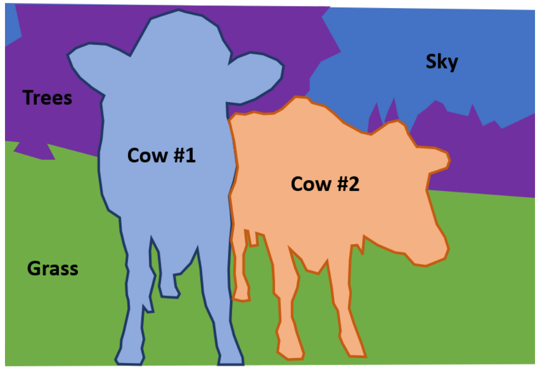
DL Frameworks and More

Computer Vision (UW EE/CSE 576)



Richard Szeliski

Facebook & UW

Lecture 11 – May 5, 2020

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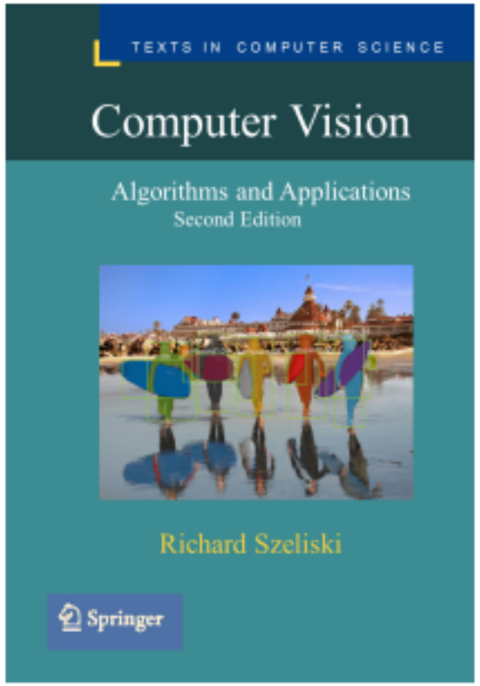
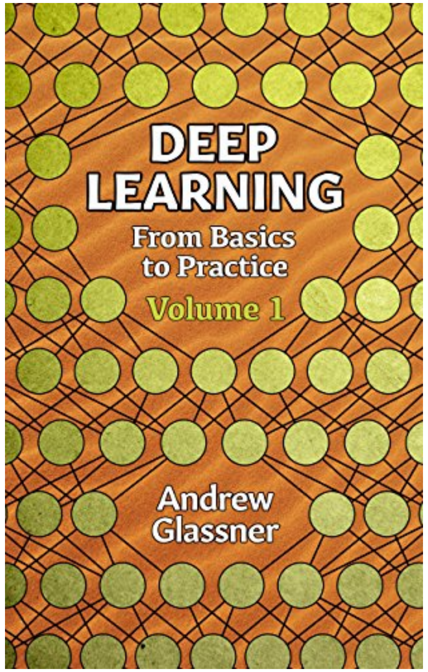
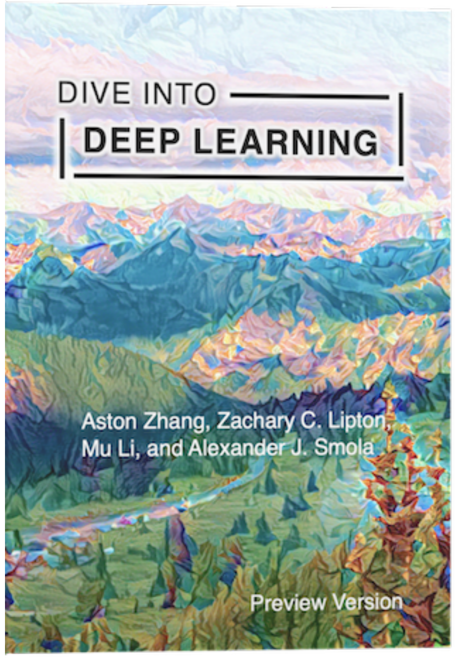
Class calendar

Date	Topic	Slides	Reading	Homework
April 9	Filters and convolutions	Google Slides	Szeliski, Chapter 3	HW1 due, HW2 assigned
April 14	Interpolation and Optimization	pdf, pptx	Szeliski, Chapter 4	
April 16	Machine Learning	pdf, pptx	Szeliski, Chapter 5.1-5.2	
April 21	Deep Neural Networks	pdf, pptx	Szeliski, Chapter 5.3	
April 23	Convolutional Neural Networks	pdf, pptx	Szeliski, Chapter 5.4	HW2 due, HW3 assigned
April 28	Network Architectures	pdf, pptx	Szeliski, Chapter 5.4	
April 30	Segmentation and Detection	pdf, pptx	Szeliski, Chapter 6.3	
May 5	DL Languages, Instance Segmentation		Szeliski, Chapter 6.4	
May 7	Edges, features, matching, RANSAC		Szeliski, Chapter 7.1-7.2, 8.1-8.2	HW3 due, HW4 assigned

References







https://d2l.ai/

Readings

Chapter 6

Recognition

Unfortunately, not yet ready ☹

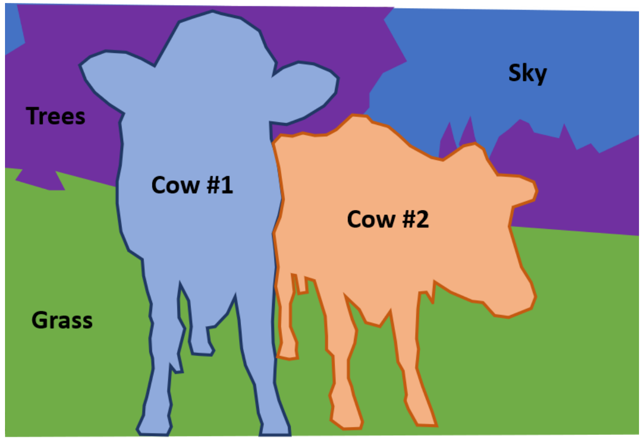
DL software and more

- Deep learning frameworks
- Instance segmentation
- 3D neural networks
- Video

```python
class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        # 1 input image channel, 6 output channels, 5x5 square convolution
        # kernel
        self.conv1 = nn.Conv2d(1, 6, 5)
        self.conv2 = nn.Conv2d(6, 16, 5)
        # an affine operation: y = Wx + b
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        # Max pooling over a (2, 2) window
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        # If the size is a square you can only specify a single number
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = x.view(-1, self.num_flat_features(x))
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```



clink glass → drink

As before, I'm borrowing slides from

Lecture 9:
Deep Learning Frameworks

A zoo of frameworks!

Caffe
(UC Berkeley)

→

Caffe2
(Facebook)

Torch
(NYU / Facebook)

→

PyTorch
(Facebook)

Theano
(U Montreal)

→

TensorFlow
(Google)

PaddlePaddle
(Baidu)

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

JAX
(Google)

Chainer

CNTK
(Microsoft)

Keras

A zoo of frameworks!

Caffe
(UC Berkeley)

Caffe2
(Facebook)

Torch
(NYU / Facebook)

PyTorch
(Facebook)

Theano
(U Montreal)

TensorFlow
(Google)

We'll focus on this one

PaddlePaddle
(Baidu)

Chainer

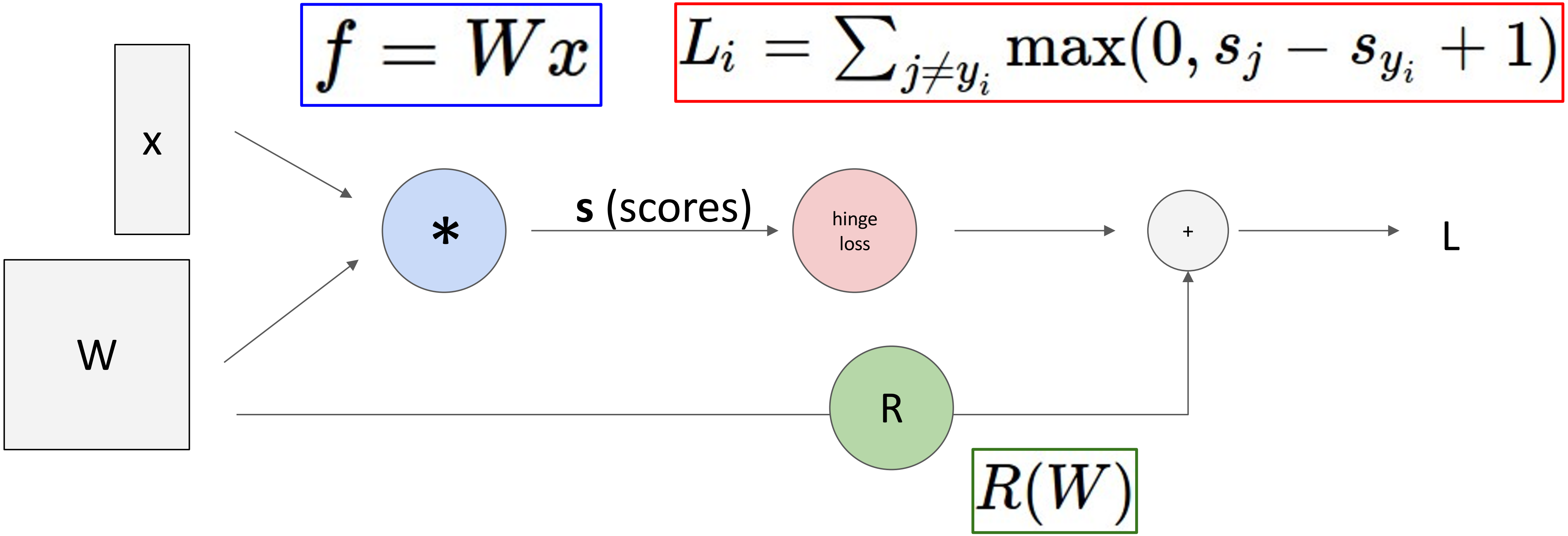
MXNet
(Amazon)
Developed by U Washington, CMU, MIT, Hong Kong U, etc but main framework of choice at AWS

CNTK
(Microsoft)

JAX
(Google)

Keras

Recall: Computational Graphs



The point of deep learning frameworks

1. Allow rapid prototyping of new ideas
2. Automatically compute gradients for you
3. Run it all efficiently on GPU (or TPU)

PyTorch

PyTorch: Versions

For this class we are using **PyTorch version 1.5** (Released April 2020), running on Google Colab

Be careful if you are looking at older PyTorch code – the API changed a lot before 1.0
(0.3 to 0.4 had big changes!)

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: 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

```
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
```

Gradient descent step on weights

PyTorch: Tensors

To run on GPU, just use a different device!

```
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: Autograd

Creating Tensors with **requires_grad=True** enables autograd

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

```python
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
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        w1.grad.zero_()
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```

PyTorch: Autograd

```python
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_()
```

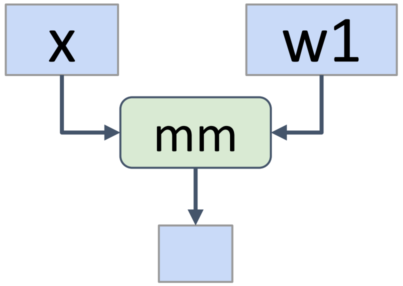
Forward pass looks exactly the same as before, but we don't need to track intermediate values - PyTorch keeps track of them for us in the graph

PyTorch: Autograd

Computes gradients with respect to all inputs that 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)
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




```python
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)

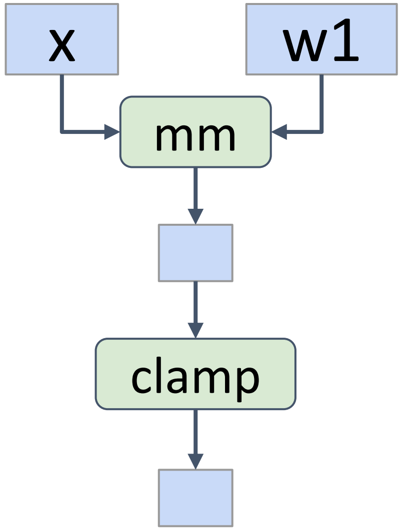
learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

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

Every operation on a tensor with requires_grad=True will add to the computational graph, and the resulting tensors will also have requires_grad=True

PyTorch: Autograd



Every operation on a tensor with requires_grad=True will add to the computational graph, and the resulting tensors will also have requires_grad=True

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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
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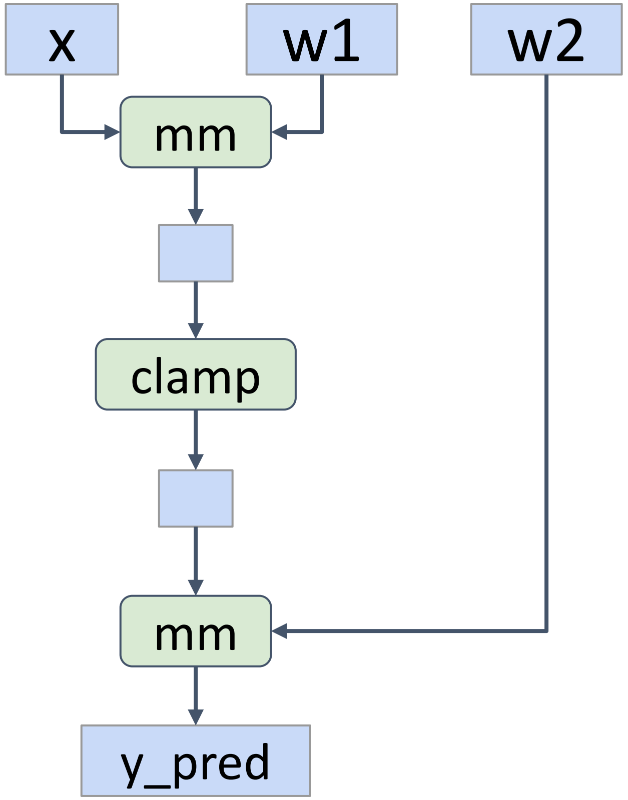
```

PyTorch: Autograd




```python
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
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        w1.grad.zero_()
        w2.grad.zero_()
```
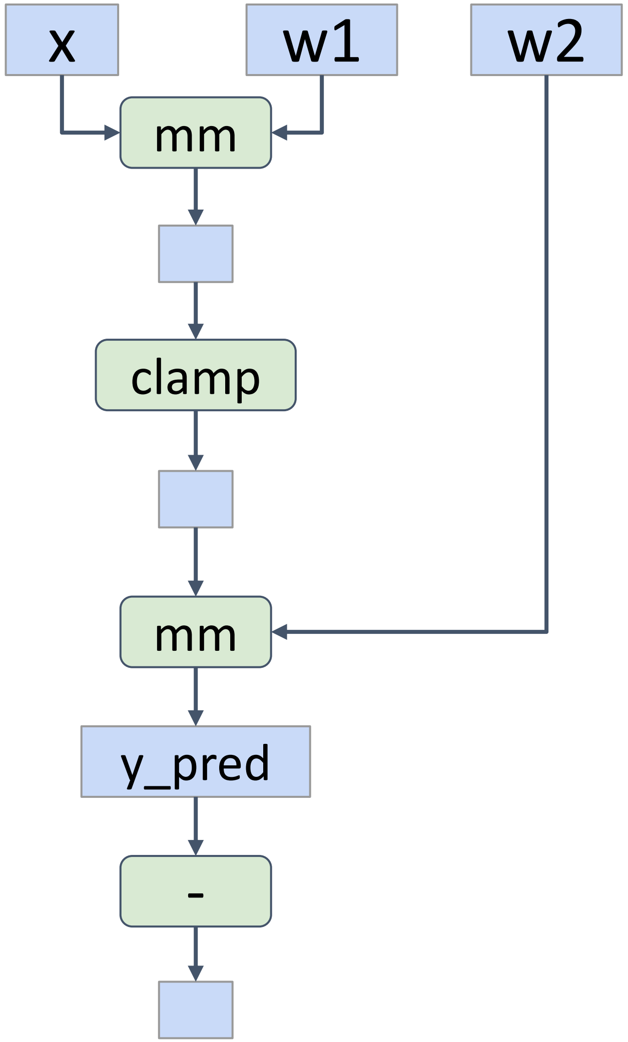

PyTorch: Autograd




```
import torch

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

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

    loss.backward()

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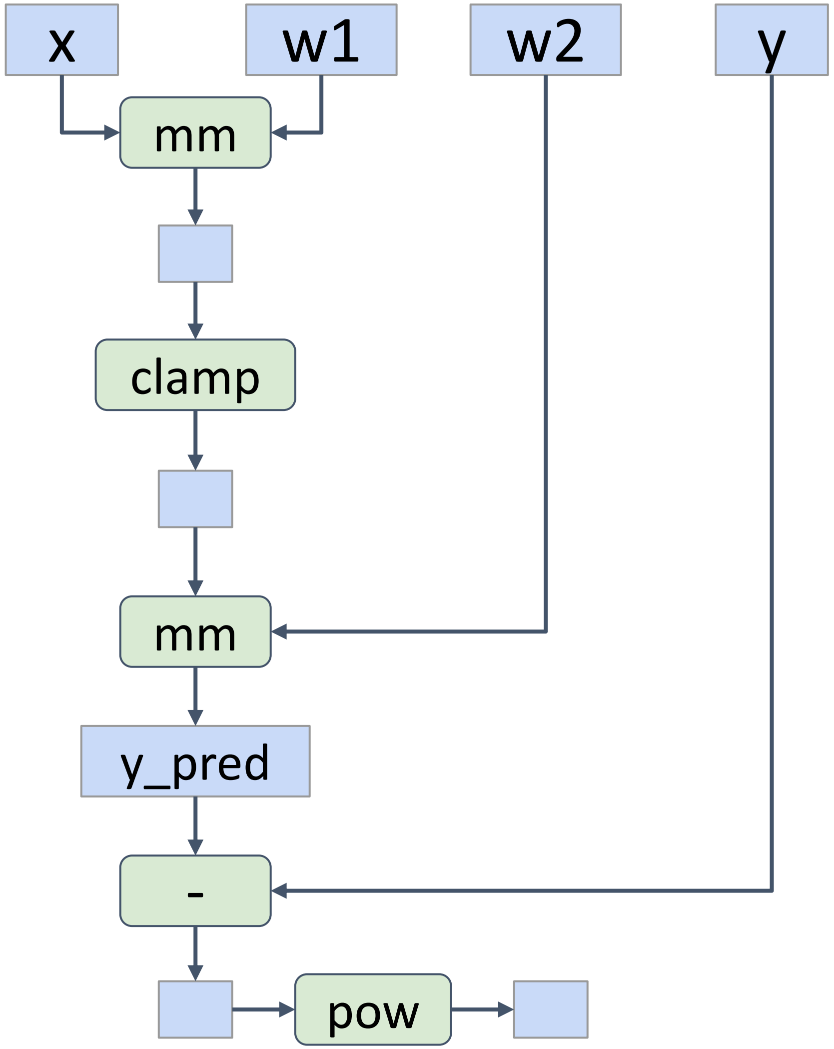
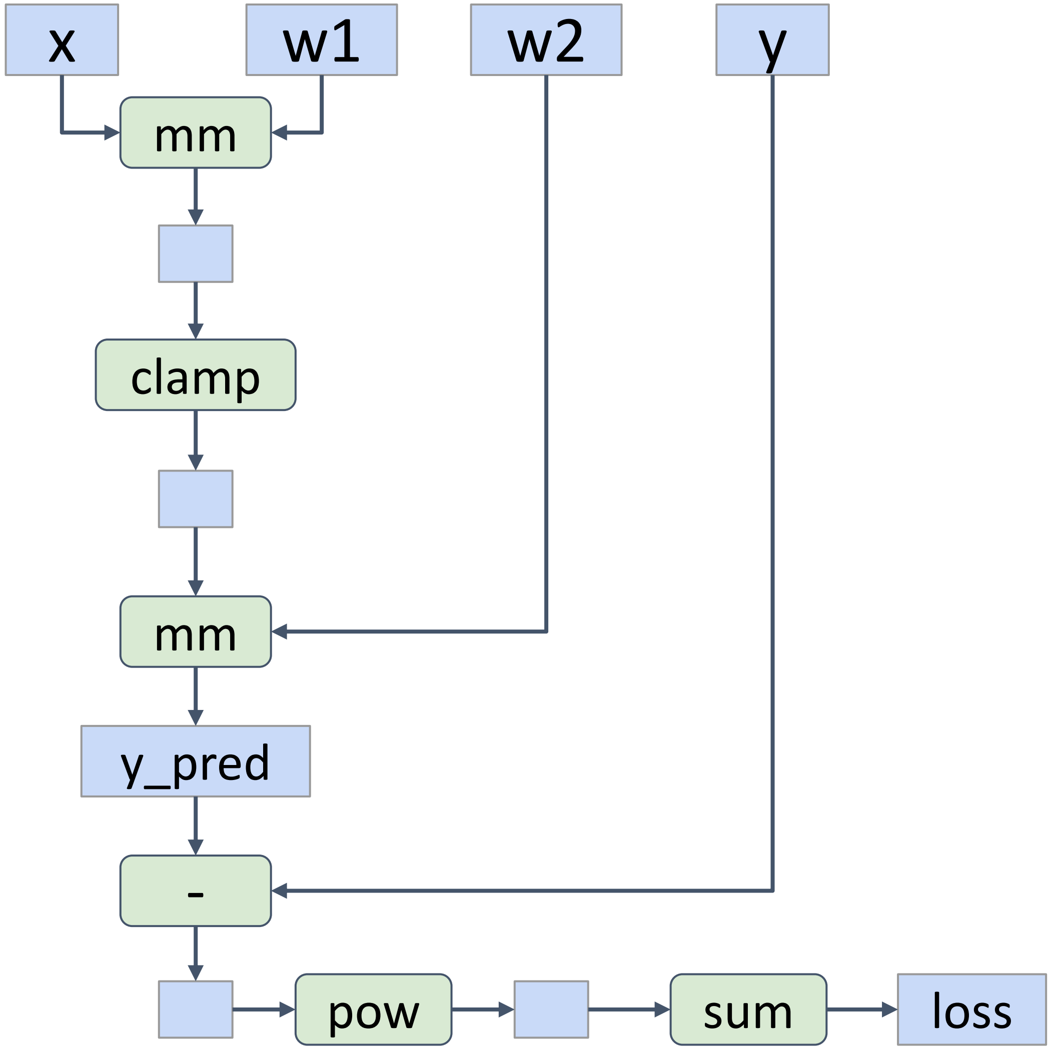

PyTorch: Autograd



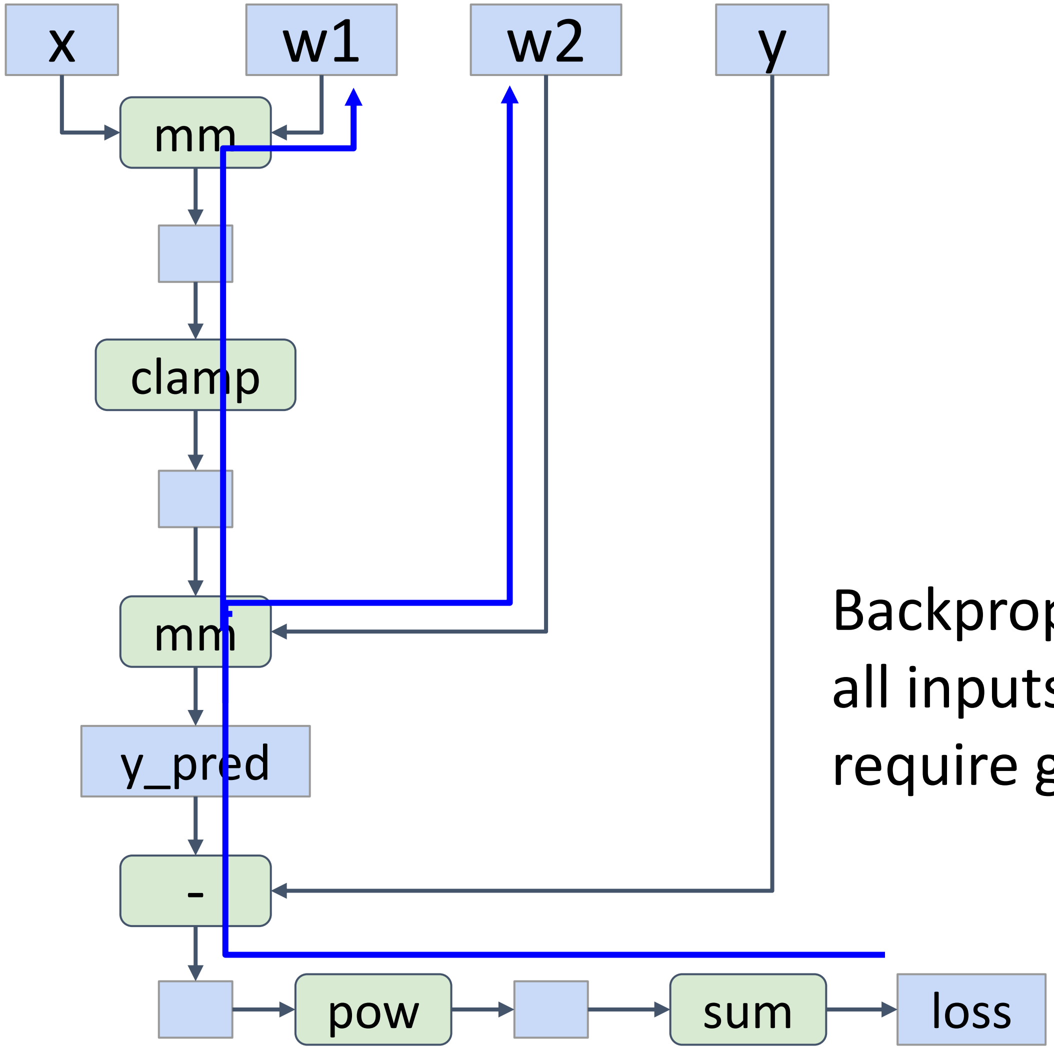

```python
import torch

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




```python
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



Backprop to all inputs that require grad

```
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

x w1 w2 y

After backward finishes, gradients are **accumulated** into w1.grad and w2.grad and the graph is destroyed

```
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

x | w1 | w2 | y

After backward finishes, gradients are **accumulated** into w1.grad and w2.grad and the graph is destroyed

Make gradient step on 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

x w1 w2 y

```python
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_()
```

After backward finishes, gradients are **accumulated** into w1.grad and w2.grad and the graph is destroyed

Set gradients to zero – forgetting this is a common bug!

PyTorch: Autograd

x w1 w2 y

After backward finishes, gradients are **accumulated** into w1.grad and w2.grad and the graph is destroyed

Tell PyTorch not to build a graph for these operations

```
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 functions

Can define new operations using Python functions

```
def sigmoid(x):
  return 1.0 / (1.0 + (-x).exp())
```

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10

x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
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 = sigmoid(x.mm(w1)).mm(w2)
  loss = (y_pred - y).pow(2).sum()

  loss.backward()
  if t % 50 == 0:
    print(t, loss.item())

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

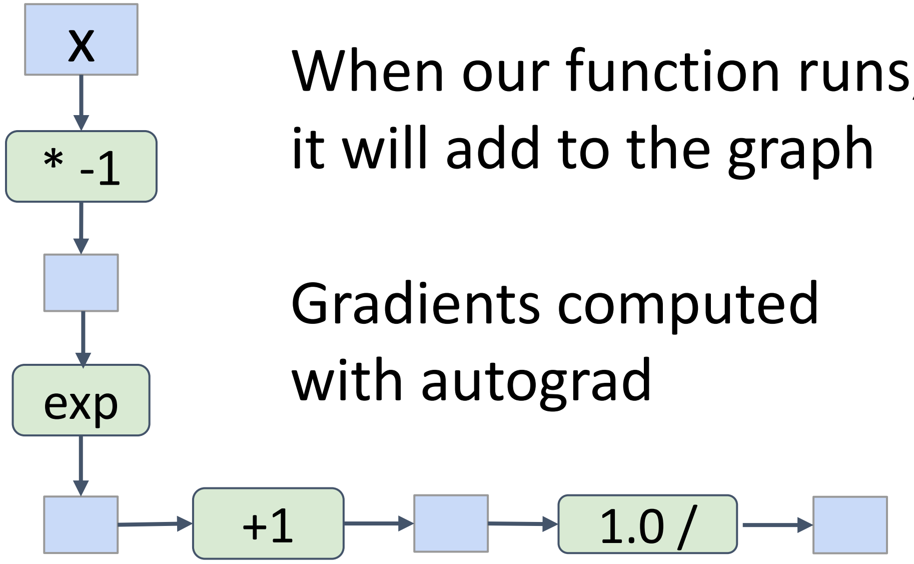
PyTorch: New functions

Can define new operations using Python functions

```
def sigmoid(x):
  return 1.0 / (1.0 + (-x).exp())
```

When our function runs, it will add to the graph

Gradients computed with autograd

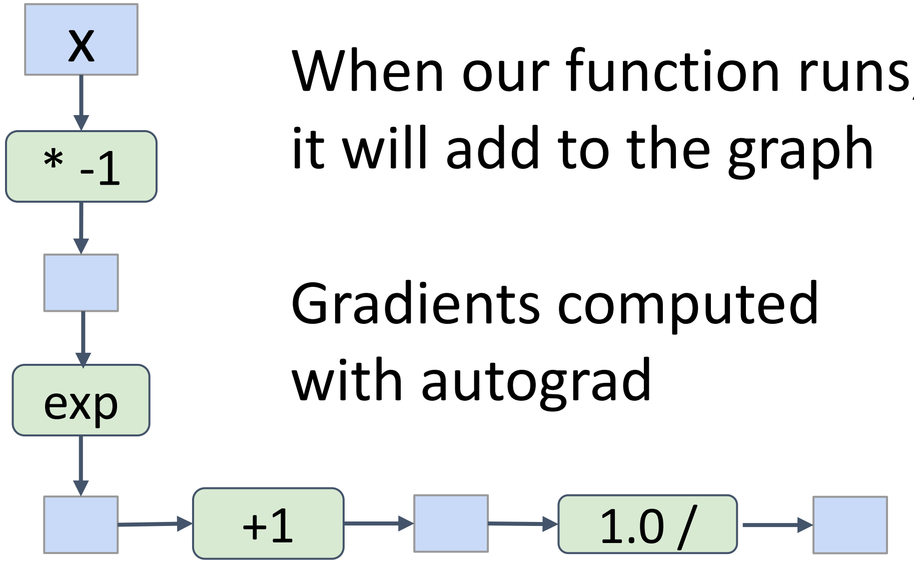



```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10

x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
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 = sigmoid(x.mm(w1)).mm(w2)
  loss = (y_pred - y).pow(2).sum()

  loss.backward()
  if t % 50 == 0:
    print(t, loss.item())

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

PyTorch: New functions

Can define new operations using Python functions

```
def sigmoid(x):
  return 1.0 / (1.0 + (-x).exp())
```



When our function runs, it will add to the graph

Gradients computed with autograd

Define new autograd operators by subclassing Function, define forward and backward

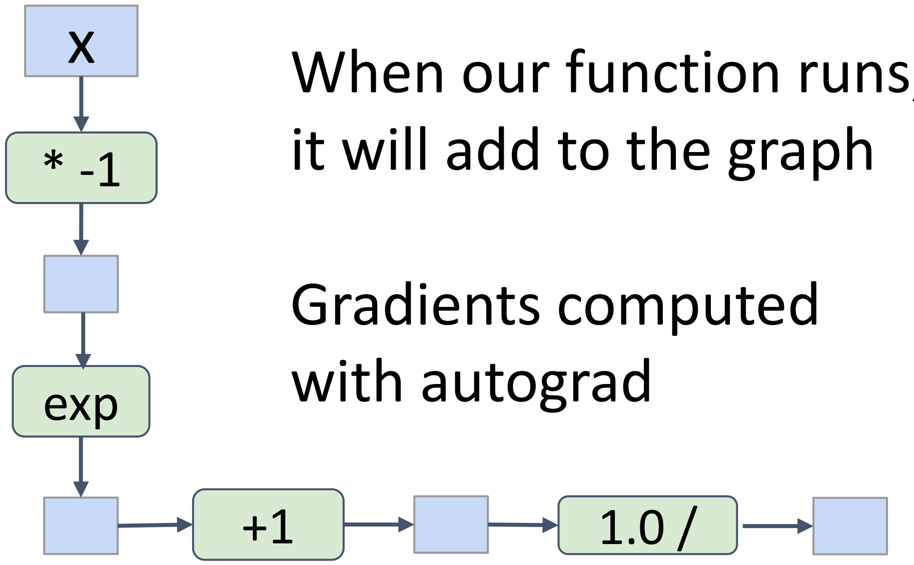
```
class Sigmoid(torch.autograd.Function):
  @staticmethod
  def forward(ctx, x):
    y = 1.0 / (1.0 + (-x).exp())
    ctx.save_for_backward(y)
    return y

  @staticmethod
  def backward(ctx, grad_y):
    y, = ctx.saved_tensors
    grad_x = grad_y * y * (1.0 - y)
    return grad_x

def sigmoid(x):
  return Sigmoid.apply(x)
```

Recall: $$\frac{\partial}{\partial x}\left[\sigma(x)\right] = (1 - \sigma(x))\sigma(x)$$

PyTorch: New functions

Can define new operations using Python functions

```python
def sigmoid(x):
  return 1.0 / (1.0 + (-x).exp())
```



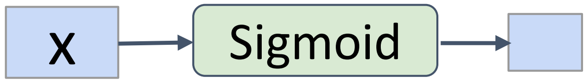
When our function runs, it will add to the graph

Gradients computed with autograd

Define new autograd operators by subclassing Function, define forward and backward

```python
class Sigmoid(torch.autograd.Function):
  @staticmethod
  def forward(ctx, x):
    y = 1.0 / (1.0 + (-x).exp())
    ctx.save_for_backward(y)
    return y

  @staticmethod
  def backward(ctx, grad_y):
    y, = ctx.saved_tensors
    grad_x = grad_y * y * (1.0 - y)
    return grad_x

def sigmoid(x):
  return Sigmoid.apply(x)
```

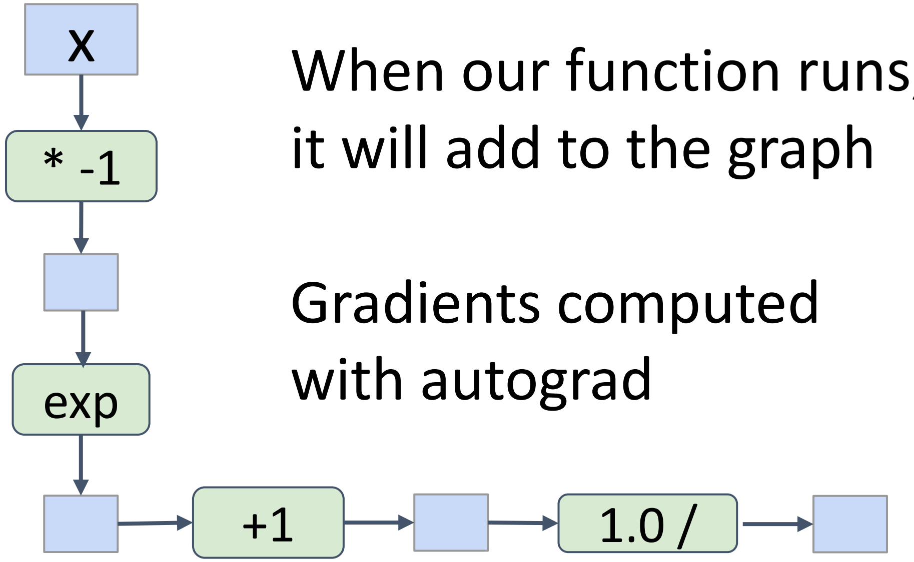
Now when our function runs, it adds one node to the graph!



