Assignment Lecture 3

Convolutional Neural Networks

Transfer Learning

Deep learning frameworks

Neural Networks on GPU

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Practical

- Assignment 1 grades are out!

- Additional lab hour tomorrow 14-16
- Group sign up sheet is up!

Deep Learning Hardware

CPU, GPU, TPU

Computer Hardware

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We have two hardware choices:

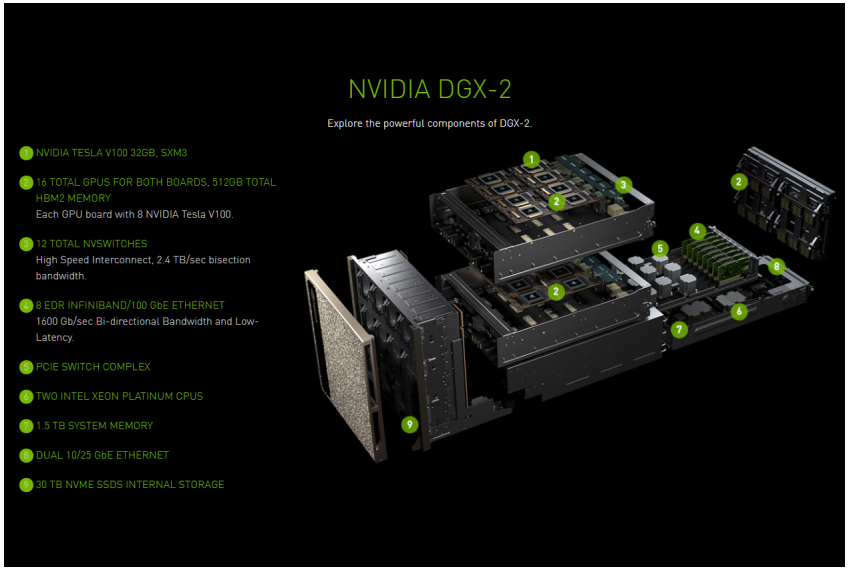
- NVIDIA GPU
- Google Tensor Processing Unit (TPU)

- AMD? Really not used.

Nvidia Country

Tesla V100

IDI HPC newest arrival



GPU vs CPU

	Cores	Clock Speed	Memory	Price	Speed
CPU (Intel Core i7-7700k)	4 (8 threads with hyperthreading)	4.2 GHz	System RAM	$339	~540 GFLOPs FP32
GPU (NVIDIA GTX 1080 Ti)	3584	1.6 GHz	11 GB GDDR5 X	$699	~11.4 TFLOPs FP32

GPU: thousands of “dumb” cores: Great for parallel tasks

Neural Networks: “Only” matrix multiplication, easy in parallel

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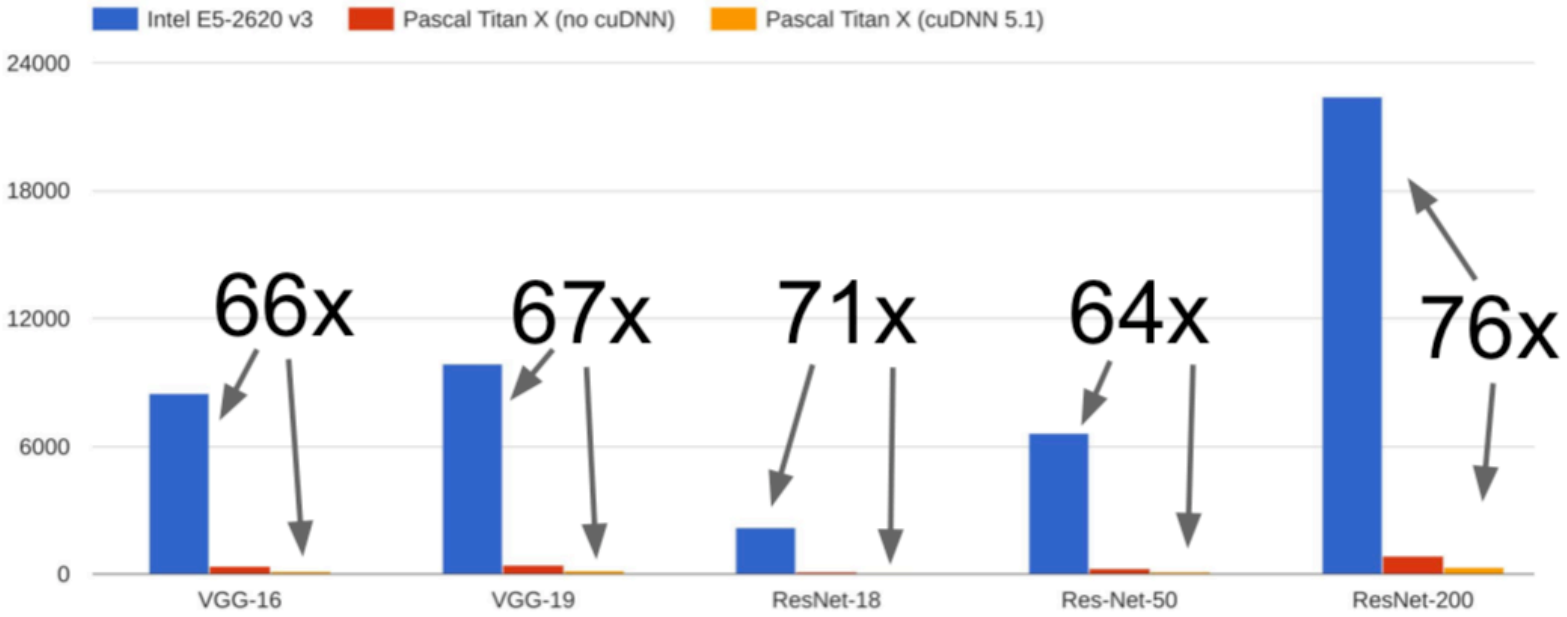
GPU vs CPU for CNNs



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GPU vs CPU: ResNet-200

- Forward pass:
  - Pascal Titan X: 104ms
  - CPU: Dual Xeon E5-2630 v3: 8,666ms (83x slower)
- Backward pass:
  - Pascal Titan X: 191 ms
  - CPU: Dual Xeon E5-2630 v3: 13,758 ms (72x slower)

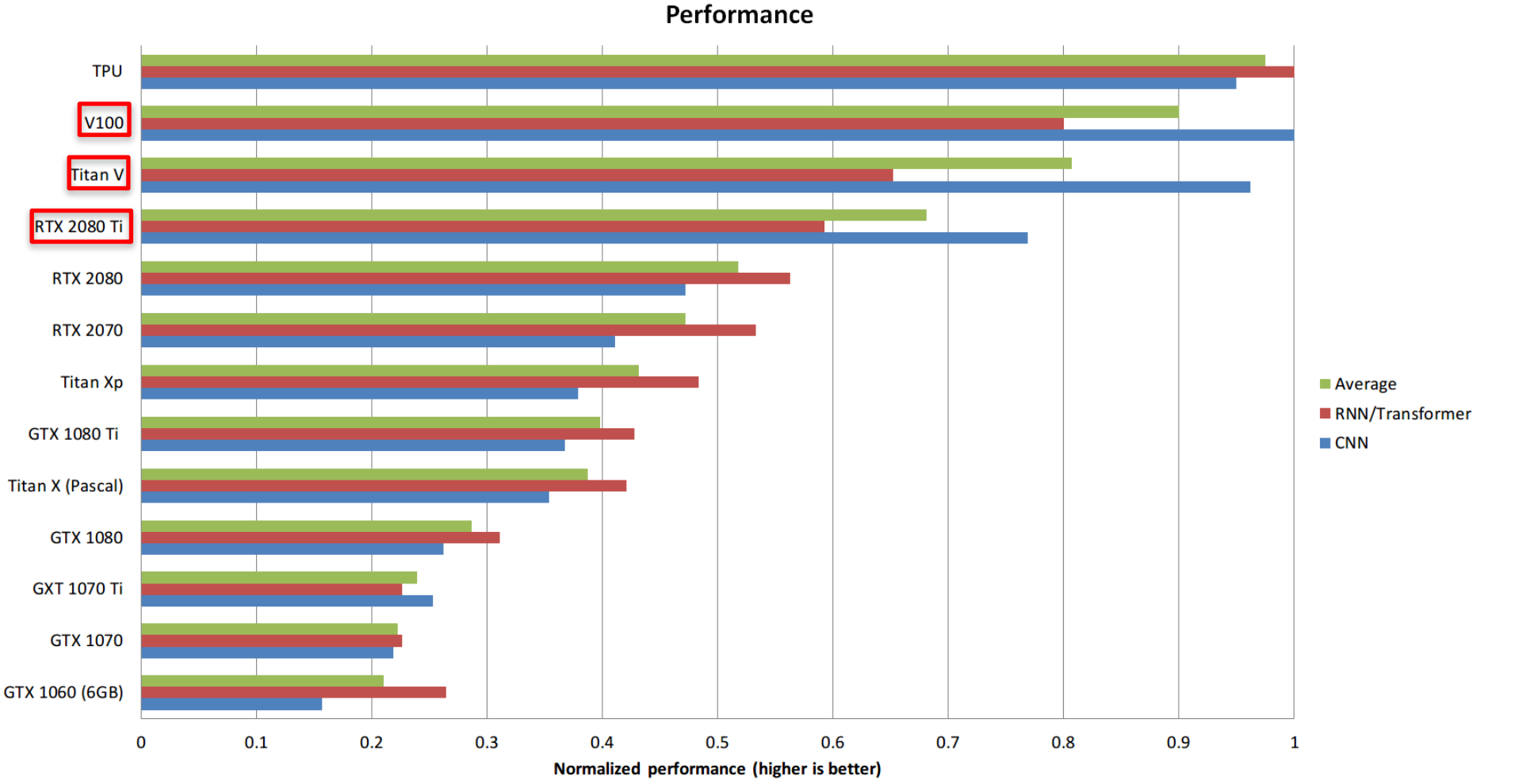
New in GPU hardware

- CUDA cores
  - General parallelization cores in GPU
- **Tensor cores:**
  - Cores specialized for neural networks

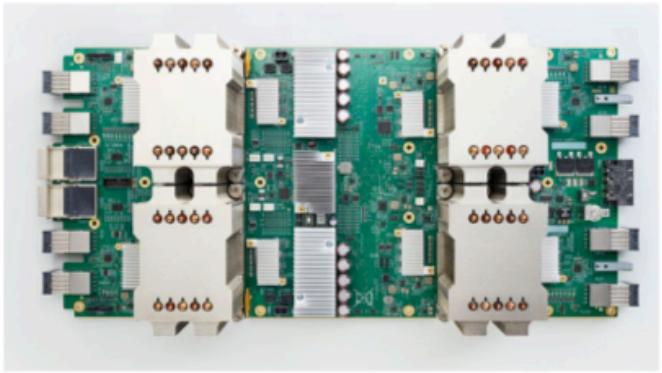
Pascal Architecture

Volta Architecture

NTNU


Performance
TPU
V100
Titan V
RTX 2080 Ti
RTX 2080
RTX 2070
Titan Xp
GTX 1080 Ti
Titan X (Pascal)
GTX 1080
GXT 1070 Ti
GTX 1070
GTX 1060 (6GB)
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Normalized performance (higher is better)
Average
RNN/Transformer
CNN

Tensor Processing Units (TPU)



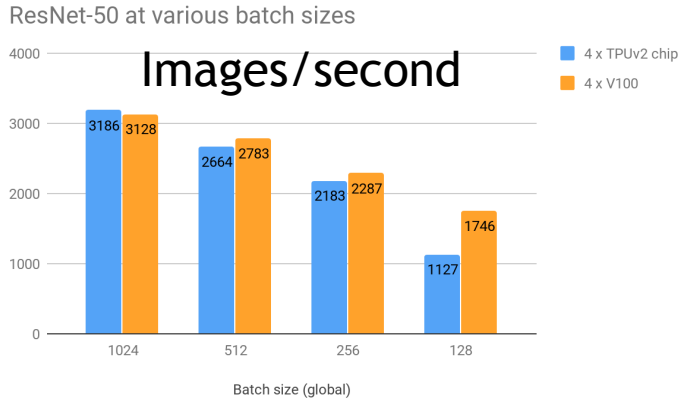
Google Cloud TPU
= 180 TFLOPs of compute!

NVIDIA Tesla V100
= 125 TFLOPs of compute

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

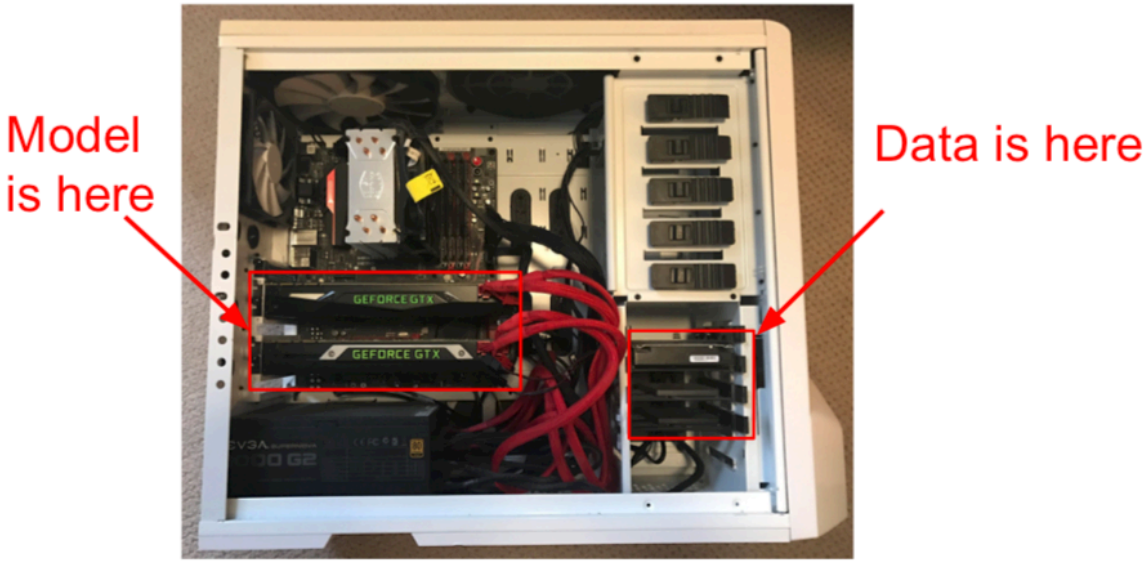
Tensor Processing Units (TPU)

- Special made for neural networks
- Produced by Google
- Not possible to buy, only rent on GCP!



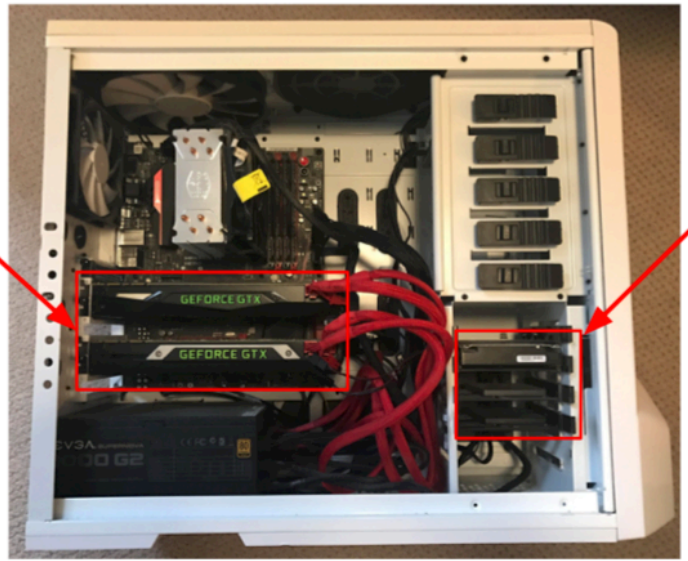
Source: HPC Wire

Issue: CPU <-> GPU Communication



Justin Johnson's Computer!

Issue: CPU <-> GPU Communication



Transferring/reading data can bottleneck your GPU

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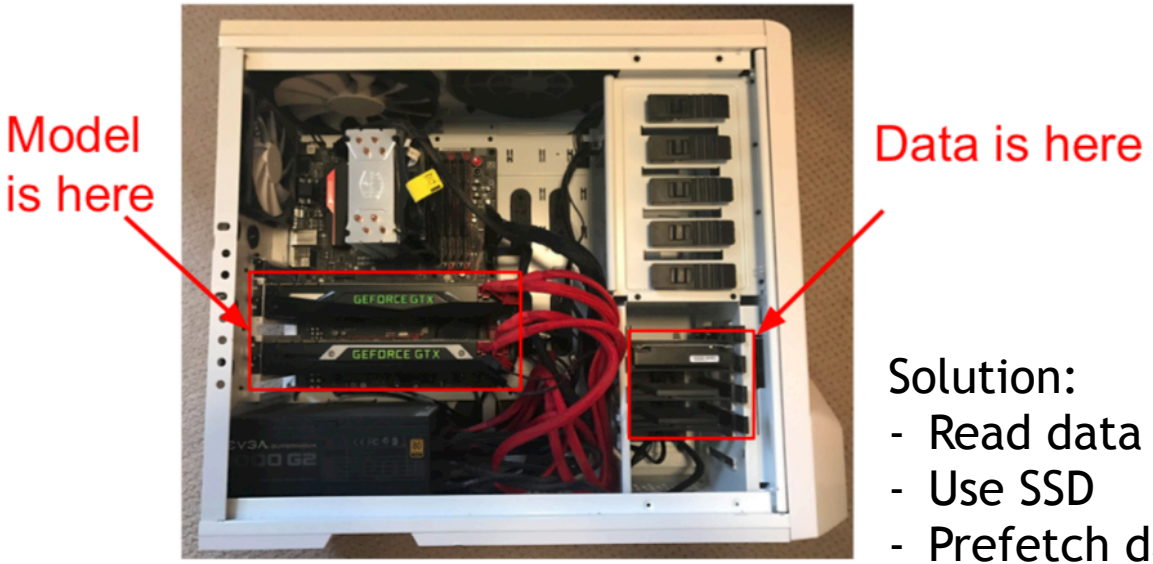
Issue: CPU <-> GPU Communication

