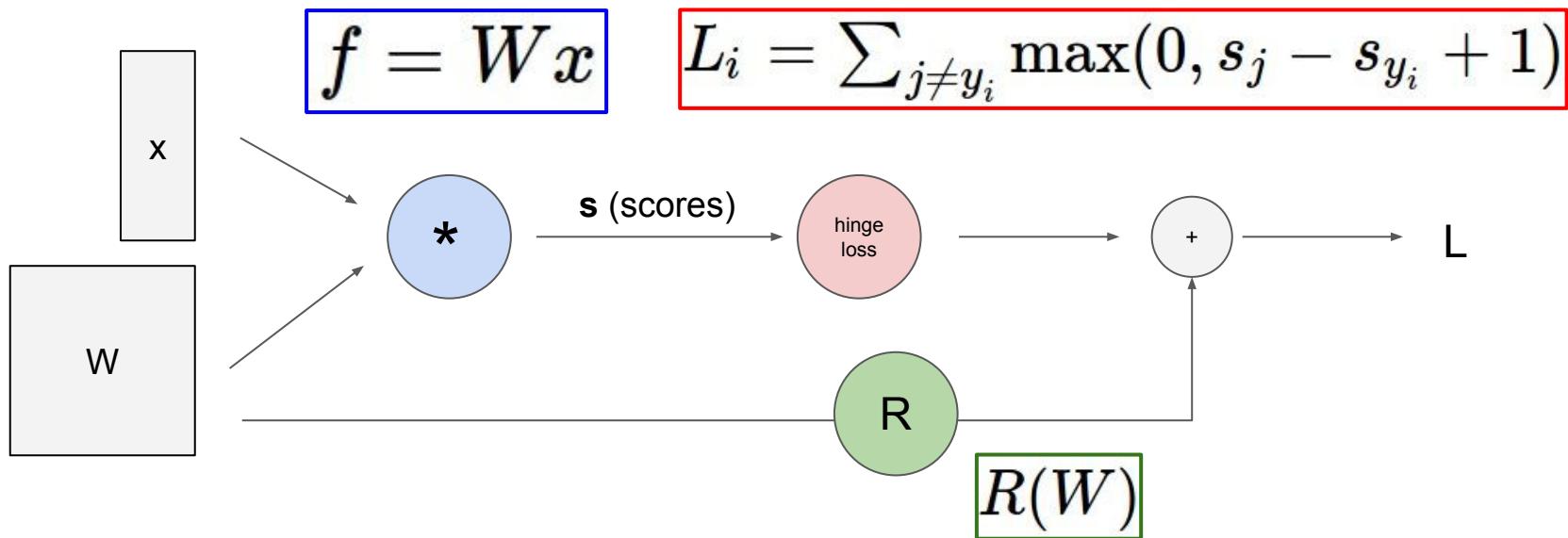


# Lecture 6: Hardware and Software

Hardware Computation Units, Dynamic & Static Computational  
Graph, PyTorch & TensorFlow

Where we are now...

# Computational graphs



Where we are now...

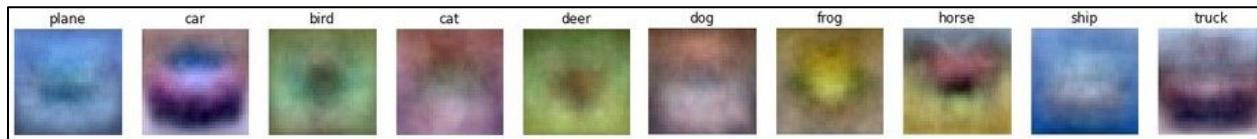
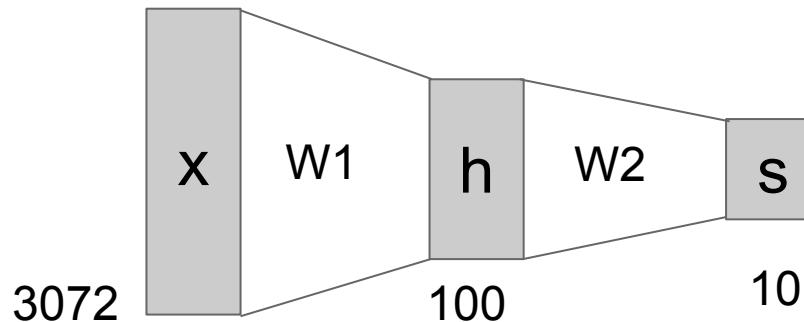
# Neural Networks

Linear score function:

$$f = Wx$$

2-layer Neural Network

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



Where we are now...

# Convolutional Neural Networks

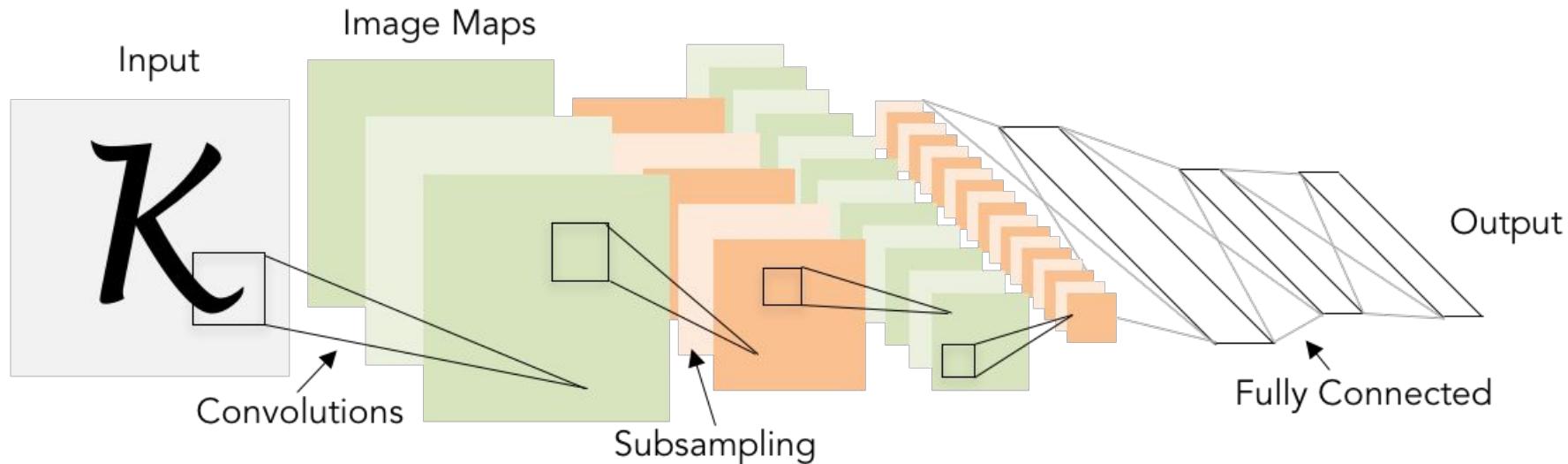
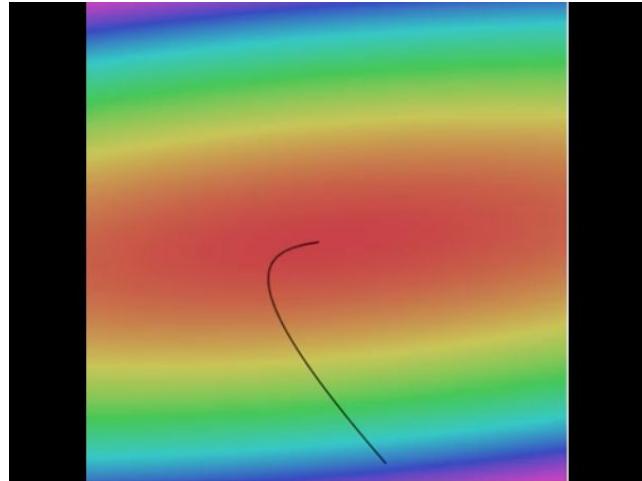
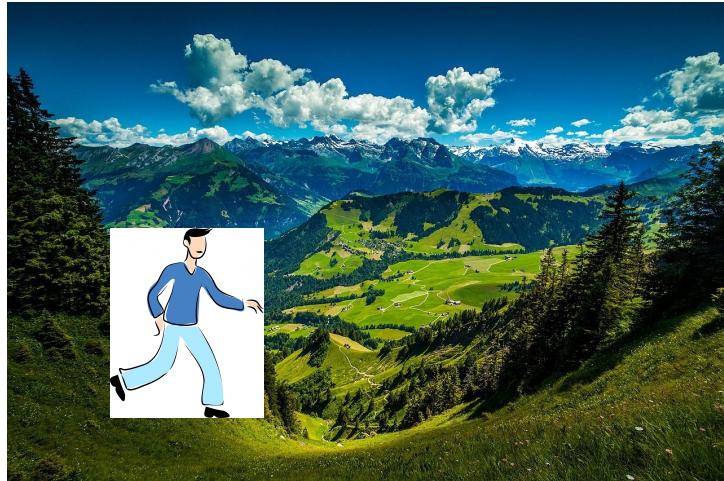


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

# Where we are now...

## 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
- Deep learning software
  - PyTorch and TensorFlow
  - Static and Dynamic computation graphs

