15-494/694: Cognitive Robotics

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Lecture 14:
ImageNet and Transfer Learning

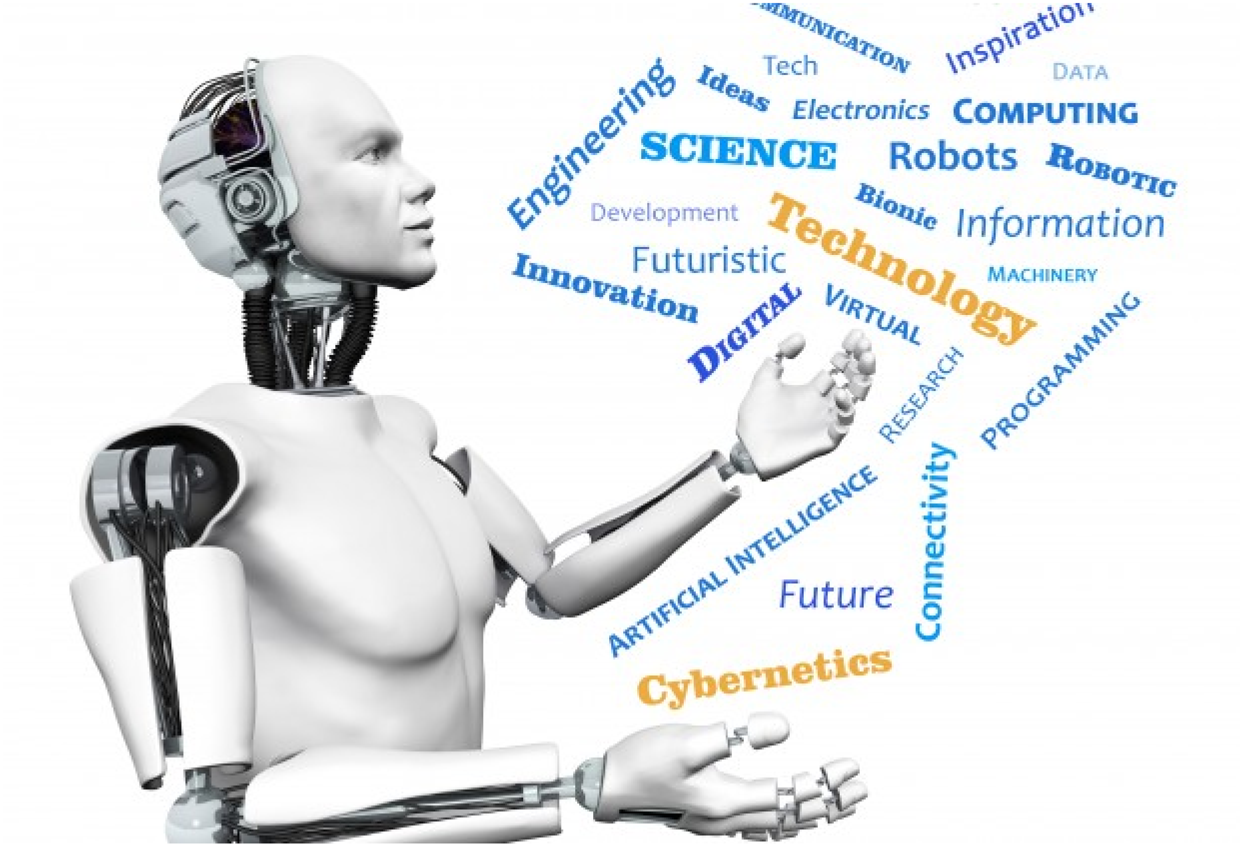


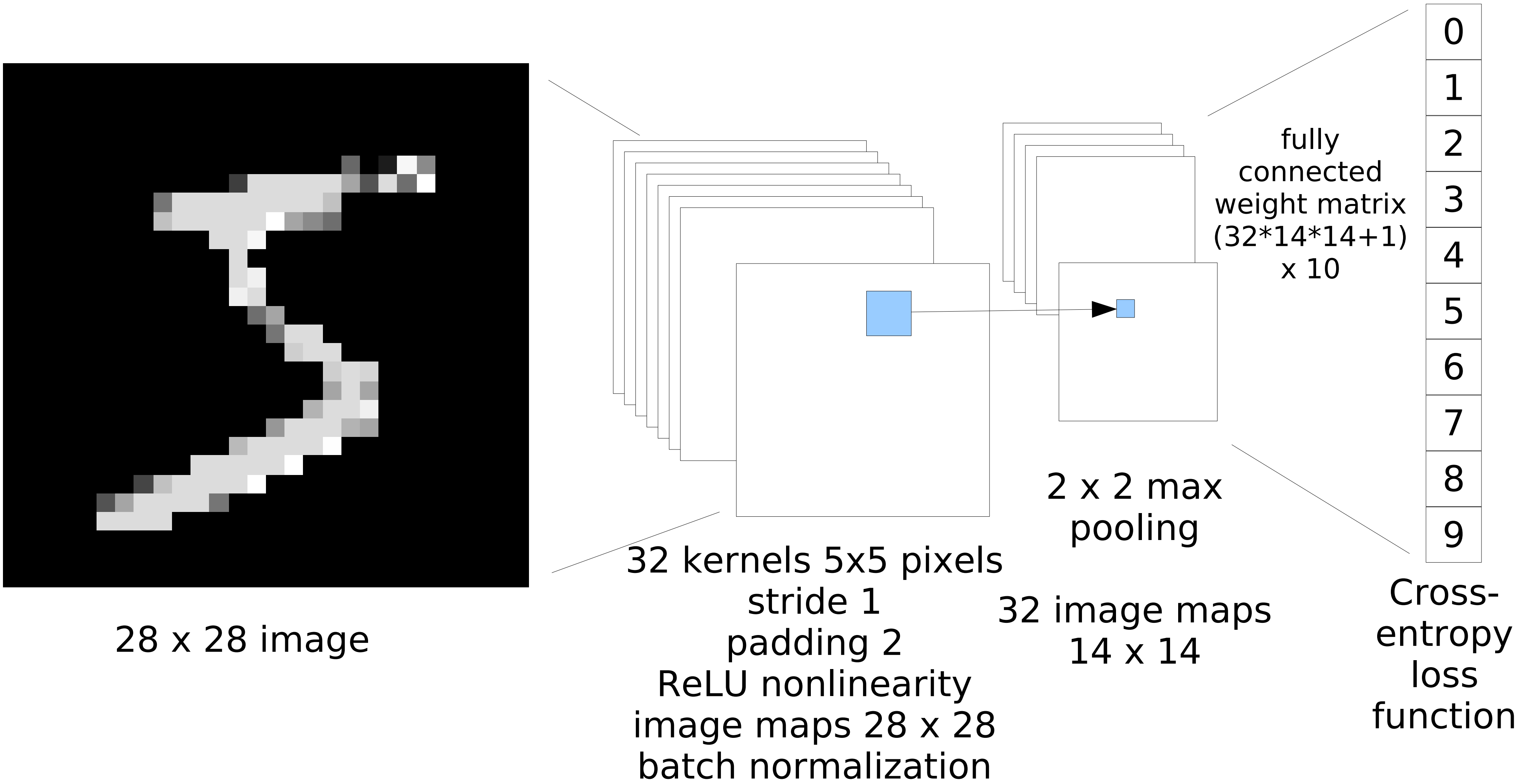
Image from http://www.futuristgerd.com/2015/09/10

Training With Pytorch

Components needed to train a classifier:

- Model:
  - Specify the input and output size
  - Define the layers and connections
  - Perform forward propagation
- Dataset loader: provides the training data
- Loss criterion: how we measure error
- Optimizer: updates the model parameters

MNIST3 Model Is A CNN



parameters = 63,626
How many connections?

Accuracy on training set: 98.3%

Defining the Model mnist3

```
class OneConvLayer(nn.Module):

  def __init__(self, in_dim, out_dim, nkernels):
    super(OneConvLayer, self).__init__()
    self.network1 = nn.Sequential(
      nn.Conv2d(in_channels=1,
                out_channels=nkernels,
                kernel_size=5,
                stride=1,
                padding=2),
      nn.BatchNorm2d(nkernels),
      nn.ReLU(),
      nn.MaxPool2d(kernel_size=2)
    )
    self.network2 = nn.Linear(nkernels*14*14,
                              out_dim)
```

Defining mnist3 (cont.)

```
def forward(self, x):
    out = self.network1(x)
    out = out.view(out.size(0), -1)
    out = self.network2(out)
    return out
```

```
model = OneConvLayer(28*28, 10, 32)
```

Automatic Differentiation

- Each layer of the model (Conv2D, ReLU, MaxPool, Linear) knows how to calculate its own derivative.

