Neural Nets

Schwartz

August 2, 2017

Making machines that think

The perceptron – a single layer feedforward neural network – was invented in 1957 at the Cornell Aeronautical Laboratory by Frank Rosenblatt with funding from the United States Office of Naval Research. In a 1958 press conference organized by the US Navy, based on Rosenblatt's statements, The New York Times reported the perceptron to be "the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence."

Upon his death, the titular Reverend Thomas Bayes (1701–1761) of the renowned theorem left an unpublished manuscript deriving the distribution for the parameter of a binomial distribution. This found its way to Richard Price, who prior to posthumously reading the manuscript at the Royal Society, dutifully edited the manuscript and added an introduction that forms much of the philosophical basis for Bayesian analysis. Mathematical historians have argued that "by modern standards, we should refer to the Bayes-Price rule. Price discovered Bayes' work, recognized its importance, corrected it, contributed to the article, and found a use for it. The modern convention of employing Bayes' name alone is unfair but so entrenched that anything else makes little sense." Quite unaware of Bayes' work, the French mathematician Pierre-Simon Laplace reproduced and extended Bayes' results in 1774. It was also suggested that the blind English mathematician Nicholas Saunderson discovered the theorem some time before Bayes, but this is disputed.

The elegant simplicity and effectiveness of Bayes' theorem for "learning" has prompted some psychologists to ask if the human brain itself might be a Bayesian-reasoning machine. They suggest that the Bayesian capacity to draw strong inferences from sparse data could be crucial to the way the mind perceives the world, plans actions, comprehends and learns language, reasons from correlation to causation, and even understands the goals and beliefs of other minds. The key to successful Bayesian reasoning is not in having an extensive, unbiased sample, which is the eternal worry of frequentists, but rather in having an appropriate "prior". This prior is an assumption about the way the world works. With the correct prior, even a single piece of data can be used to make meaningful Bayesian predictions. By contrast, frequentism is perhaps not well suited to making decisions on the basis of limited information – which is something that people have to do all the time.

It is thought by cognitive neuroscientists that neocortical development occurs in sequential layers, driven by waves of nerve growth factors which result in a self-organizating system. Modern so-called *deep learning* successors of the perceptron use Bayesian model fitting techniques to analogously sequentially train layer upon layer of neurons to produce unsupervised (self-organizing) classification networks.

Objectives

- neural networks
- activating functions
- neural networks $\Longrightarrow$ regression
- abstract feature encoding via layers
- backpropegation (gradient decent via chain rule)

- backpropegation parameter tuning
- images as data
- convolutions
- convolutional networks

Artificial Neural Network (NN)

- *NN's* are a collection of nodes $\eta_j^{(l)}$ that take on various states $\left\{\eta_j^{(l)}\right\}$

$$\left\{\eta_1^{(1)}\right\}$$

$$\left\{\eta_2^{(1)}\right\}$$

$$\left\{\eta_3^{(1)}\right\}$$

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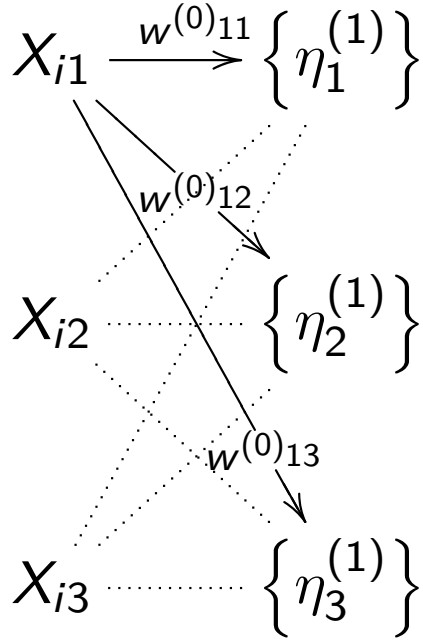

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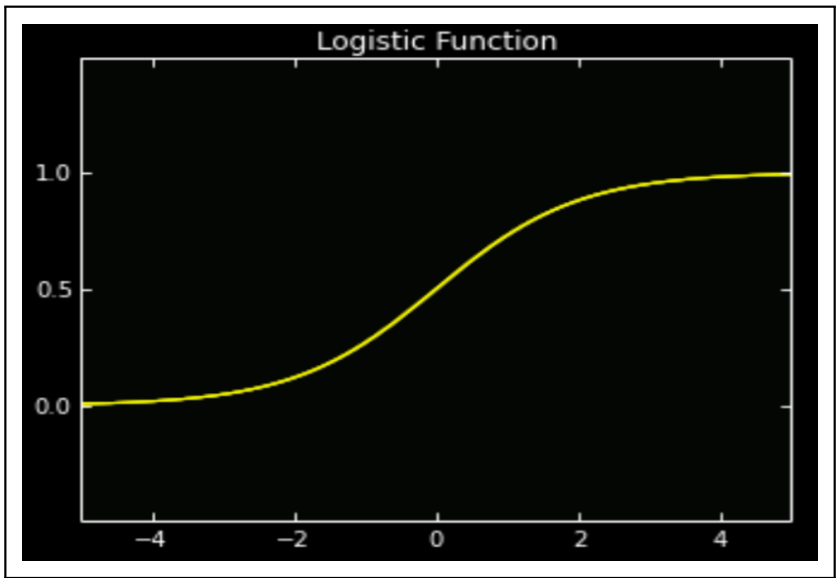
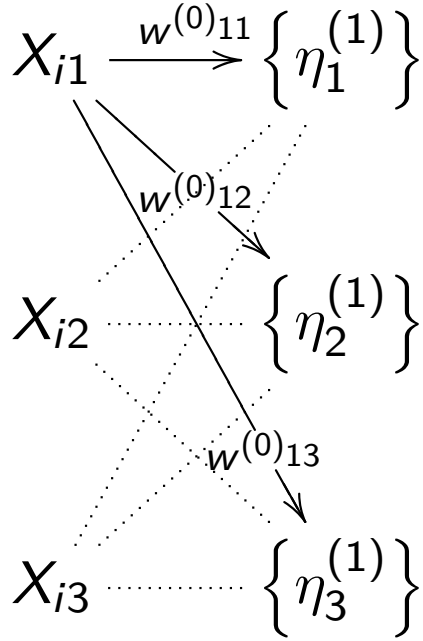
$$X_i = (X_{i1}, X_{i2}, X_{i3})^T$$