PyTorch: New functions

Can define new operations using Python functions

```
def sigmoid(x):
  return 1.0 / (1.0 + (-x).exp())
```



When our function runs, it will add to the graph

Gradients computed with autograd

Define new autograd operators by subclassing Function, define forward and backward

```
class Sigmoid(torch.autograd.Function):
  @staticmethod
  def forward(ctx, x):
    y = 1.0 / (1.0 + (-x).exp())
    ctx.save_for_backward(y)
    return y

  @staticmethod
  def backward(ctx, grad_y):
    y, = ctx.saved_tensors
    grad_x = grad_y * y * (1.0 - y)
    return grad_x

def sigmoid(x):
  return Sigmoid.apply(x)
```

In practice this is pretty rare – in most cases Python functions are good enough

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

Object-oriented API: Define model object as sequence of layers objects, each of which holds weight tensors

```
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

```
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()
```

Forward pass: Feed data to model and compute loss

torch.nn.functional has useful helpers like loss functions

PyTorch: nn

```
import torch

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

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

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

    loss.backward()

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

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

PyTorch: nn

```
import torch

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

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

learning_rate = 1e-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()
```

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 and zero gradients

PyTorch: nn
Defining Modules

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

Modules can contain weights or other modules

Very common to define your own models or layers as custom 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
Defining 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
Defining 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
Defining Modules

Define forward pass using child modules and tensor operations

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()
```

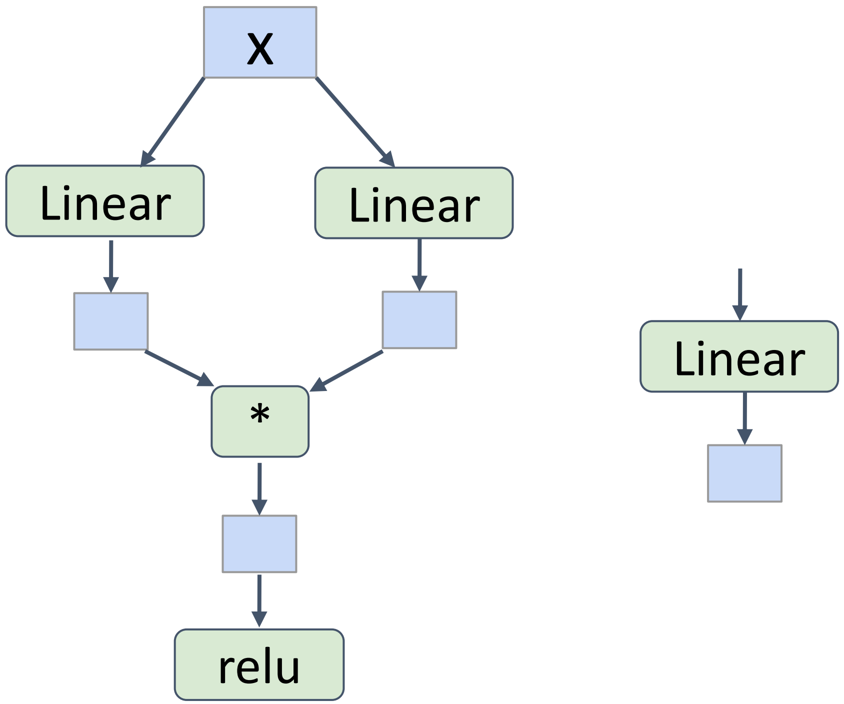
PyTorch: nn
Defining Modules

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
Defining Modules

Define network component as a Module subclass

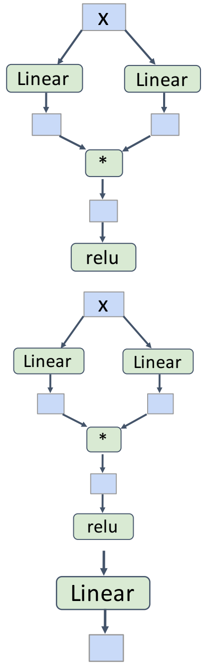



```python
import torch

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
Defining Modules

Stack multiple instances of the component in a sequential

Very easy to quickly build complex network architectures!




```python
import torch

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

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

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

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

PyTorch: DataLoaders

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

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

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

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

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

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

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

PyTorch: DataLoaders

Iterate over loader to form minibatches

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

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

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

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

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

PyTorch: Pretrained Models

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

```
import torch
import torchvision

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

Static vs Dynamic Graphs

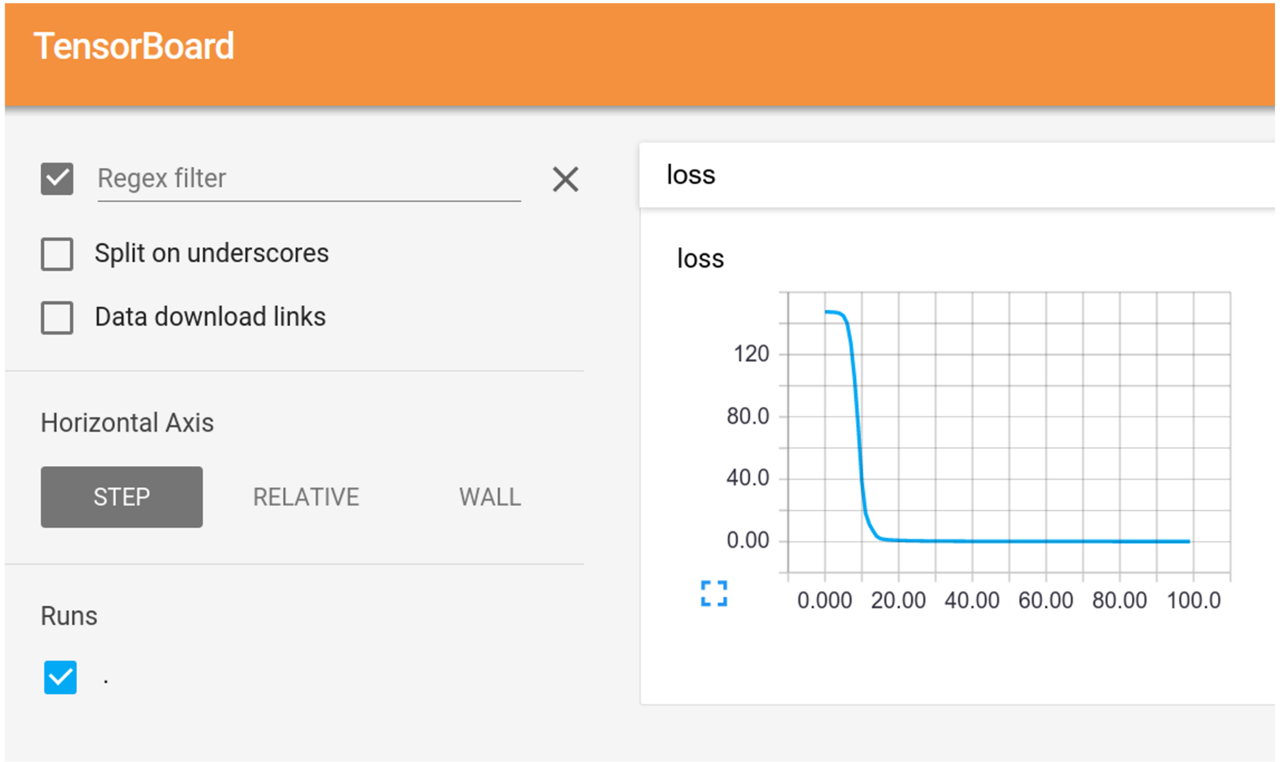
- See Justin's Lecture 8 for more slides…

TensorFlow and Keras

- See Justin's Lecture 8 for more slides…

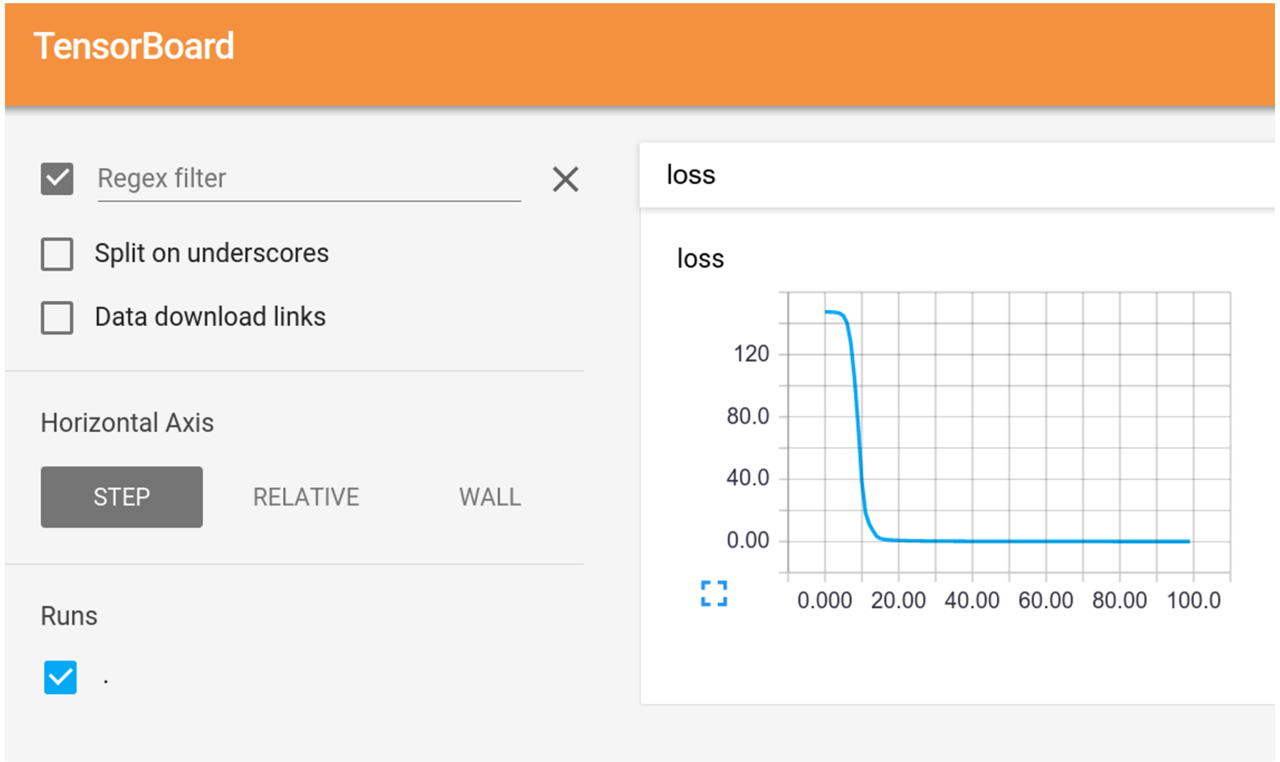
TensorBoard

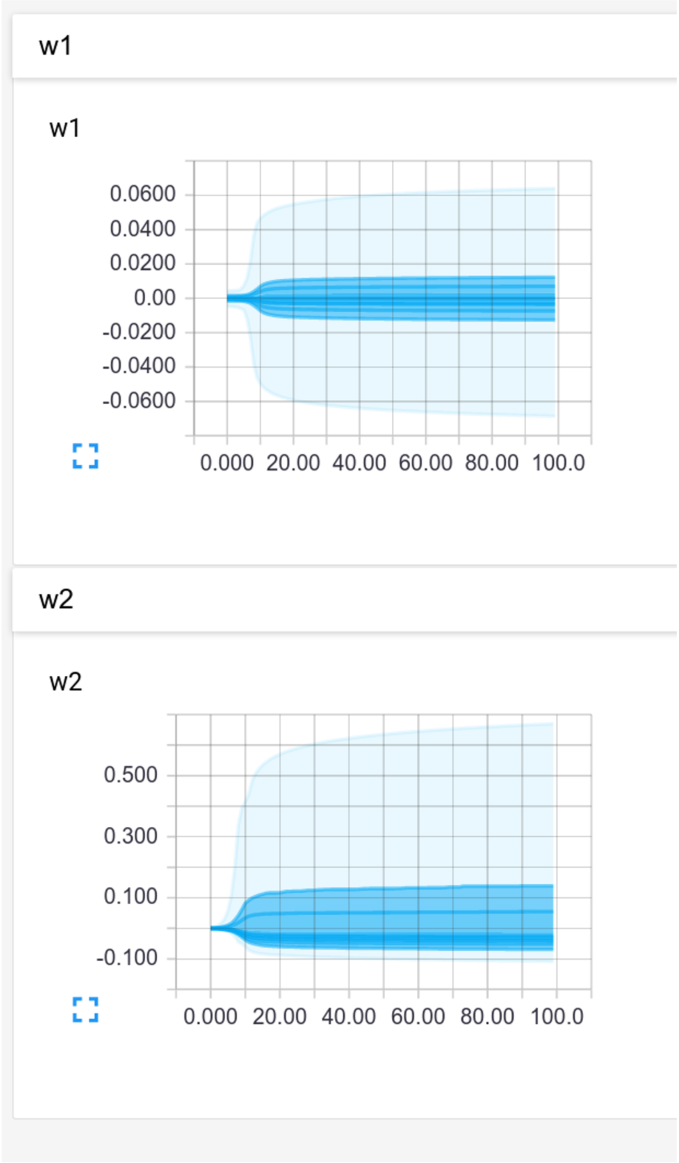
Add logging to code to record loss, stats, etc
Run server and get pretty graphs!



TensorBoard

Also works with PyTorch: torch.utils.tensorboard





PyTorch vs TensorFlow

PyTorch
- My personal favorite
- Clean, imperative API
- Easy dynamic graphs for debugging
- JIT allows static graphs for production
- Cannot use TPUs
- Not easy to deploy on mobile

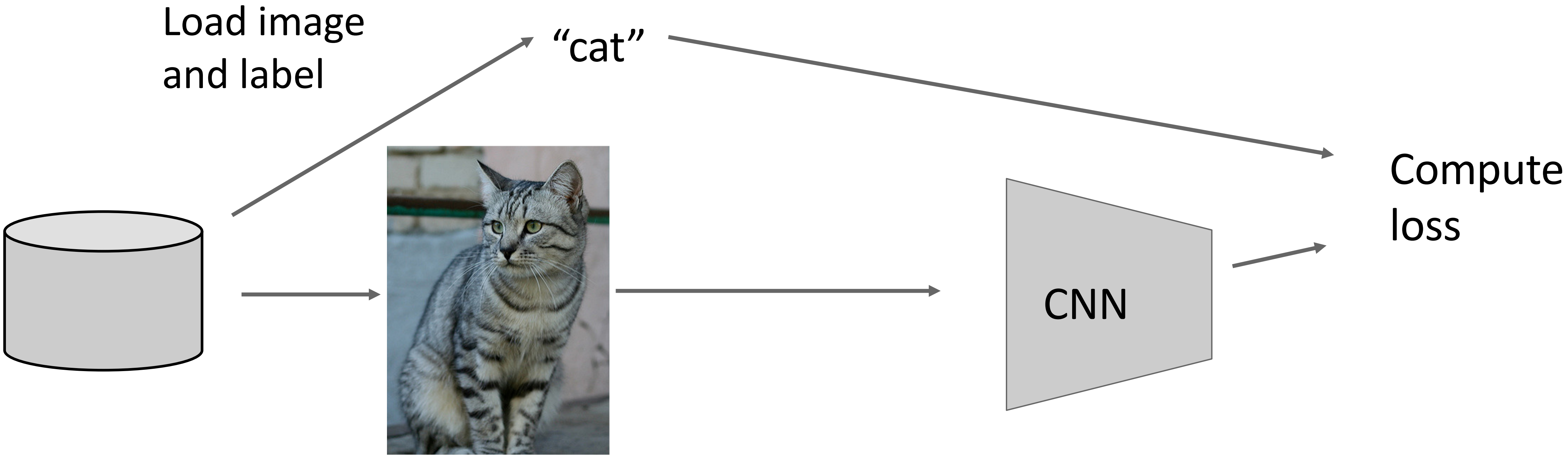
TensorFlow 1.0
- Static graphs by default
- Can be confusing to debug
- API a bit messy

TensorFlow 2.0
- Dynamic by default
- Standardized on Keras API
- Just came out (9/19), no consensus yet

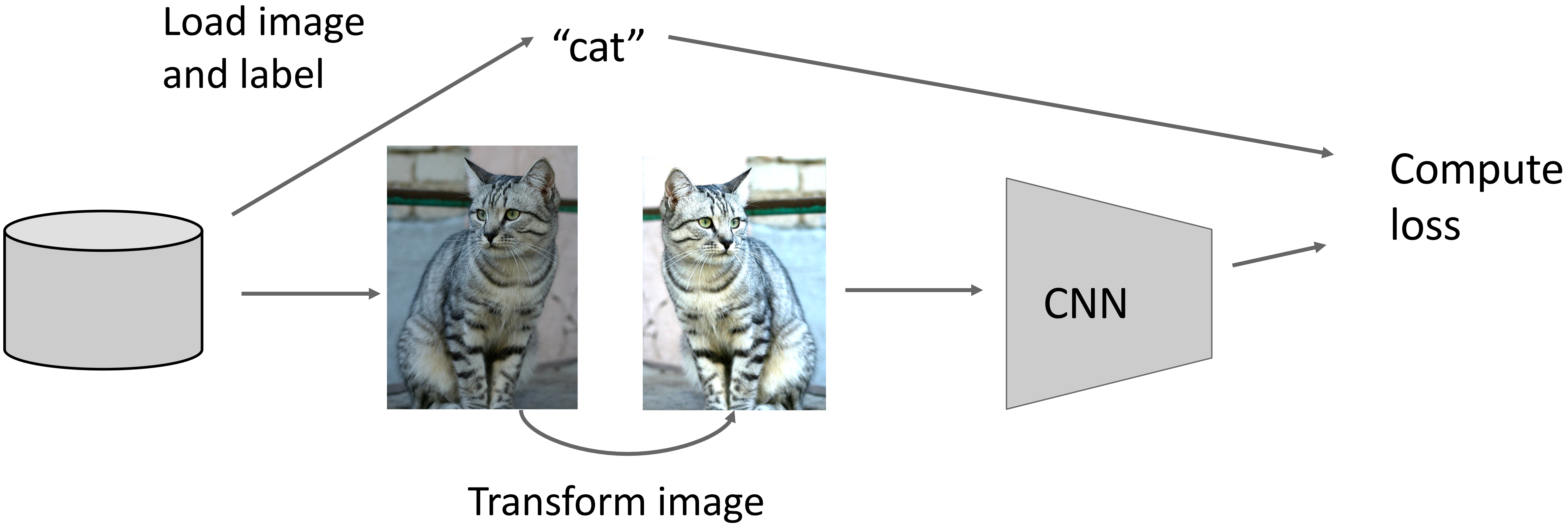
Lecture 10: Training Neural Networks

… just the data augmentation slides, for today …

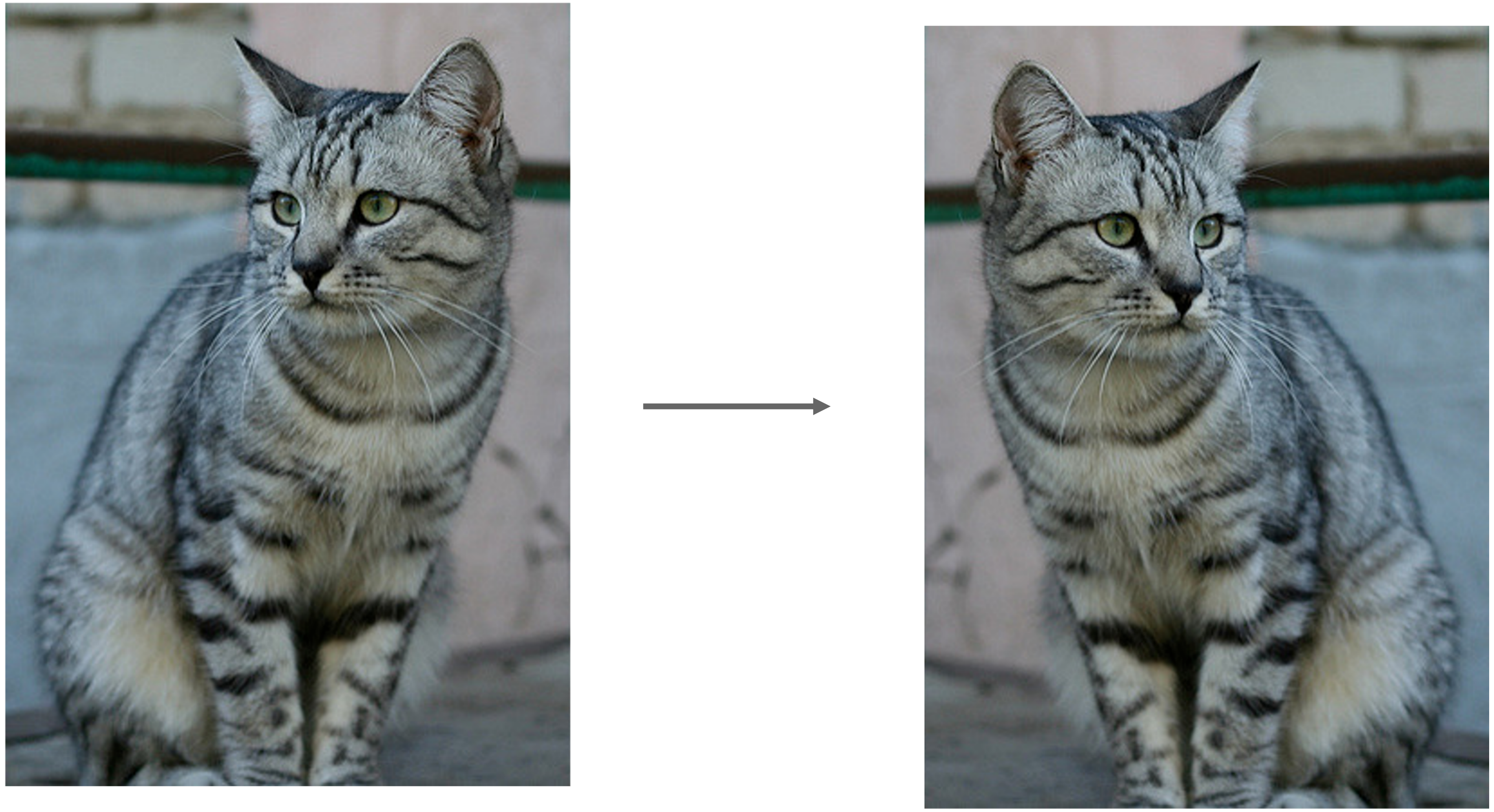
Data Augmentation



Data Augmentation



Data Augmentation: Horizontal Flips

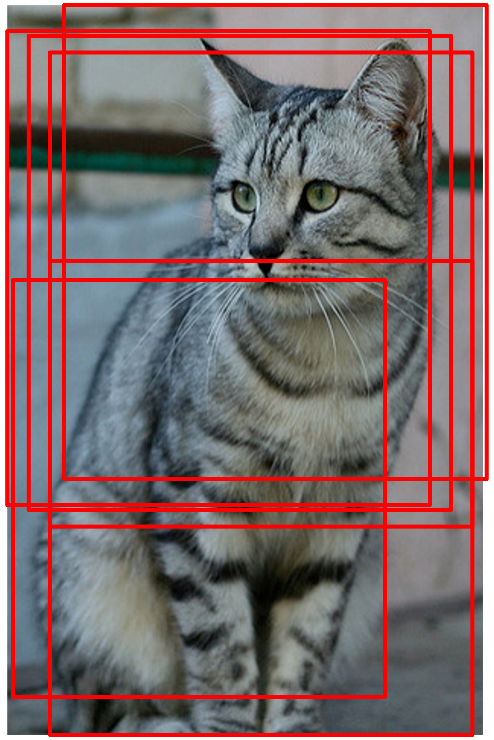


Data Augmentation: Random Crops and Scales

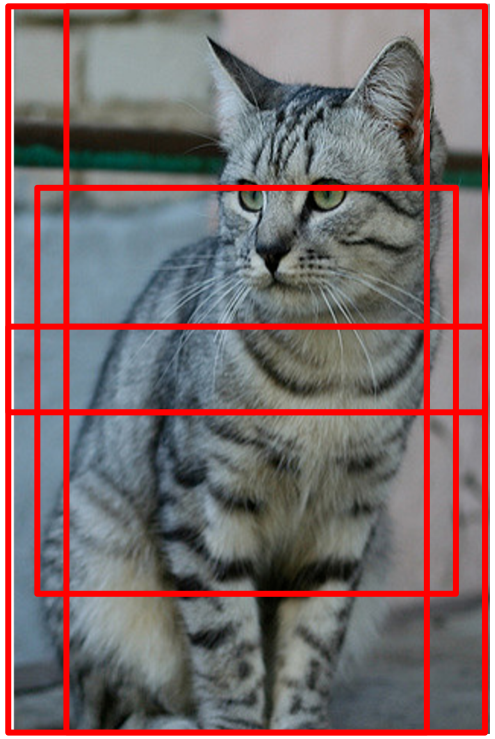
Training: sample random crops / scales

ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short side = L
3. Sample random 224 x 224 patch



Data Augmentation: Random Crops and Scales



Training: sample random crops / scales

ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short side = L
3. Sample random 224 x 224 patch

Testing: average a fixed set of crops

ResNet:

1. Resize image at 5 scales: {224, 256, 384, 480, 640}
2. For each size, use 10 224 x 224 crops: 4 corners + center, + flips

Data Augmentation: Color Jitter

Simple: Randomize contrast and brightness

More Complex:

1. Apply PCA to all [R, G, B] pixels in training set
2. Sample a “color offset” along principal component directions
3. Add offset to all pixels of a training image

(Used in AlexNet, ResNet, etc)

Data Augmentation: Get creative for your problem!

Random mix/combinations of :

- translation
- rotation
- stretching
- shearing,
- lens distortions, … (go crazy)

HW4 and PyTorch tutorial

CSE 576 (Spring 2020) Homework 4

Welcome friends, it's time for Deep Learning with PyTorch! This homework might need a longer running time. Keep this in mind and start early.

PyTorch is a deep learning framework for fast, flexible experimentation. We are going to use it to train our classifiers.

For this homework you need to turn in this file `hw4.ipynb` after running your results and answering questions in-line.

Notes:

- This assignment was designed to be used with Google Colab, but feel free to set up your own environment if you wish. Just bear in mind that we cannot provide support for custom environments.
- Feel free to create new cells as needed, but please **do not delete existing cells**.

Before you get started, we suggest you do the PyTorch tutorial first.

You should at least do the 60 Minute Blitz up until "Training a Classifier".

Introduction by Keunhong on Thursday

PyTorch tutorial

- Deep Learning with PyTorch: A 60 Minute Blitz
  - What is PyTorch?
  - Autograd: Automatic Differentiation
  - Neural Networks
  - Training a Classifier
  - Optional: Data Parallelism
- Data Loading and Processing Tutorial
- Learning PyTorch with Examples
  - Tensors
    - Warm-up: numpy
    - PyTorch: Tensors
  - Autograd
    - PyTorch: Tensors and autograd
    - PyTorch: Defining New autograd Functions
    - TensorFlow: Static Graphs
  - nn module
    - PyTorch: nn

Neural Networks

Neural networks can be constructed using the `torch.nn` package.

Now that you had a glimpse of `autograd`, `nn` depends on `autograd` to define models and differentiate them. An `nn.Module` contains layers, and a method `forward(input)` \ that returns the `output`.

For example, look at this network that classifies digit images:

.. figure:: /_static/img/mnist.png :alt: convnet

convnet

It is a simple feed-forward network. It takes the input, feeds it through several layers one after the other, and then finally gives the output.

A typical training procedure for a neural network is as follows:

- Define the neural network that has some learnable parameters (or weights)
- Iterate over a dataset of inputs
- Process input through the network
- Compute the loss (how far is the output from being correct)
- Propagate gradients back into the network's parameters
- Update the weights of the network, typically using a simple update rule: `weight = weight - learning_rate * gradient`

Define the network

Let's define this network:

```
[ ]  import torch
     import torch.nn as nn
     import torch.nn.functional as F


     class Net(nn.Module):

         def __init__(self):
             super(Net, self).__init__()
             # 1 input image channel, 6 output channels, 5x5 square convolution
             # kernel
             self.conv1 = nn.Conv2d(1, 6, 5)
             self.conv2 = nn.Conv2d(6, 16, 5)
             # an affine operation: y = Wx + b
             self.fc1 = nn.Linear(16 * 5 * 5, 120)
             self.fc2 = nn.Linear(120, 84)
             self.fc3 = nn.Linear(84, 10)

         def forward(self, x):
             # Max pooling over a (2, 2) window
             x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
             # If the size is a square you can only specify a single number
             x = F.max_pool2d(F.relu(self.conv2(x)), 2)
             x = x.view(-1, self.num_flat_features(x))
             x = F.relu(self.fc1(x))
             x = F.relu(self.fc2(x))
             x = self.fc3(x)
             return x

         def num_flat_features(self, x):
             size = x.size()[1:]  # all dimensions except the batch dimension
             num_features = 1
             for s in size:
                 num_features *= s
             return num_features


     net = Net()
     print(net)
```

```
Net(
  (conv1): Conv2d(1, 6, kernel_size=(5, 5), stride=(1, 1))
  (conv2): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1))
  (fc1): Linear(in_features=400, out_features=120, bias=True)
  (fc2): Linear(in_features=120, out_features=84, bias=True)
  (fc3): Linear(in_features=84, out_features=10, bias=True)
)
```

Data augmentation in PyTorch

TORCHVISION.TRANSFORMS

Transforms are common image transformations. They can be chained together using `Compose`. Additionally, there is the `torchvision.transforms.functional` module. Functional transforms give fine-grained control over the transformations. This is useful if you have to build a more complex transformation pipeline (e.g. in the case of segmentation tasks).

CLASS `torchvision.transforms.Compose(transforms)` [SOURCE]

Composes several transforms together.

Parameters

transforms (list of `Transform` objects) – list of transforms to compose.

Example

```
>>> transforms.Compose([
>>>     transforms.CenterCrop(10),
>>>     transforms.ToTensor(),
>>> ])
```

CLASS `torchvision.transforms.TenCrop(size, vertical_flip=False)` [SOURCE]

Crop the given PIL Image into four corners and the central crop plus the flipped version of these (horizontal flipping is used by default)

• NOTE

This transform returns a tuple of images and there may be a mismatch in the number of inputs and targets your Dataset returns. See below for an example of how to deal with this.

