Deep Learning for Computer Vision

Beginnings (sorta)

How it works

Some uses

Simple Example using Fastai

Imagenet
14 million images in 1000 categories

airplane

automobile

bird

cat

deer

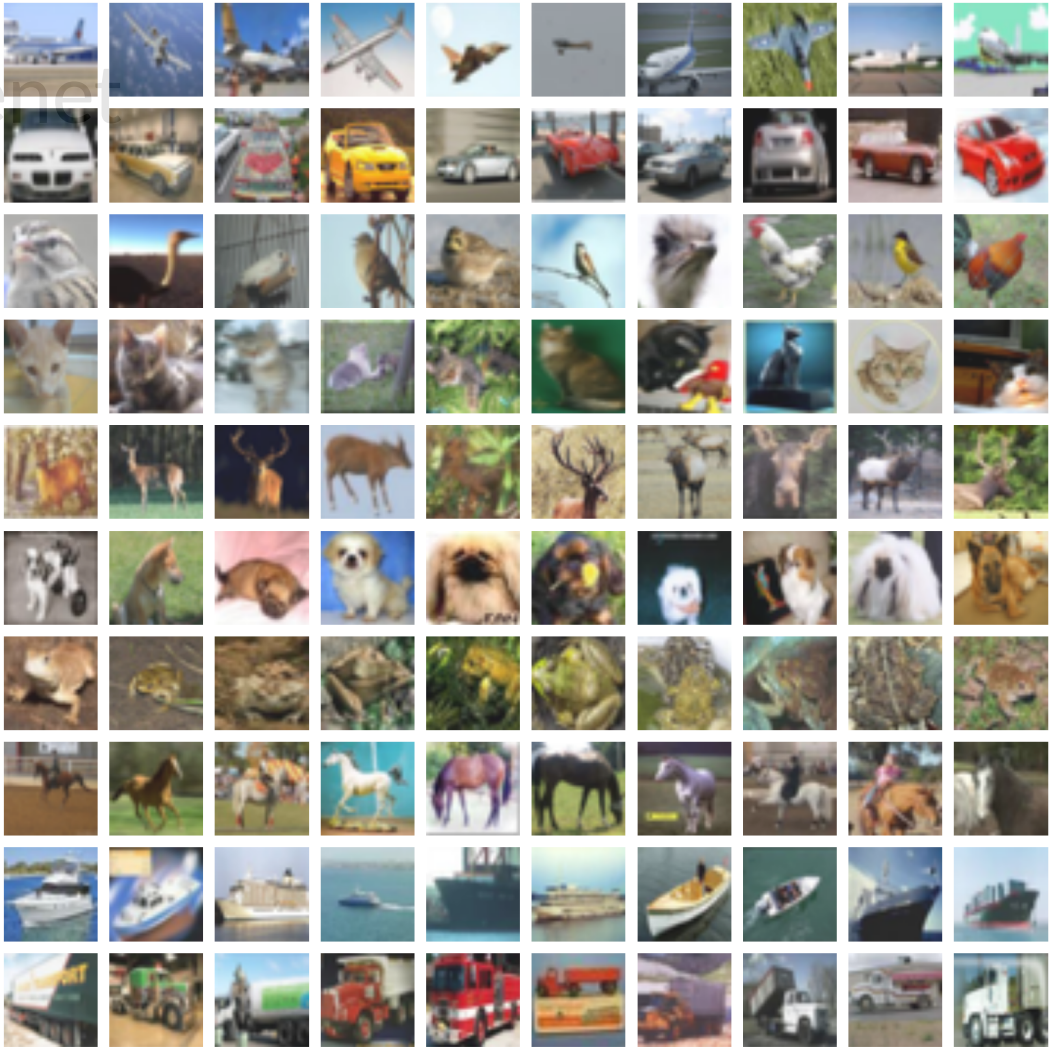
dog

frog

horse

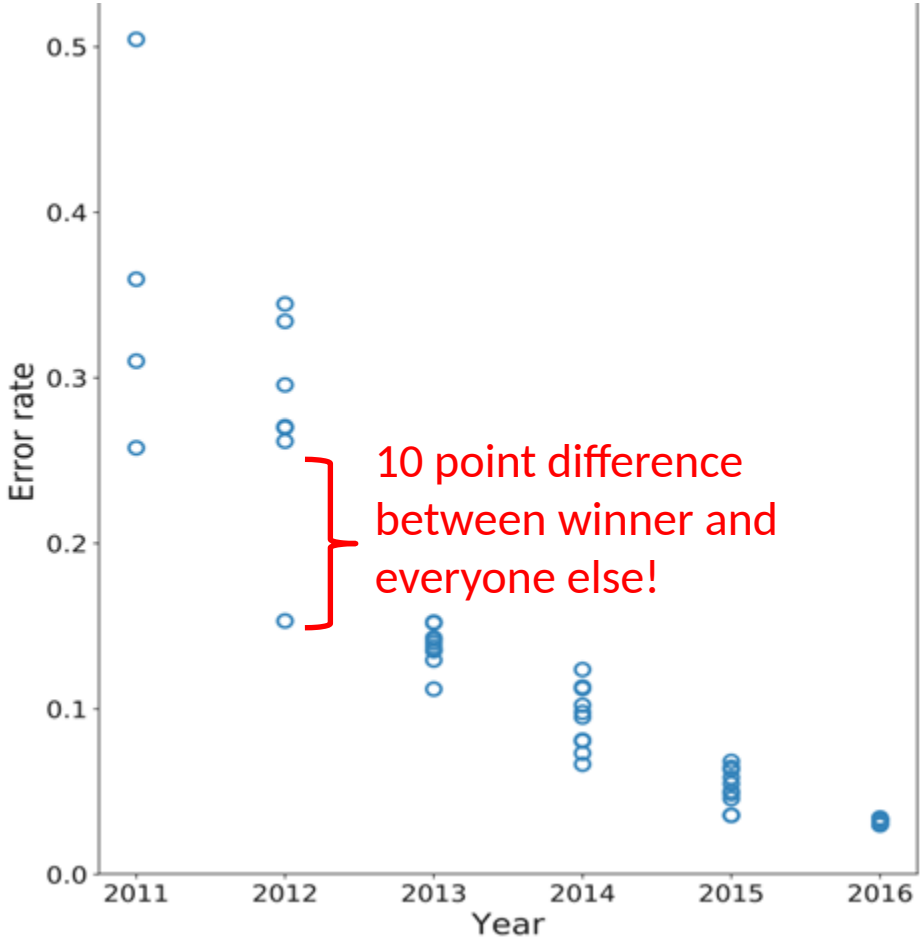
ship

truck

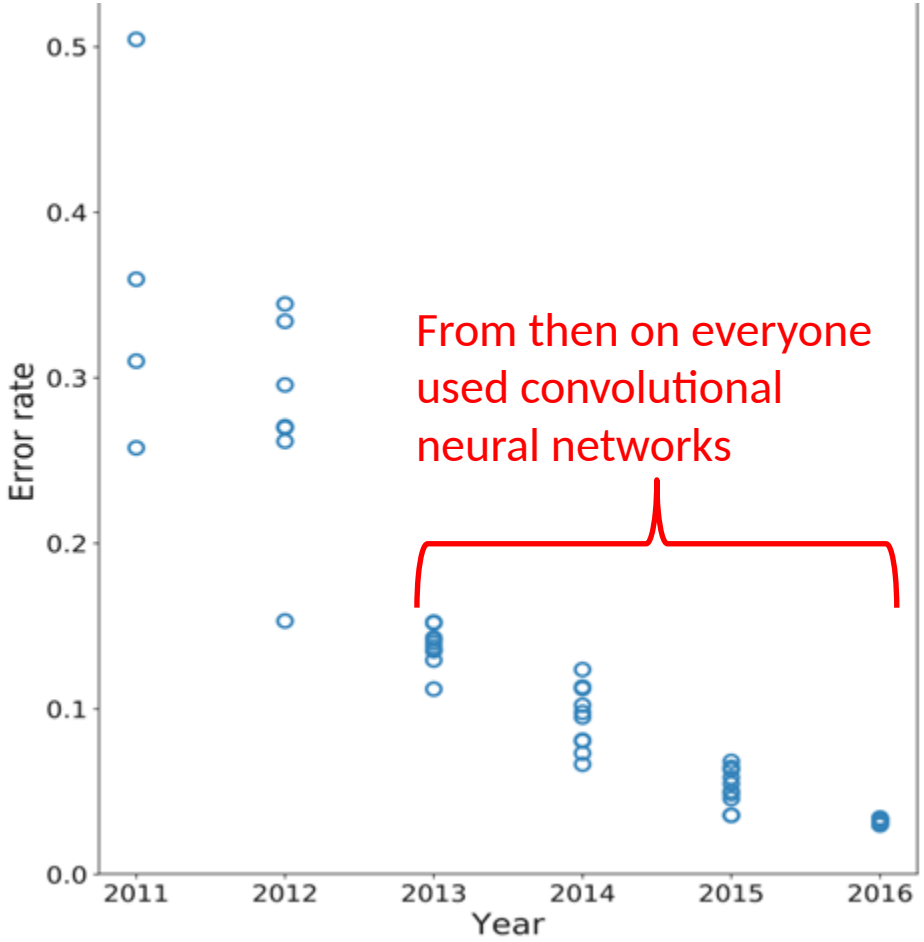


1 million also Have bounding box data which frames object

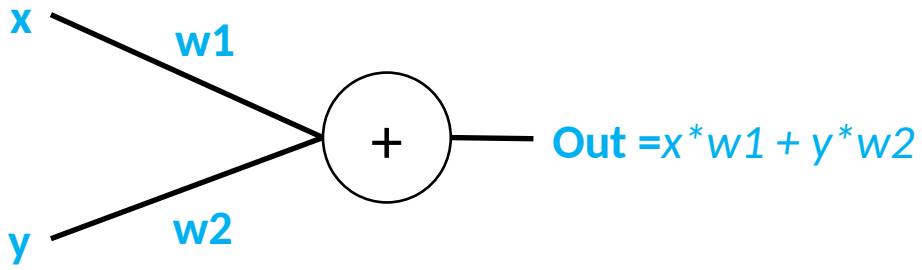
ImageNet Large Scale Visual Recognition Challenge