- When the layer produces its output (a tensor), the tensor is given attributes that allow backpropagation of the gradient.
  - This is another way that tensors differ from ordinary numpy arrays.

Dataset Loader

- Reads in training data from a file
- Supplies data in chunks according to the batch size we specify
- Shuffles the data if asked to do so

```
trainset = torchvision.datasets.MNIST(
                root='./mnist_data',
                download = True,
                transform = transforms.ToTensor())

trainloader = torch.utils.data.DataLoader(
                    dataset = trainset,
                    batch_size = batchSize,
                    shuffle = True)
```

Loss Functions

How do we measure error?

- Mean Square Error: nn.MSELoss

$$E = \frac{1}{2P}\sum_p \left(d^p - y^p\right)^2$$

- Cross-Entropy: nn.CrossEntropyLoss

$$E = \sum_p -d^p \log\left(y^p\right) - \left(1 - d^p\right)\log\left(1 - y^p\right)$$

- Lots of other choices.

criterion = nn.CrossEntropyLoss()

Optimizers

- Once we’ve measured the error gradient, what do we do about it?
- An optimizer adjusts the weights based on the gradient and various parameters: learning rate, momentum, etc.
- Lots of choices: SGD, ADAM, etc.

```
optimizer = torch.optim.SGD(model.parameters(), lr=0.005)
```

Training the Model

```
for epoch in range(nepochs):

  for (images,labels) in trainloader:

    images = images.view(-1, 28*28).to(device)
    labels = labels.to(device)
    outputs = model(images)

    optimizer.zero_grad()
    loss = criterion(outputs, labels)
    loss.backward()

    optimizer.step()
```