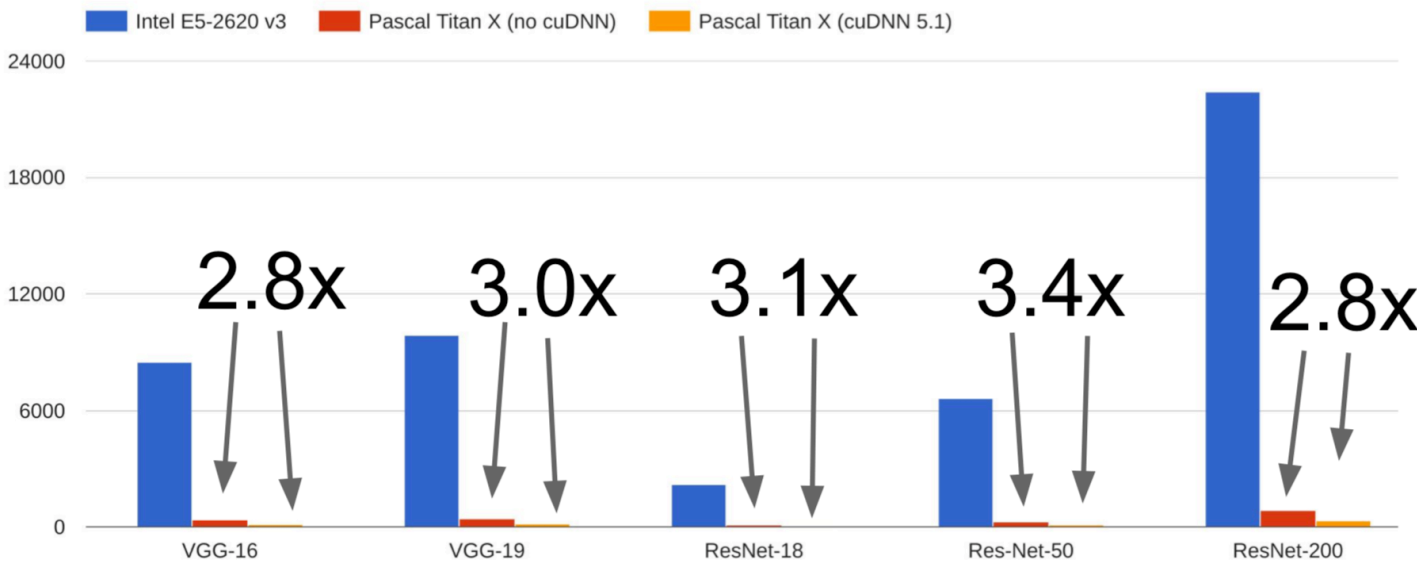


Solution:
- Read data into RAM
- Use SSD
- Prefetch data with threads
- Minimize GPU<->CPU communication

Deep Learning Software

Deep Learning Software

- Deep learning software runs on (NVIDIA):
  - CUDA
  - cudNN



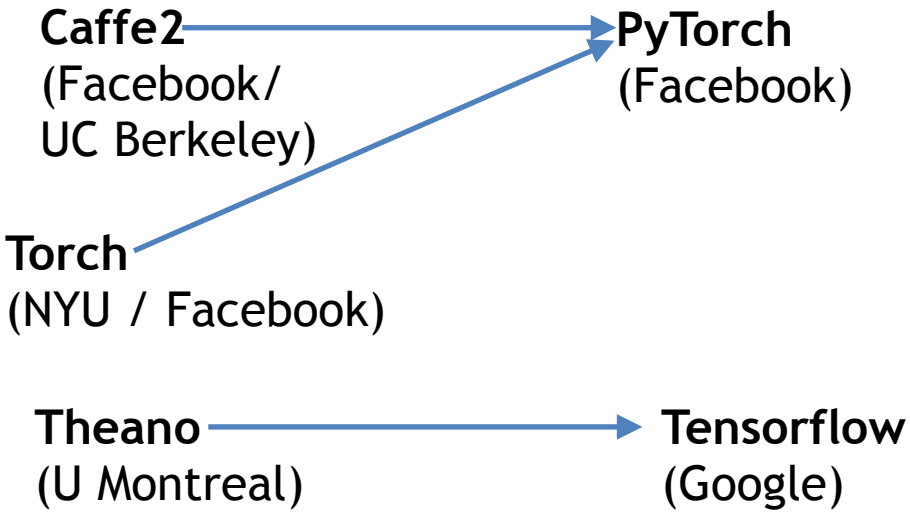
Frameworks

Caffe2
(Facebook/
UC Berkeley)

Torch
(NYU / Facebook)

Theano
(U Montreal)

Frameworks


Caffe2
(Facebook/
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PyTorch
(Facebook)
Torch
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Theano
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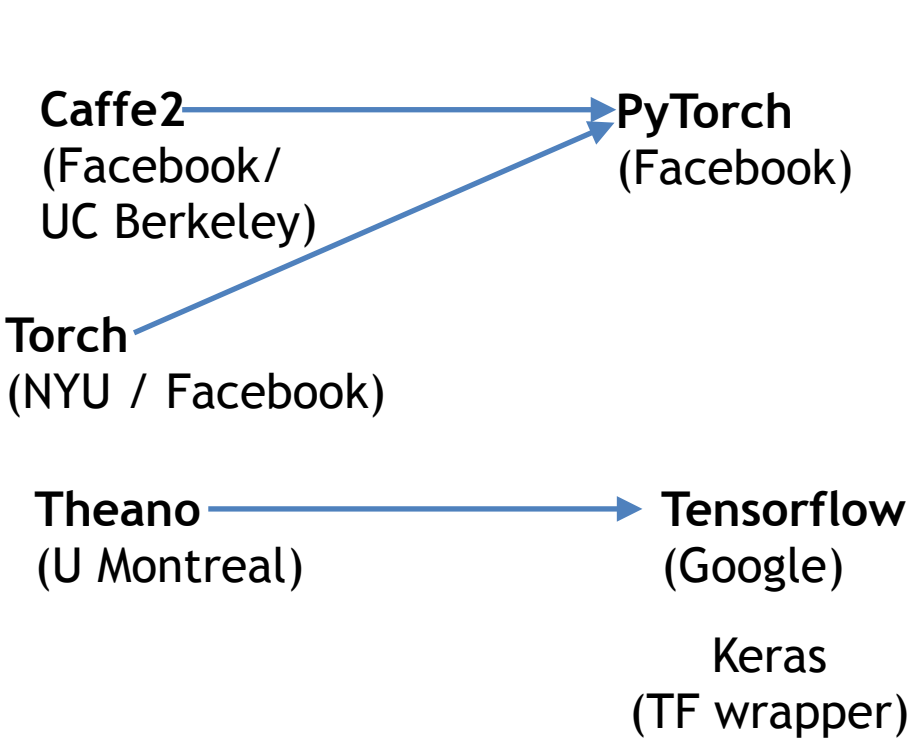
Tensorflow
(Google)

Frameworks



Less popular stuff

PaddlePaddle
(Baidu)

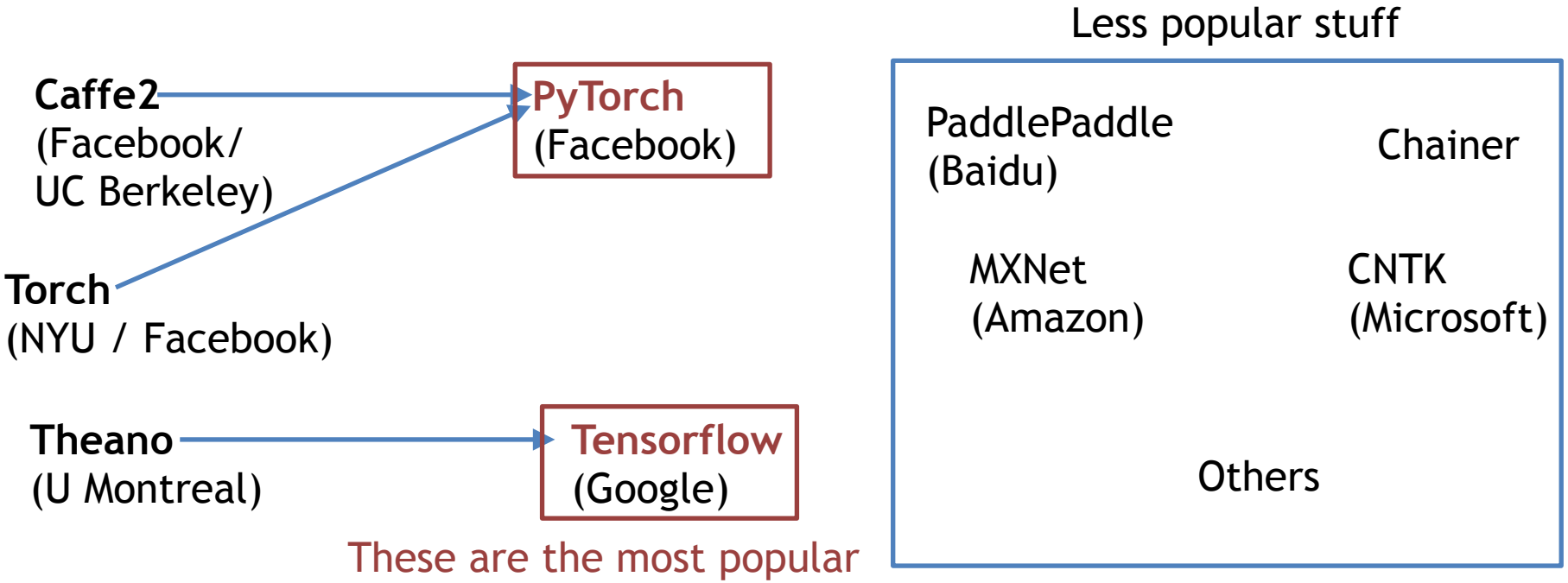
Chainer

MXNet
(Amazon)

CNTK
(Microsoft)

Others

Frameworks


Caffe2
(Facebook/
UC Berkeley)
PyTorch
(Facebook)
Torch
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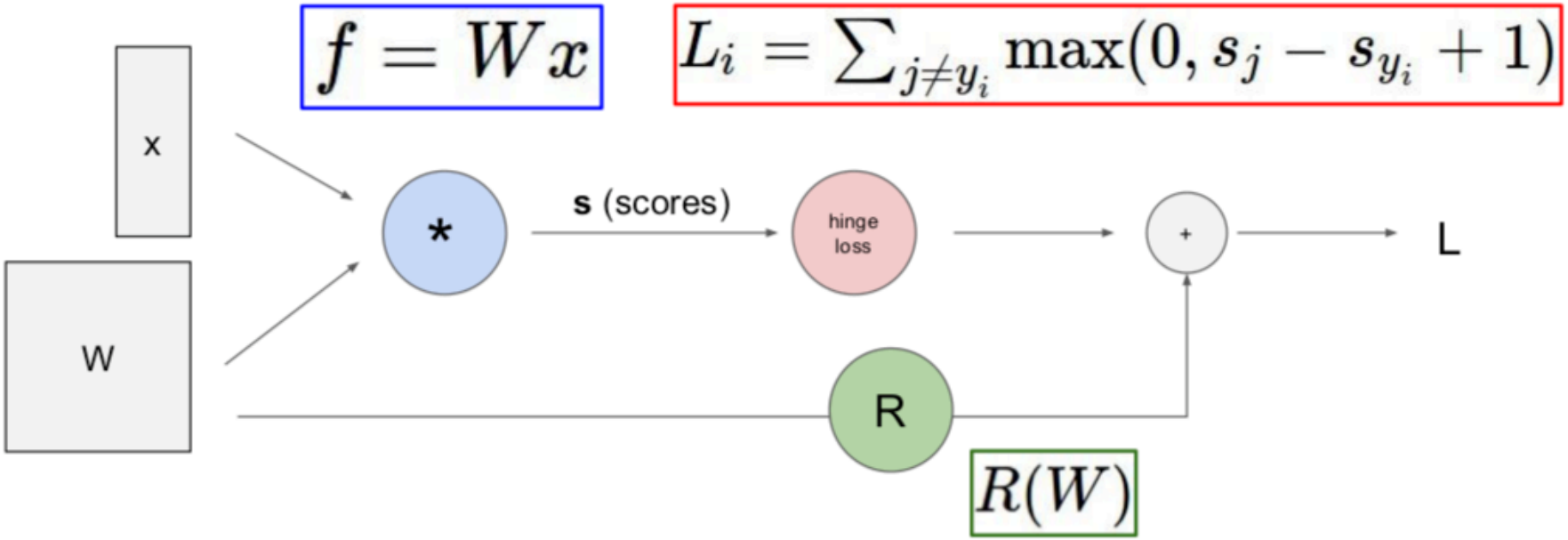
Theano
(U Montreal)
Tensorflow
(Google)
These are the most popular
Less popular stuff
PaddlePaddle
(Baidu)
Chainer
MXNet
(Amazon)
CNTK
(Microsoft)
Others

Requirement of deep learning frameworks

- Quickly implement and test ideas
- Automatically compute gradients
- Run it efficient

Neural Networks = Directed Acyclic Graphs



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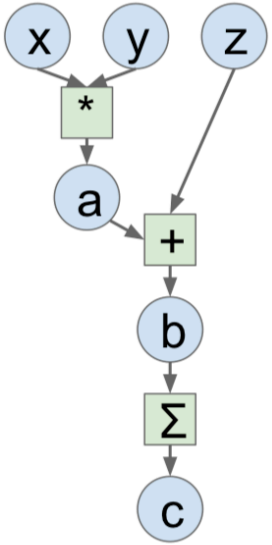
Computational Graph



Slide source: CS231n Lecture 8

Computational Graph

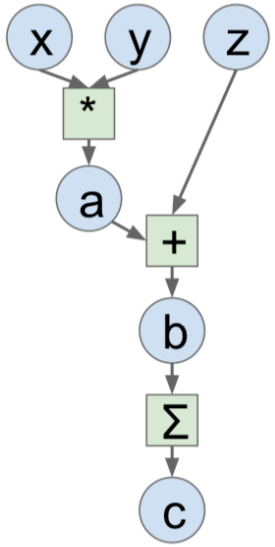
Numpy

```
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)
```



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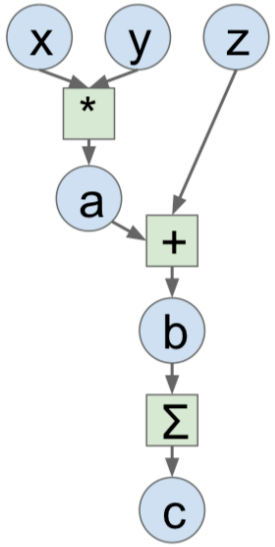
a = x * y
b = a + z
c = np.sum(b)

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
```



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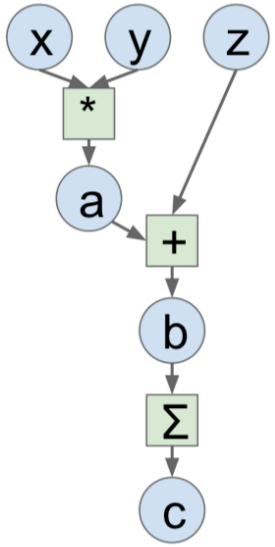

Good:
- Simple, clean API

Bad:
- Have to compute gradients ourself
- Can't run on GPU

Computational Graph

Numpy

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grad_x = grad_a * y
grad_y = grad_a * x
```

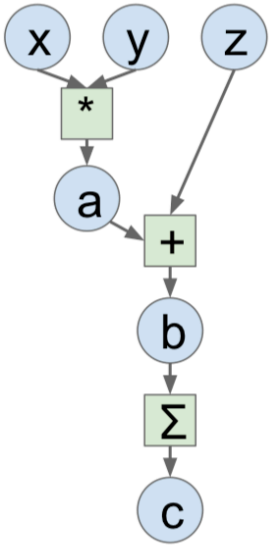

PyTorch

```
import torch

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a = x * y
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```

Computational Graph

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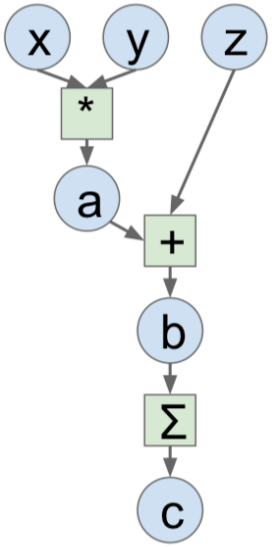


PyTorch

```
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)
```

Torch handles all gradients!

Small sidetrack: Tensorflow vs Pytorch

Computational Graph

- Both tensorflow and pytorch define a **D**irected **A**cyclic **G**raph
- Tensorflow/Keras: **Static graph**, defined before training.
- Pytorch: **Dynamic graph**, defined during training

Pytorch: Dynamic Graph

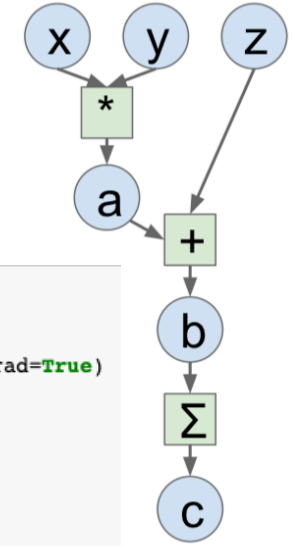
- Pros:
  - Intuitive code
  - “Numpy on GPU”
  - Easy debugging
  - “Pythonic code”
- Cons:
  - Dynamic graph is slower (really though?)
  - Smaller community, but its growing!

A graph is created on the fly


```
W_h = torch.randn(20, 20, requires_grad=True)
W_x = torch.randn(20, 10, requires_grad=True)
x = torch.randn(1, 10)
prev_h = torch.randn(1, 20)
```

GIF source

Computational Graph



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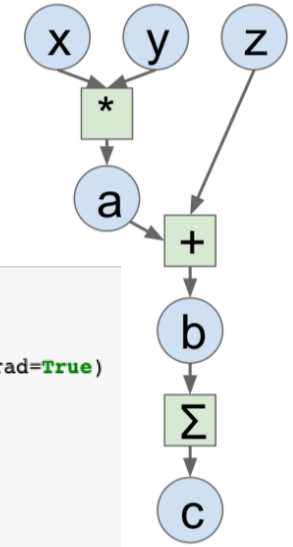
Slide source: CS231n Lecture 8

Computational Graph



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Tensorflow

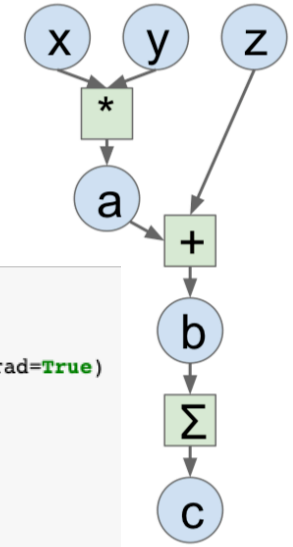
```
N, D = 3, 4

x = tf.placeholder(tf.float32, shape=(N,D))
y = tf.placeholder(tf.float32, shape=(N,D))
z = tf.placeholder(tf.float32, shape=(N,D))

a = tf.multiply(x,y)
b = tf.add(a,z)
c = tf.reduce_sum(b)
grad_x = tf.gradients(c, [x])
```

First, define the graph

Computational Graph



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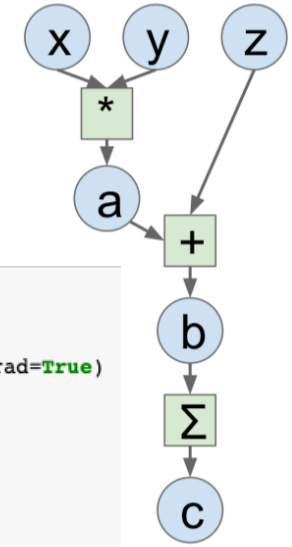
b = tf.add(a,z)
c = tf.reduce_sum(b)
grad_x = tf.gradients(c, [x])

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

Then, initialize a tf.Session

Computational Graph



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a = tf.multiply(x,y)
b = tf.add(a,z)
c = tf.reduce_sum(b)
grad_x = tf.gradients(c, [x])

with tf.Session() as sess:
  sess.run(tf.global_variables_initializer())
  values = {
    x: np.random.randn(N,D),
    y: np.random.randn(N,D),
    z: np.random.randn(N,D)
  }
  gradient_x = sess.run(grad_x, feed_dict=values)
```
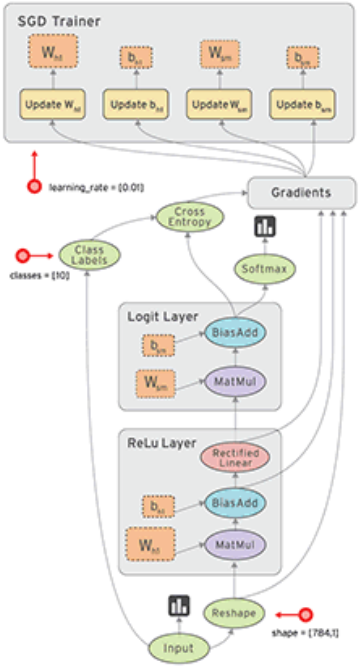

