15-494/694: Cognitive Robotics

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Lecture 13:
Convolutional Neural Nets

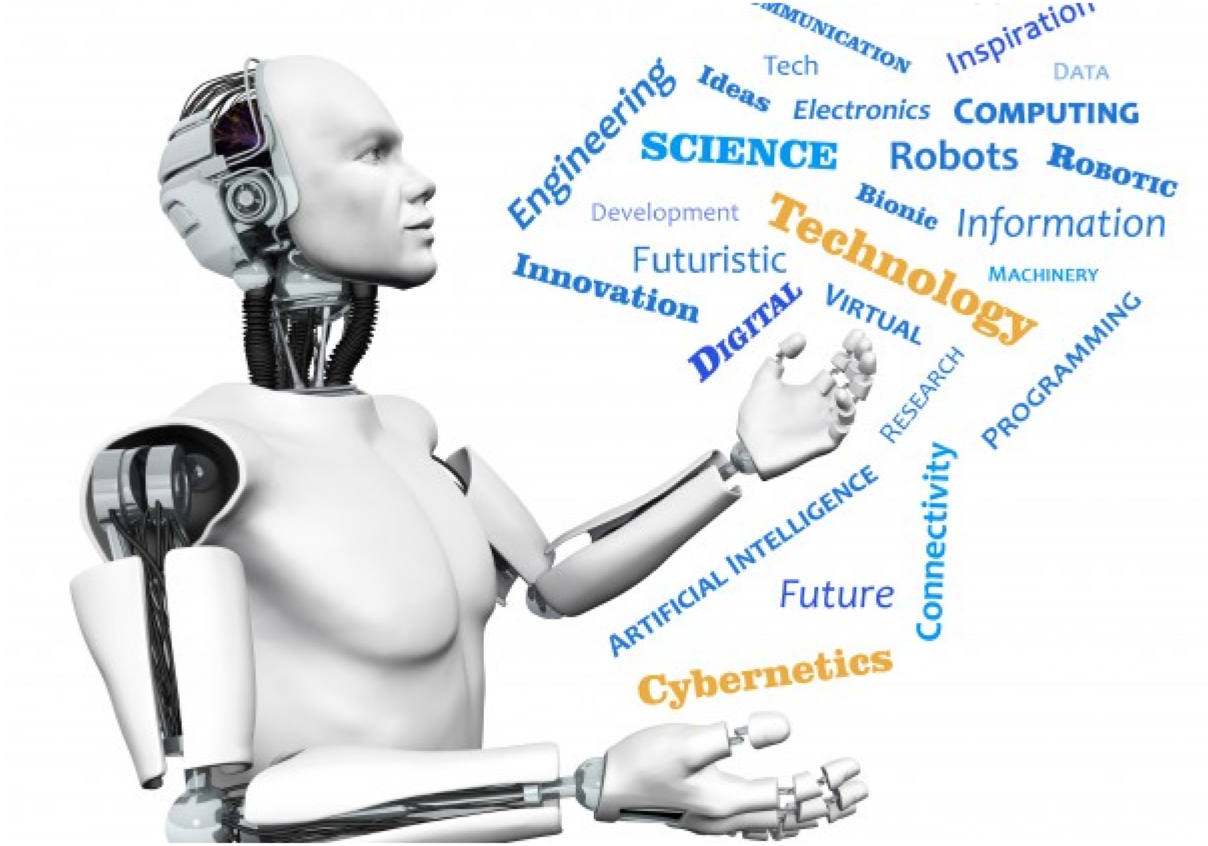
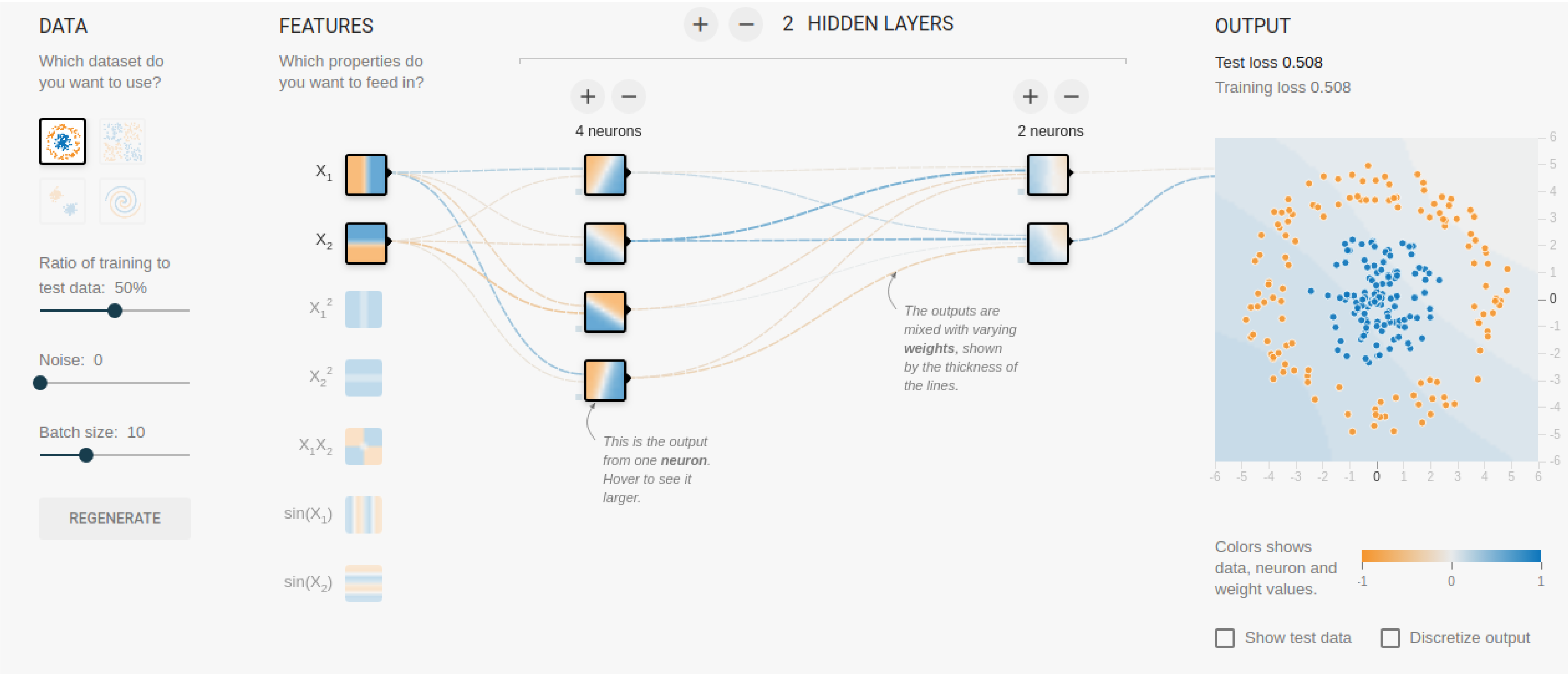


