



Developer Circles

from **facebook**

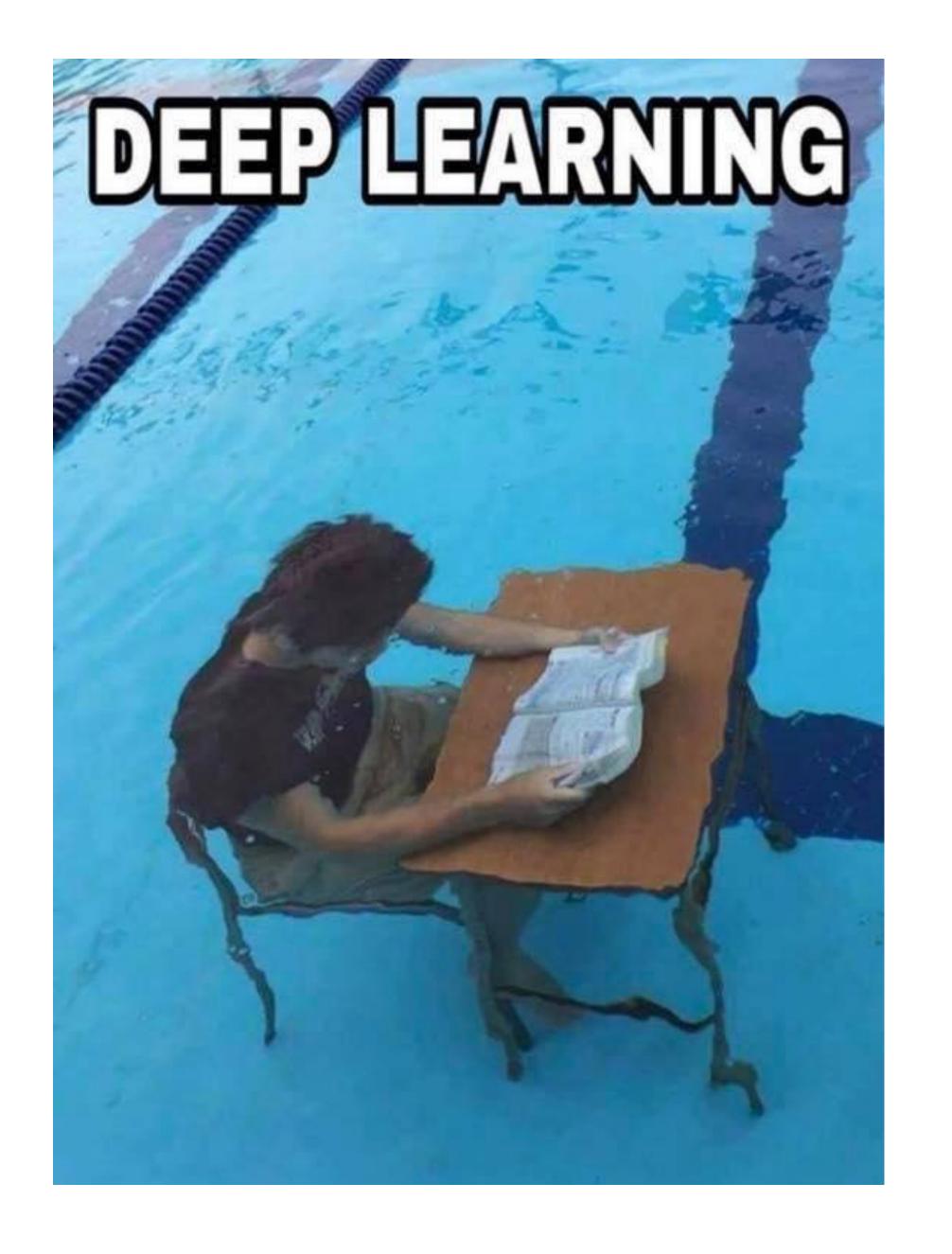
Deep learning with PyTorch & applications