$$w_j^{(0)} = \left(w^{(0)}{}_{1j}, w^{(0)}{}_{2j}, w^{(0)}{}_{3j}\right)^T$$

with activation function f





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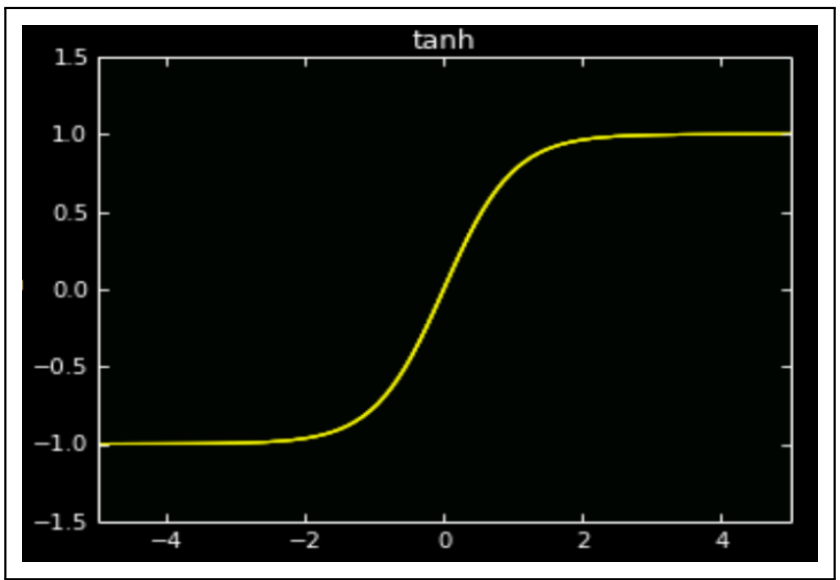

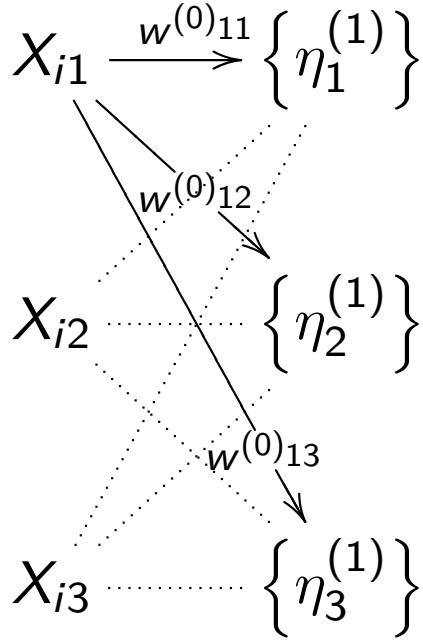

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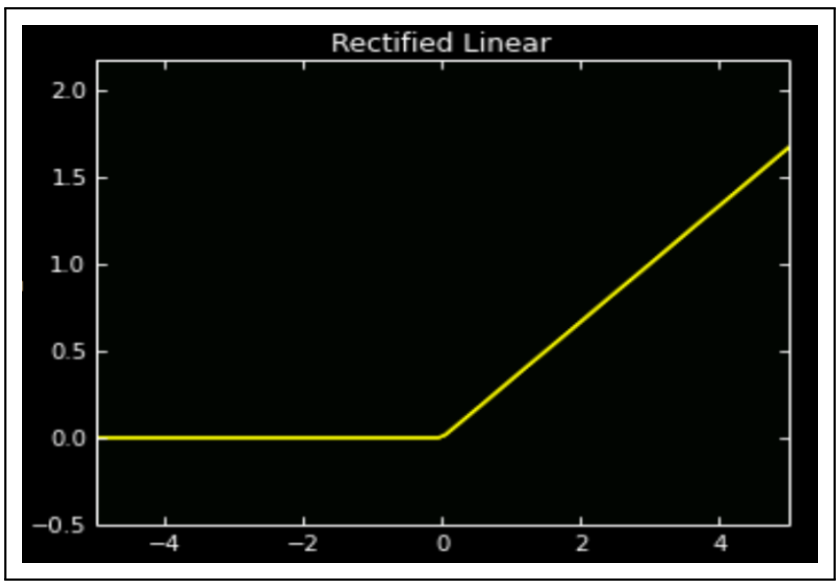

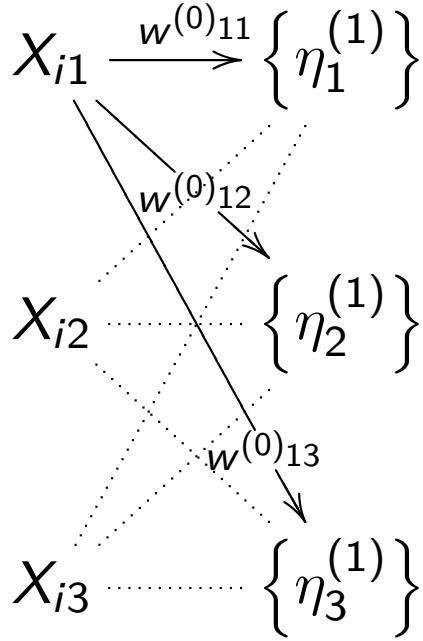

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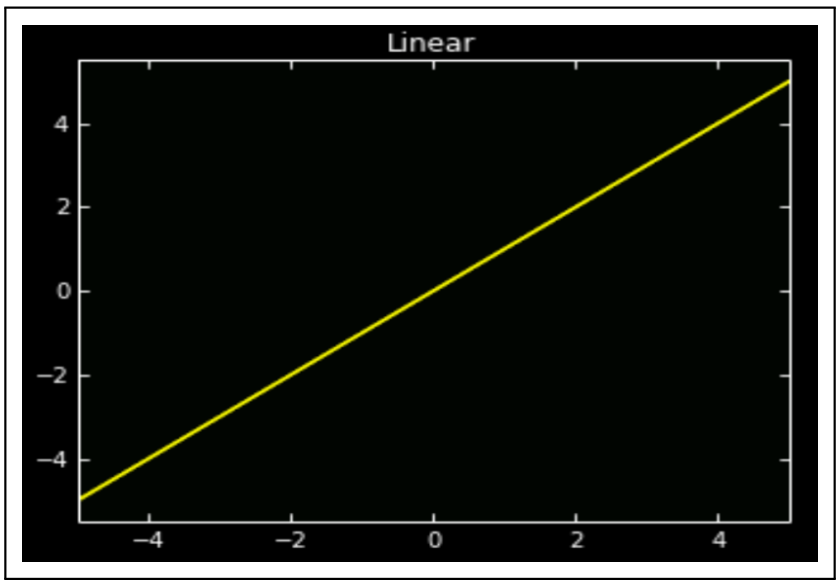

