PyTorch

PyTorch: A flexible approach for computer vision models

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Tutorial Github Repo.:
http://bit.ly/aiconfsf18cv

O'REILLY
Artificial Intelligence
CONFERENCE
San Francisco September 2018

Slack Channel for Tutorial:
https://pytorchcvtutorial.slack.com/
Invite Link: http://bit.ly/cvpytorchslack
Password: #AIConfNY2018

Introductions & Networking

Agenda

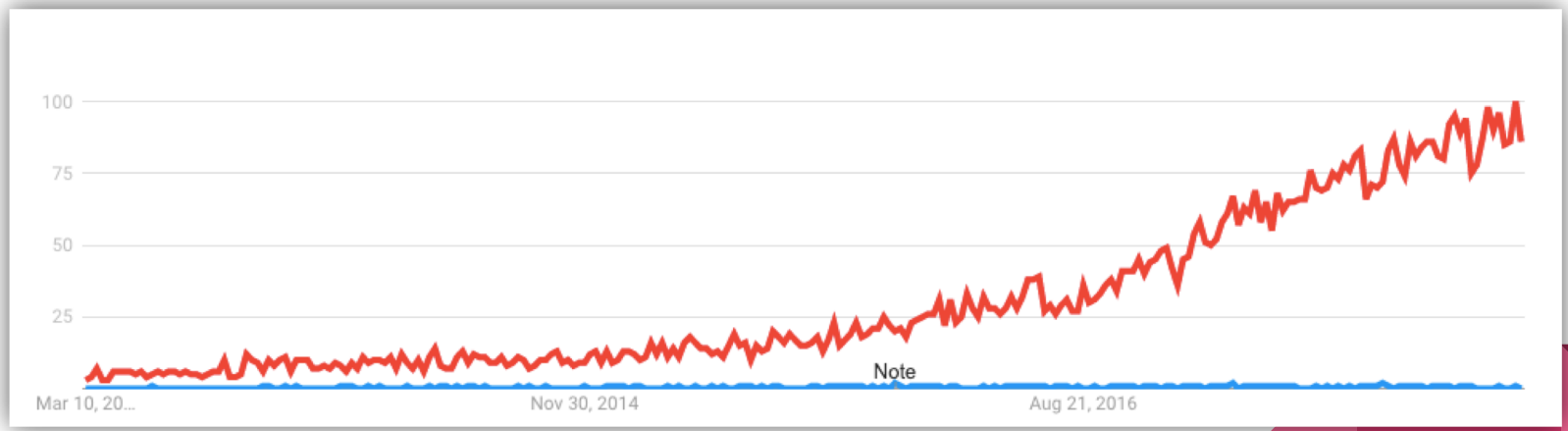
- PyTorch Overview
- Computer Vision Overview
- Getting started with PyTorch
- Computer Vision Models using PyTorch
  - Image Classification
  - Transfer Learning
  - Object Detection
- Break
- Computer Vision Models using PyTorch
  - Object Detection (Continued)
  - Object Segmentation
- Computer Vision Thoughts
- Discussion: Q & A

PyTorch Overview

PyTorch Origins

- Torch – Lua
- Chainer
- HIPS Autograd

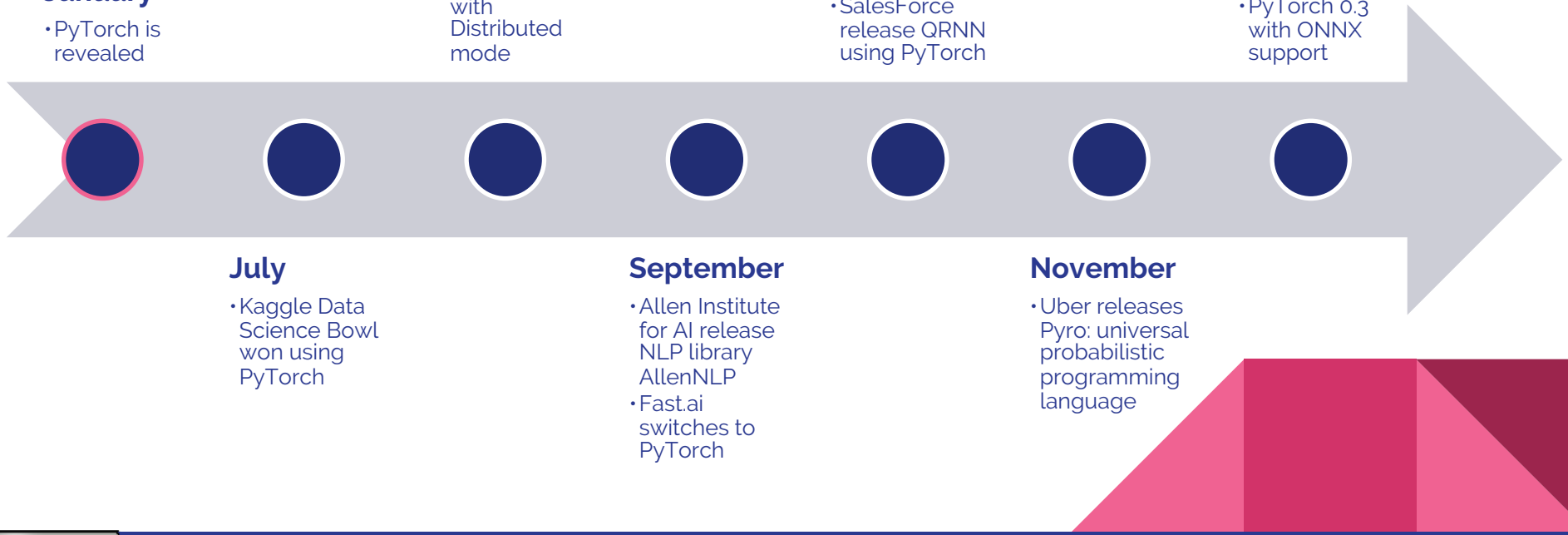
- Need for Dynamic execution library
- Popularity of Python in Machine Learning Community



Google Trends Last Five Years
Terms: Lua Machine Learning Python Machine Learning

http://bit.ly/aiconfsf18cv

PyTorch – 2017 Year in Review



Source: http://pytorch.org/2018/01/19/a-year-in.html

PyTorch 2018

- April 2018: PyTorch 0.4.x
  - **Tensors**: Fast Fourier Transforms
  - **Neural Networks**: bottleneck - a tool to identify hotspots in your code
  - **torch.distributions**
    - 24 basic probability distributions
    - Added cdf, variance, entropy, perplexity etc.
  - Distributed Training: NCCL2 backend
  - Windows Support

- October 2018: PyTorch 1.0?
  - Production improvements: PyTorch + Caffe 2
  - Tracing mode & Script mode

- PyTorch Developer Conference
  - October 2nd 2018
  - San Francisco
  - https://pytorch.fbreg.com/