Le Thanh Hung

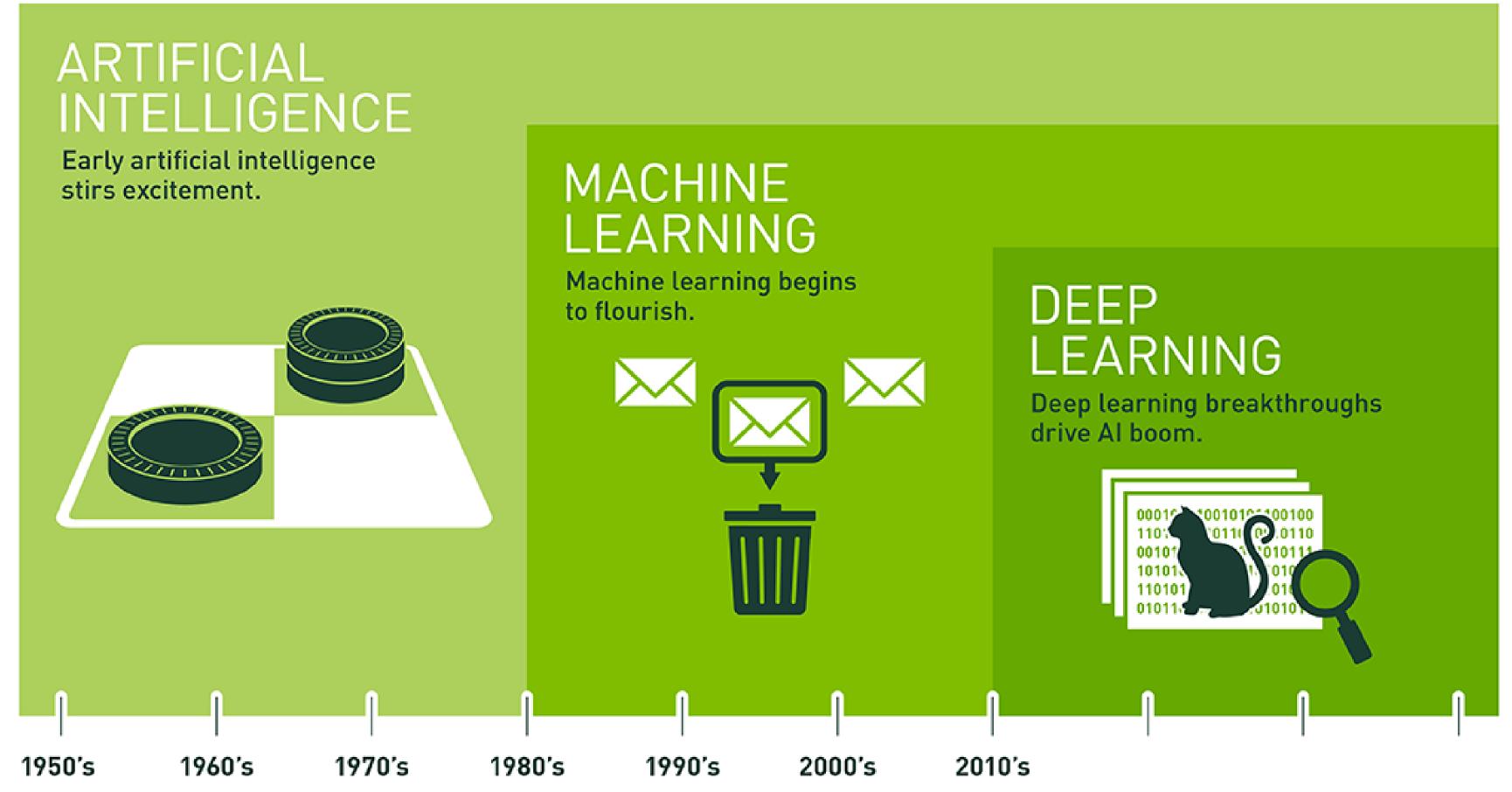
Community Leader Facebook Developer Circle Hanoi

facebook for developers



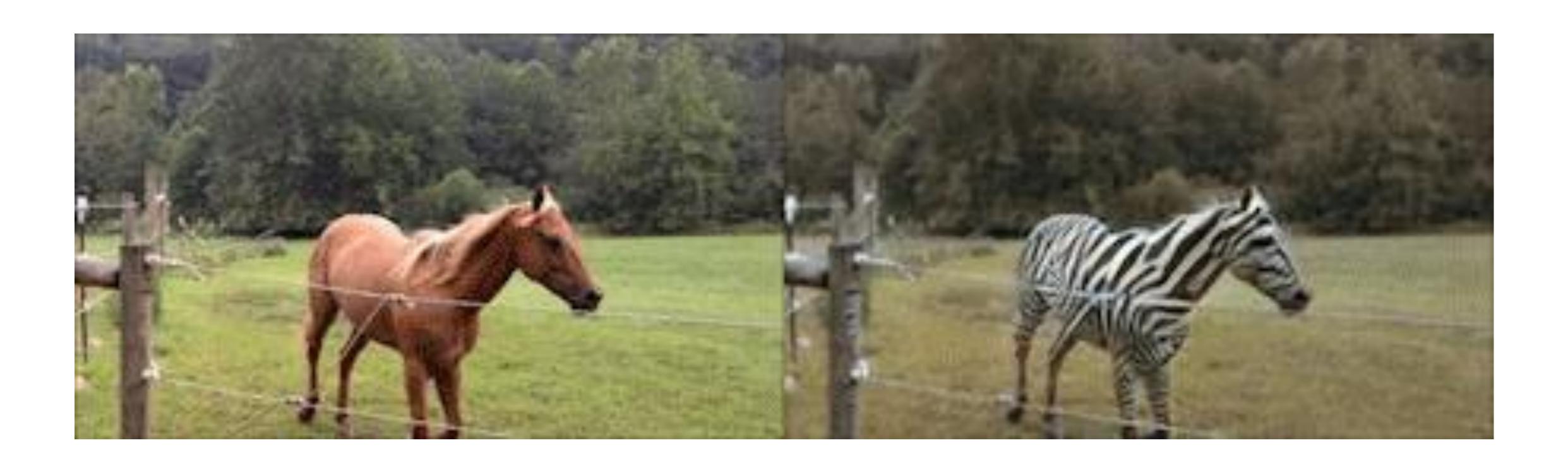






Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.





Berkeley Al Research Lab, UC Berkeley





PYTÖRCH

- Open source DL Framework
- Only a year ½ old!!!
- Thanks Facebook Al research group!!!
- Tons of Community