Move data to GPU

Object Recognition

Object Recognition Challenge

- Computer vision researchers use challenge events to measure progress in the state of the art.
- PASCAL VOC (Visual Object Classes) Challenge:
    - Ran from 2005 to 2012
    - 2005 version had 4 categories (bicycles, motorcycles, people, cars) and 1,578 training images
    - 2012 version had 20 categories and 5,717 training images

ImageNet

- Created by Fei-Fei Li at Stanford.
- See www.image-net.org
- 15 million labeled images, 22,000 categories
- ILSVRC: ImageNet Large Scale Visual Recognition Challenge: 2009-2017
  - 1000 categories, including 118 dog breeds
  - 1.2 million training images

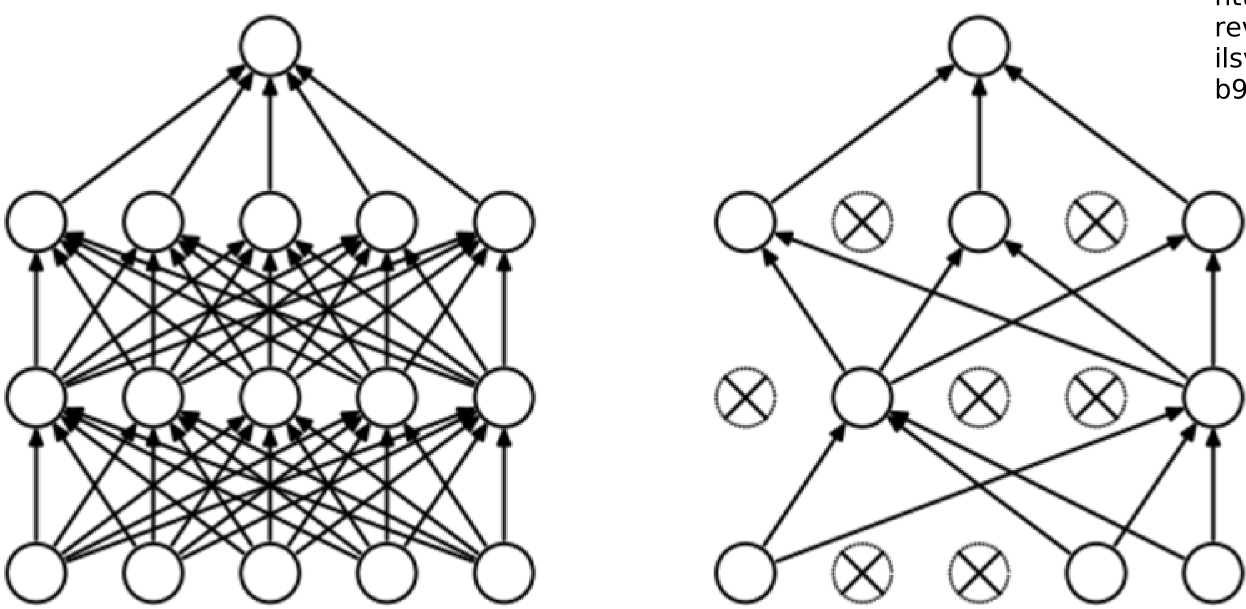
AlexNet

- The winners of the 2012 ILSVRC:
  - Alex Krizhevsky, Ilya Sutsker, and Geoffrey Hinton
  - Deep convolutional neural net (DCNN) called AlexNet
  - Trained using two GPU boards
  - Introduced ReLU in place of tanh
  - Used “dropout” to reduce overfitting
  - Error rate of 15.3% was 10% better than the runner-up
  - Put deep neural nets on the map

Dropout in AlexNet

- For each training step, disable 50% of the neurons for both the forward and backward pass.
- Reduces overfitting.

Figure from https://medium.com/coinmonks/paper-review-of-alexnet-caffenet-winner-in-ilsvrc-2012-image-classification-b93598314160