Use Case Diversity: Research & Applications

Computer Vision Overview

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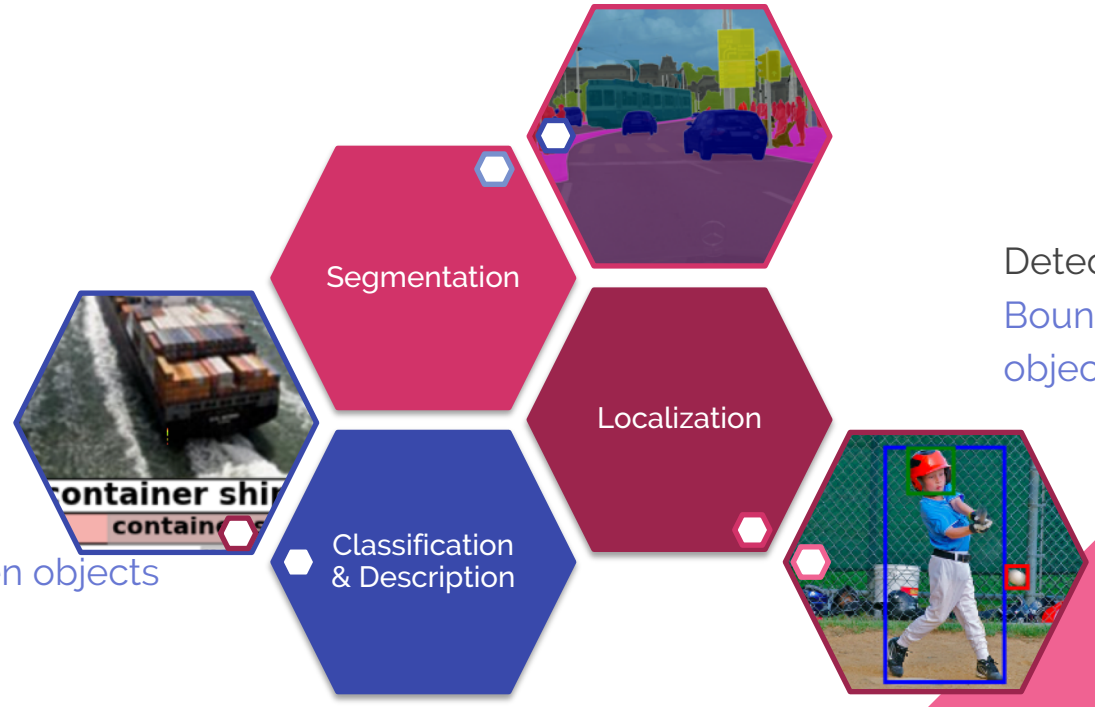
Computer Vision 101

Segmentation: Pixel-wise segments of objects in any image



Classification: Label Item(s) in Image

Description: Relationship between objects

Detection/Localization: Bounding Boxes around objects

Goal: Build models that can perform visual tasks

Classification & Description

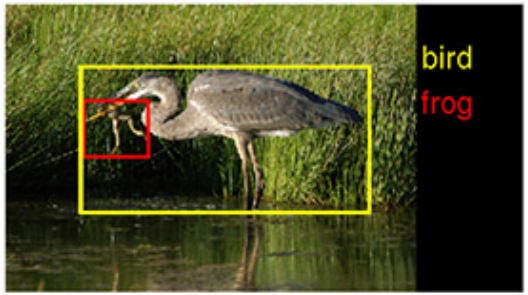
What is the man doing?

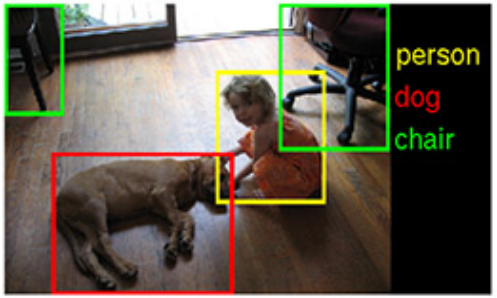
Submit

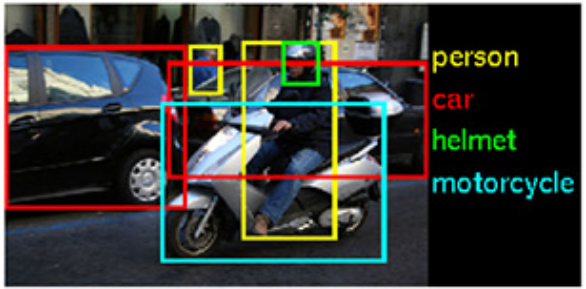
Predicted top-5 answers with confidence:

playing	99.126%
tennis	
tennis	0.553%
skateboarding	0.139%
serving	0.075%
jumping	0.033%

Localization







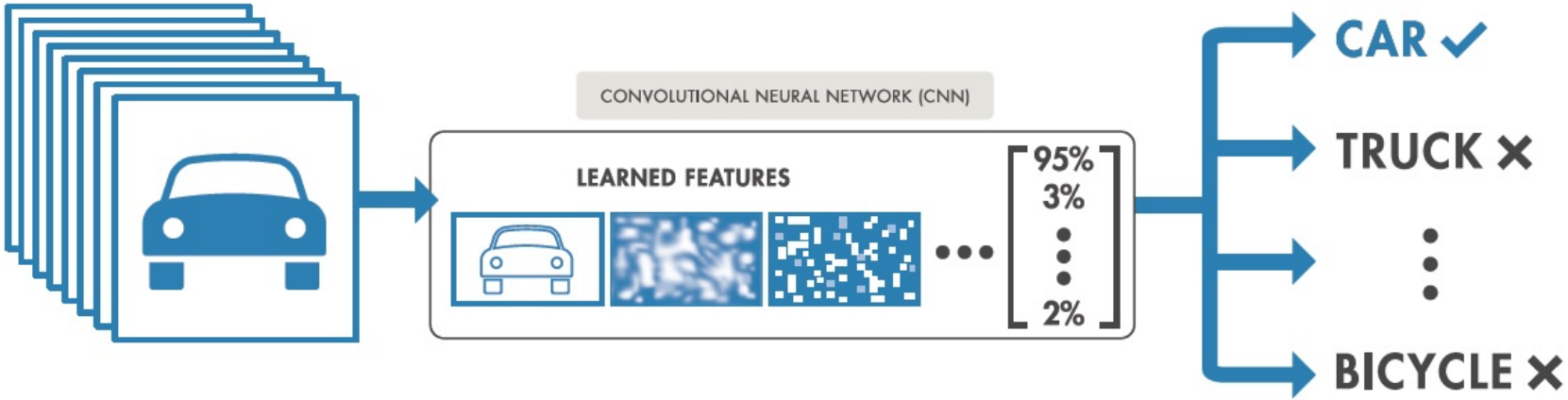
Source: Kaggle ImageNet Object Detection Challenge

Segmentation

Source: The Cityscapes Dataset - Semantic, instance-wise, dense pixel annotations of 30 classes