ImageNet Large Scale Visual Recognition Challenge



How it works – single neuron



Error=½(CA-Out)2**
Out=current answer
CA=correct answer

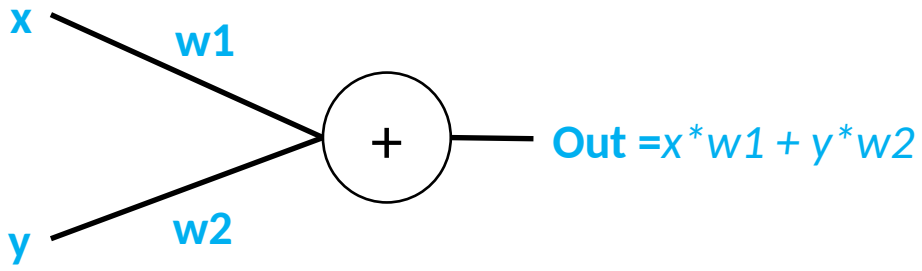
*Error =½(x*w1 + y*w2 – CA)**2*

Chain rule->the derivative of f(g(x)) = f'(g(z))g'(z)
Error** is made up of **f(g)=½(g)**2** and **g(z)=CA - x*w1 - y*w2
f'(g(x)) = df/dg= g (by the power rule)
g'(w1)=dg/dw1=-x
g'(w2)=dg/dw2=-y

Chain rule
*df/dg*dg/dw1 = (CA - x*w1 - y*w2)*-x*