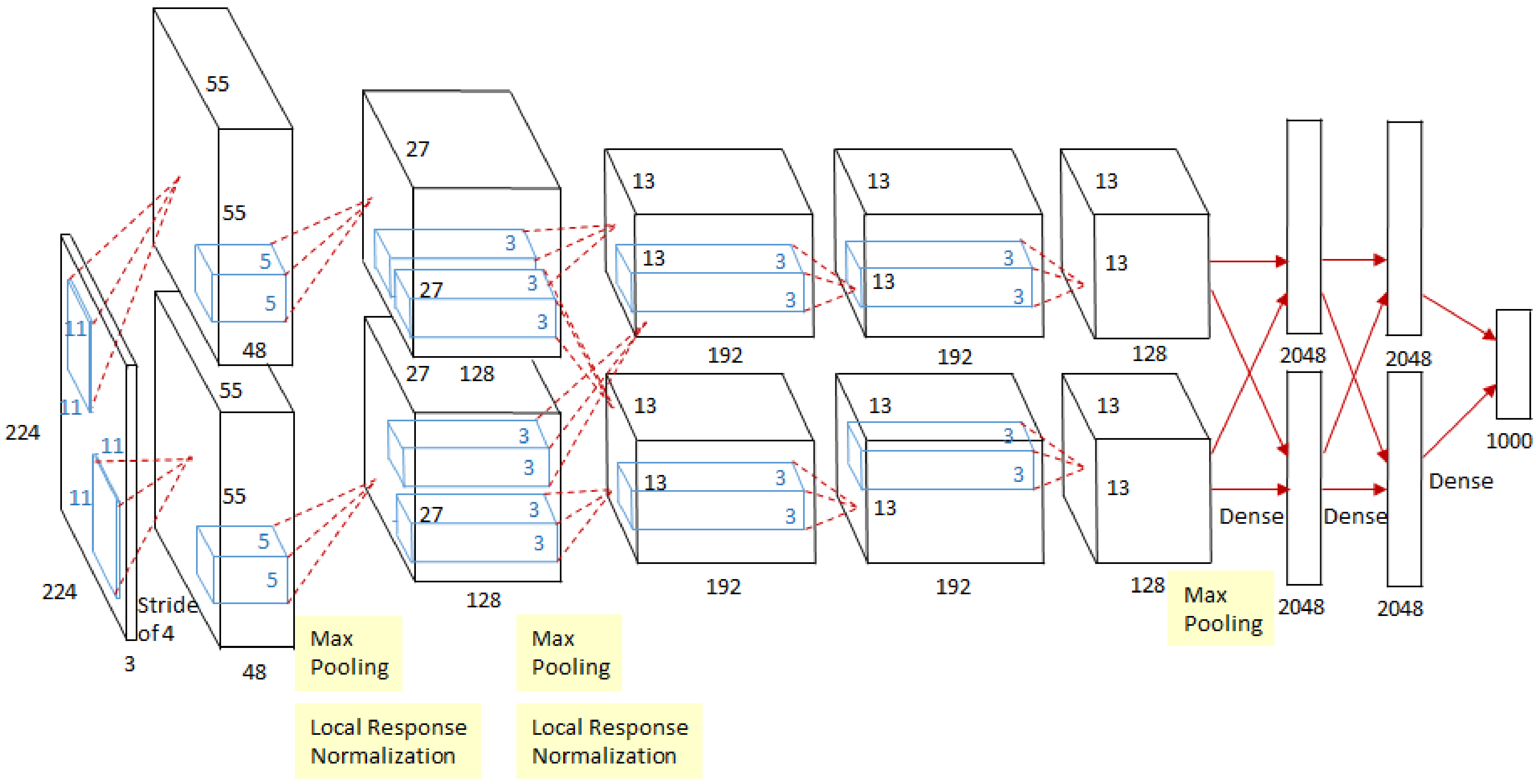


(a) Standard Neural Net (b) After applying dropout.

Data Augmentation in AlexNet

- Take random 224x224 crops of a 256x256 image, plus their horizontal reflections. Increases training set size by a factor of $32^2 \times 2 = 2048$.
- Add random factors to RGB values to simulate variations in lighting.
- These steps help the network generalize better.

AlexNet Architecture



All hidden layers were split in two and trained on different GPU boards due to GPU memory limitations.

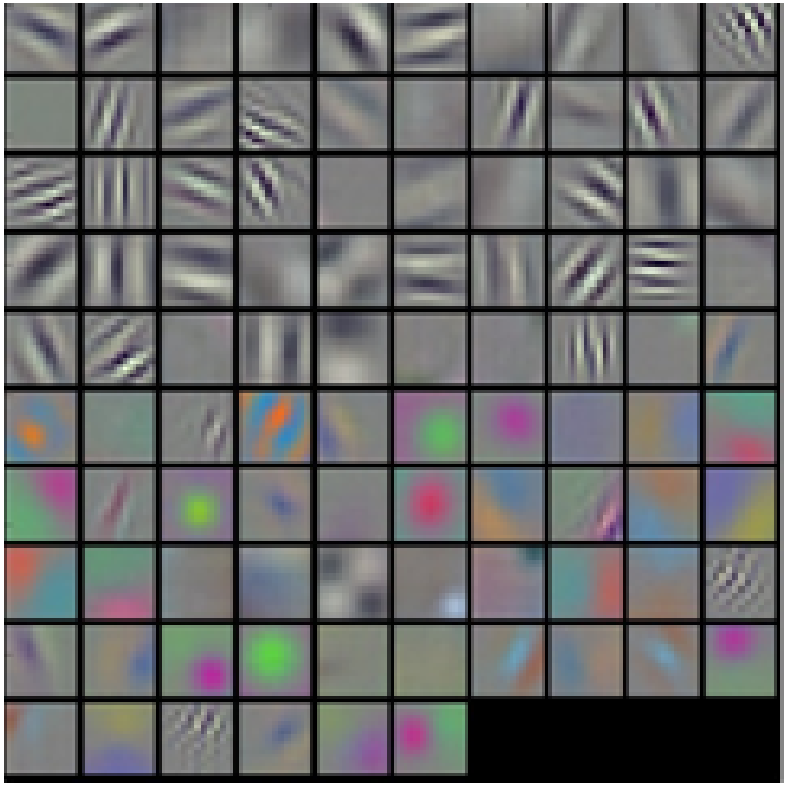
AlexNet Layer 1 Kernels

AlexNet's 96 11x11 layer 1 kernels.

