grad_w2_val = out
```

TensorFlow: Neural Net (Pre-2.0)

First define
computational graph

```
N, D, H = 64, 1000, 100
x = tf.placeholder(tf.float32, shape=(N, D))
y = tf.placeholder(tf.float32, shape=(N, D))
w1 = tf.placeholder(tf.float32, shape=(D, H))
w2 = tf.placeholder(tf.float32, shape=(H, D))

h = tf.maximum(tf.matmul(x, w1), 0)
y_pred = tf.matmul(h, w2)
diff = y_pred - y
loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

grad_w1, grad_w2 = tf.gradients(loss, [w1, w2])
```

Then run the graph
many times

```
with tf.Session() as sess:
    values = {x: np.random.randn(N, D),
              w1: np.random.randn(D, H),
              w2: np.random.randn(H, D),
              y: np.random.randn(N, D),}
    out = sess.run([loss, grad_w1, grad_w2],
                  feed_dict=values)
    loss_val, grad_w1_val, grad_w2_val = out
```

TensorFlow: 2.0 vs. pre-2.0

```
N, D, H = 64, 1000, 100

x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights

with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
gradients = tape.gradient(loss, [w1, w2]).
```

Tensorflow 2.0:
“Eager” Mode by default

```
assert(tf.executing_eagerly())
```

```
N, D, H = 64, 1000, 100
x = tf.placeholder(tf.float32, shape=(N, D))
y = tf.placeholder(tf.float32, shape=(N, D))
w1 = tf.placeholder(tf.float32, shape=(D, H))
w2 = tf.placeholder(tf.float32, shape=(H, D))

h = tf.maximum(tf.matmul(x, w1), 0)
y_pred = tf.matmul(h, w2)
diff = y_pred - y
loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

grad_w1, grad_w2 = tf.gradients(loss, [w1, w2])

with tf.Session() as sess:
    values = {x: np.random.randn(N, D),
              w1: np.random.randn(D, H),
              w2: np.random.randn(H, D),
              y: np.random.randn(N, D),}
    out = sess.run([loss, grad_w1, grad_w2],
                  feed_dict=values)
    loss_val, grad_w1_val, grad_w2_val = out
```

Tensorflow 1.15

TensorFlow: 2.0 vs. pre-2.0

```
N, D, H = 64, 1000, 100
```

```
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights

with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
gradients = tape.gradient(loss, [w1, w2]).
```

```
N, D, H = 64, 1000, 100
x = tf.placeholder(tf.float32, shape=(N, D))
y = tf.placeholder(tf.float32, shape=(N, D))
w1 = tf.placeholder(tf.float32, shape=(D, H))
w2 = tf.placeholder(tf.float32, shape=(H, D))

h = tf.maximum(tf.matmul(x, w1), 0)
y_pred = tf.matmul(h, w2)
diff = y_pred - y
loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

grad_w1, grad_w2 = tf.gradients(loss, [w1, w2])

with tf.Session() as sess:
    values = {x: np.random.randn(N, D),
              w1: np.random.randn(D, H),
              w2: np.random.randn(H, D),
              y: np.random.randn(N, D),}
    out = sess.run([loss, grad_w1, grad_w2],
                  feed_dict=values)
    loss_val, grad_w1_val, grad_w2_val = out
```

Tensorflow 2.0:

“Eager” Mode by default

Tensorflow 1.15

TensorFlow: 2.0 vs. pre-2.0

```
N, D, H = 64, 1000, 100
```

```
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights
```

```
with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
gradadients = tape.gradient(loss, [w1, w2]).
```

```
N, D, H = 64, 1000, 100
x = tf.placeholder(tf.float32, shape=(N, D))
y = tf.placeholder(tf.float32, shape=(N, D))
w1 = tf.placeholder(tf.float32, shape=(D, H))
w2 = tf.placeholder(tf.float32, shape=(H, D))

h = tf.maximum(tf.matmul(x, w1), 0)
y_pred = tf.matmul(h, w2)
diff = y_pred - y
loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

grad_w1, grad_w2 = tf.gradients(loss, [w1, w2])

with tf.Session() as sess:
    values = {x: np.random.randn(N, D),
              w1: np.random.randn(D, H),
              w2: np.random.randn(H, D),
              y: np.random.randn(N, D),}
    out = sess.run([loss, grad_w1, grad_w2],
                  feed_dict=values)
    loss_val, grad_w1_val, grad_w2_val = out
```

Tensorflow 2.0:

“Eager” Mode by default

Tensorflow 1.15

TensorFlow: Neural Net

Convert input numpy arrays to **TF tensors**.
Create weights as **tf.Variable**

`N, D, H = 64, 1000, 100`

```
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights

with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
gradients = tape.gradient(loss, [w1, w2]).
```

TensorFlow: Neural Net

Use `tf.GradientTape()` context to build **dynamic** computation graph.

```
N, D, H = 64, 1000, 100
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights
with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
gradients = tape.gradient(loss, [w1, w2]).
```

TensorFlow: Neural Net

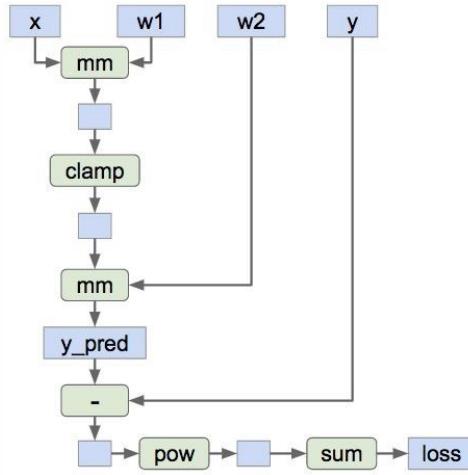
All forward-pass operations in the contexts (including function calls) gets traced for computing gradient later.

```
N, D, H = 64, 1000, 100
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights

with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
    gradients = tape.gradient(loss, [w1, w2]).
```



TensorFlow: Neural Net



Forward pass

$N, D, H = 64, 1000, 100$

```
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights

with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
gradients = tape.gradient(loss, [w1, w2]).
```

TensorFlow: Neural Net

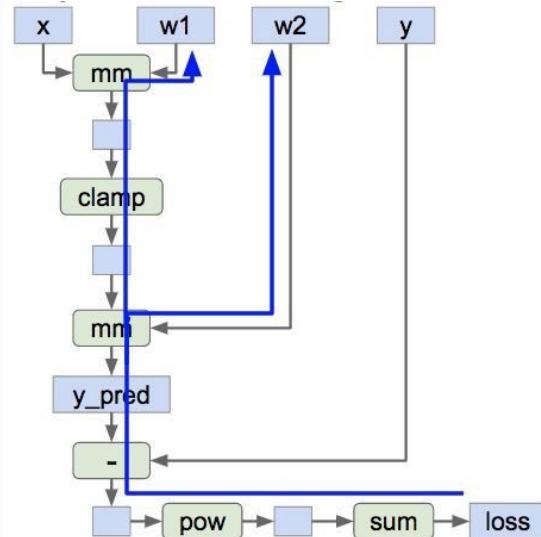
tape.gradient() uses the traced computation graph to compute gradient for the weights

```
N, D, H = 64, 1000, 100

x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights

with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
gradients = tape.gradient(loss, [w1, w2])
```

TensorFlow: Neural Net



Backward pass

$N, D, H = 64, 1000, 100$

```
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights

with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
gradients = tape.gradient(loss, [w1, w2])
```

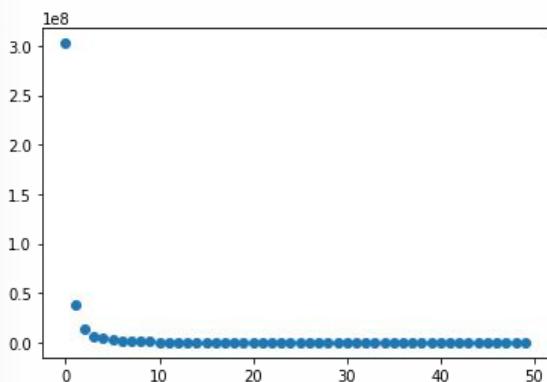
TensorFlow: Neural Net