*df/dg*dg/dw2 = (CA - x*w1 - y*w2)*-y*

direction of greatest increase in error! Reverse sign get greatest decrease in error.
Use this to make Error go to 0 by adding a fraction (Learning rate) *of these values to w1 and w2.*

How it works – single neuron



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Run backpropagation.py to demo

Chain rule
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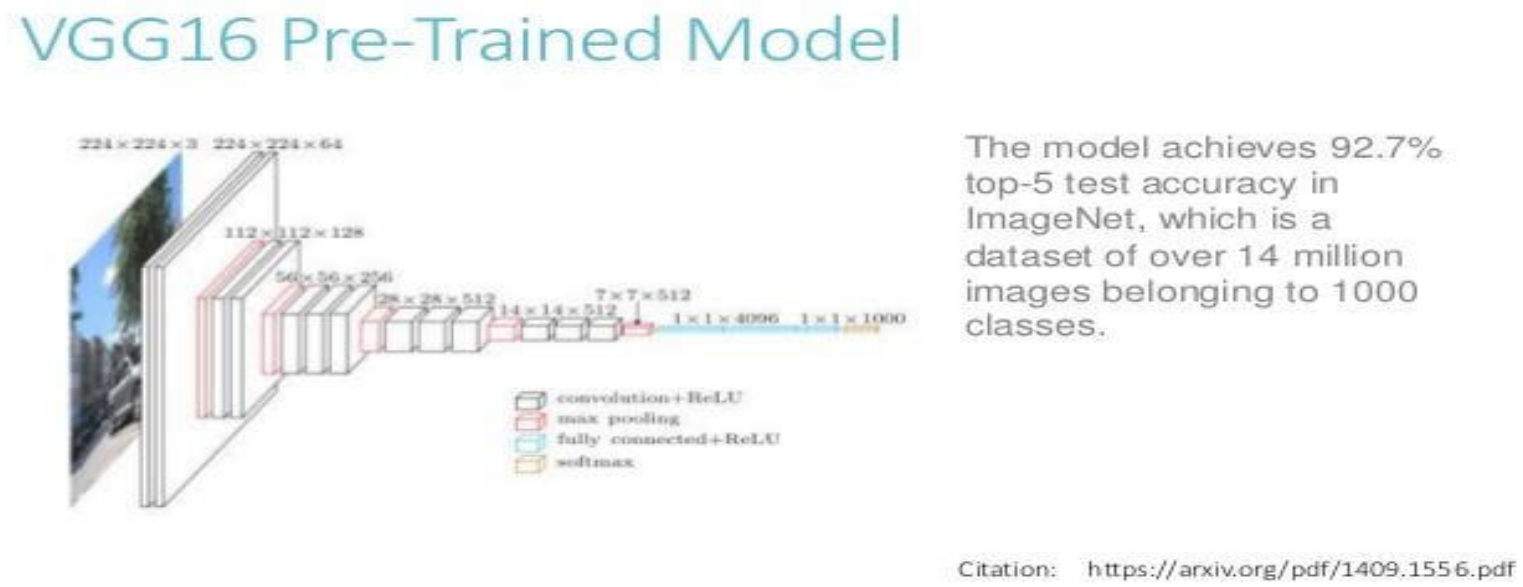
*df/dg*dg/dw2 = (CA - x*w1 - y*w2)*-y*