# Deep Learning Hardware

# Inside a computer

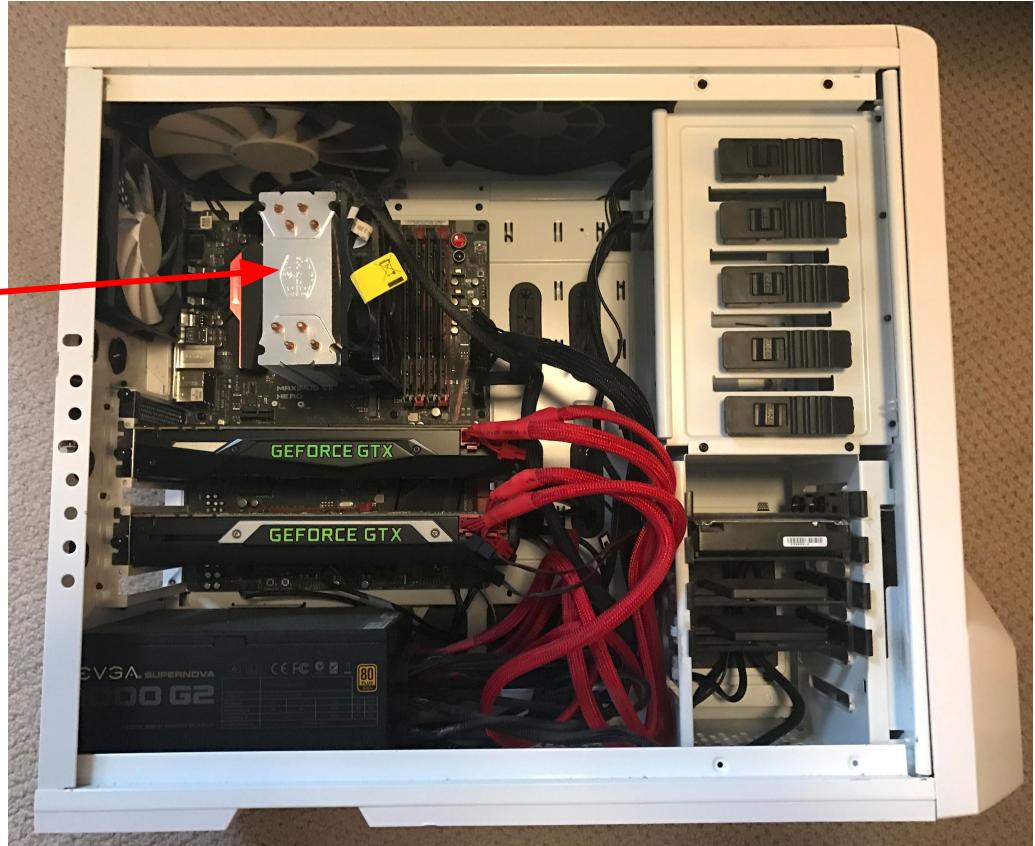


# Spot the CPU!

(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



# CPU vs GPU

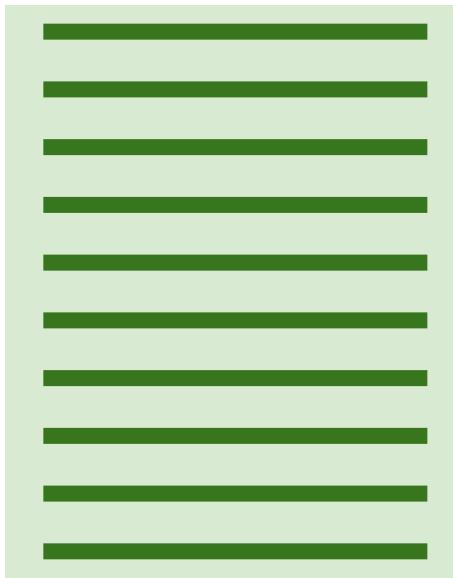
	<b>Cores</b>	<b>Clock Speed</b>	<b>Memory</b>	<b>Price</b>	<b>Speed</b>
<b>CPU</b> (Intel Core i7-7700k)	4 (8 threads with hyperthreading)	4.2 GHz	System RAM	\$385	~540 GFLOPs FP32
<b>GPU</b> (NVIDIA RTX 2080 Ti)	3584	1.6 GHz	11 GB GDDR6	\$1199	~13.4 TFLOPs FP32

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

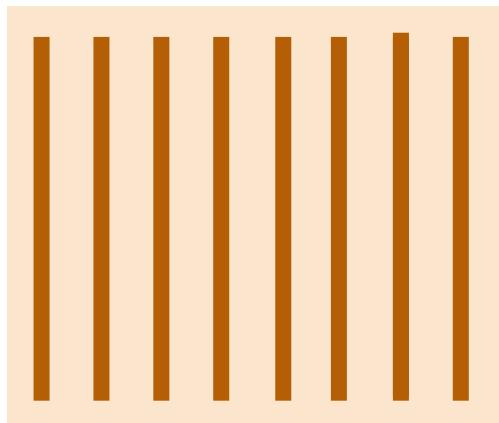
**GPU:** More cores, but each core is much slower and “dumber”; great for parallel tasks

# Example: Matrix Multiplication

$A \times B$

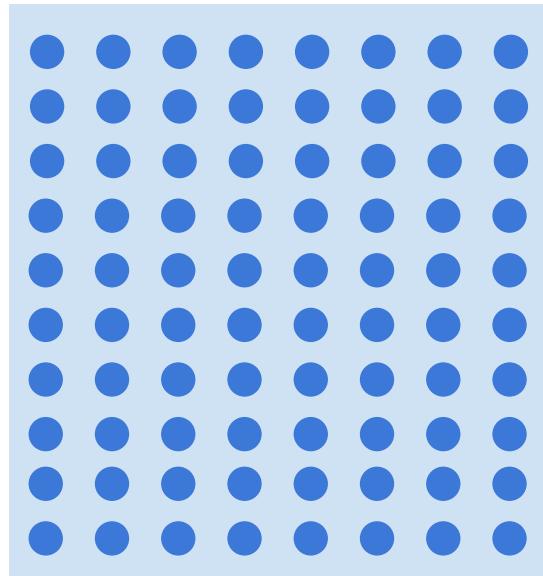


$B \times C$



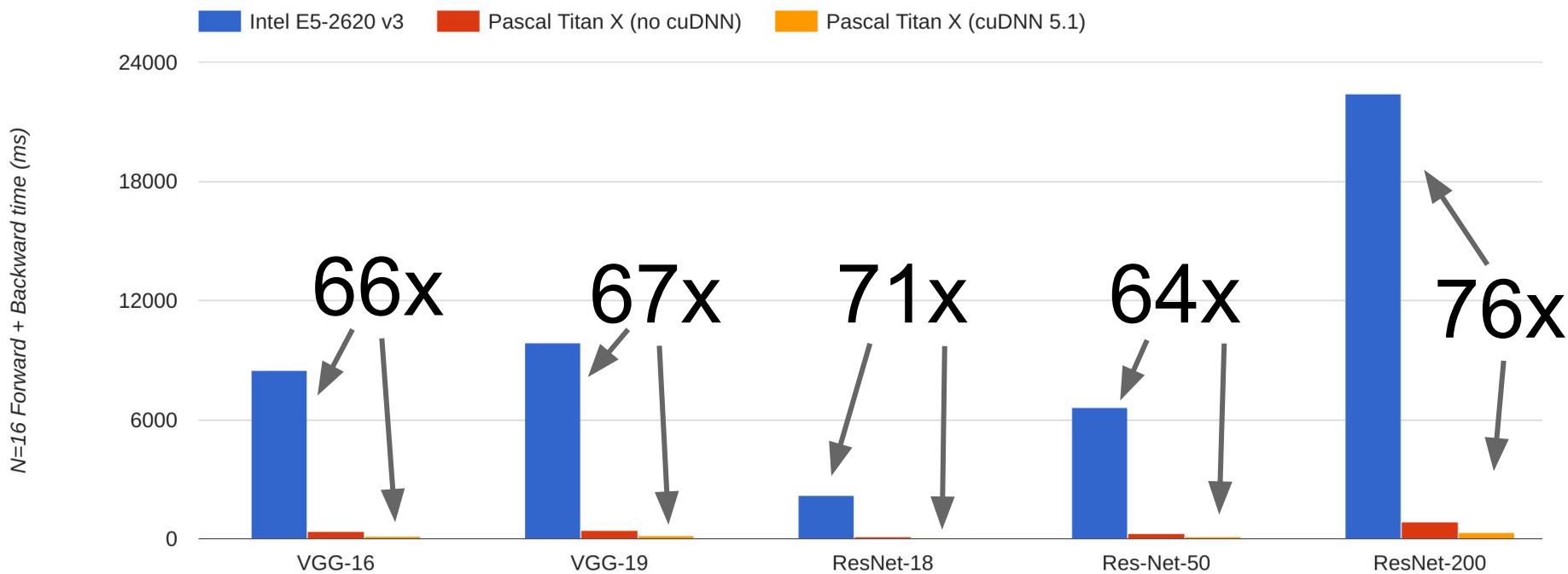
=

$A \times C$



# CPU vs GPU in practice

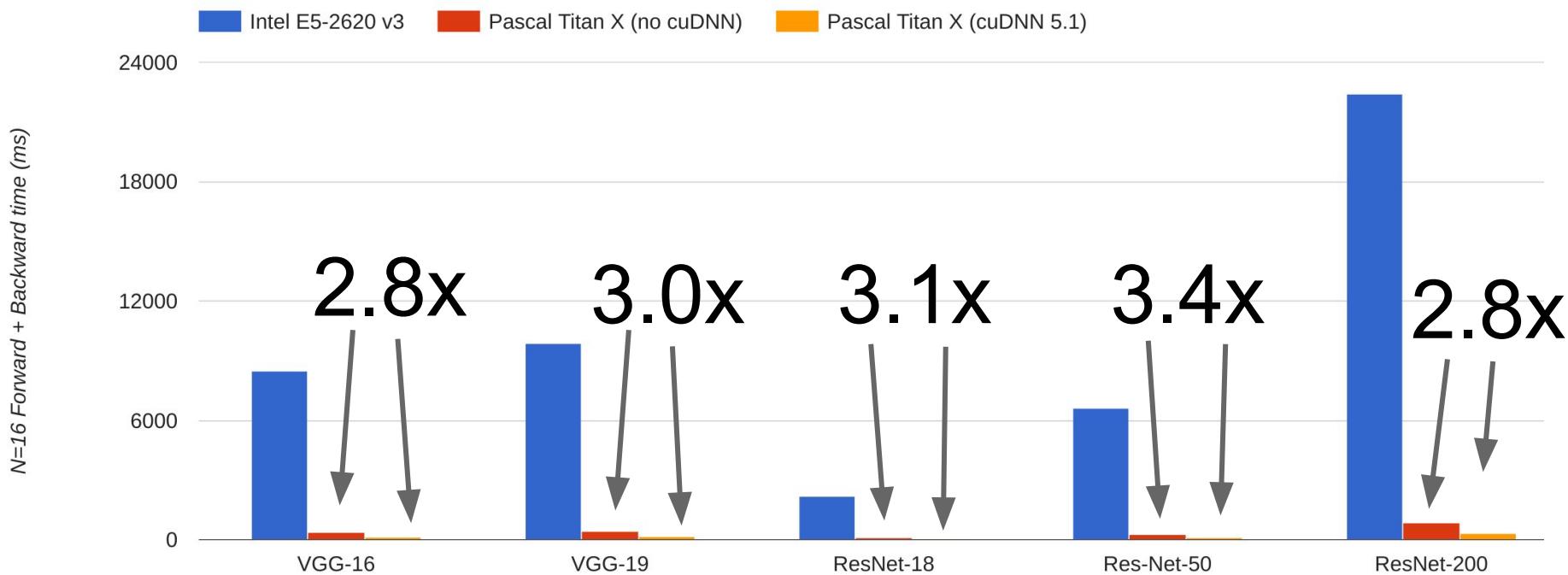
(CPU performance not well-optimized, a little unfair)