```
N, D, H = 64, 1000, 100
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights

learning_rate = 1e-6
for t in range(50):
    with tf.GradientTape() as tape:
        h = tf.maximum(tf.matmul(x, w1), 0)
        y_pred = tf.matmul(h, w2)
        diff = y_pred - y
        loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
    gradients = tape.gradient(loss, [w1, w2])
    w1.assign(w1 - learning_rate * gradients[0])
    w2.assign(w2 - learning_rate * gradients[1])
```

Train the network: Run the training step over and over, use gradient to update weights

TensorFlow: Neural Net



Train the network: Run the graph over and over, use gradient to update weights

`N, D, H = 64, 1000, 100`

```
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights

learning_rate = 1e-6
for t in range(50):
    with tf.GradientTape() as tape:
        h = tf.maximum(tf.matmul(x, w1), 0)
        y_pred = tf.matmul(h, w2)
        diff = y_pred - y
        loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
    gradients = tape.gradient(loss, [w1, w2])
    w1.assign(w1 - learning_rate * gradients[0])
    w2.assign(w2 - learning_rate * gradients[1])
```

TensorFlow: Optimizer

Can use an **optimizer** to compute gradients and update weights

```
N, D, H = 64, 1000, 100
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights
optimizer = tf.optimizers.SGD(1e-6)
learning_rate = 1e-6
for t in range(50):
    with tf.GradientTape() as tape:
        h = tf.maximum(tf.matmul(x, w1), 0)
        y_pred = tf.matmul(h, w2)
        diff = y_pred - y
        loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
    gradients = tape.gradient(loss, [w1, w2])
    optimizer.apply_gradients(zip(gradients, [w1, w2])).
```

TensorFlow: Loss

Use predefined common losses

```
N, D, H = 64, 1000, 100

x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
w1 = tf.Variable(tf.random.uniform((D, H))) # weights
w2 = tf.Variable(tf.random.uniform((H, D))) # weights

optimizer = tf.optimizers.SGD(1e-6)

for t in range(50):
    with tf.GradientTape() as tape:
        h = tf.maximum(tf.matmul(x, w1), 0)
        y_pred = tf.matmul(h, w2)
        diff = y_pred - y
        loss = tf.losses.MeanSquaredError()(y_pred, y)
    gradients = tape.gradient(loss, [w1, w2])
    optimizer.apply_gradients(zip(gradients, [w1, w2]))
```

Keras: High-Level Wrapper

Keras is a layer on top of TensorFlow, makes common things easy to do

(Used to be third-party, now merged into TensorFlow)

```
N, D, H = 64, 1000, 100

x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(H, input_shape=(D, ),
                                activation=tf.nn.relu))
model.add(tf.keras.layers.Dense(D))
optimizer = tf.optimizers.SGD(1e-1)

losses = []
for t in range(50):
    with tf.GradientTape() as tape:
        y_pred = model(x)
        loss = tf.losses.MeanSquaredError()(y_pred, y)
    gradients = tape.gradient(
        loss, model.trainable_variables)
    optimizer.apply_gradients(
        zip(gradients, model.trainable_variables))
```

Keras: High-Level Wrapper

Define model as a sequence of layers

Get output by calling the model

Apply gradient to all trainable variables (weights) in the model

```
N, D, H = 64, 1000, 100
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(H, input_shape=(D,), activation=tf.nn.relu))
model.add(tf.keras.layers.Dense(D))
optimizer = tf.optimizers.SGD(1e-1)

losses = []
for t in range(50):
    with tf.GradientTape() as tape:
        y_pred = model(x)
        loss = tf.losses.MeanSquaredError()(y_pred, y)
    gradients = tape.gradient(loss, model.trainable_variables)
    optimizer.apply_gradients(zip(gradients, model.trainable_variables))
```

Keras: High-Level Wrapper

Keras can handle the training loop for you!

```
N, D, H = 64, 1000, 100
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(H, input_shape=(D, ),
                                activation=tf.nn.relu))
model.add(tf.keras.layers.Dense(D))
optimizer = tf.optimizers.SGD(1e-1)
model.compile(loss=tf.keras.losses.MeanSquaredError(),
               optimizer=optimizer)
history = model.fit(x, y, epochs=50, batch_size=N.)
```

TensorFlow: High-Level Wrappers

- Keras (<https://keras.io/>)
- tf.keras (https://www.tensorflow.org/api_docs/python/tf/keras)
- tf.estimator (https://www.tensorflow.org/api_docs/python/tf/estimator)
- Sonnet (<https://github.com/deepmind/sonnet>)
- TFLearn (<http://tflearn.org/>)
- TensorLayer (<http://tensorlayer.readthedocs.io/en/latest/>)

@tf.function: compile static graph

tf.function decorator
(implicitly) compiles
python functions to
static graph for better
performance

```
N, D, H = 64, 1000, 100
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(H, input_shape=(D,), activation=tf.nn.relu))
model.add(tf.keras.layers.Dense(D))
optimizer = tf.optimizers.SGD(1e-1)

@tf.function
def model_func(x, y):
    y_pred = model(x)
    loss = tf.losses.MeanSquaredError()(y_pred, y)
    return y_pred, loss

for t in range(50):
    with tf.GradientTape() as tape:
        y_pred, loss = model_func(x, y)
    gradients = tape.gradient(
        loss, model.trainable_variables)
    optimizer.apply_gradients(
        zip(gradients, model.trainable_variables))
```

@tf.function: compile static graph

Here we compare the forward-pass time of the same model under dynamic graph mode and static graph mode

```
N, D, H = 64, 1000, 100
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(H, input_shape=(D,),
                                activation=tf.nn.relu))
model.add(tf.keras.layers.Dense(D))
optimizer = tf.optimizers.SGD(1e-1)

@tf.function
def model_static(x, y):
    y_pred = model(x)
    loss = tf.losses.MeanSquaredError()(y_pred, y)
    return y_pred, loss

def model_dynamic(x, y):
    y_pred = model(x)
    loss = tf.losses.MeanSquaredError()(y_pred, y)
    return y_pred, loss

print("static graph:",
      timeit.timeit(lambda: model_static(x, y), number=10))
print("dynamic graph:",
      timeit.timeit(lambda: model_dynamic(x, y), number=10))

static graph: 0.14495624600000667
dynamic graph: 0.02945919699999422
```

@tf.function: compile static graph

Static graph is in general faster than dynamic graph, but the performance gain depends on the type of model / layer.

```
N, D, H = 64, 1000, 100
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(H, input_shape=(D,),
                                activation=tf.nn.relu))
model.add(tf.keras.layers.Dense(D))
optimizer = tf.optimizers.SGD(1e-1)

@tf.function
def model_static(x, y):
    y_pred = model(x)
    loss = tf.losses.MeanSquaredError()(y_pred, y)
    return y_pred, loss

def model_dynamic(x, y):
    y_pred = model(x)
    loss = tf.losses.MeanSquaredError()(y_pred, y)
    return y_pred, loss

print("static graph:",
      timeit.timeit(lambda: model_static(x, y), number=10))
print("dynamic graph:",
      timeit.timeit(lambda: model_dynamic(x, y), number=10))

static graph: 0.14495624600000667
dynamic graph: 0.02945919699999422
```

@tf.function: compile static graph

There are some caveats in defining control loops (for, if) with @tf.function.