Image from http://www.futuristgerd.com/2015/09/10

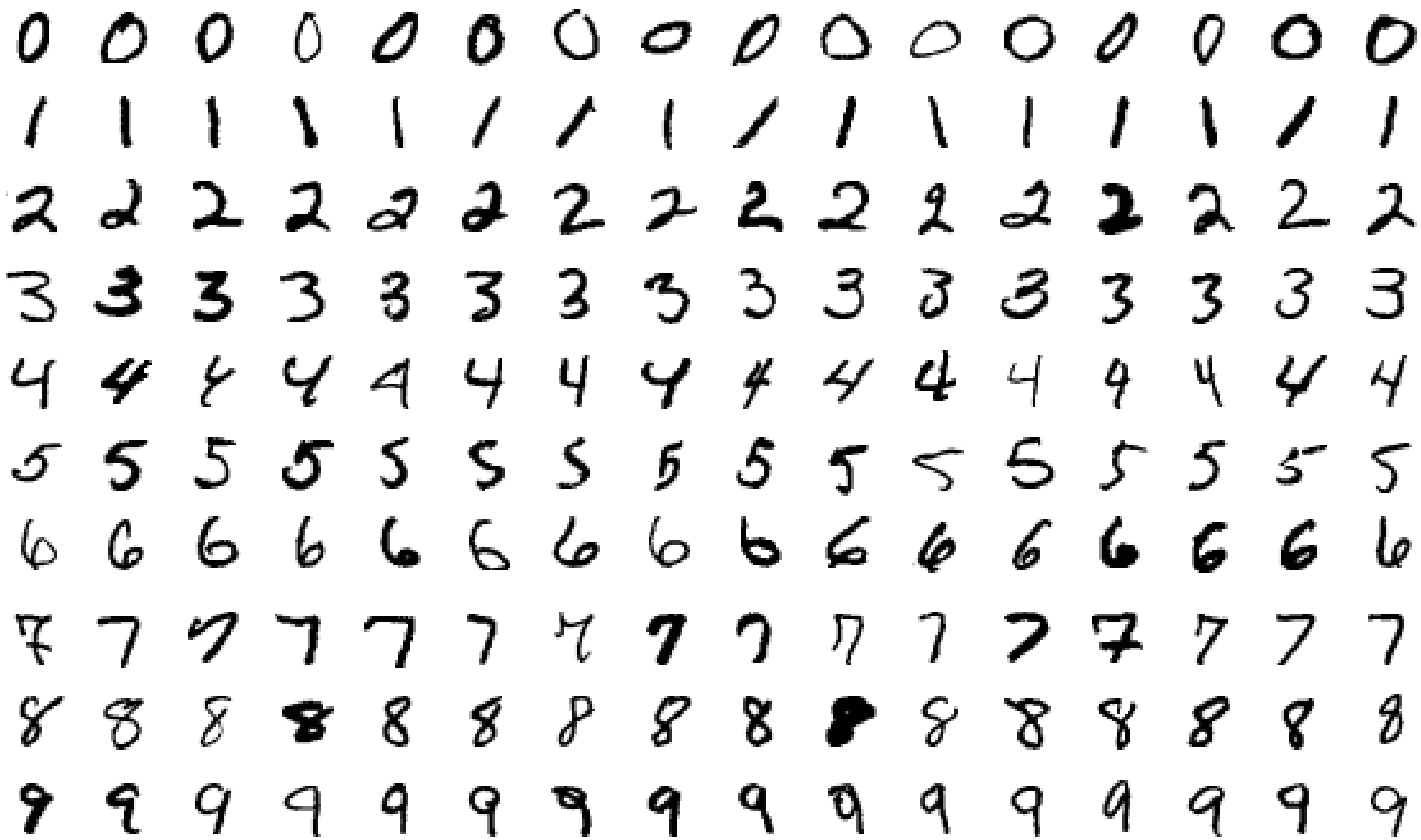
TensorFlow Playground

Google's interactive backprop simulator.
https://playground.tensorflow.org

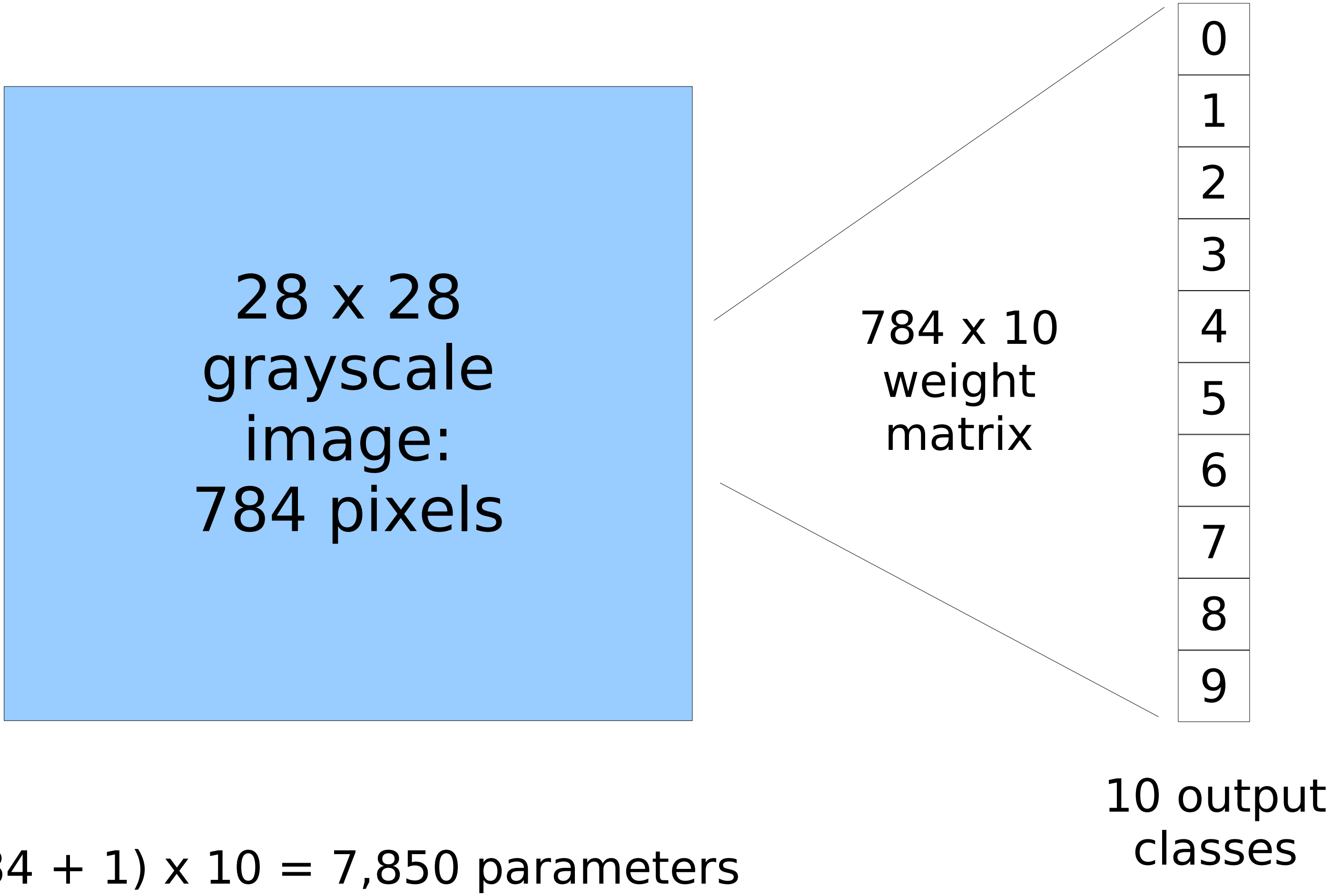


MNIST Dataset

- 60,000 labeled handwritten digits
- 28 x 28 pixel grayscale images



Recognition With a Linear Network



(784 + 1) x 10 = 7,850 parameters

PyTorch

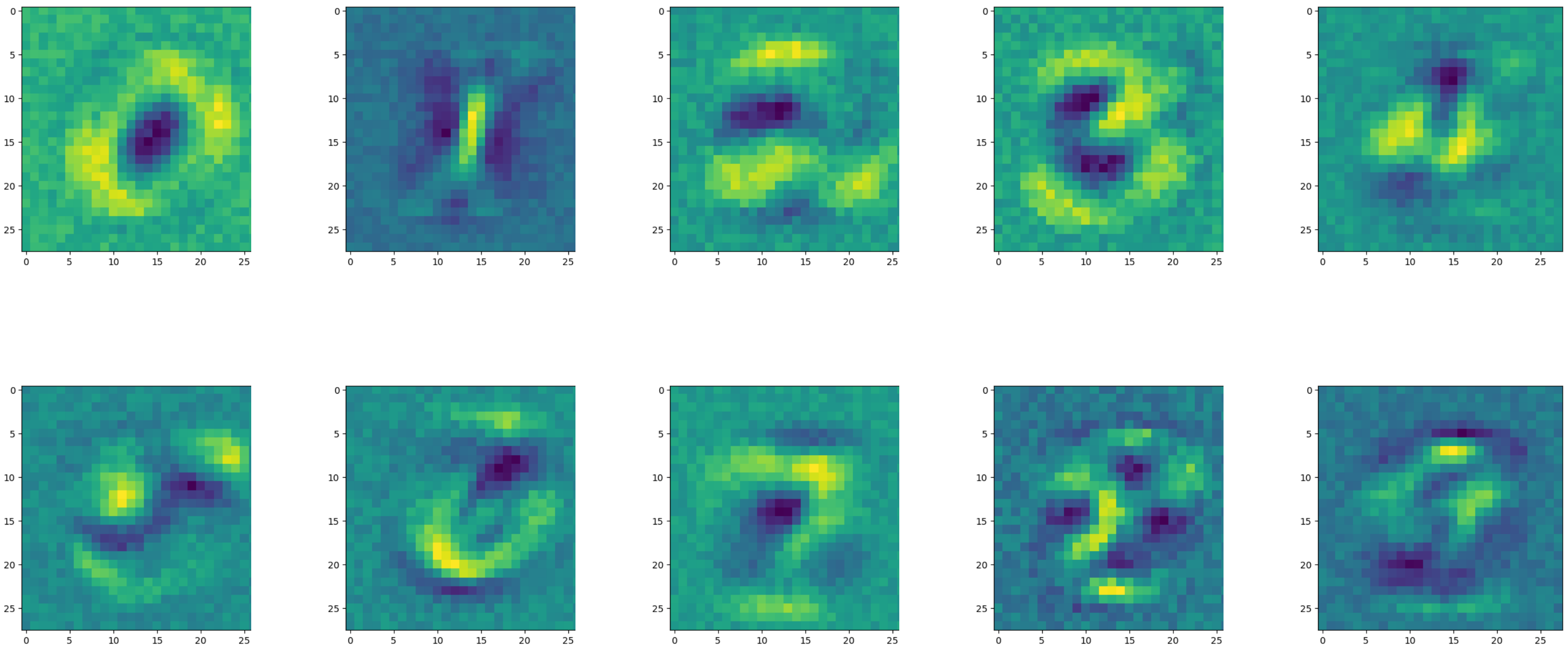
- Python package for tensor manipulation and vectorized computations, including neural net learning.
  - Replacement for numpy
  - Optimized for GPUs
- Tensors are multi-dimensional arrays, similar to numpy's ndarray structure.
- Code can run on either CPU or GPU.

Defining the Model mnist1

```
class MultiLogisticModel(nn.Module):

  def __init__(self, in_dim, out_dim):
    super(MultiLogisticModel, self).__init__()
    self.linear = nn.Linear(in_dim, out_dim)

  def forward(self, x):
    out = self.linear(x)
    return out
```

```
model = MultiLogisticModel(28*28, 10)
```

Learned Weights to Output Units

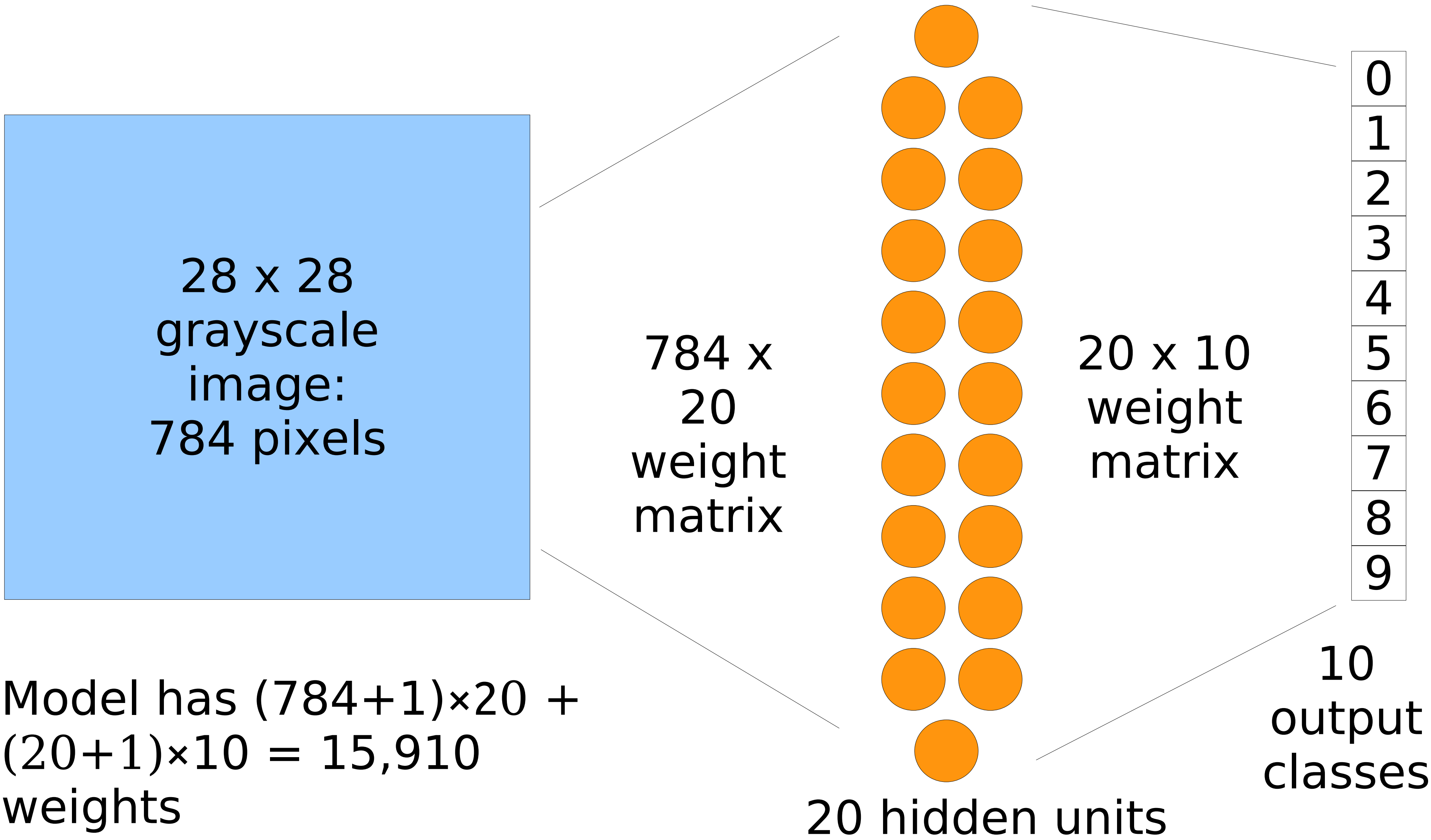


Training set performance: 89% correct.