Convolutional Neural Networks

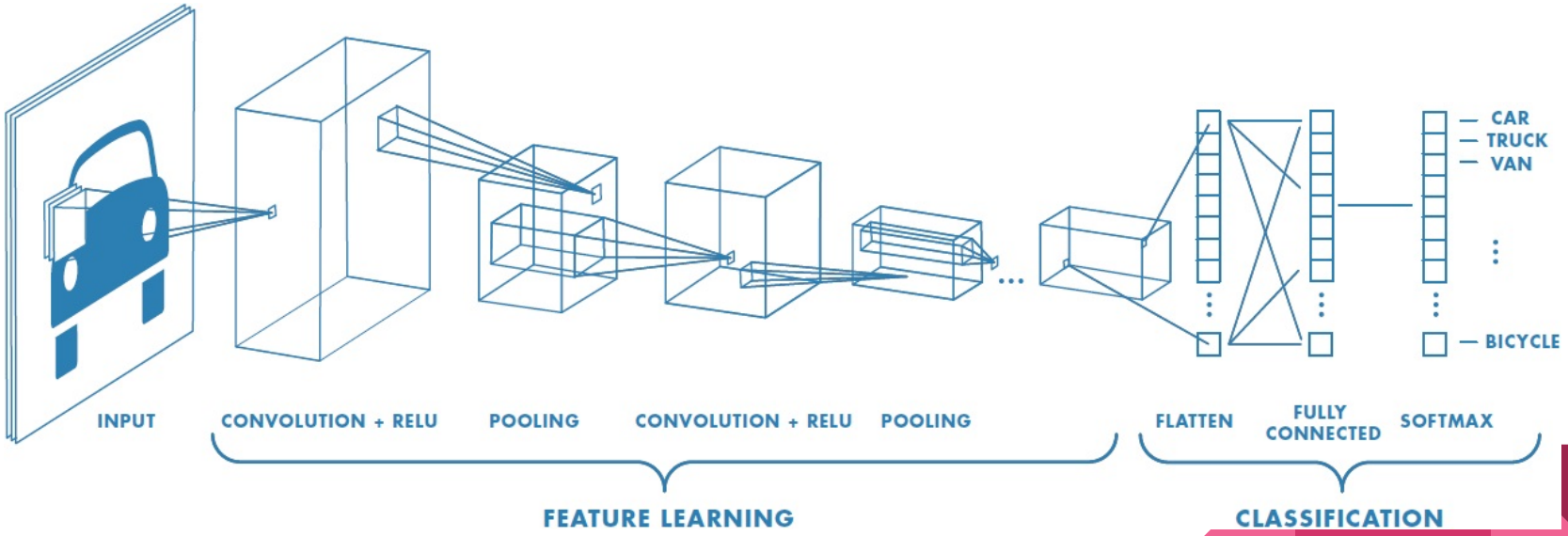
Convolutional Neural Networks



Source: Mathworks

http://bit.ly/aiconfsf18cv

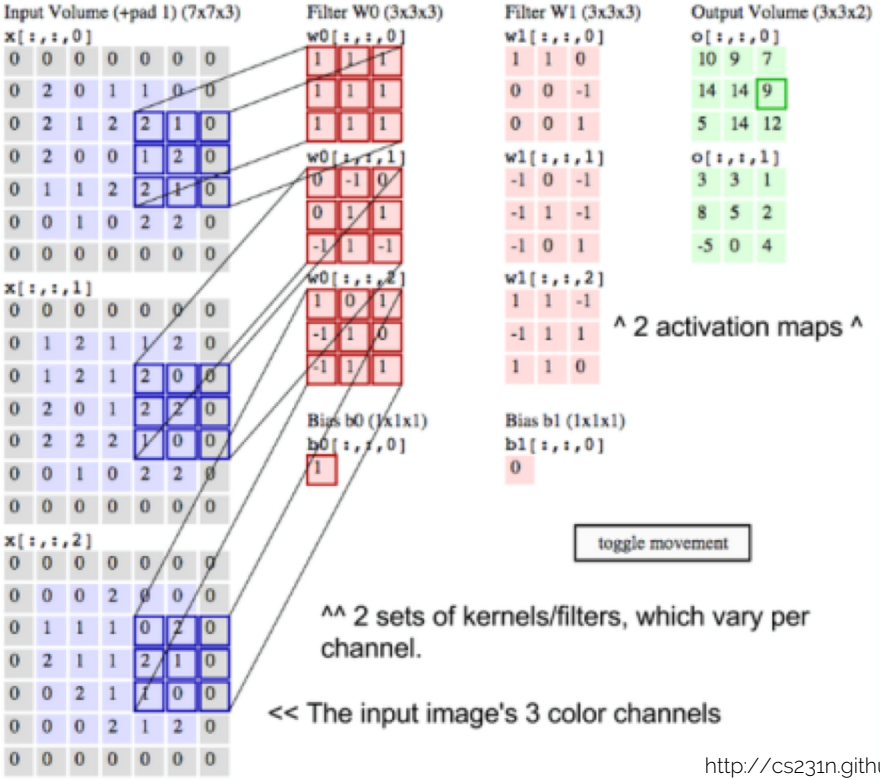
Convolutional Neural Networks

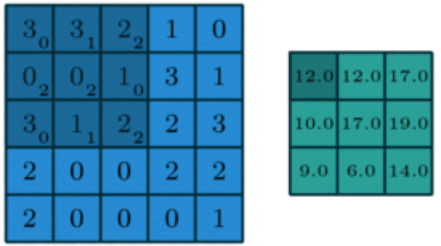


Source: Mathworks

http://bit.ly/aiconfsf18cv

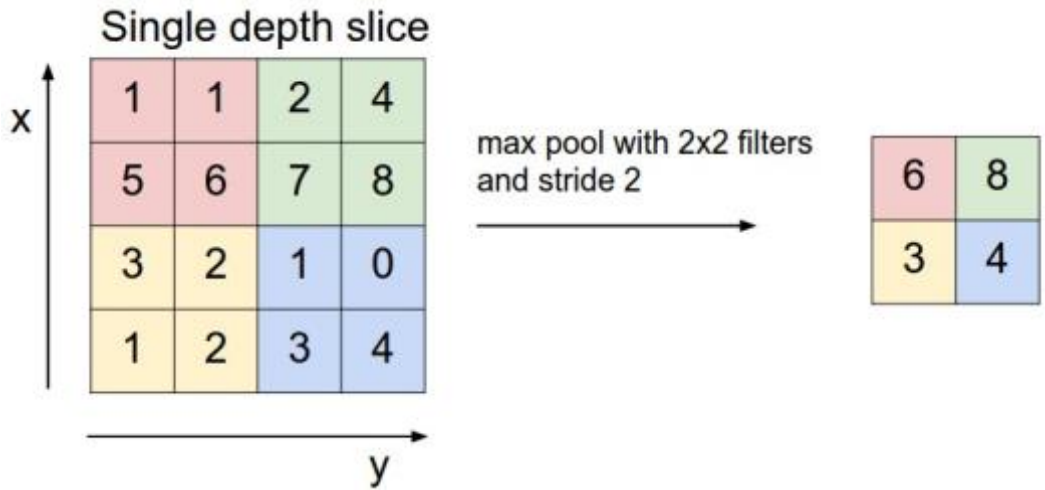
Convolution





http://cs231n.github.io/convolutional-networks/
https://m2dsupsdlclass.github.io/lectures-labs/slides/03_conv_nets/index.html
https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

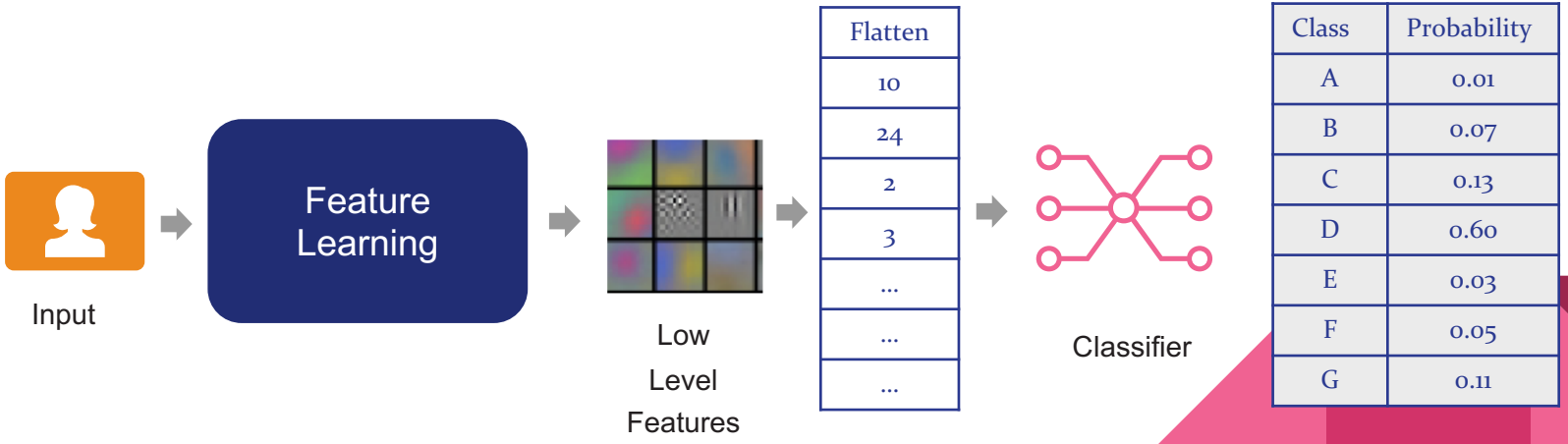
Pooling



Source: Stanford University CS 231 Course:
http://cs231n.github.io/convolutional-networks/#pool

Fully Connected

- Traditional Machine Learning: Feature Engineering
- Deep Learning: Feature Learning
- Learned Features are fed to traditional classifier such as Multivariate Logistic Regression (Softmax)



Loss Reduction

Class	Probability	Truth	Loss/ Error
A	0.01	0	0
B	0.07	0	0
C	0.13	0	0
D	0.60	1	0.22
E	0.03	0	0
F	0.05	0	0
G	0.11	0	0

Cross Entropy Loss

One-Hot Encoded Vector of Class Label

Back Propagation

- Account for loss across the weights and biases in the network
- Use cost function provided by Back Propagation to optimize the weights and biases to reduce loss
- Variety of Stochastic Gradient Descent techniques used for optimization

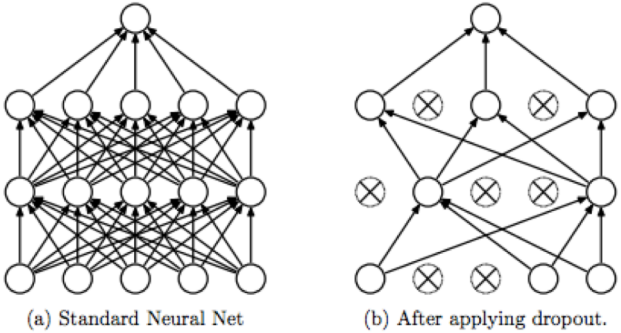
Overview of Gradient Descent Techniques:
http://ruder.io/optimizing-gradient-descent/

https://rdipietro.github.io/friendly-intro-to-cross-entropy-loss/

Generalization

Dropout

Randomly remove learned nodes from network



(a) Standard Neural Net (b) After applying dropout.