direction of greatest increase in error! Reverse sign get greatest decrease in error.
*Use this to make Error go to 0 by adding a fraction (*Learning rate*) of these values to w1 and w2.*

How it works – at scale

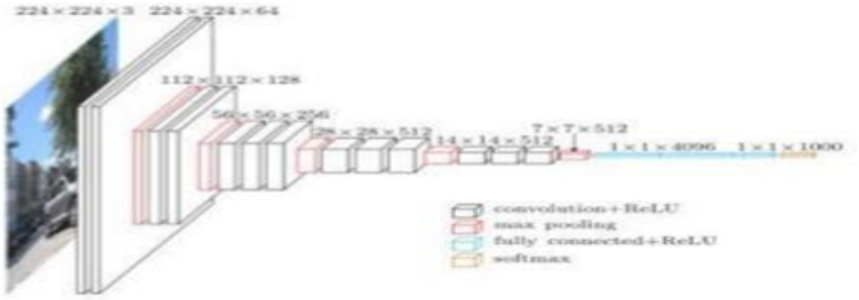
- Most models have hundreds of thousands of neurons and 100s of millions of parameters (like w1 and w2)
- So there are lots of forward and backwards computations
- GPUs do most of the calculations using huge multidimensional matrices

What's a Model?



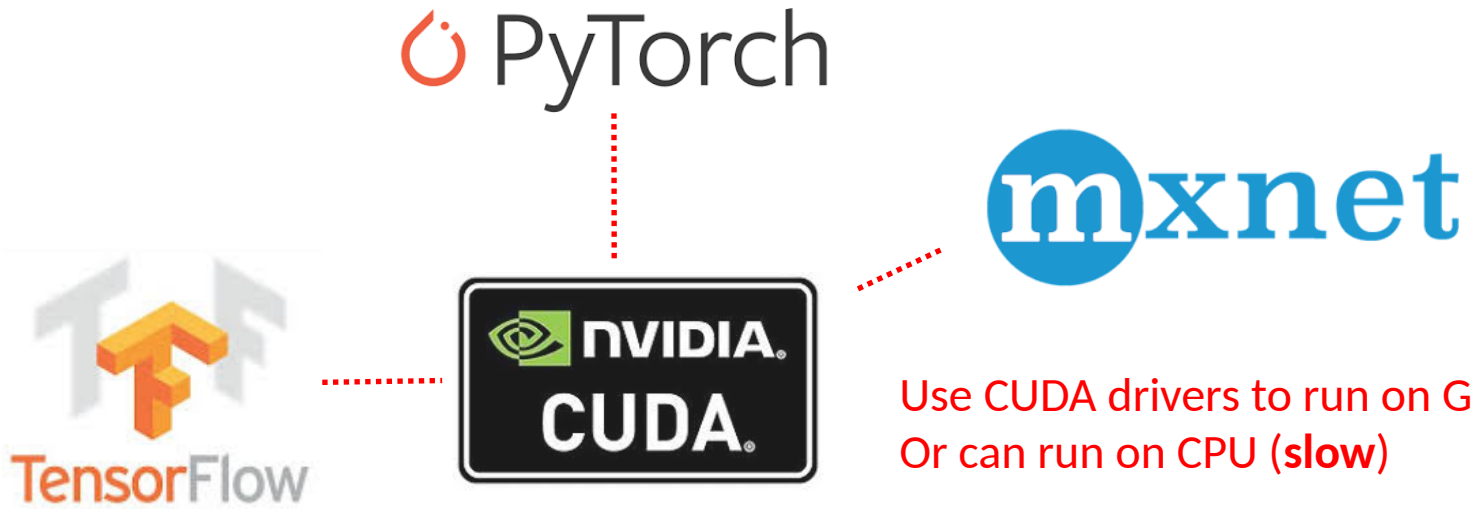
- A pretrained Neural Network.
  - Each layer consists of hundreds of convolutional filters which are in turn built from neurons
  - Each layer connected to next layer
- There are a bunch of these pretrained models, useful for 'transfer learning' which is coming up