Batch Size

- An *epoch* is one pass through all the training data.
- With a large training set (60,000 images), we don't need to see all the training examples in order to estimate the error gradient.
- We set a batch size of 100 to indicate we want to do a weight update after every 100 training examples.
  - The examples need to be mixed together.
  - What if we trained on all the 2's first?

Adding A Hidden Layer



Model has (784+1)×20 + (20+1)×10 = 15,910 weights

Batch Normalization

- We want the activity patterns in each layer to have nice statistical properties (mean and variance) because this helps speed up learning.

- But each weight update changes the statistical distribution.

- Solution: “batch normalization”, a trick for making the distributions more uniform.

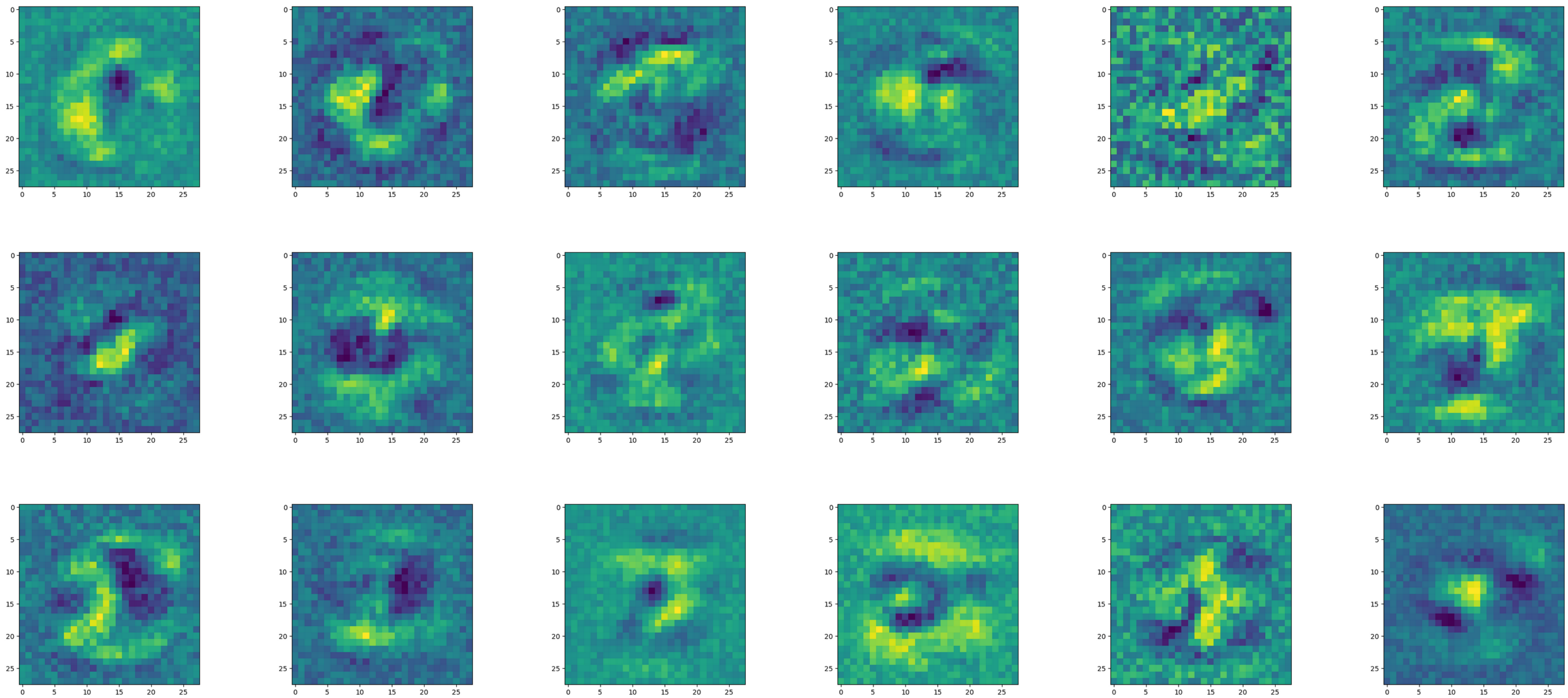
- Built in to PyTorch.

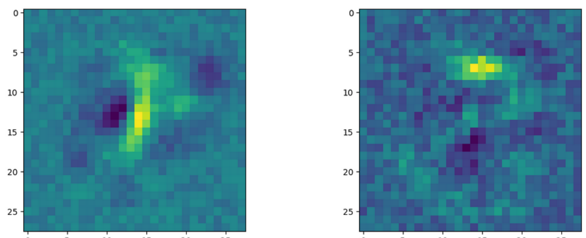
Defining the Model mnist2

```
class OneHiddenLayer(nn.Module):

  def __init__(self, in_dim, out_dim, nhiddens):
    super(OneHiddenLayer, self).__init__()
    self.network = nn.Sequential(
      nn.Linear(in_dim, nhiddens),
      nn.BatchNorm1d(nhiddens),
      nn.ReLU(),
      nn.Linear(nhiddens, out_dim)
    )

  def forward(self, x):
    out = self.network(x)
    return out
```

```
model = OneHiddenLayer(28*28, 10, 20)
```

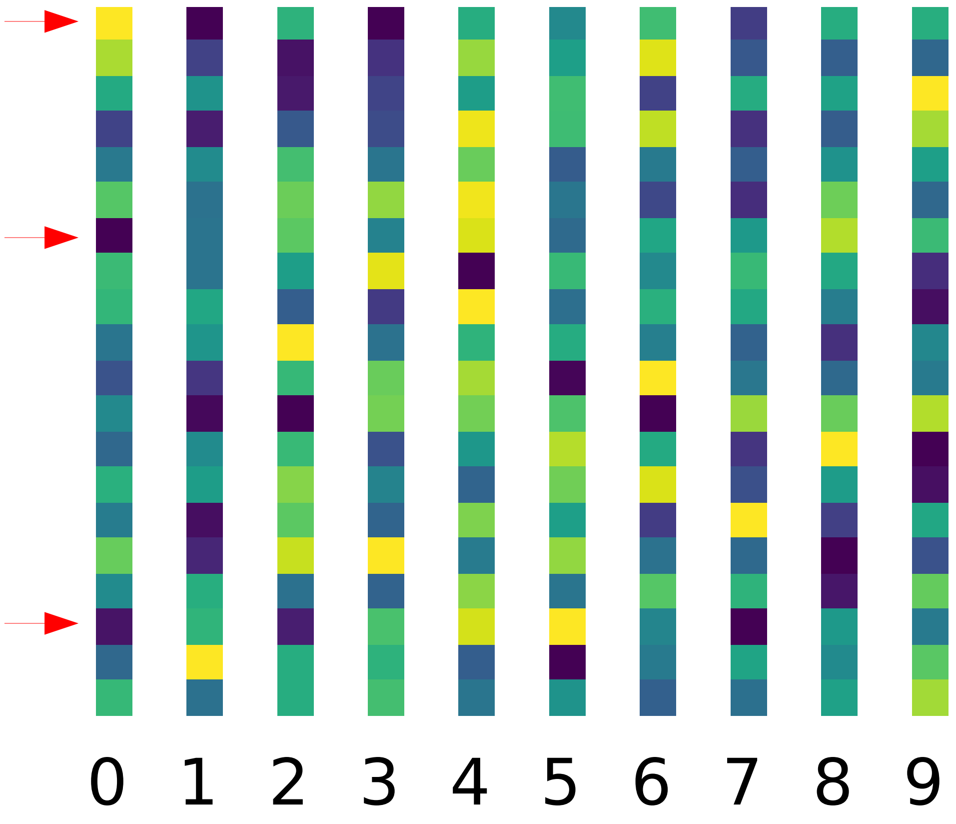
Learned Weights to Hidden Units





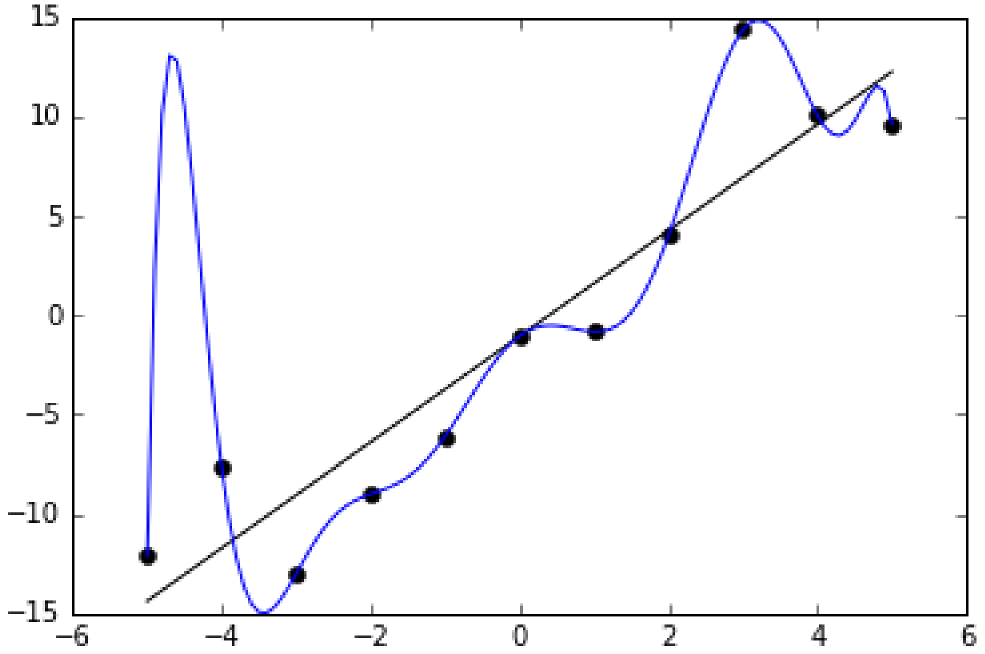
Training set performance: 91% correct.