CycleGAN and pix2pix in PyTorch

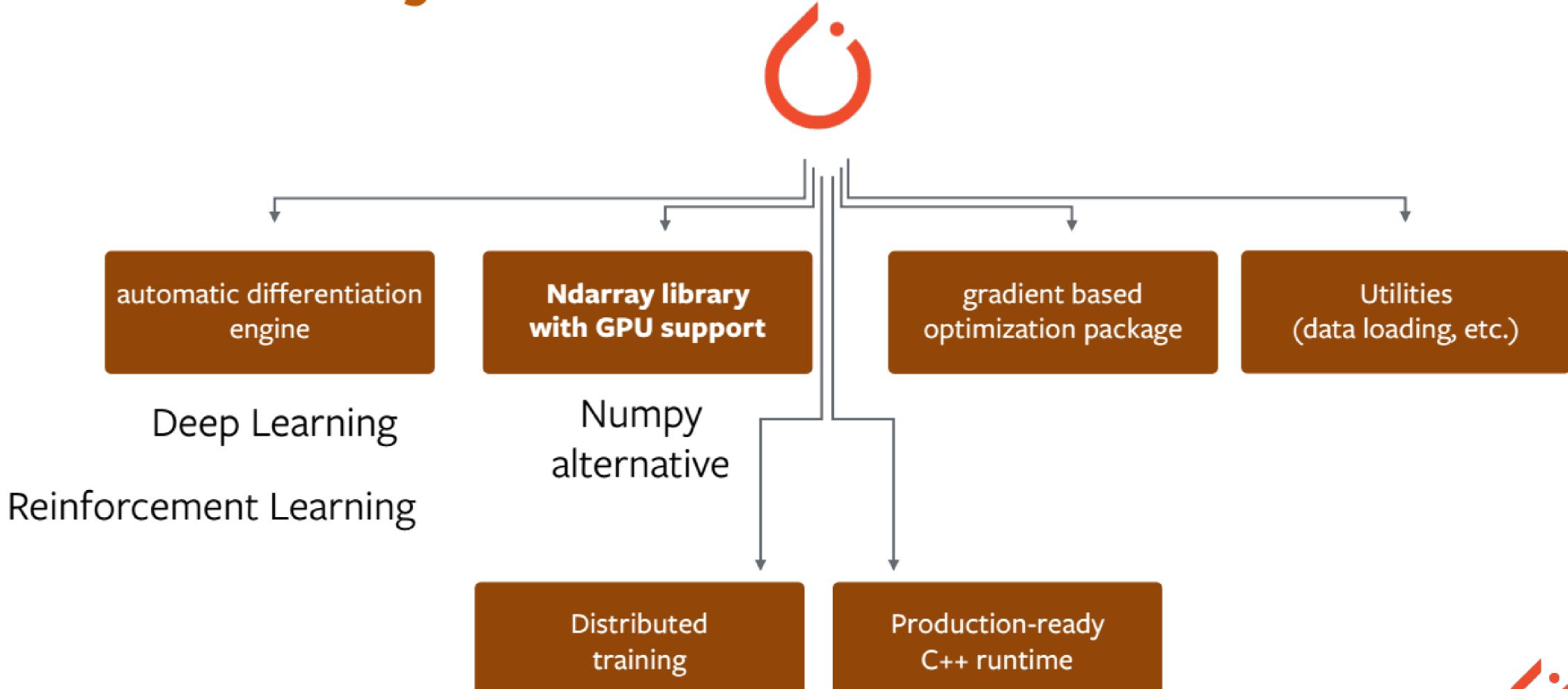
Jun-Yan Zhu and Taesung Park.





What is PyTorch?









ndarray library

- np.ndarray <-> torch.Tensor
- •200+ operations, similar to numpy
- •very fast acceleration on NVIDIA GPUs

```
# -*- coding: utf-8 -*-
import numpy as np
# N is batch size; D_in is input dimension;
# H is hidden dimension; D out is output dimension.
N, D_in, H, D_out = 64, 1000, 100, 10
# Create random input and output data
x = np.random.randn(N, D_in)
y = np.random.randn(N, D out)
# Randomly initialize weights
                                            Numpy
w1 = np.random.randn(D_in, H)
w2 = np.random.randn(H, D_out)
learning_rate = 1e-6
for t in range (500):
    # Forward pass: compute predicted y
   h = x.dot(w1)
   h_relu = np.maximum(h, 0)
   y_pred = h_relu.dot(w2)
    # Compute and print loss
   loss = np.square(y_pred - y).sum()
    print(t. loss)
    # Backprop to compute gradients of w1 and w2 with respect to loss
    grad_y pred = 2.0 * (y_pred - y)
    grad_w2 = h_relu.T.dot(grad_y_pred)
    grad_h_relu = grad_y_pred.dot(w2.T)
    grad_h = grad_h_relu.copy()
    grad_h[h < 0] = 0
    grad_wl = x.T.dot(grad_h)
    # Update weights
    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```



```
import torch
dtype = torch.FloatTensor
# dtype = torch.cuda.FloatTensor # Uncomment this to run on GPU
# N is batch size; D in is input dimension;
# H is hidden dimension; D out is output dimension.
N, D in, H, D out = 64, 1000, 100, 10
# Create random input and output data
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
                                             PyTorch
# Randomly initialize weights
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)
learning_rate = 1e-6
for t in range(500):
   # Forward pass: compute predicted y
   h = x.mm(w1)
   h_relu = h.clamp(min=0)
   y_pred = h_relu.mm(w2)
   # Compute and print loss
   loss = (y_pred - y).pow(2).sum()
   print(t, loss)
    # Backprop to compute gradients of w1 and w2 with respect to loss
   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)
    # Update weights using gradient descent
   w1 -= learning_rate * grad_wl
```

w2 -= learning_rate * grad_w2



Neural Networks