```
N, D, H = 64, 1000, 100
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(H, input_shape=(D,),
                                activation=tf.nn.relu))
model.add(tf.keras.layers.Dense(D))
optimizer = tf.optimizers.SGD(1e-1)

@tf.function
def model_static(x, y):
    y_pred = model(x)
    loss = tf.losses.MeanSquaredError()(y_pred, y)
    return y_pred, loss

def model_dynamic(x, y):
    y_pred = model(x)
    loss = tf.losses.MeanSquaredError()(y_pred, y)
    return y_pred, loss

print("static graph:",
      timeit.timeit(lambda: model_static(x, y), number=10))
print("dynamic graph:",
      timeit.timeit(lambda: model_dynamic(x, y), number=10))

static graph: 0.14495624600000667
dynamic graph: 0.02945919699999422
```

TensorFlow: More on Eager Mode

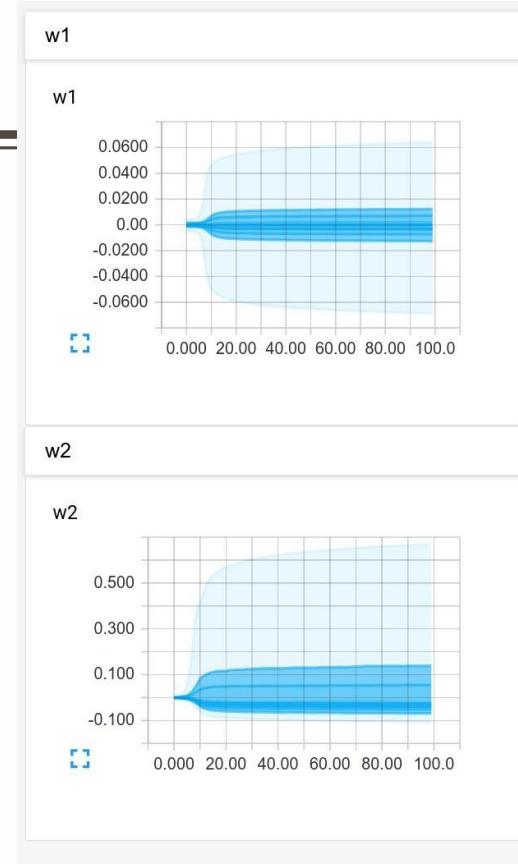
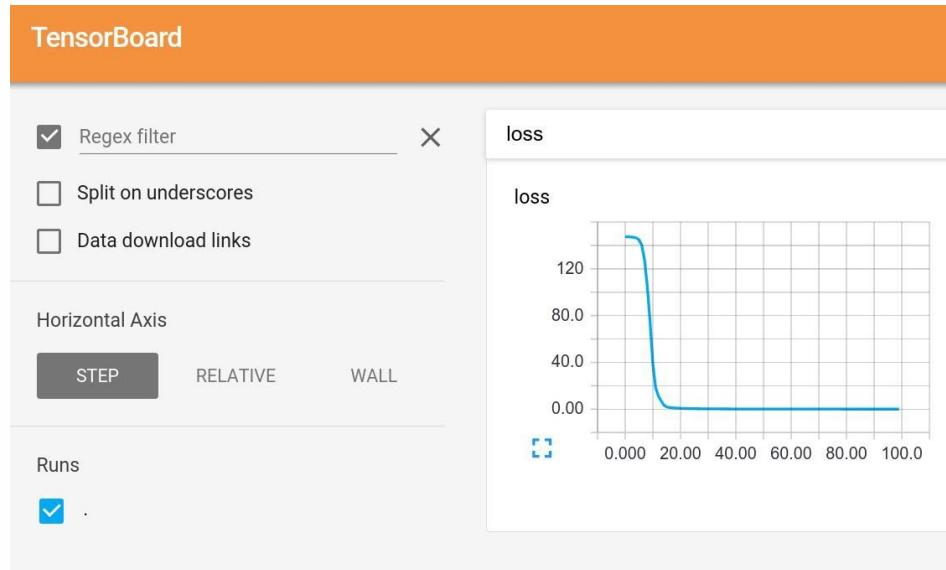
- Eager mode: (<https://www.tensorflow.org/guide/eager>)
- `tf.function`: (https://www.tensorflow.org/alpha/tutorials/eager/tf_function)

TensorFlow: Pretrained Models

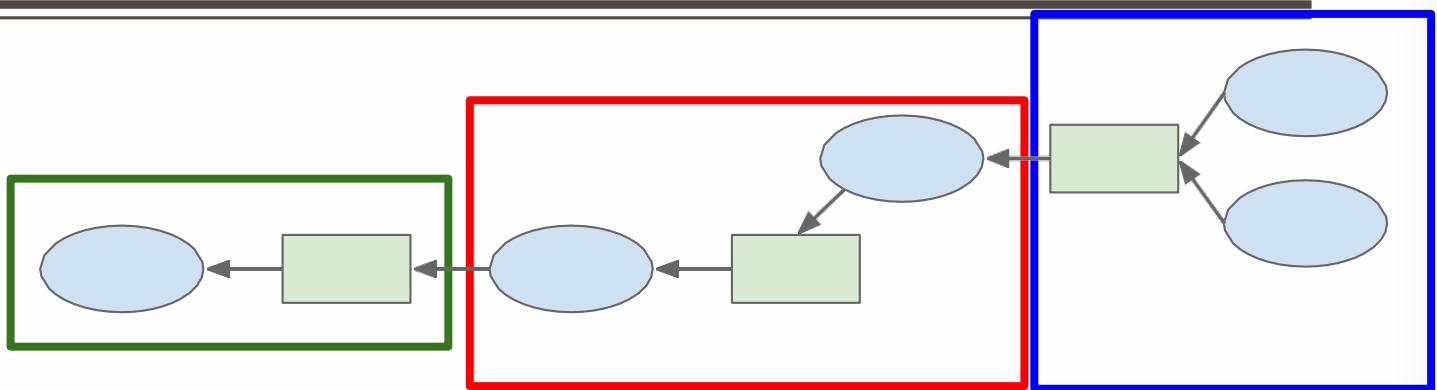
- `tf.keras`: (https://www.tensorflow.org/api_docs/python/tf/keras/applications)
- `TF-Slim`: (<https://github.com/tensorflow/models/tree/master/research/slim>)

TensorFlow: Tensorboard

Add logging to code to record loss, stats, etc
Run server and get pretty graphs!



TensorFlow: Distributed Version



Split one graph
over multiple
machines!



<https://www.tensorflow.org/deploy/distributed>

TensorFlow: Tensor Processing Units



Google Cloud TPU
= 180 TFLOPs of compute!

TensorFlow: Tensor Processing Units



Google Cloud TPU
= 180 TFLOPs of compute!



NVIDIA Tesla V100
= 125 TFLOPs of compute

TensorFlow: Tensor Processing Units



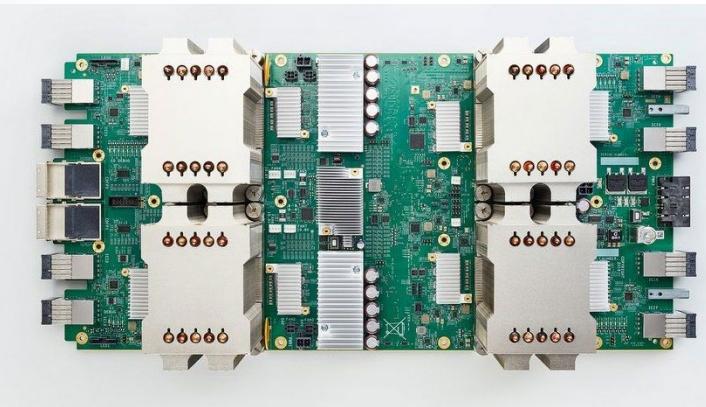
Google Cloud TPU
= 180 TFLOPs of compute!



NVIDIA Tesla V100
= 125 TFLOPs of compute

NVIDIA Tesla P100 = 11 TFLOPs of compute
GTX 580 = 0.2 TFLOPs

TensorFlow: Tensor Processing Units



Google Cloud TPU
= 180 TFLOPs of compute!



Google Cloud TPU Pod
= 64 Cloud TPUs
= 11.5 PFLOPs of compute!

https://www.tensorflow.org/versions/master/programmers_guide/using_tpu

TensorFlow: Tensor Processing Units



Edge TPU = 64 GFLOPs (16 bit)

<https://cloud.google.com/edge-tpu/>

Static vs Dynamic Graphs

TensorFlow (tf.function): Build graph once, then run many times (**static**)

```
N, D, H = 64, 1000, 100
x = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
y = tf.convert_to_tensor(np.random.randn(N, D), np.float32)
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(H, input_shape=(D,), activation=tf.nn.relu))
model.add(tf.keras.layers.Dense(D))
optimizer = tf.optimizers.SGD(1e-1)