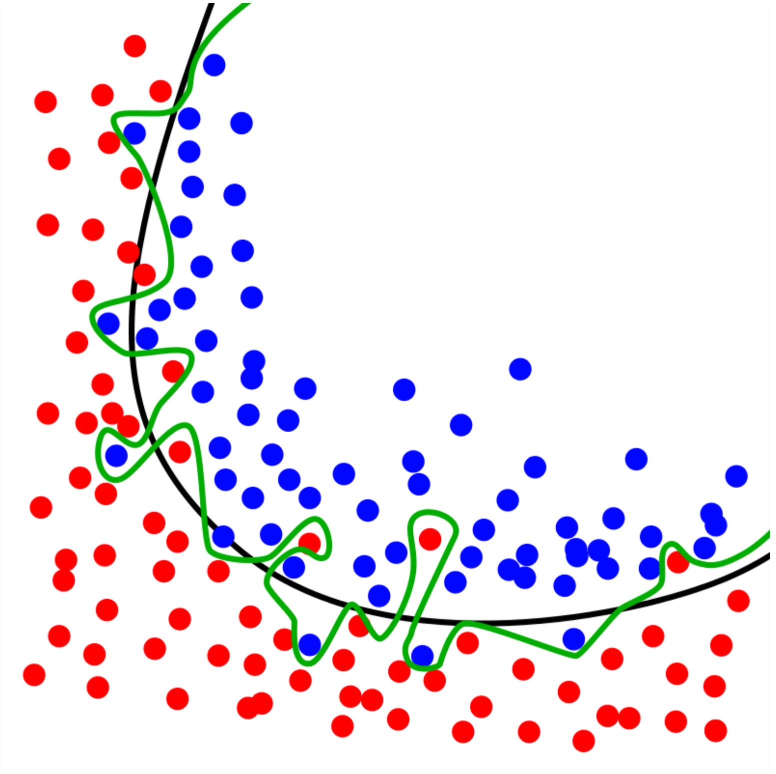
Learned Weights to Output Units



Training set performance: 91% correct.

Overfitting



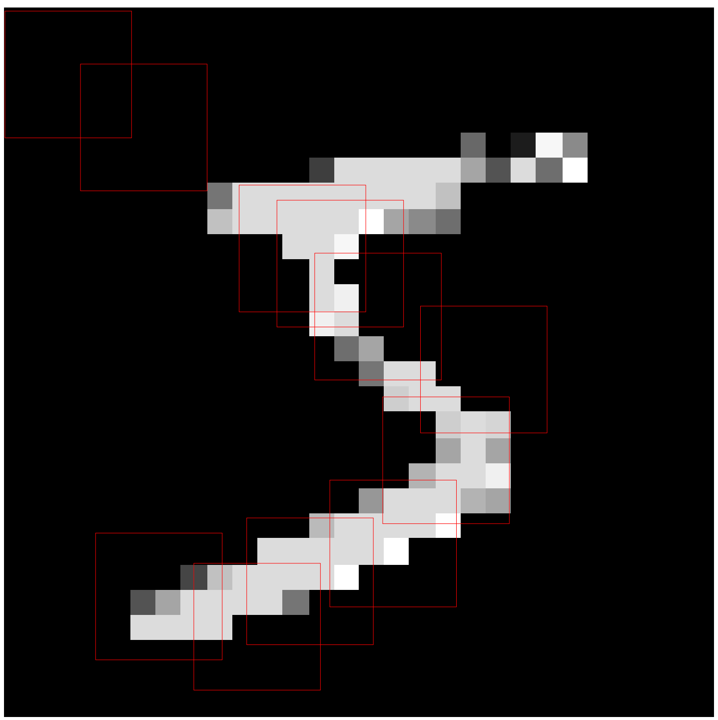


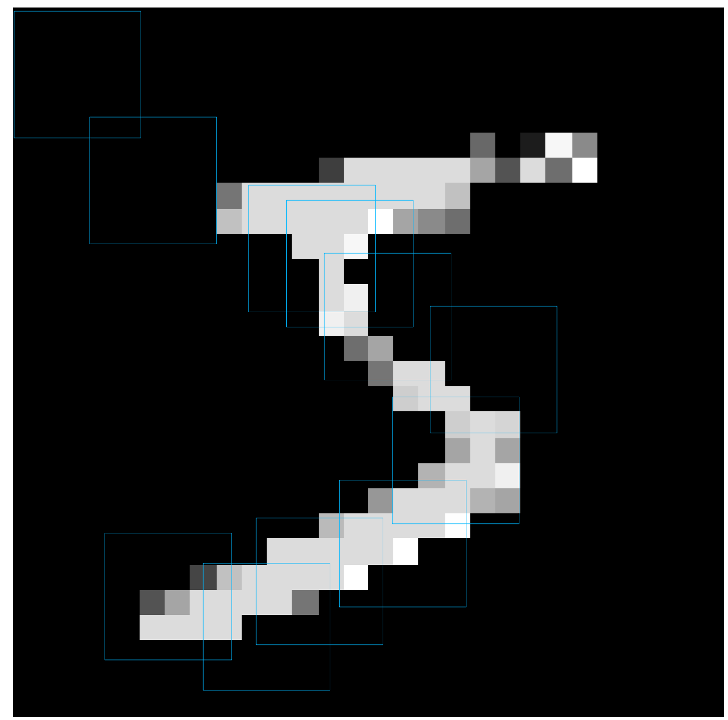
How to Avoid Overfitting

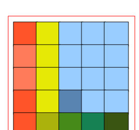
- Increase the size of the training set.
- Reduce the number of parameters:
  - Fewer hidden units
  - Shared weights (convolutional network)
- Regularization: penalize large weights to encourage making more weights be zero.
- Dropout: randomly disable some fraction of the units on every iteration.
- Early stopping:
  - Maintain a separate cross-validation set
  - Stop training when the CV error rises

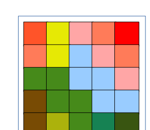
Convolutional Neural Networks

- Learn small (3x3 or 5x5) feature detectors or *kernels* that can be applied anywhere in the image.

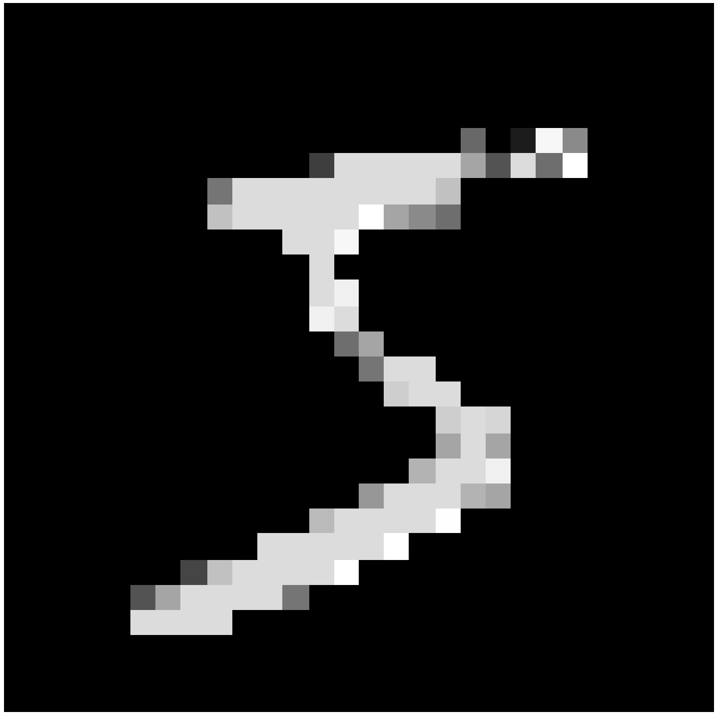




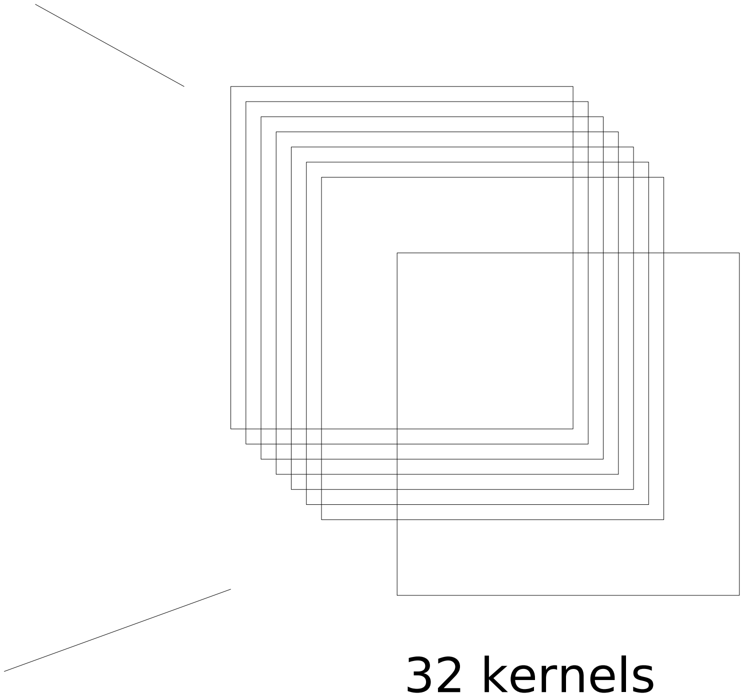
Feature 1: 

Feature 2: 