Parameters

- **size** (*sequence or int*) – Desired output size of the crop. If size is an int instead of sequence like (h, w), a square crop (size, size) is made.
- **vertical_flip** (*bool*) – Use vertical flipping instead of horizontal

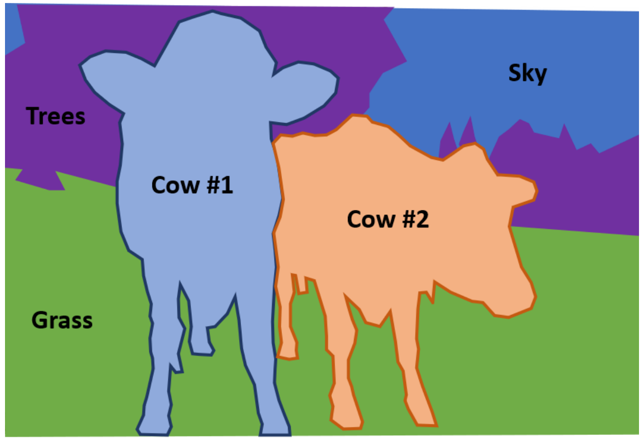
Example

```
>>> transform = Compose([
>>>    TenCrop(size), # this is a list of PIL Images
>>>    Lambda(lambda crops: torch.stack([ToTensor()(crop) for crop in crops])) # returns a 4D tensor
>>> ])
>>> #In your test loop you can do the following:
>>> input, target = batch # input is a 5d tensor, target is 2d
>>> bs, ncrops, c, h, w = input.size()
>>> result = model(input.view(-1, c, h, w)) # fuse batch size and ncrops
>>> result_avg = result.view(bs, ncrops, -1).mean(1) # avg over crops
```