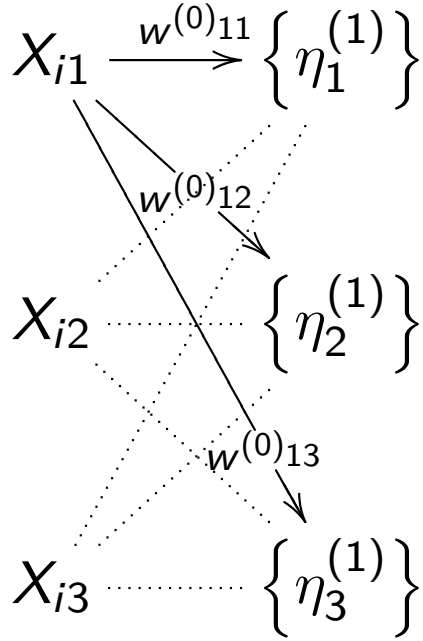

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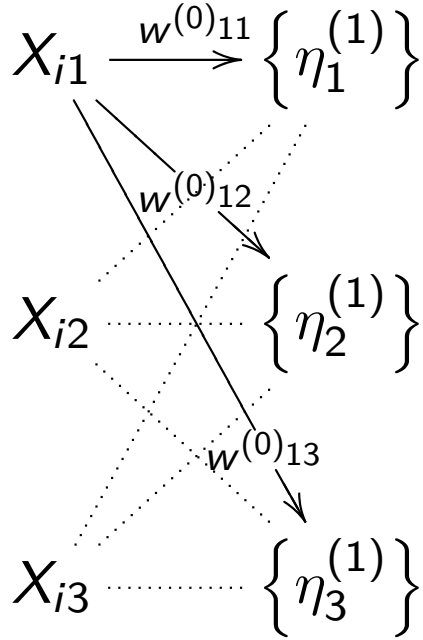

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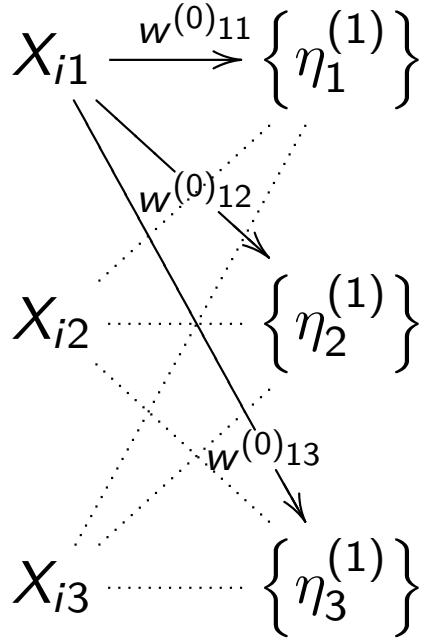

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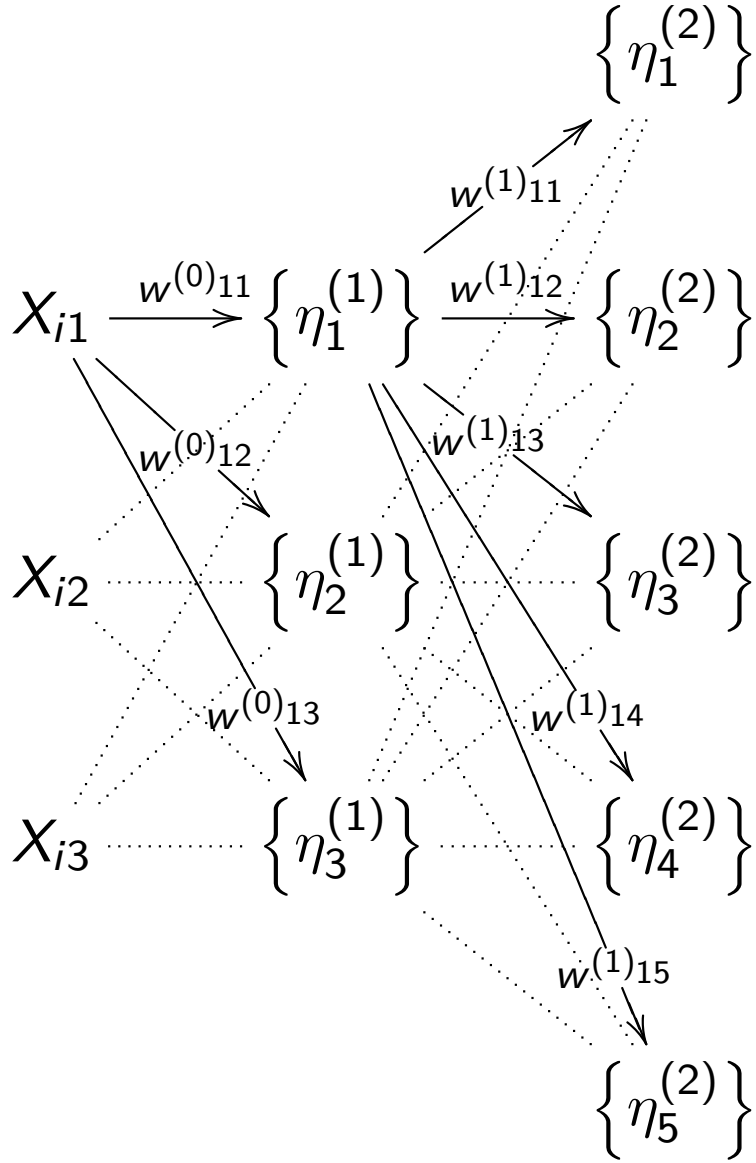

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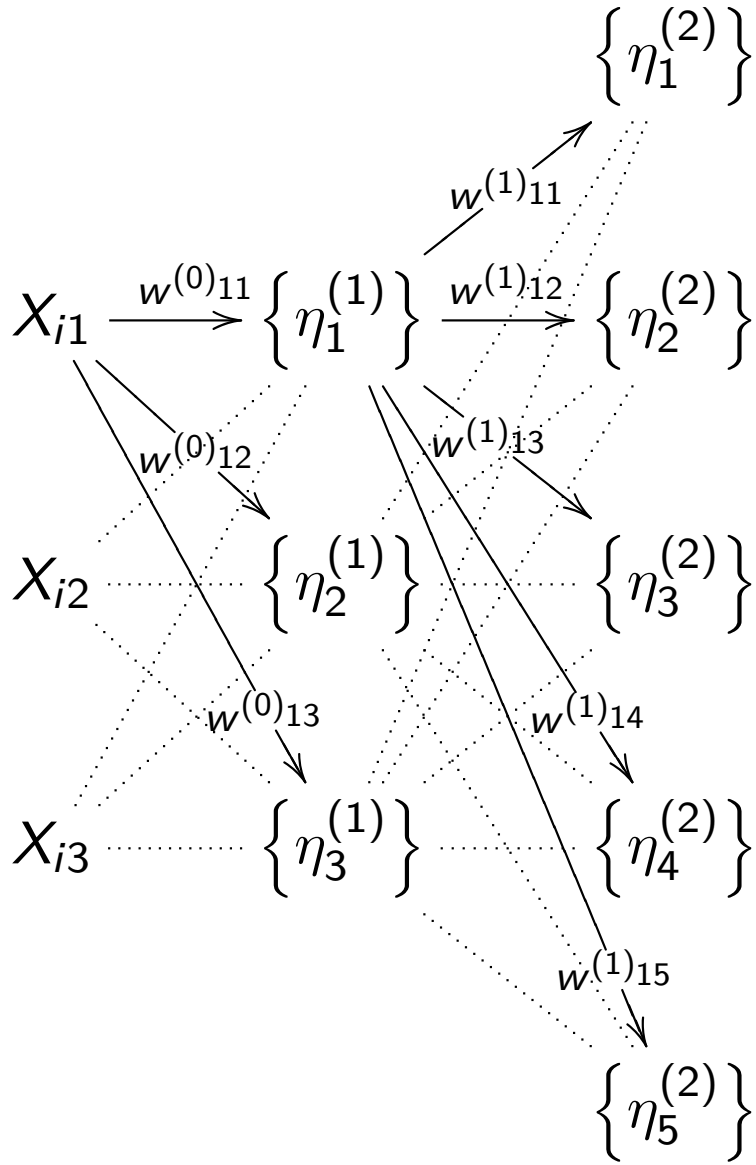