Feature Maps



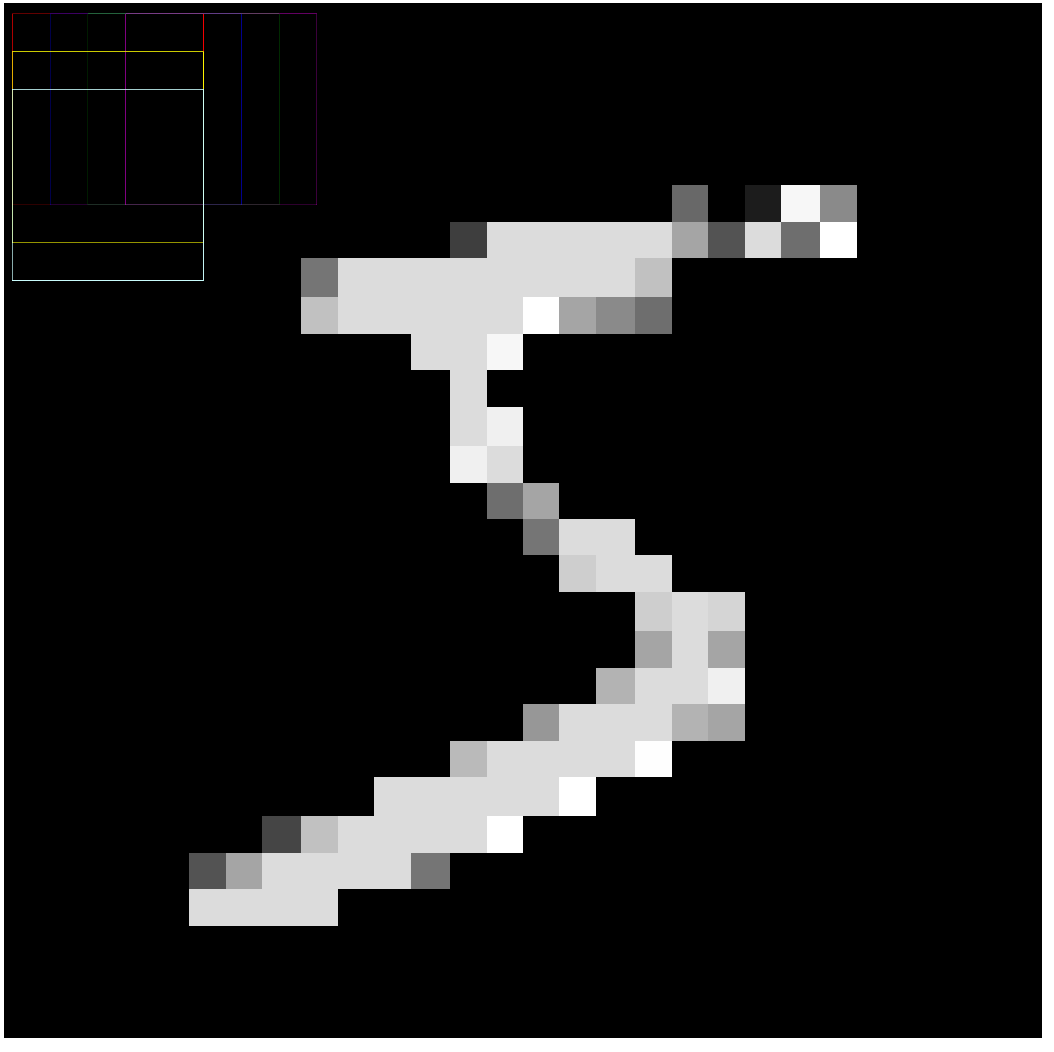
28 x 28 image



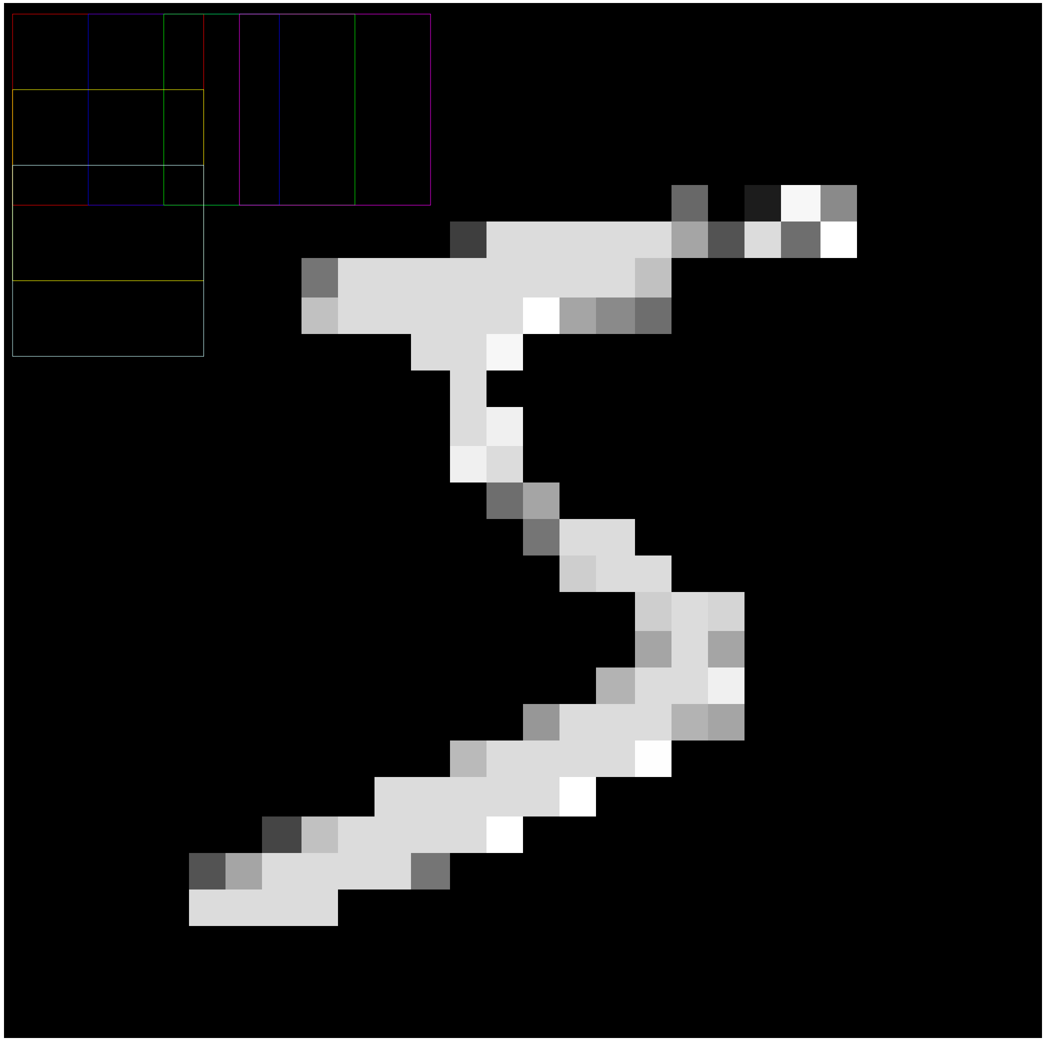
32 kernels
5x5 pixels
stride 1
padding 1

\# weights = 32 x (5x5+1) = 832 (small!)
\# connections = 32 x (26x26) x (5x5+1) = 562,432