Dropout: A Simple Way to Prevent Neural Networks from Overfitting
http://www.jmlr.org/papers/volume15/srivastava14a/srivastava14a.pdf

Batch Normalization

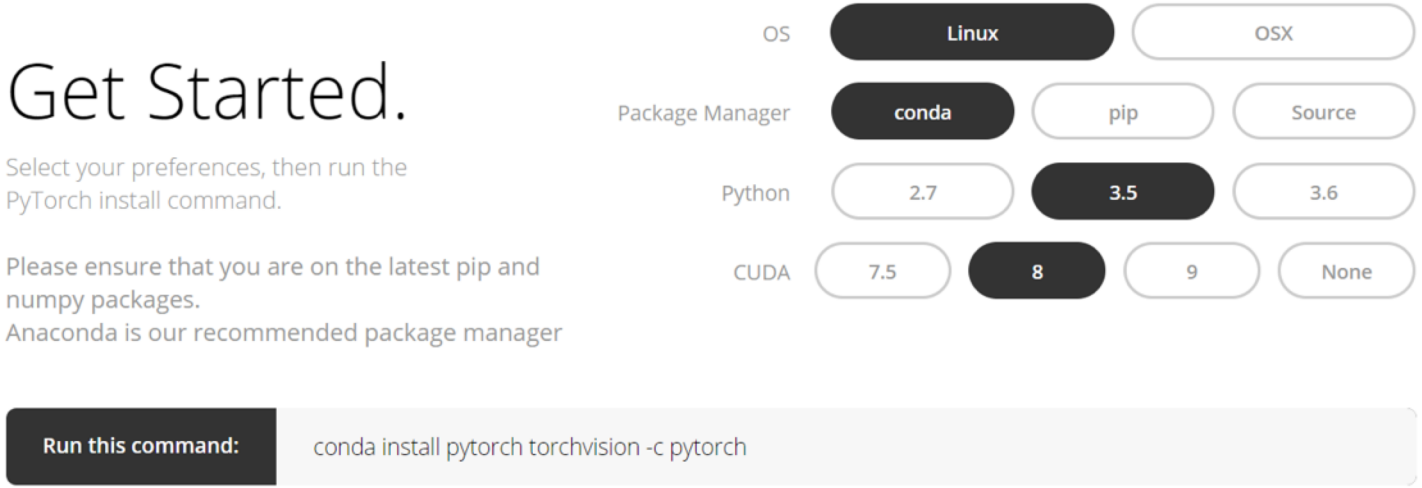
- During training input data shifts as weights and parameter adjust values
- To prevent internal covariate shift, normalize each batch by mean and variance

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift
https://arxiv.org/abs/1502.03167

Getting started with PyTorch

Installation

http://pytorch.org/

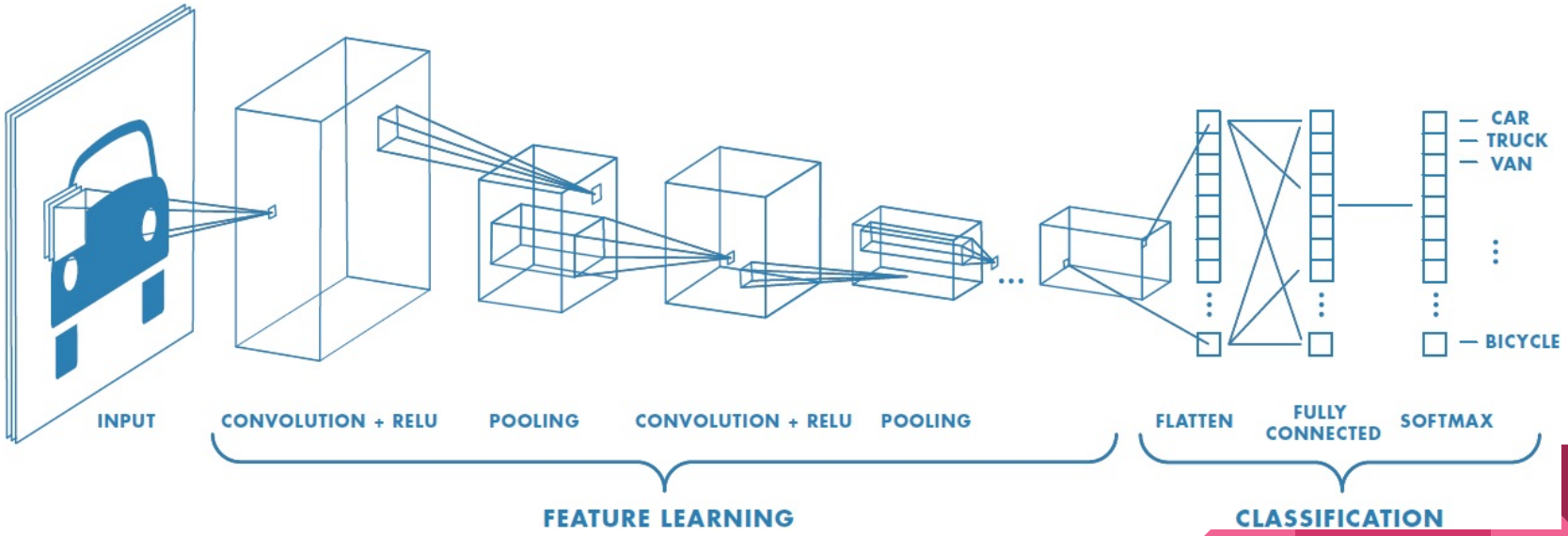


PyTorch Basics Jupyter Notebook

- Using Jupyter Notebook, please open *01-Basics.ipynb* from the tutorial repository on Github.

Anatomy of a PyTorch Model

Image Classification



Source: Mathworks

Typical PyTorch CNN Training Code

1. Imports
2. Declare Hyperparameters
3. Define Train & Test data
4. Define the network
5. Define the Loss Function
6. Define the Backward Propagation using Automatic Differentiation
7. Define Optimizer
8. Define Training method
9. Define Accuracy calculation
10. Calculate Accuracy on Test data

Define the network

```
import torch
from torch.autograd import Variable
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)
  (fc2): Linear(in_features=120, out_features=84)
  (fc3): Linear(in_features=84, out_features=10)
)
```

LeNet Image Input

Define the network

```
input = Variable(torch.randn(1, 1, 32, 32))
out = net(input)
print(out)
```

```
Variable containing:
-0.0573 -0.0559 -0.1204  0.1070 -0.0275 -0.0118  0.0264  0.0515 -0.0257  0.0483
[torch.FloatTensor of size 1x10]
```

```
net.zero_grad()
out.backward(torch.randn(1, 10))
```