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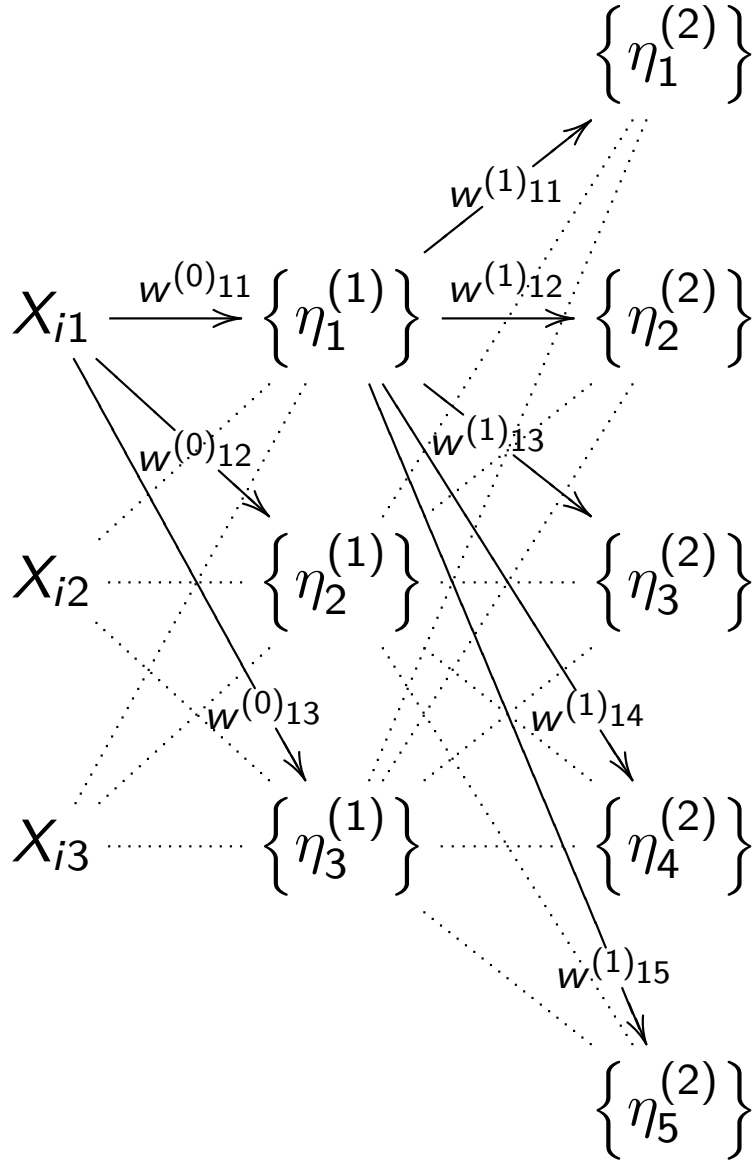

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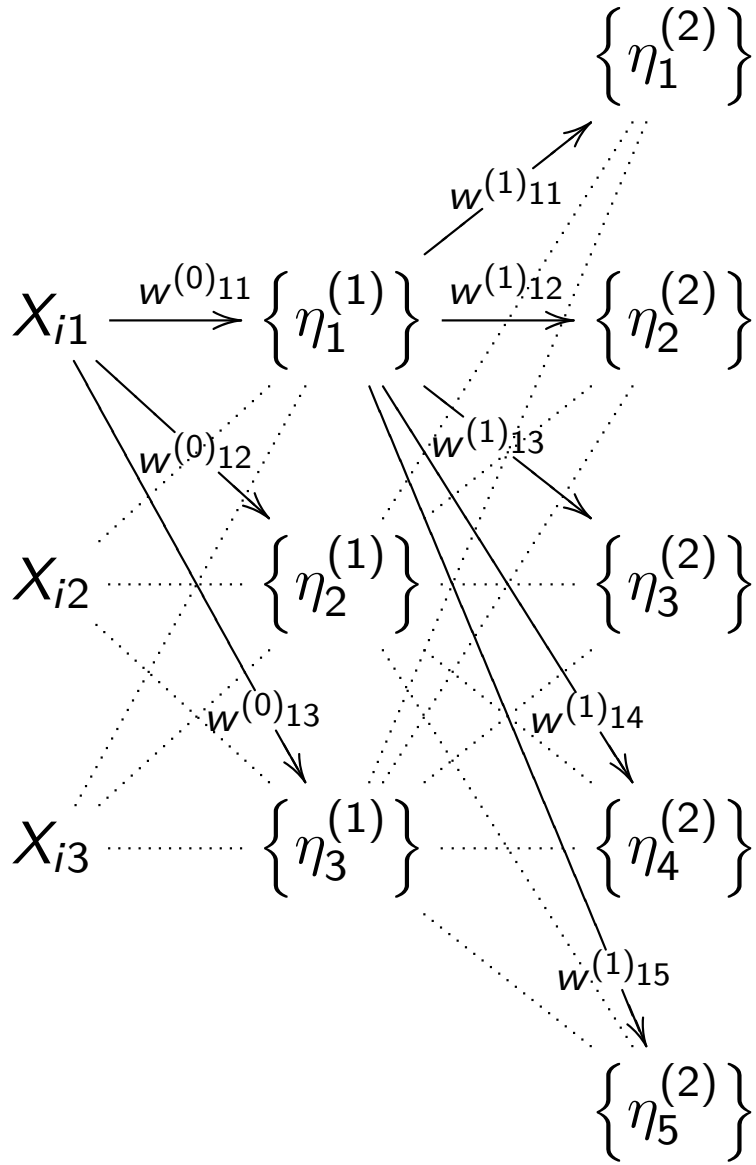
  Similar states for "similar" X_i's means the NN knows, or understands or recognizes X_i