Training, Testing



- Need: Data, Architecture (model), Error Function
- Train
  - Define an Error function
  - Feed images through, error is difference between what model thinks image is verses what the image actually is
  - Backpropegate to reduce this error
  - Do this lots of times
  - Eventually error is low for images, ignoring overfitting, model should generalize and recognize new images similar to old
- Test
  - Feed previously unseen images to model, see if it predicts correctly

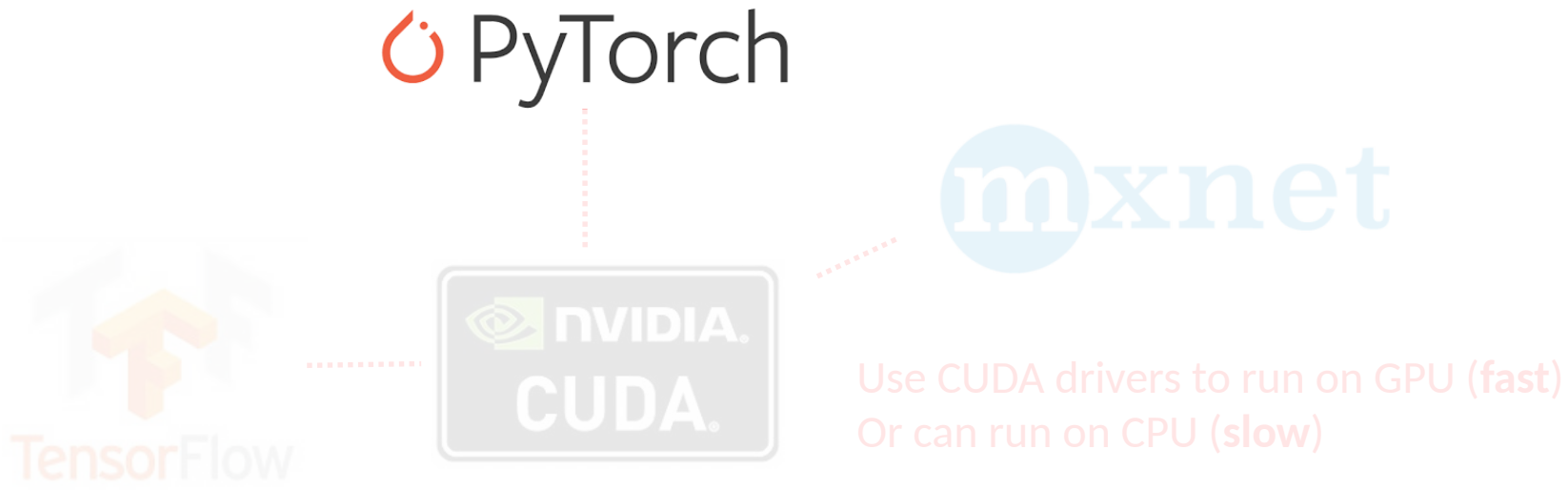
Frameworks do the heavy lifting



Use CUDA drivers to run on GPU (**fast**)
Or can run on CPU (**slow**)

See https://en.wikipedia.org/wiki/Comparison_of_deep_learning_software for others