```
class Net(nn.Module):
        def __init__(self):
             super(Net, self).__init__()
             self.conv1 = nn.Conv2d(1, 10, kernel_size=5)
4
            self.conv2 = nn.Conv2d(10, 20, kernel_size=5)
 6
            self.conv2_drop = nn.Dropout2d()
            self.fc1 = nn.Linear(320, 50)
             self.fc2 = nn.Linear(50, 10)
8
9
        def forward(self, x):
10
            x = F.relu(F.max_pool2d(self.conv1(x), 2))
11
            x = F.relu(F.max_pool2d(self.conv2_drop(self.conv2(x)), 2))
            x = x.view(-1, 320)
13
            x = F.relu(self.fc1(x))
14
            x = F.dropout(x, training=self.training)
15
            x = self.fc2(x)
16
             return F.log_softmax(x)
17
18
    model = Net()
    input = Variable(torch.randn(10, 20))
20
    output = model(input)
```

Debugging

- PyTorch is a Python extension
- Use your favorite Python debugger
- Use the most popular debugger:

print (foo)





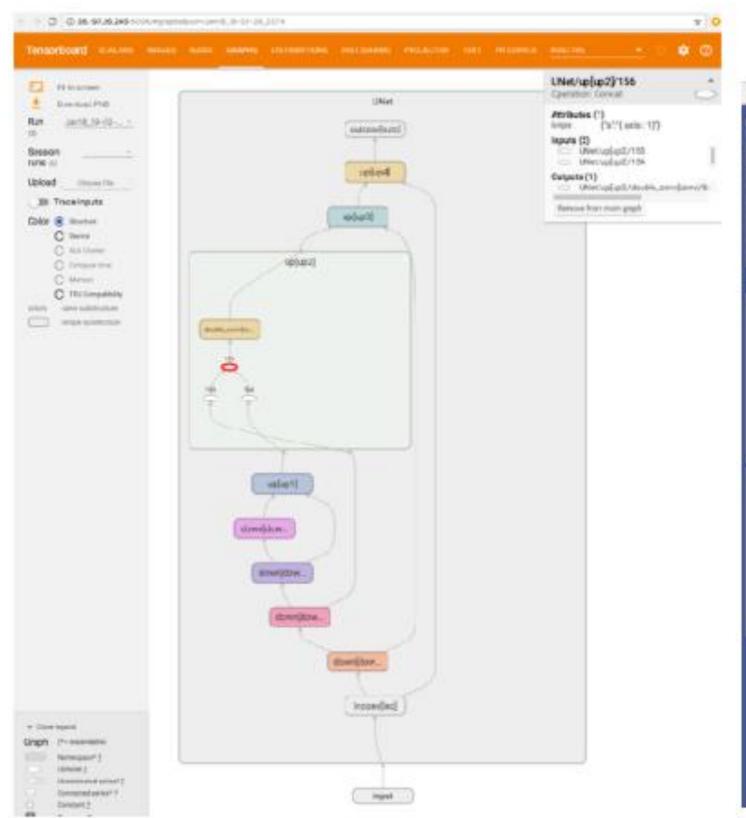
Visualization

WEB SUMMIT

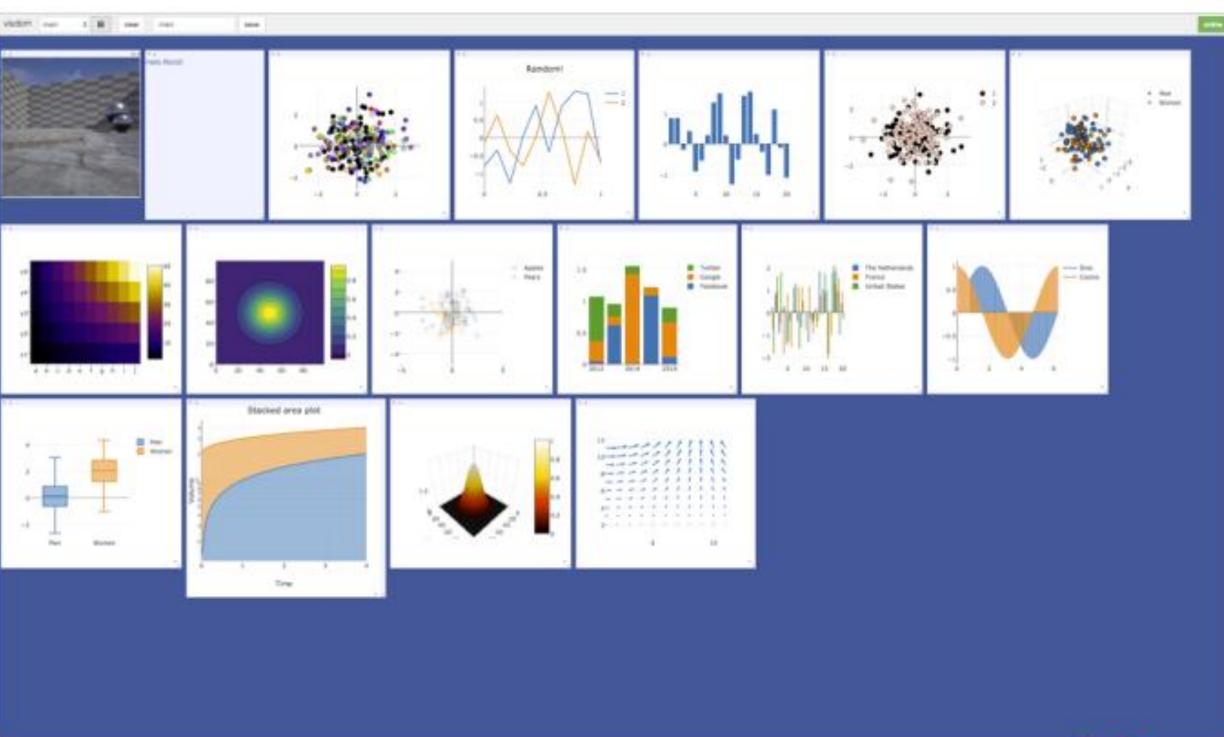
TensorBoard-PyTorch

Visdom

https://github.com/lanpa/tensorboard-pytorch



https://github.com/facebookresearch/visdom







Writing
Dataset loaders

Building models

Implementing
Training loop

Checkpointing models

Python + PyTorch - an environment to do all of this

Interfacing with environments

Building optimizers

Dealing with GPUs

Building Baselines

+ tools for making your model production-ready

Distributed training

Performance optimization

Deployment for inference







DEVELOPER EFFICIENCY

Debuggability

Interactivity

Simplicity

Intuitiveness

INFRASTRUCTURE EFFICIENCY

Efficiency

Reliability

Scalability

Cross Platform



Hybrid front-end workflow

PROTOTYPE

Prototype an ambitious idea using the familiarity and flexibility of Python and PyTorch eager mode.