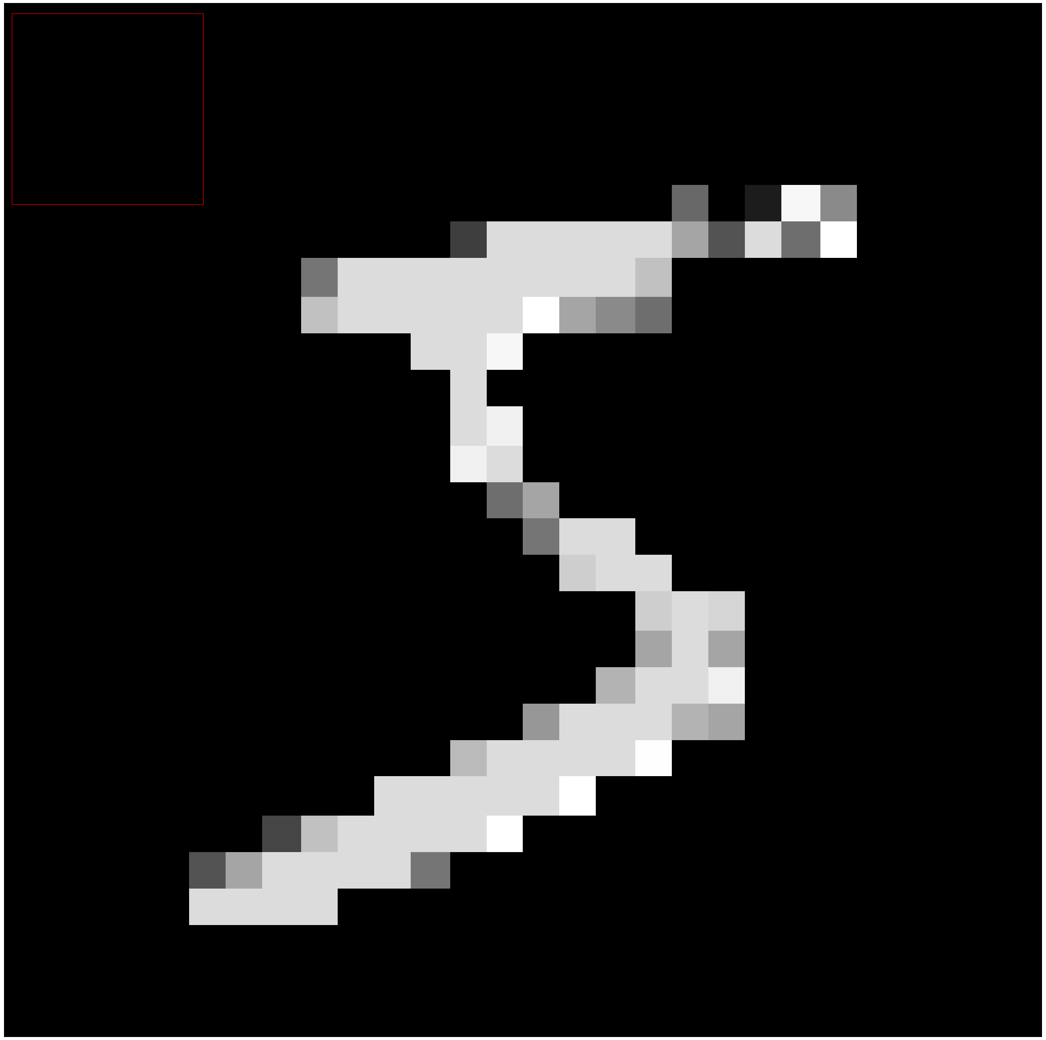
Stride 1



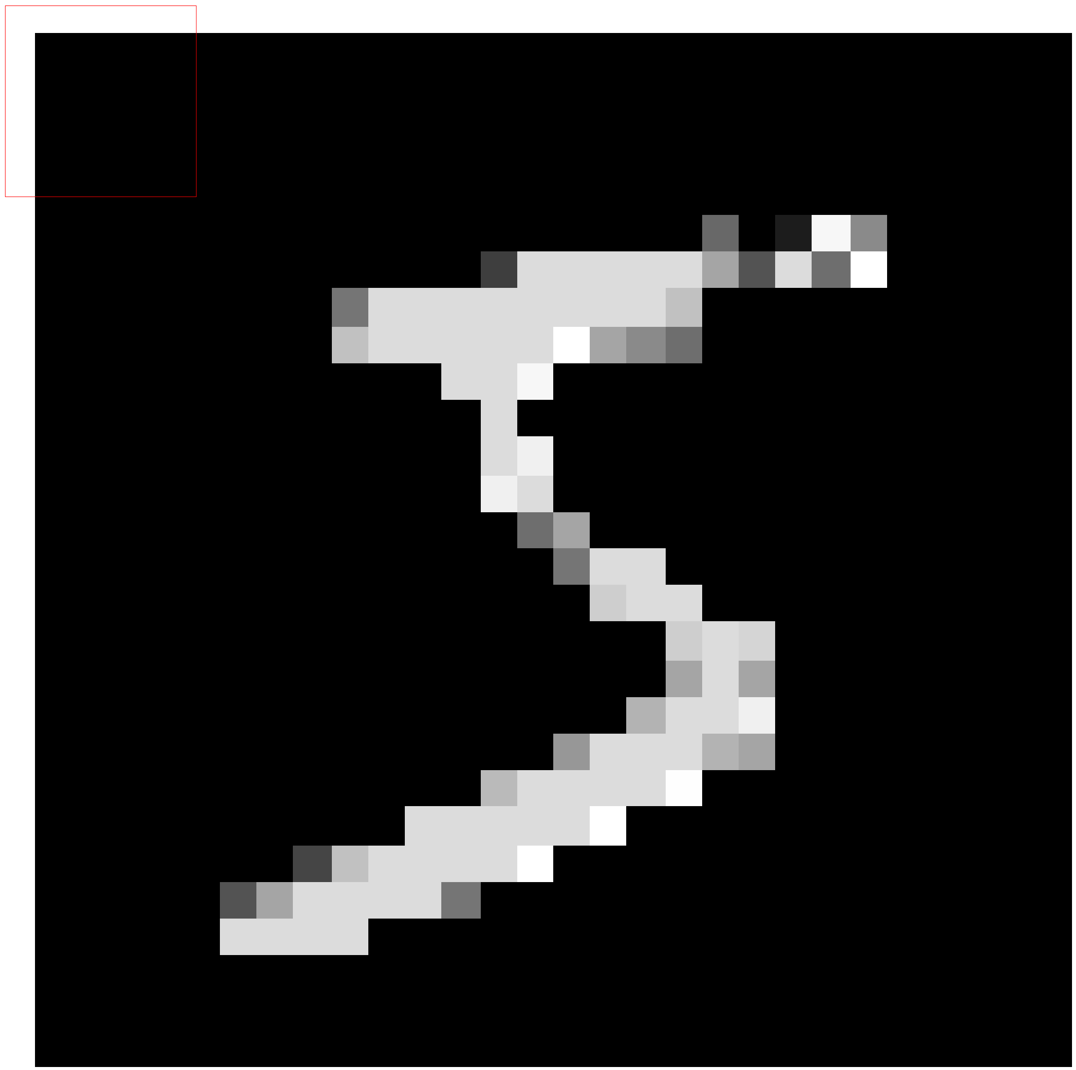
Stride 2



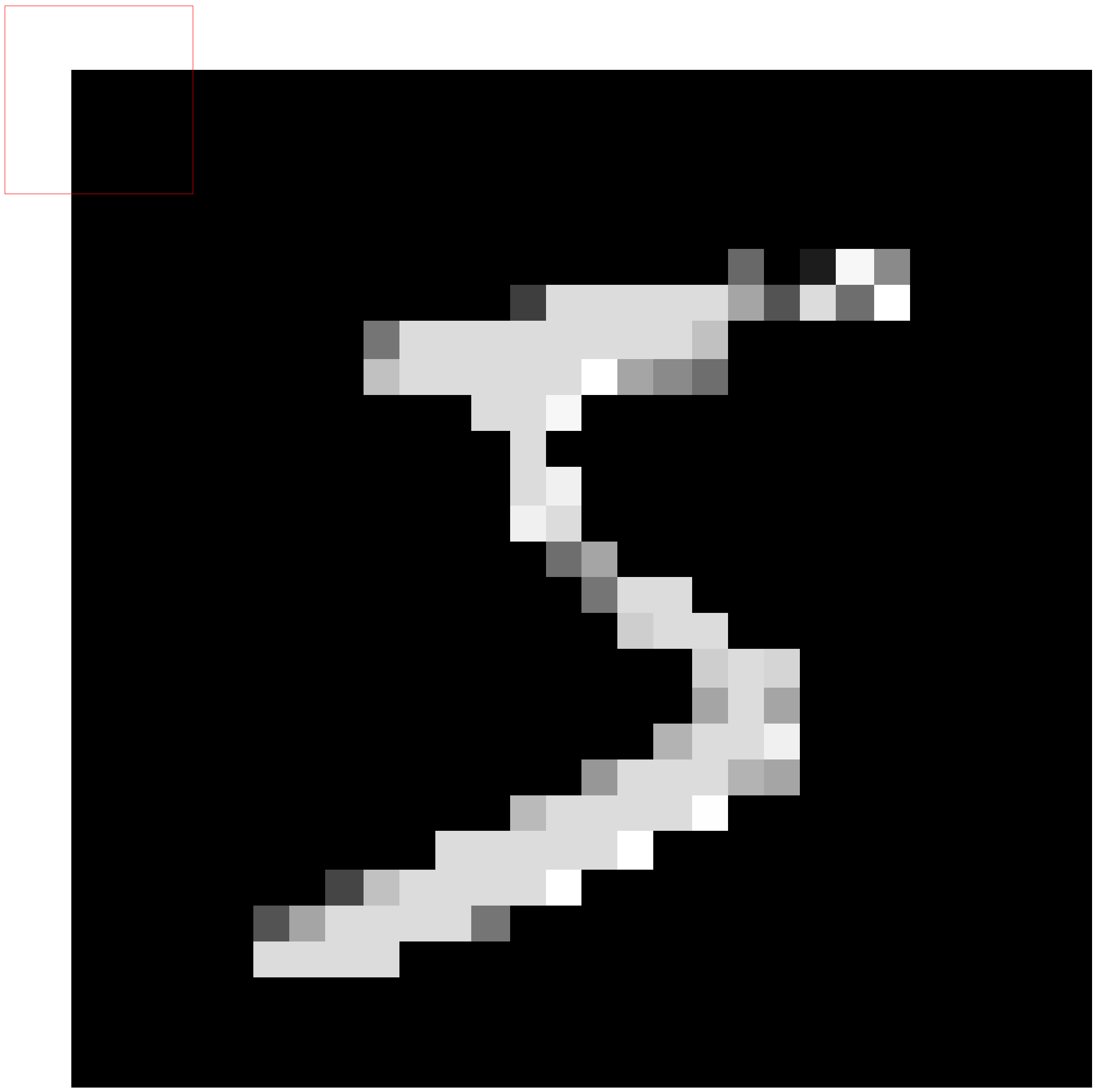
First Kernel: Padding 0



First Kernel: Padding 1

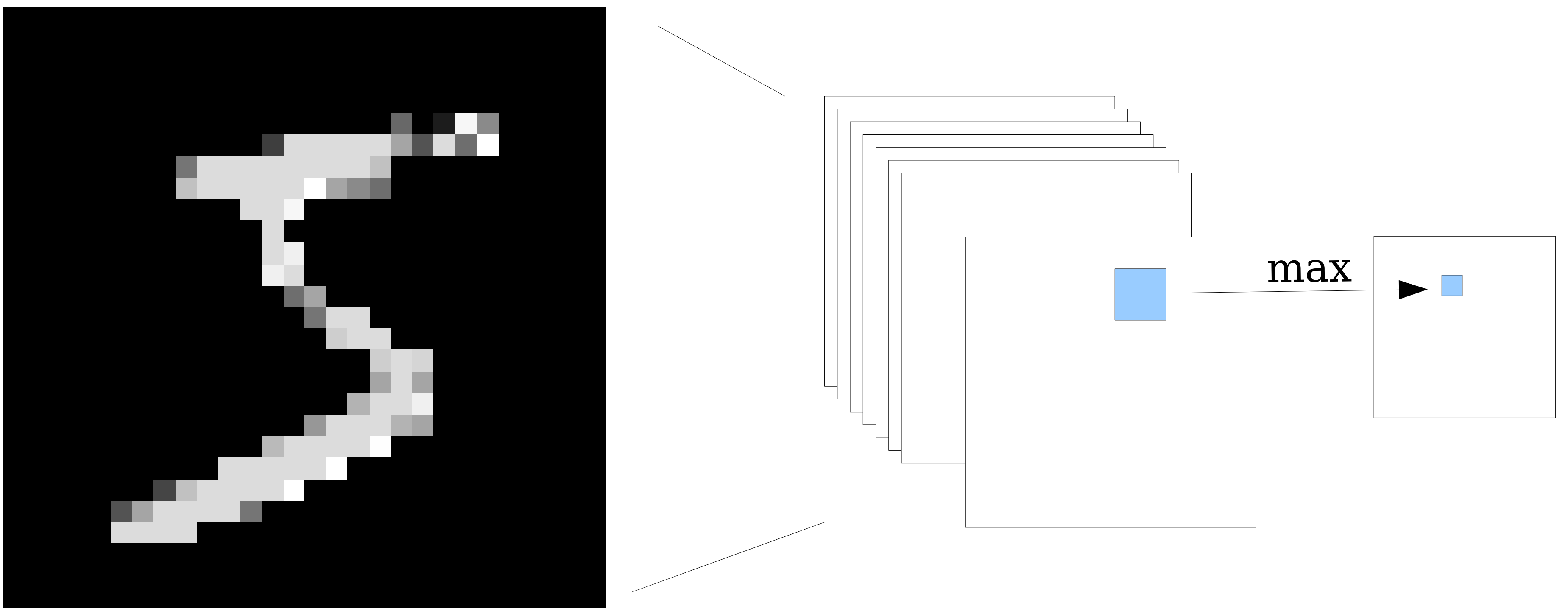


First Kernel: Padding 2



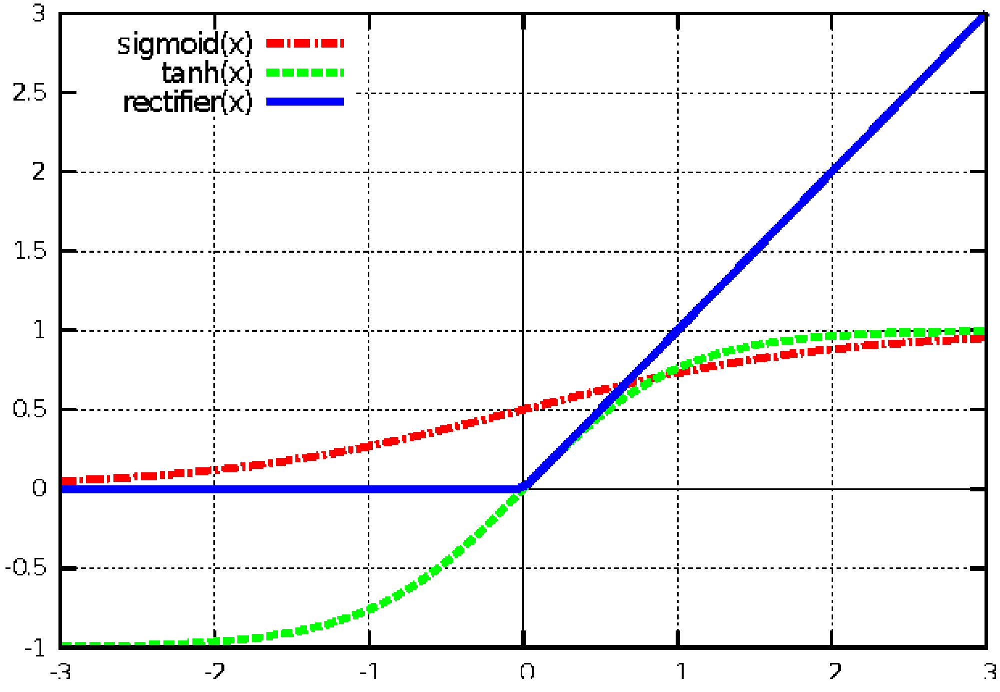
Max Pooling

- We might not care exactly where a feature appears in the image.
- Downsampling by max pooling reduces the number of units and connections.



Choice of Activation Function

- Sigmoid and tanh were popular early on:



- Now it's more common to use ReLU: Rectified Linear Unit. g(x) = max(x,0)
  - Derivative doesn't go to zero for large x.