Frameworks do the heavy lifting



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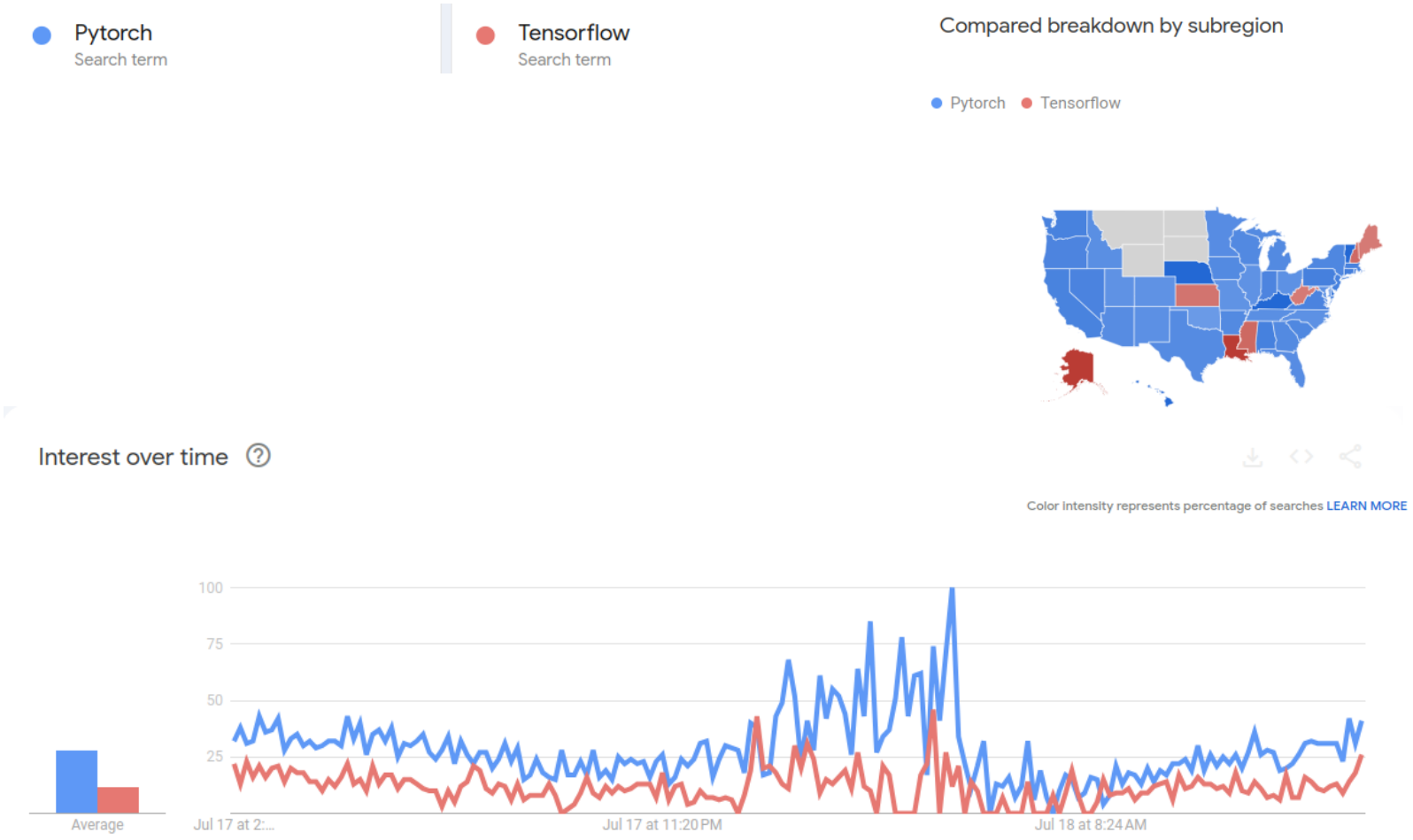
Pytorch -Why?