First 48 trained on GPU 1 look for edges.

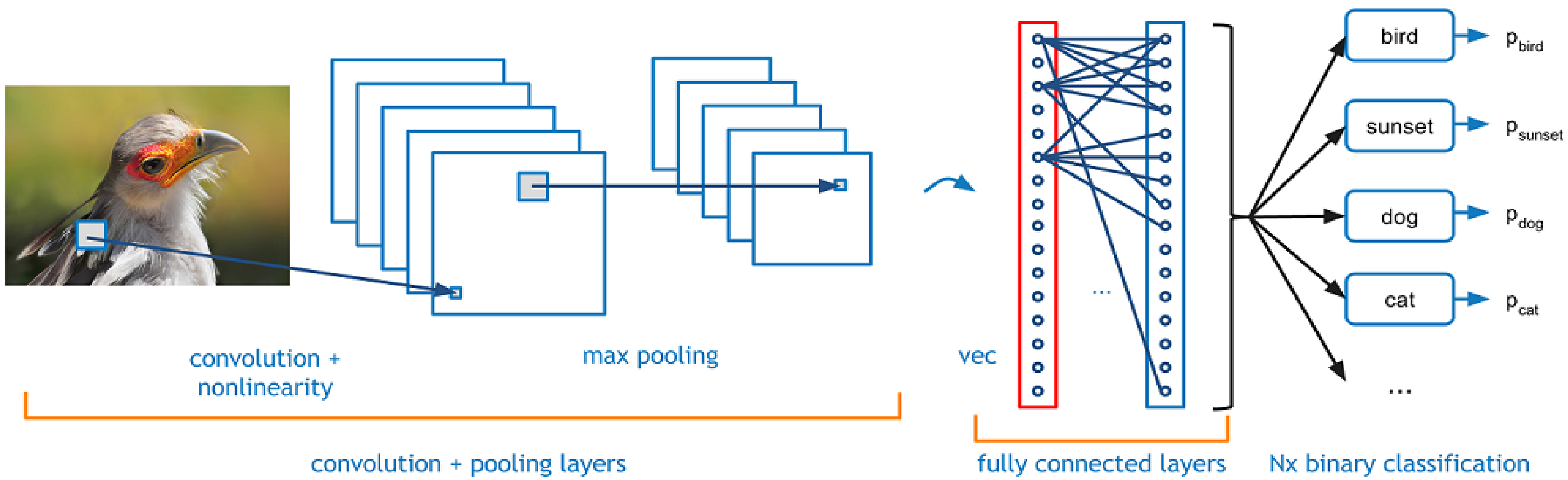
Second 48 trained on GPU 2 look for color.

This separation is a natural consequence of the normalization terms in the early layers.



Visualizations of filters

Generic Object Recognition CNN



https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

After AlexNet

- AlexNet had 8 layers: 5 convolutional and 3 fully connected.

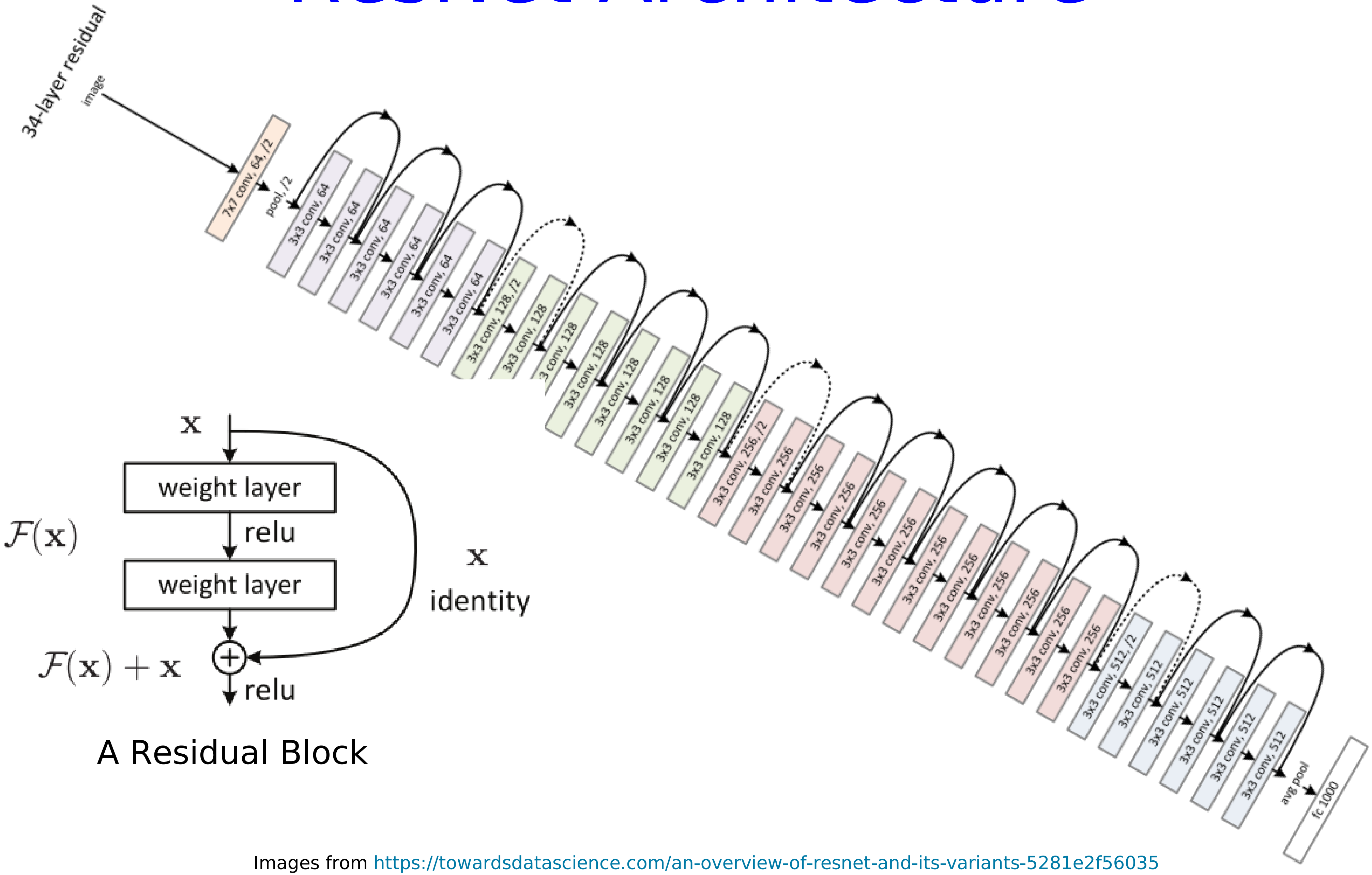
- In 2015 Microsoft won the ILSVRC using a deep neural network with 100 layers.