@tf.function
def model_func(x, y):
    y_pred = model(x)
    loss = tf.losses.MeanSquaredError()(y_pred, y)
    return y_pred, loss

for t in range(50):
    with tf.GradientTape() as tape:
        y_pred, loss = model_func(x, y)
        gradients = tape.gradient(
            loss, model.trainable_variables)
        optimizer.apply_gradients(
            zip(gradients, model.trainable_variables))
```

Compile python code into static graph

Run each iteration

PyTorch: Each forward pass defines a new graph (**dynamic**)

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

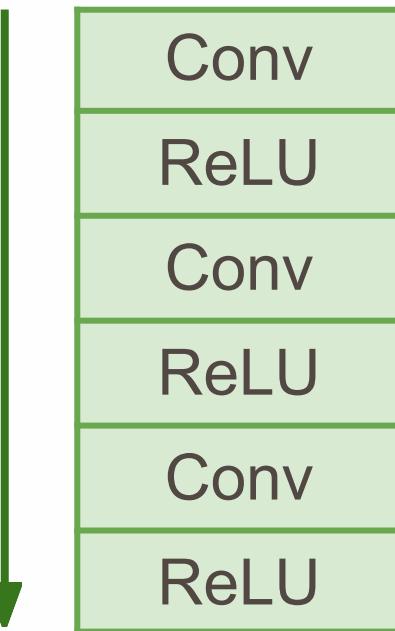
    loss.backward()
```

New graph each iteration

Static vs Dynamic: Optimization

With static graphs, framework can **optimize** the graph for you before it runs!

The graph you wrote



Equivalent graph with **fused operations**



Static vs Dynamic: Serialization

Static

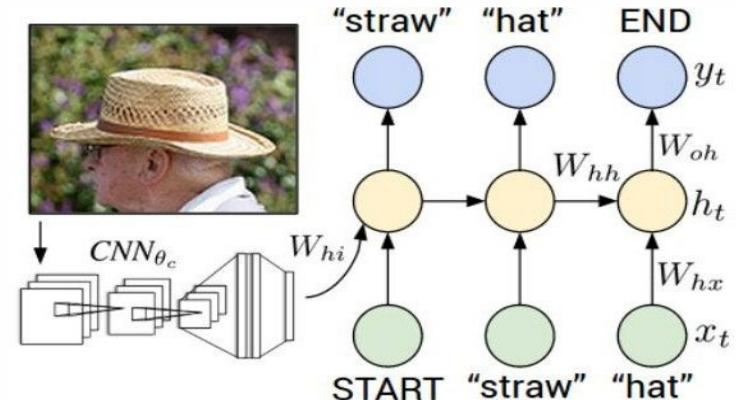
Once graph is built, can **serialize** it and run it without the code that built the graph!

Dynamic

Graph building and execution are intertwined, so always need to keep code around

Dynamic Graph Applications

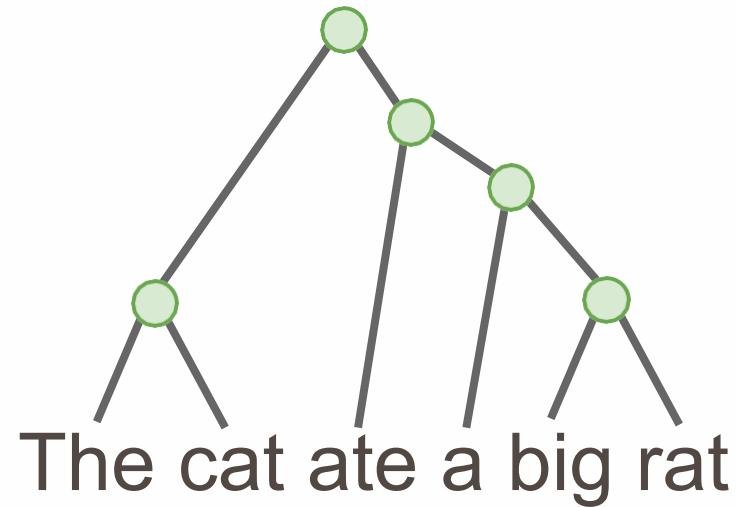
-Recurrent networks



Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
Figure copyright IEEE, 2015. Reproduced for educational purposes.

Dynamic Graph Applications

- Recurrent networks
- Recursive networks



Dynamic Graph Applications

- Recurrent networks
- Recursive networks
- Modular Networks

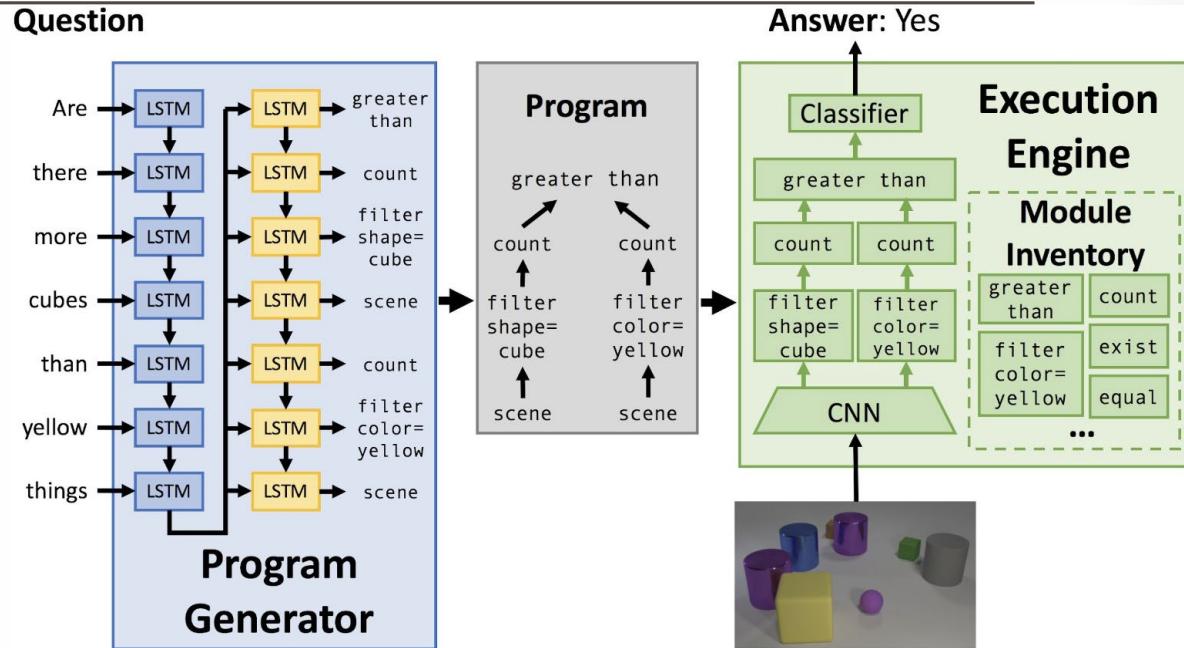


Figure copyright Justin Johnson, 2017. Reproduced with permission.

Andreas et al, "Neural Module Networks", CVPR 2016

Andreas et al, "Learning to Compose Neural Networks for Question Answering", NAACL 2016
Johnson et al, "Inferring and Executing Programs for Visual Reasoning", ICCV 2017

Dynamic Graph Applications

- Recurrent networks
- Recursive networks
- Modular Networks
- (Your creative idea here)

PyTorch vs TensorFlow, Static vs Dynamic

- PyTorch
- Dynamic Graphs
- TensorFlow
- Pre-2.0: Default Static Graph 2.0+: Default Dynamic Graph
- 2.x: Eager mode

Static PyTorch: Caffe2 <https://caffe2.ai/>

- Deep learning framework developed by Facebook
- Static graphs, somewhat similar to TensorFlow
- Core written in C++
- Nice Python interface
- Can train model in Python, then serialize and deploy without Python
- Works on iOS / Android, etc

Static PyTorch: ONNX Support

- ONNX is an open-source standard for neural network models
- Goal: Make it easy to train a network in one framework, then run it in another framework
- Supported by PyTorch, Caffe2, Microsoft CNTK, Apache MXNet
<https://github.com/onnx/onnx>