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

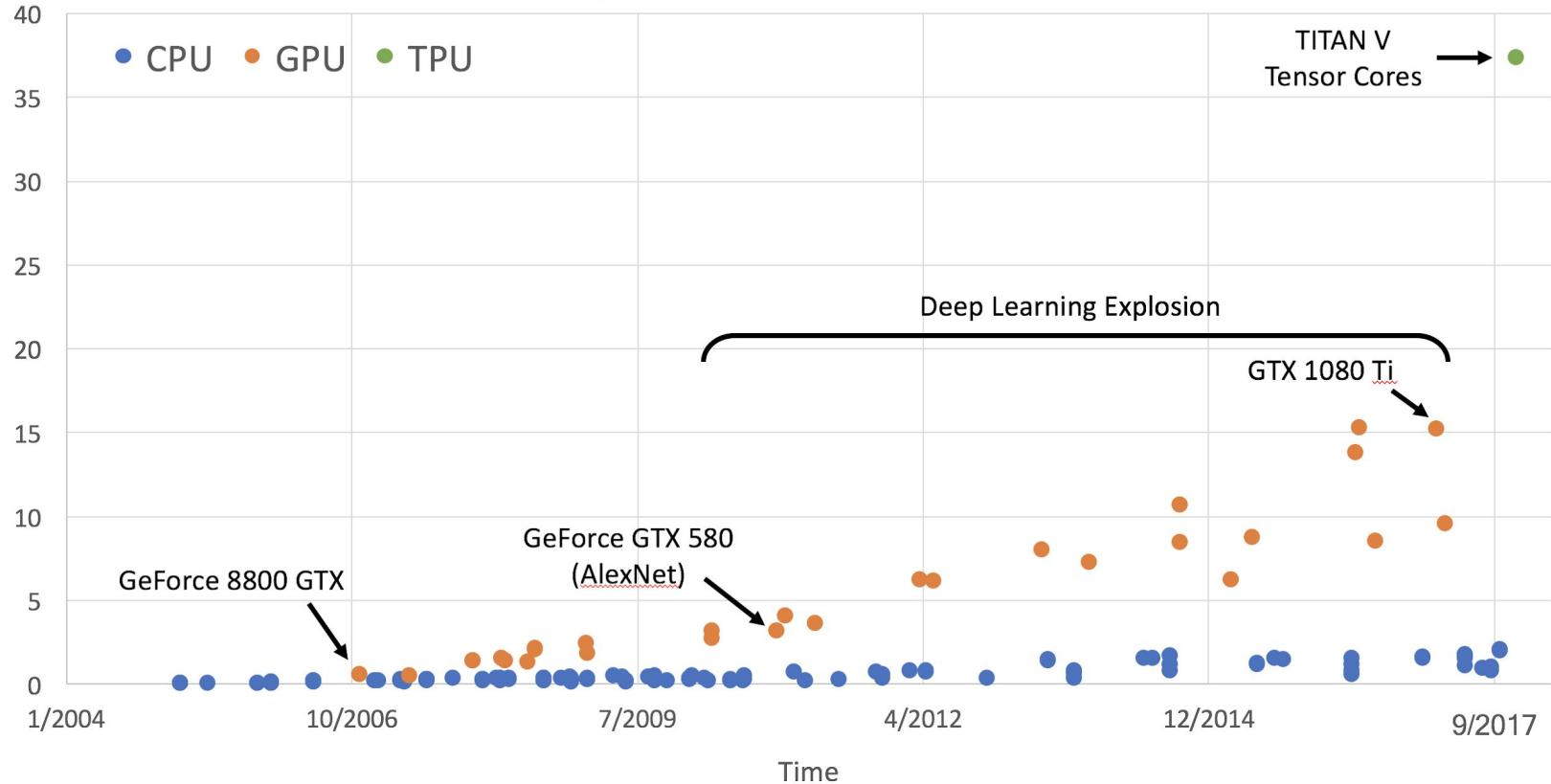
# CPU vs GPU in practice

cuDNN much faster than  
“unoptimized” CUDA



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

# GigaFLOPs per Dollar



NVIDIA      vs      AMD

NVIDIA

vs

AMD

# CPU vs GPU

	Cores	Clock Speed	Memory	Price	Speed
<b>CPU</b> (Intel Core i7-7700k)	4 (8 threads with hyperthreading)	4.2 GHz	System RAM	\$385	~540 GFLOPs FP32
<b>GPU</b> NVIDIA RTX 2080 Ti	3584	1.6 GHz	11 GB GDDR 6	\$1099	~13 TFLOPs FP32 ~114 TFLOPs FP16
<b>GPU</b> <b>(Data Center)</b> NVIDIA V100	5120 CUDA, 640 Tensor	1.5 GHz	16/32 GB HBM2	\$2.5/hr (GCP)	~8 TFLOPs FP64 ~16 TFLOPs FP32 ~125 TFLOPs FP16
<b>TPU</b> Google Cloud TPUv3	2 Matrix Units (MXUs) per core, 4 cores	?	128 GB HBM	\$8/hr (GCP)	~420 TFLOPs (non-standard FP)

**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

**TPU:** Specialized hardware for deep learning

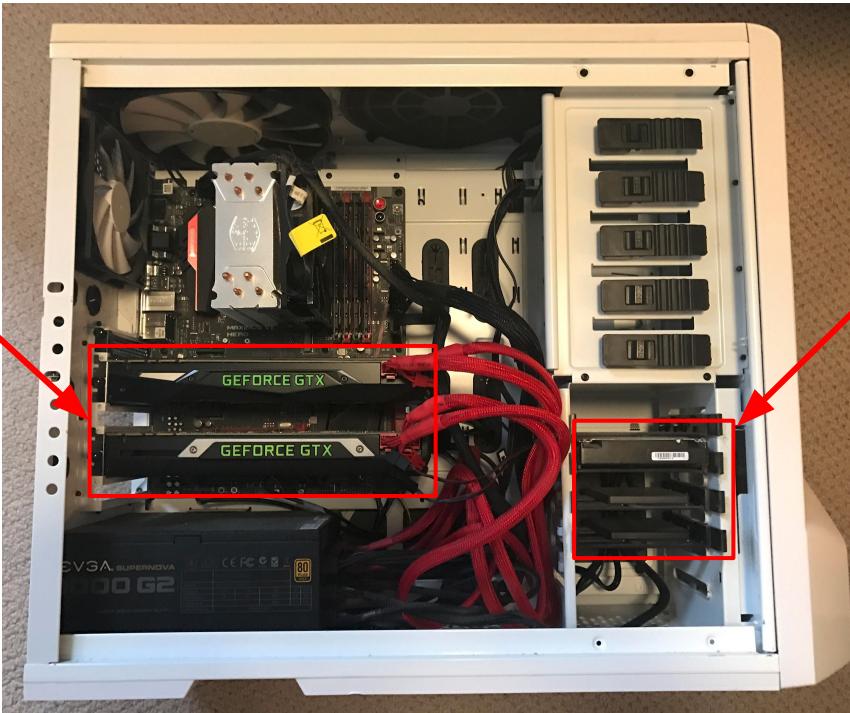
# Programming GPUs

- 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>
  - New project that automatically converts CUDA code to something that can run on AMD GPUs
- Stanford CS 149: <http://cs149.stanford.edu/fall19/>

# CPU / GPU Communication

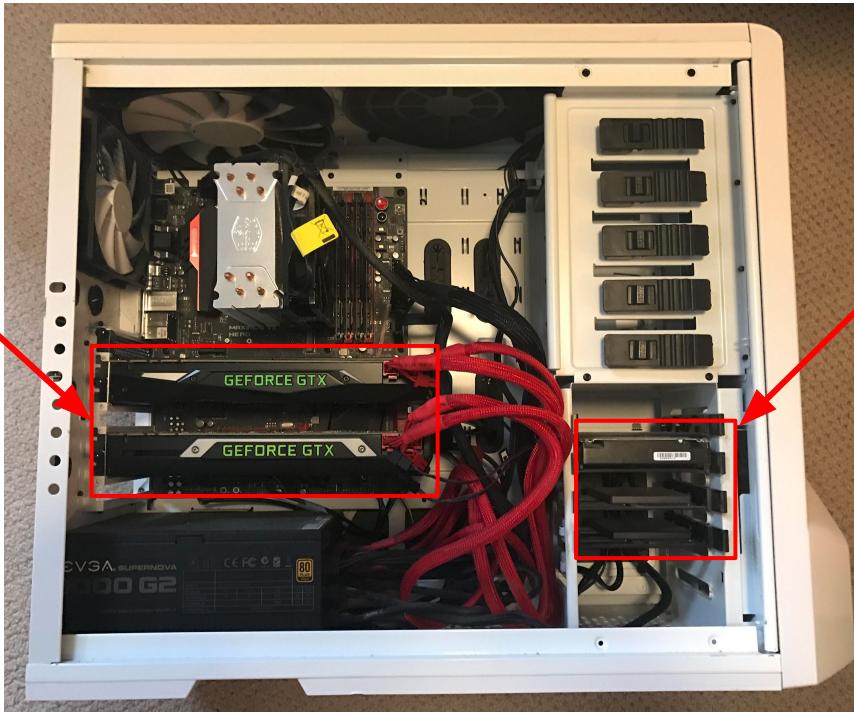
Model  
is here

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!