- By the end of the ILSVRC in 2017, the best entrants were seeing accuracies of over 95% (error rate < 5%).

Residual Blocks

- Residual blocks were introduced in ResNet:
  - For really deep networks, it’s hard for the error signal to propagate backwards through many layers.
  - Solution: add shortcut connections, e.g., from layer i to layer i+2, so that error can back-propagate more quickly.
  - A residual block contains hidden layers with a shortcut connection.

ResNet Architecture



A Residual Block

Images from https://towardsdatascience.com/an-overview-of-resnet-and-its-variants-5281e2f56035

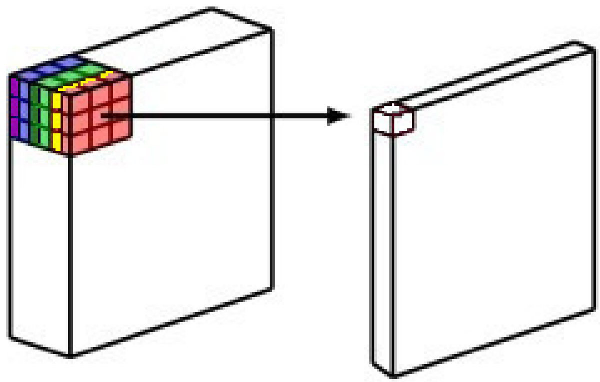
Mobile Implementations

- People want to implement computer vision on mobile phones. Networks must be reduced in size.

- Various architectures explore ways to reduce the size of the network and the number of multiply-add operations.
  - Separable convolutions
  - Bottlenecks