Static PyTorch: ONNX Support

You can export a PyTorch model to ONNX

Run the graph on a dummy input, and save the graph to a file

Will only work if your model doesn't actually make use of dynamic graph - must build same graph on every forward pass, no loops / conditionals

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out))

dummy_input = torch.randn(N, D_in)
torch.onnx.export(model, dummy_input,
                  'model.proto',
                  verbose=True)
```

Static PyTorch: ONNX Support

```
graph(%0 : Float(64, 1000)
      %1 : Float(100, 1000)
      %2 : Float(100)
      %3 : Float(10, 100)
      %4 : Float(10)) {
  %5 : Float(64, 100) =
  onnx::Gemm[alpha=1, beta=1, broadcast=1,
  transB=1](%0, %1, %2), scope:
  Sequential/Linear[0]
  %6 : Float(64, 100) = onnx::Relu(%5),
  scope: Sequential/ReLU[1]
  %7 : Float(64, 10) = onnx::Gemm[alpha=1,
  beta=1, broadcast=1, transB=1](%6, %3,
  %4), scope: Sequential/Linear[2]
  return (%7);
}
```

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out))

dummy_input = torch.randn(N, D_in)
torch.onnx.export(model, dummy_input,
                  'model.proto',
                  verbose=True)
```

After exporting to ONNX, can run the PyTorch model in Caffe2

Static PyTorch

[pytorch / pytorch](#)

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Code Issues 2,317 Pull requests 574 Projects 5 Wiki Insights

Branch: master ▾ pytorch / caffe2 / Create new file Upload files Find file History

 jerryzh168 and facebook-github-bot Testing for folded conv_bn_relu (#19298) ... Latest commit ff0a7ae 5 hours ago

..

 contrib	Fix aten op output assignment (#18581)	7 days ago
 core	Change is_variable() to check existence of AutogradMeta, and remove i...	5 days ago
 cuda_RTC	Change ConvPoolOp<Context>::SetOutputSize to ConvPoolOp<Context>::Get...	a month ago
 db	Apply modernize-use-override (2nd iteration)	2 months ago
 distributed	Manual hipify caffe2/distributed and rocm update (no hcc modules supp...	19 days ago
 experiments	Tensor construction codemod(ResizeLike) - 1/7 (#15073)	4 months ago
 ideep	implement operators for DNNLOWP (#18656)	6 days ago
 image	Open registration for c10 thread pool (#17788)	a month ago
 mobile	Remove ComputeLibrary submodule	a month ago

PyTorch vs TensorFlow, Static vs Dynamic

PyTorch

Dynamic Graphs

Static: ONNX, Caffe2

TensorFlow

Dynamic: Eager

Static: `@tf.function`

My Advice:

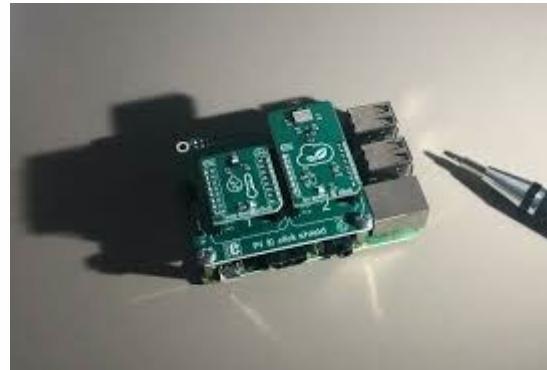
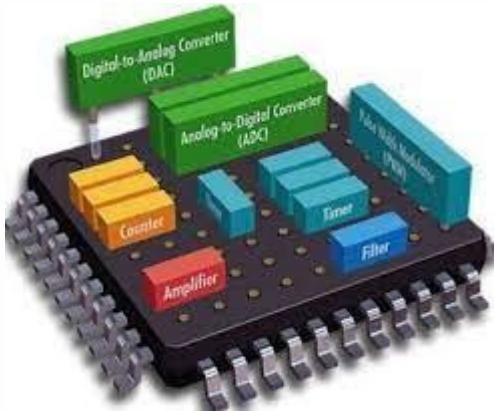
- PyTorch is my personal favorite. Clean API, native dynamic graphs make it very easy to develop and debug. Can build model in PyTorch then export to Caffe2 with ONNX for production / mobile
- TensorFlow is a safe bet for most projects. Syntax became a lot more intuitive after 2.x. Not perfect but has huge community and wide usage. Can use same framework for research and production. Probably use a high-level framework. Only choice if you want to run on TPUs.



MODEL COMPRESSION

Low-power required? Mobile Device?

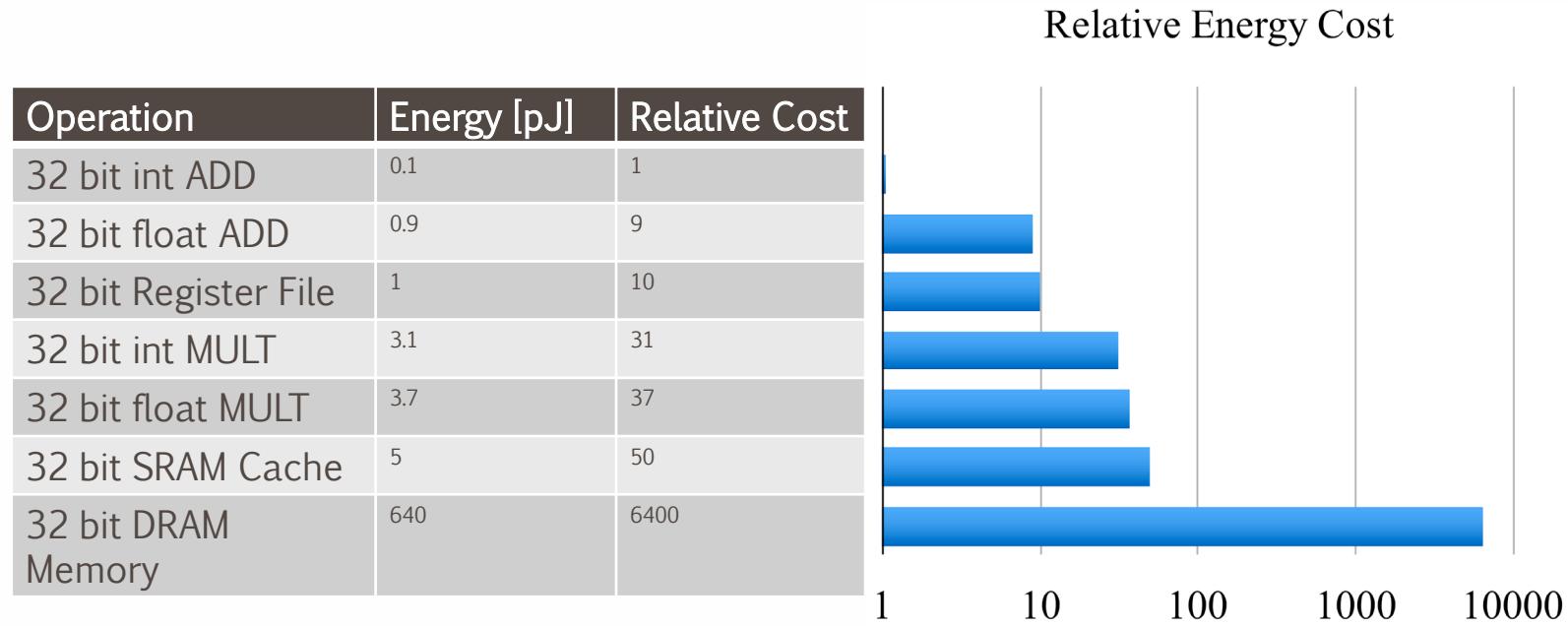
DL looks great. How about the low-power devices?



Why model compression?

- Deep Neural Networks are BIG ... and getting BIGGER
 - e.g. AlexNet (240 MB), VGG-16 (520 MB)
- Too big to store on-chip SRAM and DRAM accesses use a lot of energy
- Not suitable for low-power mobile/embedded systems
- Solution: Deep Compression

Why smaller models?