DL software and more

- Deep learning frameworks
- Instance segmentation
- 3D neural networks
- Video

```
class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        # 1 input image channel, 6 output channels, 5x5 square convolution
        # kernel
        self.conv1 = nn.Conv2d(1, 6, 5)
        self.conv2 = nn.Conv2d(6, 16, 5)
        # an affine operation: y = Wx + b
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        # Max pooling over a (2, 2) window
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        # If the size is a square you can only specify a single number
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = x.view(-1, self.num_flat_features(x))
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```



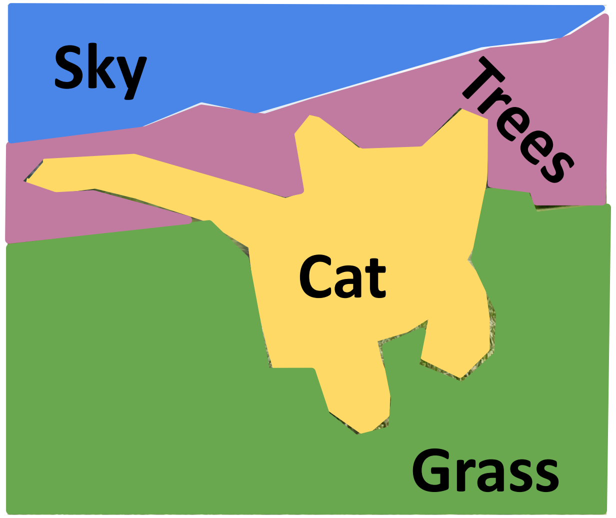
clink glass → drink

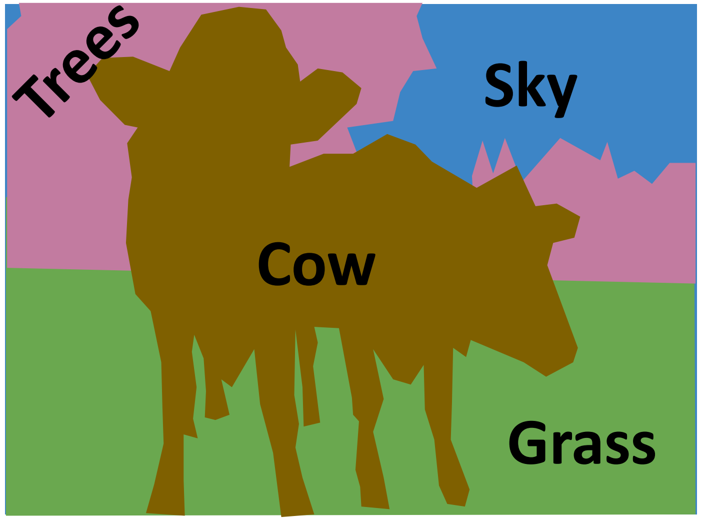
Lecture 16:
Detection + Segmentation

Things and Stuff

Things: Object categories that can be separated into object instances
(e.g. cats, cars, person)

Stuff: Object categories that cannot be separated into instances
(e.g. sky, grass, water, trees)

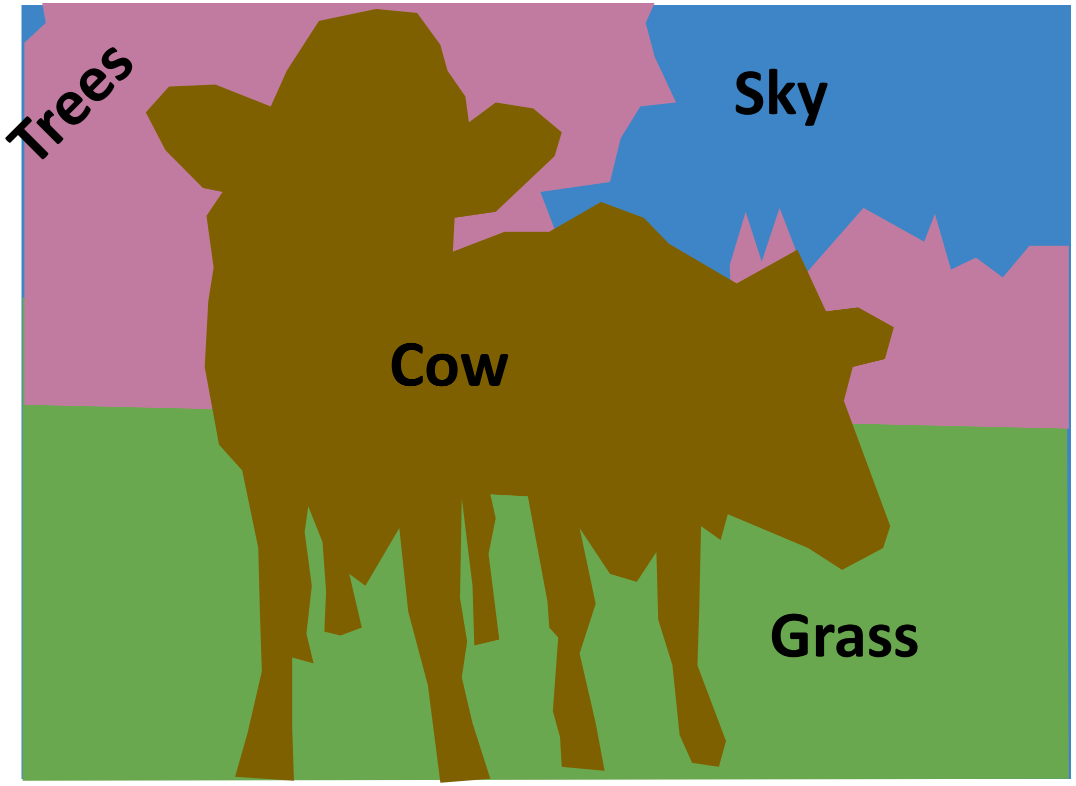




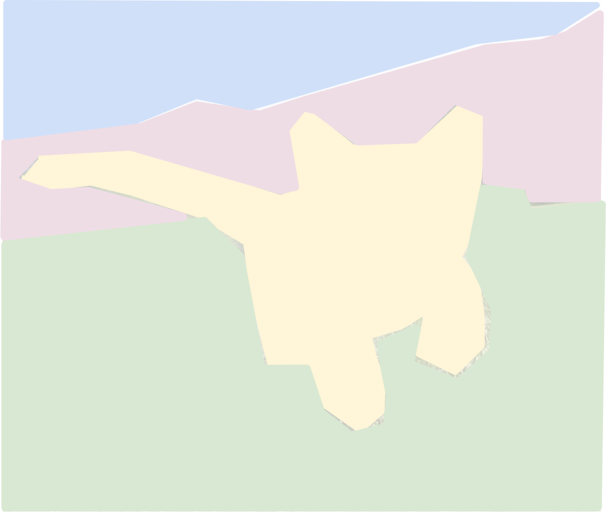
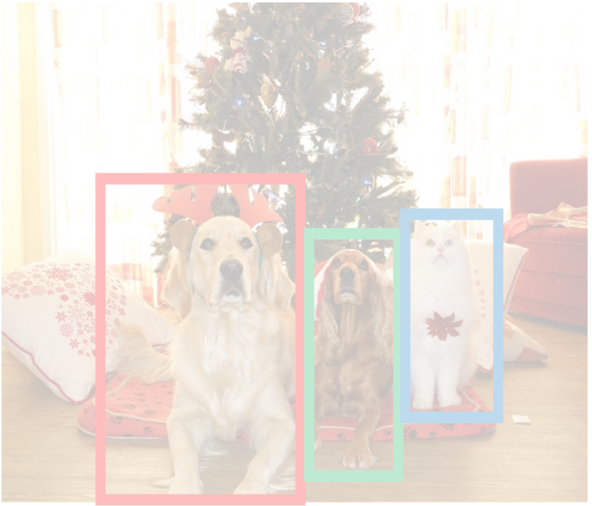
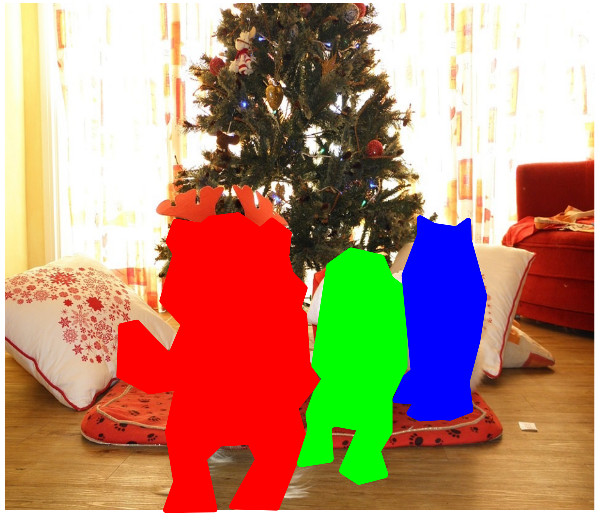
Computer Vision Tasks

Object Detection: Detects individual object instances, but only gives box (Only things!)

Semantic Segmentation: Gives per-pixel labels, but merges instances (Both things and stuff)

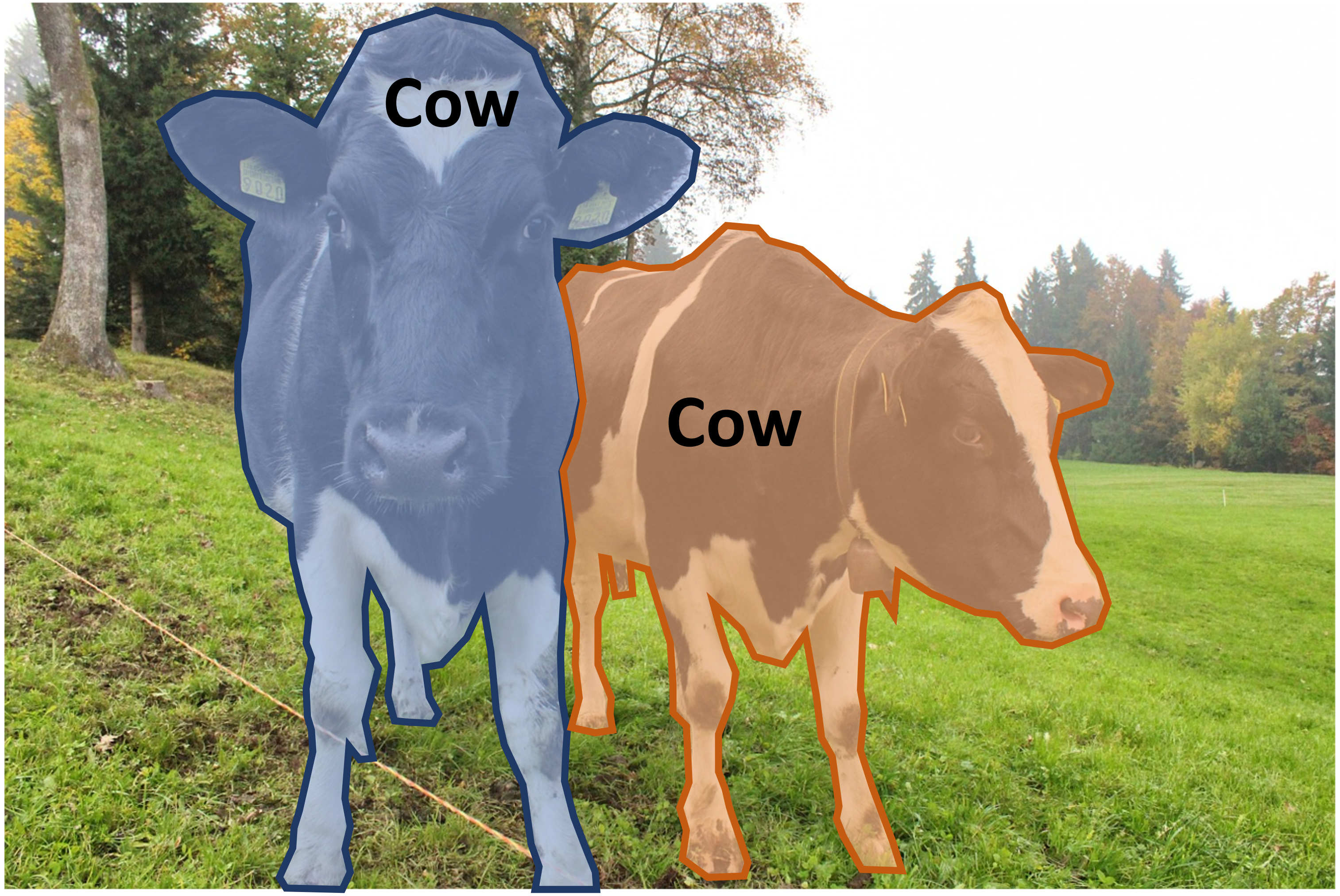


Computer Vision Tasks: Instance Segmentation

Classification	Semantic Segmentation	Object Detection	**Instance Segmentation**
			
CAT	GRASS, CAT, TREE, SKY	DOG, DOG, CAT	DOG, DOG, CAT
No spatial extent	No objects, just pixels	Multiple Objects	

Computer Vision Tasks: Instance Segmentation

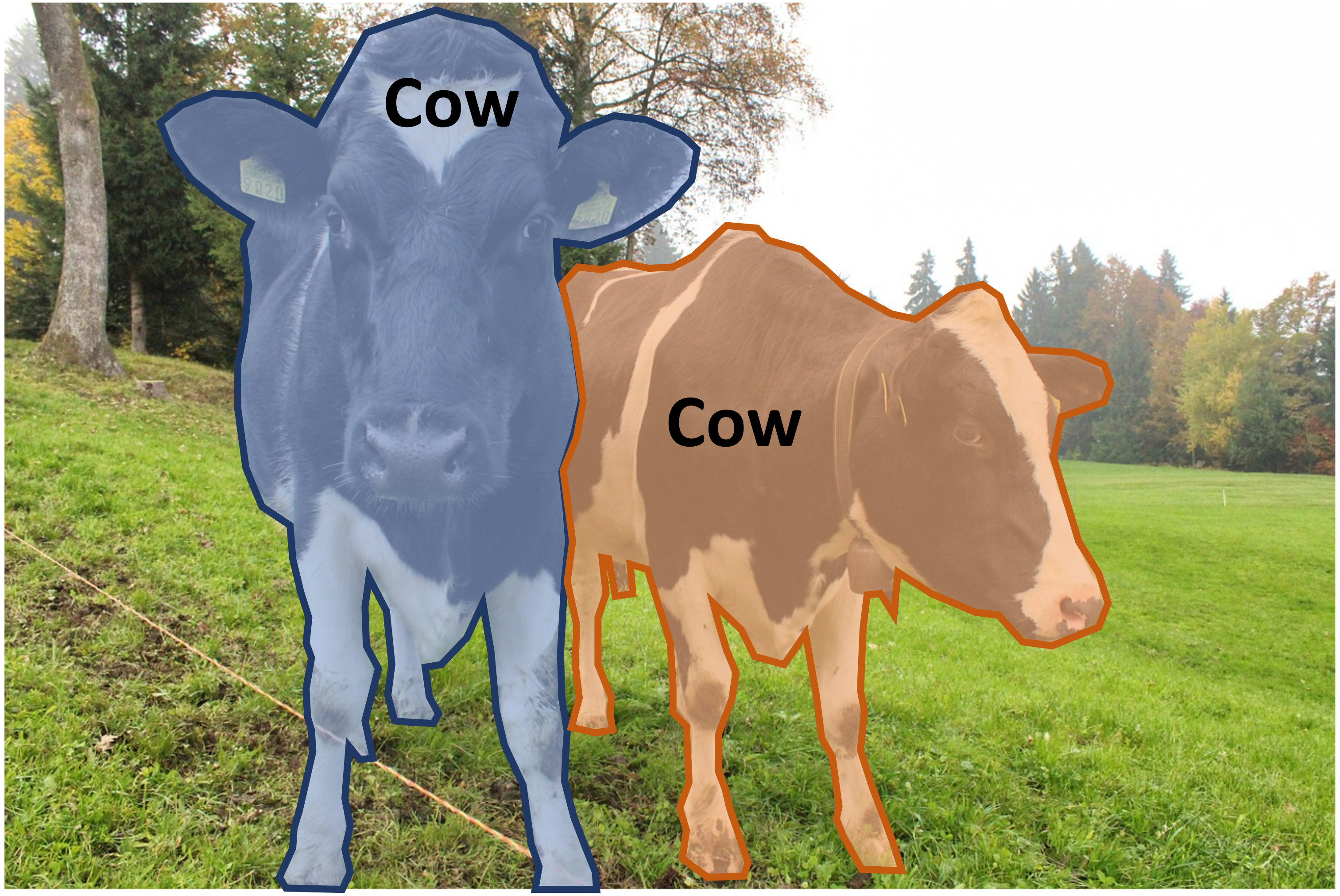
Instance Segmentation: Detect all objects in the image, and identify the pixels that belong to each object (Only things)



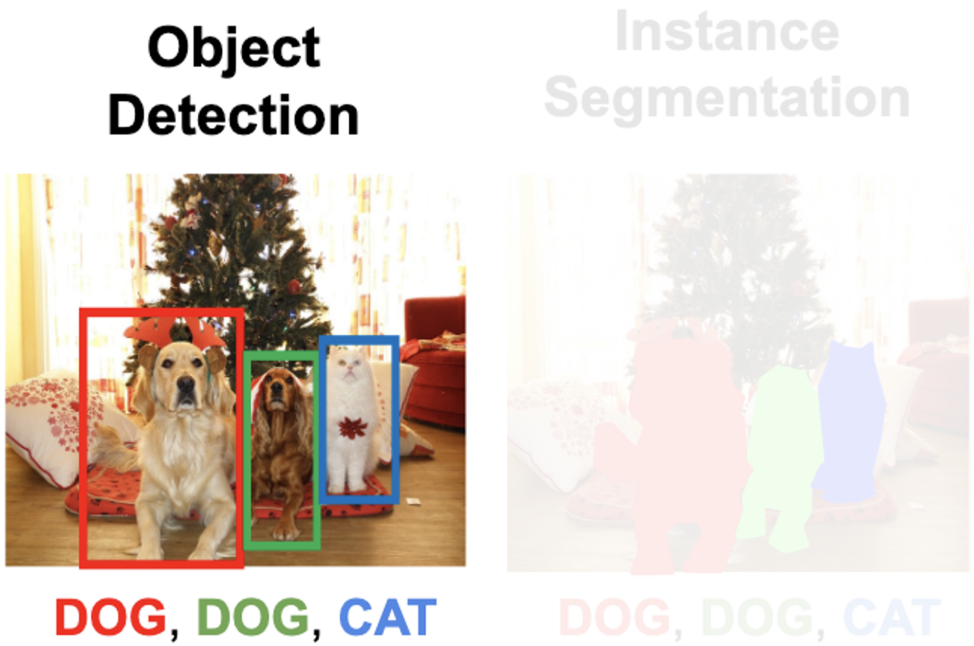
Computer Vision Tasks: Instance Segmentation

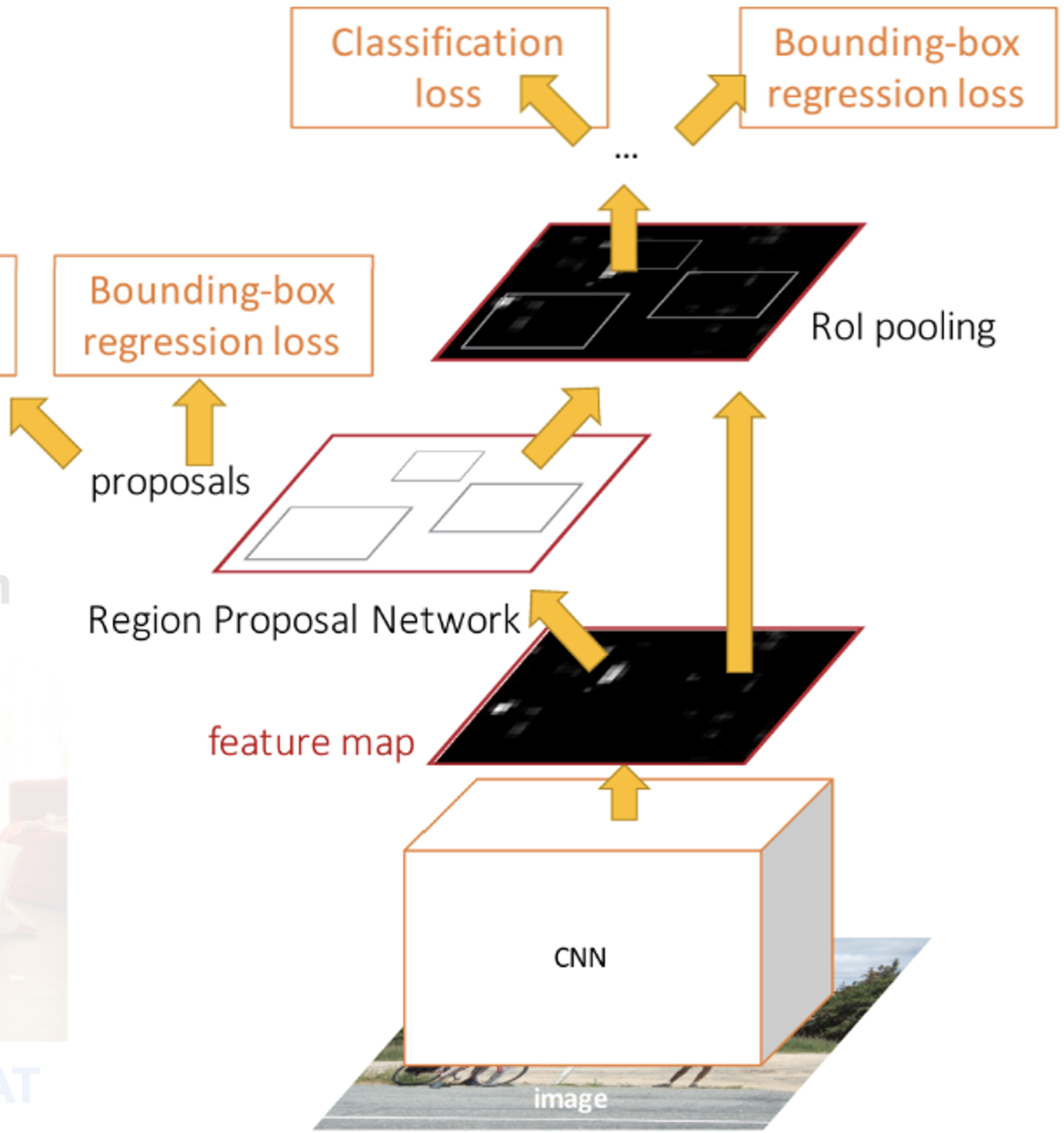
Instance Segmentation: Detect all objects in the image, and identify the pixels that belong to each object (Only things)

Approach: Perform object detection, then predict a segmentation mask for each object



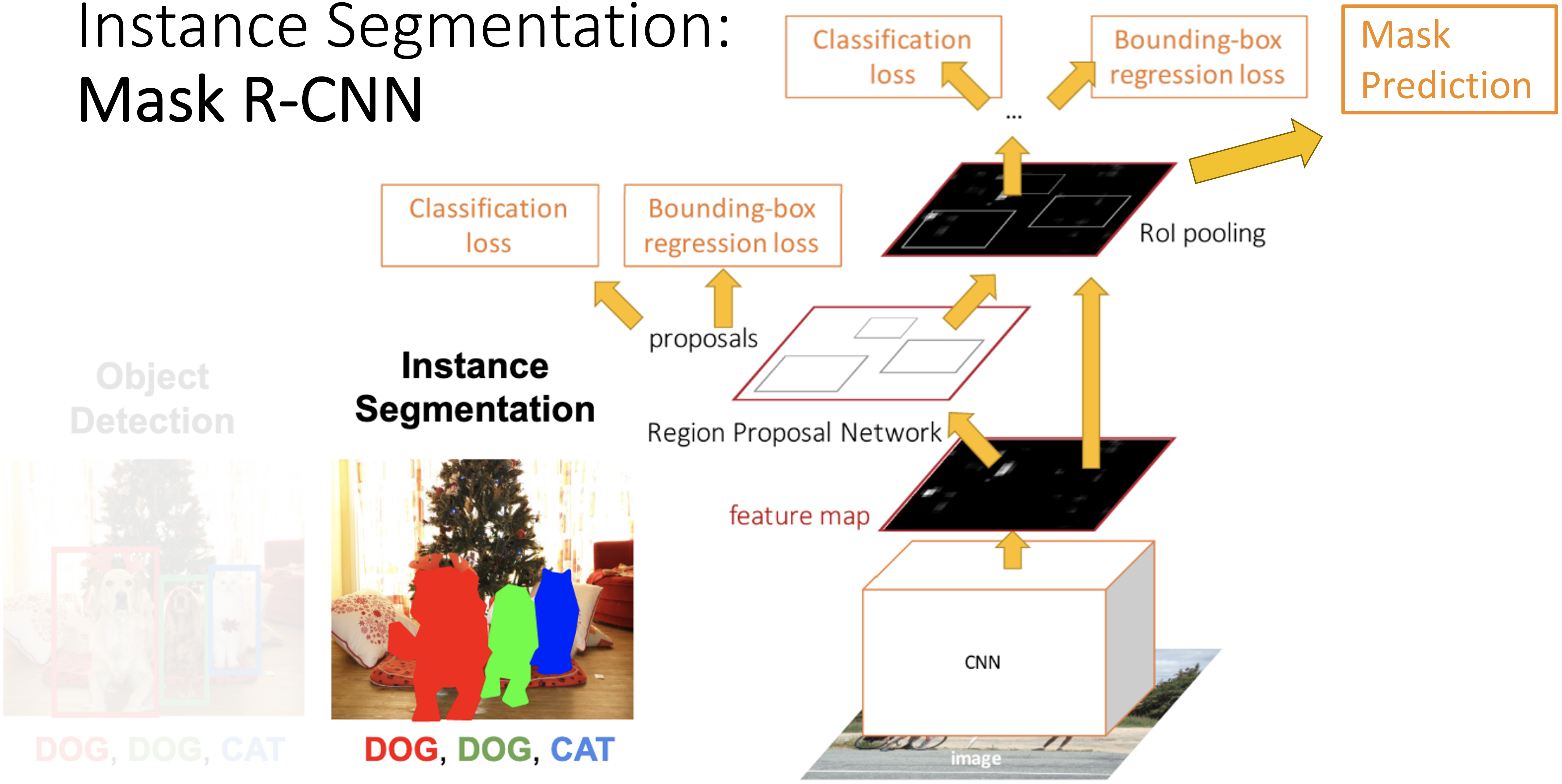
Object Detection: Faster R-CNN





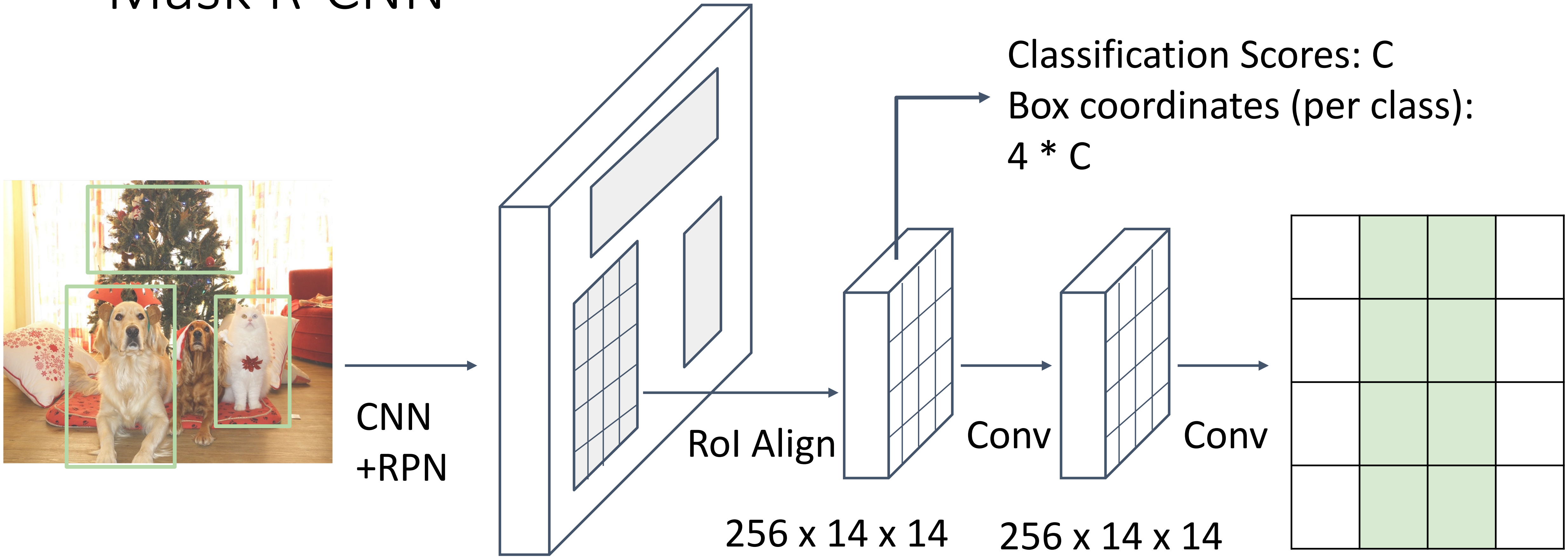
Ren et al, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”, NeurIPS 2015

Instance Segmentation: Mask R-CNN



He et al, "Mask R-CNN", ICCV 2017

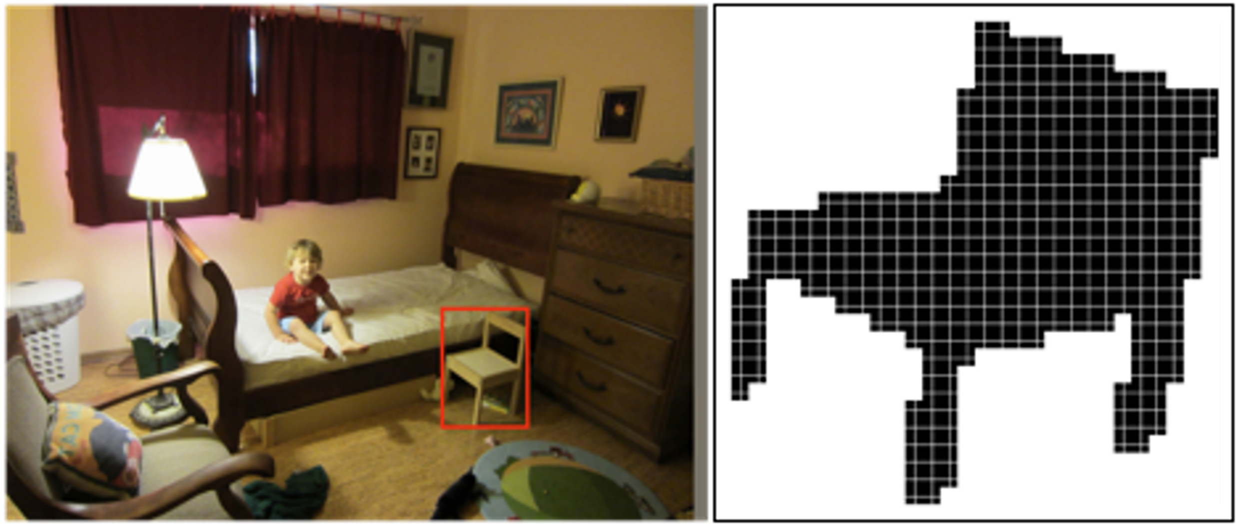
Mask R-CNN



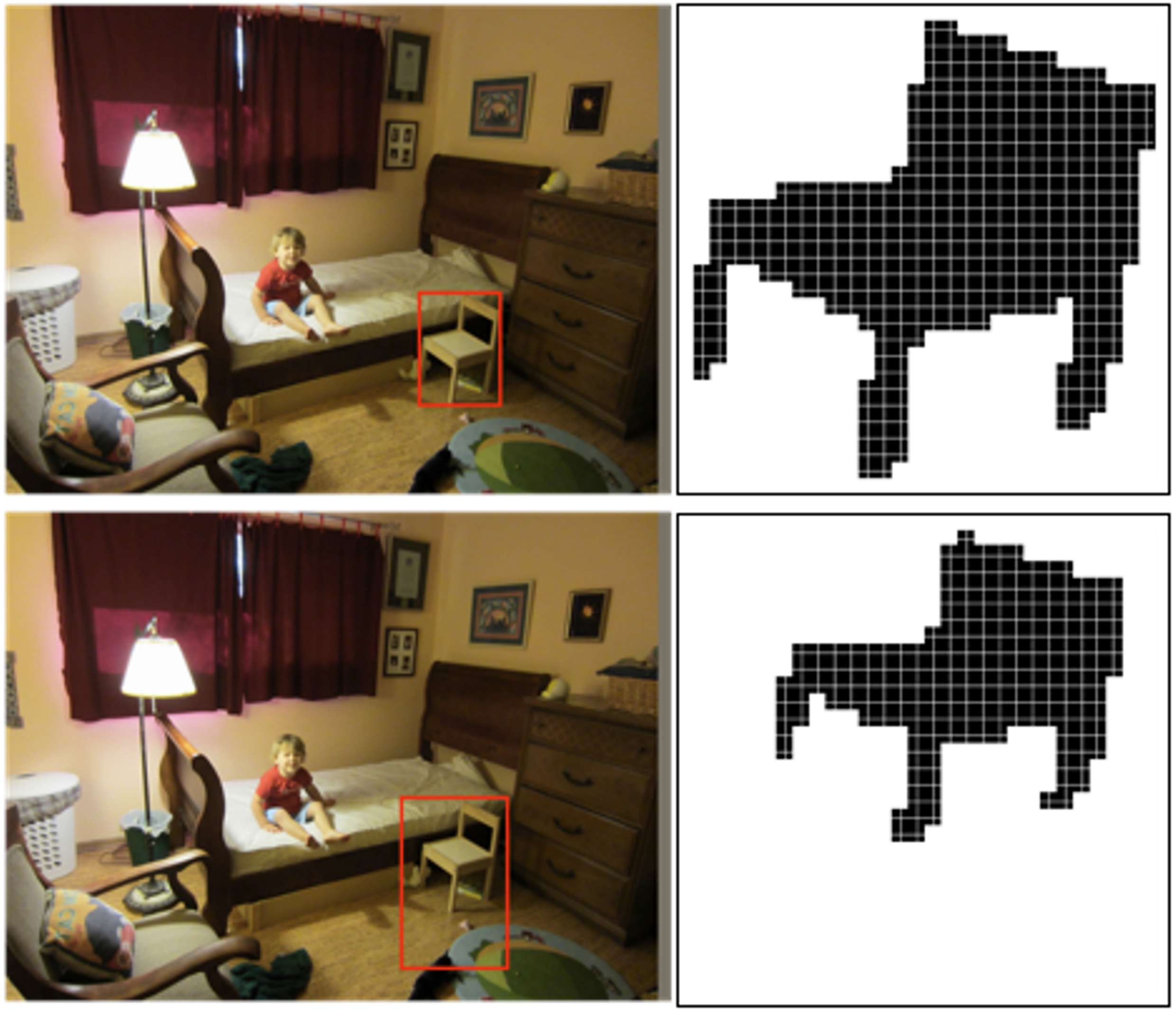
Predict a mask for each of C classes:
C x 28 x 28

He et al, "Mask R-CNN", ICCV 2017

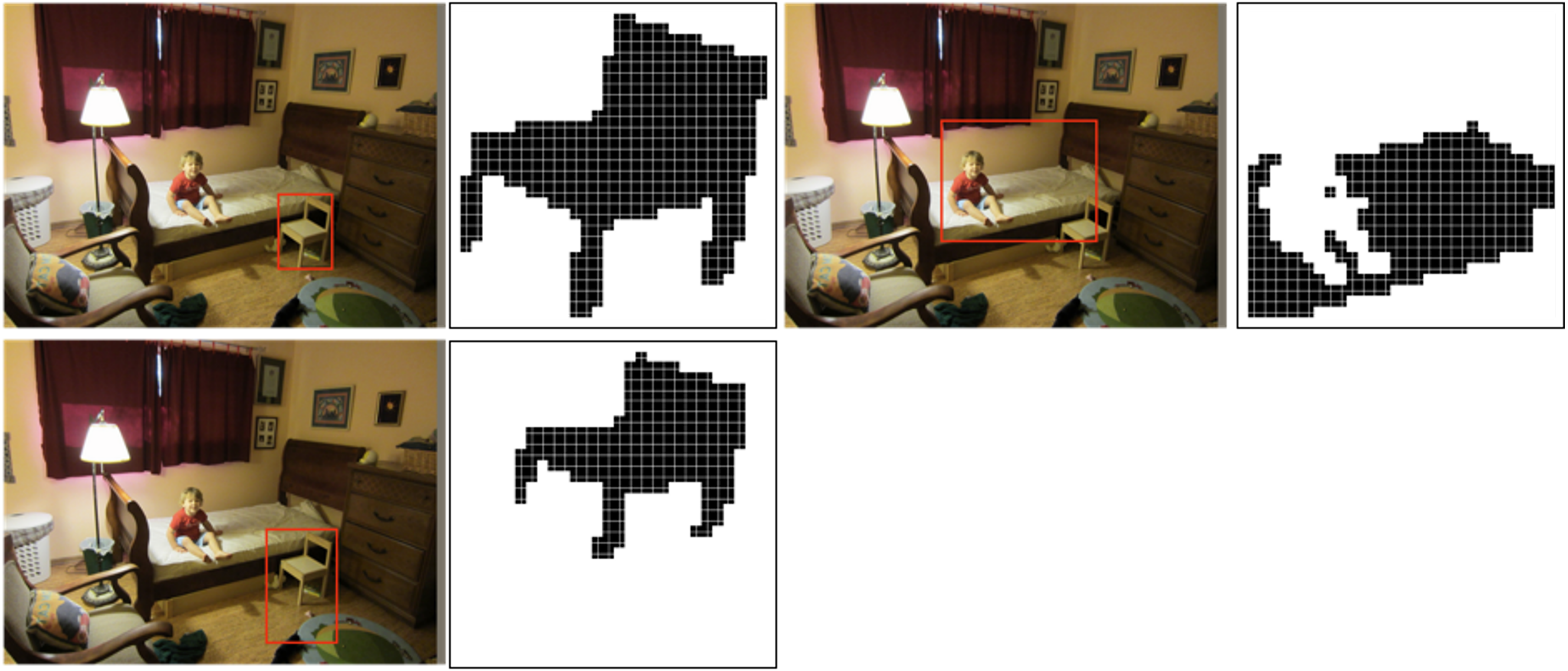
Mask R-CNN: Example Training Targets



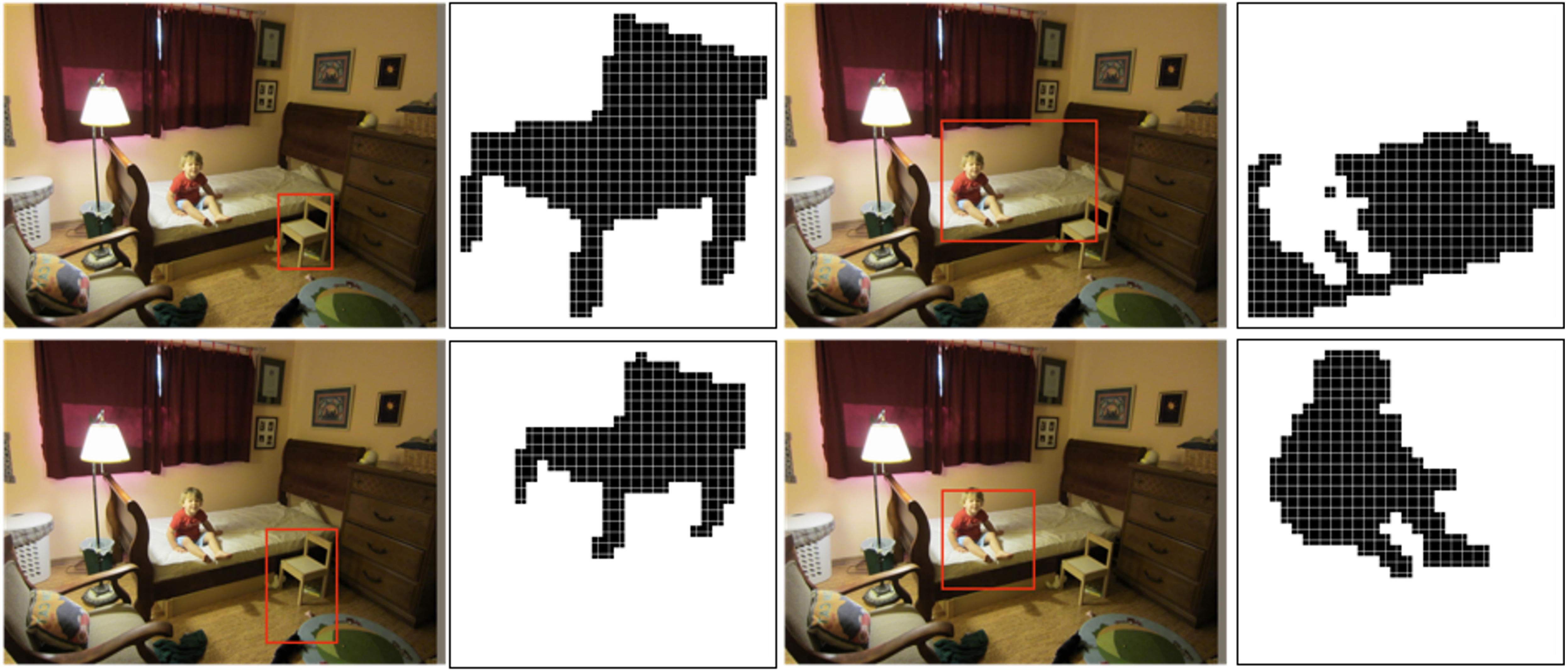
Mask R-CNN: Example Training Targets



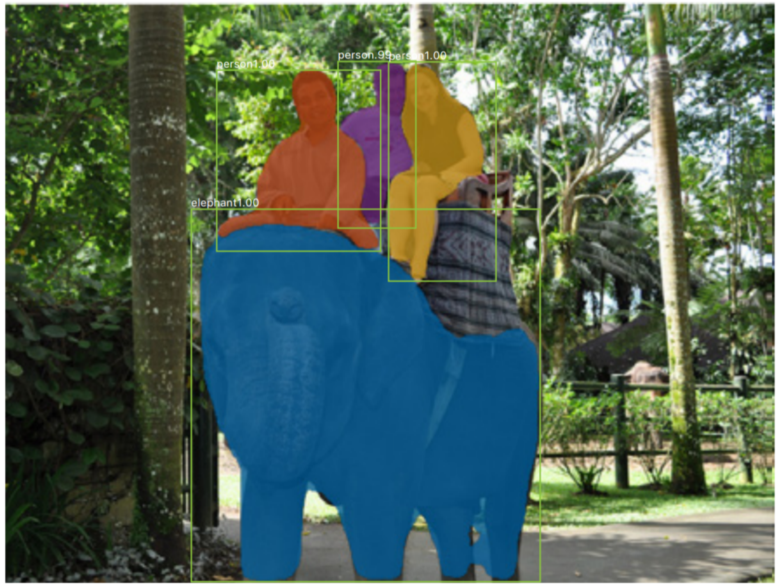
Mask R-CNN: Example Training Targets

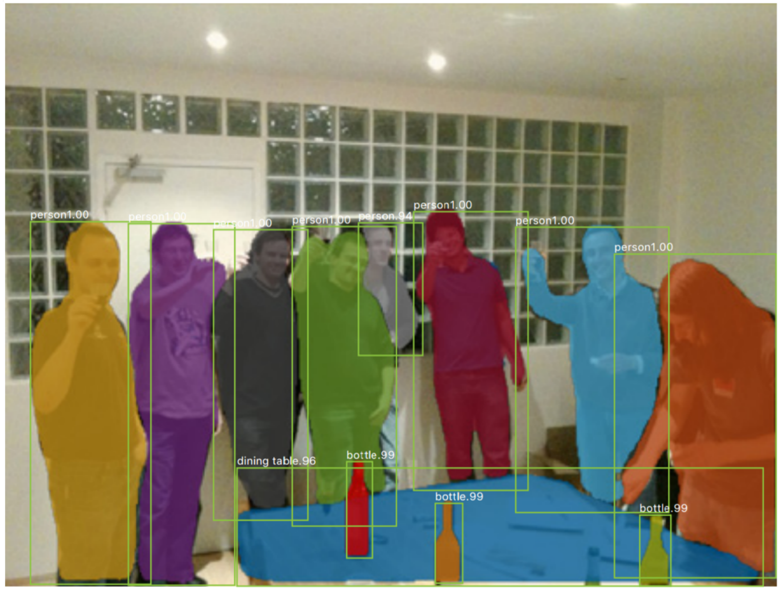


Mask R-CNN: Example Training Targets



Mask R-CNN: Very Good Results!

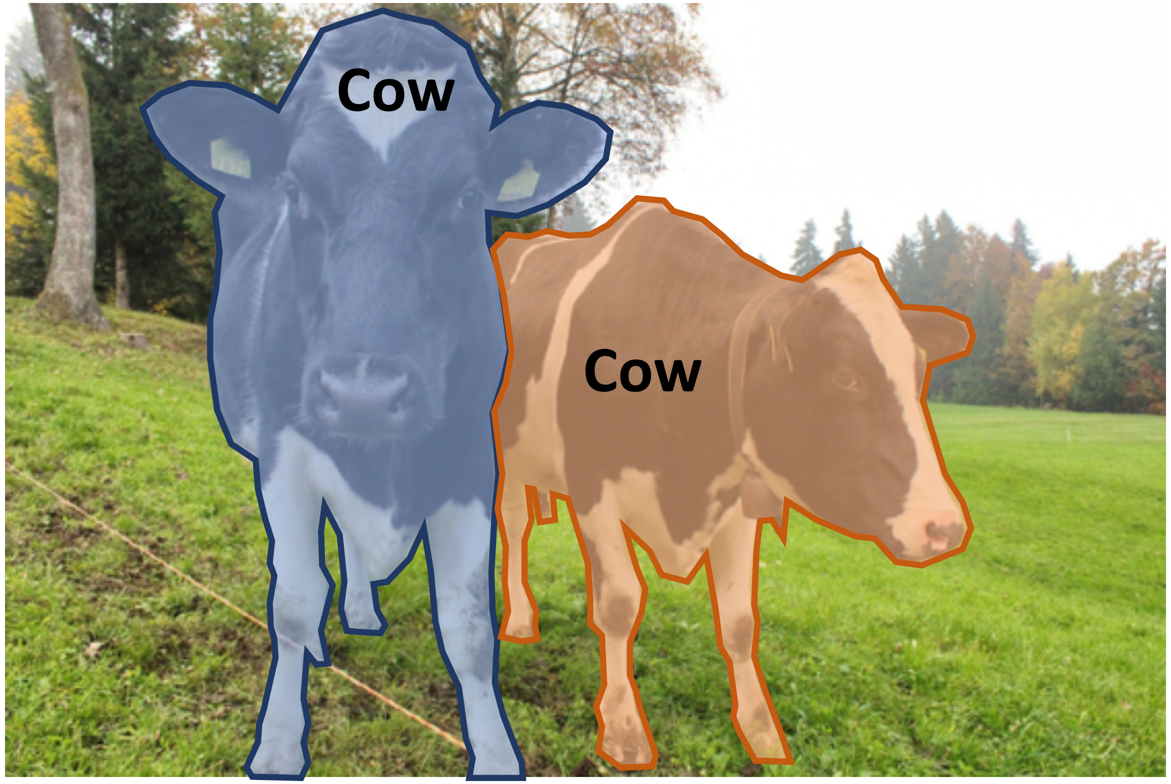




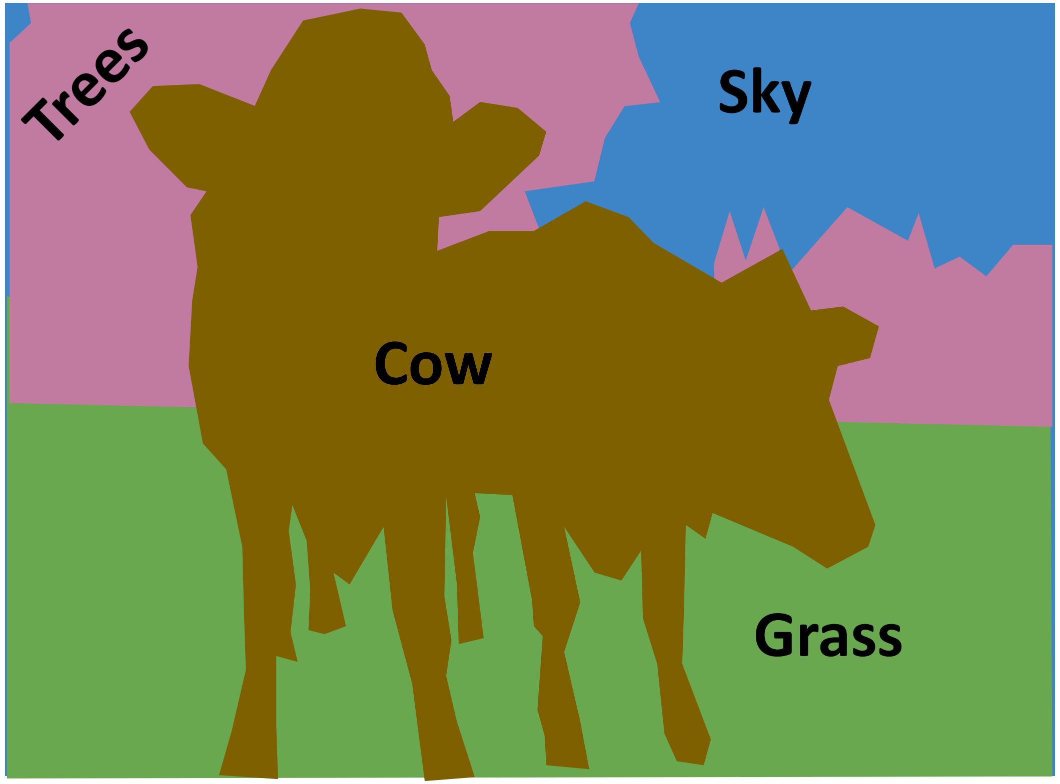

The Generalized R-CNN
Framework for Object Detection
ICCV 2019 Tutorial
Visual Recognition for Images, Video, and 3D
Ross Girshick
facebook Artificial Intelligence Research

Beyond Instance Segmentation

Instance Segmentation: Separate object instances, but only things



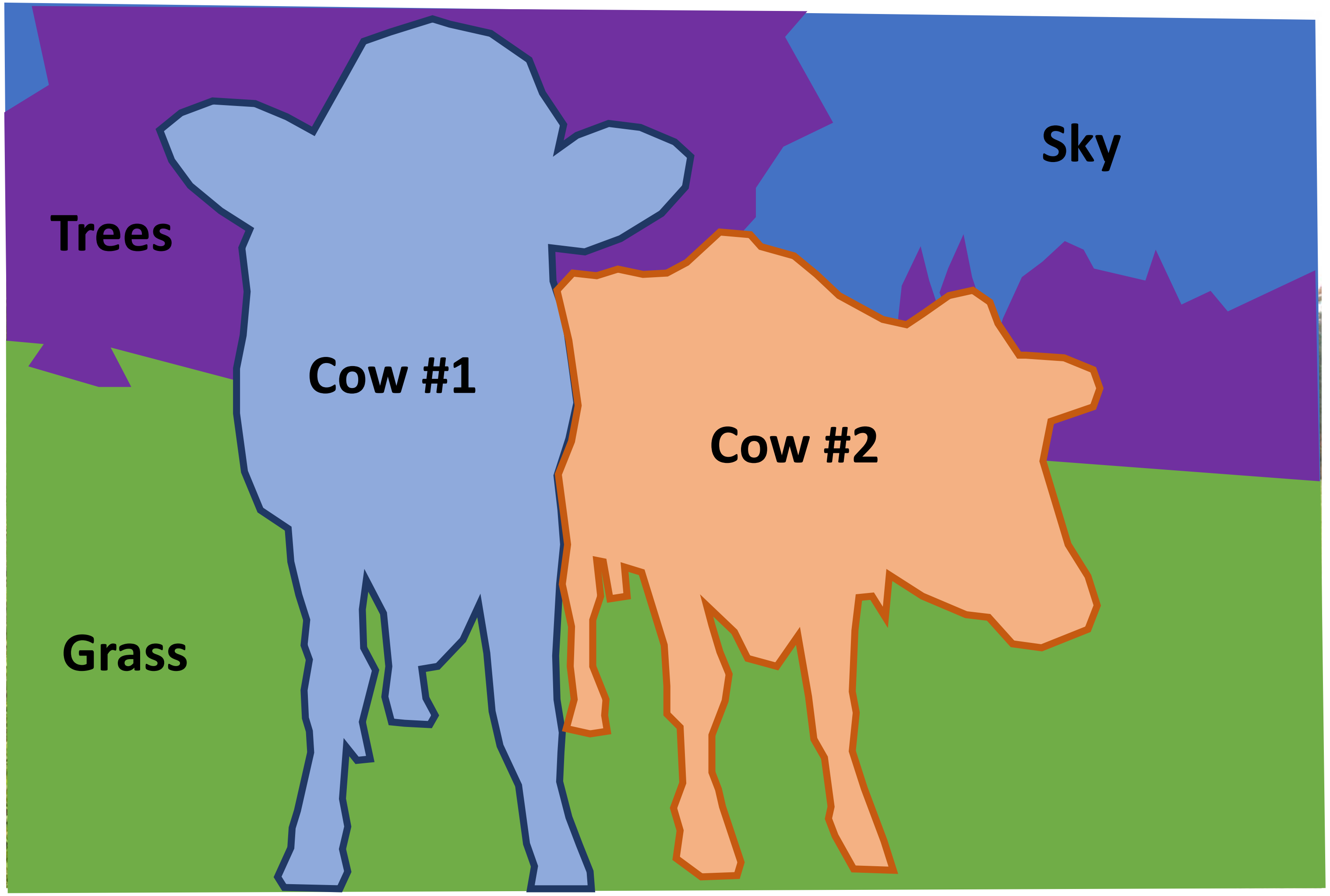
Semantic Segmentation: Identify both things and stuff, but doesn't separate instances



Beyond Instance Segmentation: **Panoptic Segmentation**

Label all pixels in the image (both things and stuff)

For "thing" categories also separate into instances



Kirillov et al, "Panoptic Segmentation", CVPR 2019
Kirillov et al, "Panoptic Feature Pyramid Networks", CVPR 2019

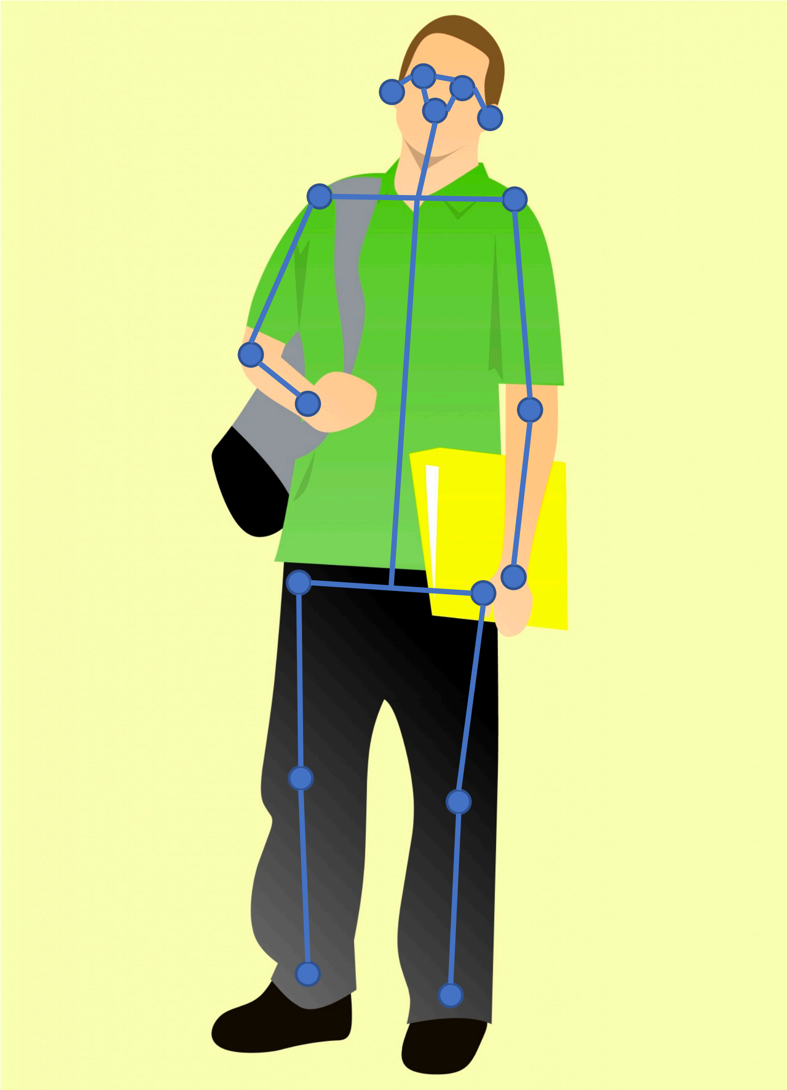
Beyond Instance Segmentation: **Panoptic Segmentation**

Kirillov et al, "Panoptic Feature Pyramid Networks", CVPR 2019

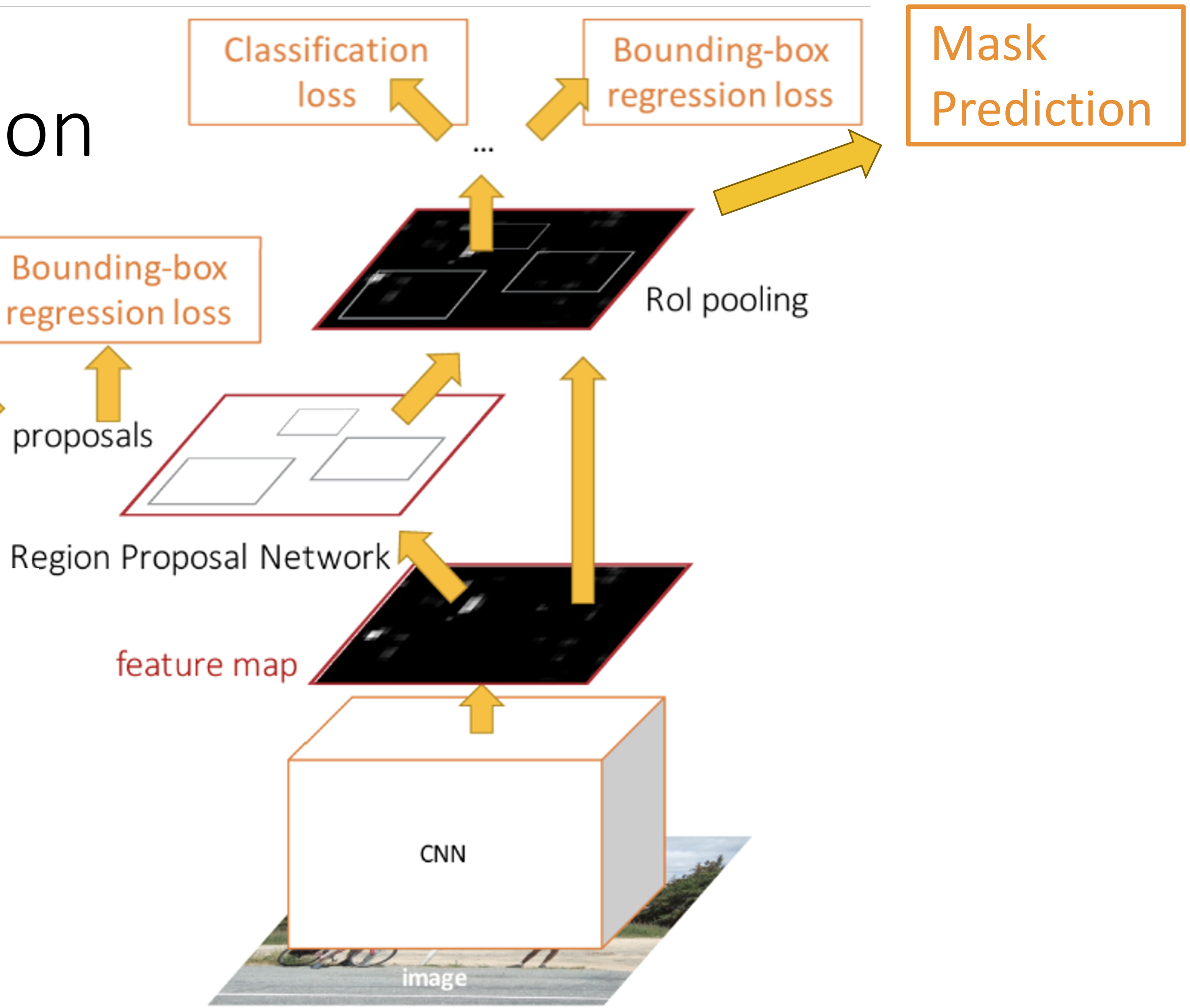
Beyond Instance Segmentation: Human Keypoints

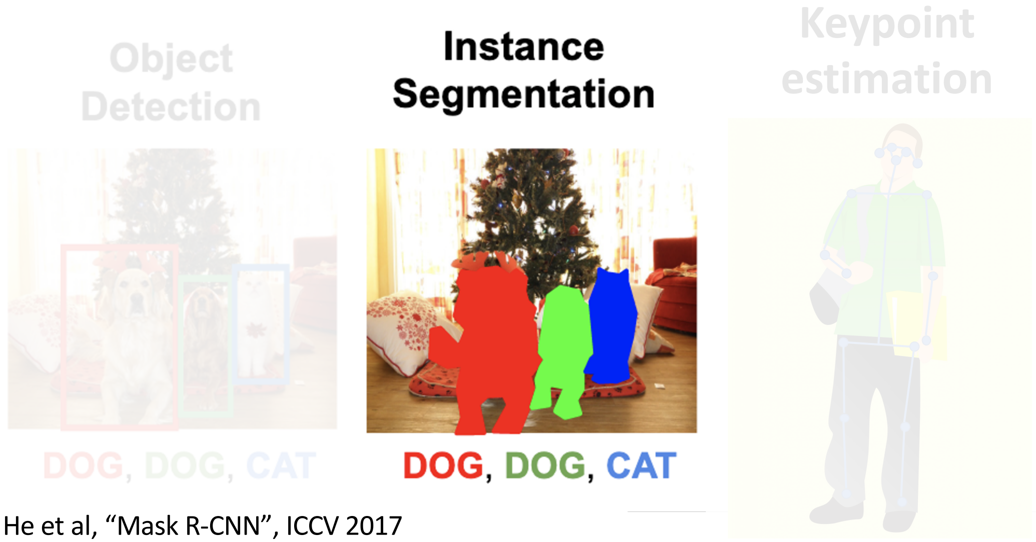
Represent the pose of a human
by locating a set of **keypoints**

e.g. 17 keypoints:
- Nose
- Left / Right eye
- Left / Right ear
- Left / Right shoulder
- Left / Right elbow
- Left / Right wrist
- Left / Right hip
- Left / Right knee
- Left / Right ankle



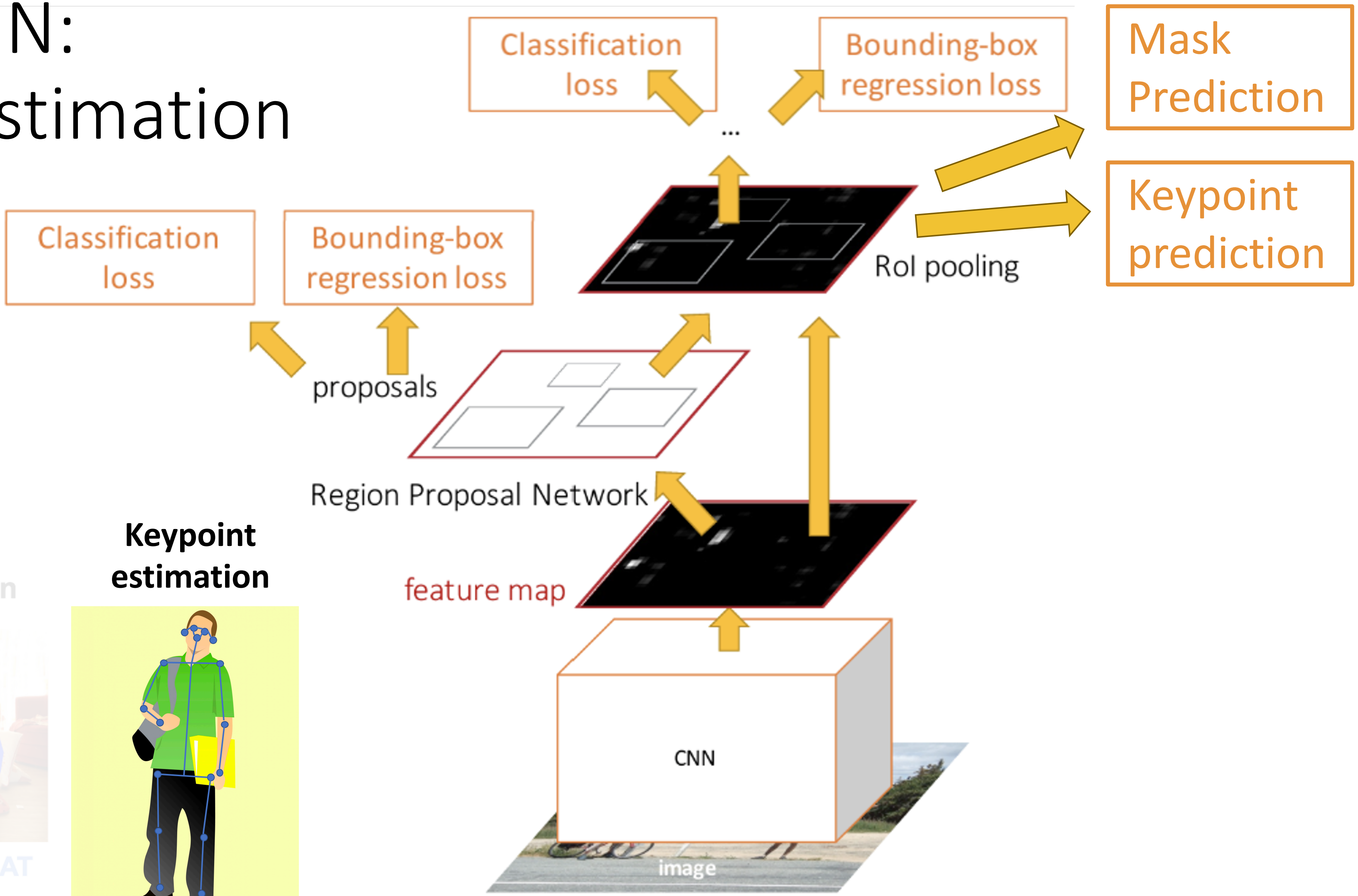
Mask R-CNN: Instance Segmentation

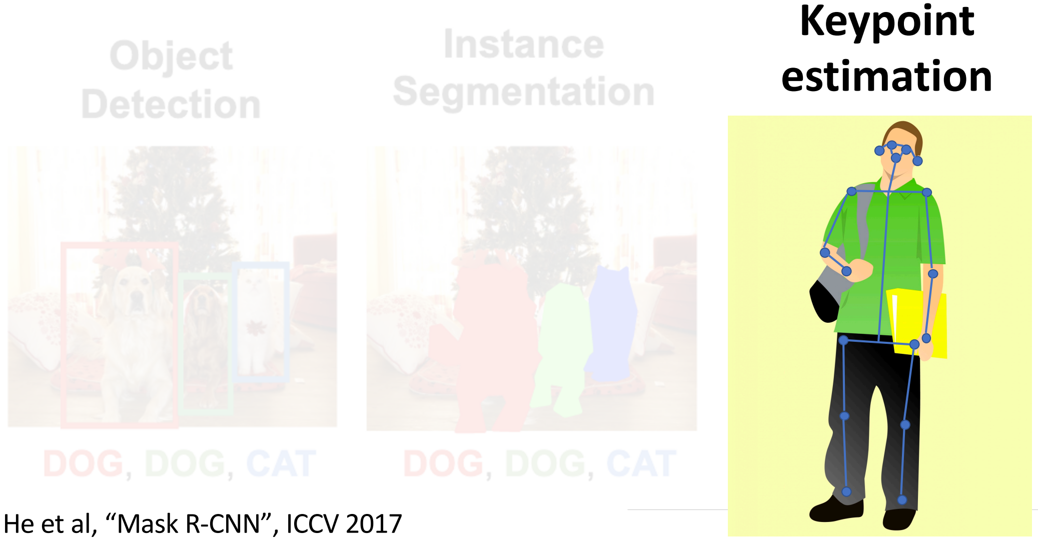




He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN: Keypoint Estimation



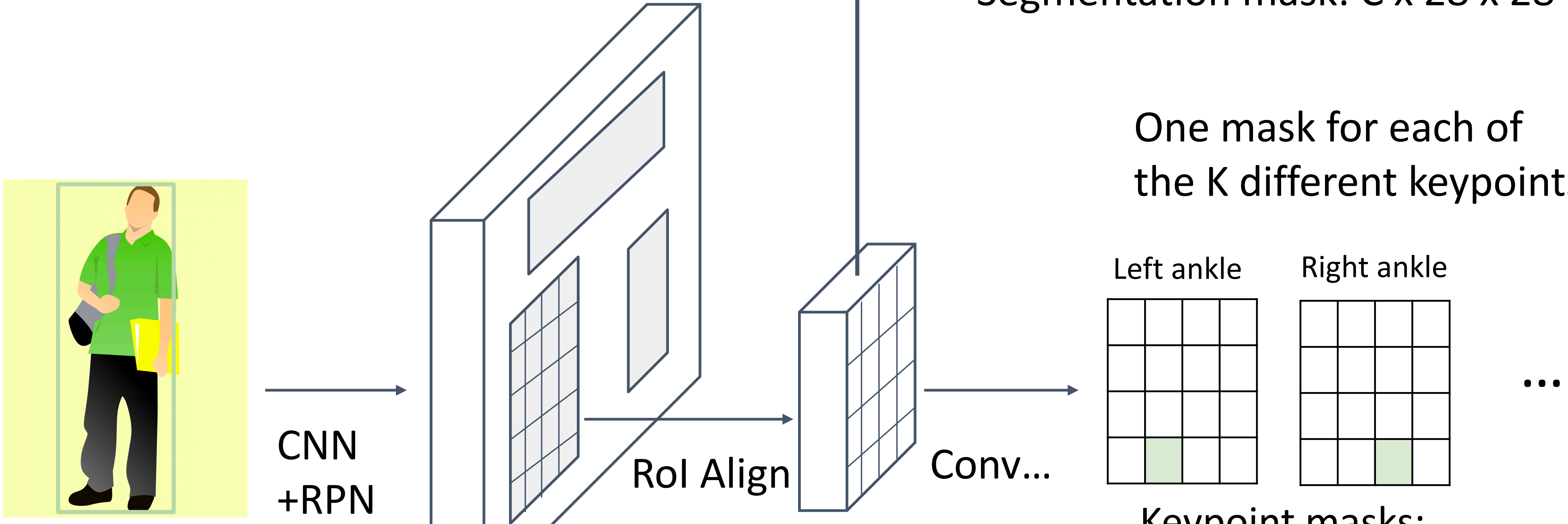


He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN: Keypoints

Classification Scores: C
Box coordinates (per class): 4 * C
Segmentation mask: C x 28 x 28

One mask for each of the K different keypoints



256 x 14 x 14

Keypoint masks:
K x 56 x 56

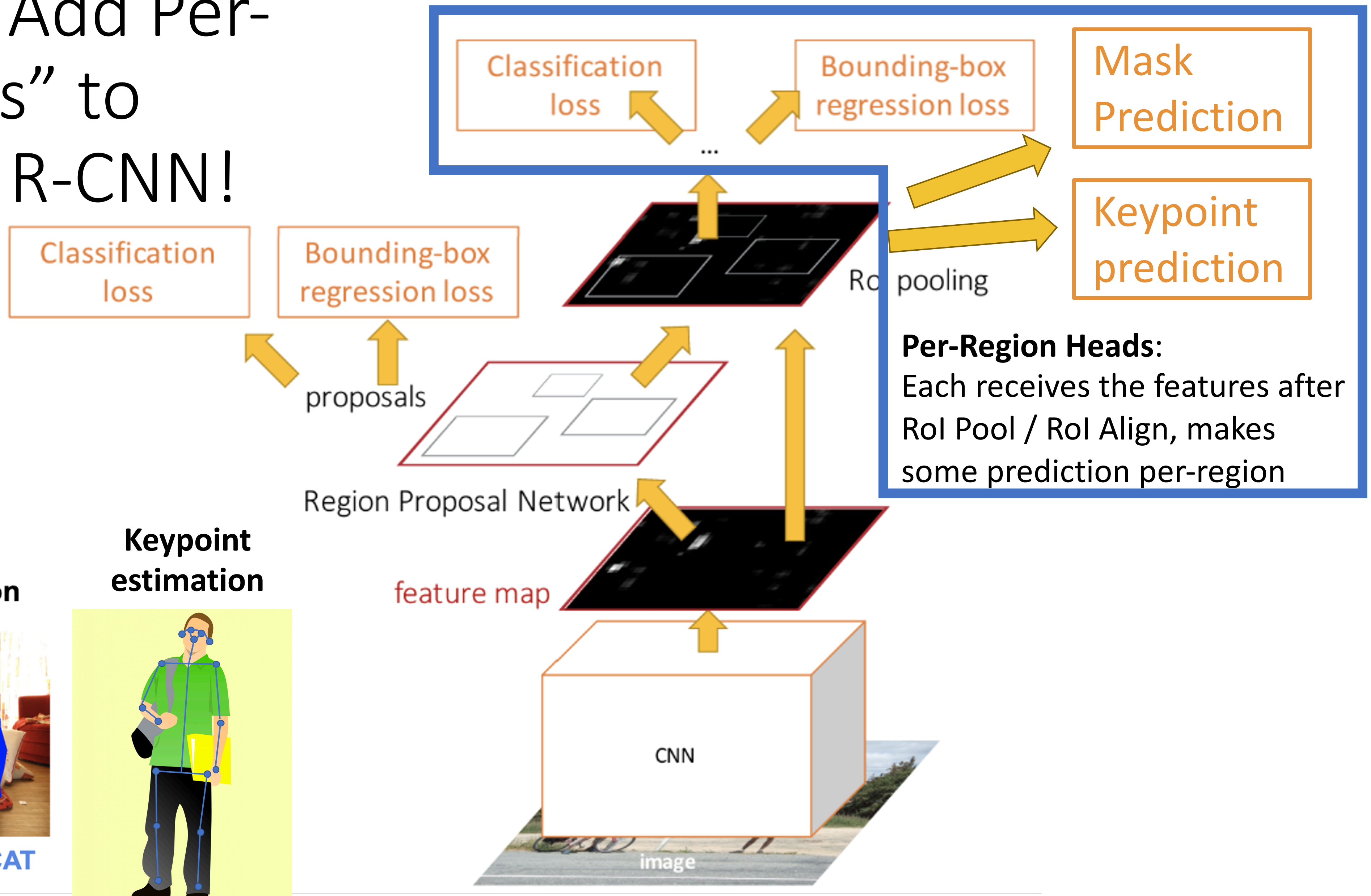
Ground-truth has one "pixel" turned on per keypoint. Train with softmax loss

He et al, "Mask R-CNN", ICCV 2017

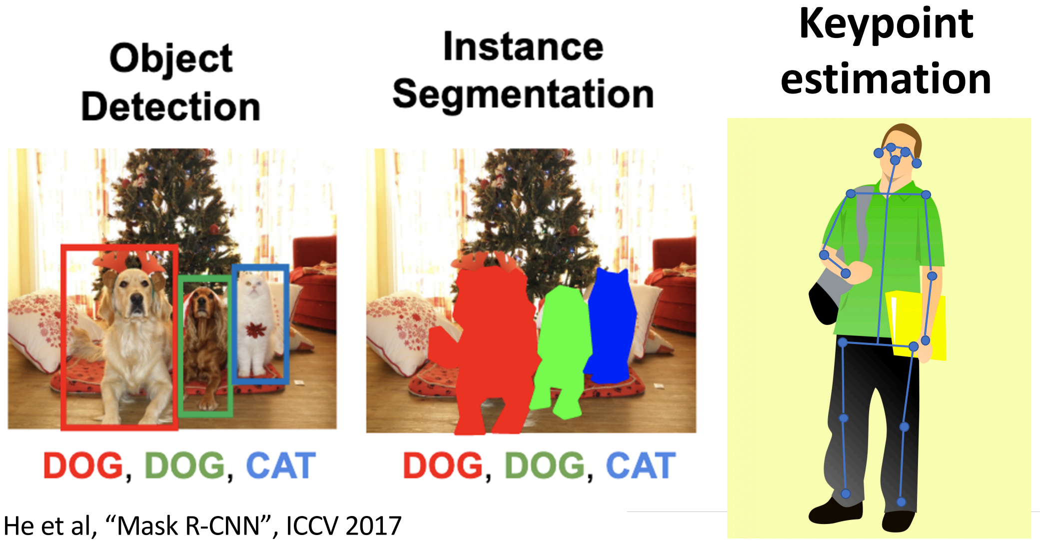
Joint Instance Segmentation and Pose Estimation

He et al, "Mask R-CNN", ICCV 2017

General Idea: Add Per-Region "Heads" to Faster / Mask R-CNN!

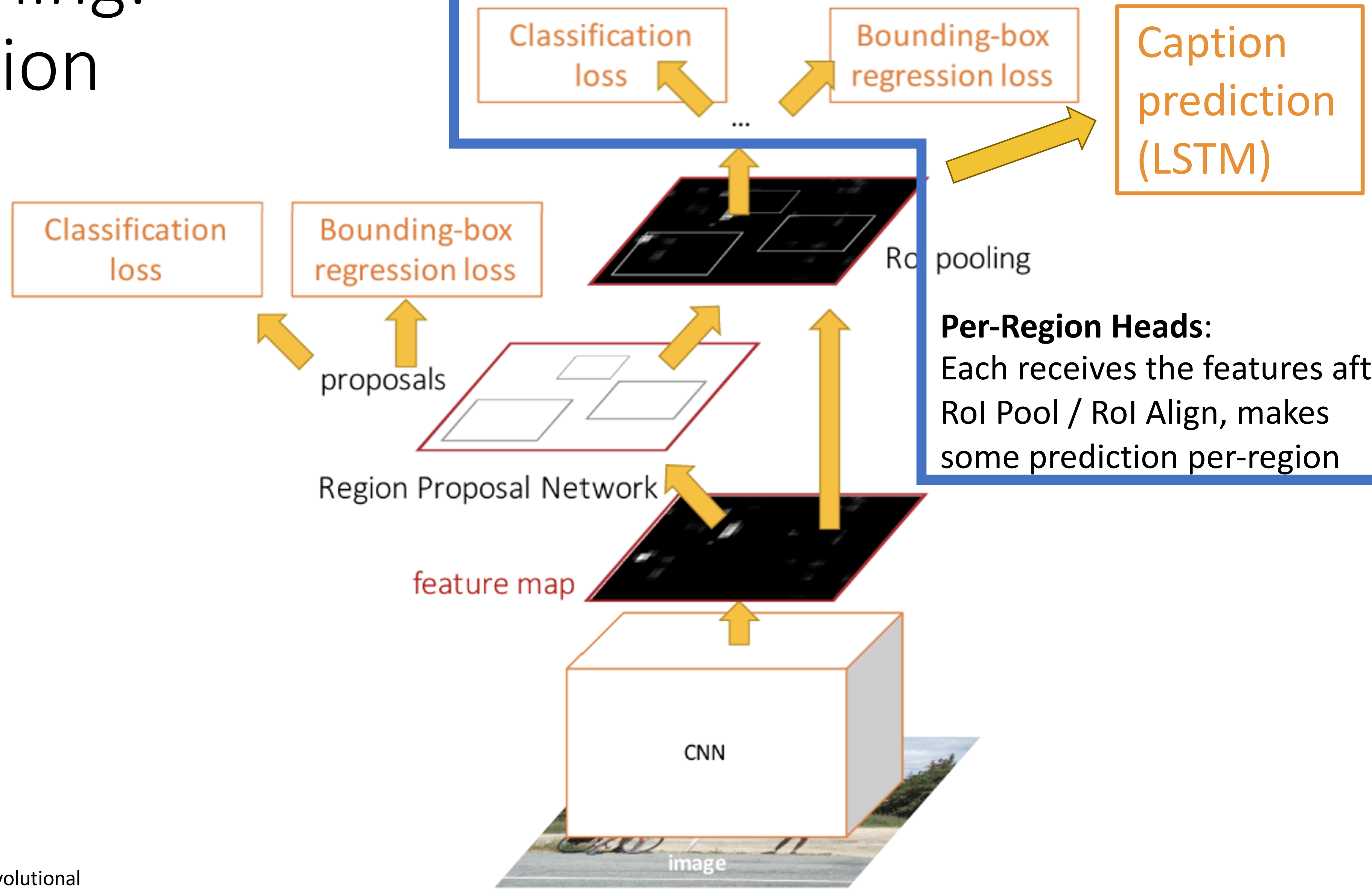


Per-Region Heads:
Each receives the features after RoI Pool / RoI Align, makes some prediction per-region



He et al, "Mask R-CNN", ICCV 2017

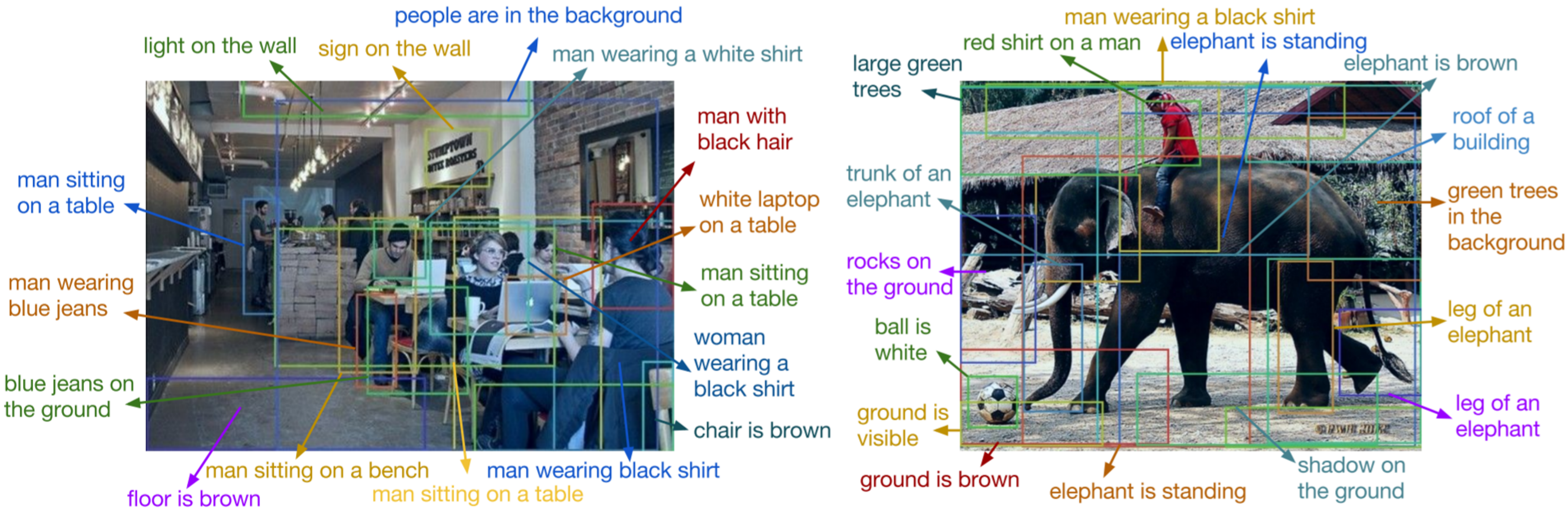
Dense Captioning: Predict a caption per region!



Per-Region Heads: Each receives the features after RoI Pool / RoI Align, makes some prediction per-region

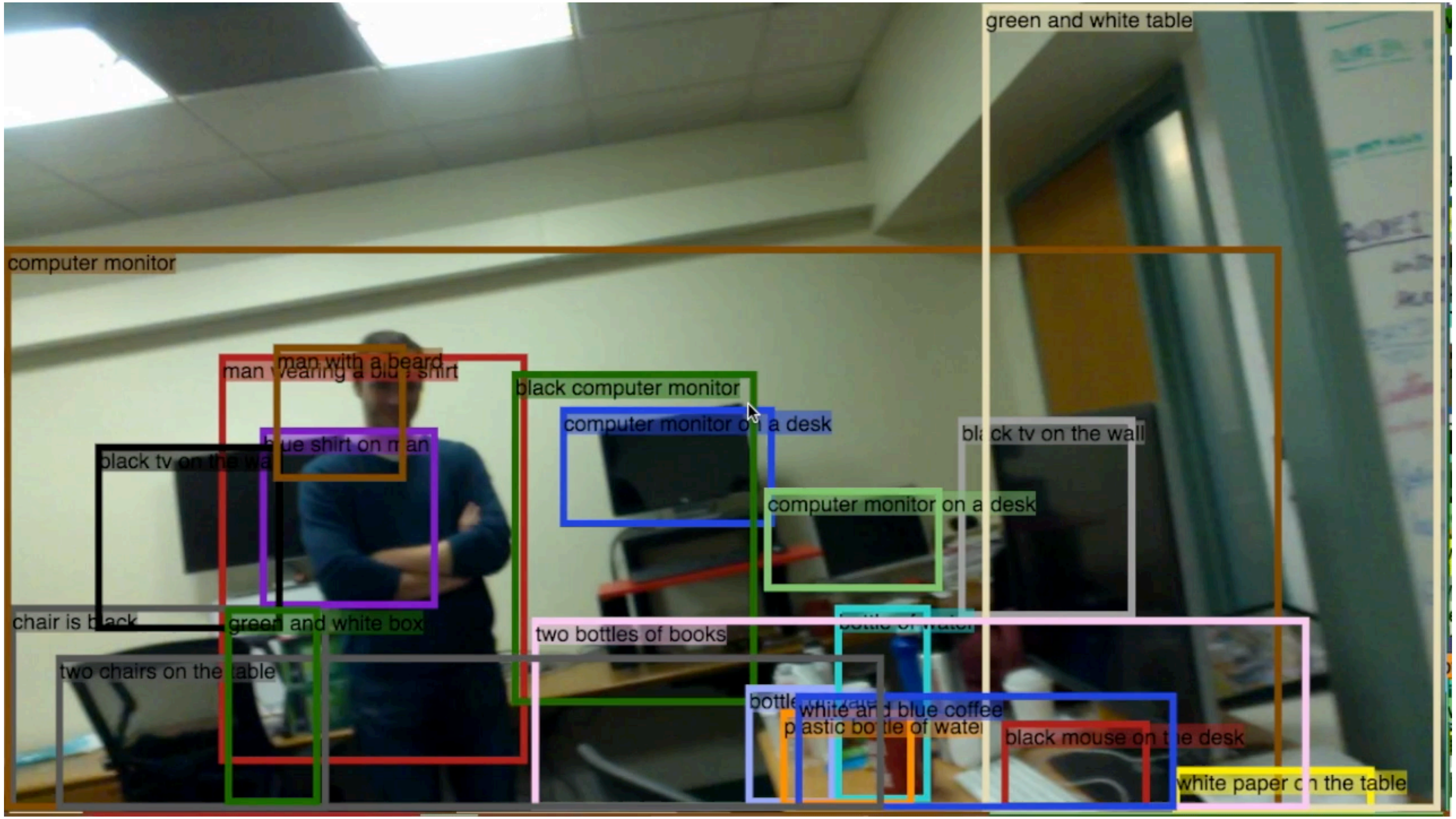
Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016

Dense Captioning



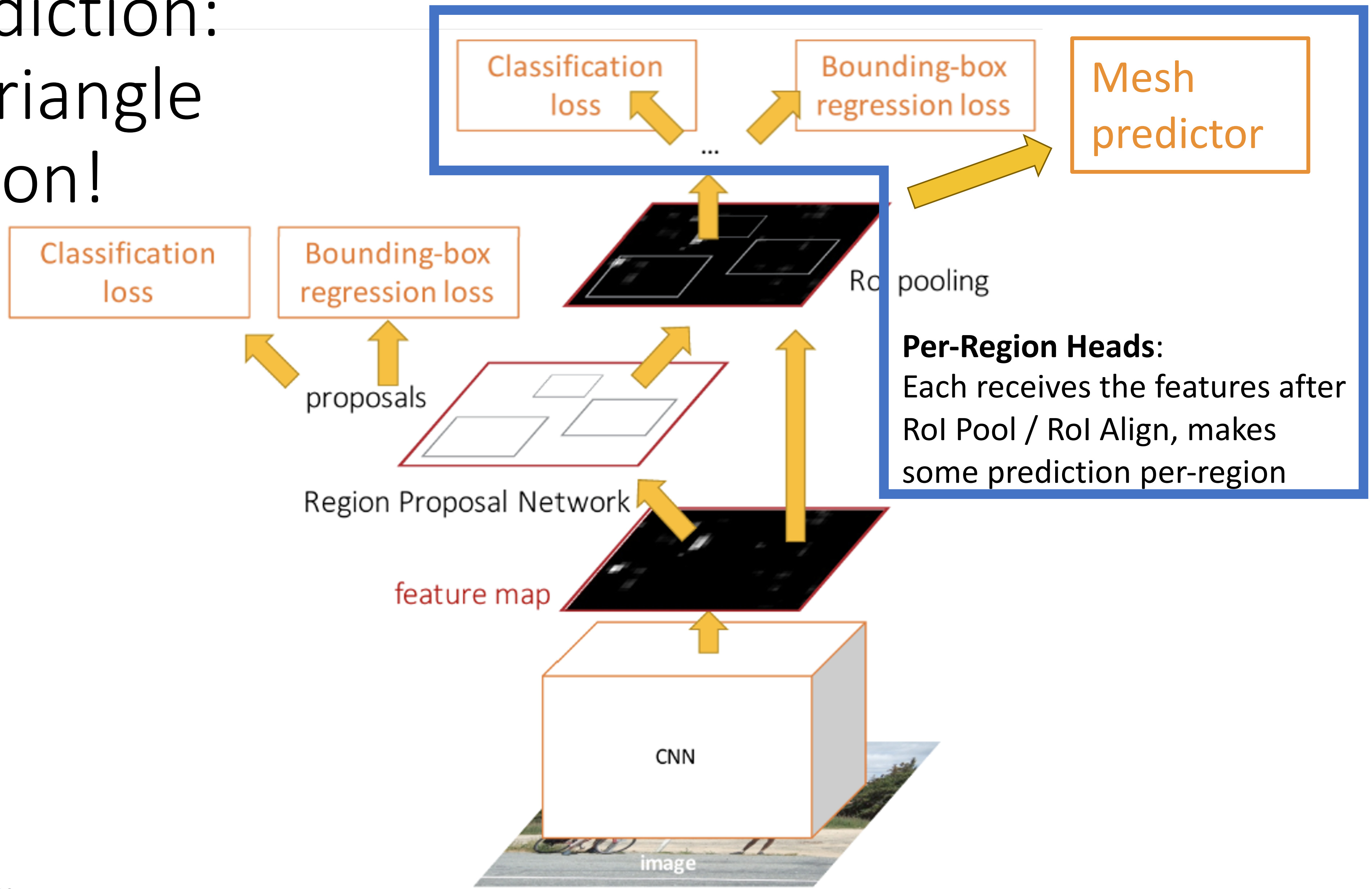
Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016

Dense Captioning



Johnson, Karpathy, and Fei-Fei, “DenseCap: Fully Convolutional Localization Networks for Dense Captioning”, CVPR 2016

3D Shape Prediction: Predict a 3D triangle mesh per region!



Gkioxari, Malik, and Johnson, “Mesh R-CNN”, ICCV 2019

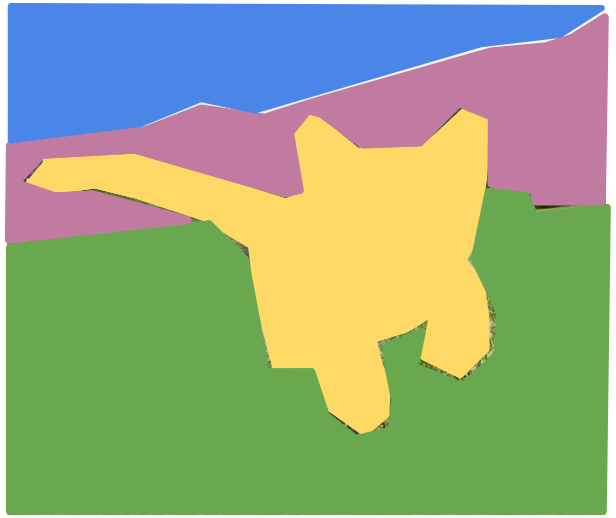
Summary: Many Computer Vision Tasks!

Classification

CAT

No spatial extent

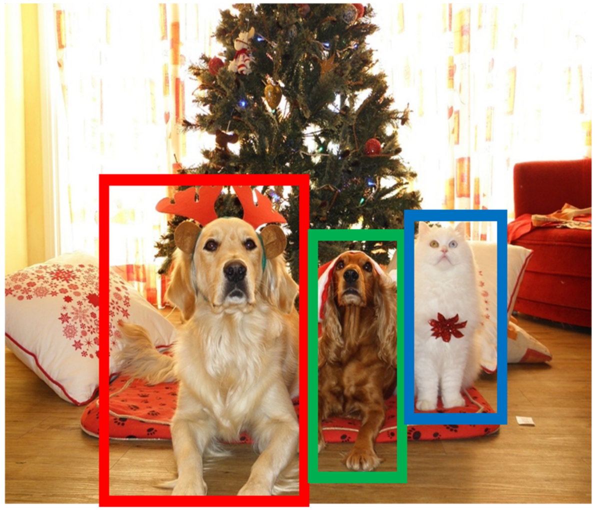
Semantic Segmentation



GRASS, CAT, TREE, SKY

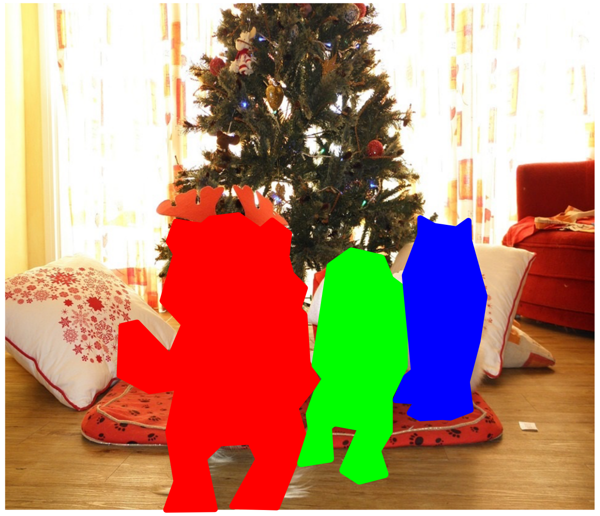
No objects, just pixels

Object Detection



DOG, DOG, CAT

Instance Segmentation



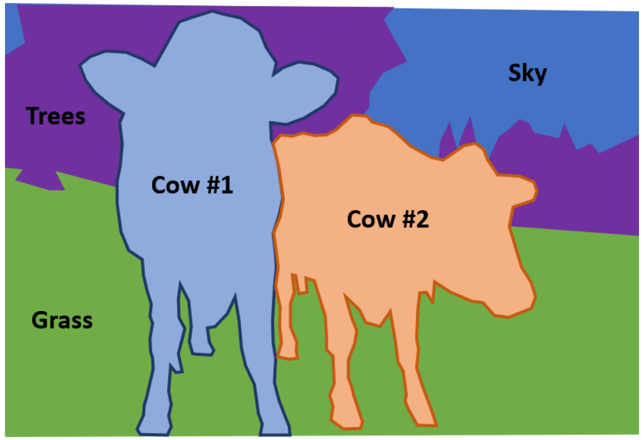
DOG, DOG, CAT

Multiple Objects

DL software and more

- Deep learning frameworks
- Instance segmentation
- ~~3D neural networks~~
- Video