- Examples: MobileNet, SqueezeNet

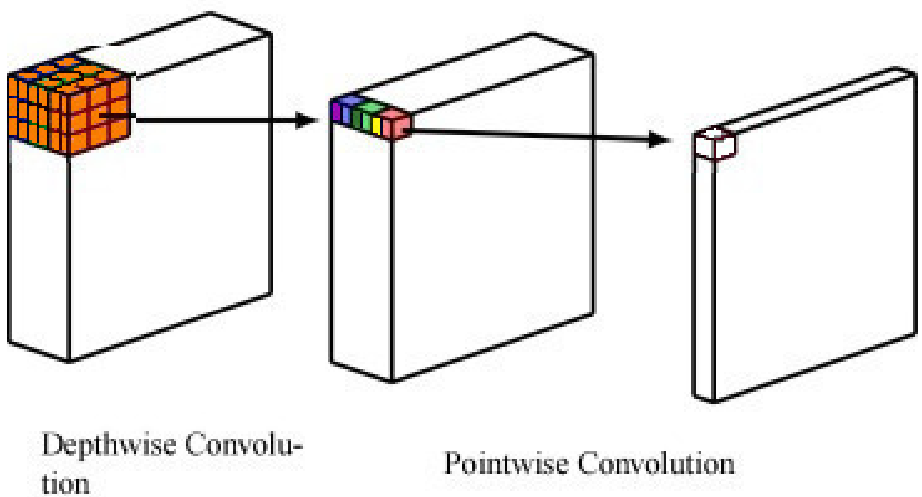
Separable Convolutions



(a) Conventional Convolutional Neural Network

3x3 kernel covering 6 channels

3x3x6 = 54 weights



(b) Depthwise Separable Convolutional Neural Network

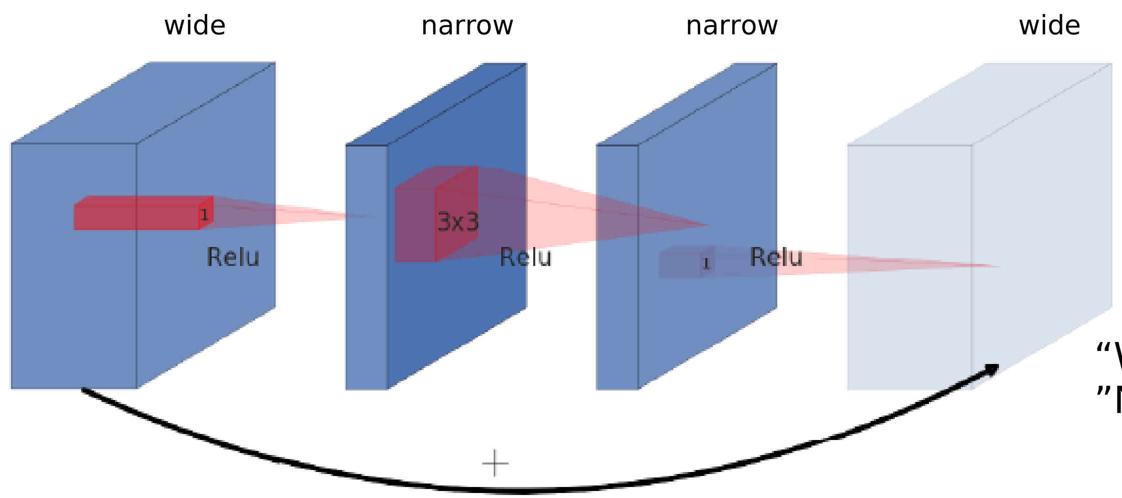
One 3x3 kernel applied
to all 6 channels
(depthwise convolution)

Linear weighted
combination of the 6
results (pointwise
convolution)

3x3 + 6 = 15 weights

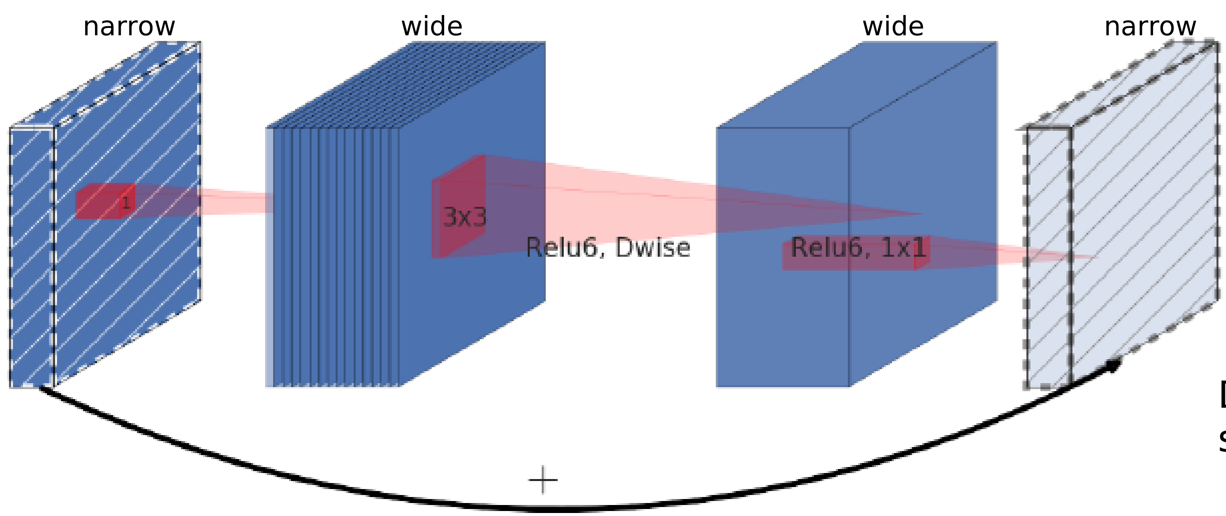
Image modified from
https://www.sciencedirect.com/science/article/pii/S0168169918318696

Bottlenecks with Residuals



MobileNet:
residual
bottleneck

“Wide” layers have many channels.
”Narrow” layers have few channels.



MobileNetV2:
inverted residual
bottleneck

Depthwise convolution applies the same 3x3 kernel to all channels.

Images from https://towardsdatascience.com/mobilenetv2-inverted-residuals-and-linear-bottlenecks-8a4362f4ffd5

PyTorch Vision Models

- PyTorch contains several pre-trained object recognition models, including AlexNet, ResNet, Inception, VGG, and MobileNetV2.

- Look in torchvision.models for a list.

- Models are trained on the ImageNet dataset.

MobileNetV2 on Cozmo

- See the course's demos folder.
- Uses pre-trained MobileNetV2 model from torchvision.models.
- Feeds a 224x224 Cozmo camera image into the network and reports the top 5 labels.