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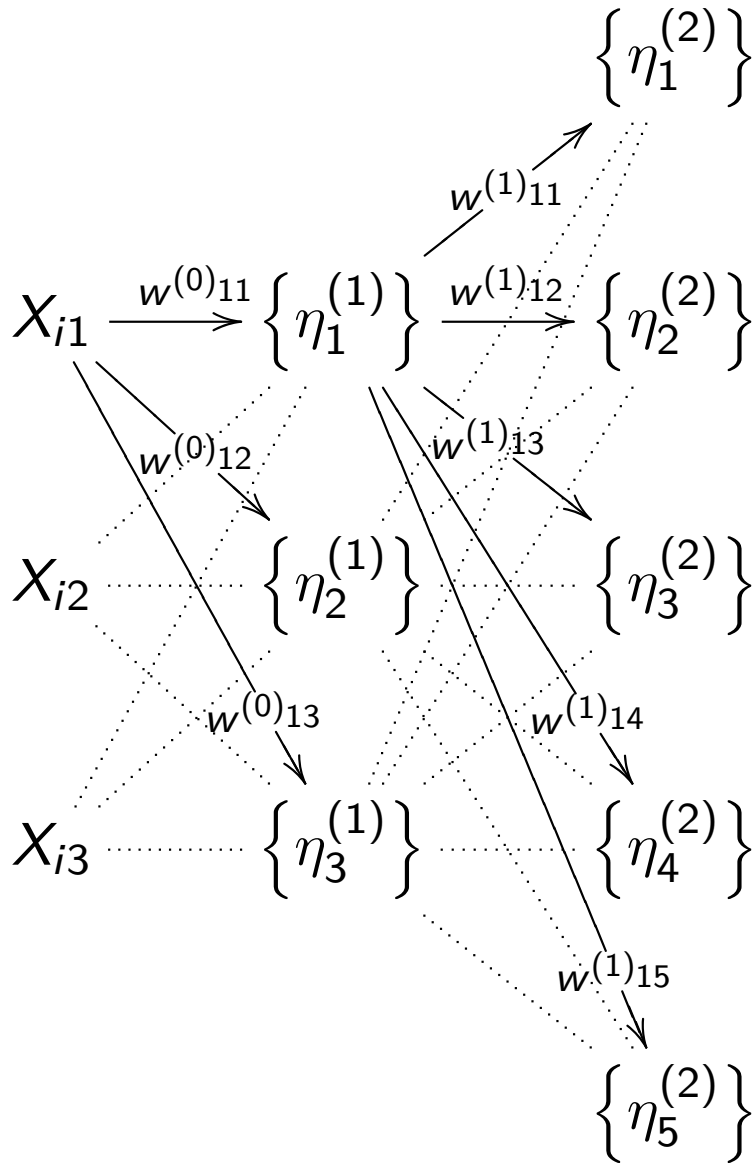

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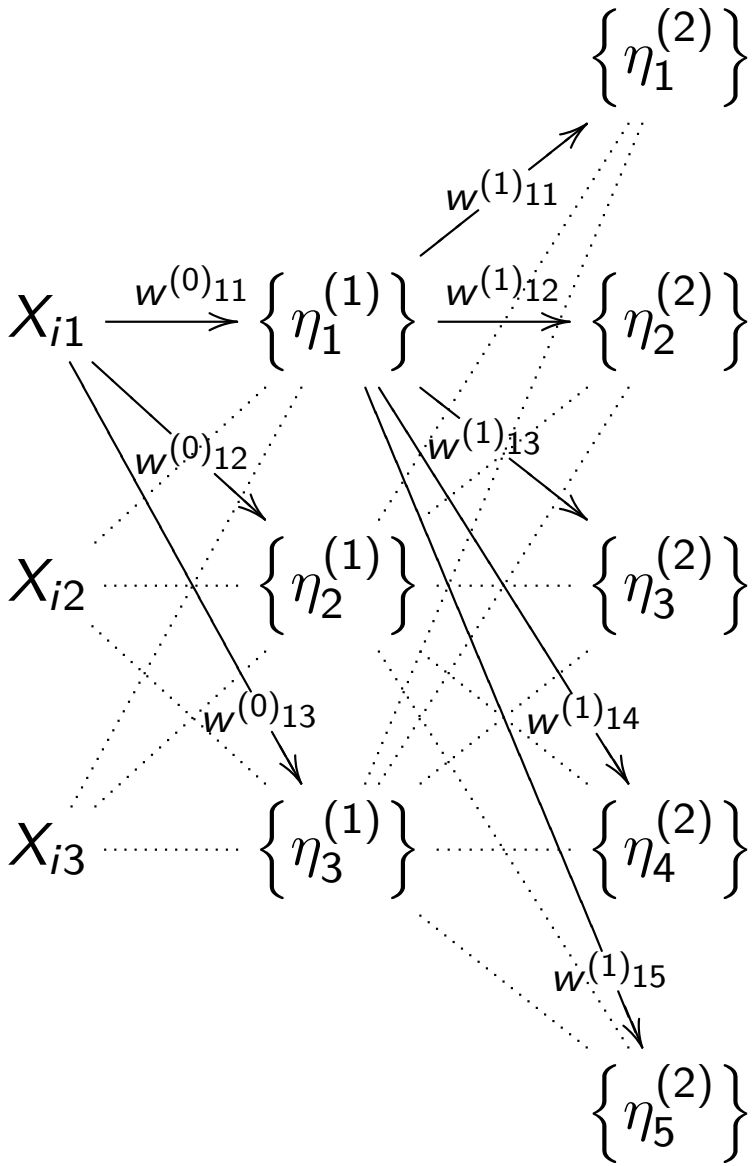