Always zero out the gradients they are accumulated

The Loss Function and Back Propagation

Example loss calculation

```
output = net(input)
target = Variable(torch.arange(1, 11))
criterion = nn.MSELoss()

loss = criterion(output, target)
print(loss)
```

```
Variable containing:
 38.3962
[torch.FloatTensor of size 1]
```

```
net.zero_grad()     # zeroes the gradient buffers of all parameters

print('conv1.bias.grad before backward')
print(net.conv1.bias.grad)

loss.backward()

print('conv1.bias.grad after backward')
print(net.conv1.bias.grad)
```

```
conv1.bias.grad before backward
Variable containing:
 0
 0
 0
 0
 0
 0
[torch.FloatTensor of size 6]

conv1.bias.grad after backward
Variable containing:
1.00000e-02 *
 -6.1643
 -2.5201
 -4.5238
  6.8188
 -0.2024
  3.4750
[torch.FloatTensor of size 6]
```

```
import torch.optim as optim

# create your optimizer
optimizer = optim.SGD(net.parameters(), lr=0.01)

# in your training loop:
optimizer.zero_grad()   # zero the gradient buffers
output = net(input)
loss = criterion(output, target)
loss.backward()
optimizer.step()    # Does the update
```

Updating the weights

```
for epoch in range(2):  # loop over the dataset multiple times

    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # get the inputs
        inputs, labels = data

        # wrap them in Variable
        inputs, labels = Variable(inputs), Variable(labels)

        # zero the parameter gradients
        optimizer.zero_grad()

        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        # print statistics
        running_loss += loss.data[0]
        if i % 2000 == 1999:    # print every 2000 mini-batches
            print('[%d, %5d] loss: %.3f' %
                  (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0

print('Finished Training')
```

```
[1,  2000] loss: 2.220
[1,  4000] loss: 1.887
[1,  6000] loss: 1.676
[1,  8000] loss: 1.578
[1, 10000] loss: 1.511
[1, 12000] loss: 1.462
[2,  2000] loss: 1.404
[2,  4000] loss: 1.373
[2,  6000] loss: 1.373
[2,  8000] loss: 1.325
[2, 10000] loss: 1.315
[2, 12000] loss: 1.267
Finished Training
```

Training

Accuracy

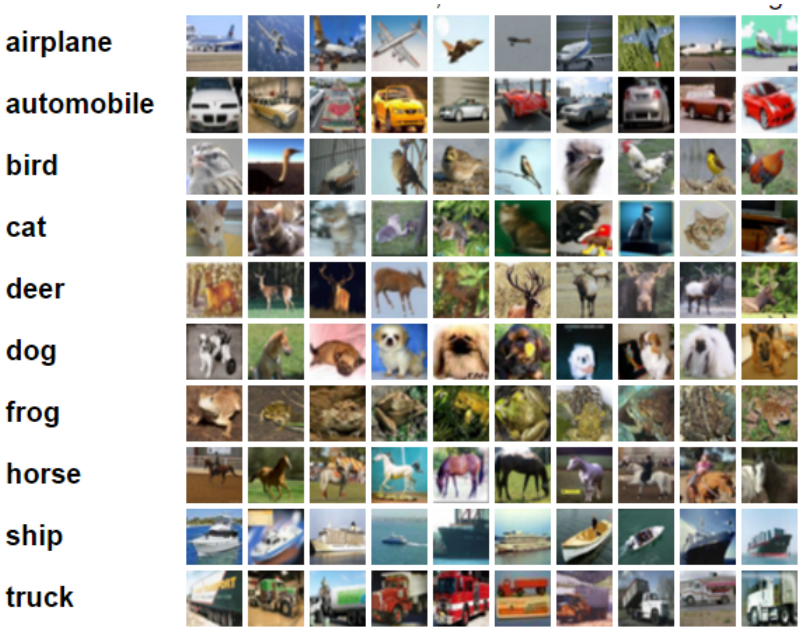
```
correct = 0
total = 0
for data in testloader:
    images, labels = data
    outputs = net(Variable(images))
    _, predicted = torch.max(outputs.data, 1)
    total += labels.size(0)
    correct += (predicted == labels).sum()

print('Accuracy of the network on the 10000 test images: %d %%' % (
    100 * correct / total))
```

```
Accuracy of the network on the 10000 test images: 55 %
```

Computer Vision Models

PyTorch CIFAR10 Tutorial

- Ten classes
- Dataset:
  - 60,000 32x32 color images in 10 classes
  - 6000 images per class.
  - 50,000 training images
  - 10,000 test images



https://www.cs.toronto.edu/~kriz/cifar.html

PyTorch CIFAR10 Tutorial

- Please download Jupyter Notebook from PyTorch:
  https://pytorch.org/tutorials/_downloads/cifar10_tutorial.ipynb

Why Transfer Learning?

Deep Learning Challenges

- Not enough data
- Not enough labeled data
- Not enough hardware
- Training time too long

Transfer Learning

Domain to Domain Learning

- Learn Features, Weights, Biases in one domain
- Find domain with similar data characteristics and distribution
- Apply model in new domain

Retraining

- Freeze layers in a "good" model up to tunable depth of feature extraction but before final prediction layer
- Remove final layer(s)
- Relearn final and classification layers using your own data

Bonus: Combine Domain to Domain and Retraining

PyTorch Transfer Learning Tutorial

- Please download Jupyter Notebook from PyTorch:
  https://pytorch.org/tutorials/_downloads/transfer_learning_tutorial.ipynb

Object Detection

PyTorch Object Detection

- Object Detection Introduction
- Dual stage detection methods
- Single Shot detection methods
- Using Jupyter Notebook, please open *02-Object-Detection.ipynb* from the tutorial repository on Github.
- Followed by *02-Object-Detection-YOLO.ipynb*

Break

Object Segmentation

Challenge with Object Segmentation: Annotation


```
{"coco_url":"http://mscoco.org/images/405628",
"date_captured":"2013-11-21 00:26:09",
"file_name":"COCO_train2014_000000405628.jpg",
"flickr_url":"http://farm5.staticflickr.com/4130/5133418813_61f33c
9633_z.jpg",
"height":426,
"id":405628,
"license":5,
"width":640}
```

```
{"area":7581.427150000003,
"bbox":[95.28,146.43,131.92,142.0],
"category_id":1,"id":188293,
"image_id":405628,
"iscrowd":0,
"segmentation":[[219.87,177.58,224.45,172.08,225.37,157.42,218.95
,146.43,208.88,149.18,208.88,149.18,202.46,151.92,198.8,153.76,19
8.8,153.76,196.97,154.67,184.14,153.76,183.23,153.76,158.49,157.4
2,133.75,157.42,95.28,186.74,105.35,183.99,153.91,164.75,169.48,1
74.83,169.48,197.73,135.59,231.63,131.92,235.29,133.75,247.2,152.
99,247.2,155.74,247.2,175.9,241.71,179.56,228.88,184.14,278.35,19
5.14,280.18,194.22,288.43,200.63,282.93,198.8,271.02,224.45,227.0
5,224.45,227.05,227.2,196.82,219.87,183.99]]},
```


Data Annotation

	BOUNDING BOX	DOTS	POLYGON	SEMANTIC SEGMENTATION
COST	Least expensive	More expensive	More expensive	Most expensive
TIME COMMITMENT	Lowest	Medium	Medium	Highest
PRECISION	Good	Great	Great	Excellent
INSTANCE-BASED (OUTPUT CONTAINS DISCRETE OBJECTS)	Yes	Yes	Yes	No
POSSIBLE TO LABEL SEVERAL OBJECTS?	Yes	Yes	Yes	Yes
POSSIBLE TO LABEL SEVERAL CLASSES OF OBJECT IN A SINGLE JOB?	No	No	No	Yes
OUTPUT*	X,Y coordinate, width and length of each box	Series of x,y coordinates	Series of x,y coordinates, with shapes resolving	Coded RGB pixels as an image