Caffe  
(UC Berkeley)



Caffe2  
(Facebook)  
mostly features absorbed  
by PyTorch

Torch  
(NYU / Facebook)



PyTorch  
(Facebook)

Theano  
(U Montreal)



TensorFlow  
(Google)

PaddlePaddle  
(Baidu)

Chainer  
(Preferred Networks)  
The company has officially migrated its research  
infrastructure to PyTorch

CNTK  
(Microsoft)

MXNet  
(Amazon)

Developed by U Washington, CMU, MIT,  
Hong Kong U, etc main framework of  
choice at AWS

JAX  
(Google)

And others...

# A zoo of frameworks!

Caffe  
(UC Berkeley)



Caffe2  
(Facebook)  
mostly features absorbed  
by PyTorch

Torch  
(NYU / Facebook)



PyTorch  
(Facebook)

Theano  
(U Montreal)



TensorFlow  
(Google)

We'll focus on these

PaddlePaddle  
(Baidu)

Chainer  
(Preferred Networks)  
The company has officially migrated its research  
infrastructure to PyTorch

MXNet  
(Amazon)

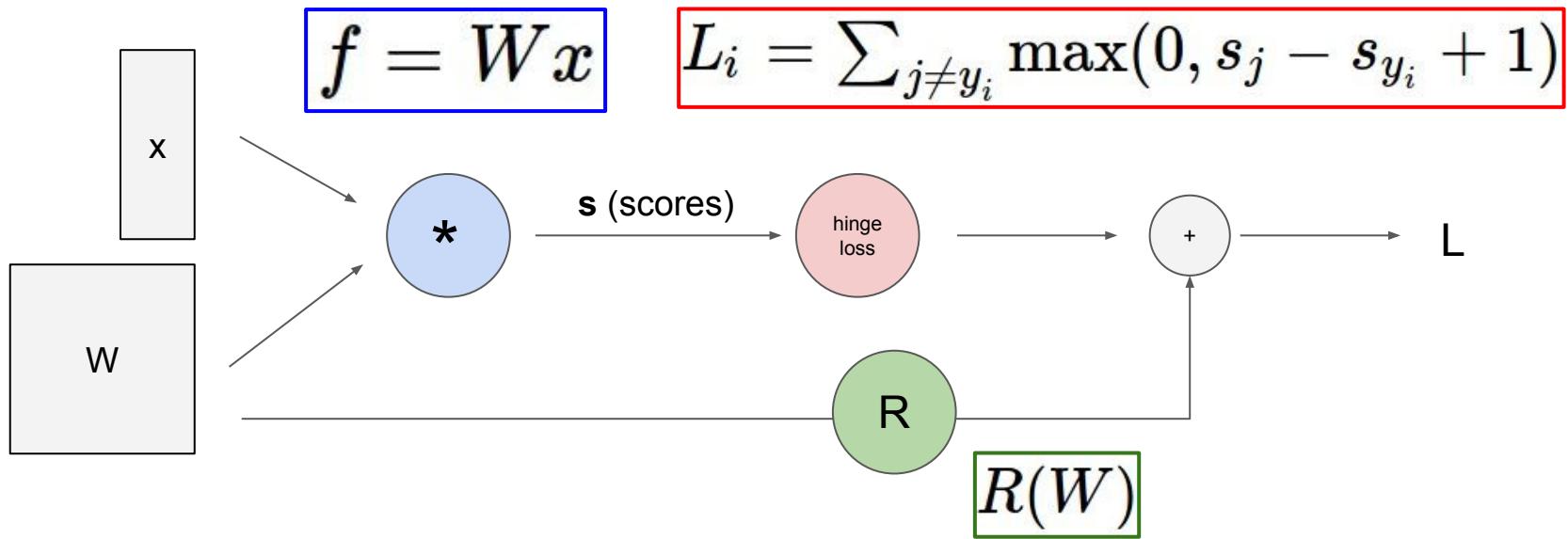
Developed by U Washington, CMU, MIT,  
Hong Kong U, etc but main framework of  
choice at AWS

CNTK  
(Microsoft)

JAX  
(Google)

And others...

# Recall: Computational Graphs



# Recall: Computational Graphs

input image

weights

loss

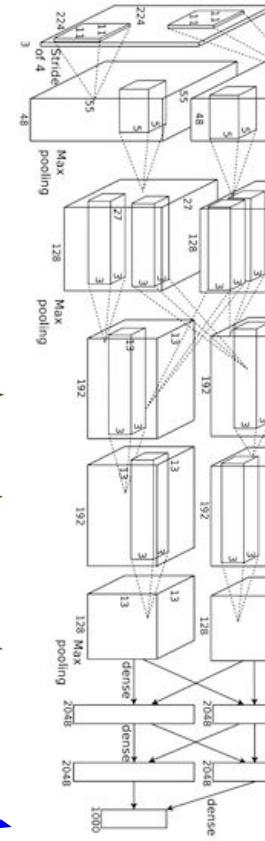


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

# Recall: Computational Graphs

input image

loss

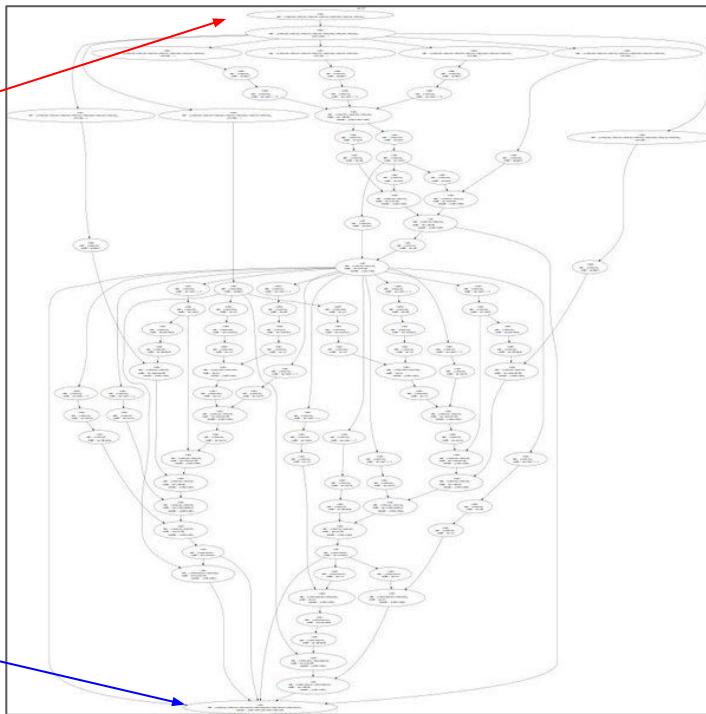


Figure reproduced with permission from a [Twitter post](#) by Andrej Karpathy.

# The point of deep learning frameworks

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

# Computational Graphs

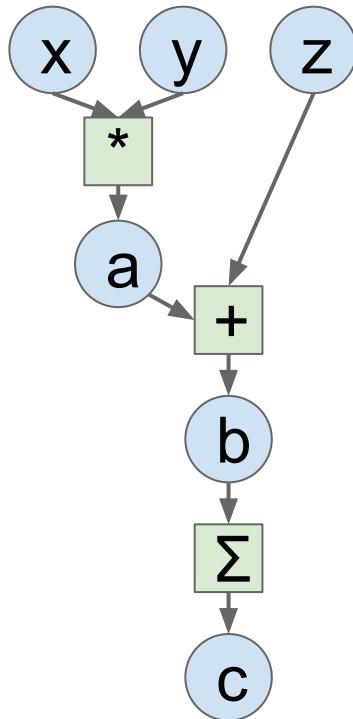
## Numpy

```
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

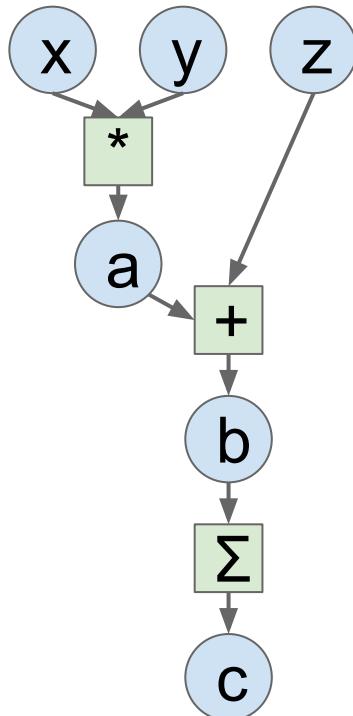
```
import numpy as np
np.random.seed(0)