Then, perform the forward pass

Tensorflow/Keras: Static Graph

- Pros:
  - Faster?
  - Large community
  - Keras is a simpler API
- Cons:
  - Not intuitive
  - Hard to debug



GIF source

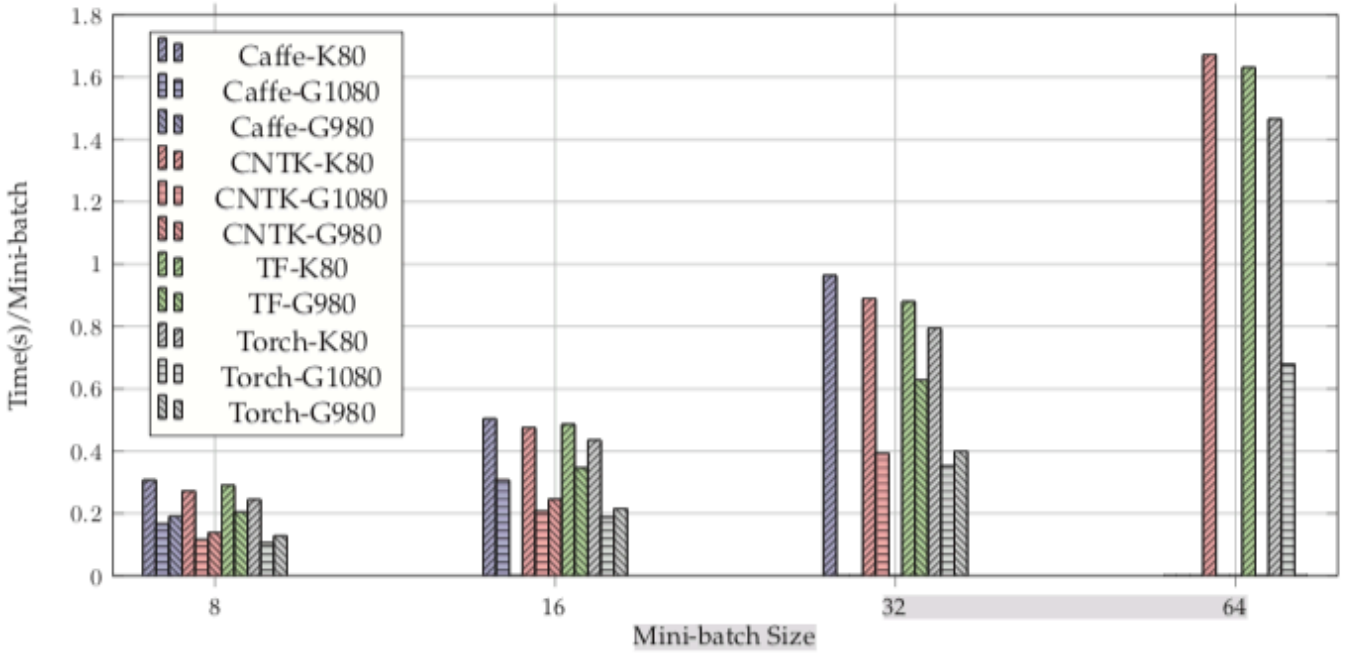
Dynamic vs Static Graphs

- Tensorflow is adding dynamic graphs in TF 2.0
- Pytorch 1.0 includes static graph

- Lines are blurring….

GIF source

Framework speed comparison



(d) ResNet-50 training speed on GPUs.

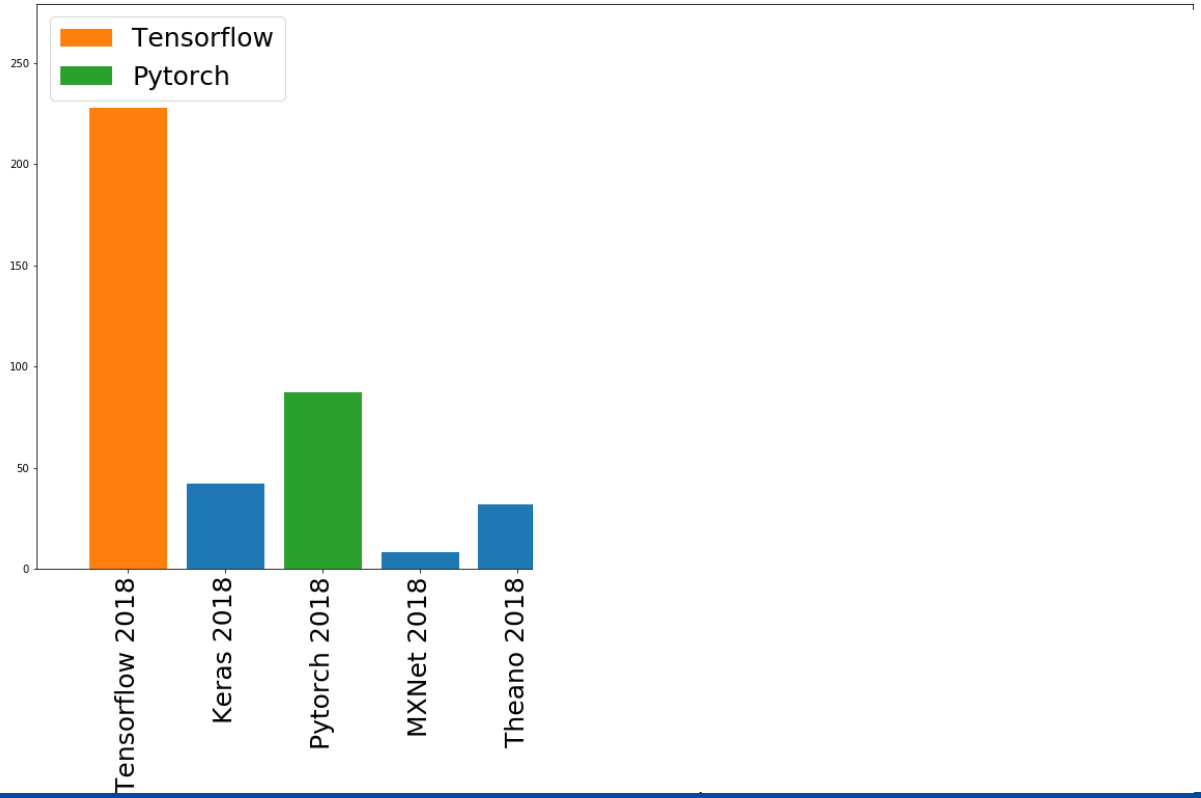
Slide source: Shi et. al.

Framework comparison

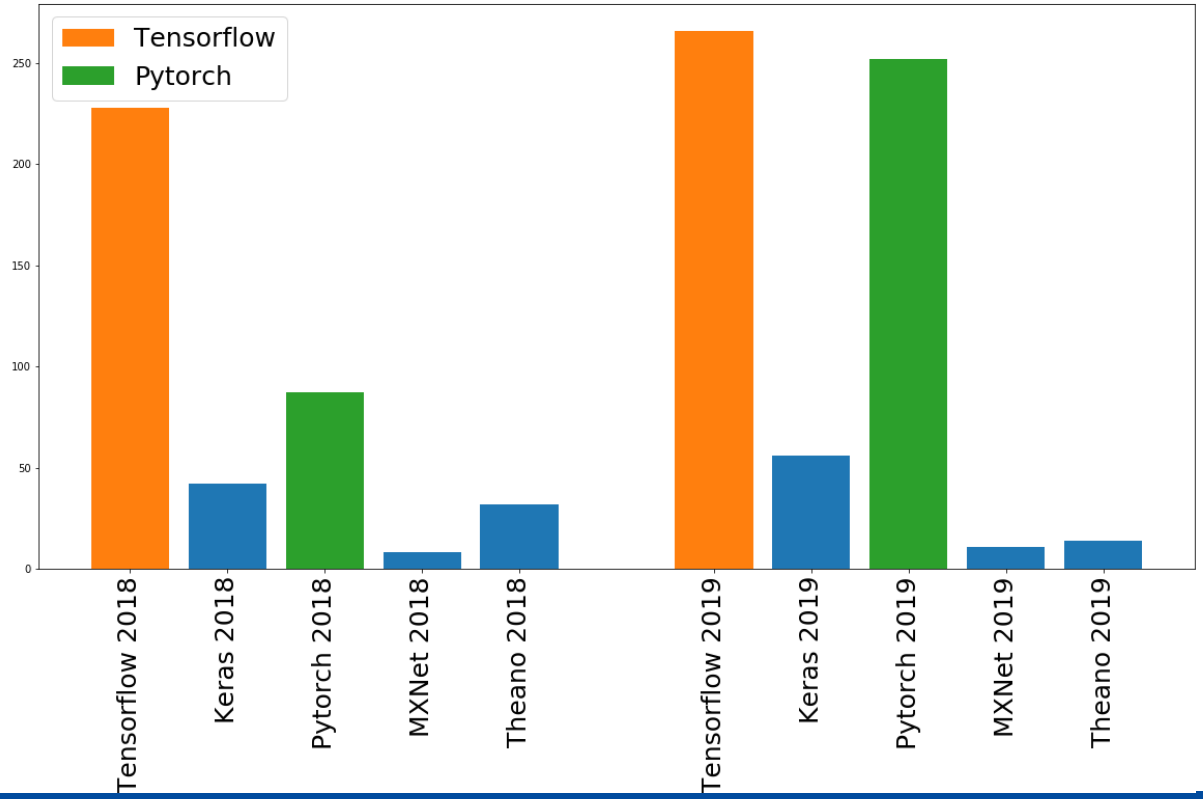
“There is no single software tool that can consistently outperform others”

Slide source: Shi et. al.

What is actually used? (ICLR 2018/19)



What is actually used? (ICLR 2018/19)



My advice:

- **Pytorch(My favorite):** Has an intuitive API that works for both high level and low level neural networks. Dynamic graphs make it easy to develop and debug.

- **Tensorflow/Keras:** Has a larger community and a wide usage in companies. Is hard to debug and graph setup is initially hard to understand. Probably have to use Keras.

PyTorch (in-depth)

Pytorch: Fundamental Concepts

- Tensor: Like a numpy array, but can run on GPUs

- Module: A neural network layer; stores states and learnable weights

Pytorch version

- We recommend Pytorch 1.0, which was released November 2018
- Pytorch 0.4.0/0.4.1 is fine too, not much syntax change
- **NB:** Be careful when looking at older Pytorch code!

Pytorch: Tensors

Example: The 2-layer neural network from Assignment 2

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
w1 = torch.randn(I, J, requires_grad=True)
w2 = torch.randn(J, C, requires_grad=True)

loss_function = torch.nn.NLLLoss()
losses = []
for i in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    z_j = X.mm(w1)
    a_j = torch.sigmoid(z_j)
    z_k = a_j.mm(w2)
    y_k = torch.softmax(z_k, dim=1)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      w1 -= learning_rate * w1.grad
      w2 -= learning_rate * w2.grad
      w1.grad.zero_()
      w2.grad.zero_()
```


This is a running example! Do not implement your network like this!

Pytorch: Tensors

Initialize the weights randomly

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
w1 = torch.randn(I, J, requires_grad=True)
w2 = torch.randn(J, C, requires_grad=True)

loss_function = torch.nn.NLLLoss()
losses = []
for i in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    z_j = X.mm(w1)
    a_j = torch.sigmoid(z_j)
    z_k = a_j.mm(w2)
    y_k = torch.softmax(z_k, dim=1)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      w1 -= learning_rate * w1.grad
      w2 -= learning_rate * w2.grad
      w1.grad.zero_()
      w2.grad.zero_()
```


This is a running example! Do not implement your network like this!

Pytorch: Tensors

Do want to save gradients w.r.t weights

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
w1 = torch.randn(I, J, requires_grad=True)
w2 = torch.randn(J, C, requires_grad=True)

loss_function = torch.nn.NLLLoss()
losses = []
for i in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    z_j = X.mm(w1)
    a_j = torch.sigmoid(z_j)
    z_k = a_j.mm(w2)
    y_k = torch.softmax(z_k, dim=1)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      w1 -= learning_rate * w1.grad
      w2 -= learning_rate * w2.grad
      w1.grad.zero_()
      w2.grad.zero_()
```

Pytorch: Tensors

Define our loss function:
Cross Entropy Loss

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
w1 = torch.randn(I, J, requires_grad=True)
w2 = torch.randn(J, C, requires_grad=True)

loss_function = torch.nn.NLLLoss()
losses = []
for i in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    z_j = X.mm(w1)
    a_j = torch.sigmoid(z_j)
    z_k = a_j.mm(w2)
    y_k = torch.softmax(z_k, dim=1)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      w1 -= learning_rate * w1.grad
      w2 -= learning_rate * w2.grad
      w1.grad.zero_()
      w2.grad.zero_()
```

Pytorch: Tensors

Pytorch uses “dataloaders” to efficiently load datasets

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
w1 = torch.randn(I, J, requires_grad=True)
w2 = torch.randn(J, C, requires_grad=True)

loss_function = torch.nn.NLLLoss()
losses = []
for i in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    z_j = X.mm(w1)
    a_j = torch.sigmoid(z_j)
    z_k = a_j.mm(w2)
    y_k = torch.softmax(z_k, dim=1)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      w1 -= learning_rate * w1.grad
      w2 -= learning_rate * w2.grad
      w1.grad.zero_()
      w2.grad.zero_()
```

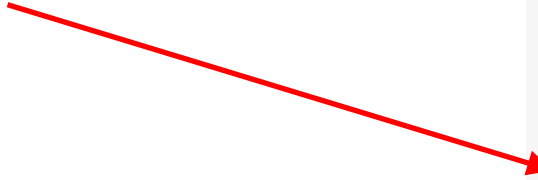
Pytorch: Tensors

Bias trick and normalization

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
w1 = torch.randn(I, J, requires_grad=True)
w2 = torch.randn(J, C, requires_grad=True)

loss_function = torch.nn.NLLLoss()
losses = []
for i in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    z_j = X.mm(w1)
    a_j = torch.sigmoid(z_j)
    z_k = a_j.mm(w2)
    y_k = torch.softmax(z_k, dim=1)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      w1 -= learning_rate * w1.grad
      w2 -= learning_rate * w2.grad
      w1.grad.zero_()
      w2.grad.zero_()
```

Pytorch: Tensors

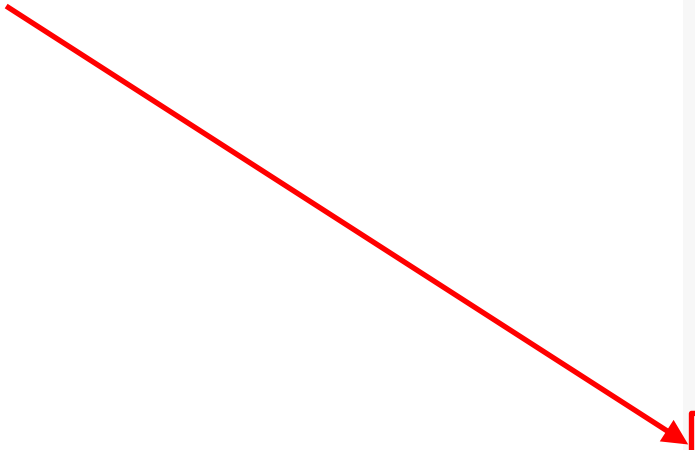
Define the forward pass



```
I = 785
J = 64
C = 10
learning_rate = 1e-5
w1 = torch.randn(I, J, requires_grad=True)
w2 = torch.randn(J, C, requires_grad=True)

loss_function = torch.nn.NLLLoss()
losses = []
for i in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    z_j = X.mm(w1)
    a_j = torch.sigmoid(z_j)
    z_k = a_j.mm(w2)
    y_k = torch.softmax(z_k, dim=1)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      w1 -= learning_rate * w1.grad
      w2 -= learning_rate * w2.grad
      w1.grad.zero_()
      w2.grad.zero_()
```

Pytorch: Tensors

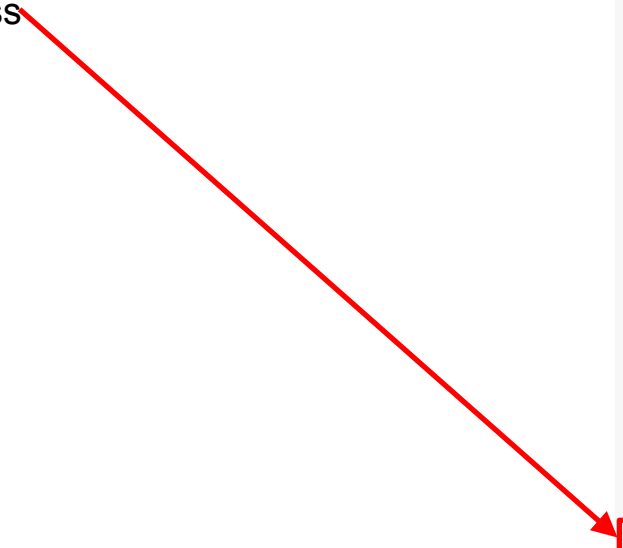
Compute the loss



```
I = 785
J = 64
C = 10
learning_rate = 1e-5
w1 = torch.randn(I, J, requires_grad=True)
w2 = torch.randn(J, C, requires_grad=True)

loss_function = torch.nn.NLLLoss()
losses = []
for i in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    z_j = X.mm(w1)
    a_j = torch.sigmoid(z_j)
    z_k = a_j.mm(w2)
    y_k = torch.softmax(z_k, dim=1)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      w1 -= learning_rate * w1.grad
      w2 -= learning_rate * w2.grad
      w1.grad.zero_()
      w2.grad.zero_()
```

Pytorch: Tensors

Backpropagate the loss



```
I = 785
J = 64
C = 10
learning_rate = 1e-5
w1 = torch.randn(I, J, requires_grad=True)
w2 = torch.randn(J, C, requires_grad=True)

loss_function = torch.nn.NLLLoss()
losses = []
for i in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    z_j = X.mm(w1)
    a_j = torch.sigmoid(z_j)
    z_k = a_j.mm(w2)
    y_k = torch.softmax(z_k, dim=1)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      w1 -= learning_rate * w1.grad
      w2 -= learning_rate * w2.grad
      w1.grad.zero_()
      w2.grad.zero_()
```

Pytorch: Tensors

Make gradient step on weights

torch.no_grad() means “don’t build a computational graph here

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
w1 = torch.randn(I, J, requires_grad=True)
w2 = torch.randn(J, C, requires_grad=True)

loss_function = torch.nn.NLLLoss()
losses = []
for i in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    z_j = X.mm(w1)
    a_j = torch.sigmoid(z_j)
    z_k = a_j.mm(w2)
    y_k = torch.softmax(z_k, dim=1)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      w1 -= learning_rate * w1.grad
      w2 -= learning_rate * w2.grad
      w1.grad.zero_()
      w2.grad.zero_()
```

Pytorch: torch.nn

Higher lever wrapper for defining neural networks

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
model = nn.Sequential(
  nn.Linear(I, J),
  nn.Sigmoid(),
  nn.Linear(J, C)
  # No need for softmax, since its included in
  # nn.CrossEntropyLoss()
)

loss_function = torch.nn.CrossEntropyLoss()
losses = []
for epoch in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      for param in model.parameters():
        param -= learning_rate * param.grad
```


This is a running example! Do not implement your network like this!