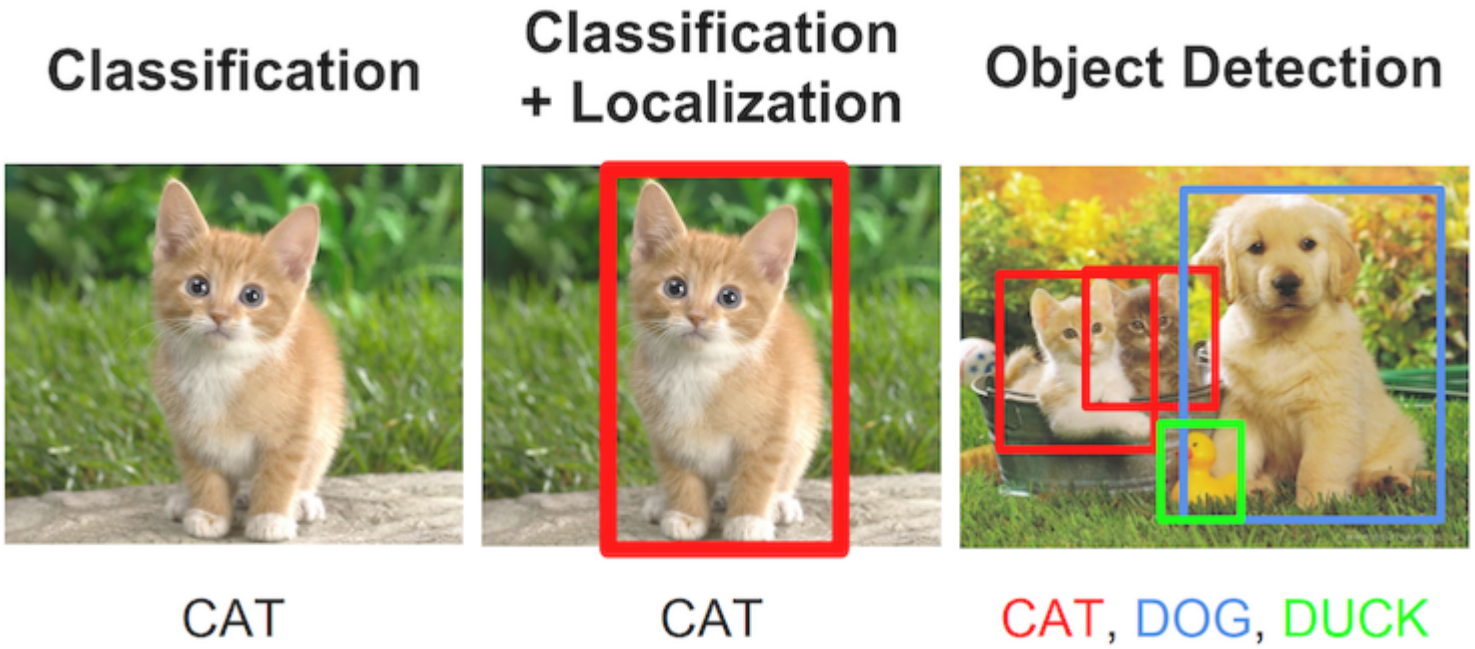


https://trends.google.com/trends/explore?date=now%201-d&geo=US&q=Pytorch,Tensorflow&hl=en

What can DL do?

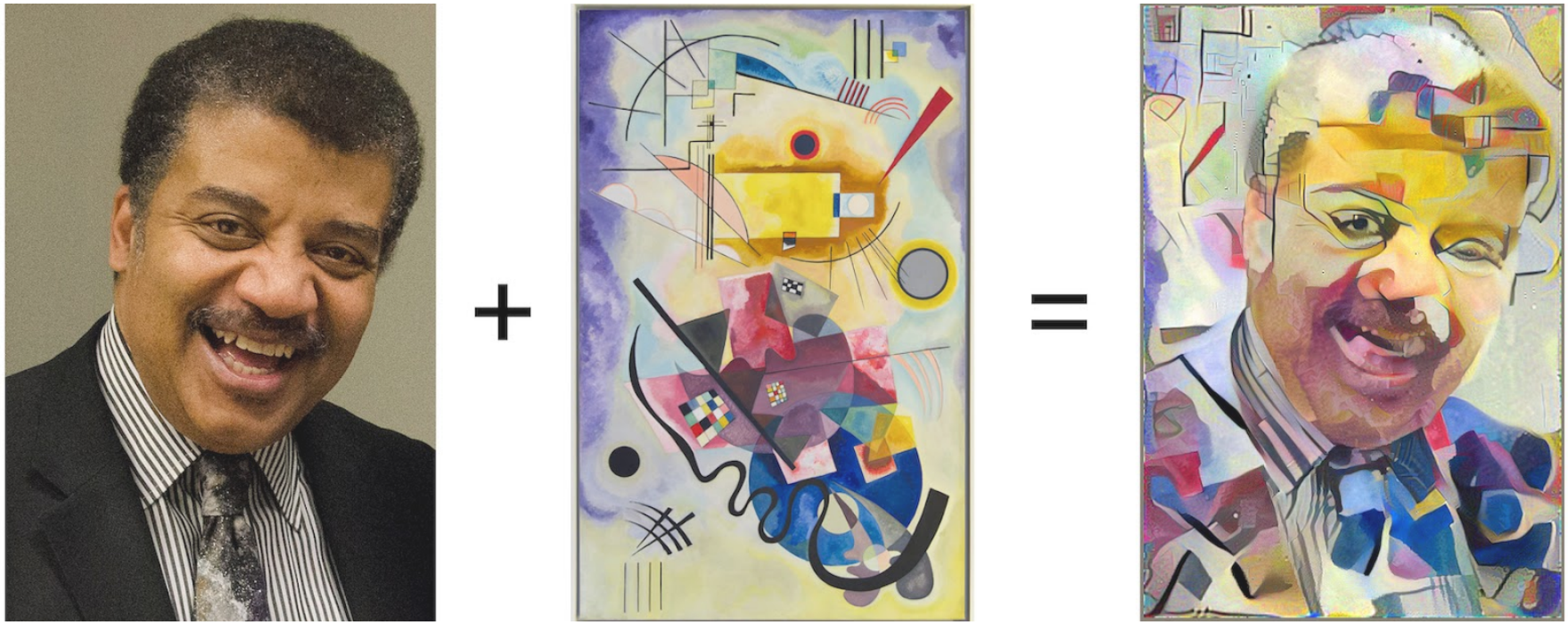
- It is not Artificial General Intelligence (AGI)! But can handle defined problems in:
  - Sequential Data (speech, character) recognition, prediction, translation, comprehension in the form of sentiment analysis
  - Time series structured data- A big deal. Analyzing data, predicting outcomes. (in store sales, failure prediction, cancer datasets)
  - Reinforcement Learning – learning from the environment (AlphaGo, GPT4)
  - Computer Vision (CV)