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

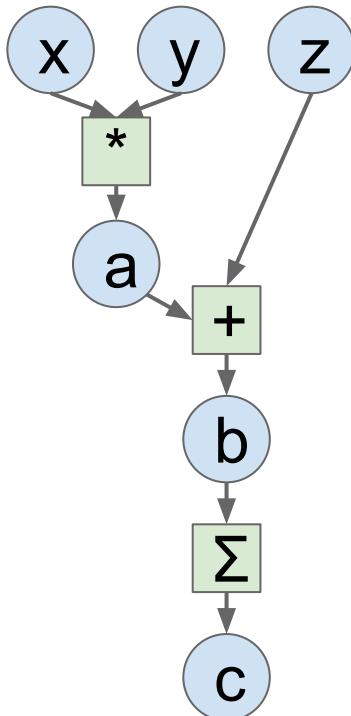
```
import numpy as np
np.random.seed(0)

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

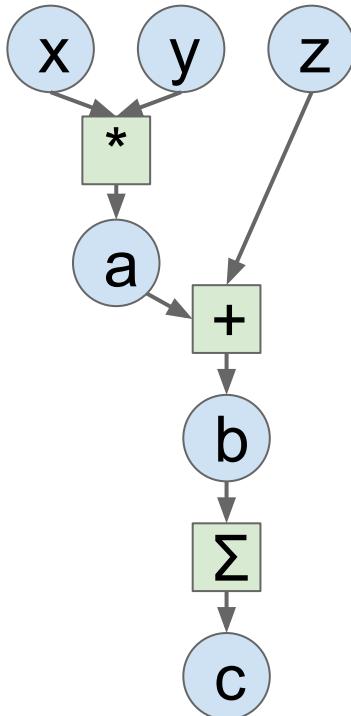
```
import numpy as np
np.random.seed(0)

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

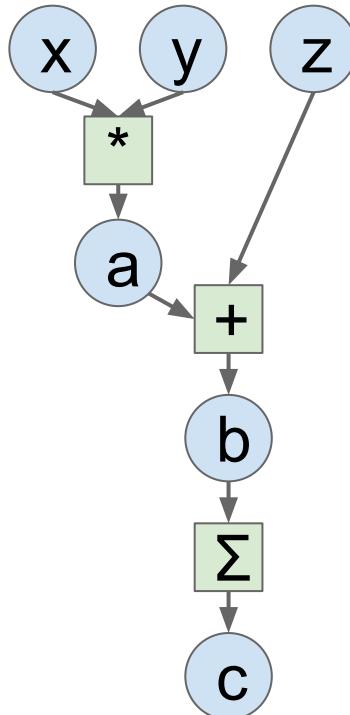
```
import numpy as np
np.random.seed(0)

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

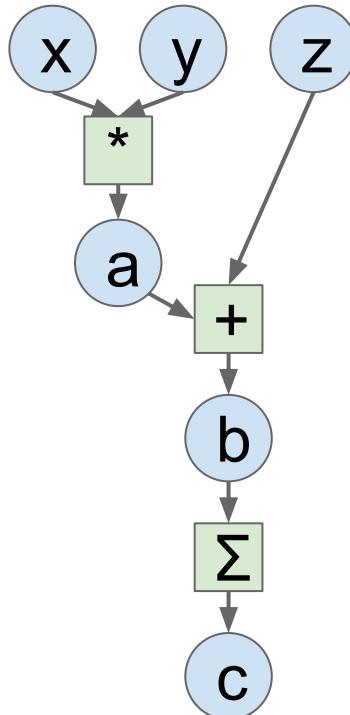
```
import numpy as np
np.random.seed(0)

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 details)

# 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 we are using **PyTorch version 1.4**  
(Released January 2020)

Major API change in release 1.0

Be careful if you are looking at older PyTorch code (<1.0)!

# 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

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

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

```
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: 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

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

```
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()
```

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: Pretrained Models

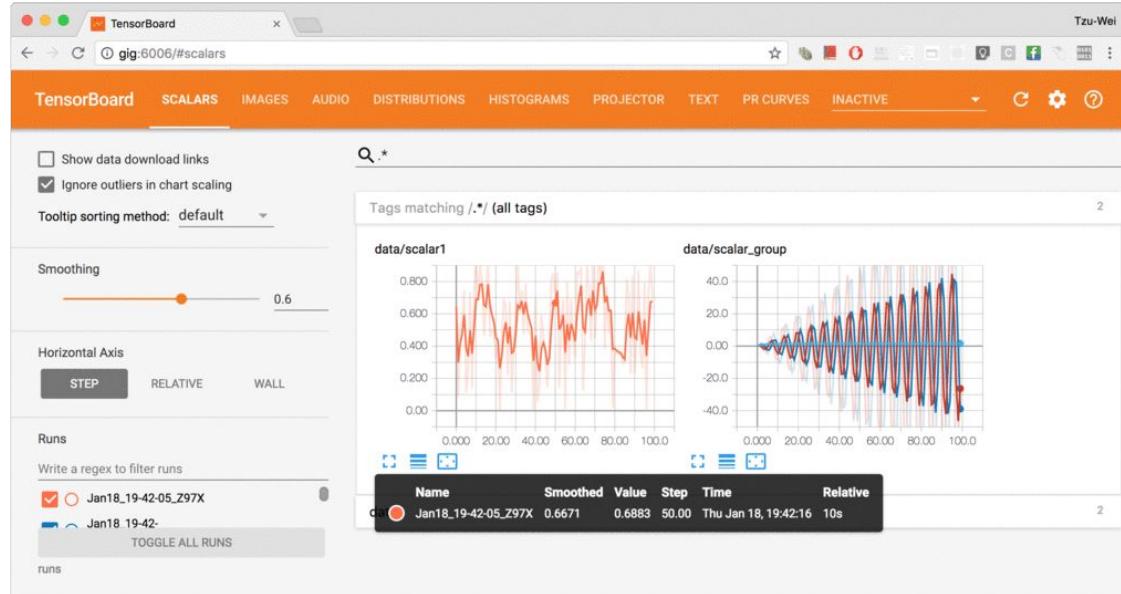
Super easy to use pretrained models with torchvision  
<https://github.com/pytorch/vision>

```
import torch
import torchvision

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

# PyTorch: torch.utils.tensorboard

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



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# PyTorch: Computational Graphs

input image

loss

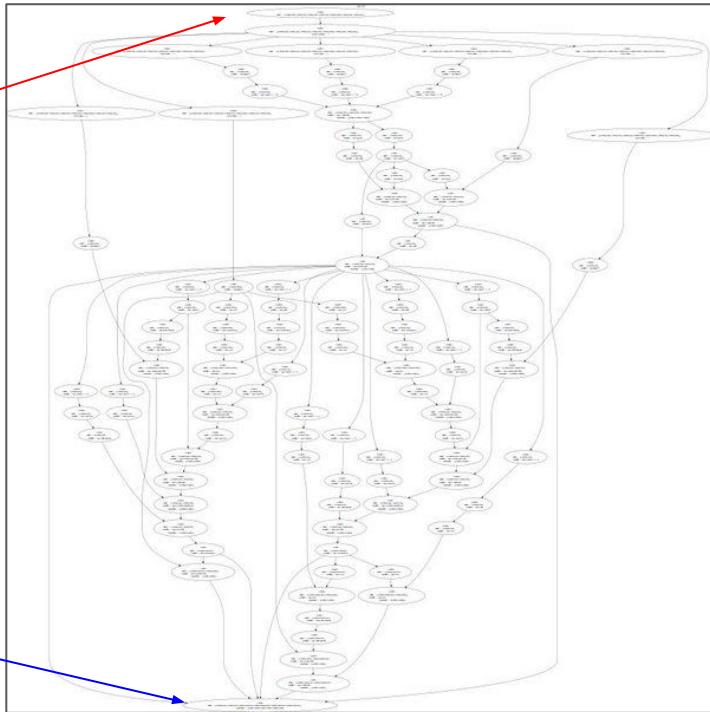


Figure reproduced with permission from a [Twitter post](#) by Andrej Karpathy.

# 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

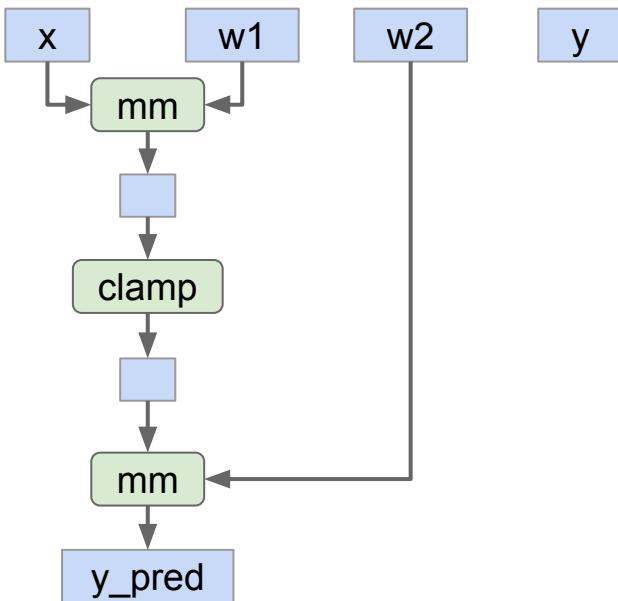
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

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

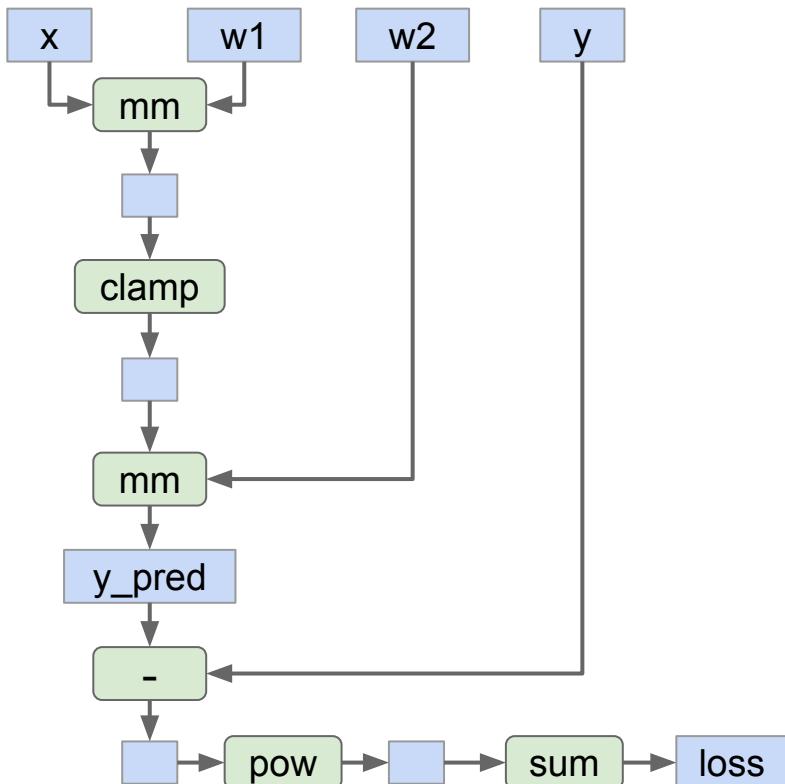
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