Pytorch: torch.nn

Higher lever wrapper for defining neural networks

Define each layer in model.

Each layer is a nn.Module() object, containing learnable weights.

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
model = nn.Sequential(
  nn.Linear(I, J),
  nn.Sigmoid(),
  nn.Linear(J, C)
  # No need for softmax, since its included in
  # nn.CrossEntropyLoss()
)

loss_function = torch.nn.CrossEntropyLoss()
losses = []
for epoch in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      for param in model.parameters():
        param -= learning_rate * param.grad
```

Pytorch: torch.nn

Changed loss function to nn.CrossEntropyLoss.

This includes the softmax!

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
model = nn.Sequential(
  nn.Linear(I, J),
  nn.Sigmoid(),
  nn.Linear(J, C)
  # No need for softmax, since its included in
  # nn.CrossEntropyLoss()
)

loss_function = torch.nn.CrossEntropyLoss()
losses = []
for epoch in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      for param in model.parameters():
        param -= learning_rate * param.grad
```

Pytorch: torch.nn

Simplifies our forward pass!

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
model = nn.Sequential(
  nn.Linear(I, J),
  nn.Sigmoid(),
  nn.Linear(J, C)
  # No need for softmax, since its included in
  # nn.CrossEntropyLoss()
)

loss_function = torch.nn.CrossEntropyLoss()
losses = []
for epoch in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      for param in model.parameters():
        param -= learning_rate * param.grad
```

Pytorch: torch.nn

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
model = nn.Sequential(
  nn.Linear(I, J),
  nn.Sigmoid(),
  nn.Linear(J, C)
  # No need for softmax, since its included in
  # nn.CrossEntropyLoss()
)

loss_function = torch.nn.CrossEntropyLoss()
losses = []
for epoch in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      for param in model.parameters():
        param -= learning_rate * param.grad
```

Compute loss and perform backward pass

Each weight in model has requires_grad=True by default

Pytorch: torch.nn

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
model = nn.Sequential(
  nn.Linear(I, J),
  nn.Sigmoid(),
  nn.Linear(J, C)
  # No need for softmax, since its included in
  # nn.CrossEntropyLoss()
)

loss_function = torch.nn.CrossEntropyLoss()
losses = []
for epoch in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    with torch.no_grad():
      for param in model.parameters():
        param -= learning_rate * param.grad
```

Perform our gradient step
(and disable gradients)

Pytorch: torch.optim

Final piece you need to know

Implements **S**tochastic **G**radient **D**escent

Input: our learnable parameters (weights + biases) + learning rate

```
I = 785
J = 64
C = 10
learning_rate = 1e-5
model = nn.Sequential(
  nn.Linear(I, J),
  nn.Sigmoid(),
  nn.Linear(J, C)
  # No need for softmax, since its included in
  # nn.CrossEntropyLoss()
)

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```


This is how its supposed to be!

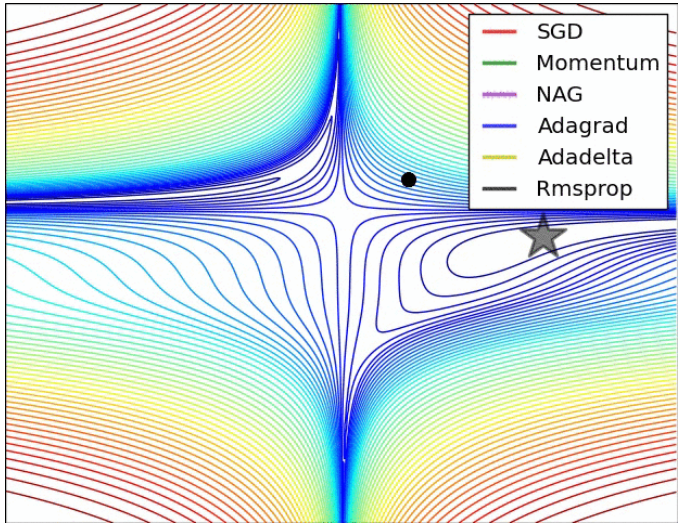
Pytorch: torch.optim

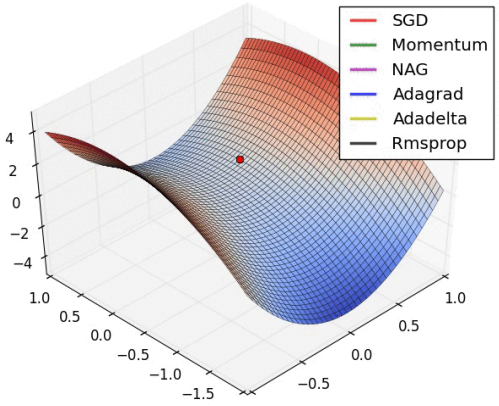
```
I = 785
J = 64
C = 10
learning_rate = 1e-5
model = nn.Sequential(
  nn.Linear(I, J),
  nn.Sigmoid(),
  nn.Linear(J, C)
  # No need for softmax, since its included in
  # nn.CrossEntropyLoss()
)

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(10):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Perform gradient step and reset the gradients

Pytorch Optim Docs

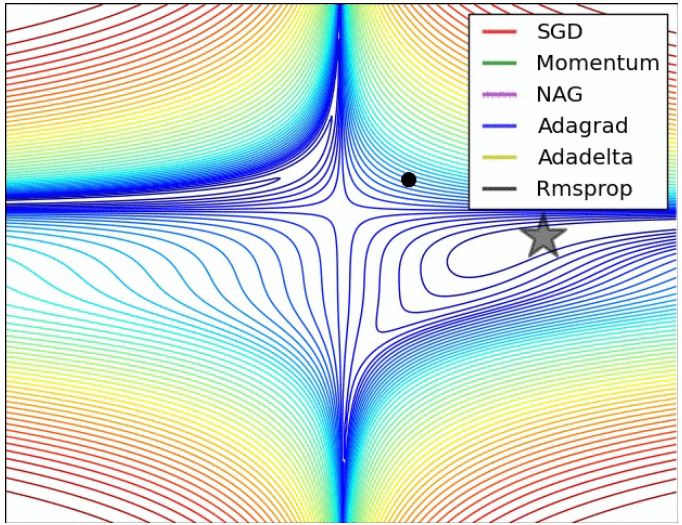
The choice of optimizer is important!

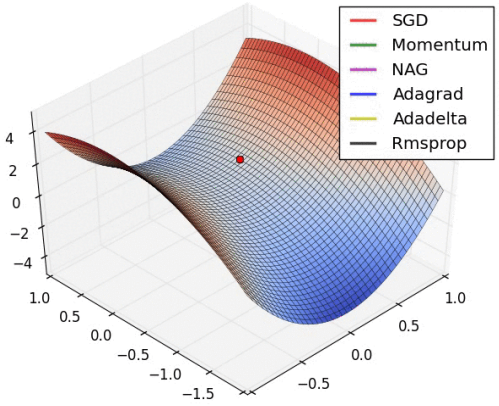




Pytorch Optim Docs

The choice of optimizer is important!





Try out optim.Adam in your assignment!

Pytorch Optim Docs

Pytorch: nn.Module

A PyTorch **Module** is a neural network layer; it inputs and outputs tensors

Can contain weights or other modules

Required for more complex layers

Easily customizable layers

```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.layer1 = nn.Sequential(
      nn.Linear(I,J),
      nn.Sigmoid()
    )
    self.layer2 = nn.Linear(J, C)
  def forward(self, x):
    x = self.layer1(x)
    x = self.layer2(x)
    return x

learning_rate = 1e-3
model = TwoLayerNet()

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(2):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()

```

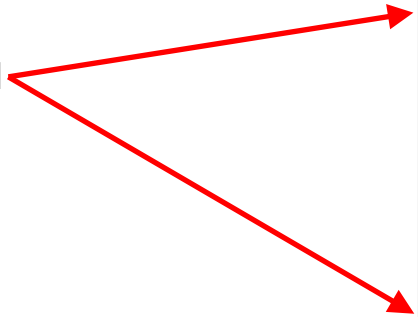
Pytorch: nn.Module

Start with defining the model

```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.layer1 = nn.Sequential(
      nn.Linear(I,J),
      nn.Sigmoid()
    )
    self.layer2 = nn.Linear(J, C)
  def forward(self, x):
    x = self.layer1(x)
    x = self.layer2(x)
    return x

learning_rate = 1e-3
model = TwoLayerNet()

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(2):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Pytorch: nn.Module

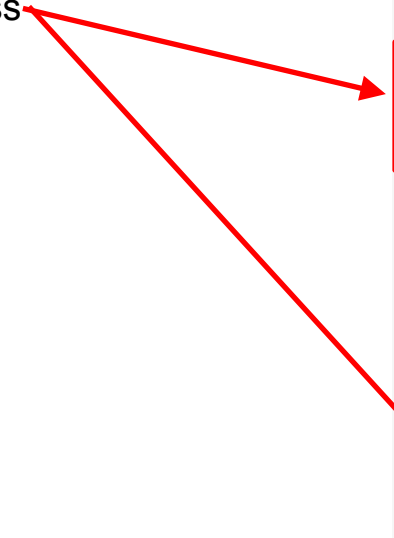
Called when we initialize our model



```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.layer1 = nn.Sequential(
      nn.Linear(I,J),
      nn.Sigmoid()
    )
    self.layer2 = nn.Linear(J, C)
  def forward(self, x):
    x = self.layer1(x)
    x = self.layer2(x)
    return x

learning_rate = 1e-3
model = TwoLayerNet()

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(2):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Pytorch: nn.Module

Called when we perform forward pass



```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.layer1 = nn.Sequential(
      nn.Linear(I,J),
      nn.Sigmoid()
    )
    self.layer2 = nn.Linear(J, C)
  def forward(self, x):
    x = self.layer1(x)
    x = self.layer2(x)
    return x

learning_rate = 1e-3
model = TwoLayerNet()

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(2):
  for (X,Y) in dataloader:
    X = pre_process_image(X)
    # forward pass
    y_k = model(X)
    # Compute loss
    loss = loss_function(y_k, Y)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Pytorch: DataLoaders

A **DataLoader** wraps a dataset and provides features such as:

- Data augmentation
- Data pre-processing
- mini-batch shuffling and splitting

```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.layer1 = nn.Sequential(
      nn.Linear(I,J),
      nn.Sigmoid()
    )
    self.layer2 = nn.Linear(J, C)
  def forward(self, x):
    x = self.layer1(x)
    x = self.layer2(x)
    return x

learning_rate = 1e-3
batch_size=32
model = TwoLayerNet()

dataloader_train, dataloader_test = load_mnist(batch_size

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(2):
  for (X_batch,Y_batch) in dataloader_train:
    X_batch = pre_process_image(X_batch)
    # forward pass
    y_k = model(X_batch)
    # Compute loss
    loss = loss_function(y_k, Y_batch)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Pytorch: DataLoaders

Iterates over each batch in a epoch

```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.layer1 = nn.Sequential(
      nn.Linear(I,J),
      nn.Sigmoid()
    )
    self.layer2 = nn.Linear(J, C)
  def forward(self, x):
    x = self.layer1(x)
    x = self.layer2(x)
    return x

learning_rate = 1e-3
batch_size=32
model = TwoLayerNet()

dataloader_train, dataloader_test = load_mnist(batch_size

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(2):
  for (X_batch,Y_batch) in dataloader_train:
    X_batch = pre_process_image(X_batch)
    # forward pass
    y_k = model(X_batch)
    # Compute loss
    loss = loss_function(y_k, Y_batch)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Pytorch: On GPU

Utilizing GPU resources is simple!

```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.layer1 = nn.Sequential(
      nn.Linear(I,J),
      nn.Sigmoid()
    )
    self.layer2 = nn.Linear(J, C)
  def forward(self, x):
    x = self.layer1(x)
    x = self.layer2(x)
    return x

learning_rate = 1e-3
batch_size=32
model = TwoLayerNet().cuda()

dataloader_train, dataloader_test = load_mnist(batch_size)

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(2):
  for (X_batch,Y_batch) in dataloader_train:
    X_batch = pre_process_image(X_batch)
    X_batch, Y_batch = X_batch.cuda(), Y_batch.cuda()
    # forward pass
    y_k = model(X_batch)
    # Compute loss
    loss = loss_function(y_k, Y_batch)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Pytorch: On GPU

Utilizing GPU resources is simple!

.cuda() transfers weights/tensors to GPU VRAM

```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.layer1 = nn.Sequential(
      nn.Linear(I,J),
      nn.Sigmoid()
    )
    self.layer2 = nn.Linear(J, C)
  def forward(self, x):
    x = self.layer1(x)
    x = self.layer2(x)
    return x

learning_rate = 1e-3
batch_size=32
model = TwoLayerNet().cuda()

dataloader_train, dataloader_test = load_mnist(batch_size)

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(2):
  for (X_batch,Y_batch) in dataloader_train:
    X_batch = pre_process_image(X_batch)
    X_batch, Y_batch = X_batch.cuda(), Y_batch.cuda()
    # forward pass
    y_k = model(X_batch)
    # Compute loss
    loss = loss_function(y_k, Y_batch)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Pytorch: On GPU

Utilizing GPU resources is simple!

.cuda() transfers weights/tensors to GPU VRAM

```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.layer1 = nn.Sequential(
      nn.Linear(I,J),
      nn.Sigmoid()
    )
    self.layer2 = nn.Linear(J, C)
  def forward(self, x):
    x = self.layer1(x)
    x = self.layer2(x)
    return x

learning_rate = 1e-3
batch_size=32
model = TwoLayerNet().cuda()

dataloader_train, dataloader_test = load_mnist(batch_size)

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(2):
  for (X_batch,Y_batch) in dataloader_train:
    X_batch = pre_process_image(X_batch)
    X_batch, Y_batch = X_batch.cuda(), Y_batch.cuda()
    # forward pass
    y_k = model(X_batch)
    # Compute loss
    loss = loss_function(y_k, Y_batch)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Pytorch: On GPU

Utilizing GPU resources is simple!

.cuda() transfers weights/tensors to GPU VRAM

CAREFUL: Calling .cuda() without a NVIDIA GPU available will cause error!

```python
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.layer1 = nn.Sequential(
      nn.Linear(I,J),
      nn.Sigmoid()
    )
    self.layer2 = nn.Linear(J, C)
  def forward(self, x):
    x = self.layer1(x)
    x = self.layer2(x)
    return x

learning_rate = 1e-3
batch_size=32
model = TwoLayerNet().cuda()

dataloader_train, dataloader_test = load_mnist(batch_size)

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(2):
  for (X_batch,Y_batch) in dataloader_train:
    X_batch = pre_process_image(X_batch)
    X_batch, Y_batch = X_batch.cuda(), Y_batch.cuda()
    # forward pass
    y_k = model(X_batch)
    # Compute loss
    loss = loss_function(y_k, Y_batch)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Pytorch: On GPU