Source:

<http://isca2016.eecs.umich.edu/wp-content/uploads/2016/07/>

Methods to Model Compression

- Technique to reduce size of neural networks without losing accuracy
- **Matrix factorization**
- **Pruning to Reduce Number of Weights**
- **Quantization to Reduce Bits per Weight**

Fully Connected Layers: Singular Value Decomposition

- Most weights are in the fully connected layers (according to Denton et al.)
- $W = USV^T$
 - $W \in \mathbb{R}^{m \times k}, U \in \mathbb{R}^{m \times m}, S \in \mathbb{R}^{m \times k}, V^T \in \mathbb{R}^{k \times k}$
- S is diagonal, decreasing magnitudes along the diagonal

$$\begin{pmatrix} & & \\ & \ddots & \\ & & \end{pmatrix} = \begin{pmatrix} & & & & \\ & \ddots & & & \\ & & \ddots & & \\ & & & \ddots & \\ & & & & \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ w_3 \\ \vdots \end{pmatrix} \begin{pmatrix} & & \\ & \ddots & \\ & & \end{pmatrix}$$
$$A = U S V^T$$

<http://www.alglib.net/matrixops/general/i/svd1.gif>

Singular Value Decomposition

- By only keeping the t singular values with largest magnitude:

- $\tilde{W} = \tilde{U}\tilde{S}\tilde{V}^\top$

- $\tilde{W} \in \mathbb{R}^{m \times k}, \tilde{U} \in \mathbb{R}^{m \times t}, \tilde{S} \in \mathbb{R}^{t \times t}, \tilde{V}^\top \in \mathbb{R}^{t \times k}$

- $\text{Rank}(\tilde{W}) = t$

$$\begin{pmatrix} & & \\ & \ddots & \\ & & \end{pmatrix} = \begin{pmatrix} & & & & \\ & \ddots & & & \\ & & \ddots & & \\ & & & \ddots & \\ & & & & \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ w_3 \\ \vdots \end{pmatrix} \begin{pmatrix} & & \\ & \ddots & \\ & & \end{pmatrix}$$
$$A = U \tilde{S} V^\top$$

<http://www.alglib.net/matrixops/general/i/svd1.gif>

SVD: Compression

- $W = USV^\top, W \in \mathbb{R}^{m \times k}, U \in \mathbb{R}^{m \times m}, S \in \mathbb{R}^{m \times k}, V^\top \in \mathbb{R}^{k \times k}$
- $\tilde{W} = \tilde{U}\tilde{S}\tilde{V}^\top, \tilde{W} \in \mathbb{R}^{m \times k}, \tilde{U} \in \mathbb{R}^{m \times t}, \tilde{S} \in \mathbb{R}^{t \times t}, \tilde{V}^\top \in \mathbb{R}^{t \times k}$
- Storage for W : $O(mk)$
- Storage for \tilde{W} : $O(mt + t + tk)$
- Compression Rate: $O\left(\frac{mk}{t(m+k+1)}\right)$
- Theoretical error: $\|A\tilde{W} - AW\|_F \leq s_{t+1}\|A\|_F$

Gong, Yunchao, et al. "Compressing deep convolutional networks using vector quantization." *arXiv preprint arXiv:1412.6115* (2014).

SVD: Compression Results

- Trained on ImageNet 2012 database, then compressed
- 5 convolutional layers, 3 fully connected layers, softmax output layer

Approximation method	Number of parameters	Approximation hyperparameters	Reduction in weights	Increase in error
Standard FC	NM			
FC layer 1: Matrix SVD	$NK + KM$	$K = 250$ $K = 950$	$13.4 \times$ $3.5 \times$	0.8394% 0.09%
FC layer 2: Matrix SVD	$NK + KM$	$K = 350$ $K = 650$	$5.8 \times$ $3.14 \times$	0.19% 0.06%
FC layer 3: Matrix SVD	$NK + KM$	$K = 250$ $K = 850$	$8.1 \times$ $2.4 \times$	0.67% 0.02%

K refers to rank of approximation, t in the previous slides.

Denton, Emily L., et al. "Exploiting linear structure within convolutional networks for efficient evaluation." *Advances in Neural Information Processing Systems*. 2014.

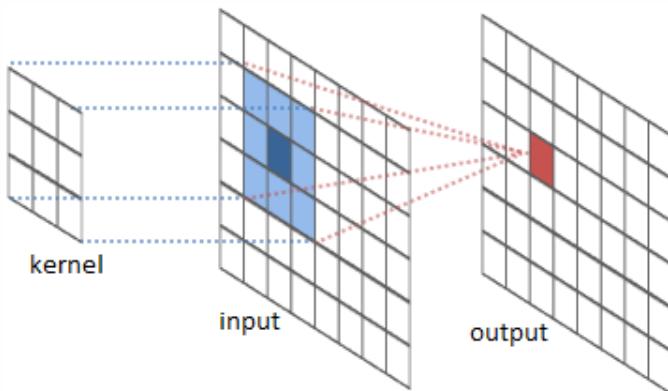
SVD: Side Benefits

- Reduced memory footprint
 - Reduced in the dense layers by 5-13x
- Speedup: $A\tilde{W}$, $A \in \mathbb{R}^{n \times m}$, computed in $O(nmt + nt^2 + ntk)$ instead of $O(nmk)$
 - Speedup factor is $O\left(\frac{mk}{t(m+t+k)}\right)$
- Regularization
 - “Low-rank projections effectively decrease number of learnable parameters, suggesting that they might improve generalization ability.”
 - Paper applies SVD after training

Denton, Emily L., et al. "Exploiting linear structure within convolutional networks for efficient evaluation." *Advances in Neural Information Processing Systems*. 2014.

Convolutions: Matrix Multiplication

Most time is spent in the convolutional layers

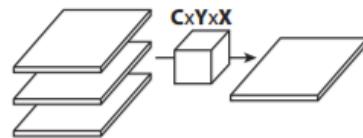


$$F(x, y) = I * W$$

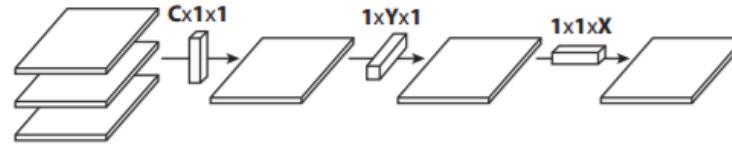
<http://stackoverflow.com/questions/15356153/how-do-convolution-matrices-work>

Flattened Convolutions

- Replace $c \times y \times x$ convolutions with $c \times 1 \times 1$, $1 \times y \times 1$, and $1 \times 1 \times x$ convolutions



(a) 3D convolution



(b) 1D convolutions over different directions

Jin, Jonghoon, Aysegul Dundar, and Eugenio Culurciello. "Flattened convolutional neural networks for feedforward acceleration." *arXiv preprint arXiv:1412.5474* (2014).

Flattened Convolutions

$$\hat{F}(x, y) = I * \hat{W} = \sum_{x'=1}^X \left(\sum_{y'=1}^Y \left(\sum_{c=1}^C I(c, x - x', y - y') \alpha(c) \right) \beta(y') \right) \gamma(x')$$
$$\alpha \in \mathbb{R}^C, \beta \in \mathbb{R}^Y, \gamma \in \mathbb{R}^X$$

- Compression and Speedup:
 - Parameter reduction: $O(XYC)$ to $O(X + Y + C)$
 - Operation reduction: $O(mnCXY)$ to $O(mn(C + X + Y))$ (where $W_f \in \mathbb{R}^{m \times n}$)

Jin, Jonghoon, Aysegul Dundar, and Eugenio Culurciello. "Flattened convolutional neural networks for feedforward acceleration." *arXiv preprint arXiv:1412.5474* (2014).