Choice of Loss Function

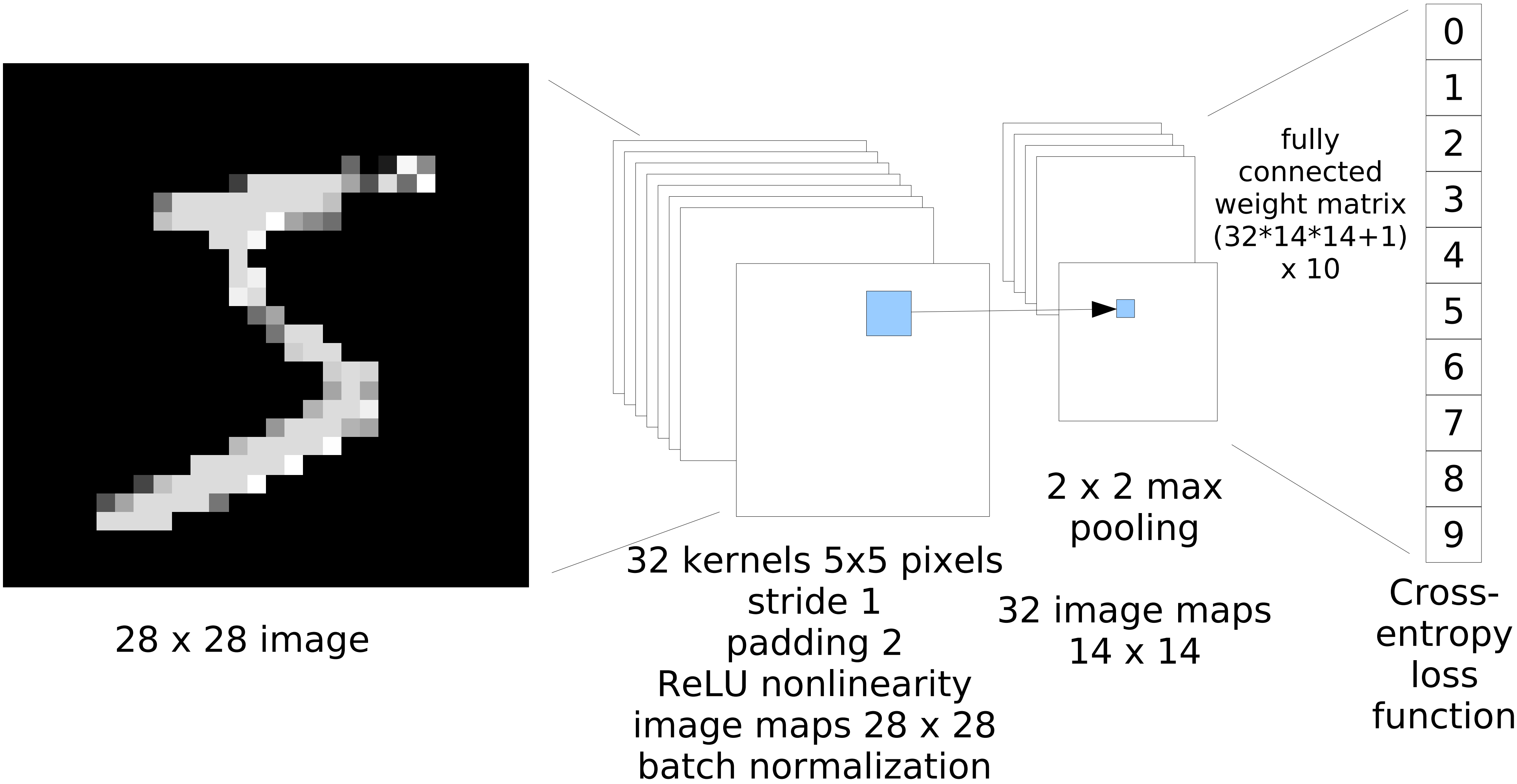
- Mean Squared Error is a general loss function but not always the best to use.

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

- If desired outputs are probabilities (values between 0 and 1), use cross-entropy instead. Heavily penalizes <u>really</u> wrong outputs.

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

MNIST With A CNN



\# parameters = 63,626
How many connections?

Accuracy on training set: 98.7%

Defining the Model mnist3

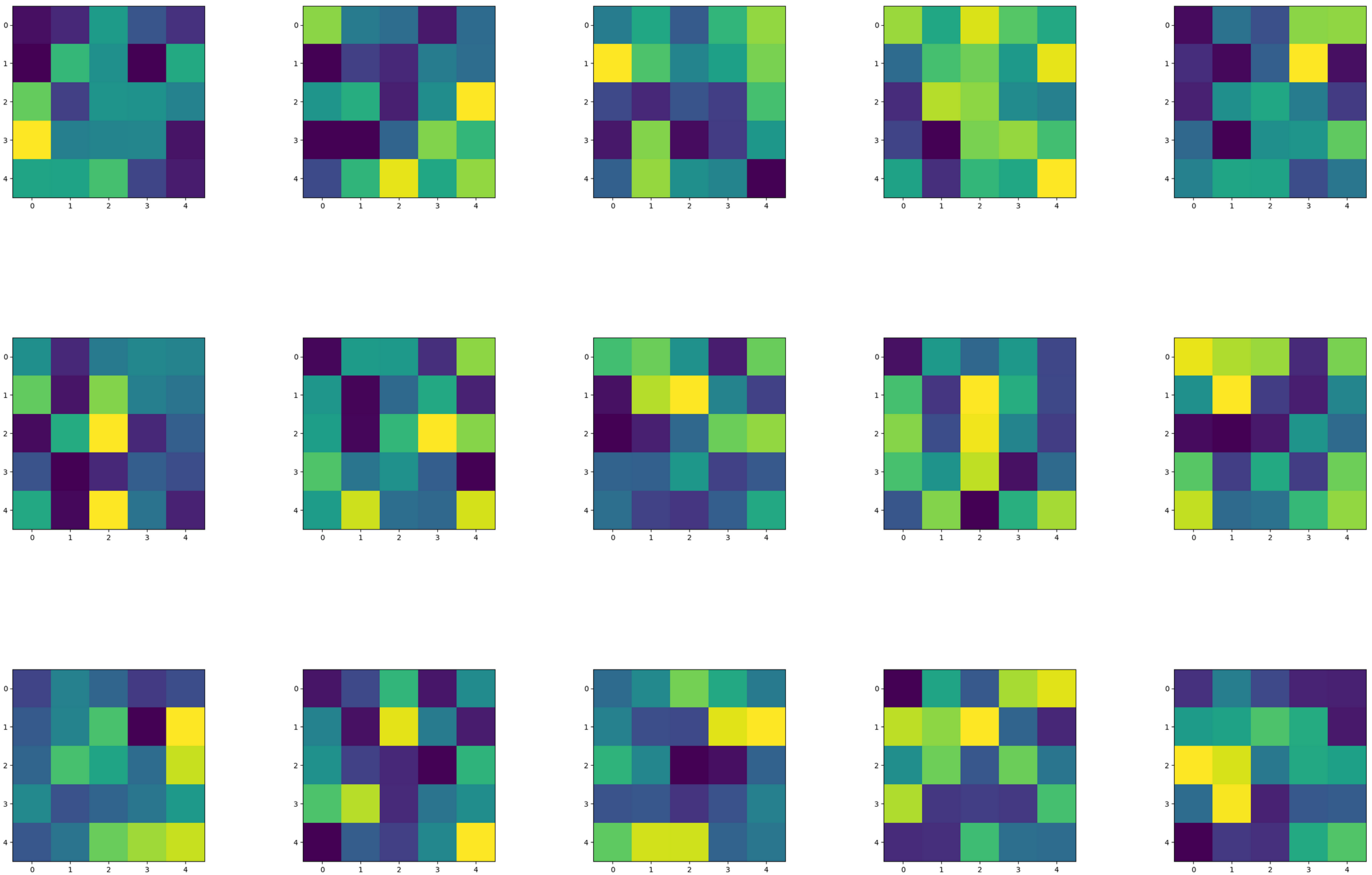
```
class OneConvLayer(nn.Module):

  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)
```