Instead: Implement a to_cuda() function

```python
def to_cuda(elements):
    if torch.cuda.is_available():
        if type(elements) == tuple or type(elements) == list:
            return [x.cuda() for x in elements]
        return elements.cuda()
    return elements
```

```python
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.layer1 = nn.Sequential(
      nn.Linear(I,J),
      nn.Sigmoid()
    )
    self.layer2 = nn.Linear(J, C)
  def forward(self, x):
    x = self.layer1(x)
    x = self.layer2(x)
    return x

learning_rate = 1e-3
batch_size=32
model = to_cuda(TwoLayerNet())

dataloader_train, dataloader_test = load_mnist(batch_size)

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(),
                            lr=learning_rate)
losses = []
for epoch in range(2):
  for (X_batch,Y_batch) in dataloader_train:
    X_batch = pre_process_image(X_batch)
    X_batch, Y_batch = to_cuda([X_batch, Y_batch])
    # forward pass
    y_k = model(X_batch)
    # Compute loss
    loss = loss_function(y_k, Y_batch)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

Convolutional Neural Networks

Short Recap

LeNet (LeCun et al. 1998)

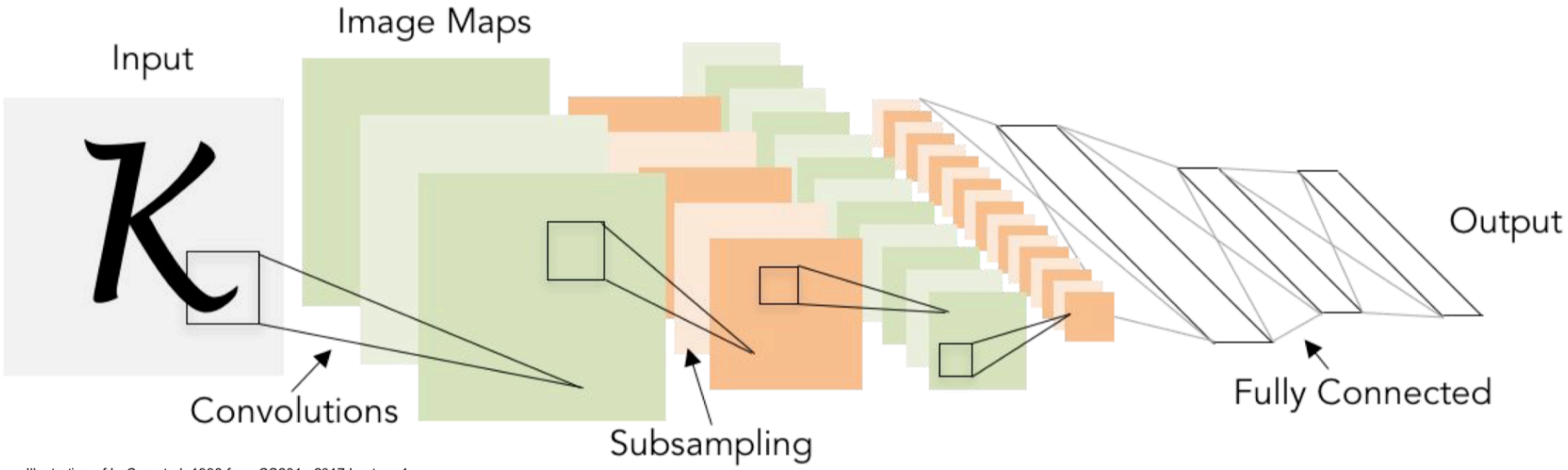
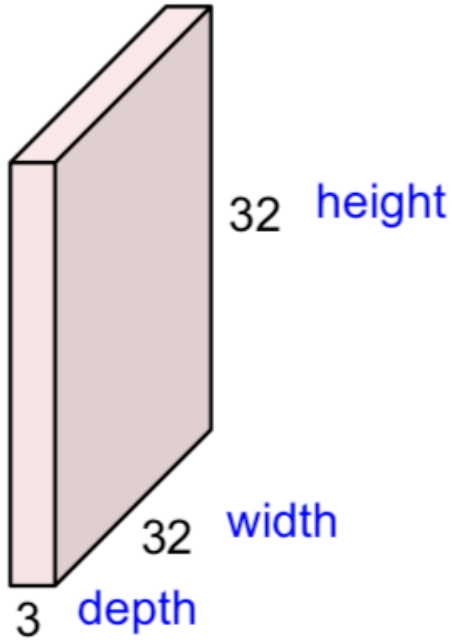


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

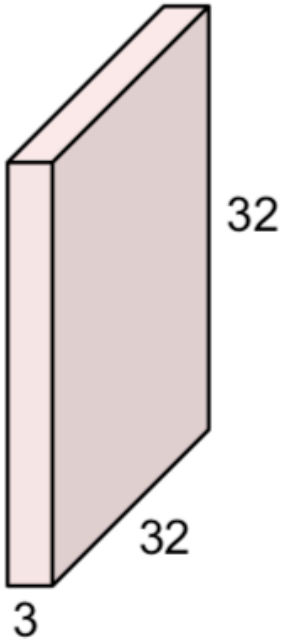
Convolution Layer

32x32x3 image -> preserve spatial structure

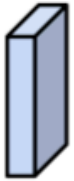


Convolution Layer

32x32x3 image



5x5x3 filter

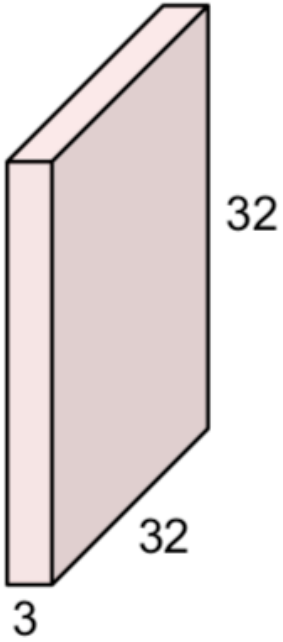


Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

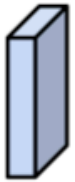
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image

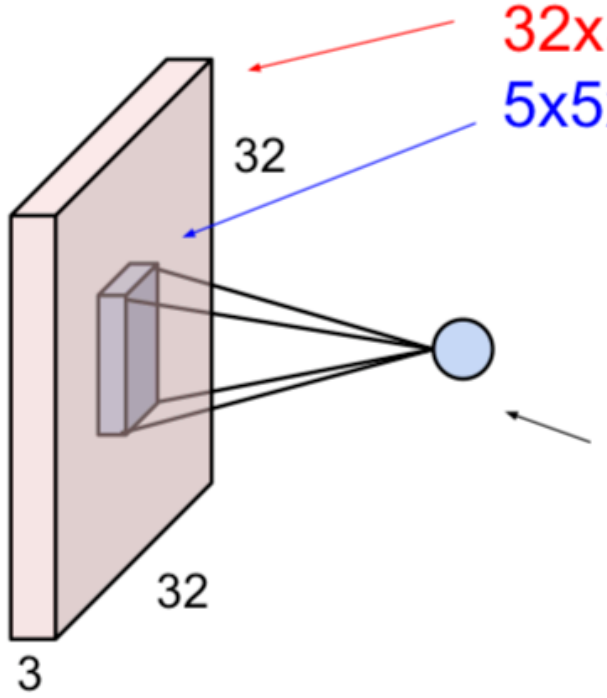


5x5x3 filter



Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

Convolution Layer



1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image (i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

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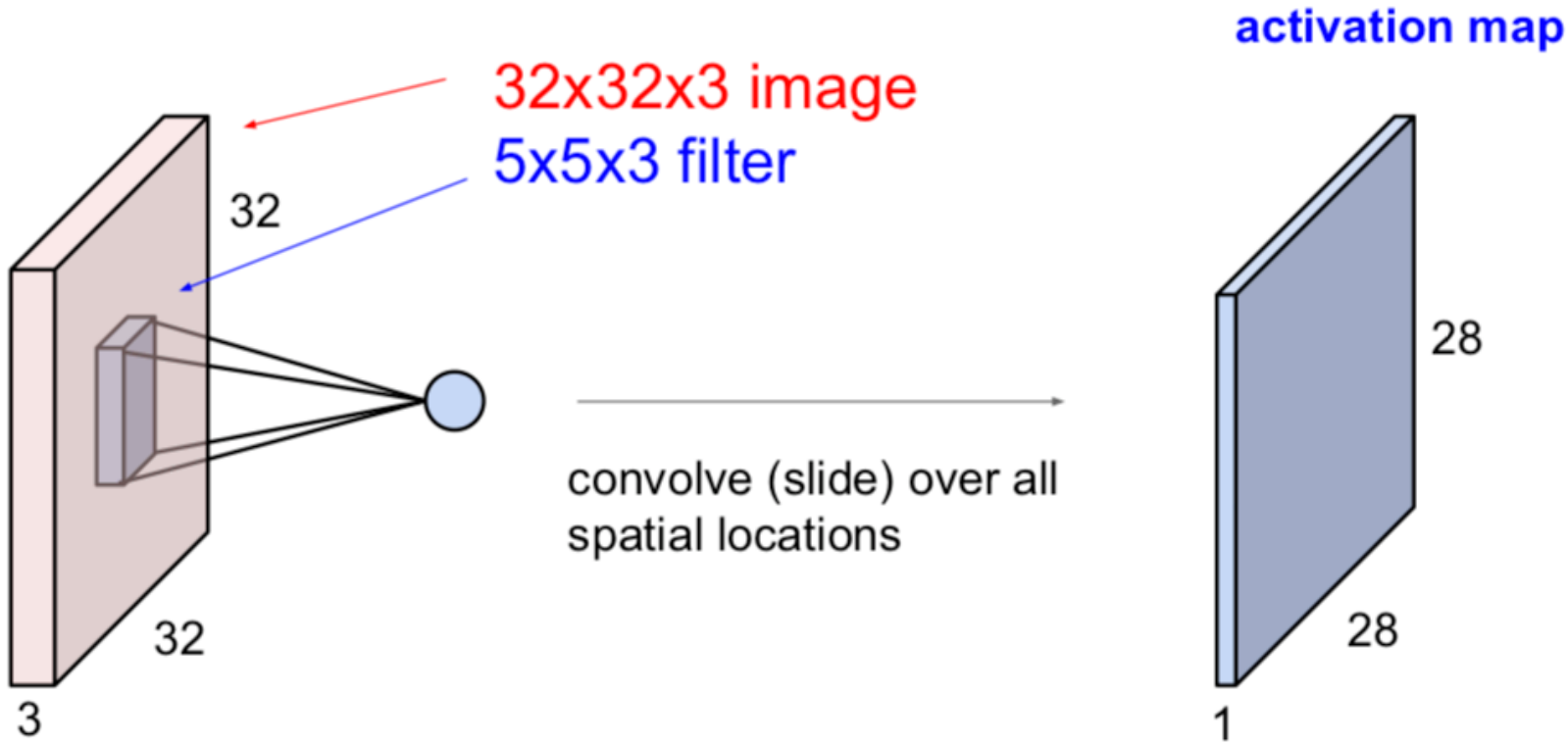
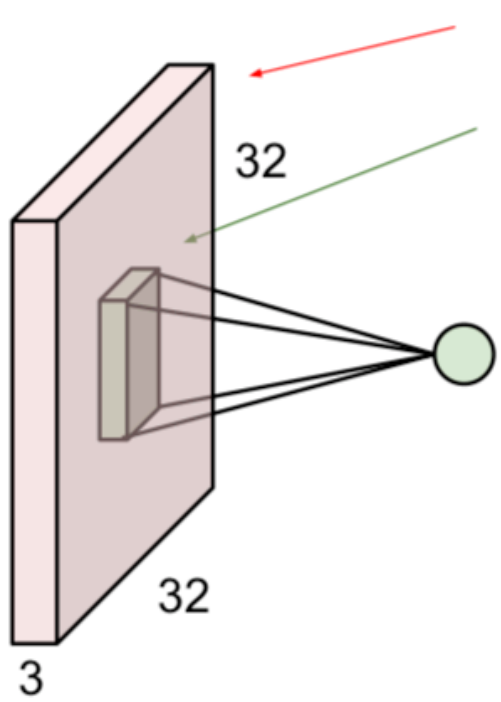
Convolution Layer

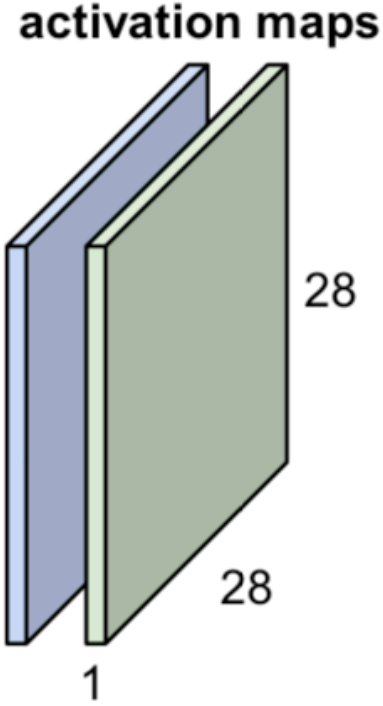


Convolution Layer

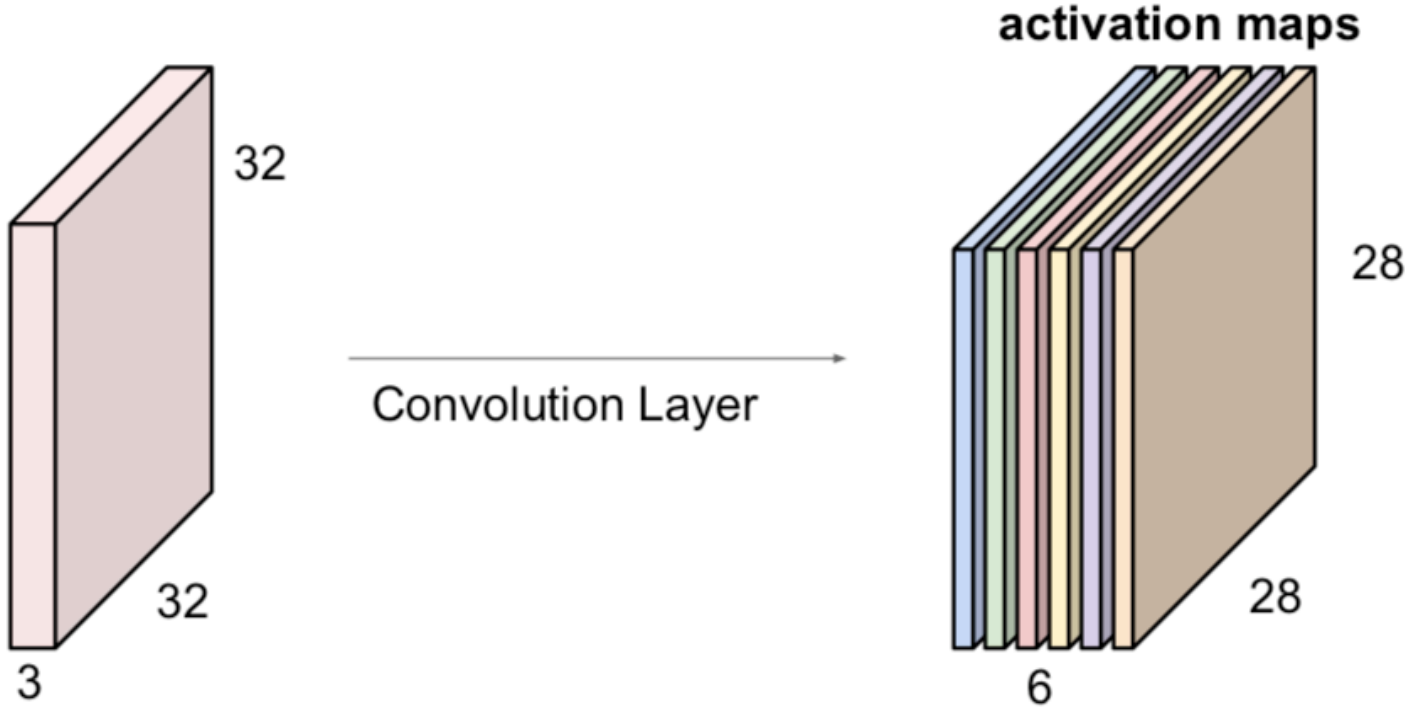
consider a second, green filter



convolve (slide) over all spatial locations



For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a "new image" of size 28x28x6!

Summary. To summarize, the Conv Layer:

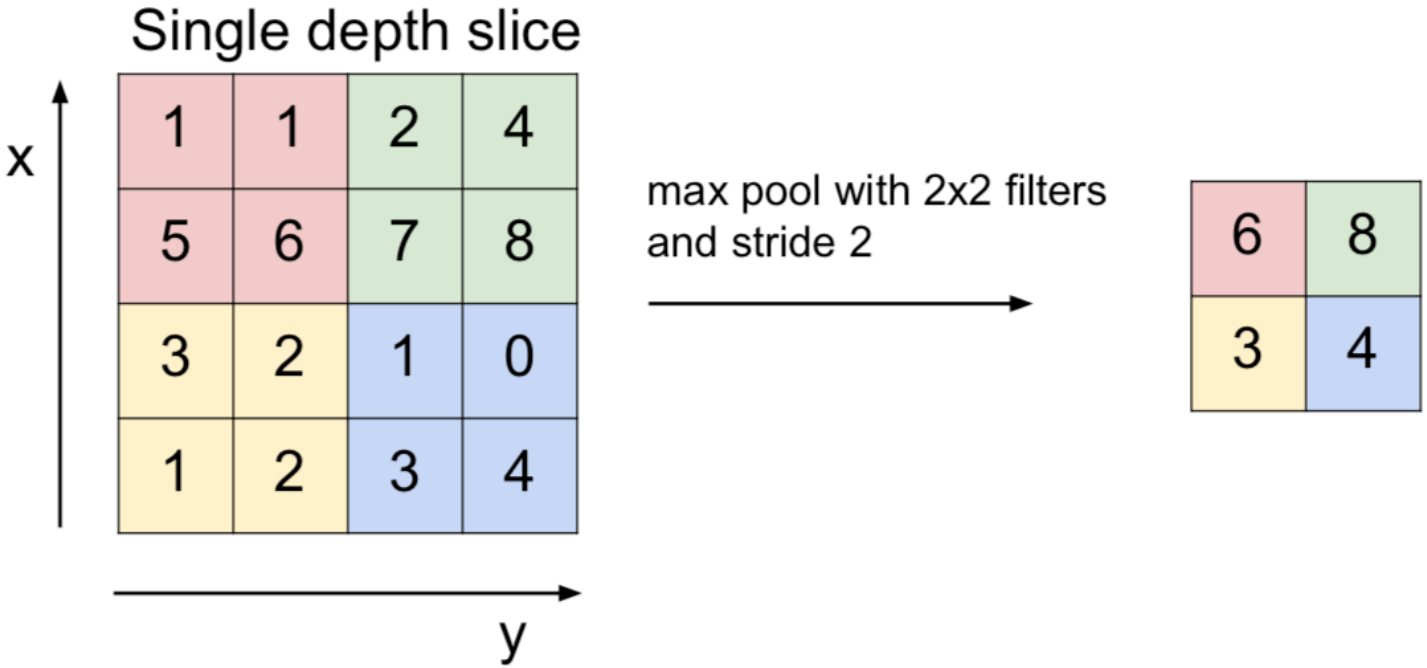
- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
  - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

Common settings:

K = (powers of 2, e.g. 32, 64, 128, 512)

- F = 3, S = 1, P = 1
- F = 5, S = 1, P = 2
- F = 5, S = 2, P = ? (whatever fits)
- F = 1, S = 1, P = 0

Max Pooling



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Max Pooling

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires three hyperparameters:
  - their spatial extent F,
  - the stride S,
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F)/S + 1$
  - $H_2 = (H_1 - F)/S + 1$
  - $D_2 = D_1$
- Introduces zero parameters since it computes a fixed function of the input
- Note that it is not common to use zero-padding for Pooling layers

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Pytorch: CNNs

Define a set of convolutional layers to extract **features**

Requires:
- in_channels=1, since MNIST is grayscale
- out_channels= number of filters in layer
- kernel_size=filter width and height
- padding = number of 0's to pad on the side of image

```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.feature_extractor = nn.Sequential(
      nn.Conv2d(in_channels=1,
                out_channels=32,
                kernel_size=3,
                padding=1),
      nn.MaxPool2d(kernel_size=2, stride=2),
      nn.Conv2d(in_channels=32,
                out_channels=64,
                kernel_size=3,
                padding=1),
      nn.MaxPool2d(kernel_size=2, stride=2)
    )
    self.classifier = nn.Sequential(
      nn.Linear(64*7*7, 64),
      nn.ReLU(),
      nn.Linear(64, 10)
    )
  def forward(self, x):
    x = self.feature_extractor(x)
    x = x.view(-1, 64*7*7) # Flatten image
    x = self.classifier(x)
    return x
```

Pytorch: CNNs

Need to flatten image before passing it to our fully-connected layer (classifier)

```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.feature_extractor = nn.Sequential(
      nn.Conv2d(in_channels=1,
                out_channels=32,
                kernel_size=3,
                padding=1),
      nn.MaxPool2d(kernel_size=2, stride=2),
      nn.Conv2d(in_channels=32,
                out_channels=64,
                kernel_size=3,
                padding=1),
      nn.MaxPool2d(kernel_size=2, stride=2)
    )
    self.classifier = nn.Sequential(
      nn.Linear(64*7*7, 64),
      nn.ReLU(),
      nn.Linear(64, 10)
    )
  def forward(self, x):
    x = self.feature_extractor(x)
    x = x.view(-1, 64*7*7) # Flatten image
    x = self.classifier(x)
    return x
```

Pytorch: CNNs

```
learning_rate = 1e-3
batch_size=32
model = to_cuda(TwoLayerNet())

dataloader_train, dataloader_test = load_mnist(batch_size)

loss_function = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
losses = []
for epoch in range(2):
  for (X_batch,Y_batch) in dataloader_train:
    X_batch, Y_batch = to_cuda([X_batch, Y_batch])
    # forward pass
    y_k = model(X_batch)
    # Compute loss
    loss = loss_function(y_k, Y_batch)
    losses.append(loss)
    # Backpropagation
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()

```

```
class TwoLayerNet(nn.Module):
  def __init__(self):
    super().__init__()
    I, J, C = 785, 64, 10
    self.feature_extractor = nn.Sequential(
      nn.Conv2d(in_channels=1,
                out_channels=32,
                kernel_size=3,
                padding=1),
      nn.MaxPool2d(kernel_size=2, stride=2),
      nn.Conv2d(in_channels=32,
                out_channels=64,
                kernel_size=3,
                padding=1),
      nn.MaxPool2d(kernel_size=2, stride=2)
    )
    self.classifier = nn.Sequential(
      nn.Linear(64*7*7, 64),
      nn.ReLU(),
      nn.Linear(64, 10)
    )
  def forward(self, x):
    x = self.feature_extractor(x)
    x = x.view(-1, 64*7*7) # Flatten image
    x = self.classifier(x)
    return x
```

Pytorch: CNNs

Lets compute the accuracy!

```
num_correct = 0
total_samples = 0
for X_test, Y_test in dataloader_test:
  output = model(X_test)
  prediction = output.argmax(dim=1)
  num_correct += (prediction == Y_test).sum().item()
  total_samples += X_test.shape[0]
print("Accuracy:", num_correct/total_samples)
```

Pytorch: CNNs

Lets compute the accuracy!