Flattening = MF

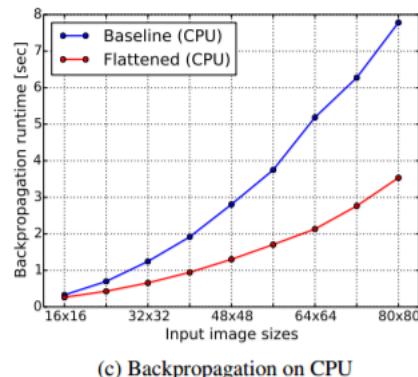
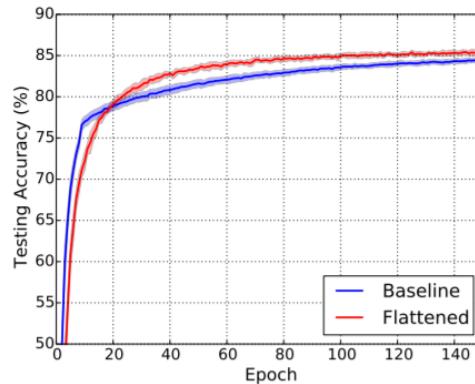
$$\begin{aligned}\hat{F}(x, y) &= \sum_{\substack{x=1 \\ x \in \bar{X}}}^X \sum_{\substack{y'=1 \\ y' \in \bar{Y}}}^Y \sum_{\substack{c=1 \\ c \in \bar{C}}}^C I(c, x - x', y - y') \alpha(c) \beta(y') \gamma(x') \\ &= \sum_{x=1}^X \sum_{y'=1}^Y \sum_{c=1}^C I(c, x - x', y - y') \hat{W}(c, x', y')\end{aligned}$$

- $\hat{W} = \alpha \otimes \beta \otimes \gamma$, $\text{Rank}(\hat{W}) = 1$
- $\hat{W}_S = \sum_{k=1}^K \alpha_k \otimes \beta_k \otimes \gamma_k$, Rank K
- SVD: Can reconstruct the original matrix as $A = \sum_{k=1}^K w_k u_k \otimes v_k$

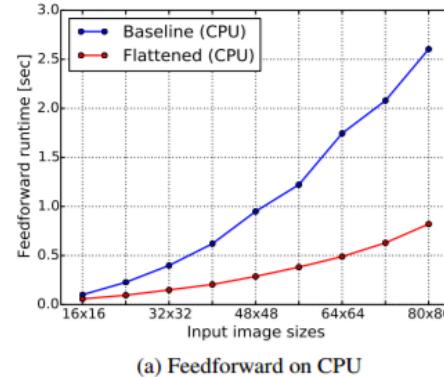
Denton, Emily L., et al. "Exploiting linear structure within convolutional networks for efficient evaluation." *Advances in Neural Information Processing Systems*. 2014.

Flattening: Speedup Results

- 3 convolutional layers (5x5 filters) with 96, 128, and 256 channels
- Used stacks of 2 rank-1 convolutions



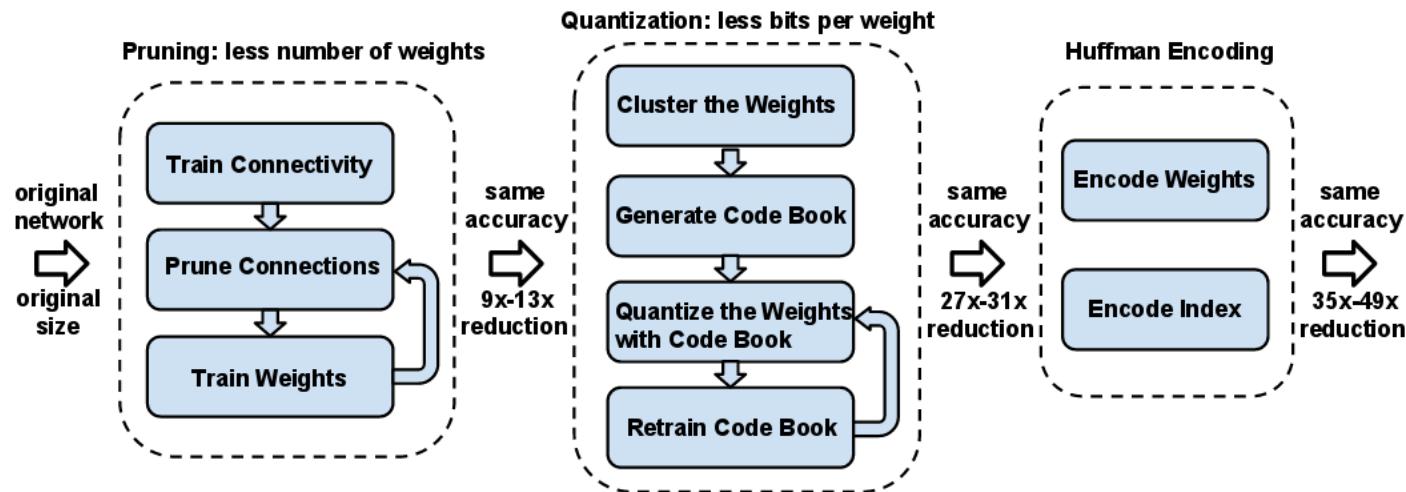
(c) Backpropagation on CPU



(a) Feedforward on CPU

Jin, Jonghoon, Aysegul Dundar, and Eugenio Culurciello. "Flattened convolutional neural networks for feedforward acceleration." *arXiv preprint arXiv:1412.5474* (2014).

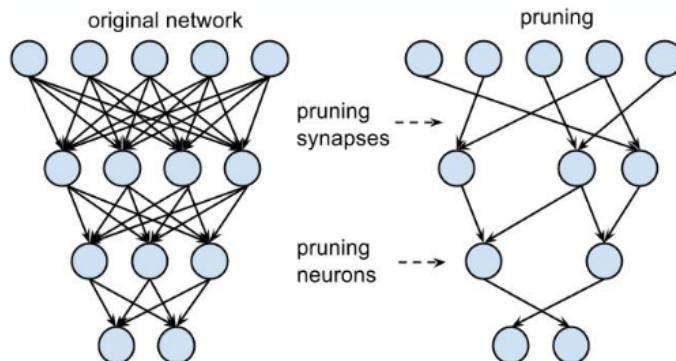
Other Deep Compressions?



Pruning, Trained Quantization and Huffman Coding", Song Han et al.,
ICLR 2016

Pruning

- Remove weights/synapses “close to zero”
- Retrain to maintain accuracy
- Repeat



Sparse Network

Pruning Results

Network	Top-1 Error	Top-5 Error	Parameters	Compression Rate
LeNet-300-100 Ref	1.64%	-	267K	
LeNet-300-100 Pruned	1.59%	-	22K	12×
LeNet-5 Ref	0.80%	-	431K	
LeNet-5 Pruned	0.77%	-	36K	12×
AlexNet Ref	42.78%	19.73%	61M	
AlexNet Pruned	42.77%	19.67%	6.7M	9×
VGG16 Ref	31.50%	11.32%	138M	
VGG16 Pruned	31.34%	10.88%	10.3M	13×

Table 1: Network pruning can save 9× to 13× parameters with no drop in predictive performance

Why Reduced Precision Computing?

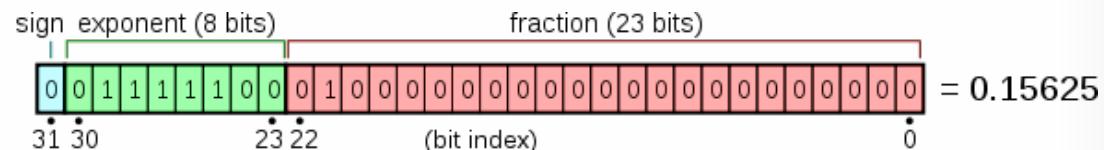
- Decrease the inference speed
- Decrease the model size (memory)
- Keeping same level of accuracy
- → Approach: Reduced Precision Computing

Default Arithmetic in Deep Learning

- The default arithmetic in deep learning frameworks (TensorFlow, PyTorch) is 32-bit floating point (float32) or single precision

- **Float32:**

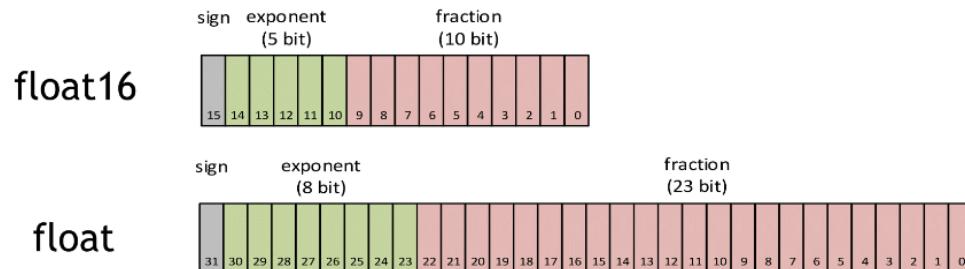
- 1 bit for the sign
- 8 bits for the exponent
- 24 bits for the fraction