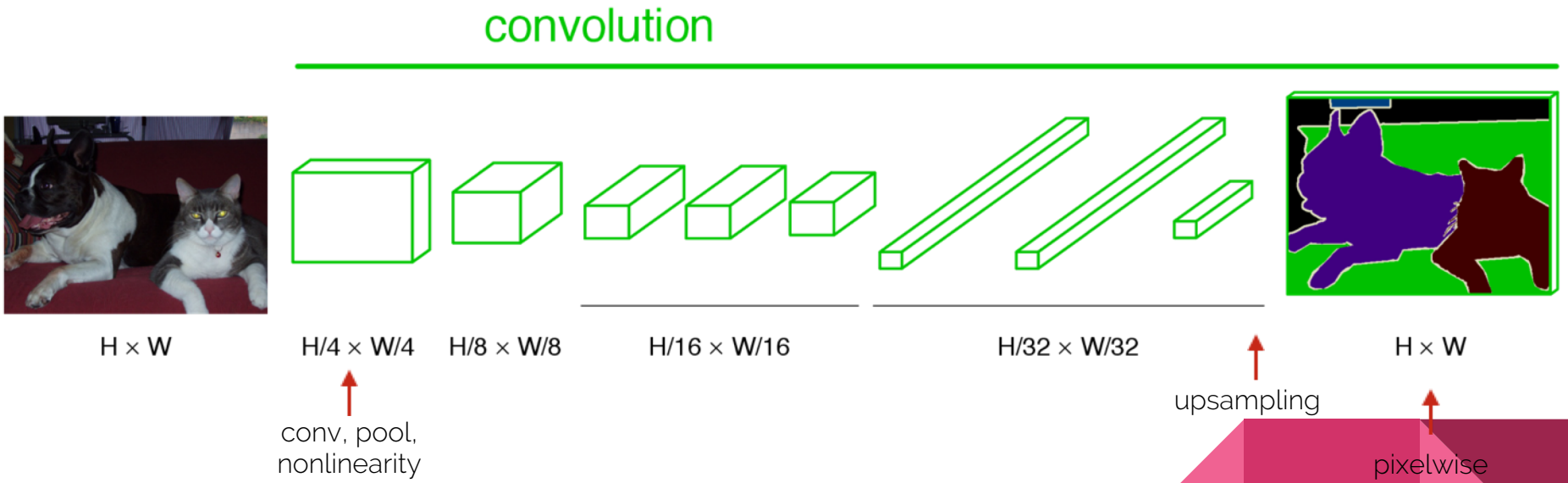
Source: CrowdFlower WHAT WE LEARNED LABELING 1 MILLION IMAGES

Two Major Approaches to Segmentation

- Encoder-Decoder
  - Extract Low Level Features and Upsample/Interpolate to Segment
  - FCN, Segnet, U-net et al.
- Region Based Segmentation
  - Segment objects along with bounding box using for object detection
  - Mask R-CNN, PSPNet, Learn to Segment All Things

Fully Convolutional Networks

Segmentation Objective: Predict Pixel Label



Fully Convolutional Networks for Semantic Segmentation
Evan Shelhamer Jonathan Long Trevor Darrell - UC Berkeley in CVPR'15, PAMI'16

Mask R-CNN

- Use existing Faster R-CNN model add another classification task (mask branch) to predict a binary object mask
- Loss is based on ROI Align rather than ROI Pool in Faster R-CNN

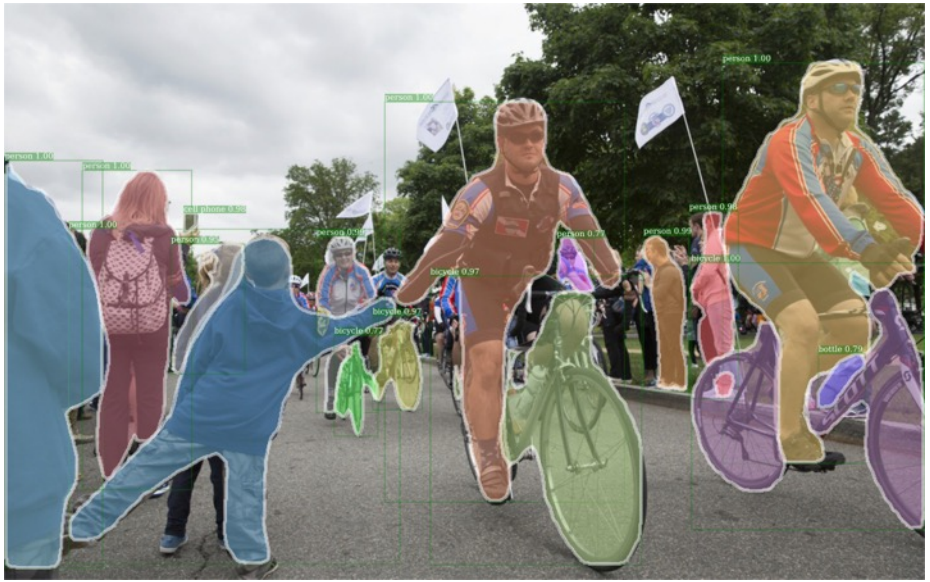
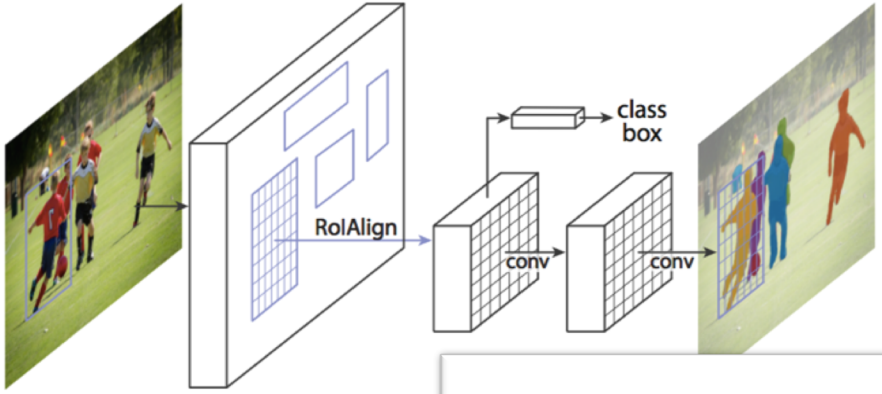
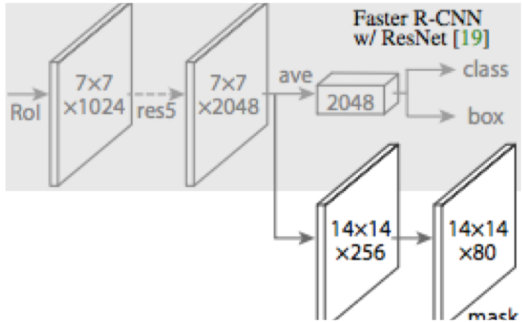


Image: Facebook Detectron

Mask R-CNN: Architecture





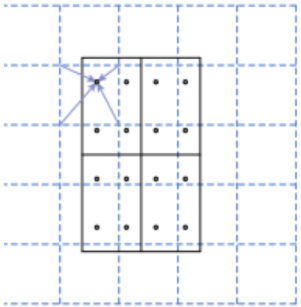
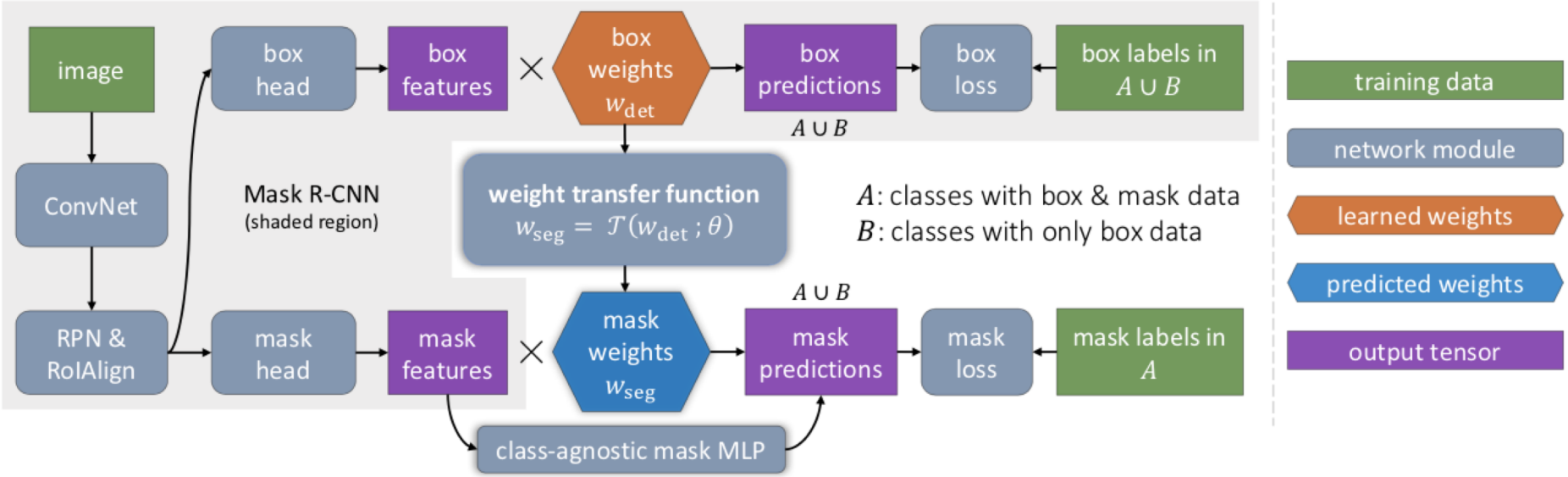


Figure 3. **RoIAlign:** The dashed grid represents a feature map, the solid lines an RoI (with 2×2 bins in this example), and the dots the 4 sampling points in each bin. RoIAlign computes the value of each sampling point by bilinear interpolation from the nearby grid points on the feature map. No quantization is performed on any coordinates involved in the RoI, its bins, or the sampling points.