```
num_correct = 0
total_samples = 0
for X_test, Y_test in dataloader_test:
  output = model(X_test)
  prediction = output.argmax(dim=1)
  num_correct += (prediction == Y_test).sum().item()
  total_samples += X_test.shape[0]
print("Accuracy:", num_correct/total_samples)
```

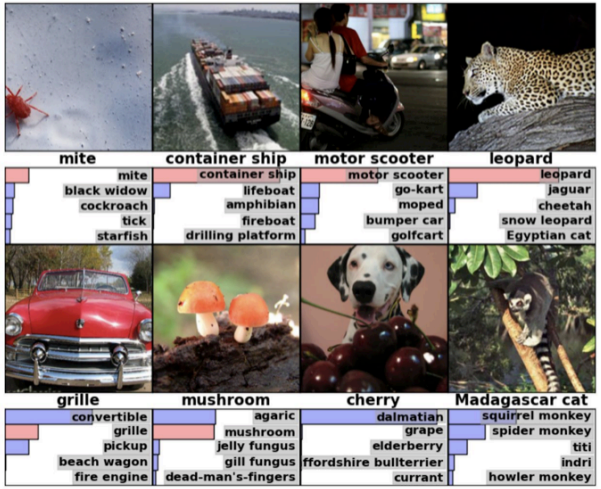
```
Accuracy: 0.9859
```

Transfer Learning

- Learn features on ImageNet

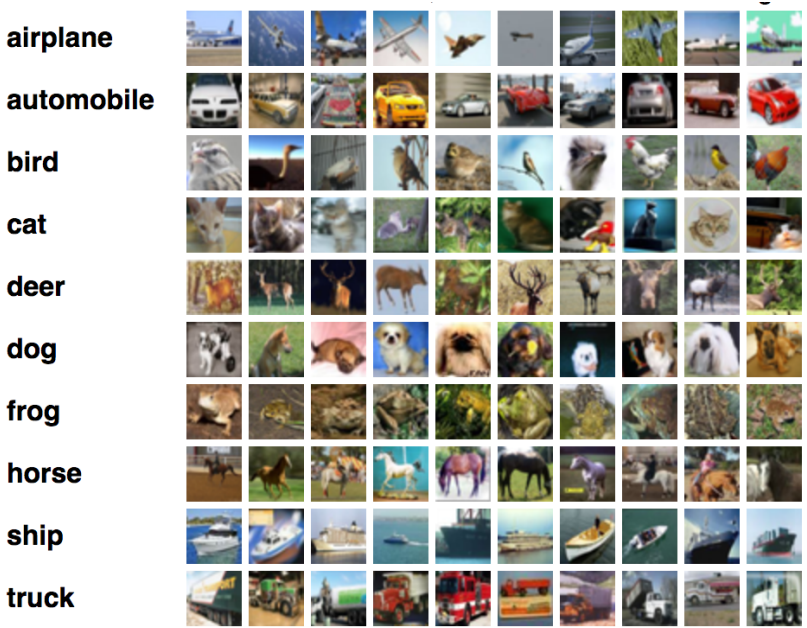
IMAGENET

- 1,000 object classes (categories).
- Images:
  - 1.2 M train
  - 100k test.

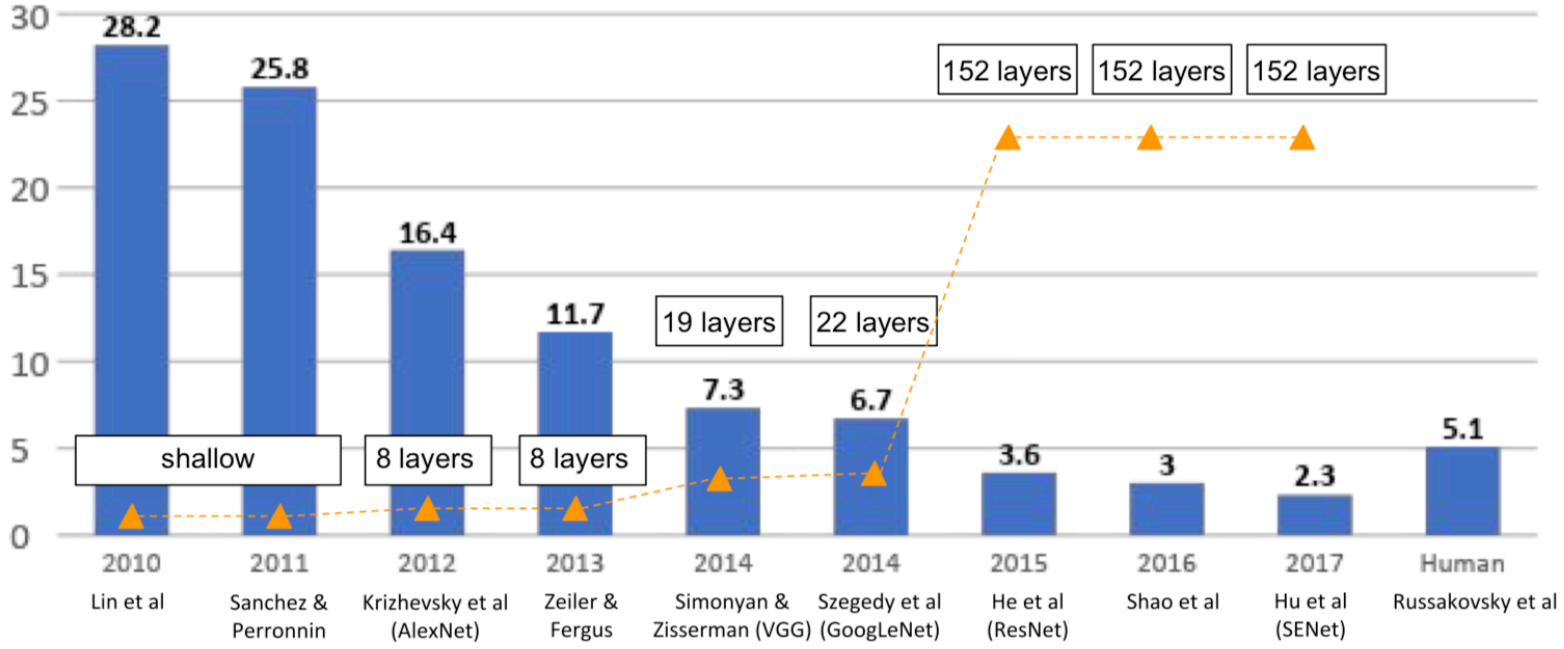


Transfer Learning

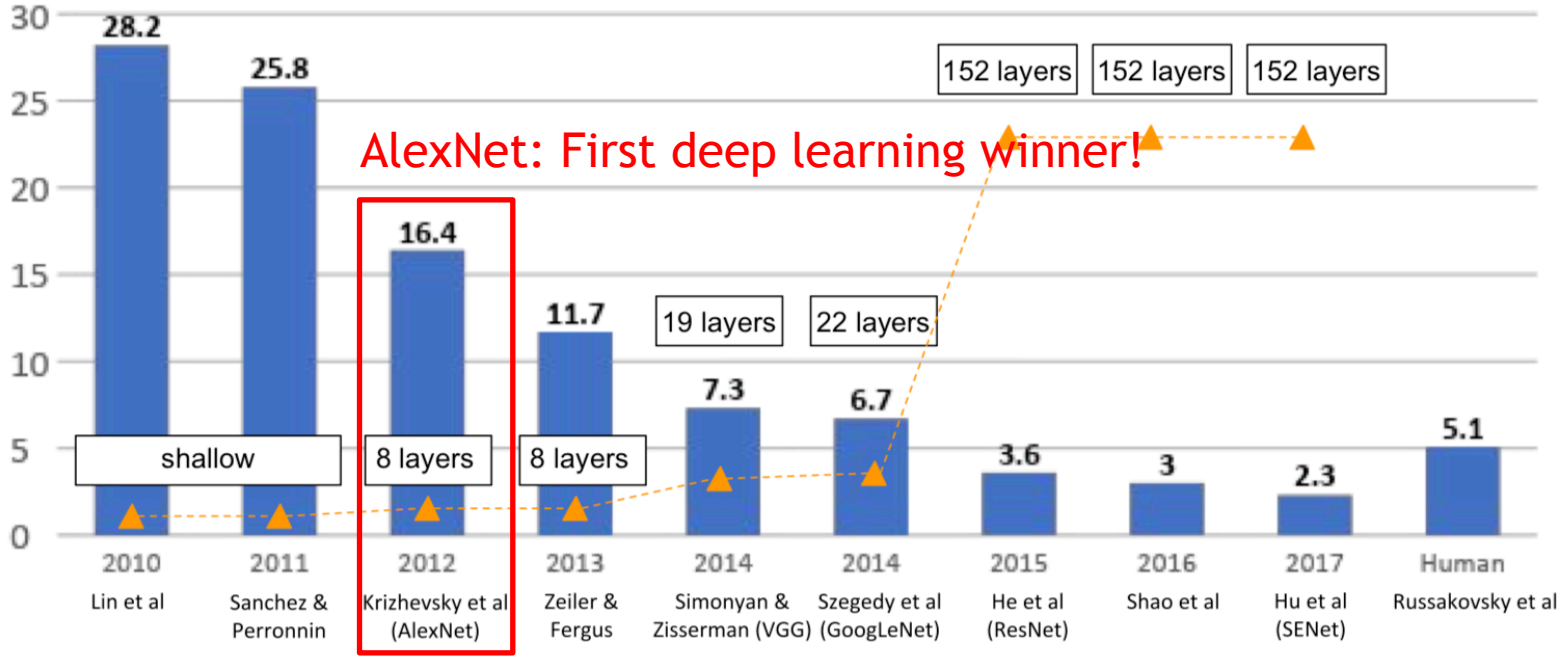
- Fine-tune on CIFAR10



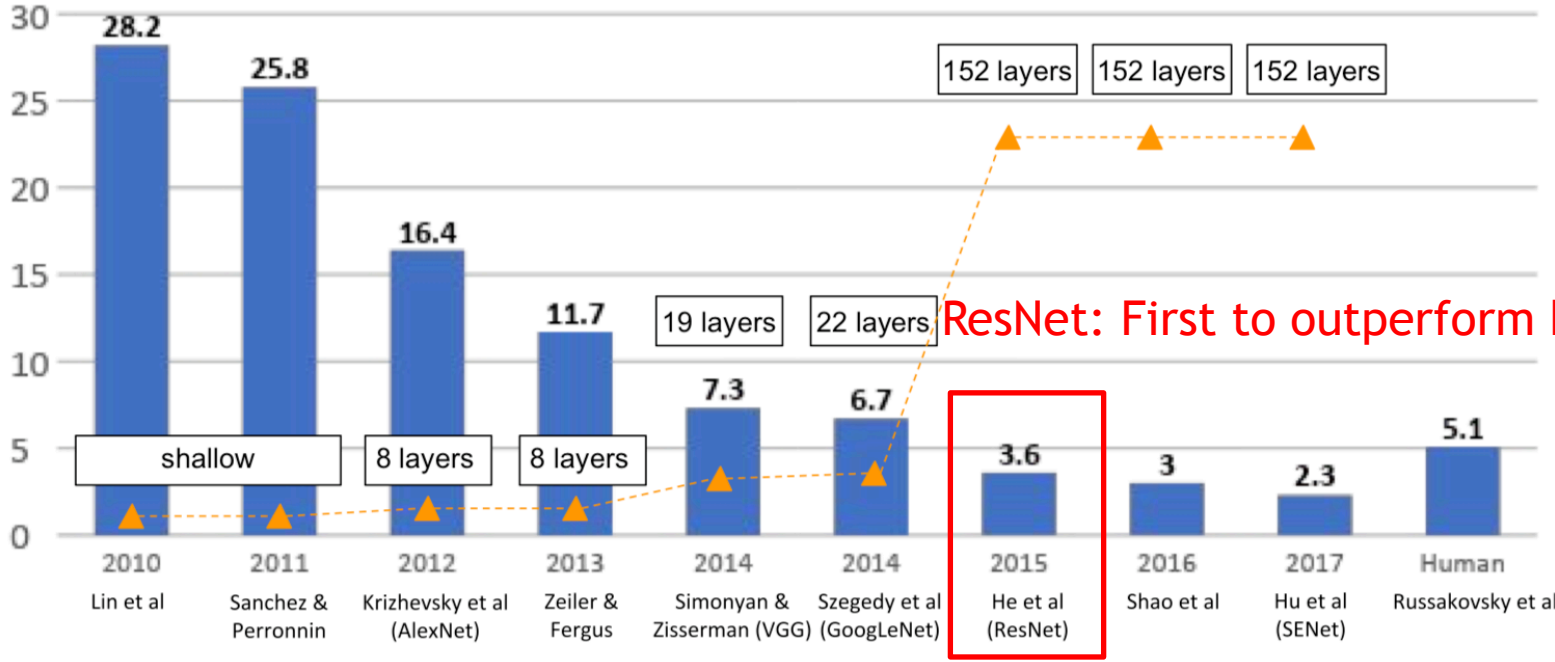
ImageNet Large Scale Visual Recognition Challenge



ImageNet Large Scale Visual Recognition Challenge

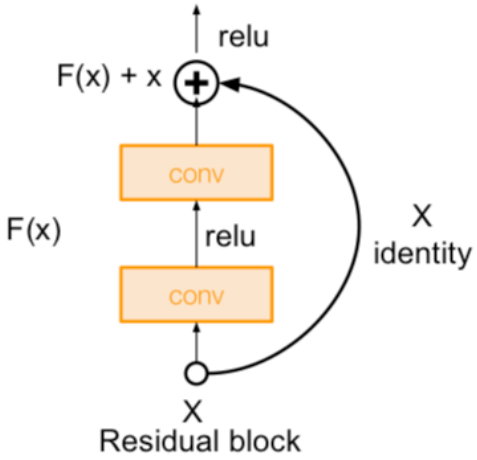


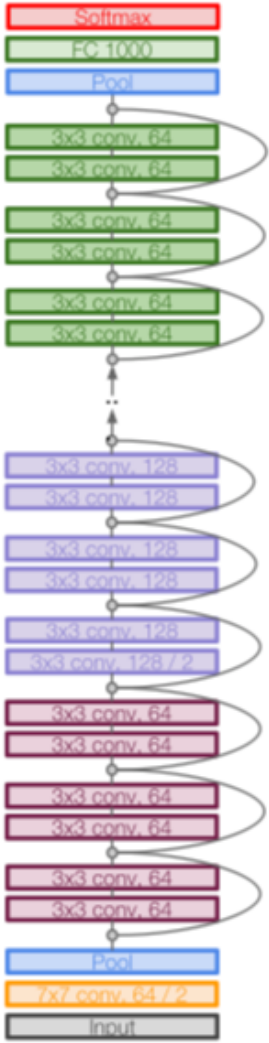
ImageNet Large Scale Visual Recognition Challenge



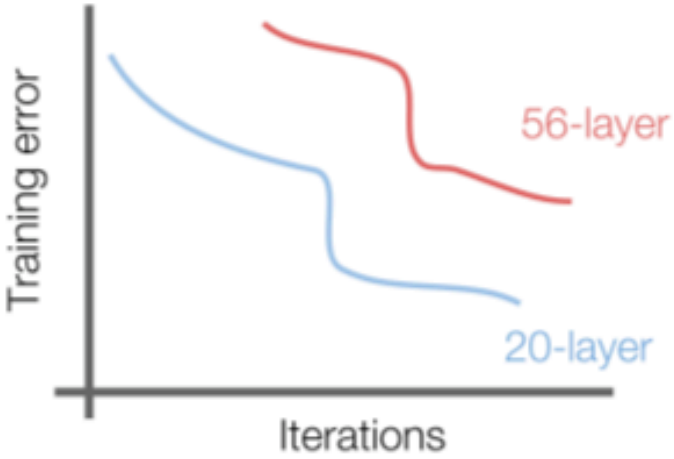
ResNet

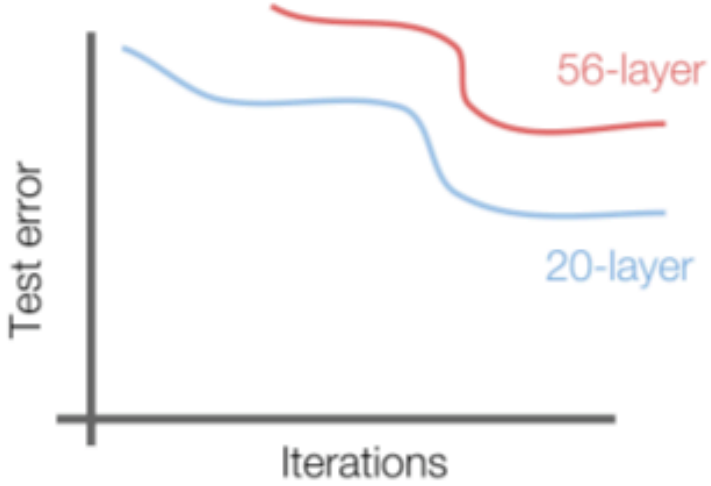
- Very deep Residual Network
  - Uses residual connections



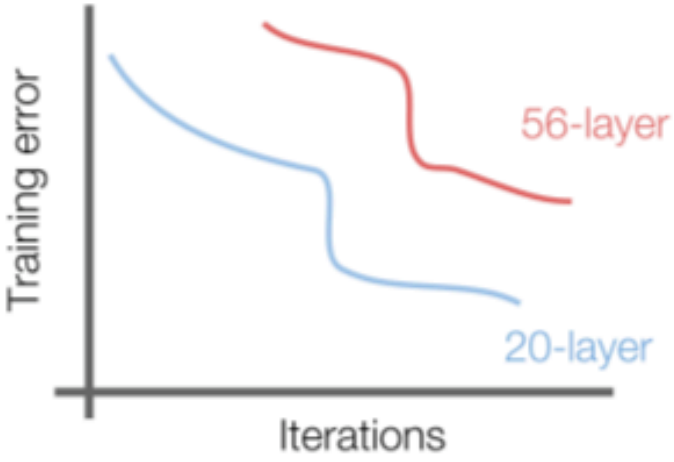


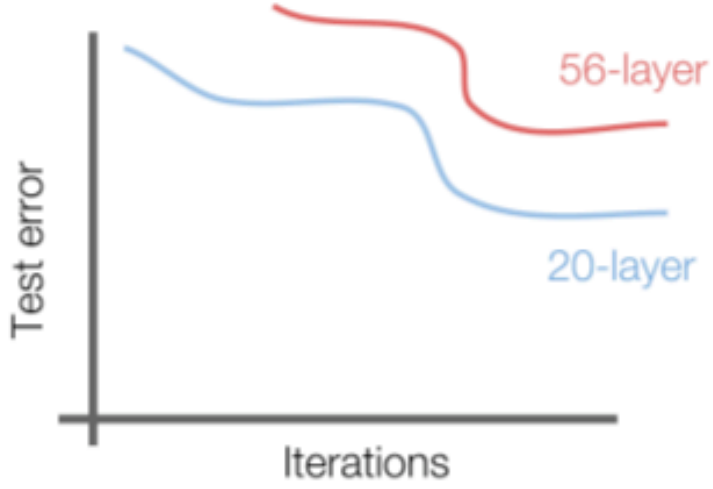
What happens without Residual Connections?





What happens without Residual Connections?





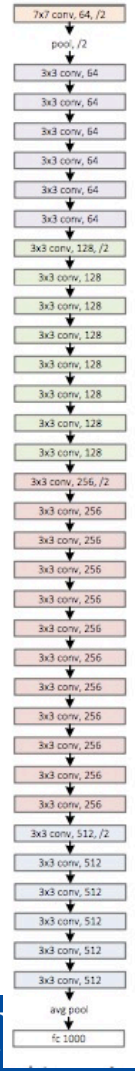
Deeper -> Worse accuracy. Not caused by overfitting!

Slide source: CS231n Lecture 8

What happens without Residual Connections?

Why?

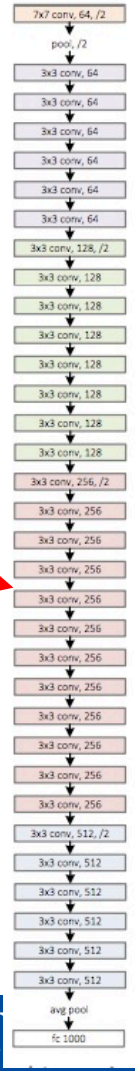
- The degredation problem



What happens without Residual Connections?

Why?

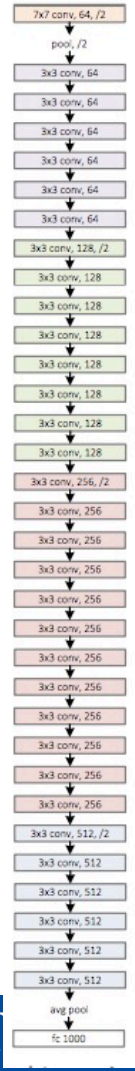
- The degredation problem
  - We have the correct prediction here, but there is still X layers left



What happens without Residual Connections?

Why?

- The degredation problem
  - We have the correct prediction here, but there is still X layers left
- Vanishing gradients
  - Backpropagation makes deltas smaller and smaller



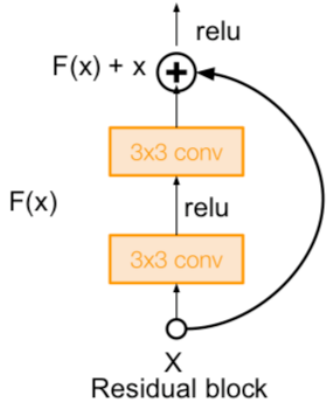
What happens without Residual Connections?

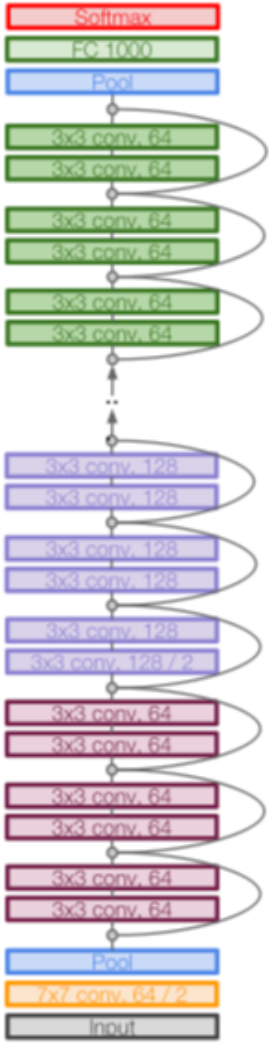
Why?

- The degredation problem
  - We have the correct prediction here, but there is still X layers left
- Vanishing gradients
  - Backpropagation makes deltas smaller and smaller

Solution:

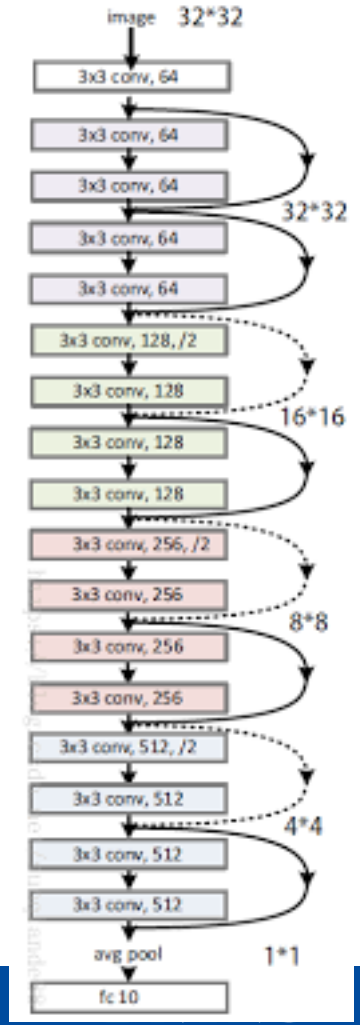
- Add skip connections





What you will use:

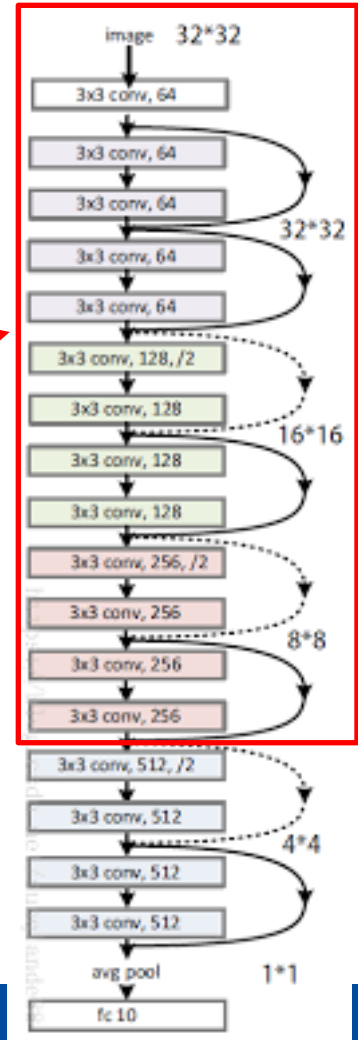
- Resnet-18
- Pre-trained on ImageNet



What you will use:

- Resnet-18
- Pre-trained on ImageNet

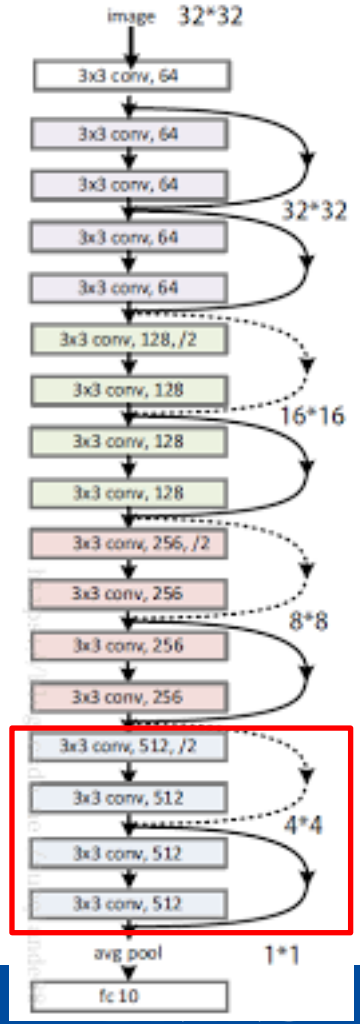
- Freeze these layers
  - = Do not update weights



What you will use:

- Resnet-18
- Pre-trained on ImageNet

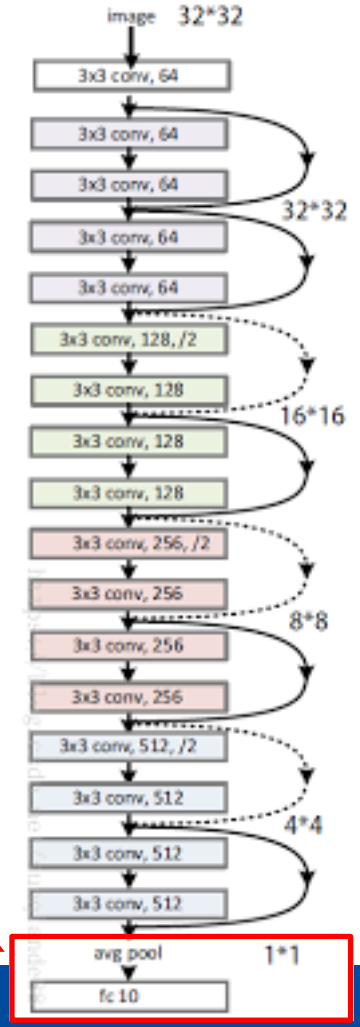
- Unfreeze these
  - = only update these weights



What you will use:

- Resnet-18
- Pre-trained on ImageNet

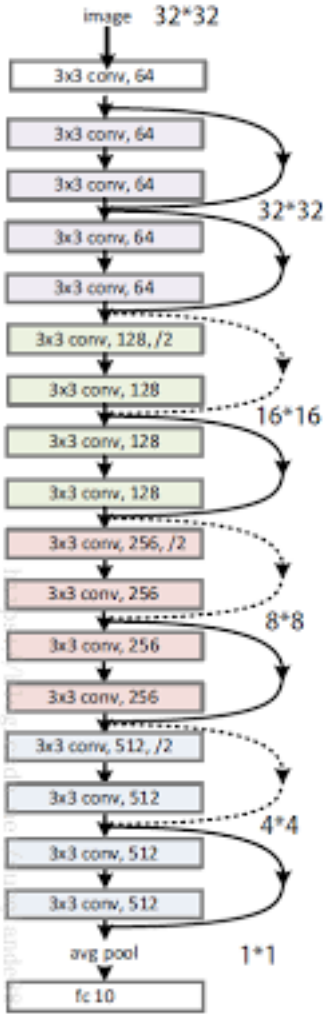
- Replace 1000-classes softmax with 10-classes softmax



In PyTorch:

Load the pretrained model

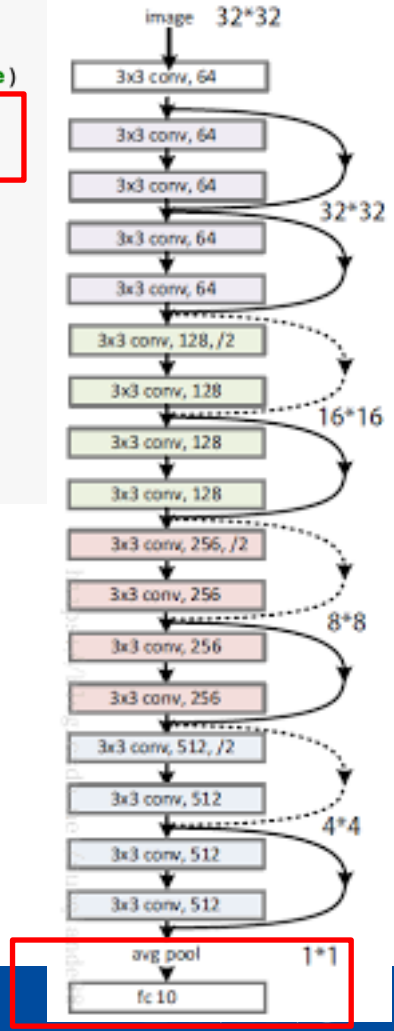
```python
class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.model = torchvision.models.resnet18(pretrained=True)
        self.model.fc = nn.Sequential(
            nn.Linear(2048, 10),
        )
        for param in self.model.parameters():
            param.requires_grad = False
        for param in self.model.fc.parameters():
            param.requires_grad = True
        for param in self.model.layer4.parameters():
            param.requires_grad = True