```python
class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        # 1 input image channel, 6 output channels, 5x5 square convolution
        # kernel
        self.conv1 = nn.Conv2d(1, 6, 5)
        self.conv2 = nn.Conv2d(6, 16, 5)
        # an affine operation: y = Wx + b
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        # Max pooling over a (2, 2) window
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        # If the size is a square you can only specify a single number
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = x.view(-1, self.num_flat_features(x))
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```



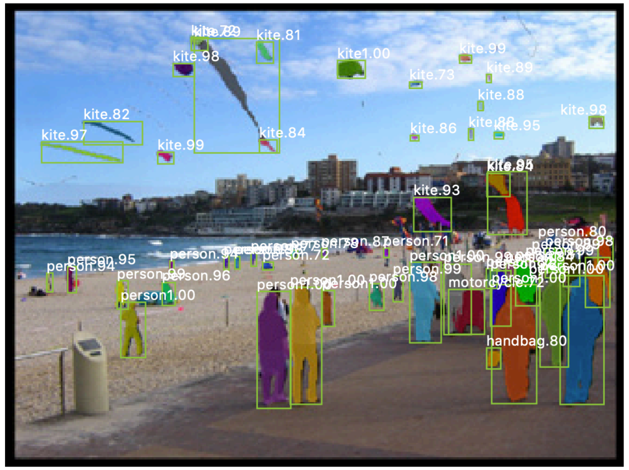
clink glass → drink

~~Lecture 17: 3D Vision~~

Covered in later part of the UW CSE 576 course

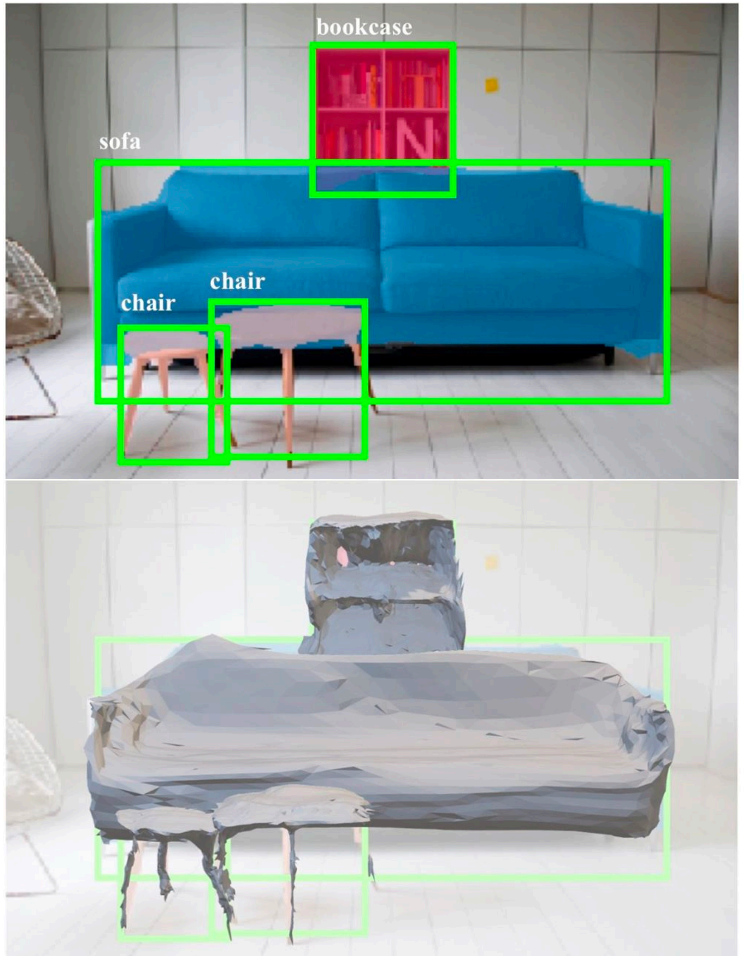
Today: Predicting **3D Shapes of Objects**

Mask R-CNN:
2D Image -> 2D shapes



He, Gkioxari, Dollár, and Girshick, "Mask R-CNN", ICCV 2017

Mesh R-CNN:
2D Image -> **3D** shapes



Gkioxari, Malik, and Johnson, "Mesh R-CNN", ICCV 2019

Many more topics in 3D Vision!