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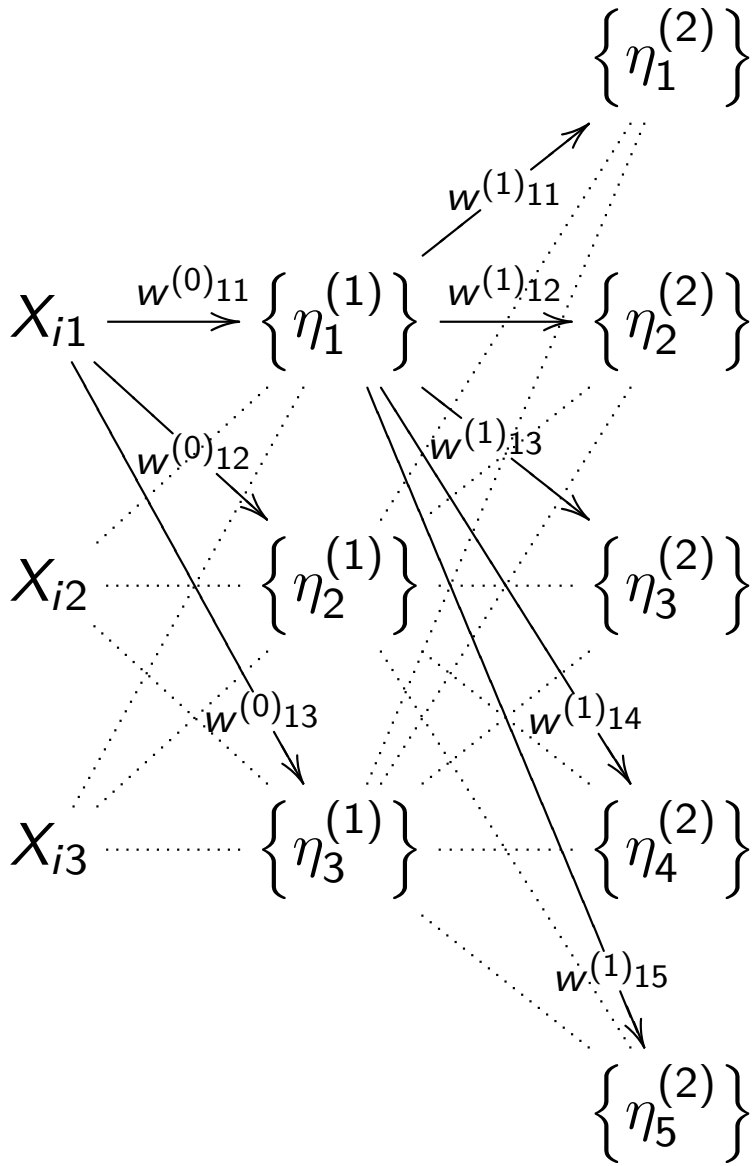

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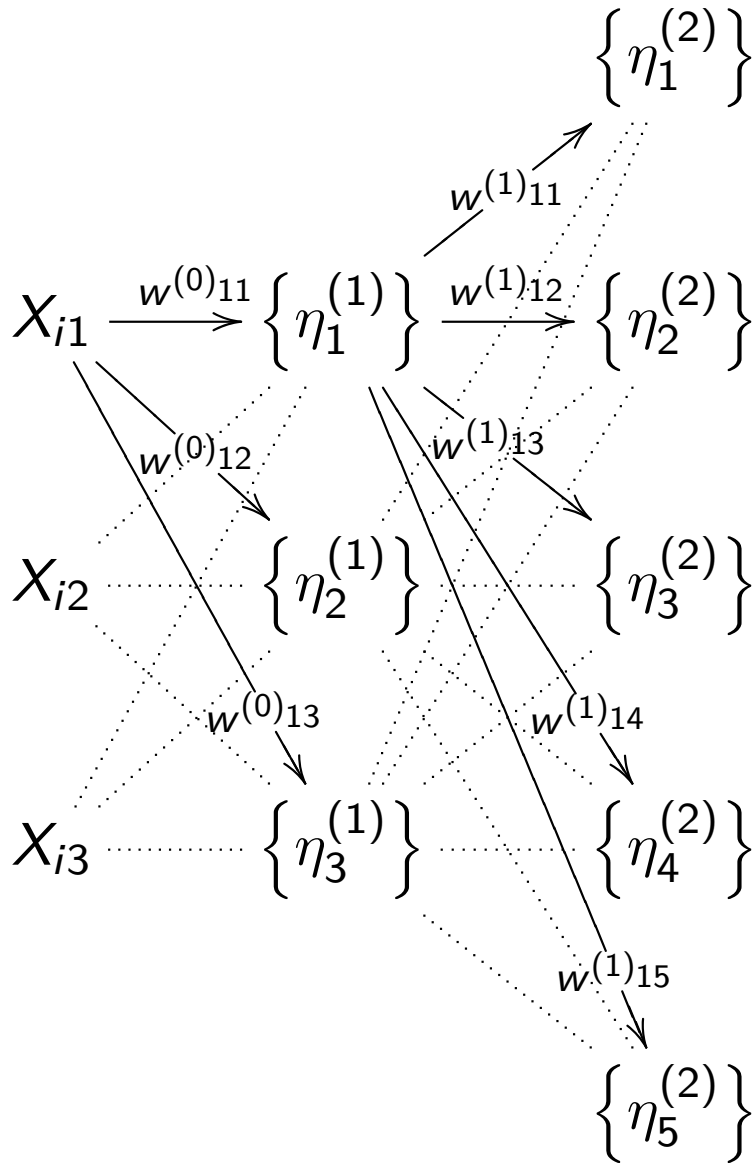
- The topology (size and number of layers) of the NN influences the number of "ideas" and level of cumulative abstraction applied
- The $w's$ are trained to identify input patterns that should map to similar NN states and "thoughts"...



Using NN's: where the fun ends and the pain begins

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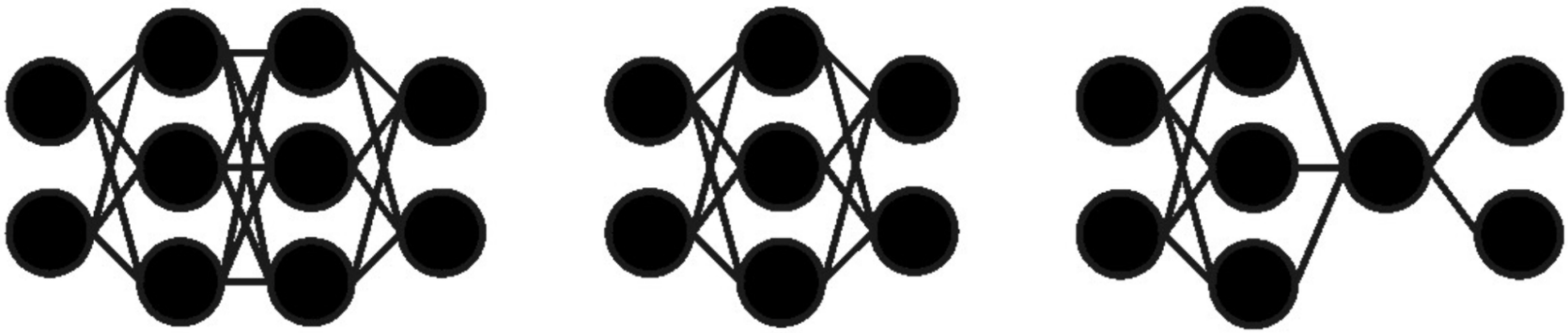