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

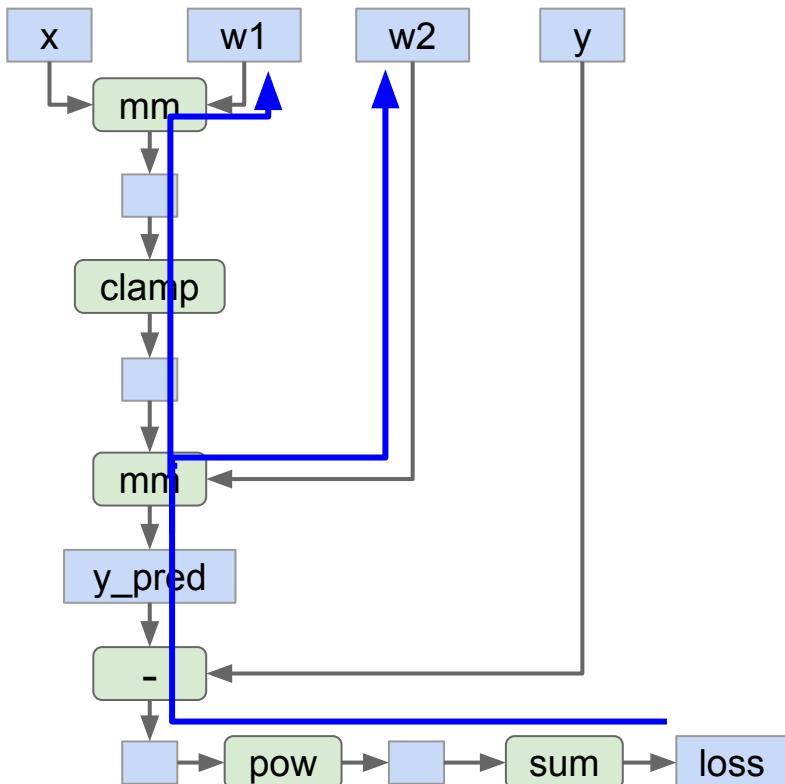
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

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

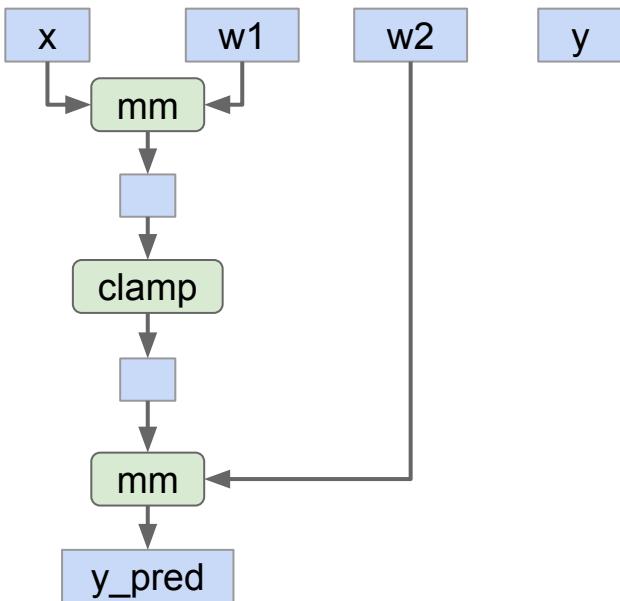
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

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

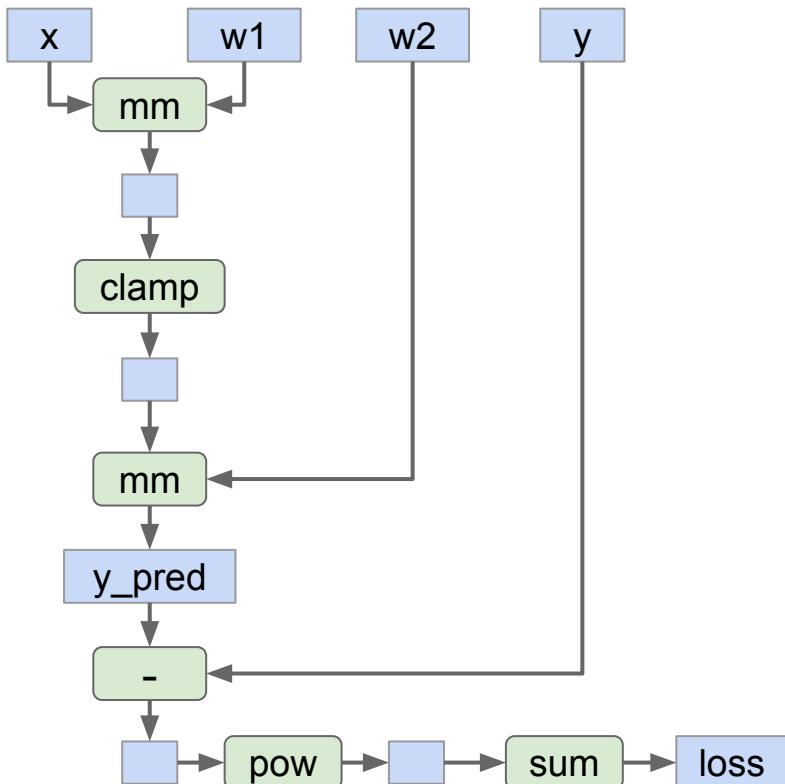
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

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

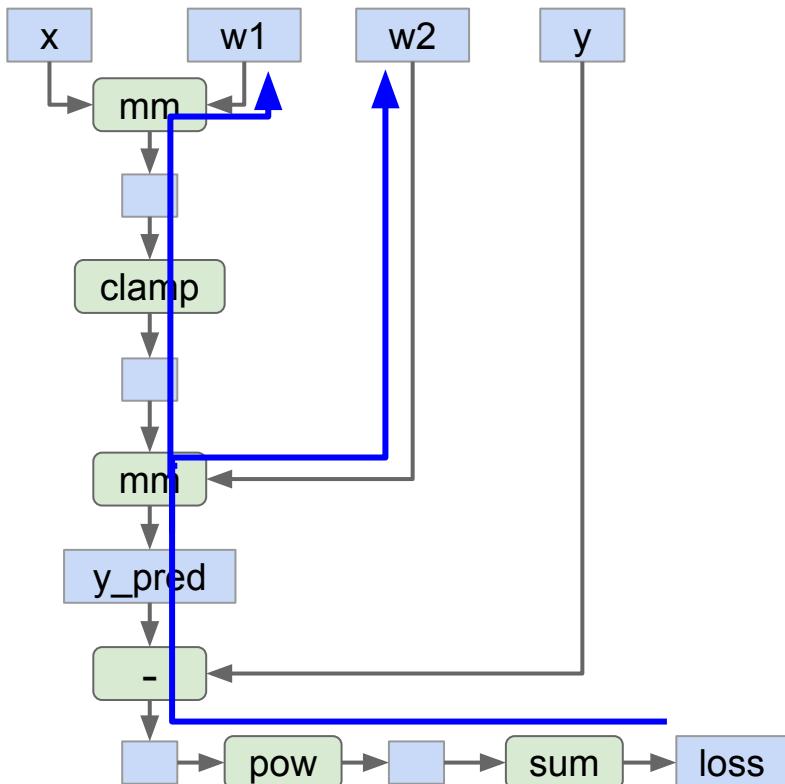
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

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()
```

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

# 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

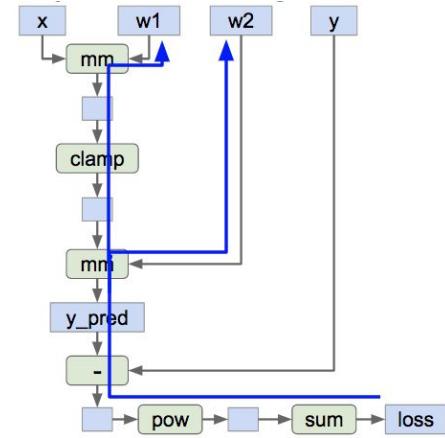
Alternative: **Static** graphs

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 (1.14 latest)

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

**2.1 (March 2020)**

**Default dynamic graph,**  
optionally static graph.  
**We use 2.1 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 1.13

# 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