    def forward(self, x):
        x = nn.functional.interpolate(x, scale_factor=8)
        x = self.model(x)
        return x
```



In PyTorch:

Replace output layer with 10 classes

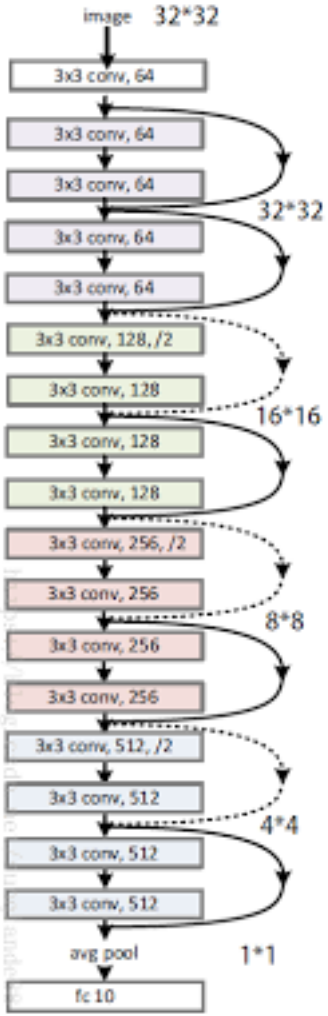
```python
class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.model = torchvision.models.resnet18(pretrained=True)
        self.model.fc = nn.Sequential(
            nn.Linear(2048, 10),
        )
        for param in self.model.parameters():
            param.requires_grad = False
        for param in self.model.fc.parameters():
            param.requires_grad = True
        for param in self.model.layer4.parameters():
            param.requires_grad = True

    def forward(self, x):
        x = nn.functional.interpolate(x, scale_factor=8)
        x = self.model(x)
        return x
```



In PyTorch:

Freeze all layers in model

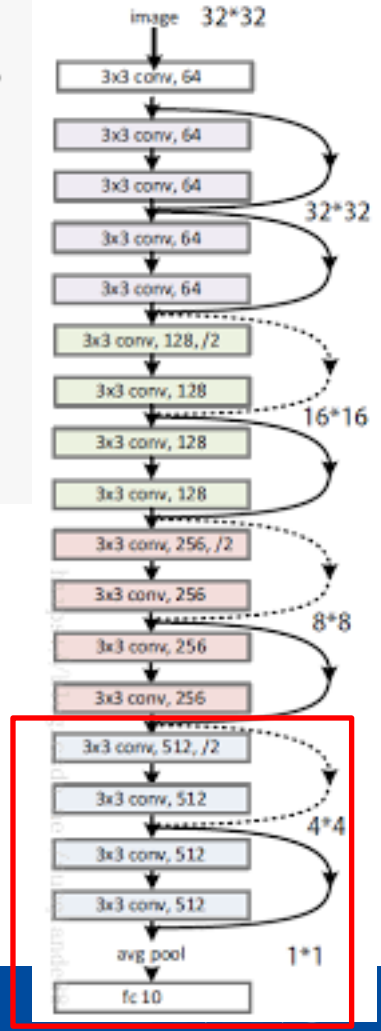
```python
class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.model = torchvision.models.resnet18(pretrained=True)
        self.model.fc = nn.Sequential(
            nn.Linear(2048, 10),
        )
        for param in self.model.parameters():
            param.requires_grad = False
        for param in self.model.fc.parameters():
            param.requires_grad = True
        for param in self.model.layer4.parameters():
            param.requires_grad = True

    def forward(self, x):
        x = nn.functional.interpolate(x, scale_factor=8)
        x = self.model(x)
        return x
```



In PyTorch:

Unfreeze last layers

```python
class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.model = torchvision.models.resnet18(pretrained=True)
        self.model.fc = nn.Sequential(
            nn.Linear(2048, 10),
        )
        for param in self.model.parameters():
            param.requires_grad = False
        for param in self.model.fc.parameters():
            param.requires_grad = True
        for param in self.model.layer4.parameters():
            param.requires_grad = True

    def forward(self, x):
        x = nn.functional.interpolate(x, scale_factor=8)
        x = self.model(x)
        return x
```



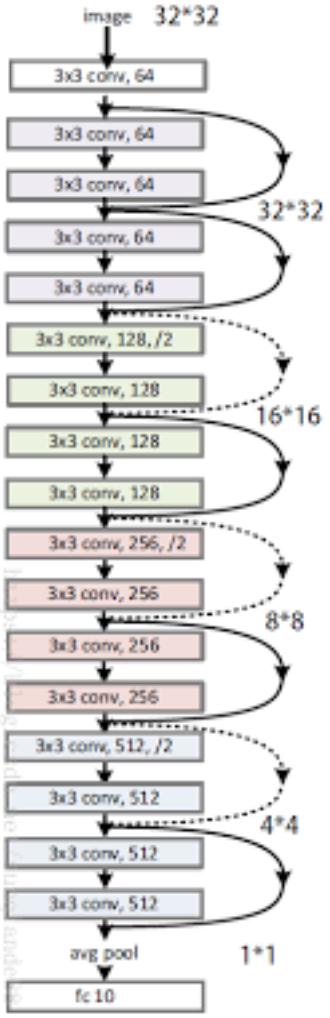
In PyTorch:

ImageNet is trained on 256x256

CIFAR-10 is 32x32.

We upsample the image to 256x256

```python
class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.model = torchvision.models.resnet18(pretrained=True)
        self.model.fc = nn.Sequential(
            nn.Linear(2048, 10),
        )
        for param in self.model.parameters():
            param.requires_grad = False
        for param in self.model.fc.parameters():
            param.requires_grad = True
        for param in self.model.layer4.parameters():
            param.requires_grad = True

    def forward(self, x):
        x = nn.functional.interpolate(x, scale_factor=8)
        x = self.model(x)
        return x
```

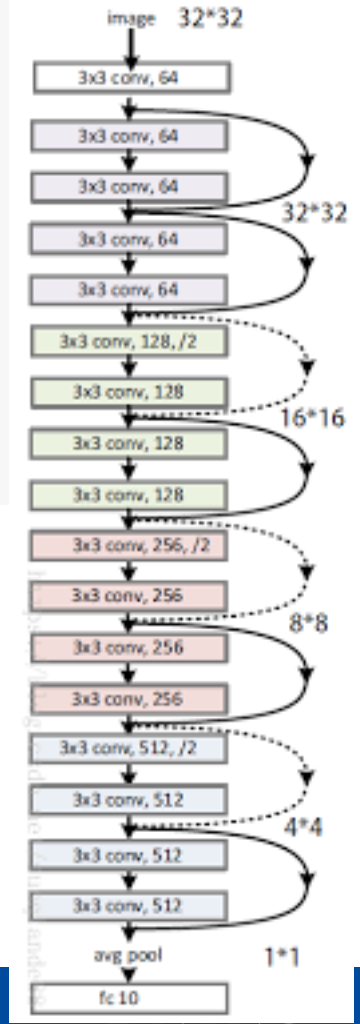


In PyTorch:

Then:

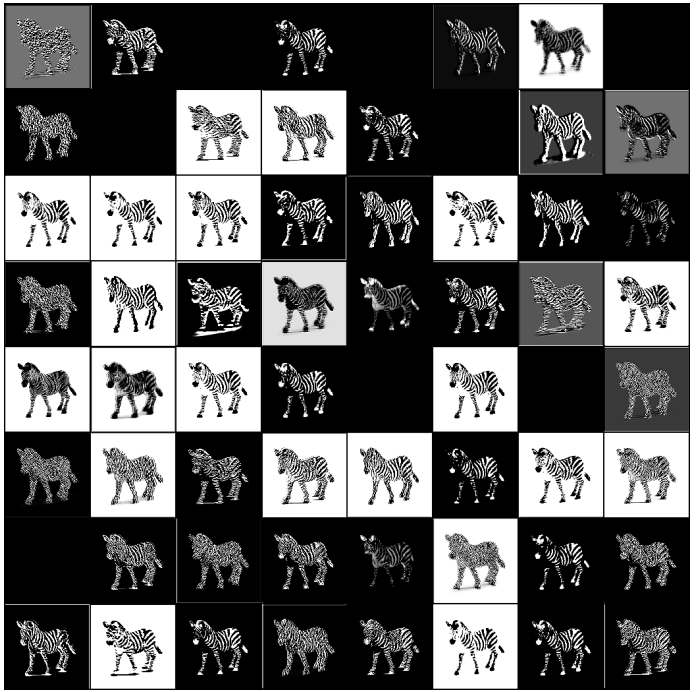
Train of CIFAR10 until early stopping