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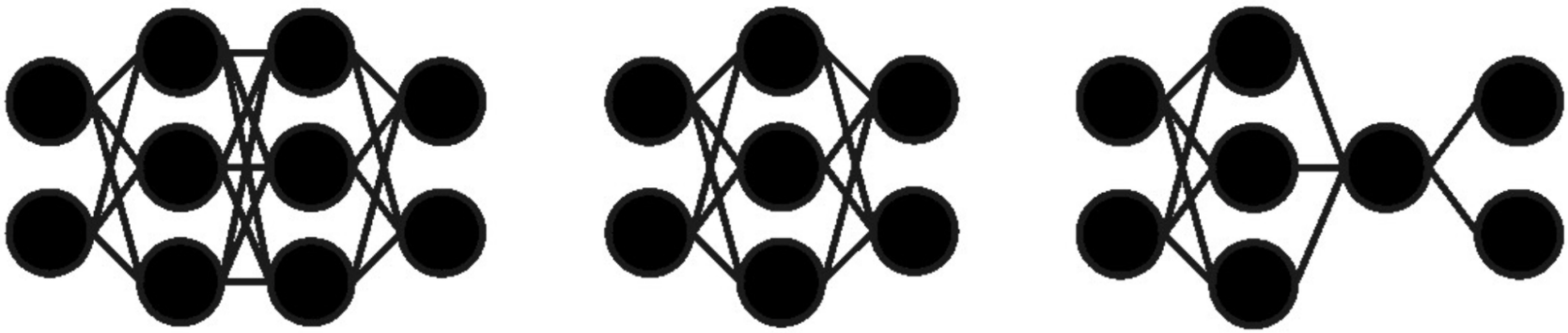

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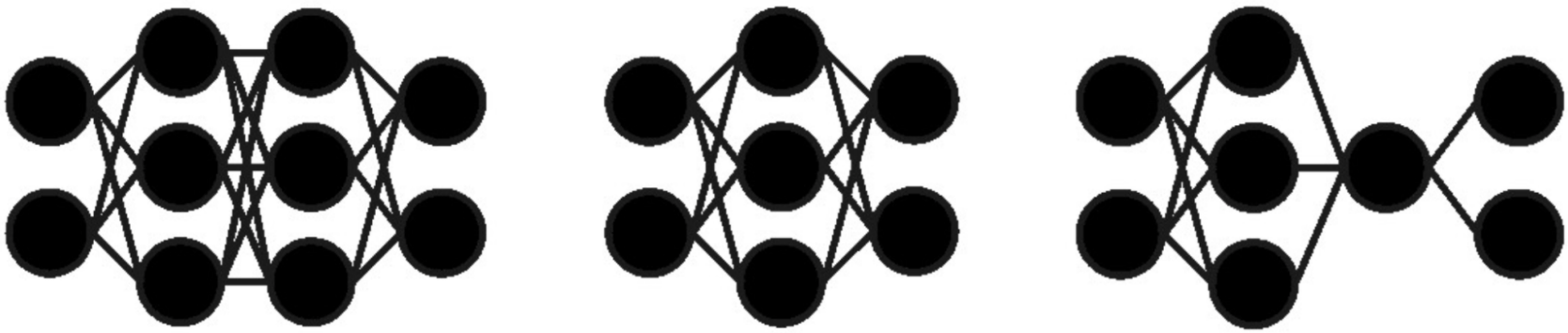

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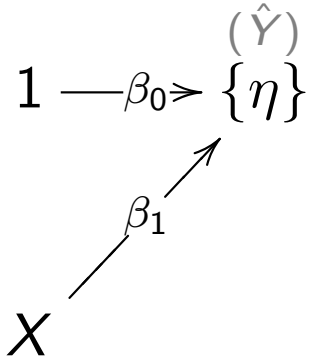
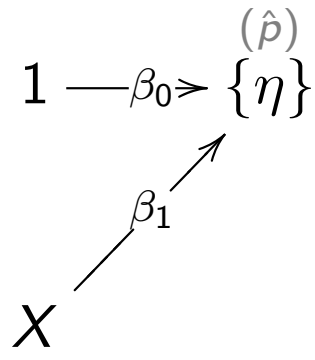
Let's start simple...

Example NNs (Regression and Logistic Regression)





$$\hat{Y} = f\left([1, x]\begin{bmatrix}\beta_0 \\ \beta_1\end{bmatrix}\right)$$
$$= [1, x]\begin{bmatrix}\beta_0 \\ \beta_1\end{bmatrix} = \beta_0 + \beta_1 x$$

$$\hat{p} = f\left([1, x]\begin{bmatrix}\beta_0 \\ \beta_1\end{bmatrix}\right)$$
$$= \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

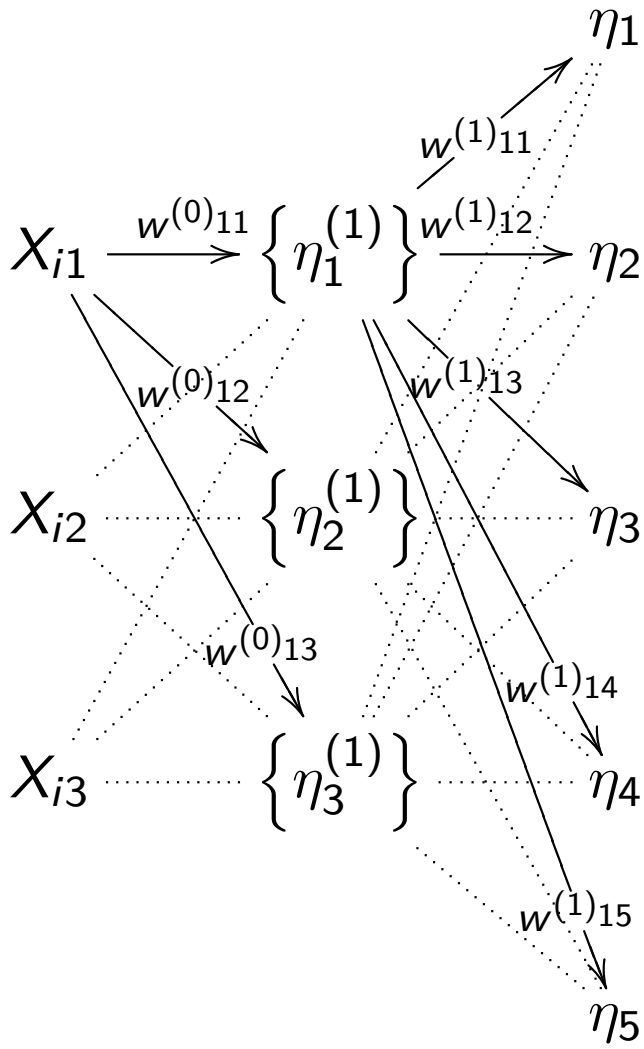
$$\min_{\hat{Y}} \frac{1}{2}\sum (Y_i - \hat{Y}_i)^2$$

$$\min_{\boldsymbol{p}} -\prod Y_i \log(p_i) + (1 - Y_i)\log(1 - p_i)$$

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \frac{1}{2}\sum (Y_i - \beta_0 + \beta_1 x_i)^2$$