Leverage autograd, training optimizers, and distributed training framework.

PRODUCTION TESTING

Prototype shows promise, so train and adapt the model to production data.

MIGRATE TO GRAPH

Migrate the model to Torch Script for production usage.

Torch.jit API allows one component to be migrated at a time, allowing for incremental code changes and easy debugging.

EXPORT

Export the non-Python representation of the model to be loaded by different environments (e.g., server or mobile).

Apply program-level optimization techniques to the exported model for efficiency gains.

IMPROVE & MAINTAIN

New features implemented in eager mode can be called from the Torch Script production model, and migrated at the development team's desired pace.





PYTORCH ECOSYSTEM

Tools, Libraries and Datasets to enable cutting-edge Al development











PyTorchVision

PyTorchReasoning

PyTorchLanguage

PyTorchSpeech

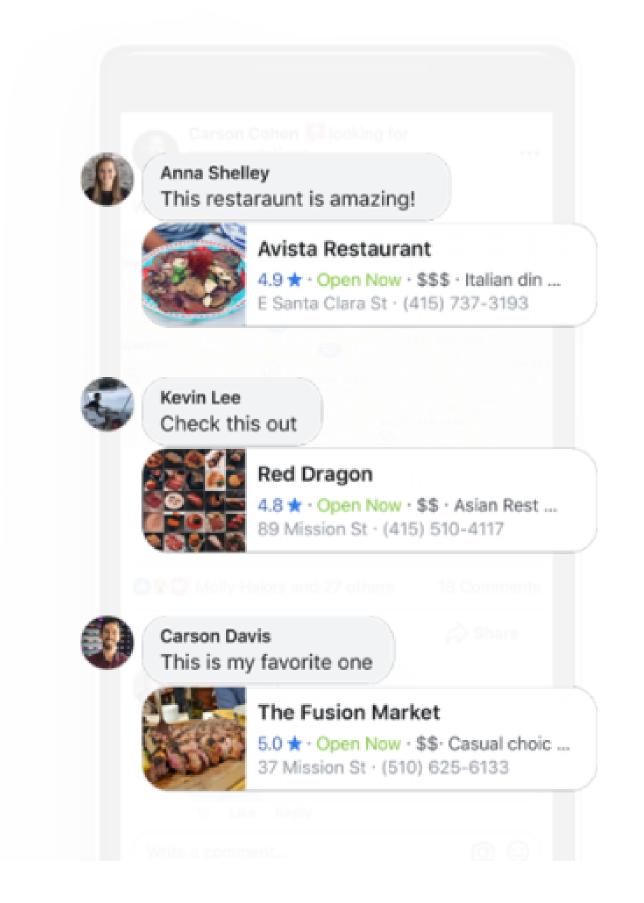
PyTorch Tools







SOCIAL RECOMMENDATIONS





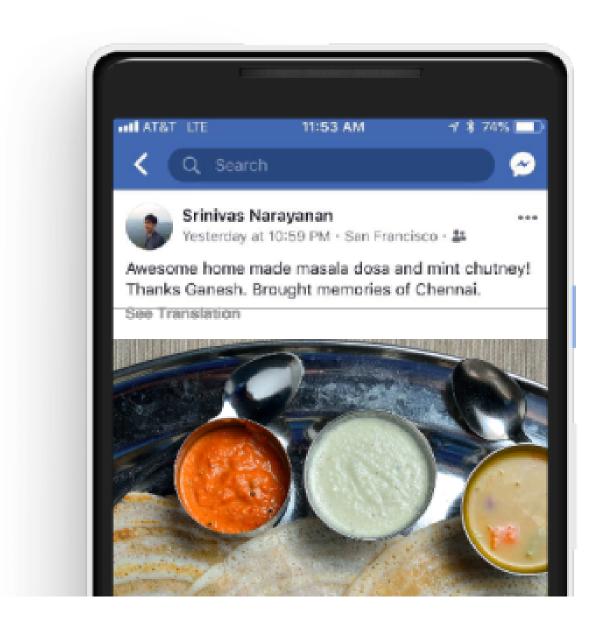


ENHANCING EXISTING PRODUCTS

SOCIAL RECOMMENDATIONS

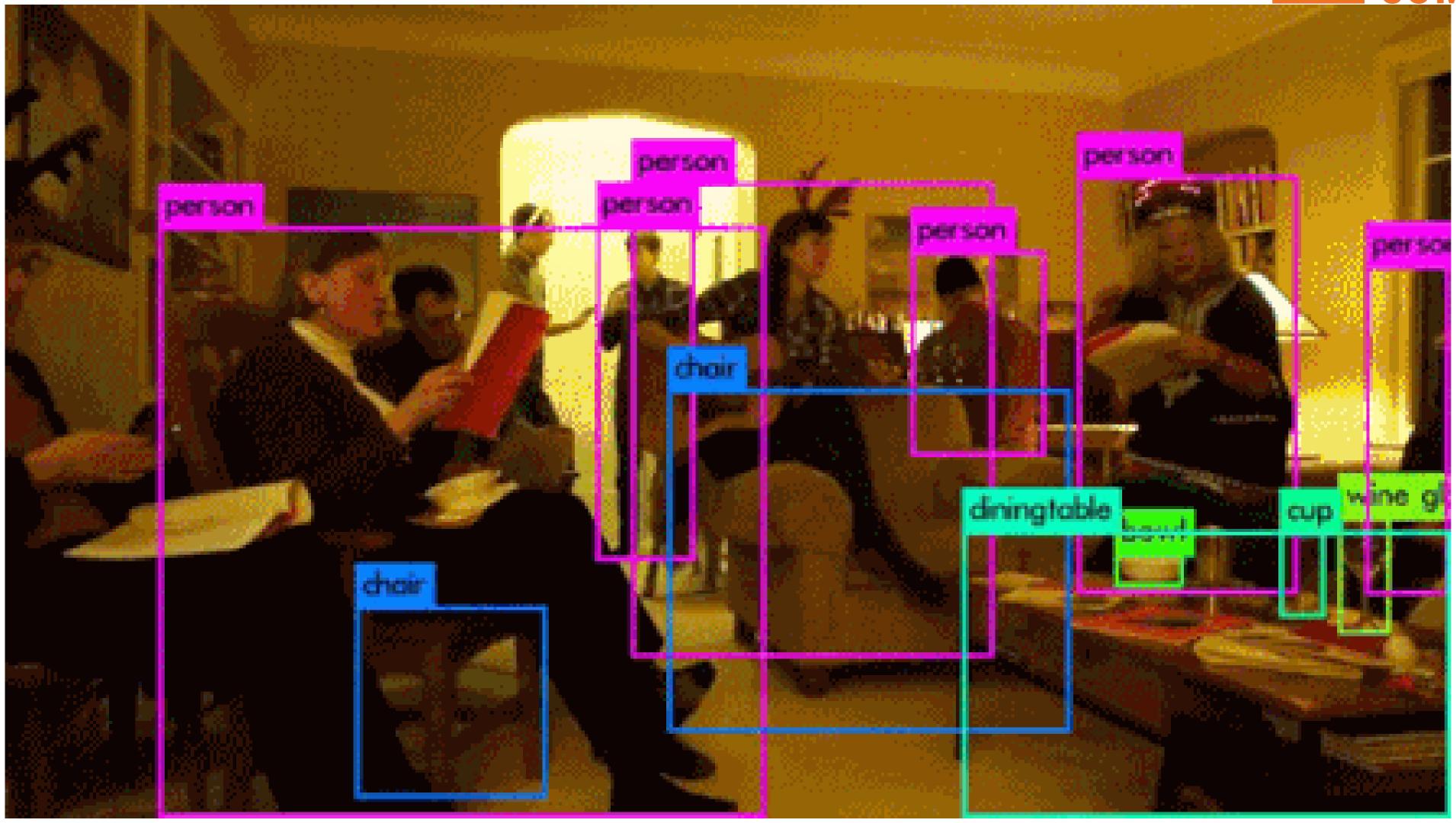






- 45+: Languages supported for
- 2K+: Translation directions
- 6B+: Translation impressions





YOLO v3 PYTORCH



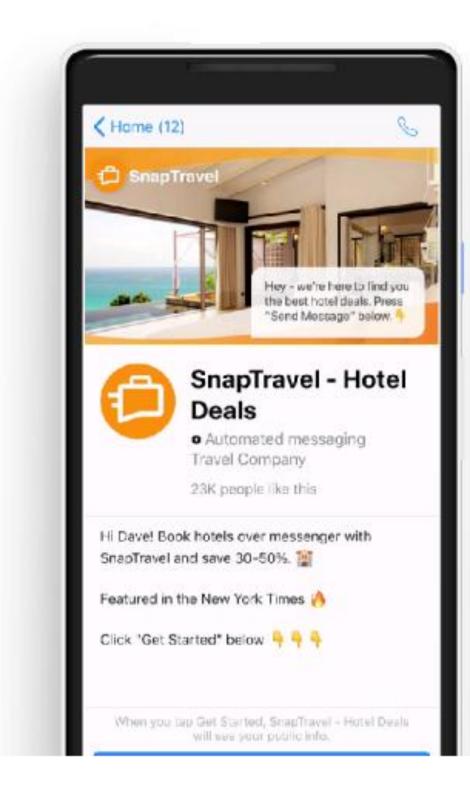
POWERING NEW EXPERIENCES

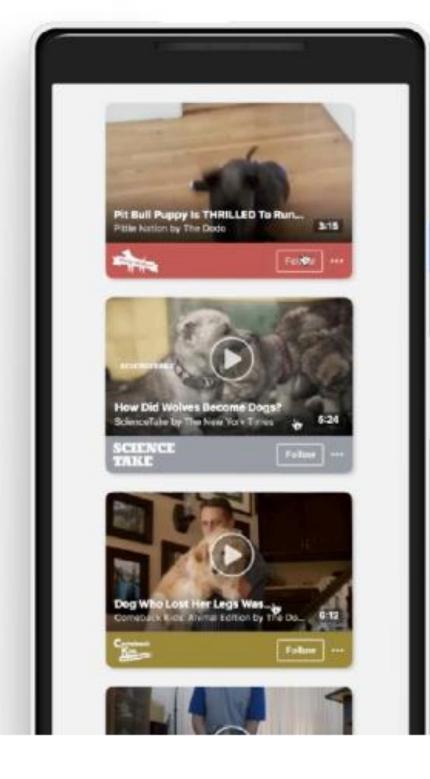


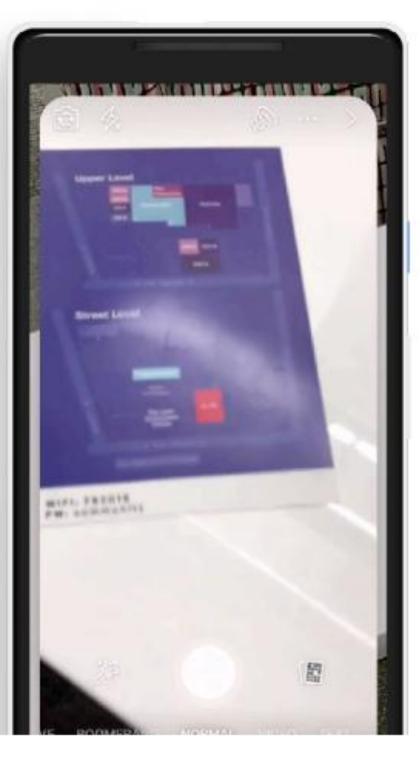
BOTS & ASSISTANTS

GENERATED CONTENT

AR EFFECTS V R H A R D W A R E



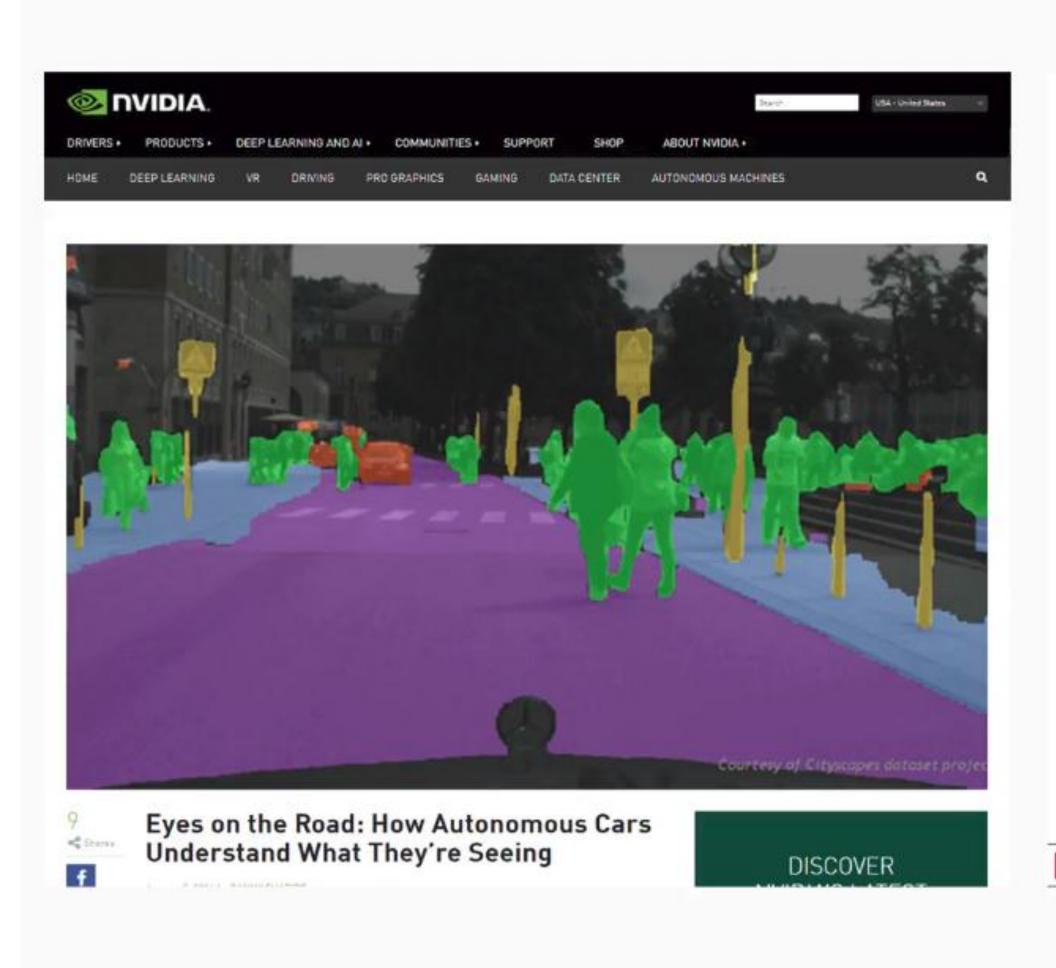






Use Cases: Self Driving Cars





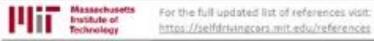
Camera

- Cheap
- Highest resolution
- Huge data = deep learning
- Human brains use similar sensor technology for driving
- · Bad at depth estimation
- Not good in extreme weather









MIT 6.5094: Deep Learning for Self-Driving Cars https://selfdrivingcars.mit.edu