Learning to Segment Every Thing

- Training datasets for Segmentation (object masks) are costly and research datasets are scarce
- Object detection (bounding box) datasets are better
- Partially supervised approach: Jointly use masks and bounding boxes to train instance segmentation models

Learning to Segment Every Thing - Architecture



Deploying PyTorch Models

Deploying PyTorch Models: ONNX

- ONNX: Open Neural Network eXchange
  - Framework fragmentation: Project goal to allow researchers and developers to port models from one framework to another allowing interoperability
  - Currently supports some of Caffe2, PyTorch, Microsoft Cognitive Toolkit, Apache MXNet
- Currently PyTorch only supports model export not import
- Resources:
  - ONNX: https://onnx.ai/ & https://github.com/onnx/tutorials
  - PyTorch: http://pytorch.org/docs/master/onnx.html

PyTorch AlexNet model to ONNX

```
from torch.autograd import Variable
import torch.onnx
import torchvision

dummy_input = Variable(torch.randn(10, 3, 224, 224)).cuda()
model = torchvision.models.alexnet(pretrained=True).cuda()

# providing these is optional, but makes working with the
# converted model nicer.
input_names = [ "learned_%d" % i for i in range(16) ] + [ "actual_input_1" ]
output_names = [ "output1" ]

torch.onnx.export(model, dummy_input,
          "alexnet.proto", verbose=True,
          input_names=input_names, output_names=output_names)
```

Readable Model

```
    # All parameters are encoded explicitly as inputs.  By convention,
    # learned parameters (ala nn.Module.state_dict) are first, and the
    # actual inputs are last.
    graph(%learned_0 : Float(10, 3, 224, 224)
          %learned_1 : Float(64, 3, 11, 11)
          # The definition sites of all variables are annotated with type
          # information, specifying the type and size of tensors.
          # For example, %learned_2 is a 192 x 64 x 5 x 5 tensor of floats.
          %learned_2 : Float(64)
          %learned_3 : Float(192, 64, 5, 5)
          # ---- omitted for brevity ----
          %learned_14 : Float(4096)
          %learned_15 : Float(1000, 4096)
          %actual_input_1 : Float(1000)) {
      # Every statement consists of some output tensors (and their types),
      # the operator to be run (with its attributes, e.g., kernels, strides,
      # etc.), its input tensors (%learned_0, %learned_1, %learned_2)
      %17 : Float(10, 64, 55, 55) = Conv[dilations=[1, 1], group=1, kernel_shape=[11, 11], pads=[2, 2, 2, 2], strides=[4, 4]](%learned_0, %learned_1, %learned_2), scope:
AlexNet/Sequential[features]/Conv2d[0]
      %18 : Float(10, 64, 55, 55) = Relu(%17), scope: AlexNet/Sequential[features]/ReLU[1]
      %19 : Float(10, 64, 27, 27) = MaxPool[kernel_shape=[3, 3], pads=[0, 0, 0, 0], strides=[2, 2]](%18), scope: AlexNet/Sequential[features]/MaxPool2d[2]
      # ---- omitted for brevity ----
      %29 : Float(10, 256, 6, 6) = MaxPool[kernel_shape=[3, 3], pads=[0, 0, 0, 0], strides=[2, 2]](%28), scope: AlexNet/Sequential[features]/MaxPool2d[12]
      %30 : Float(10, 9216) = Flatten[axis=1](%29), scope: AlexNet
      # UNKNOWN_TYPE: sometimes type information is not known.  We hope to eliminate
      # all such cases in a later release.
      %31 : Float(10, 9216), %32 : UNKNOWN_TYPE = Dropout[is_test=1, ratio=0.5](%30), scope: AlexNet/Sequential[classifier]/Dropout[0]
      %33 : Float(10, 4096) = Gemm[alpha=1, beta=1, broadcast=1, transB=1](%31, %learned_11, %learned_12), scope: AlexNet/Sequential[classifier]/Linear[1]
      # ---- omitted for brevity ----
      %output1 : Float(10, 1000) = Gemm[alpha=1, beta=1, broadcast=1, transB=1](%38, %learned_15, %actual_input_1), scope: AlexNet/Sequential[classifier]/Linear[6]
      # Finally, a network returns some tensors
      return (%output1);
    }
```

PyTorch AlexNet model to ONNX

```
import onnx
# Load the ONNX model

model = onnx.load("alexnet.proto")
# Check that the IR is well formed
onnx.checker.check_model(model)

# Print a human readable representation of the graph
onnx.helper.printable_graph(model.graph)

import caffe2.python.onnx.backend as backend
import numpy as np

rep = backend.prepare(model, device="CUDA:0") # or "CPU"
# For the Caffe2 backend:
#     rep.predict_net is the Caffe2 protobuf for the network
#     rep.workspace is the Caffe2 workspace for the network
#       (see the class caffe2.python.onnx.backend.Workspace)
outputs = rep.run(np.random.randn(10, 3, 224, 224).astype(np.float32))
# To run networks with more than one input, pass a tuple
# rather than a single numpy ndarray.

print(outputs[0])
```

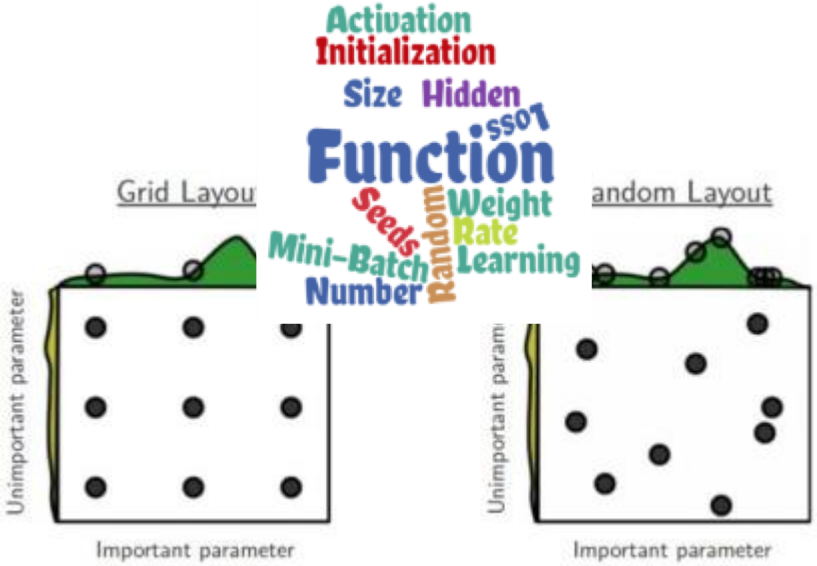
Working with Computer Vision Datasets

Data Augmentation

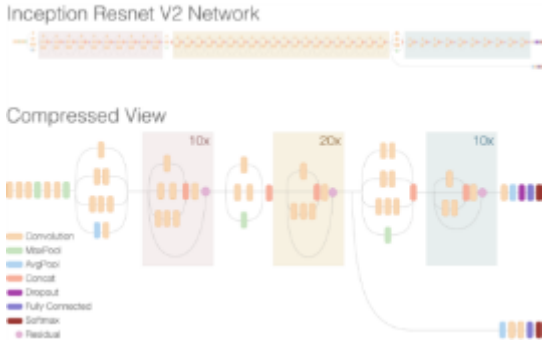
- `torchvisions.transforms`
  - `ColorJitter`
  - `Grayscale`
  - `LinearTransformation`
  - `Pad`
  - `RandomSizedCrop`
  - `RandomAffine`
  - `RandomApply`
  - `RandomChoice`
  - `RandomGrayscale`
  - `RandomHorizontalFlip`
  - `RandomOrder`
  - `RandomResizedCrop`
  - `RandomRotation`
  - `RandomSizedCrop`
  - `RandomVerticalFlip`