```
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 1.13

# 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]).
```

Tensorflow 2.0+:  
“Eager” Mode by default

```
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 1.13

# 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]).
```

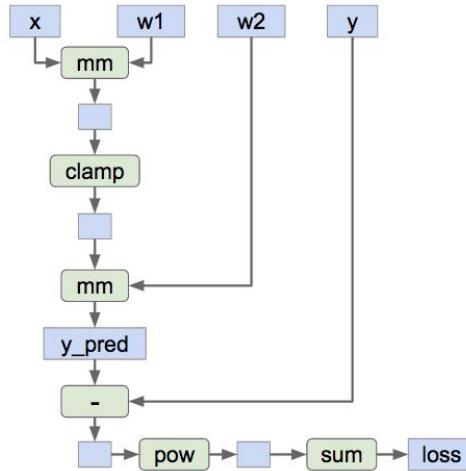
# TensorFlow: Neural Net

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

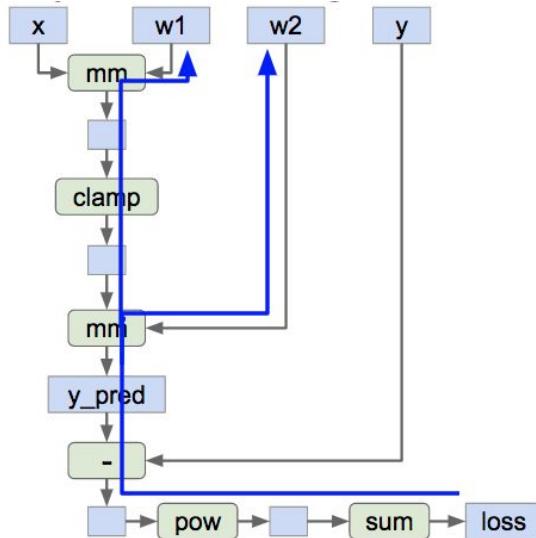
with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
gradients = tape.gradient(loss, [w1, w2]).
```

# 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



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

```
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))
gradientes = tape.gradient(loss, [w1, w2])
```

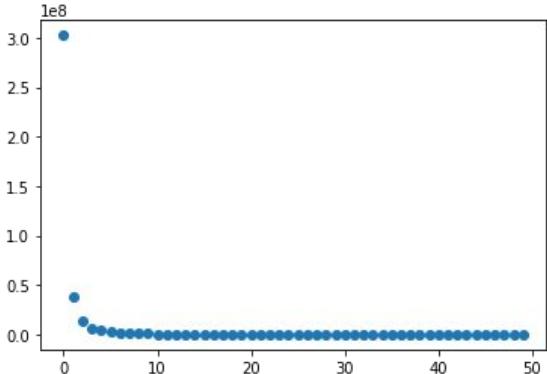
# TensorFlow: Neural Net

```
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 training step 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](https://www.tensorflow.org/api_docs/python/tf/keras))

tf.estimator ([https://www.tensorflow.org/api\\_docs/python/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

Ran on Google Colab, April 2020

```
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)

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

dynamic graph:  0.02520249200000535
static graph:  0.03932226699998864
```

# @tf.function: compile static graph

Ran on Google Colab, April 2020

```
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
```

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

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

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

dynamic graph:  0.02520249200000535
static graph:  0.03932226699998864
```

# @tf.function: compile static graph

Ran on Google Colab, April 2020

```
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
```

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

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

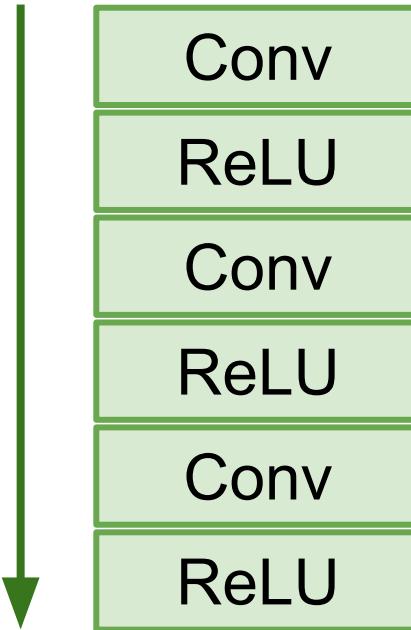
print("dynamic graph:", timeit.timeit(lambda: model_dynamic(x, y), number=1000))
print("static graph:", timeit.timeit(lambda: model_static(x, y), number=1000))

dynamic graph: 2.3648411540000325
static graph: 1.1723986679999143
```

# 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 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: 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: TorchScript

```
graph(%self.1 :  
      __torch__.torch.nn.modules.module.__torch_mangl  
e_4.Module,  
      %input : Float(3, 4),  
      %h : Float(3, 4)):  
  %19 :  
    __torch__.torch.nn.modules.module.__torch_mangl  
e_3.Module =  
    prim::GetAttr[name="linear"](%self.1)  
    %21 : Tensor =  
    prim::CallMethod[name="forward"](%19, %input)  
    %12 : int = prim::Constant[value=1] () #  
<ipython-input-40-26946221023e>:7:0  
    %13 : Float(3, 4) = aten::add(%21, %h, %12) #  
<ipython-input-40-26946221023e>:7:0  
    %14 : Float(3, 4) = aten::tanh(%13) #  
<ipython-input-40-26946221023e>:7:0  
    %15 : (Float(3, 4), Float(3, 4)) =  
    prim::TupleConstruct(%14, %14)  
    return (%15)
```

```
class MyCell(torch.nn.Module):  
    def __init__(self):  
        super(MyCell, self).__init__()  
        self.linear = torch.nn.Linear(4, 4)  
  
    def forward(self, x, h):  
        new_h = torch.tanh(self.linear(x) + h)  
        return new_h, new_h  
  