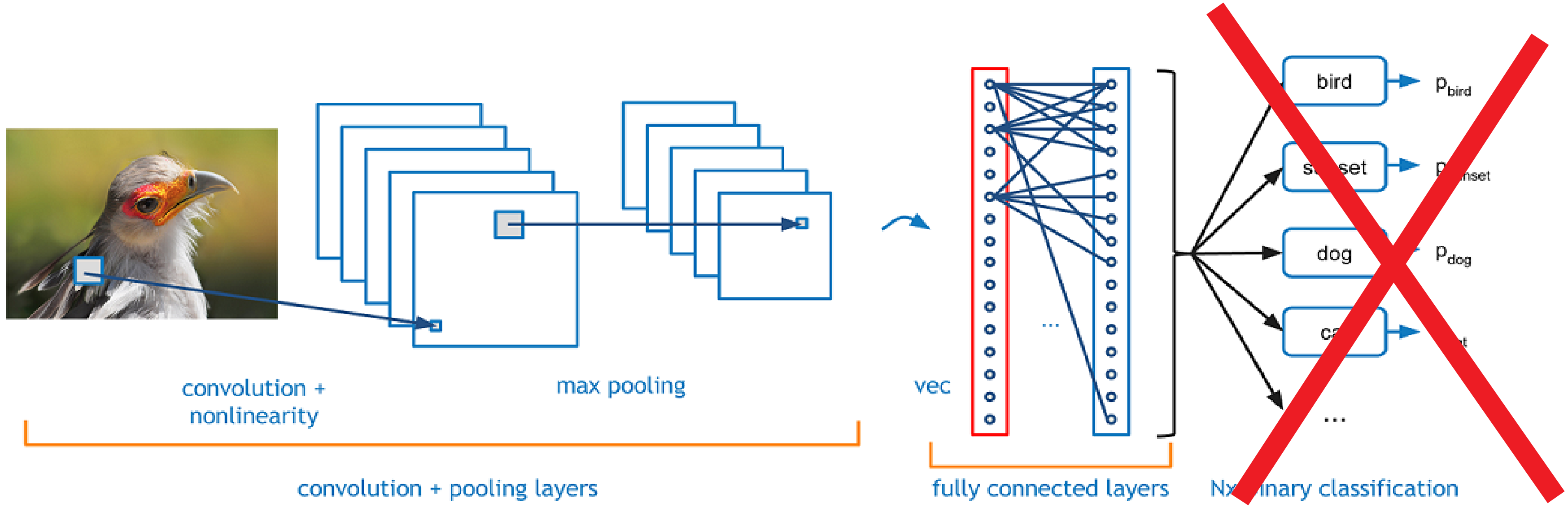
Transfer Learning

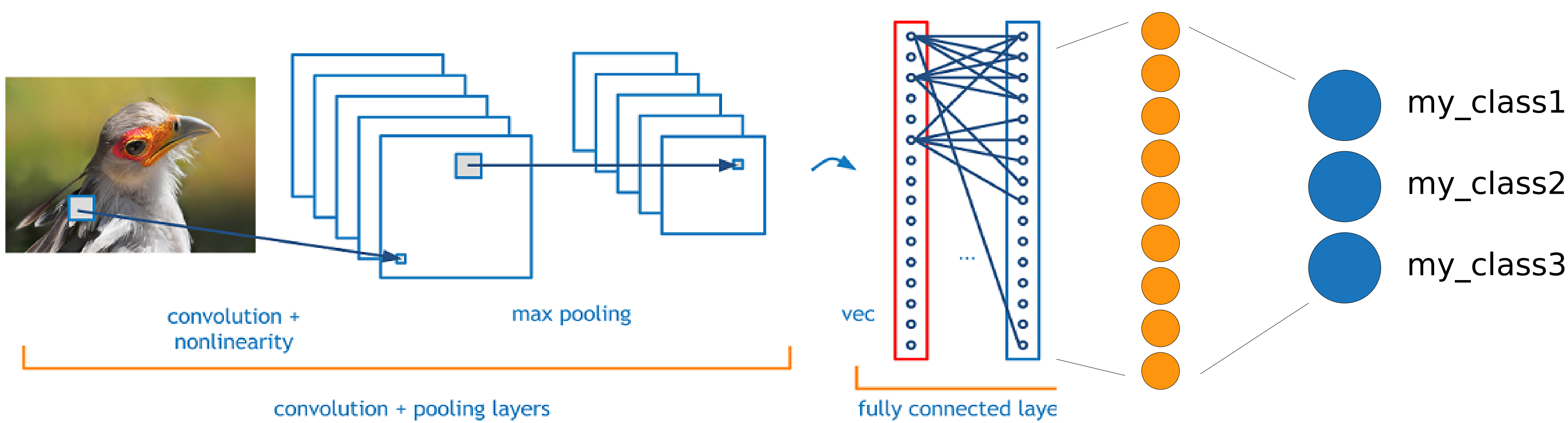
- How can we quickly train a visual classifier for a new object class?

- Use the last hidden layer of a pre-trained ImageNet classifier as a feature vector.

- Train a classifier on the new categories using just 1-2 layers of trainable weights, or just use k-nearest neighbor.

- This is how Teachable Machine works.


convolution +
nonlinearity
max pooling
convolution + pooling layers
vec
fully connected layers
bird
p bird
dog
p dog
...


convolution +
nonlinearity
max pooling
convolution + pooling layers
vec
fully connected laye
my_class1
my_class2
my_class3

Teachable Machine

https://teachablemachine.withgoogle.com