Convolutional Networks



excel in image recognition, segmentation, localization, medical image diagnosis, video manipulation… even art

Convolutional Networks



- Neural style transfer – error function optimizes image pixels to look like <u>both</u> images on left

http://gurneyjourney.blogspot.com/2016/10/style-transfer.html

How can I train a model to recognize labeled images I supply?

Called ‘transfer learning’, very common. Take an existing trained model and reuse most of it to recognize something new.

- Much faster than training model from scratch
- Need a lot less data as well
- Works well if the things you want to recognize are similar to the things the model was originally trained on

1. Load a fully trained model
2. Replace the last fully connected (FC) layers with new FC layers that have number of outputs = number of classes you want to distinguish
3. Train this model with your training data

- See https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html

Transfer Learning

Show pytorch and how its done
Show how fastai wraps much of this
Show how to pick a timm model
Demo

DL practitioner skillset 1

- Know a bit about GPUs (Nvidia not AMD)
- OS - Linux – period. Just enough to get by
- Need a powerful machine (like Paperspace Gradient)
- Get used to ssh, terminal, and some scripting.
- Get used to Jupyter notebooks (great to teach, tough to debug, awful in version control)
- Git – for everything
- Need to know your vector operations (Linear Algebra)
- A bit about probability

DL practitioner skillset 2

- Python – but not like this

```
# forward pass
out1 = (x * w1 + y * w2)
error = 1 / 2 * (correct - out1) ** 2

print(f"For pass {i}, w1 ={w1}, w2={w2}, error is{error}")

# backward pass derivitives (dout1_dw1 dout1_dw2 defined at
derror_dout1 = -(correct - out1)

# chain rule
derror_dw1 = -derror_dout1 * dout1_dw1  # shows fastest inc
derror_dw2 = -derror_dout1 * dout1_dw2

#adjust weights
w1 = w1+learning_rate * derror_dw1;
w2 = w2+learning_rate * derror_dw2;
```

DL practitioner skillset 2

- Python –more like this

```
# Decode predictions into bboxes.
for i in range(num):
    decoded_boxes = decode(loc_data[i], prior_data, self.variance)
    # For each class, perform nms
    conf_scores = conf_preds[i].clone()

    for cl in range(1, self.num_classes):
        c_mask = conf_scores[cl].gt(self.conf_thresh)
        scores = conf_scores[cl][c_mask]
        if scores.dim() == 0:
            continue
        l_mask = c_mask.unsqueeze(1).expand_as(decoded_boxes)
        boxes = decoded_boxes[l_mask].view(-1, 4)
        # idx of highest scoring and non-overlapping boxes per class
        ids, count = nms(boxes, scores, self.nms_thresh, self.top_k)
        output[i, cl, :count] = \
            torch.cat((scores[ids[:count]].unsqueeze(1),
                       boxes[ids[:count]]), 1)
```

DL practitioner skillset 2

- Python –and realistically like this

```
for i in range(num):
    decoded_boxes = decode(loc_data[i], prior_data, self.variance)

    conf_scores = conf_preds[i].clone()

    for cl in range(1, self.num_classes):
        c_mask = conf_scores[cl].gt(self.conf_thresh)
        scores = conf_scores[cl][c_mask]
        if scores.dim() == 0:
            continue
        l_mask = c_mask.unsqueeze(1).expand_as(decoded_boxes)
        boxes = decoded_boxes[l_mask].view(-1, 4)

        ids, count = nms(boxes, scores, self.nms_thresh, self.top_k)
        output[i, cl, :count] = \
            torch.cat((scores[ids[:count]].unsqueeze(1),
                       boxes[ids[:count]]), 1)
```

Lots of beta software
and missing documentation
Heavy use of list
comprehensions, iterators,
generators, matrix
Manipulation

DL practitioner skillset 3

- And… need to know data manipulation routines, image formatting, normalization data cleaning, directory and file manipulation…but you pick this up as you go

Why is this hard

- When it does not work its hard to troubleshoot 100,000,000 params
- Hyperparam selection, learning rate, architecture, FC layer depth
- Must find sweet spot where your model generalizes well but does not overfit your data
- Split dataset 80% train, 10% test, 10% validation. When accuracy on test set starts to decrease you are probably starting to overfit