my_cell = MyCell()  
x, h = torch.rand(3, 4), torch.rand(3, 4)  
traced_cell = torch.jit.trace(my_cell, (x, h))  
print(traced_cell.graph)  
traced_cell(x, h)
```

Build static graph with `torch.jit.trace`

# PyTorch vs TensorFlow, Static vs Dynamic

## PyTorch

Dynamic Graphs

Static: ONNX,

Caffe2, TorchScript

## TensorFlow

Dynamic: Eager

Static: `@tf.function`

# Static vs Dynamic: Serialization

## Static

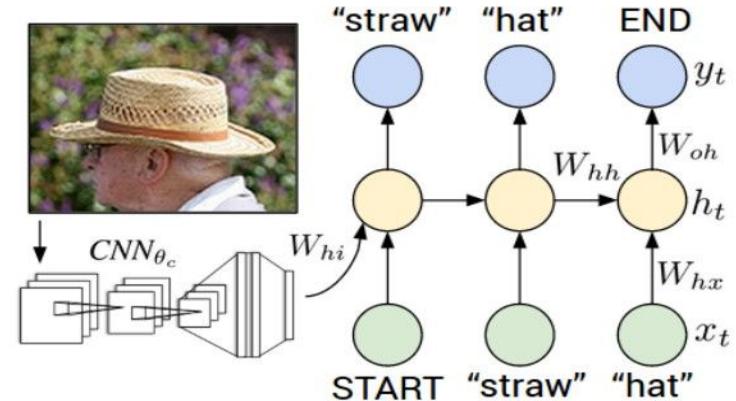
Once graph is built, can **serialize** it and run it without the code that built the graph!

## Dynamic

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

# Dynamic Graph Applications

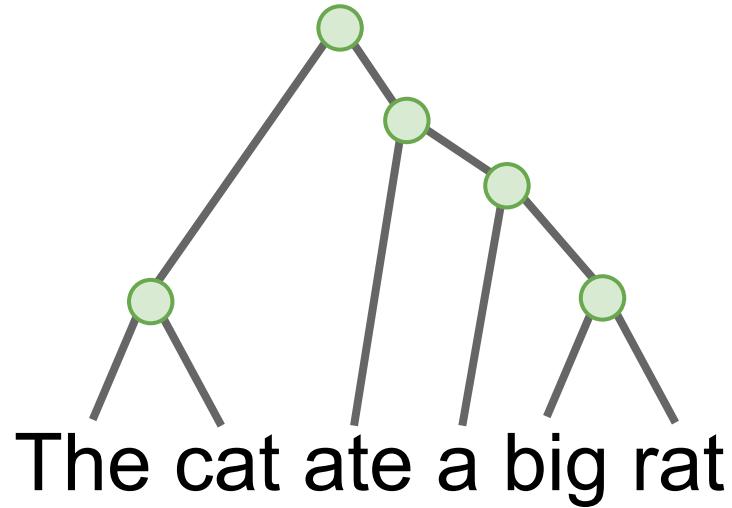
- Recurrent networks



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

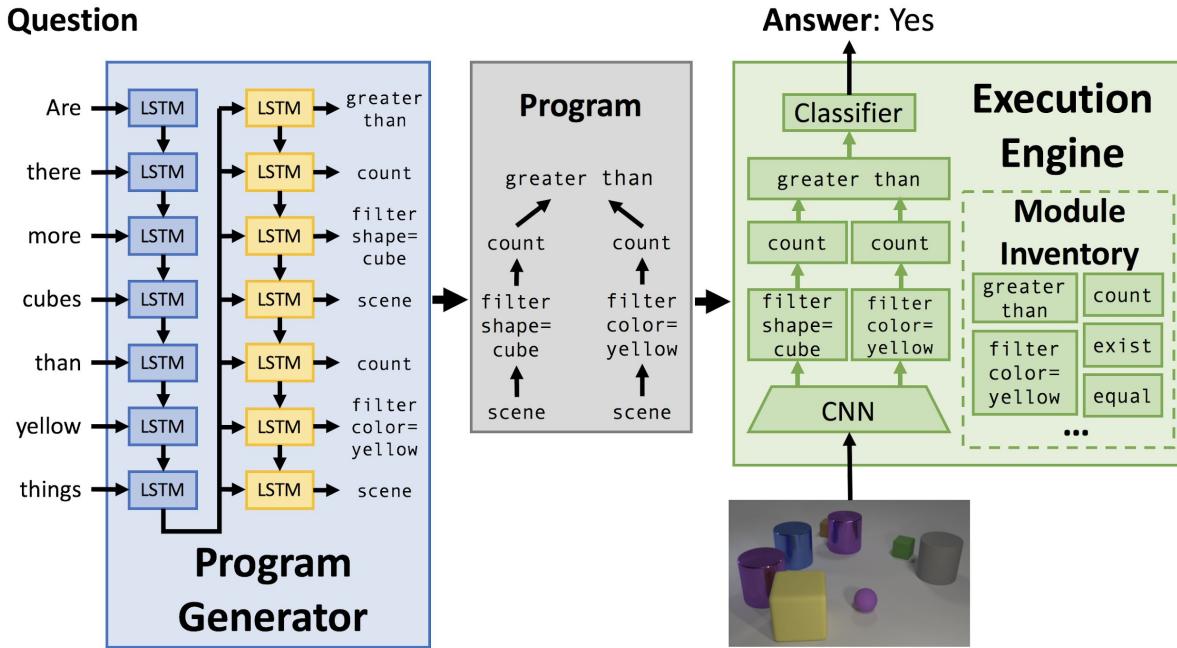
# Dynamic Graph Applications

- Recurrent networks
- Recursive networks



# Dynamic Graph Applications

- Recurrent networks
- Recursive networks
- Modular networks



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

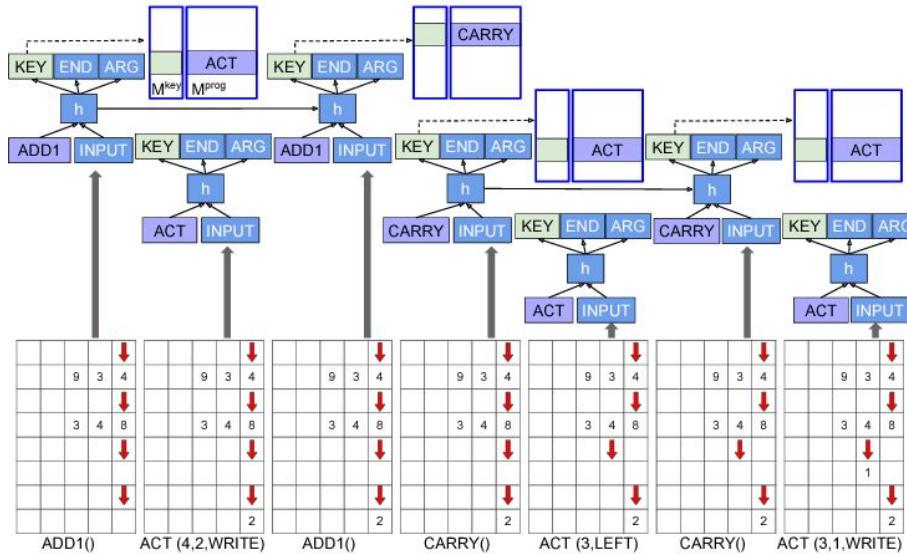
Andreas et al, "Learning to Compose Neural Networks for Question Answering", NAACL 2016

Johnson et al, "Inferring and Executing Programs for Visual Reasoning", ICCV 2017

Figure copyright Justin Johnson, 2017. Reproduced with permission.

# Dynamic Graph Applications

- Recurrent networks
- Recursive networks
- Modular networks
- Neural programs



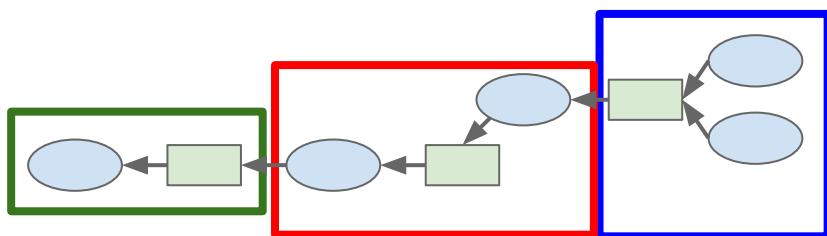
Reed et al., "Neural Programmer-Interpreters", ICLR 2016

# Dynamic Graph Applications

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

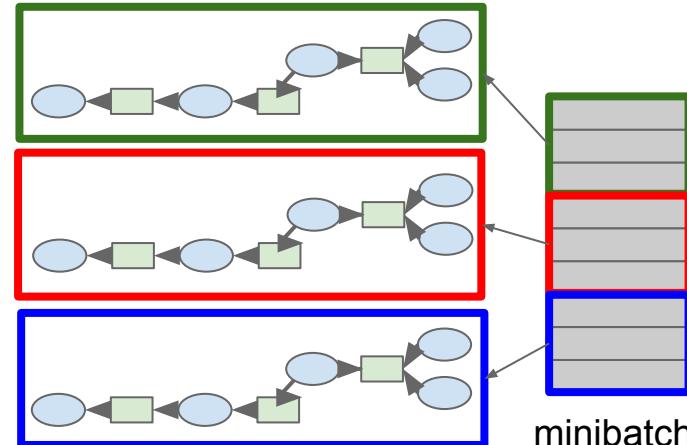
# Model Parallel vs. Data Parallel

Model parallel: split computation graph into parts & distribute to GPUs/ nodes



Model Parallel

Data parallel: split minibatch into chunks & distribute to GPUs/ nodes



Data Parallel

# PyTorch: Data Parallel

`nn.DataParallel`

Pro: Easy to use (just wrap the model and run training script as normal)

Con: Single process & single node. Can be bottlenecked by CPU with large number of GPUs (8+).

`nn.DistributedDataParallel`

Pro: Multi-nodes & multi-process training

Con: Need to hand-designate device and manually launch training script for each process / nodes.

Horovod (<https://github.com/horovod/horovod>): Supports both PyTorch and TensorFlow

<https://pytorch.org/docs/stable/nn.html#dataparallel-layers-multi-gpu-distributed>

# TensorFlow: Data Parallel

`tf.distributed.Strategy`

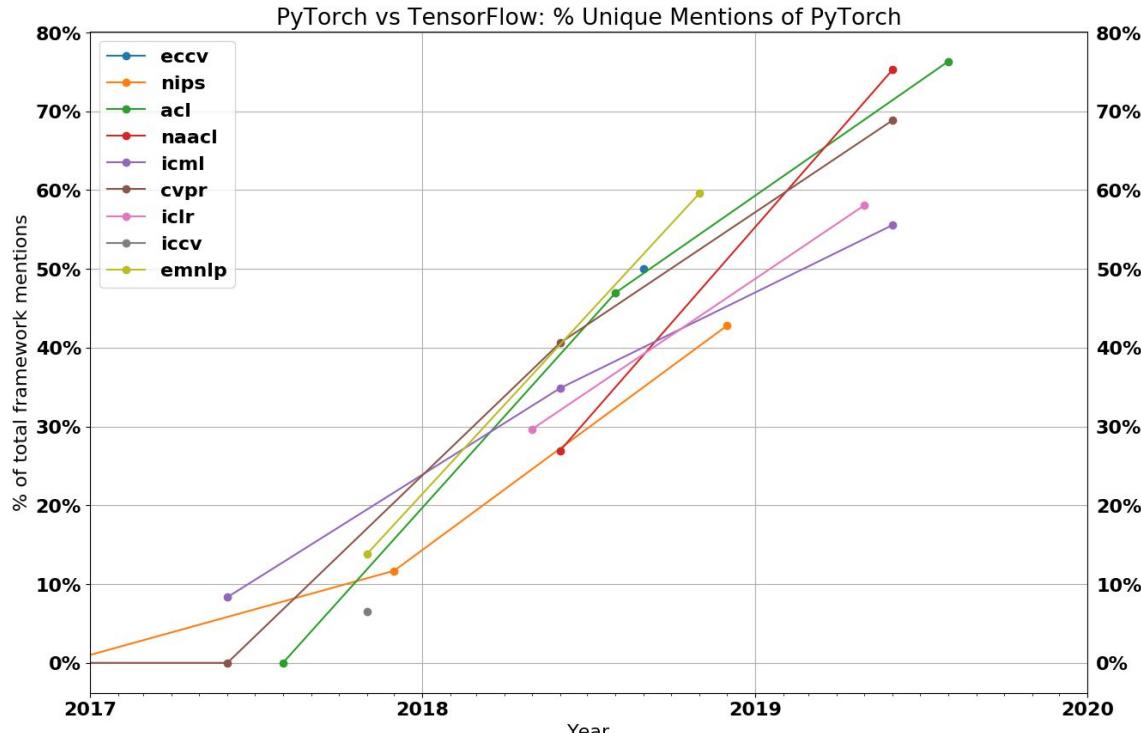
```
strategy = tf.distribute.MirroredStrategy()

with strategy.scope():
    model = tf.keras.Sequential([
        tf.keras.layers.Conv2D(32, 3, activation='relu', input_shape=(28, 28, 1)),
        tf.keras.layers.MaxPooling2D(),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(64, activation='relu'),
        tf.keras.layers.Dense(10)
    ])

    model.compile(loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
                  optimizer=tf.keras.optimizers.Adam(),
                  metrics=['accuracy'])
```

<https://www.tensorflow.org/tutorials/distribute/keras>

# PyTorch vs. TensorFlow: Academia



<https://thegradient.pub/state-of-ml-frameworks-2019-pytorch-dominates-research-tensorflow-dominates-industry/>

# PyTorch vs. TensorFlow: Academia

CONFERENCE	PT 2018	PT 2019	PT GROWTH	TF 2018	TF 2019	TF GROWTH
CVPR	82	280	240%	116	125	7.7%
NAACL	12	66	450%	34	21	-38.2%
ACL	26	103	296%	34	33	-2.9%
ICLR	24	70	192%	54	53	-1.9%
ICML	23	69	200%	40	53	32.5%

<https://thegradient.pub/state-of-ml-frameworks-2019-pytorch-dominates-research-tensorflow-dominates-industry/>

# PyTorch vs. TensorFlow: Industry

- No official survey / study on the comparison.
- A quick search on a job posting website turns up 2389 search results for TensorFlow and 1366 for PyTorch.
- The trend is unclear. Industry is also known to be slower on adopting new frameworks.
- TensorFlow mostly dominates mobile deployment / embedded systems.

# My Advice:

**PyTorch** is my personal favorite. Clean API, native dynamic graphs make it very easy to develop and debug. Can build model using the default API then compile static graph using JIT.

**TensorFlow** is a safe bet for most projects. Syntax became a lot more intuitive after 2.0. Not perfect but has huge community and wide usage. Can use same framework for research and production. Probably use a high-level framework.

# Next Time: Training Neural Networks