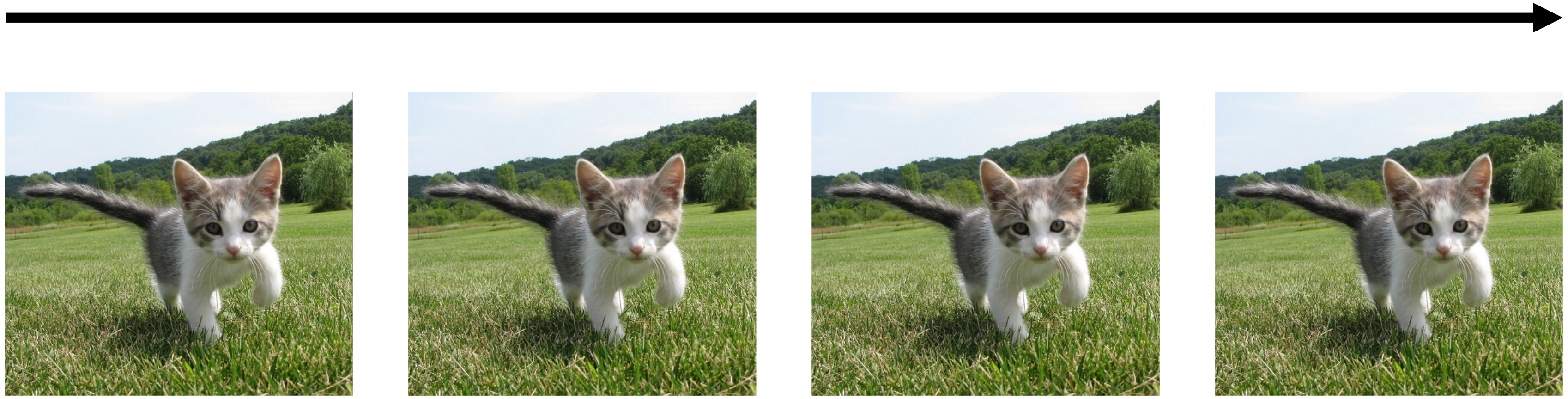
Computing correspondences
Multi-view stereo
Structure from Motion
Simultaneous Localization and Mapping (SLAM)
Self-supervised learning
View Synthesis
Differentiable graphics
3D Sensors

Many non-Deep Learning methods alive and well in 3D!

Lecture 18:
Videos

Today: **Video** = 2D + Time

A video is a **sequence** of images
4D tensor: T x 3 x H x W
(or 3 x T x H x W)



Example task: **Video Classification**

Input video:
T x 3 x H x W

Swimming
Running
Jumping
Eating
Standing

Running video is in the public domain

Example task: **Video Classification**

Images: Recognize **objects**

Dog
Cat
Fish
Truck

Videos: Recognize **actions**

Swimming
Running
Jumping
Eating
Standing

Running video is in the public domain

Problem: Videos are big!

Input video:
T x 3 x H x W

Videos are ~30 frames per second (fps)

Size of uncompressed video
(3 bytes per pixel):

SD (640 x 480): **~1.5 GB per minute**
HD (1920 x 1080): ~**10 GB per minute**

Problem: Videos are big!

Input video:
T x 3 x H x W

Videos are ~30 frames per second (fps)

Size of uncompressed video
(3 bytes per pixel):

SD (640 x 480): **~1.5 GB per minute**
HD (1920 x 1080): ~**10 GB per minute**

Solution: Train on short **clips:** low fps and low spatial resolution
e.g. T = 16, H=W=112
(3.2 seconds at 5 fps, 588 KB)

Training on Clips

Raw video: Long, high FPS

Training on Clips

Raw video: Long, high FPS

Training: Train model to classify short **clips** with low FPS

Training on Clips

Raw video: Long, high FPS

Training: Train model to classify short **clips** with low FPS

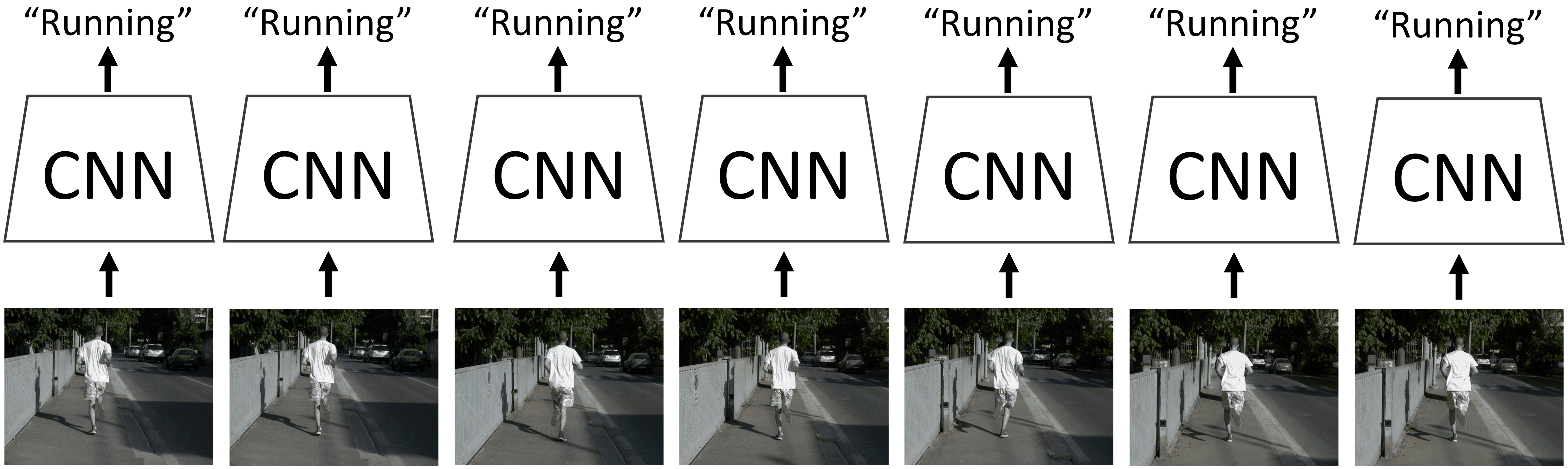
Testing: Run model on different clips, average predictions

Video Classification: Single-Frame CNN

Simple idea: train normal 2D CNN to classify video frames independently

(Average predicted probs at test-time)

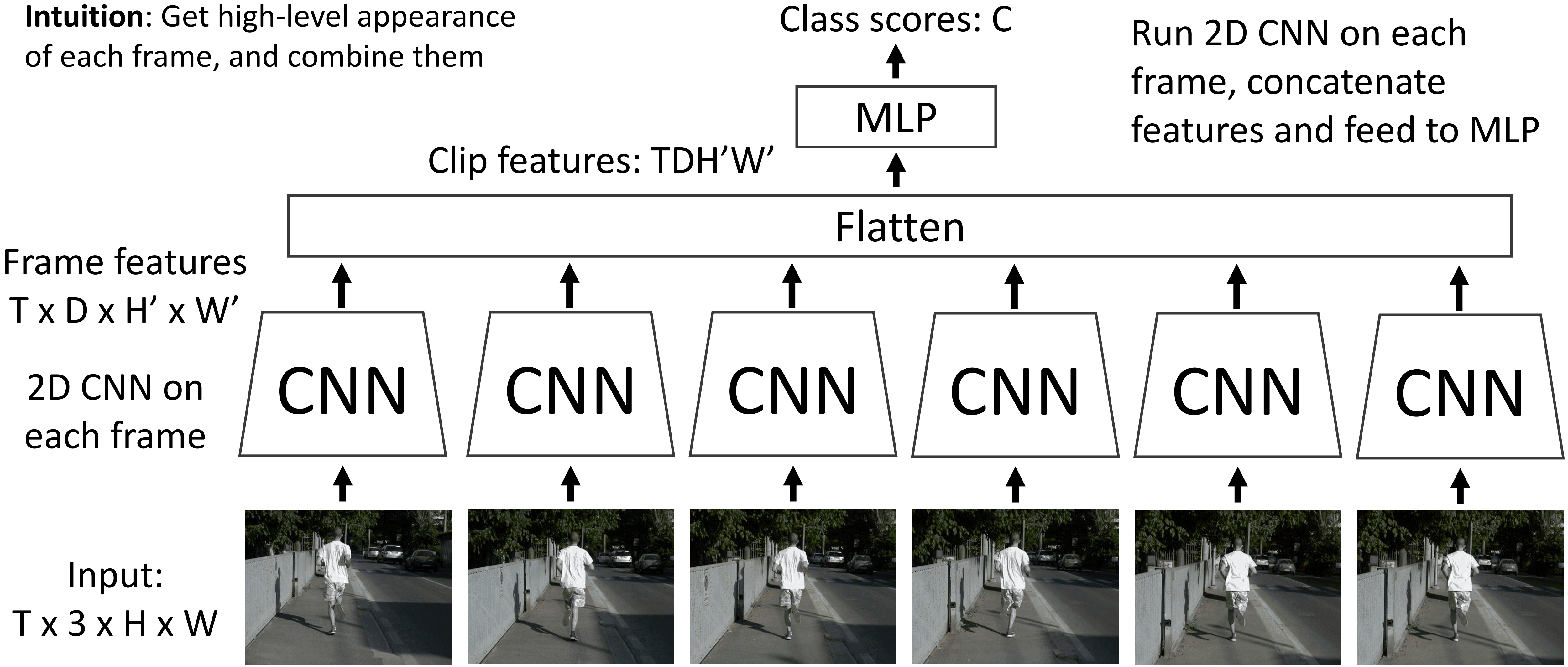
Often a **very** strong baseline for video classification



Video Classification: Late Fusion (with FC layers)

Intuition: Get high-level appearance of each frame, and combine them

Run 2D CNN on each frame, concatenate features and feed to MLP

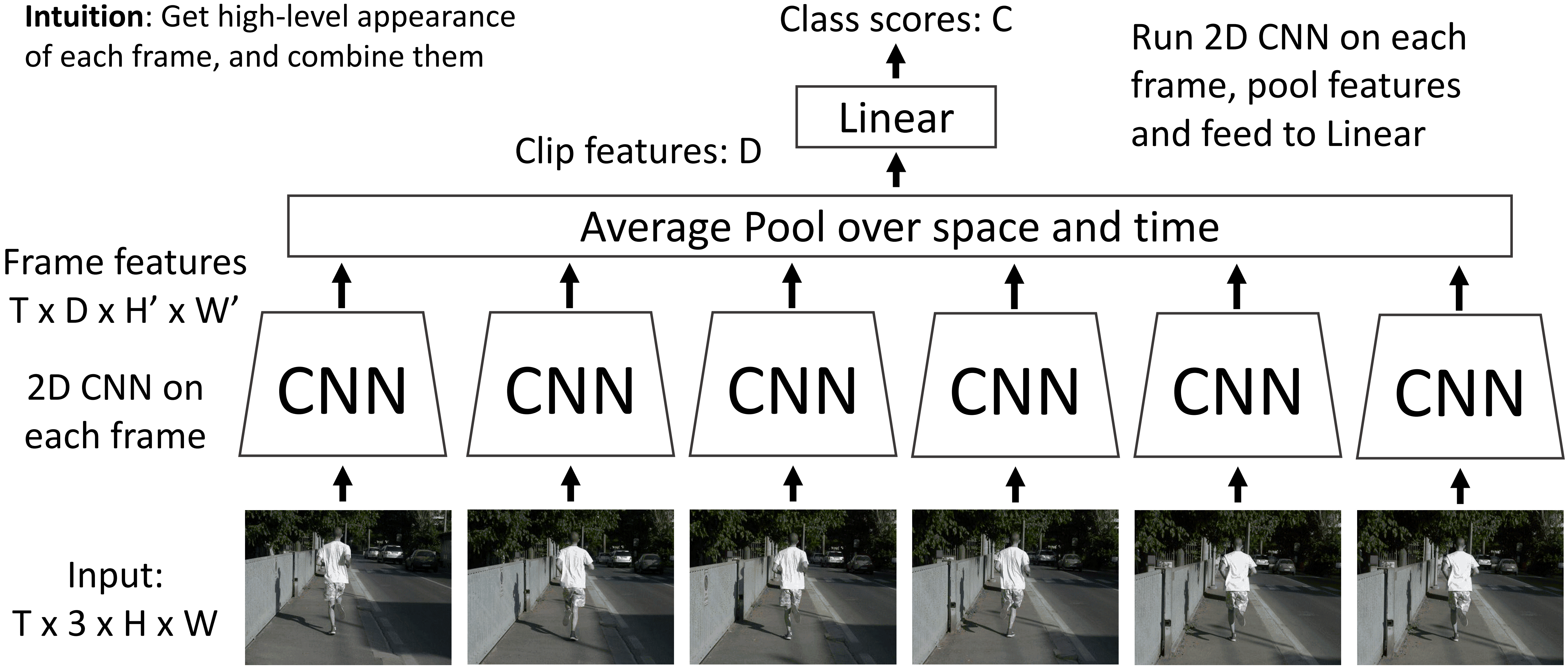


Karpathy et al, "Large-scale Video Classification with Convolutional Neural Networks", CVPR 2014

Video Classification: Late Fusion (with pooling)

Intuition: Get high-level appearance of each frame, and combine them

Run 2D CNN on each frame, pool features and feed to Linear



Video Classification: Late Fusion (with pooling)

Intuition: Get high-level appearance of each frame, and combine them
Problem: Hard to compare low-level motion between frames

Class scores: C

Linear

Clip features: D

Run 2D CNN on each frame, pool features and feed to Linear

Average Pool over space and time

Frame features
T x D x H' x W'

2D CNN on each frame

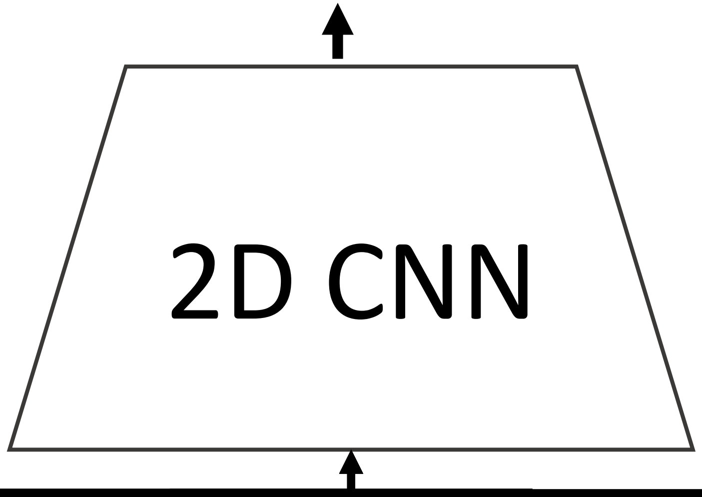
CNN | CNN | CNN | CNN | CNN | CNN

Input:
T x 3 x H x W

Video Classification: Early Fusion

Intuition: Compare frames with very first conv layer, after that normal 2D CNN

Class scores: C



Rest of the network is standard 2D CNN

First 2D convolution collapses all temporal information:
Input: 3T x H x W
Output: D x H x W

Reshape:
3T x H x W

Input:
T x 3 x H x W

Karpathy et al, "Large-scale Video Classification with Convolutional Neural Networks", CVPR 2014

Video Classification: Early Fusion

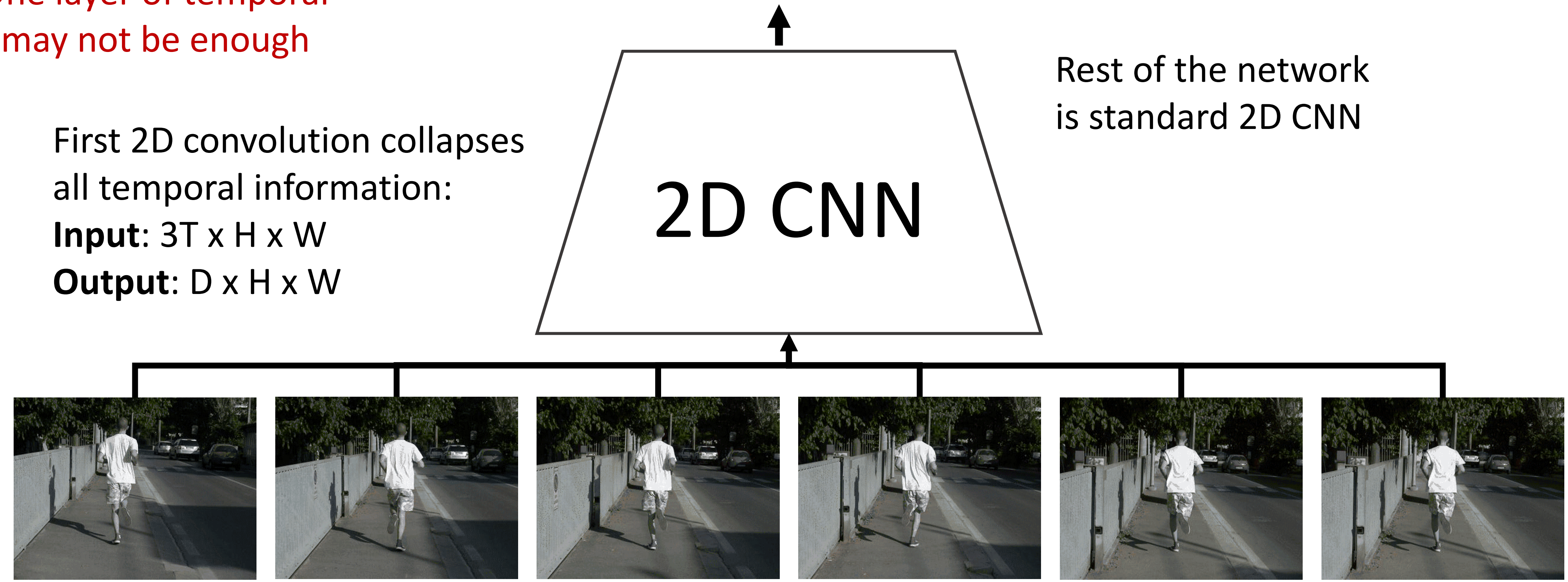
Intuition: Compare frames with very first conv layer, after that normal 2D CNN

Problem: One layer of temporal processing may not be enough

Class scores: C

Rest of the network is standard 2D CNN

First 2D convolution collapses all temporal information:
Input: 3T x H x W
Output: D x H x W



Reshape:
3T x H x W

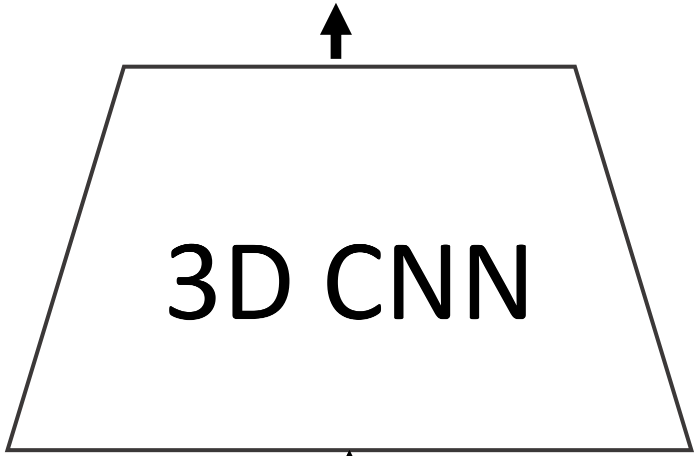
Input:
T x 3 x H x W

Karpathy et al, “Large-scale Video Classification with Convolutional Neural Networks”, CVPR 2014

Video Classification: 3D CNN

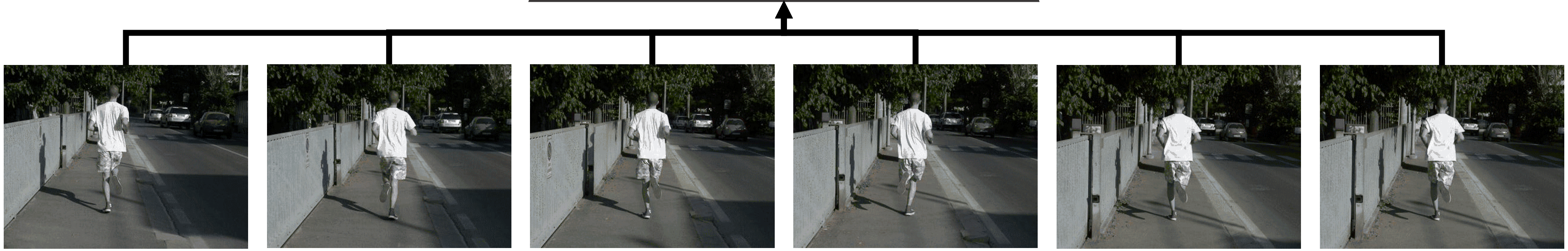
Intuition: Use 3D versions of convolution and pooling to slowly fuse temporal information over the course of the network

Class scores: C



Each layer in the network is a 4D tensor: D x T x H x W
Use 3D conv and 3D pooling operations

Input:
3 x T x H x W



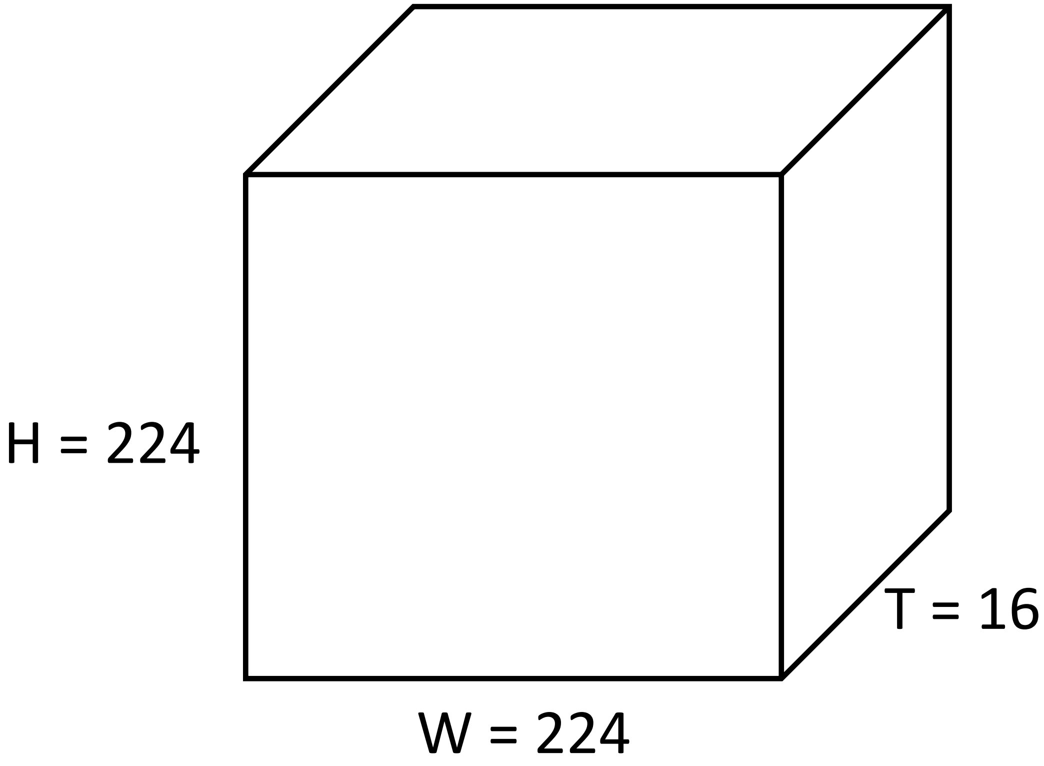
Ji et al, “3D Convolutional Neural Networks for Human Action Recognition”, TPAMI 2010 ; Karpathy et al, “Large-scale Video Classification with Convolutional Neural Networks”, CVPR 2014

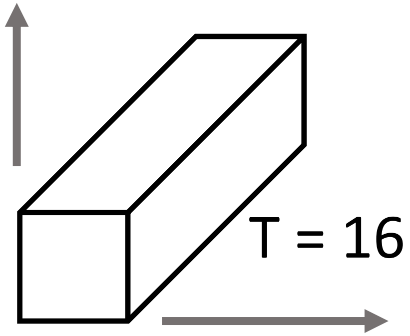
2D Conv (Early Fusion) vs 3D Conv (3D CNN)

Input: C_{in} x T x H x W
(3D grid with C_{in}-dim feat at each point)

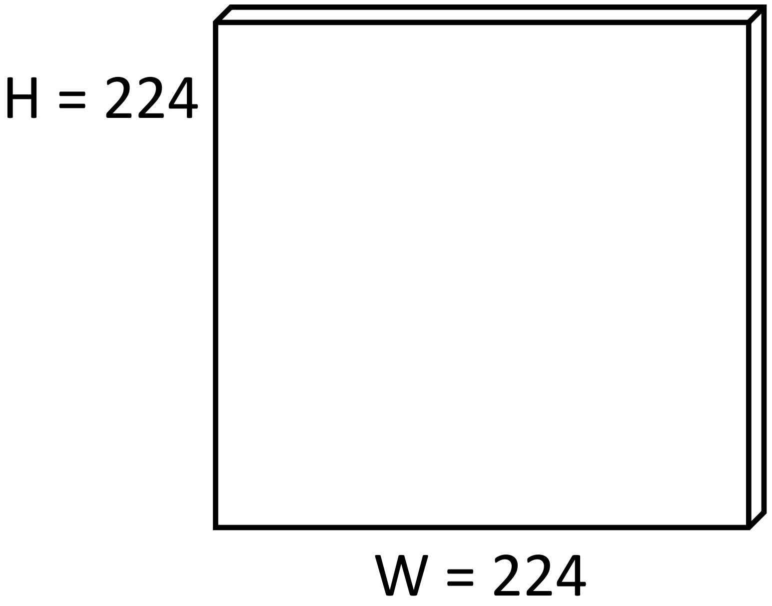
Weight:
C_{out} x C_{in} x T x 3 x 3
Slide over x and y

Output:
C_{out} x H x W
2D grid with C_{out} –dim feat at each point





C_{out} different filters



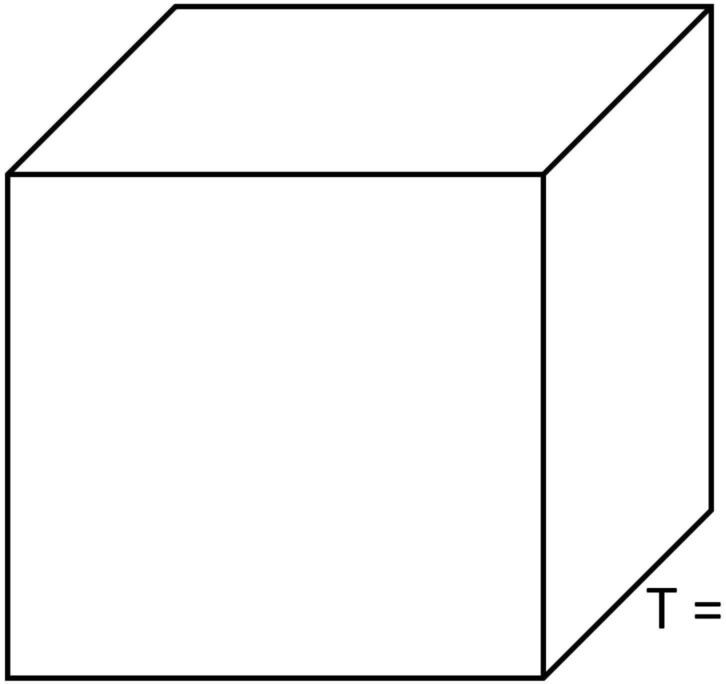
2D Conv (Early Fusion) vs 3D Conv (3D CNN)

Input: C_{in} x T x H x W
(3D grid with C_{in}-dim feat at each point)

Weight:
C_{out} x C_{in} x T x 3 x 3
Slide over x and y

Output:
C_{out} x H x W
2D grid with C_{out} –dim feat at each point

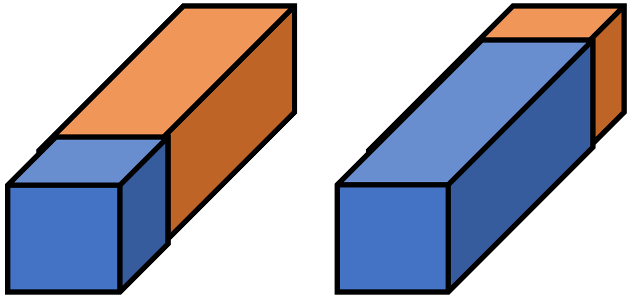
No temporal shift-invariance! Needs to learn separate filters for the same motion at different times in the clip



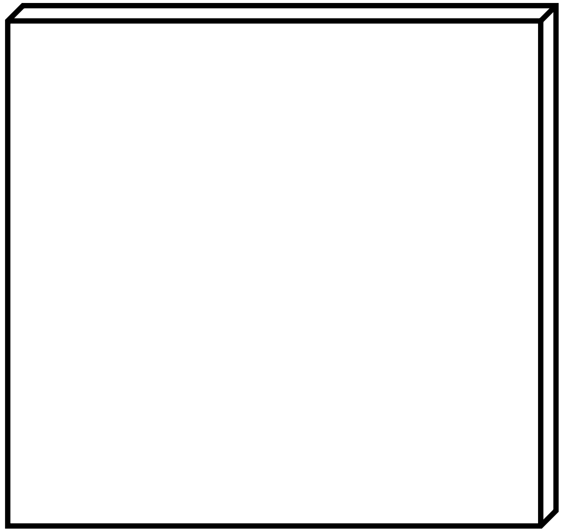
H = 224

T = 16

W = 224



C_{out} different filters



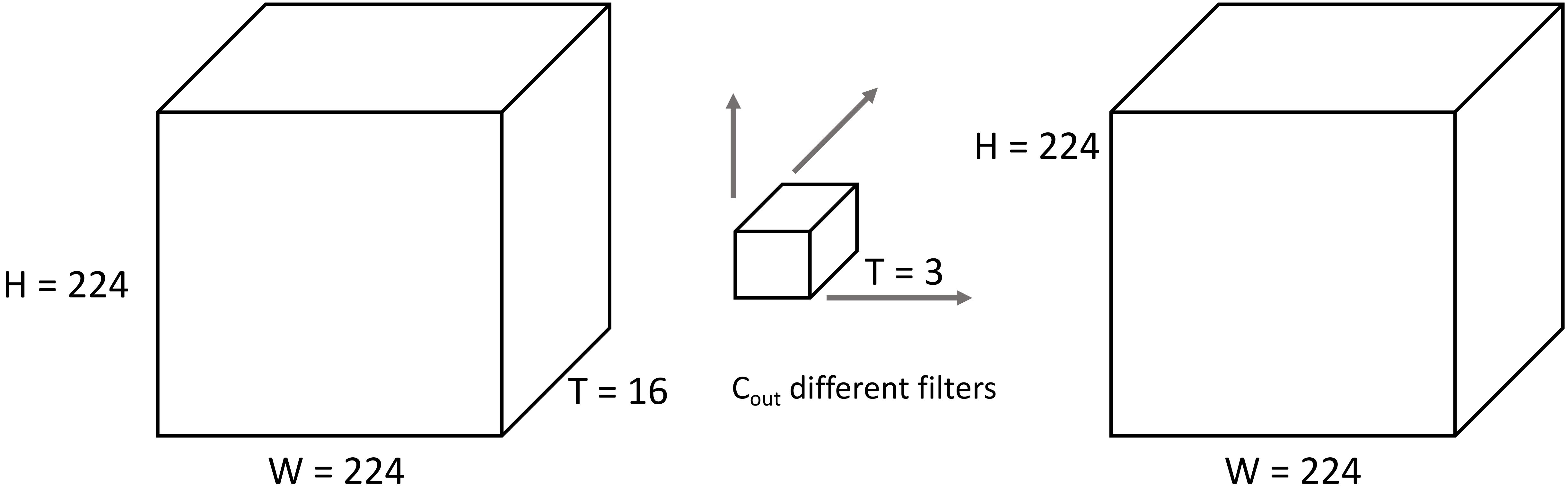
W = 224

2D Conv (Early Fusion) vs 3D Conv (3D CNN)

Input: C_{in} x T x H x W
(3D grid with C_{in}-dim
feat at each point)

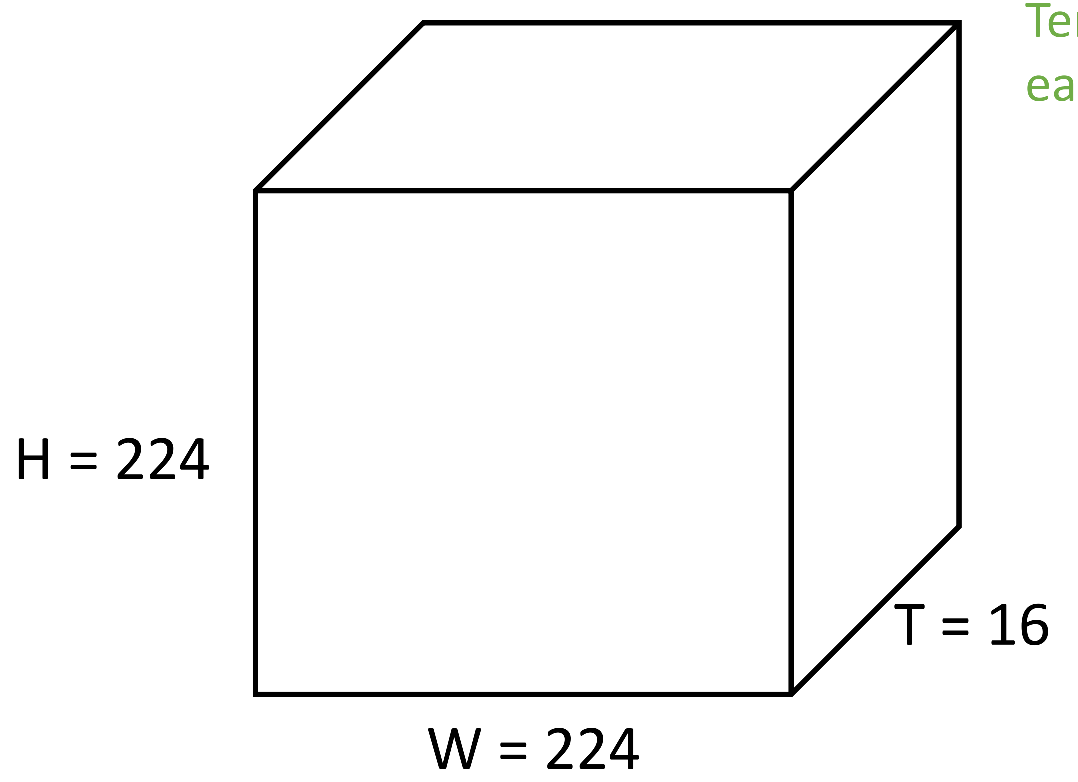
Weight:
C_{out} x C_{in} x 3 x 3 x 3
Slide over x and y

Output:
C_{out} x T x H x W
3D grid with C_{out}–dim
feat at each point



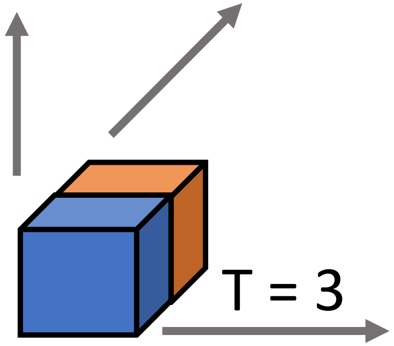
2D Conv (Early Fusion) vs 3D Conv (3D CNN)

Input: C_{in} x T x H x W
(3D grid with C_{in}-dim feat at each point)



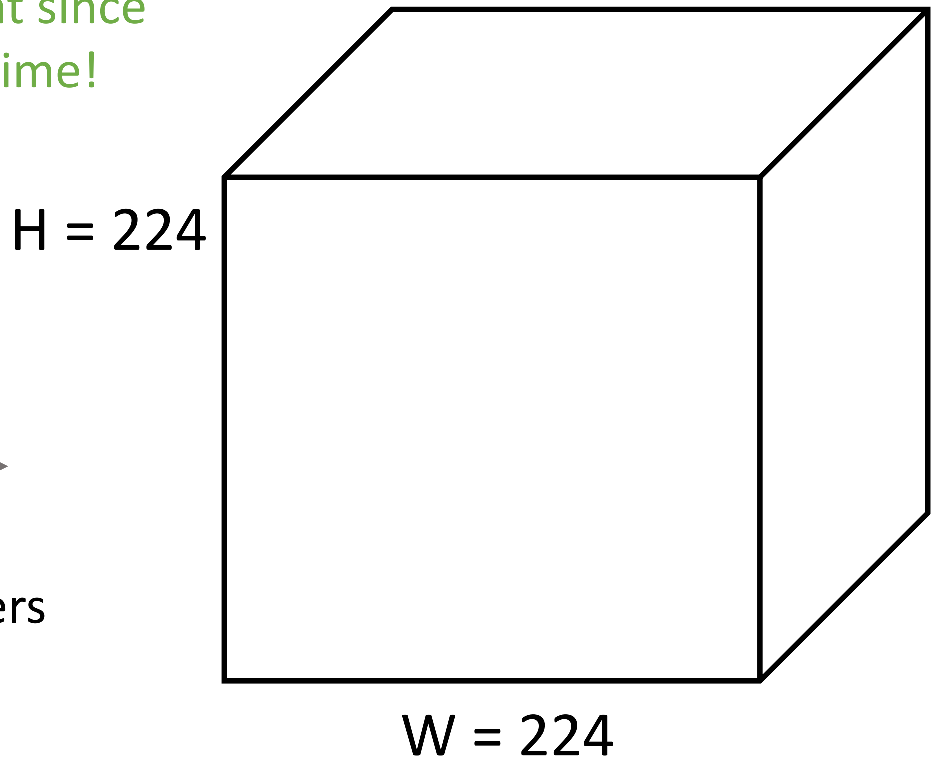
Weight:
C_{out} x C_{in} x 3 x 3 x 3
Slide over x and y

Temporal shift-invariant since each filter slides over time!