- **Max value:** $3.4 * 10^{38}$

Reduced Precision

- Float16 or half precision:
- 16 bits
 - 1 sign
 - 5 exponent
 - 10 fraction
- Max value : 65504

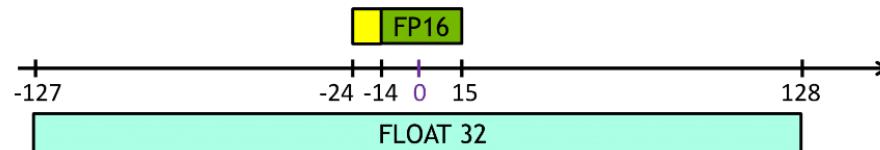


- Integer 8 (int8):
- 8 bits (no fraction!)
- Max value : 256 values
- And even smaller formats

FLOAT16 has wide range (2^{40}) ... but not as wide as FP32!

Normal range: $[6 \times 10^{-5} , 65504]$

Sub-normal range: $[6 \times 10^{-8} , 6 \times 10^{-5}]$



What is Quantization?

- Converting numbers from one format to another
- More specific: From a higher precision to a lower precision (float32 → int8)

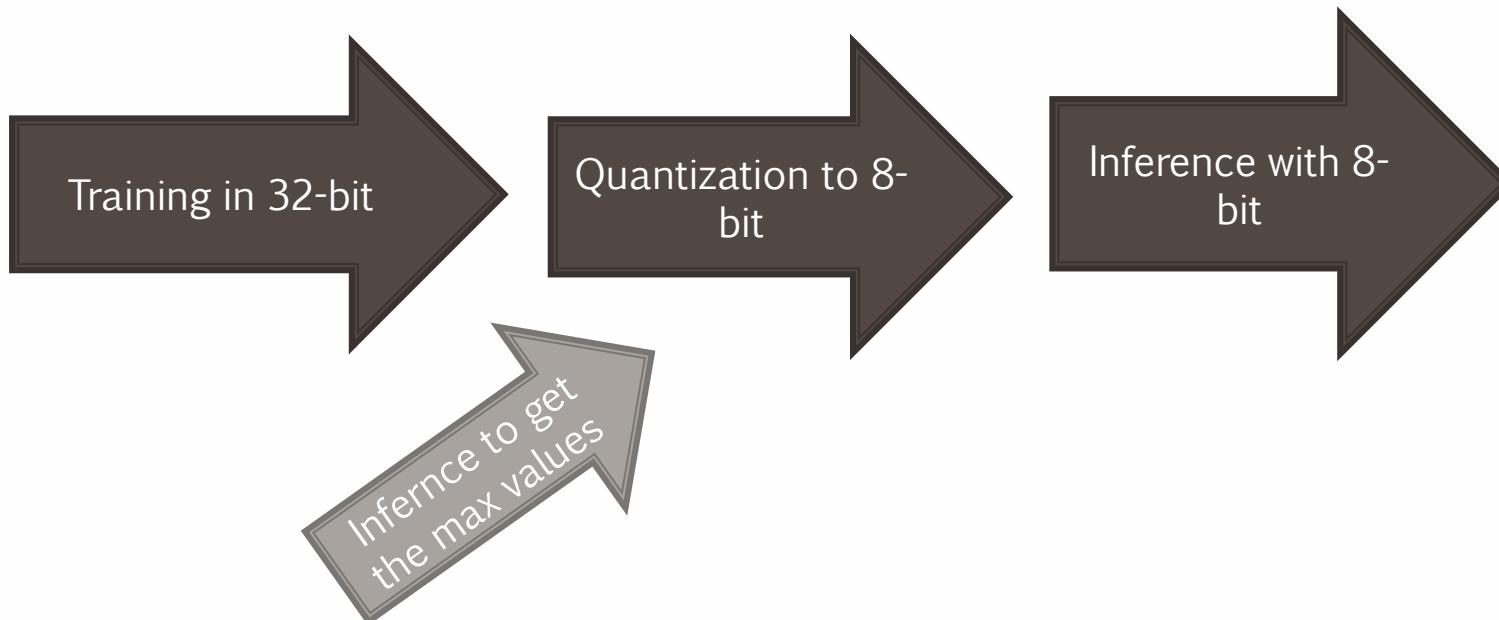
- In theory quantization is simple:
- Example float32 to int8

- Find scaling factor:
 - Search the maximum absolute number B
 - Scaling factor: $S = \frac{255}{B}$
- Quantizing:
 - $Q = \text{round}(S * N_{32})$

$$N = [15, 50, 200] \rightarrow B = 200$$
$$S = \frac{255}{200} = 1,275$$

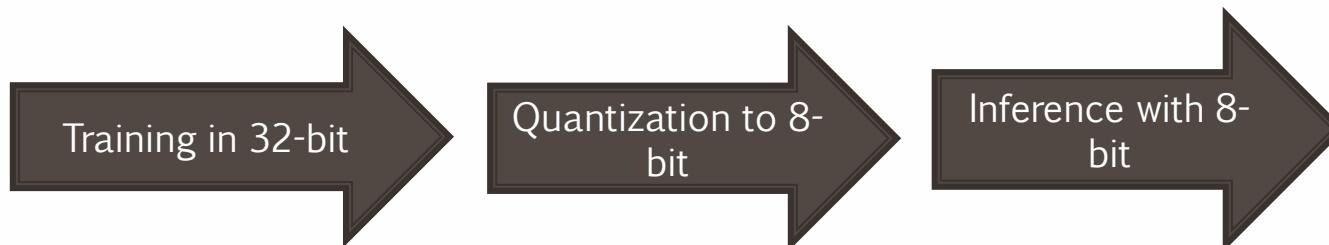
$$Q_1 = \text{round}(1,275 * 15) = 19$$
$$Q_2 = \text{round}(1,275 * 50) = 64$$
$$Q_3 = \text{round}(1,275 * 200) = 255$$

Post-Training Quantization



Quantization with Neural Networks

- Operations to quantize:
 - Weights, Bias
 - Activations
- Depending on the quantization tool, it is necessary to quantize the input into the neural network
- Depending on the tool you can get the output in quantized format



Possible Benefits of Quantization

- Reduction in model size
 - Reduction in memory bandwidth
 - Faster inference
- Example: float32 → int8
 - 4x
 - 2-4x *
 - 2-4x *
- *depending on hardware and the module

Disadvantage of Quantization

- Only one disadvantage: Slightly less accuracy
 - Roughly 2-3 %
 - Depends greatly on the model
- Constraint: Not many hardware devices support low precision computing
 - Even if low precisions are not supported yet, you can run inference with the quantized models, but you don't see any speed up

Why is 8-bit Quantization so Famous?

- Because it is the smallest format which is supported by mainstream hardware devices
- Lower bit numbers have a strong drop in accuracy
- Typically when it is talked about quantization, they mean int8

Example Quantization Tools

- In general HWs
 - TensorFlow Lite supports quantization to float16 and int8
 - Generally work well: like MTK dimensity series, Qualcomm Adreno, etc.
 - PyTorch -> Pytorch mobile
 - Intel Low-Precision Quantization tool
- In Nvidia-related platform, like nx, tx2, px2
 - Tensorrt
- In other platforms like Kneron
 - Onnx (cross-platform)
- Intel-based
 - Openvino

Many tricks on Embedding System

- TF Lite version
 - Could be affected by TF version, HW supports, and even naïve ops.
 - Quantization supporting: <TF1.3, only QUINT8 and FP32. >TF1.3.2, FP16 supported
- Pytorch mobile
 - New one, but not verified comprehensively yet.
- Intel openvino
 - OK but the supported ops are incomplete
- Other platforms
 - Many issues on “versions” from Pytorch or TF



NEXT TIME:
LATEST CNNS