Image Source: Deep Image: Scaling up Image Recognition (Baidu)
https://arxiv.org/abs/1501.02876

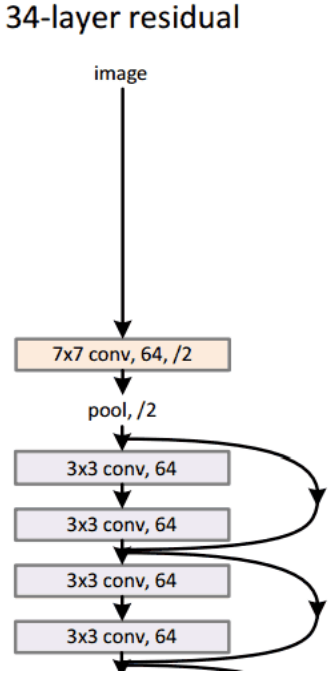
Training Challenges



Hyper-Parameter Optimization



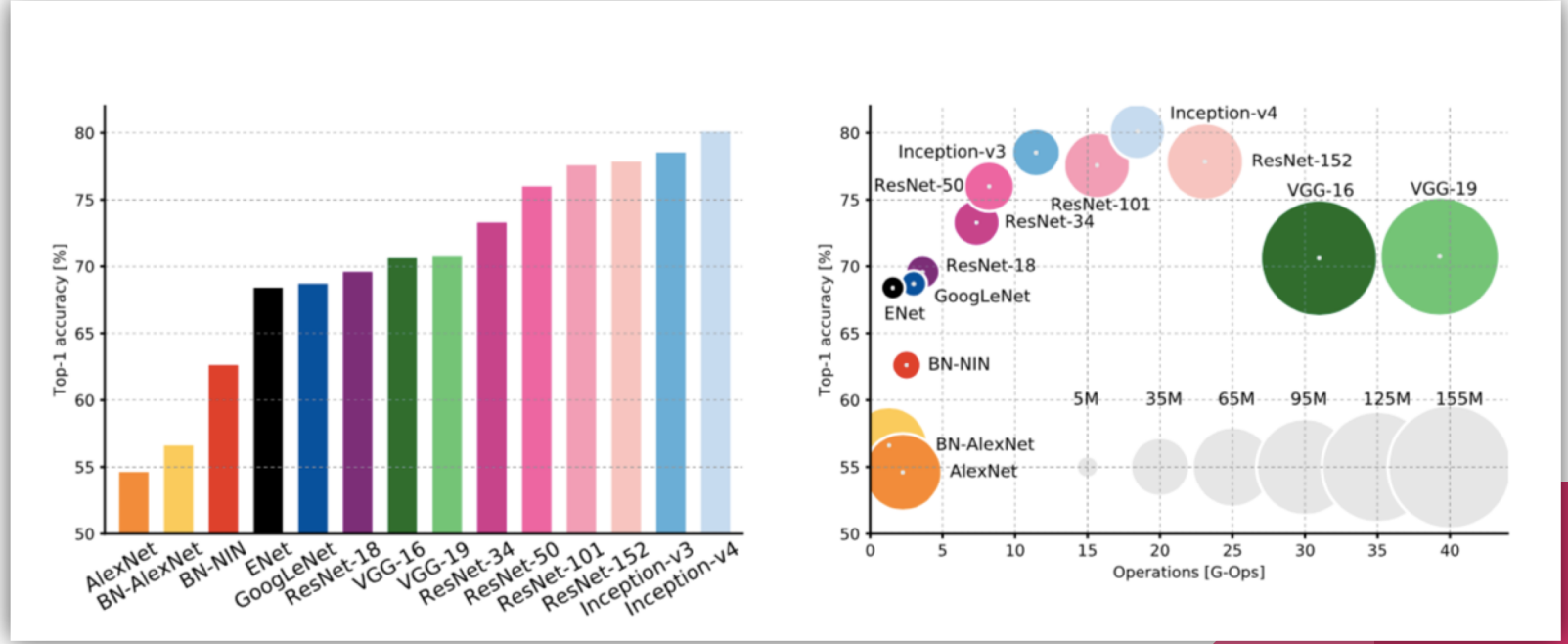
Google Inception v3



Microsoft Resnet

https://adeshpande3.github.io/adeshpande3.github.io/The-9-Deep-Learning-Papers-You-Need-To-Know-About.html
http://colinraffel.com/wiki/neural_network_hyperparameters

Analysis from training Computer Vision Models



Training Computer Vision Models: Time & Cost

Batch Size	epochs	Top-1 Accuracy	hardware	cost ($)	time
256	100	58.7%	8-core CPU + K20 GPU	3,000	144h
512	100	58.8%	1 DGX station	129,000	6h 10m
4096	100	58.4%	1 DGX station	129,000	2h 19m
32K	100	58.5%	512 KNLs	1.2 million	24m

Table 7: The speed and hardware cost for training AlexNet.
For batch size=32K, we changed local response norm in AlexNet to batch norm.

Batch Size	epochs	Top-1 Accuracy	hardware	cost ($)	time
256	90	73.0%	1 DGX station	129,000	21h
8192	90	72.7%	1 DGX station	129,000	21h
8192	90	72.7%	32 DGX stations	4.1 million	1h
32K	90	72.4%	512 KNLs	1.2 million	1h

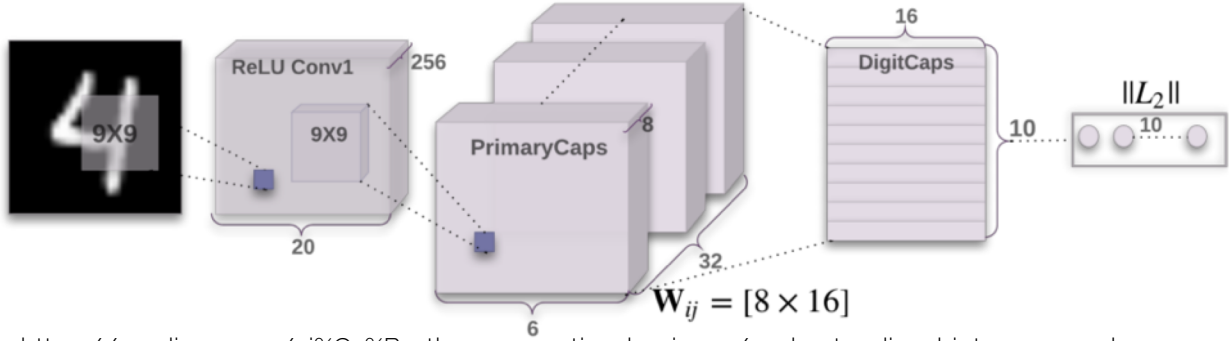
Table 8: The speed and hardware cost for training ResNet50. We did not use data augmentation.

PyTorch & Computer Vision Next

Computer Vision *Next*

- Generative Adversarial Networks (GANs)
  - Deep Convolution Generative Adversarial Networks (https://github.com/pytorch/examples/tree/master/dcgan)
- Capsule Networks

  Dynamic Routing Between Capsules (https://arxiv.org/abs/1710.09829)



https://medium.com/ai%C2%B3-theory-practice-business/understanding-hintons-capsule-networks-part-i-intuition-b4b559d1159b

PyTorch: A flexible approach for computer vision models

Discussion