```python
class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.model = torchvision.models.resnet18(pretrained=True)
        self.model.fc = nn.Sequential(
            nn.Linear(2048, 10),
        )
        for param in self.model.parameters():
            param.requires_grad = False
        for param in self.model.fc.parameters():
            param.requires_grad = True
        for param in self.model.layer4.parameters():
            param.requires_grad = True

    def forward(self, x):
        x = nn.functional.interpolate(x, scale_factor=8)
        x = self.model(x)
        return x
```



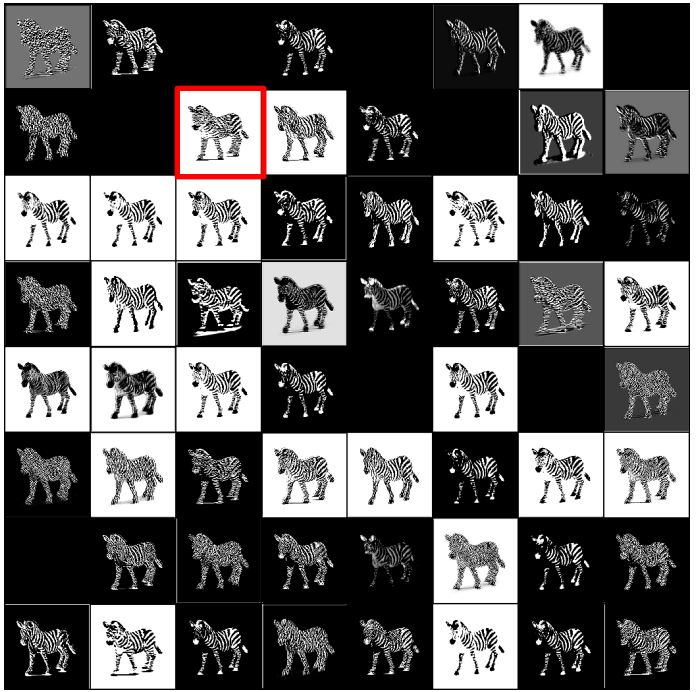
Interpreting CNNs by visualizations

Visualization: First Layer

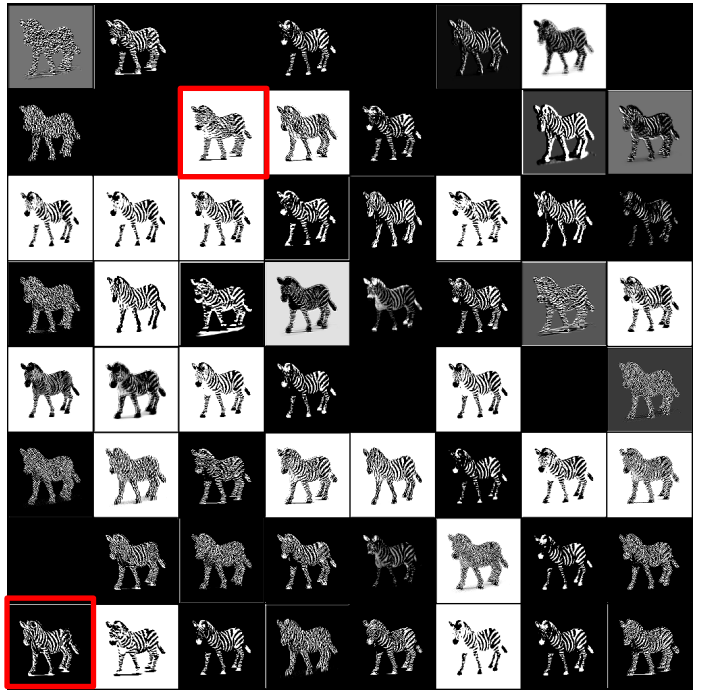


Visualization: First Layer

Horizontal filter?

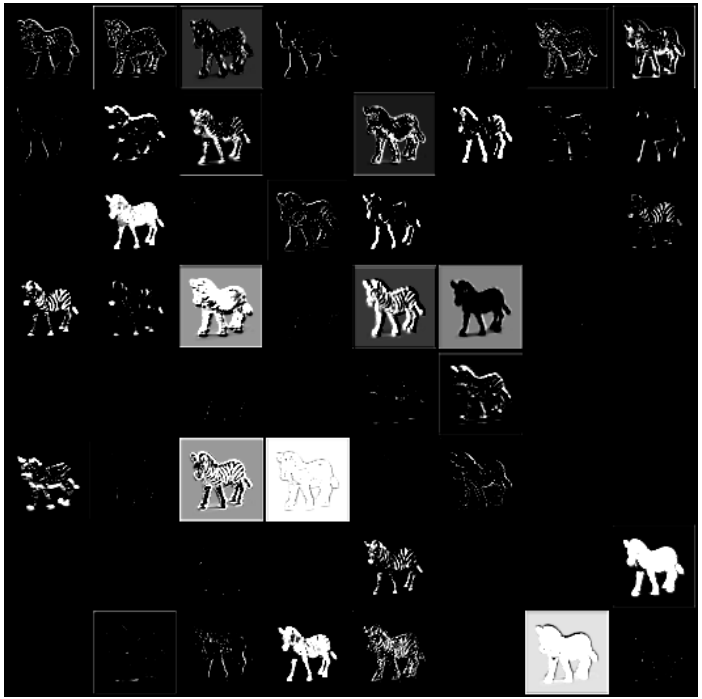


Visualization: First Layer

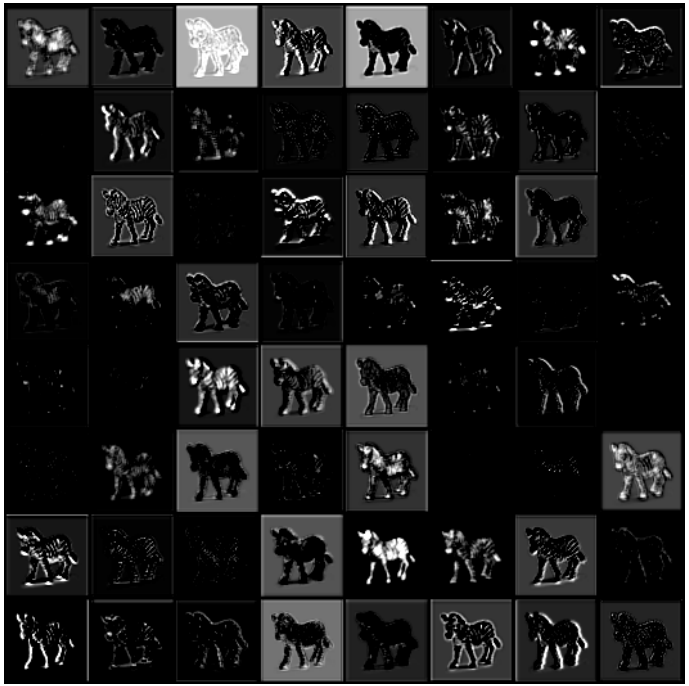


Vertical filter?

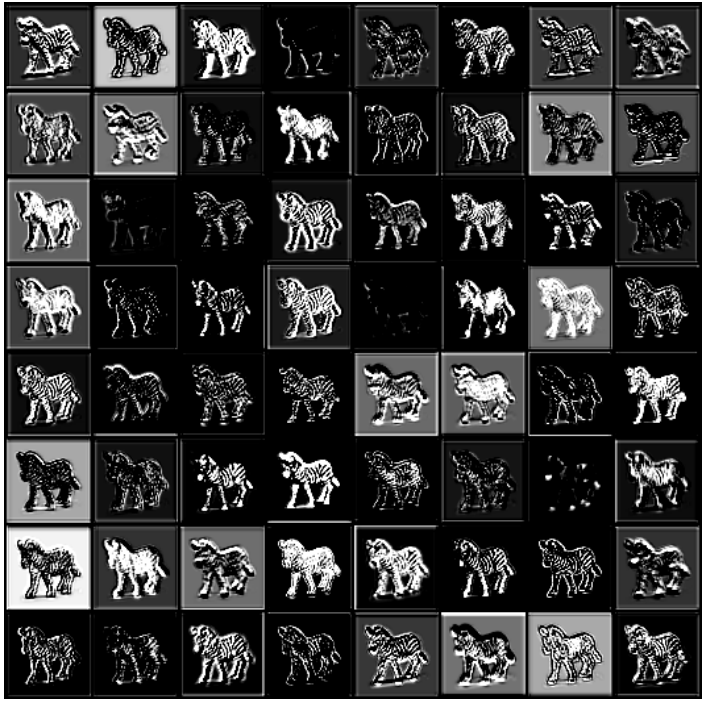
Visualization: Second Layer



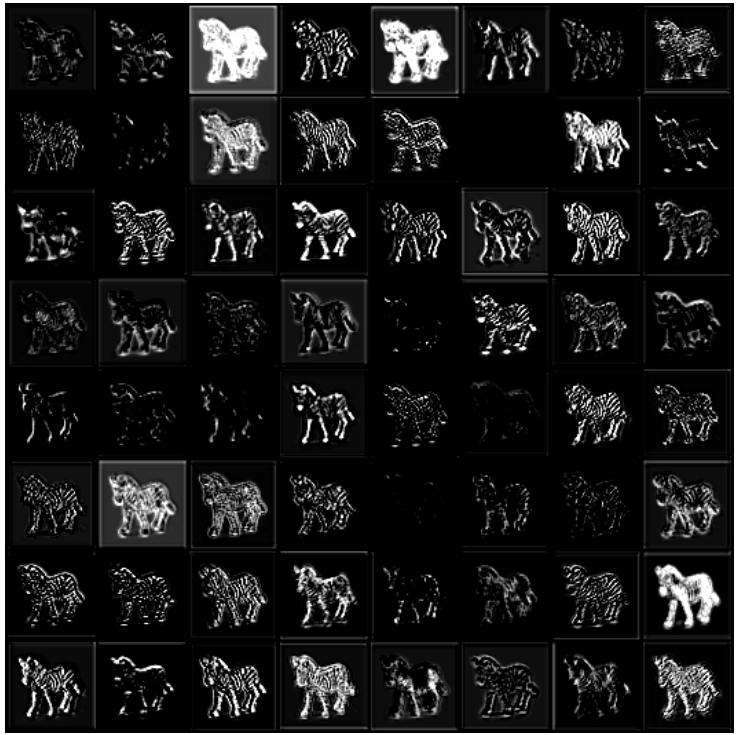
Visualization: Third Layer



Visualization: Fourth Layer

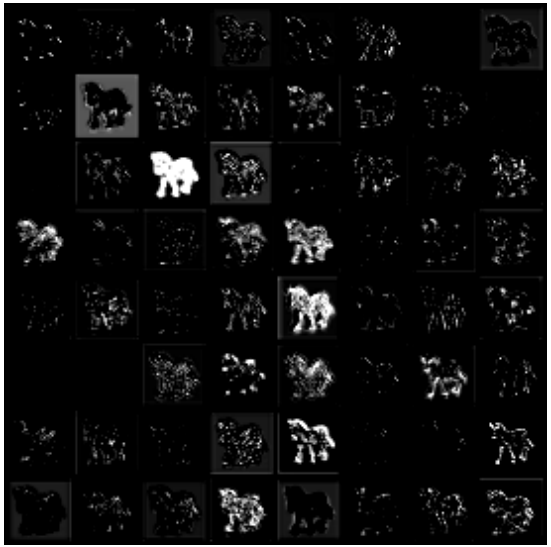


Visualization: Fifth Layer



Visualization: Sixth Layer

Visualization: Seventh Layer



Visualization: Last Layer

In PyTorch:

```
from dataloaders import mean, std
import torchvision
from torchvision.transforms.functional \
  import to_pil_image, to_tensor, normalize

image = plt.imread("test_img5.jpg")
image = to_tensor(image)
image = normalize(image.data, mean, std)
image = image.view(1, *image.shape)
image = nn.functional.interpolate(image, size=(256, 256))

model = torchvision.models.resnet18(pretrained=True)
first_layer_out = model.conv1(image)

to_visualize = first_layer_out.view(first_layer_out.shape[1],
                                    1, *first_layer_out.shape[2:])
torchvision.utils.save_image(to_visualize,
                             "filters_first_layer.png")

```

In PyTorch:

Read the data and normalize similar as we do in dataloader

```
from dataloaders import mean, std
import torchvision
from torchvision.transforms.functional \
  import to_pil_image, to_tensor, normalize

image = plt.imread("test_img5.jpg")
image = to_tensor(image)
image = normalize(image.data, mean, std)
image = image.view(1, *image.shape)
image = nn.functional.interpolate(image, size=(256, 256))

model = torchvision.models.resnet18(pretrained=True)
first_layer_out = model.conv1(image)

to_visualize = first_layer_out.view(first_layer_out.shape[1],
                                    1, *first_layer_out.shape[2:])
torchvision.utils.save_image(to_visualize,
                             "filters_first_layer.png")

```

In PyTorch:

Resize to the expected shape

```
from dataloaders import mean, std
import torchvision
from torchvision.transforms.functional \
  import to_pil_image, to_tensor, normalize

image = plt.imread("test_img5.jpg")
image = to_tensor(image)
image = normalize(image.data, mean, std)
image = image.view(1, *image.shape)
image = nn.functional.interpolate(image, size=(256, 256))

model = torchvision.models.resnet18(pretrained=True)
first_layer_out = model.conv1(image)

to_visualize = first_layer_out.view(first_layer_out.shape[1],
                                    1, *first_layer_out.shape[2:])
torchvision.utils.save_image(to_visualize,
                             "filters_first_layer.png")

```

In PyTorch:

Load pretrained model

Forward pass through **ONLY** the first layer

```
from dataloaders import mean, std
import torchvision
from torchvision.transforms.functional \
  import to_pil_image, to_tensor, normalize

image = plt.imread("test_img5.jpg")
image = to_tensor(image)
image = normalize(image.data, mean, std)
image = image.view(1, *image.shape)
image = nn.functional.interpolate(image, size=(256, 256))

model = torchvision.models.resnet18(pretrained=True)
first_layer_out = model.conv1(image)

to_visualize = first_layer_out.view(first_layer_out.shape[1],
                                    1, *first_layer_out.shape[2:])
torchvision.utils.save_image(to_visualize,
                             "filters_first_layer.png")

```

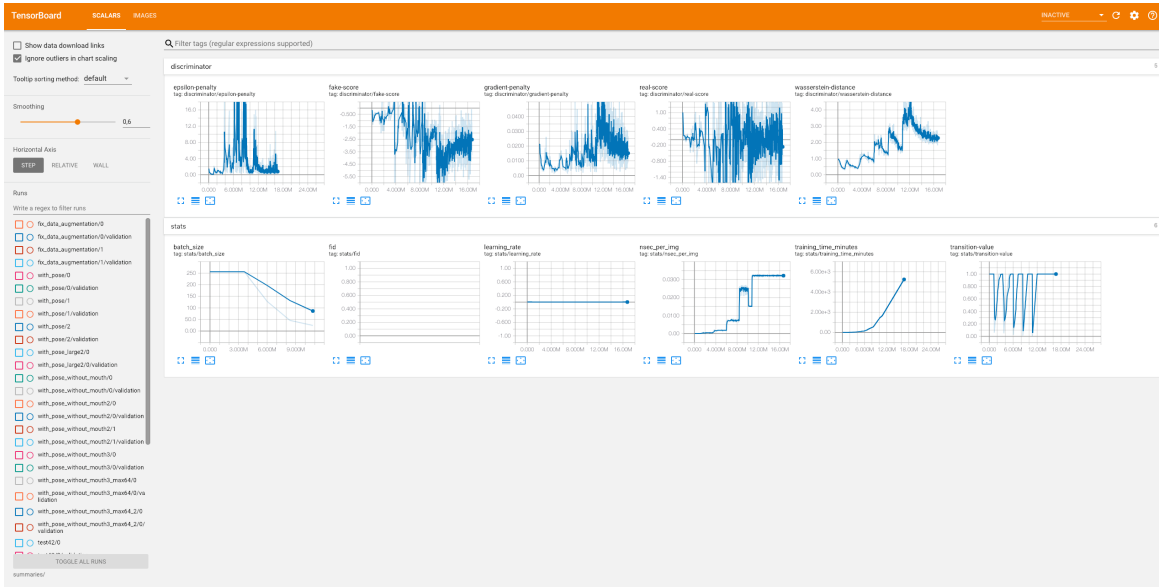
In PyTorch:

Reshape image to expected such that num_filters swap place with batch size and save image.

```
from dataloaders import mean, std
import torchvision
from torchvision.transforms.functional \
  import to_pil_image, to_tensor, normalize

image = plt.imread("test_img5.jpg")
image = to_tensor(image)
image = normalize(image.data, mean, std)
image = image.view(1, *image.shape)
image = nn.functional.interpolate(image, size=(256, 256))

model = torchvision.models.resnet18(pretrained=True)
first_layer_out = model.conv1(image)

to_visualize = first_layer_out.view(first_layer_out.shape[1],
                                    1, *first_layer_out.shape[2:])
torchvision.utils.save_image(to_visualize,
                             "filters_first_layer.png")

```

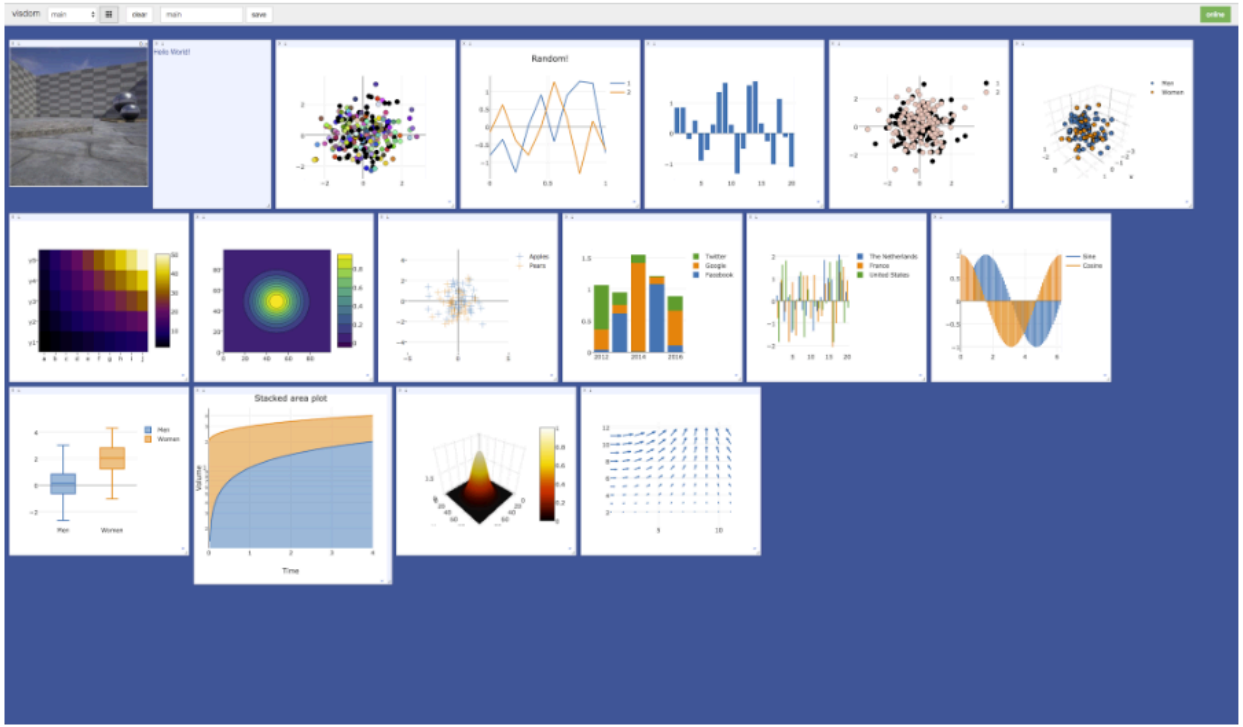
Tensorboard + TensorboardX(Pytorch)

My current Tensorboard:



NTNU

Pytorch Visdom



NTNU

Google Cloud Console

- console.cloud.google.com
-

Recommended resources

- Stanford CS231n:
  - http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture09.pdf
  - http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture08.pdf
- https://aifiddle.io
- CNN Cheat Sheet