Sample Learned Kernels (32 Total)

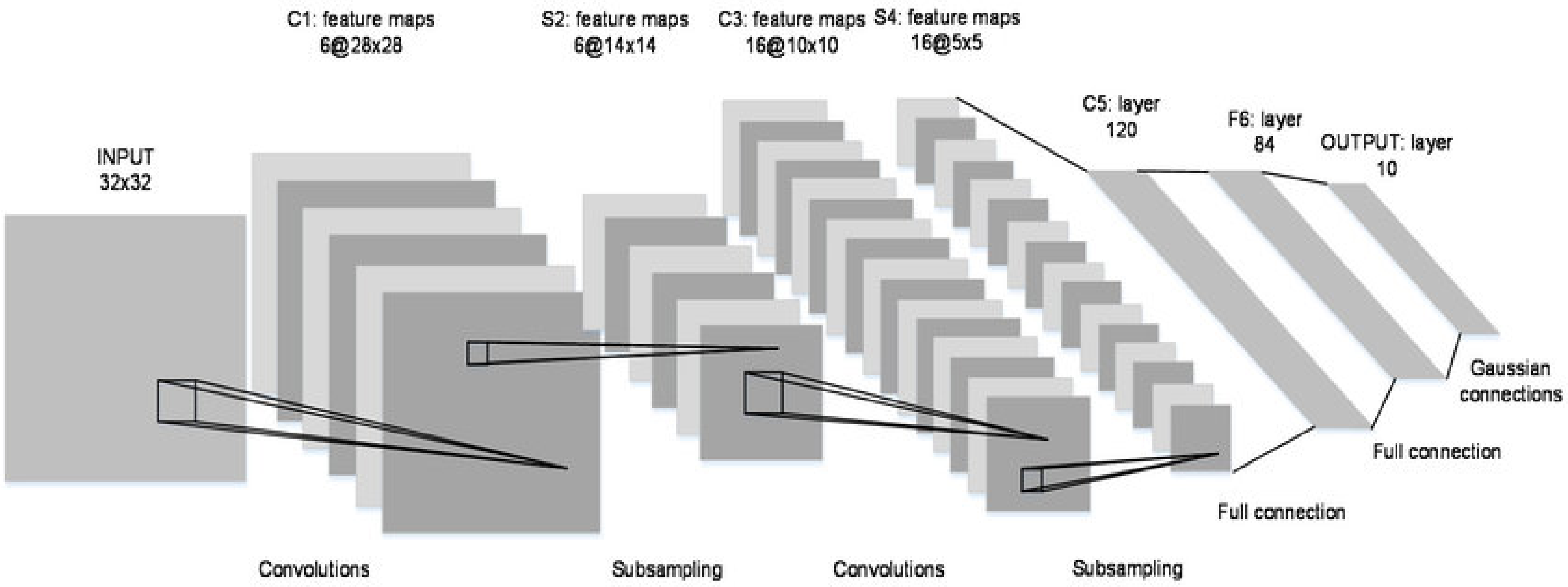


Deep Neural Networks

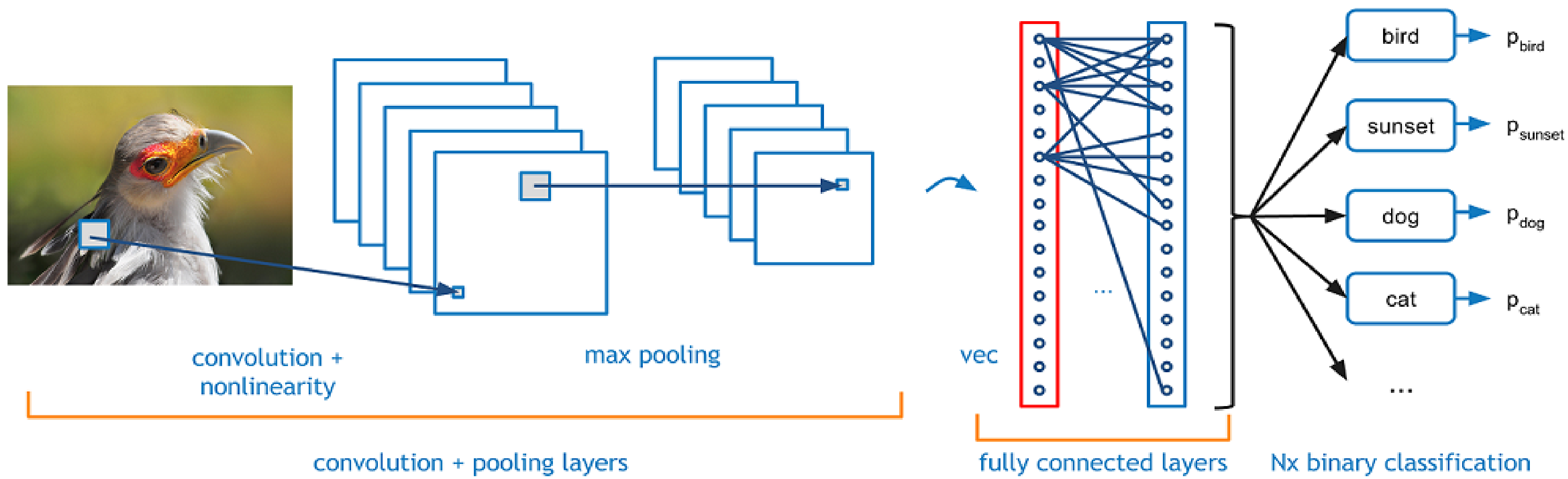
- For really hard problems (e.g., object recognition on color images) we may need many layers.
- Series of convolutional and max pooling layers, followed by some fully connected layers.
  - LeNet had 10 layers.
  - Inception V1 had 27 layers.
  - ResNet has 100 layers.
- GPUs required for training.

LeNet (Yann LuCun, 1990s)

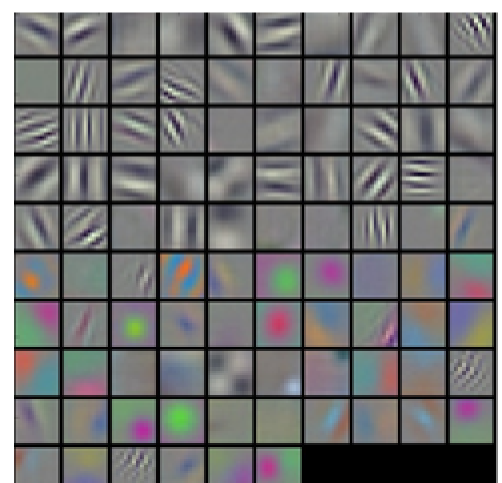
- Handwritten digit recognition



Object Recognition CNN

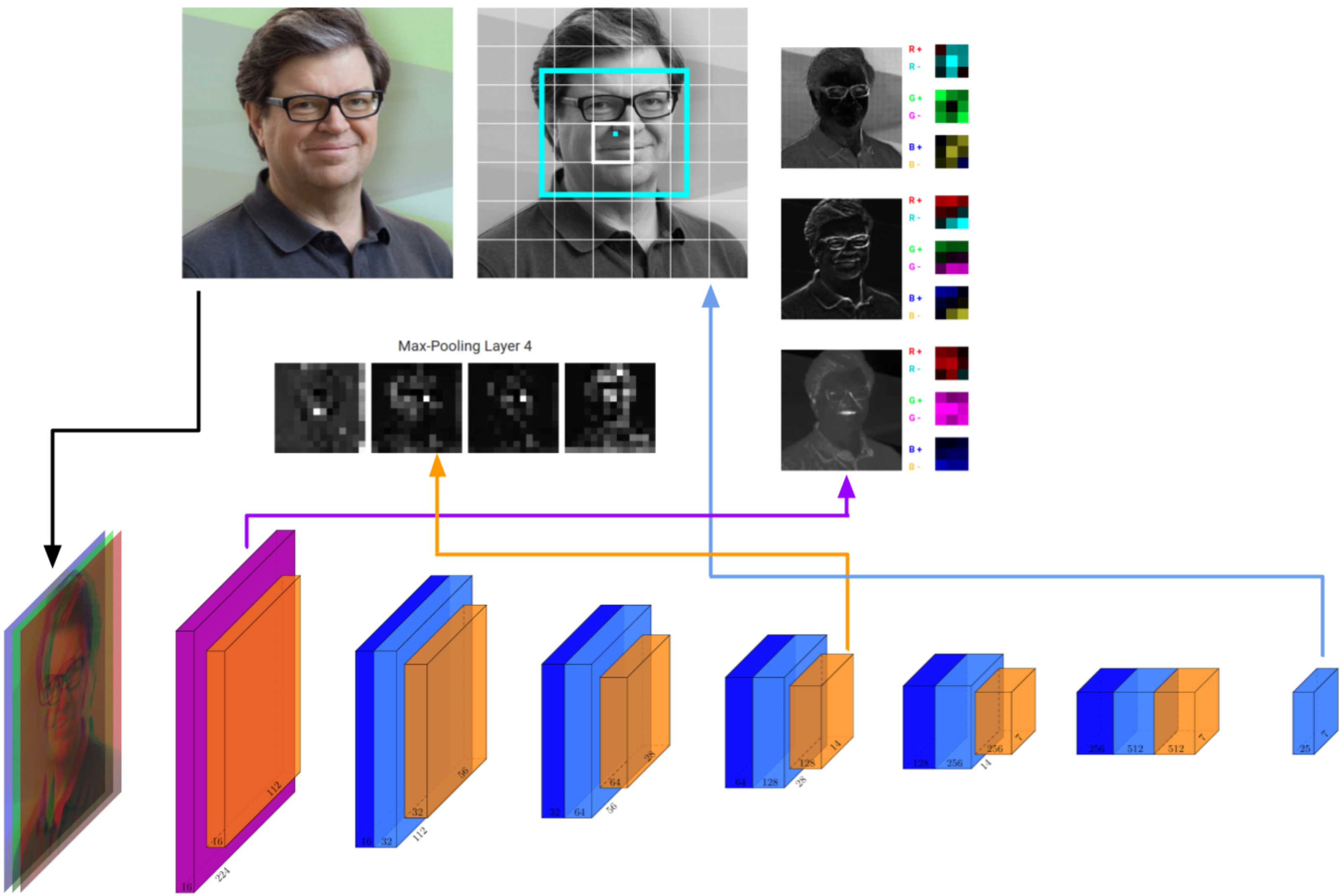


https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/



Visualizations of filters

TinyYOLOV2 Face Recognition



TinyYOLOV2 Architecture