Lex Fridman lex mit edu

2018



Ecosystem

•Pix2PixHD



https://github.com/NVIDIA/pix2pixHD

Input labels



Synthesized image









Andrej Karpathy

@karpathy

Director of Al at Tesla. Previously a Research Scientist at OpenAl, and CS PhD student at Stanford. I like to train Deep Neural Nets on large datasets.

Stanford

@ cs.stanford.edu/~karpathy/

Joined April 2009





I've been using PyTorch a few months now and I've never felt better. I have more energy. My skin is clearer. My eye sight has improved.

11:56 AM - 26 May 2017

384 Retweets 1,519 Likes

















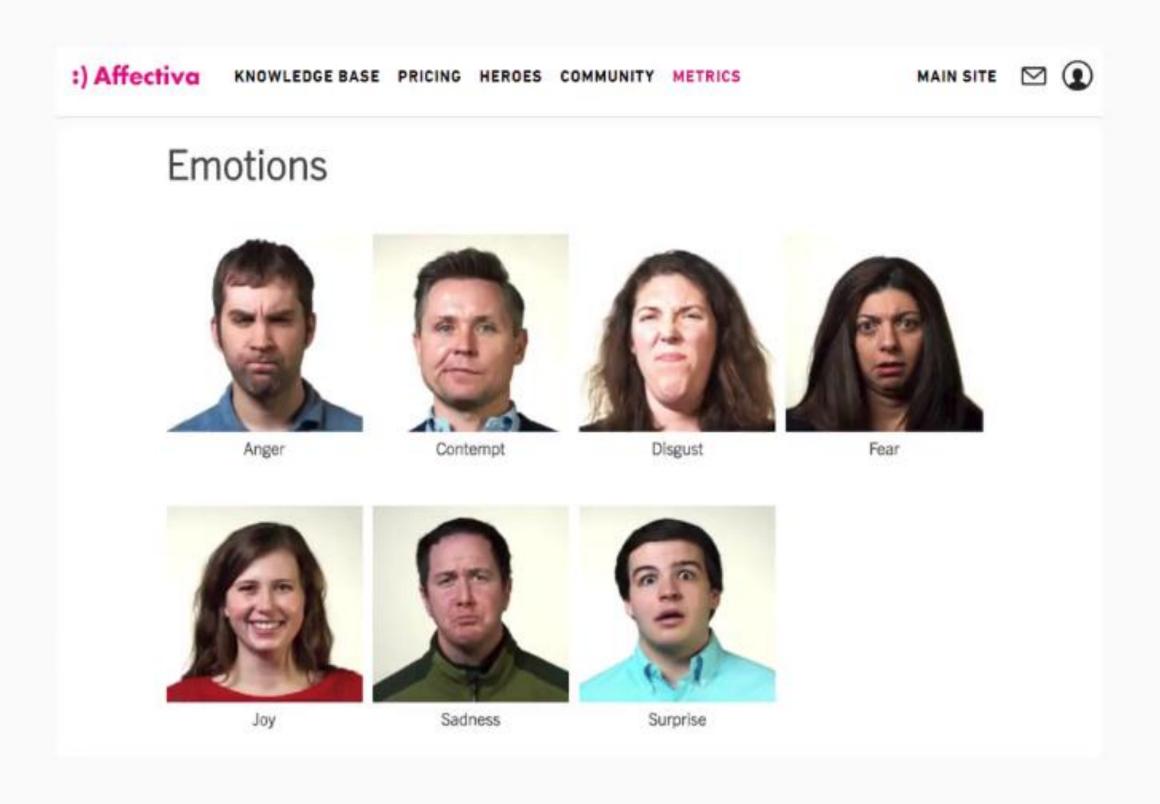






Use Cases: Emotion Detection







Tasks in Computer Vision



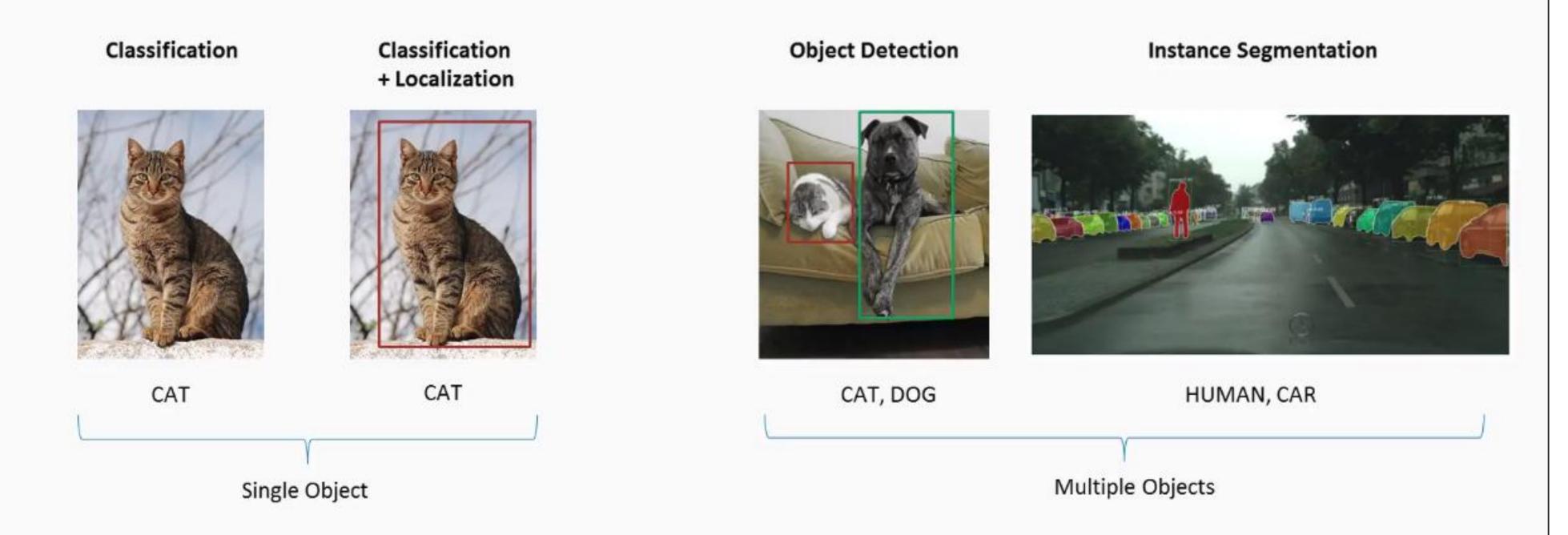


Fig: Tasks in Computer Vision (Image Credit: Wikimedia commons, Mask RCNN)





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Al Masterclass