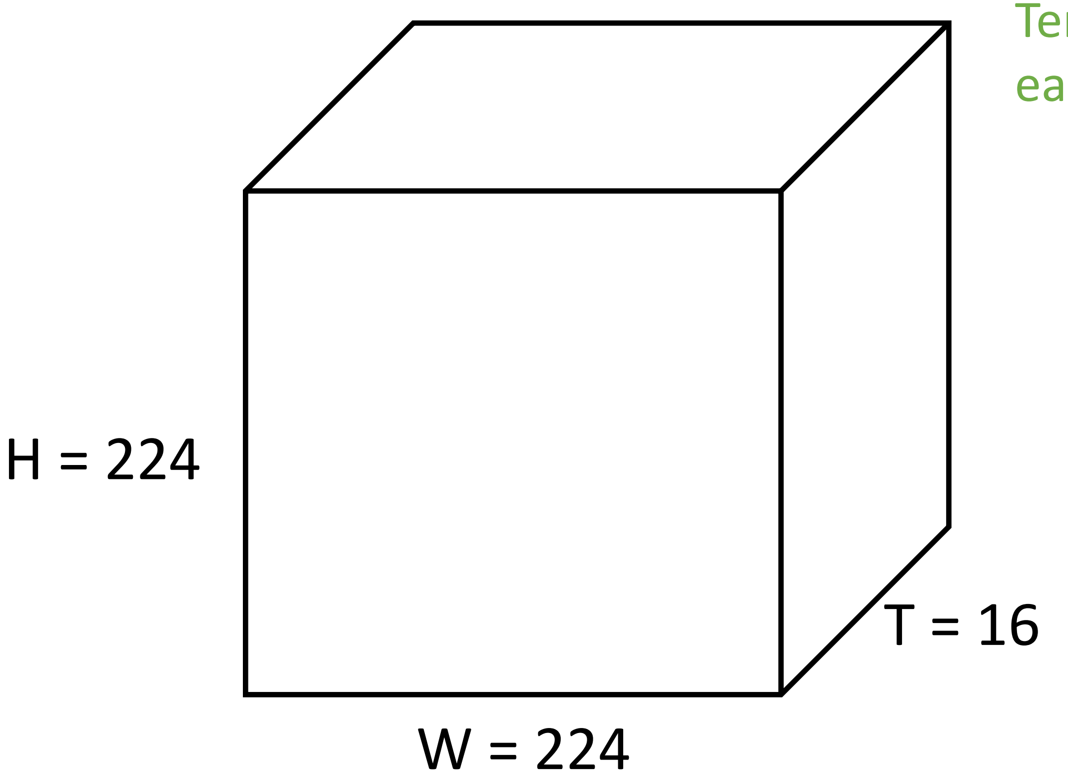
C_{out} different filters

Output:
C_{out} x T x H x W
3D grid with C_{out}–dim feat at each point



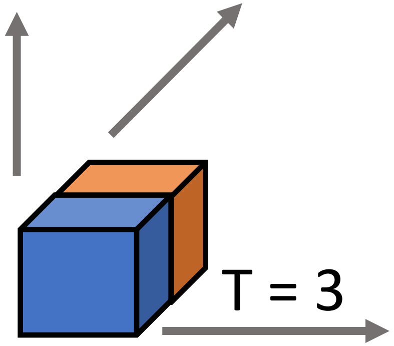
2D Conv (Early Fusion) vs 3D Conv (3D CNN)

Input: C_{in} x T x H x W
(3D grid with C_{in}-dim feat at each point)



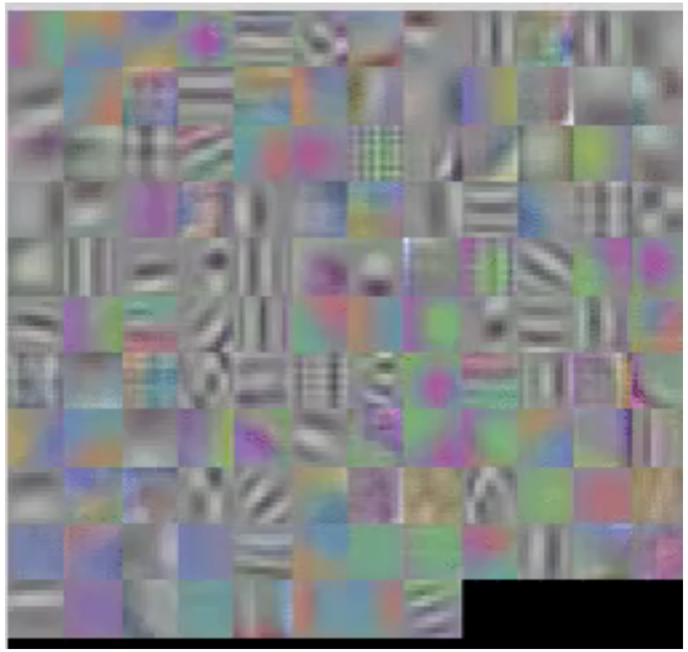
Weight:
C_{out} x C_{in} x 3 x 3 x 3
Slide over x and y

Temporal shift-invariant since each filter slides over time!



C_{out} different filters

First-layer filters have shape 3 (RGB) x 4 (frames) x 5 x 5 (space)
Can visualize as video clips!



Karpathy et al, "Large-scale Video Classification with Convolutional Neural Networks", CVPR 2014

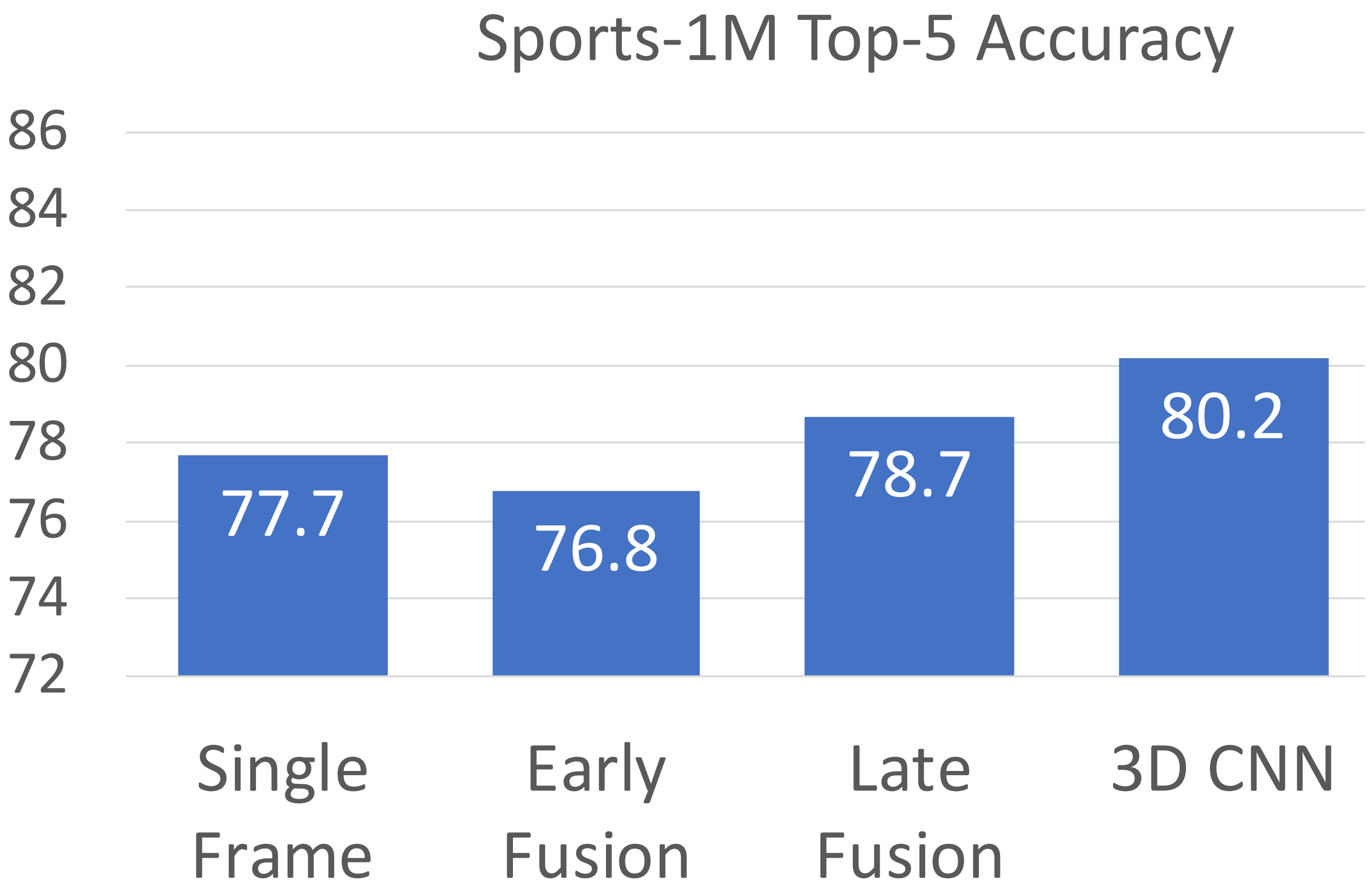
Example Video Dataset: **Sports-1M**

1 million YouTube videos annotated with labels for 487 different types of sports

Ground Truth
Correct prediction
Incorrect prediction

Karpathy et al, "Large-scale Video Classification with Convolutional Neural Networks", CVPR 2014

Early Fusion vs Late Fusion vs 3D CNN



Single Frame model works well – always try this first!

3D CNNs have improved a lot since 2014!

Karpathy et al, "Large-scale Video Classification with Convolutional Neural Networks", CVPR 2014

C3D: The VGG of 3D CNNs

3D CNN that uses all 3x3x3 conv and 2x2x2 pooling
(except Pool1 which is 1x2x2)

Released model pretrained on Sports-1M: Many people used this as a video feature extractor

Layer	Size
Input	3 x 16 x 112 x 112
Conv1 (3x3x3)	64 x 16 x 112 x 112
Pool1 (1x2x2)	64 x 16 x 56 x 56
Conv2 (3x3x3)	128 x 16 x 56 x 56
Pool2 (2x2x2)	128 x 8 x 28 x 28
Conv3a (3x3x3)	256 x 8 x 28 x 28
Conv3b (3x3x3)	256 x 8 x 28 x 28
Pool3 (2x2x2)	256 x 4 x 14 x 14
Conv4a (3x3x3)	512 x 4 x 14 x 14
Conv4b (3x3x3)	512 x 4 x 14 x 14
Pool4 (2x2x2)	512 x 2 x 7 x 7
Conv5a (3x3x3)	512 x 2 x 7 x 7
Conv5b (3x3x3)	512 x 2 x 7 x 7
Pool5	512 x 1 x 3 x 3
FC6	4096
FC7	4096
FC8	C

Tran et al, "Learning Spatiotemporal Features with 3D Convolutional Networks", ICCV 2015

C3D: The VGG of 3D CNNs

3D CNN that uses all 3x3x3 conv and 2x2x2 pooling
(except Pool1 which is 1x2x2)

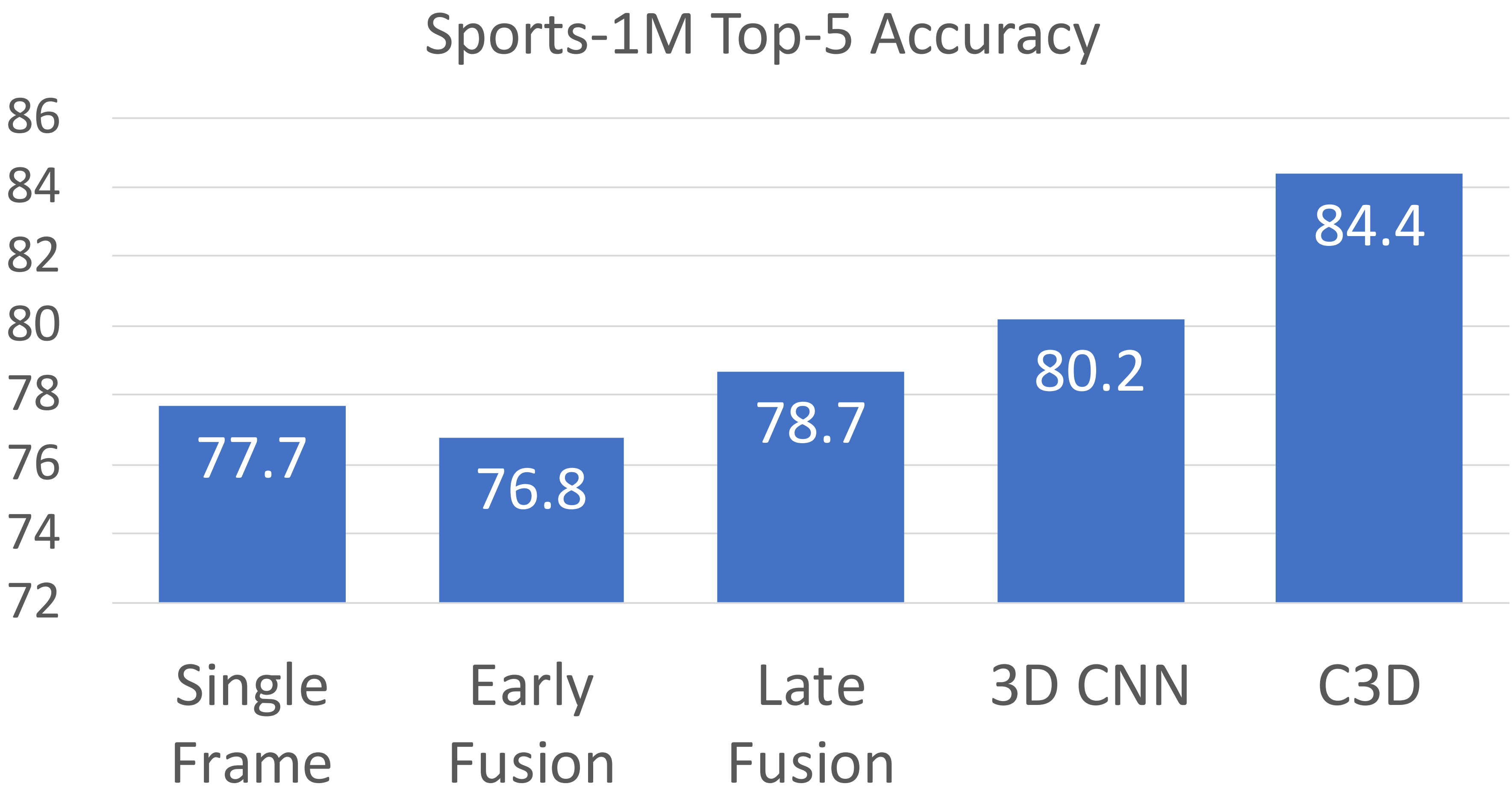
Released model pretrained on Sports-1M: Many people used this as a video feature extractor

Problem: 3x3x3 conv is very expensive!
AlexNet: 0.7 GFLOP
VGG-16: 13.6 GFLOP
C3D: **39.5 GFLOP (2.9x VGG!)**

Layer	Size	MFLOPs
Input	3 x 16 x 112 x 112	
Conv1 (3x3x3)	64 x 16 x 112 x 112	1.04
Pool1 (1x2x2)	64 x 16 x 56 x 56	
Conv2 (3x3x3)	128 x 16 x 56 x 56	11.10
Pool2 (2x2x2)	128 x 8 x 28 x 28	
Conv3a (3x3x3)	256 x 8 x 28 x 28	5.55
Conv3b (3x3x3)	256 x 8 x 28 x 28	11.10
Pool3 (2x2x2)	256 x 4 x 14 x 14	
Conv4a (3x3x3)	512 x 4 x 14 x 14	2.77
Conv4b (3x3x3)	512 x 4 x 14 x 14	5.55
Pool4 (2x2x2)	512 x 2 x 7 x 7	
Conv5a (3x3x3)	512 x 2 x 7 x 7	0.69
Conv5b (3x3x3)	512 x 2 x 7 x 7	0.69
Pool5	512 x 1 x 3 x 3	
FC6	4096	0.51
FC7	4096	0.45
FC8	C	0.05

Tran et al, "Learning Spatiotemporal Features with 3D Convolutional Networks", ICCV 2015

Early Fusion vs Late Fusion vs 3D CNN



Karpathy et al, “Large-scale Video Classification with Convolutional Neural Networks”, CVPR 2014
Tran et al, “Learning Spatiotemporal Features with 3D Convolutional Networks”, ICCV 2015

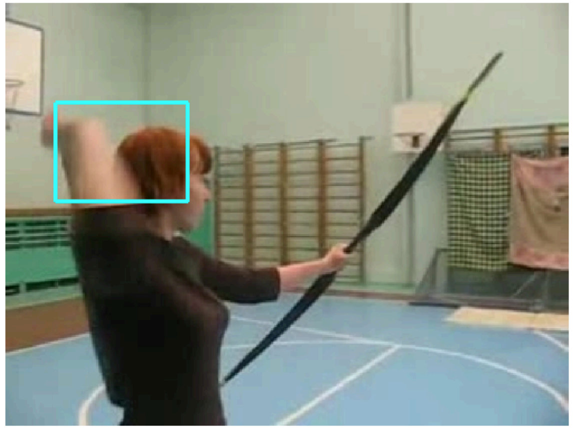
Recognizing Actions from Motion

We can easily recognize actions using only **motion information**

Johansson, "Visual perception of biological motion and a model for its analysis." Perception & Psychophysics. 14(2):201-211. 1973.

Measuring Motion: Optical Flow

Image at frame t



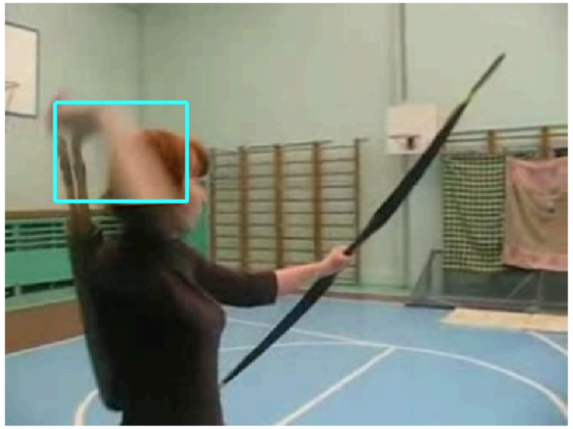
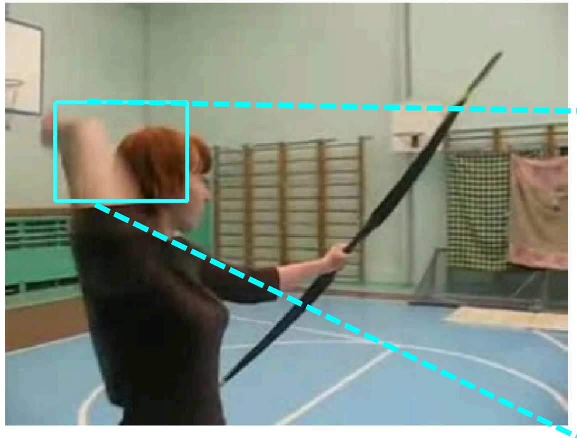


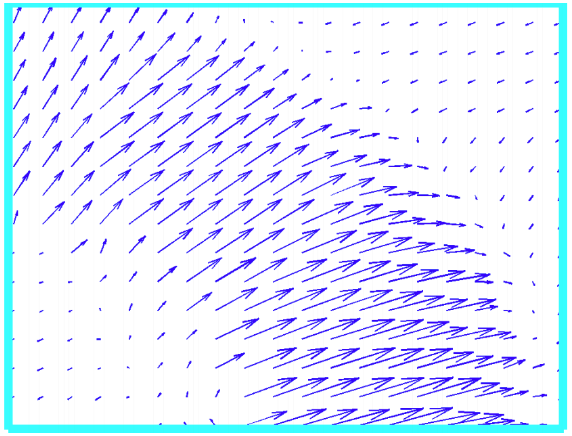
Image at frame t+1

Simonyan and Zisserman, “Two-stream convolutional networks for action recognition in videos”, NeurIPS 2014

Measuring Motion: Optical Flow

Image at frame t





Optical flow gives a displacement field F between images I_t and I_{t+1}

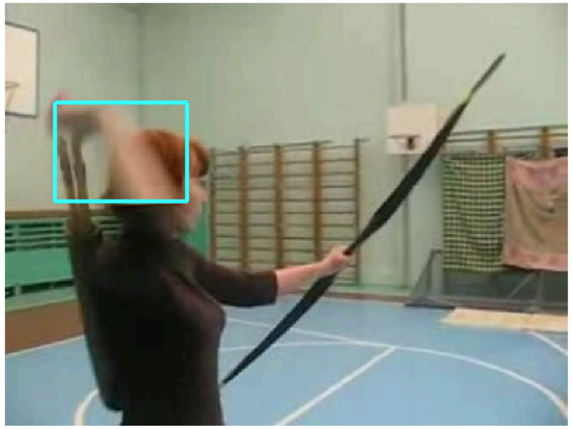


Image at frame t+1

Tells where each pixel will move in the next frame:

$F(x, y) = (dx, dy)$

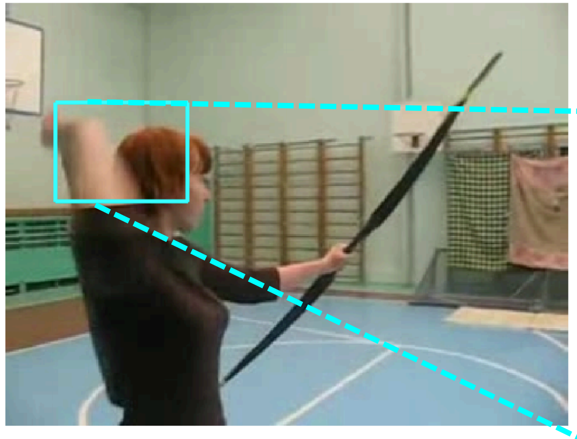
$I_{t+1}(x+dx, y+dy) = I_t(x, y)$

Simonyan and Zisserman, “Two-stream convolutional networks for action recognition in videos”, NeurIPS 2014

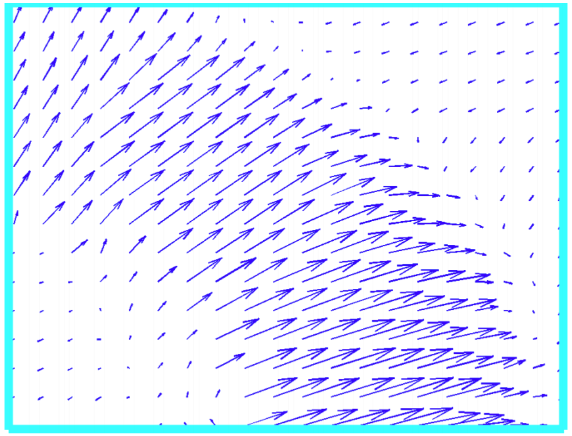
Measuring Motion: Optical Flow

Optical Flow highlights **local motion**

Image at frame t



Optical flow gives a displacement field F between images I_t and I_{t+1}



Tells where each pixel will move in the next frame:

$F(x, y) = (dx, dy)$

$I_{t+1}(x+dx, y+dy) = I_t(x, y)$

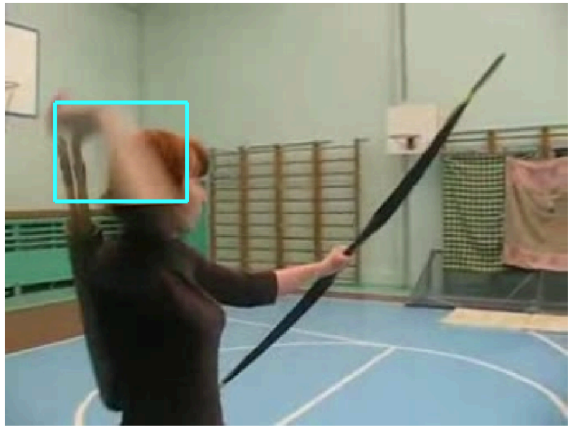
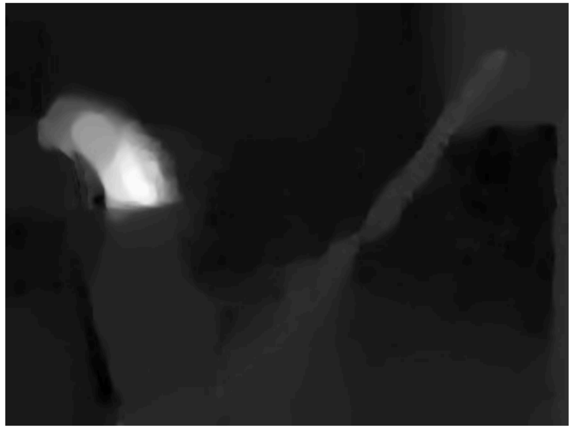
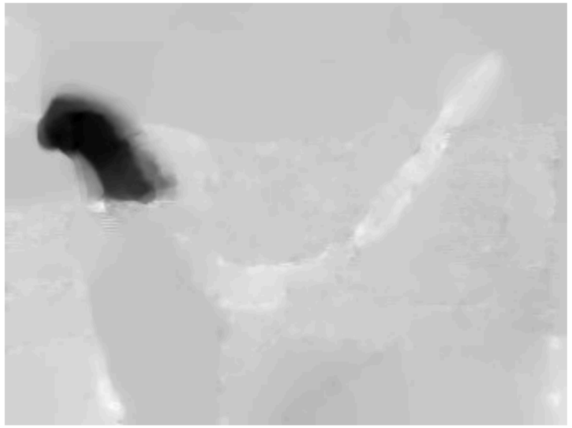


Image at frame t+1

Horizontal flow dx



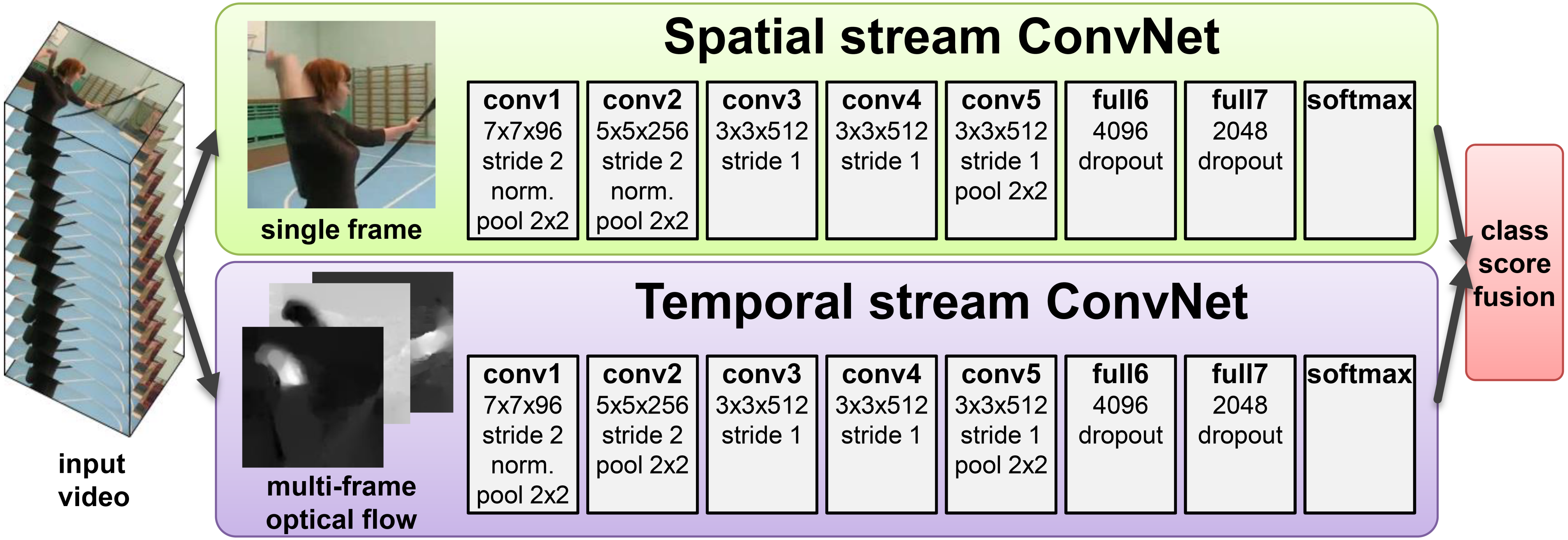


Vertical Flow dy

Simonyan and Zisserman, "Two-stream convolutional networks for action recognition in videos", NeurIPS 2014

Separating Motion and Appearance: Two-Stream Networks

Input: Single Image
3 x H x W

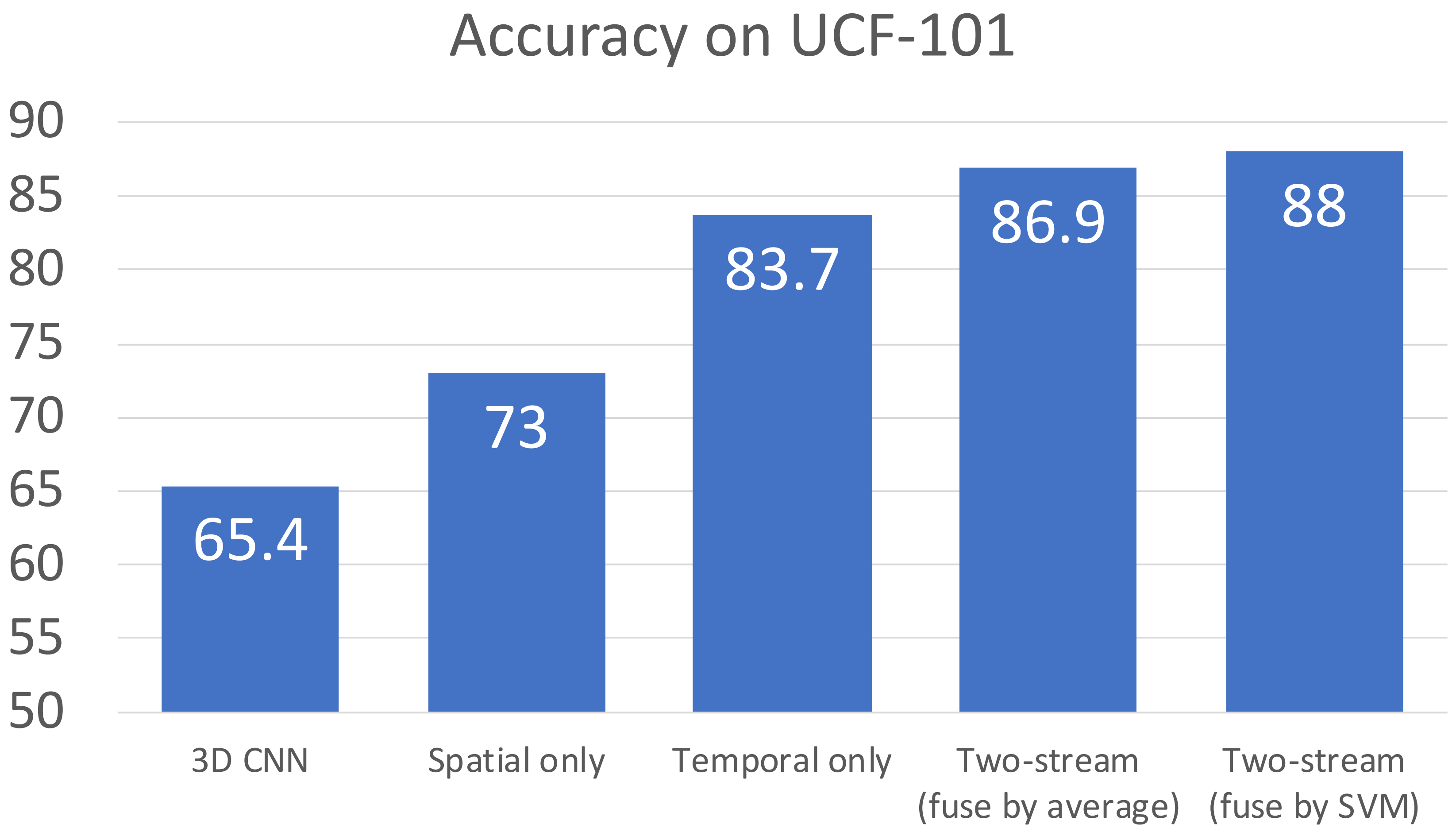


Input: Stack of optical flow:
[2*(T-1)] x H x W

Early fusion: First 2D conv processes all flow images

Simonyan and Zisserman, "Two-stream convolutional networks for action recognition in videos", NeurIPS 2014

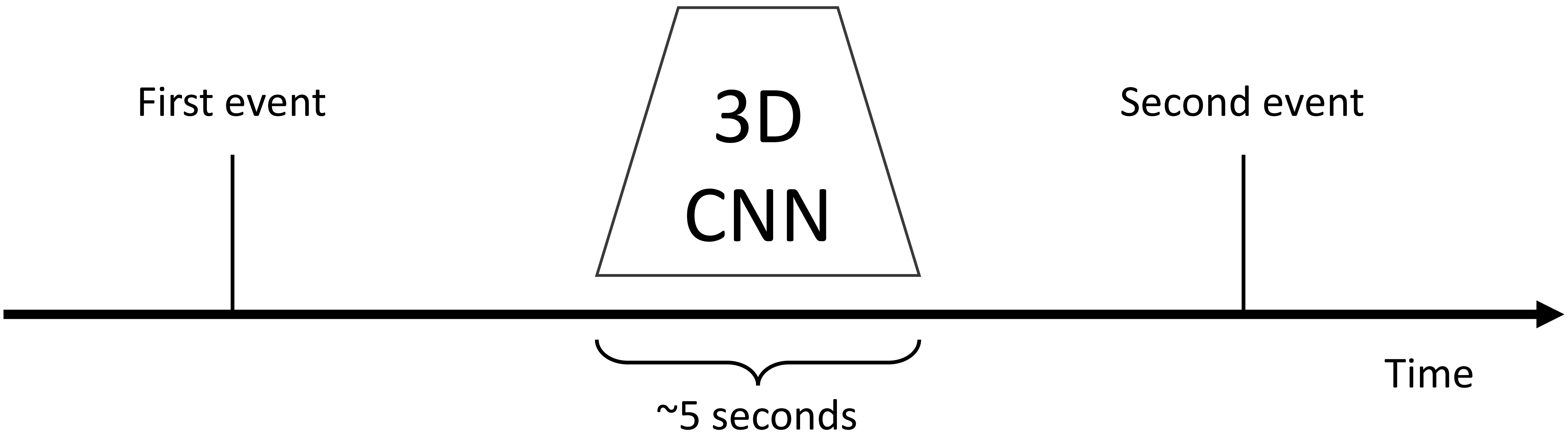
Separating Motion and Appearance: Two-Stream Networks



Simonyan and Zisserman, “Two-stream convolutional networks for action recognition in videos”, NeurIPS 2014

Modeling long-term temporal structure

So far all our temporal CNNs only model local motion between frames in very short clips of ~2-5 seconds. What about long-term structure?

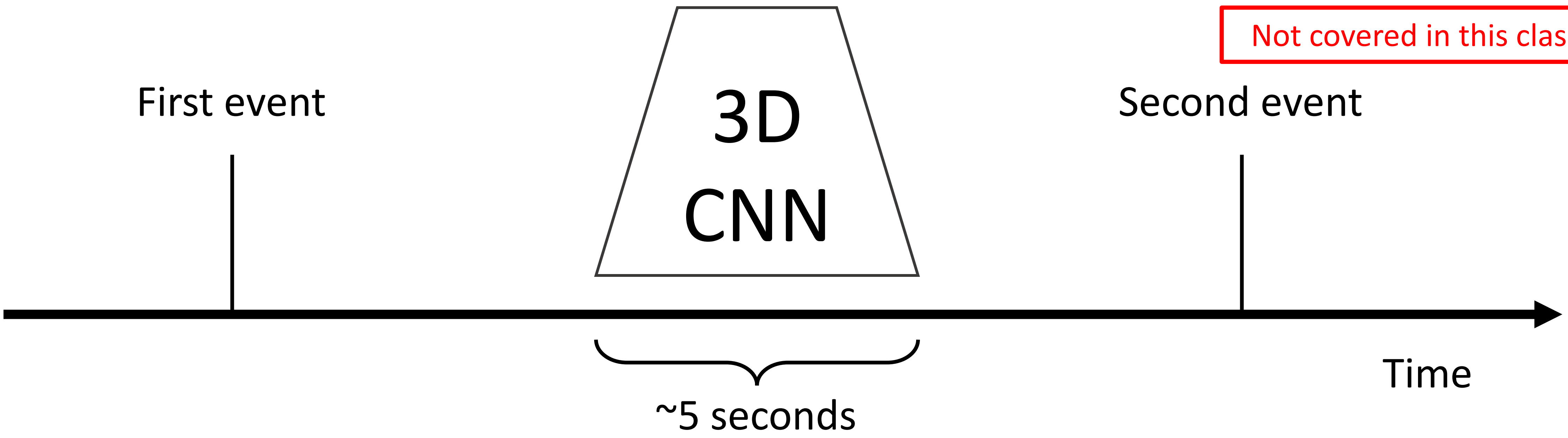


Modeling long-term temporal structure

So far all our temporal CNNs only model local motion between frames in very short clips of ~2-5 seconds. What about long-term structure?

~~We know how to handle sequences! How about recurrent networks?~~

Not covered in this class...



Inflating 2D Networks to 3D (I3D)

There has been a lot of work on architectures for images.
Can we reuse image architectures for video?

Idea: take a 2D CNN architecture.

Replace each 2D K_h x K_w conv/pool layer with a 3D K_t x K_h x K_w version

Carreira and Zisserman, "Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset", CVPR 2017

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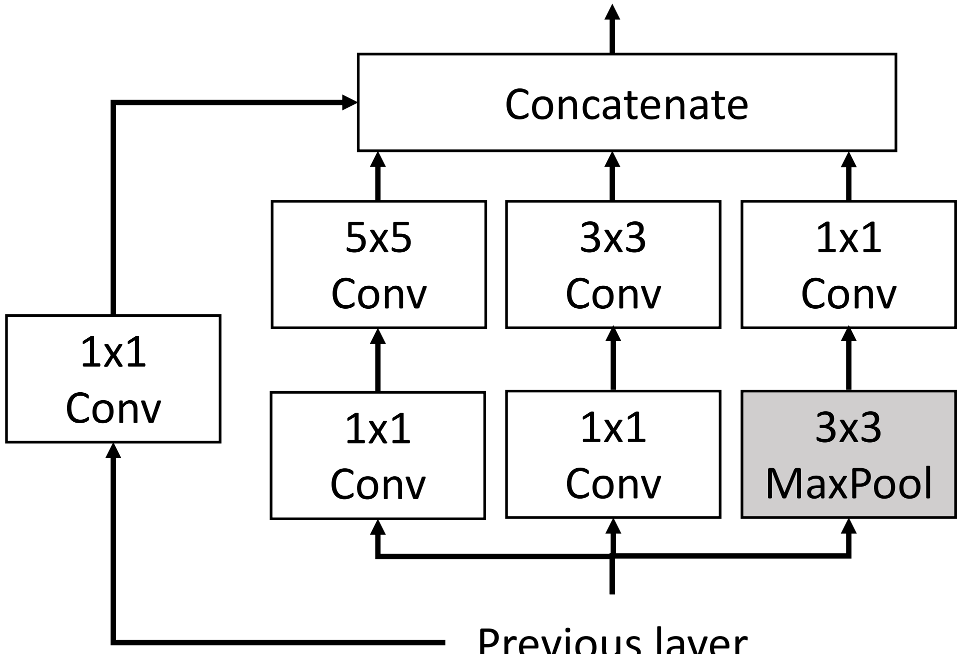
Inception Block: Original



Carreira and Zisserman, "Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset", CVPR 2017

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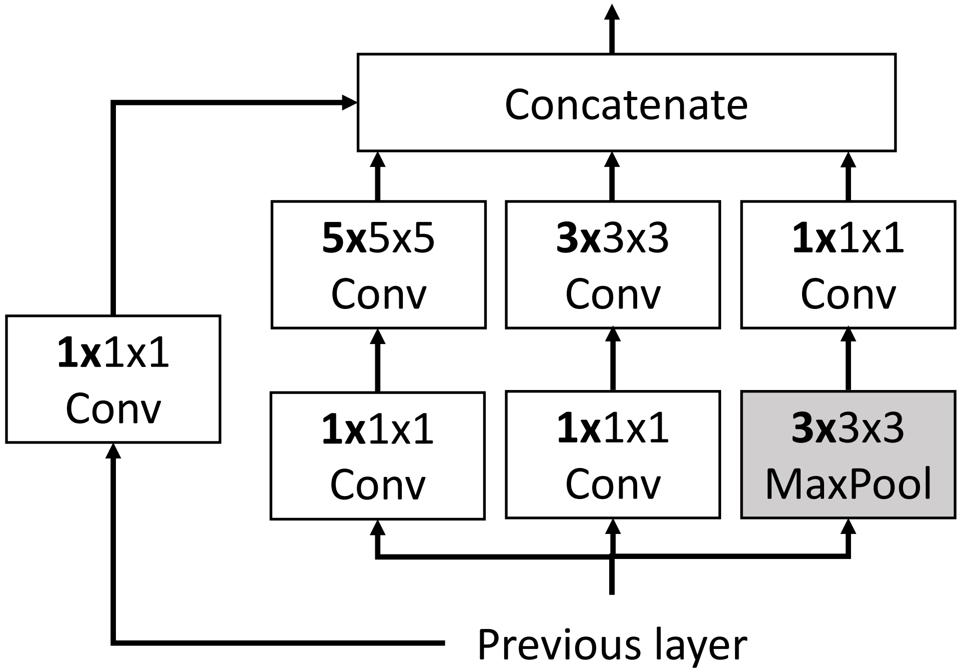
Inception Block: Inflated



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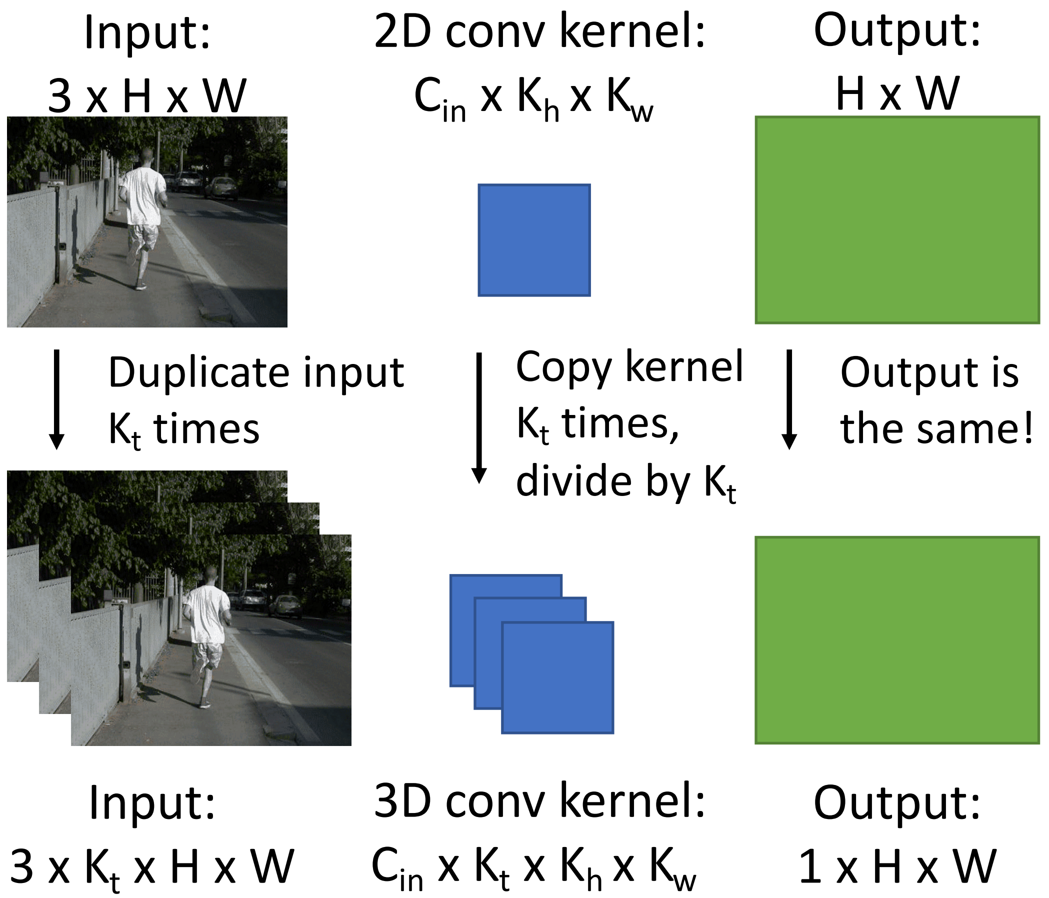
This gives the same result as 2D conv given "constant" video input



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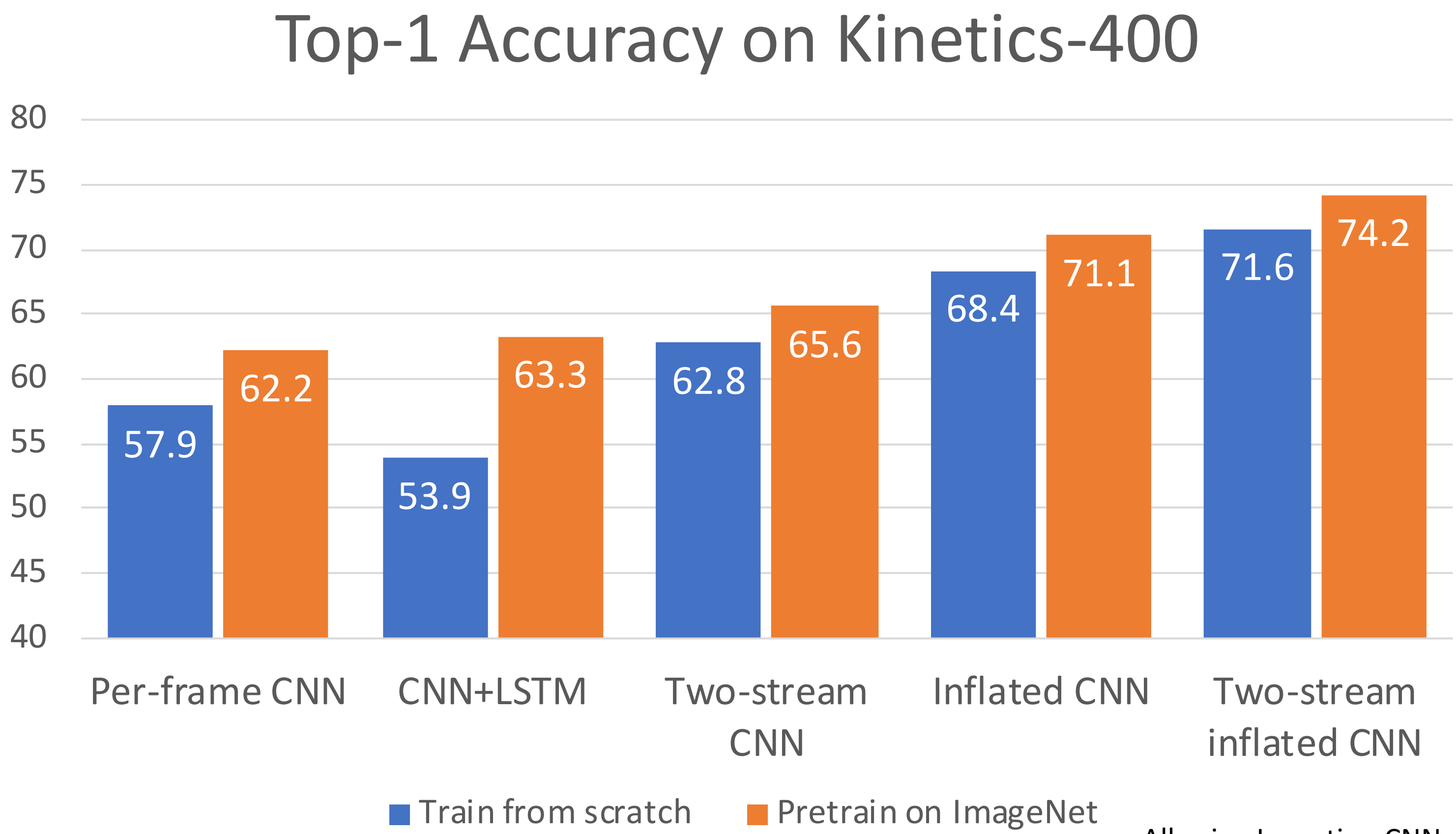


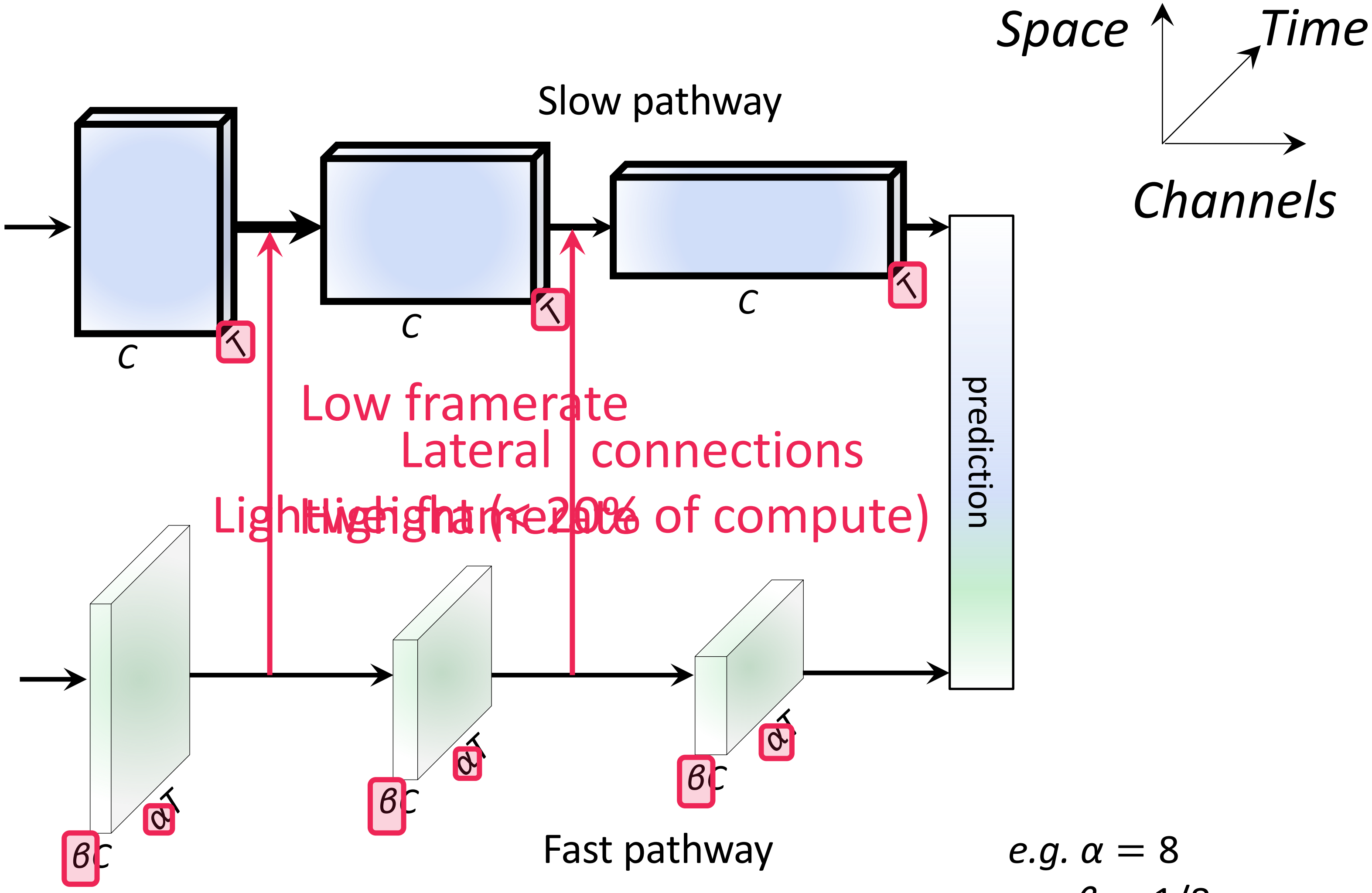
All using Inception CNN

Carreira and Zisserman, "Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset", CVPR 2017

Treating time and space differently: SlowFast Networks

Slow

Fast



e.g. $\alpha = 8$
$\beta = 1/8$

Feichtenhofer et al, "SlowFast Networks for Video Recognition", ICCV 2019
Slide credit: Christoph Feichtenhofer

Treating time and space differently: SlowFast Networks

- Dimensions are $\{T \times S^2, C\}$
- Strides are {temporal, spatial²}
- The backbone is ResNet-50
- Residual blocks are shown by brackets
- Non-degenerate temporal filters are underlined
- Here the speed ratio is $\alpha = 8$ and the channel ratio is $\beta = 1/8$
- Orange numbers mark fewer channels, for the Fast pathway
- Green numbers mark higher temporal resolution of the Fast pathway
- No temporal *pooling* is performed throughout the hierarchy

stage	*Slow* pathway	*Fast* pathway	output sizes $T \times S^2$
raw clip	-	-	64×224^2
data layer	stride 16, 1^2	stride **2**, 1^2	*Slow* : 4×224^2 *Fast* : $\mathbf{32} \times 224^2$
conv_1	1×7^2, 64 stride 1, 2^2	$\underline{5 \times 7^2}$, 8 stride 1, 2^2	*Slow* : 4×112^2 *Fast* : $\mathbf{32} \times 112^2$
pool_1	1×3^2 max stride 1, 2^2	1×3^2 max stride 1, 2^2	*Slow* : 4×56^2 *Fast* : $\mathbf{32} \times 56^2$
res_2	$\begin{bmatrix} 1 \times 1^2, 64 \\ 1 \times 3^2, 64 \\ 1 \times 1^2, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} \underline{3 \times 1^2}, 8 \\ 1 \times 3^2, 8 \\ 1 \times 1^2, 32 \end{bmatrix} \times 3$	*Slow* : 4×56^2 *Fast* : $\mathbf{32} \times 56^2$
res_3	$\begin{bmatrix} 1 \times 1^2, 128 \\ 1 \times 3^2, 128 \\ 1 \times 1^2, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} \underline{3 \times 1^2}, 16 \\ 1 \times 3^2, 16 \\ 1 \times 1^2, 64 \end{bmatrix} \times 4$	*Slow* : 4×28^2 *Fast* : $\mathbf{32} \times 28^2$
res_4	$\begin{bmatrix} \underline{3 \times 1^2}, 256 \\ 1 \times 3^2, 256 \\ 1 \times 1^2, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} \underline{3 \times 1^2}, 32 \\ 1 \times 3^2, 32 \\ 1 \times 1^2, 128 \end{bmatrix} \times 6$	*Slow* : 4×14^2 *Fast* : $\mathbf{32} \times 14^2$
res_5	$\begin{bmatrix} \underline{3 \times 1^2}, 512 \\ 1 \times 3^2, 512 \\ 1 \times 1^2, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} \underline{3 \times 1^2}, 64 \\ 1 \times 3^2, 64 \\ 1 \times 1^2, 256 \end{bmatrix} \times 3$	*Slow* : 4×7^2 *Fast* : $\mathbf{32} \times 7^2$
	global average pool, concate, fc		# classes

Feichtenhofer et al, "SlowFast Networks for Video Recognition", ICCV 2019
Slide credit: Christoph Feichtenhofer

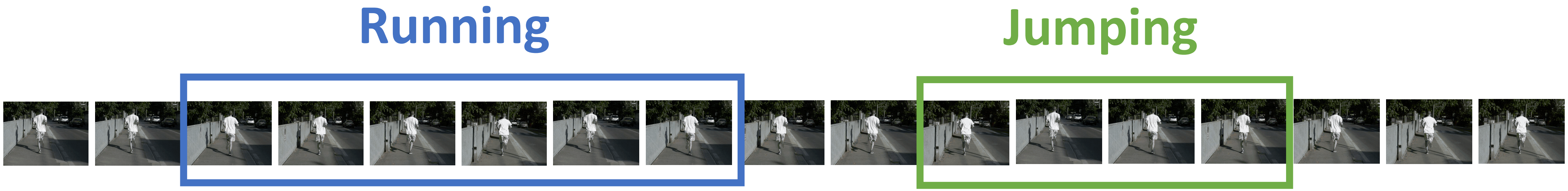
So far: Classify short clips

Videos: Recognize **actions**

Swimming
Running
Jumping
Eating
Standing

Temporal Action Localization

Given a long untrimmed video sequence, identify frames corresponding to different actions



Can use architecture similar to Faster R-CNN: first generate **temporal proposals** then **classify**

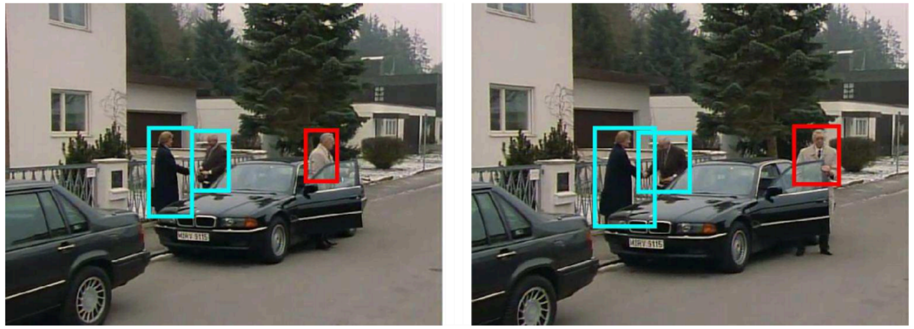
Chao et al, " Rethinking the Faster R-CNN Architecture for Temporal Action Localization", CVPR 2018

Spatio-Temporal Detection

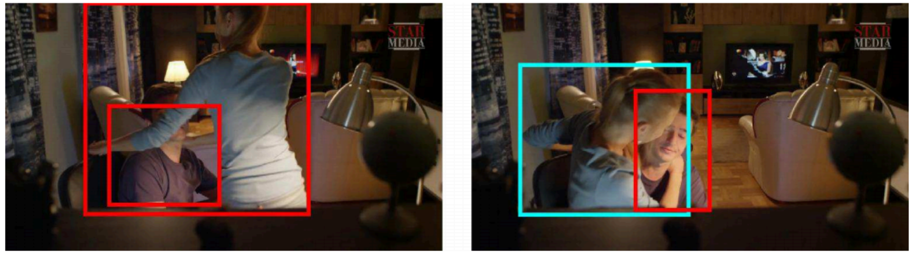
Given a long untrimmed video, detect all the people in space and time and classify the activities they are performing

Some examples from AVA Dataset:

clink glass → drink



open → close



grab (a person) → hug

look at phone → answer phone

Gu et al, “AVA: A Video Dataset of Spatio-temporally Localized Atomic Visual Actions”, CVPR 2018

Recap: Video Models

Many video models:
Single-frame CNN (Try this first!)
Late fusion
Early fusion
3D CNN / C3D
Two-stream networks
CNN + RNN
Convolutional RNN
Spatio-temporal self-attention
SlowFast networks (current SoTA)

Lots more material we won't have time for…

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Event	Description
Lecture 1	**Course Introduction** Computer vision overview Historical context Course logistics
Lecture 2	**Image Classification** Data-driven approach K-Nearest Neighbor Hyperparameters Cross-validation
Lecture 3	**Linear Classifiers** Softmax / SVM classifiers L2 regularization
Lecture 4	**Optimization** Stochastic Gradient Descent Momentum, AdaGrad, Adam Second-order optimizers
Lecture 5	**Neural Networks** Feature transforms Fully-connected networks Universal approximation Convexity
Lecture 6	**Backpropagation** Computational Graphs Backpropagation Matrix multiplication example
Lecture 7	**Convolutional Networks** Convolution Pooling Batch Normalization
Lecture 8	**CNN Architectures** AlexNet, VGG, ResNet Size vs Accuracy Grouped and Separable Convolutions Neural Architecture Search
Lecture 9	**Hardware and Software** CPUs, GPUs, TPUs Dynamic vs Static graphs PyTorch, TensorFlow
Lecture 10	**Training Neural Networks I** Activation functions Data preprocessing Weight initialization Data augmentation Regularization (Dropout, etc)
Lecture 11	**Training Neural Networks II** Learning rate schedules Hyperparameter optimization Model ensembles Transfer learning Large-batch training
Lecture 12	**Recurrent Networks** RNN, LSTM, GRU Language modeling Sequence-to-sequence Image captioning Visual question answering
Lecture 13	**Attention** Multimodal attention Self-Attention Transformers
Lecture 14	**Visualizing and Understanding** Feature visualization Adversarial examples DeepDream, Style transfer
Lecture 15	**Object Detection** Single-stage detectors Two-stage detectors
Lecture 16	**Image Segmentation** Semantic segmentation Instance segmentation Keypoint estimation
Lecture 17	**3D vision** 3D shape representations Depth estimation 3D shape prediction Voxels, Pointclouds, SDFs, Meshes
Lecture 18	**Videos** Video classification Early / Late fusion 3D CNNs Two-stream networks
Lecture 19	**Generative Models I** Supervised vs Unsupervised learning Discriminative vs Generative models Autoregressive models Variational Autoencoders
Lecture 20	**Generative Models II** More Variational Autoencoders Generative Adversarial Networks
Lecture 21	**Reinforcement Learning** RL problem setup Bellman Equation Q-Learning Policy Gradient
Lecture 22	**Conclusion** Course recap The future of computer vision

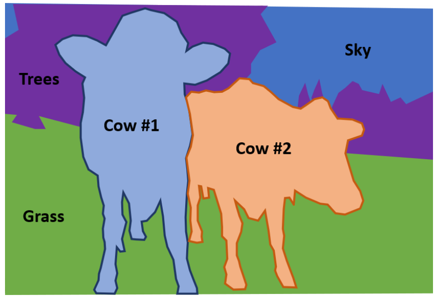
Lecture summary

```python
class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        # 1 input image channel, 6 output channels, 5x5 square convolution
        # kernel
        self.conv1 = nn.Conv2d(1, 6, 5)
        self.conv2 = nn.Conv2d(6, 16, 5)
        # an affine operation: y = Wx + b
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        # Max pooling over a (2, 2) window
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        # If the size is a square you can only specify a single number
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = x.view(-1, self.num_flat_features(x))
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

- Deep learning frameworks (PyTorch)
- Instance and panoptic segmentation
- 3D neural networks
- Video



clink glass → drink

- Next lecture:
  - HW4 – CNNs in PyTorch
  - Edges, features, and alignment (Harpreet Sawhney)