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} -\prod Y_i \log\left(\frac{1}{1 + e^{-(\beta_0 + \beta_1 x_i)}}\right)$$
$$+ (1 - Y_i)\log\left(\frac{1}{1 + e^{\beta_0 + \beta_1 x_i}}\right)$$

Softmax



Choose the class with the largest probability

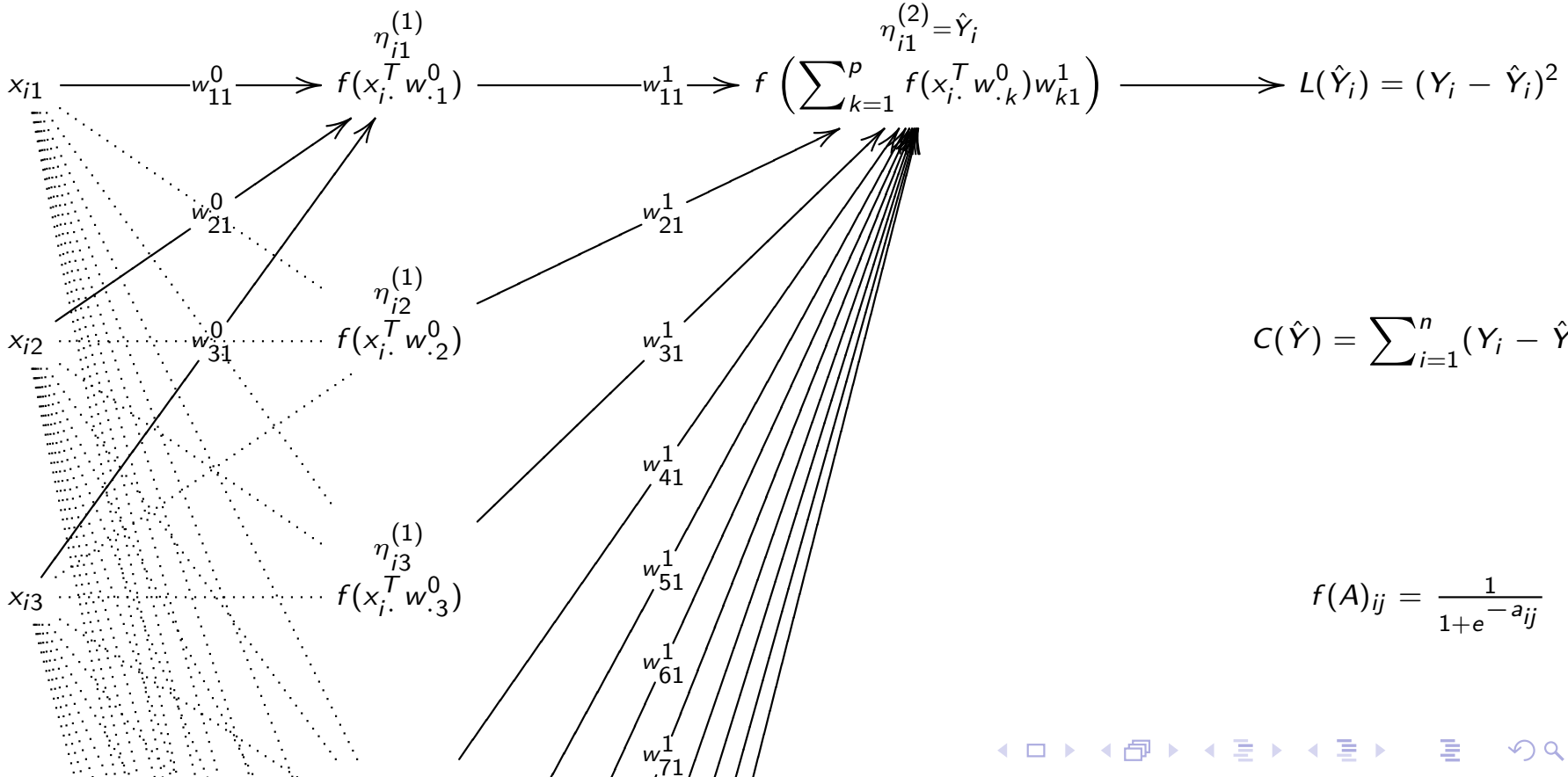
$$exp(\eta_k)/\sum_{k'=1}^{K} exp(\eta_{k'})$$

Define a loss function on those predictions

And Optimize!

Forward propagation [And how to update parameters?]

$$\hat{Y} = f\left(f\left(\underset{n\times 3}{\begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & x_{n3} \end{bmatrix}} \cdot \underset{3\times p}{\begin{bmatrix} w^0_{11} & w^0_{12} & \cdots & w^0_{1p} \\ w^0_{21} & w^0_{22} & \cdots & w^0_{2p} \\ w^0_{31} & w^0_{32} & \cdots & w^0_{3p} \end{bmatrix}} \right) \cdot \underset{p\times 1}{\begin{bmatrix} w^1_{11} \\ w^1_{21} \\ \vdots \\ w^1_{n1} \end{bmatrix}} \right)$$



$$C(\hat{Y}) = \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$$

$$f(A)_{ij} = \frac{1}{1+e^{-a_{ij}}}$$

Backpropagation (Chain Rule Extraordinaire)

$$\frac{\partial}{\partial a_{ij}} f(A)_{ij} = \frac{\partial}{\partial a_{ij}} \frac{1}{1+e^{-a_{ij}}}$$
$$= \frac{1}{1+e^{-a_{ij}}} \left(1 - \frac{1}{1+e^{-a_{ij}}}\right)$$

$$\frac{\partial}{\partial w^1_{k1}} L(\hat{Y}_i) = \frac{\partial \hat{Y}_i}{\partial w^1_{k1}} \frac{\partial}{\partial \hat{Y}_i} L(\hat{Y}_i)$$
$$= \eta^1_{ik} \hat{Y}_i (1 - \hat{Y}_i) 2(Y_i - \hat{Y}_i)$$

$$\frac{\partial}{\partial w^0_{jk}} L(\hat{Y}_i) = \frac{\partial \hat{Y}_i}{\partial w^0_{jk}} \frac{\partial}{\partial \hat{Y}_i} L(\hat{Y}_i)$$
$$= \frac{\partial \eta^1_{ik}}{\partial w^0_{jk}} \frac{\partial \hat{Y}_i}{\partial \eta^1_{ik}} \frac{\partial}{\partial \hat{Y}_i} L(\hat{Y}_i)$$
$$= x_{ij} \eta^1_{ik} (1 - \eta^1_{ik}) w^1_{k1} \hat{Y}_i (1 - \hat{Y}_i) 2(Y_i - \hat{Y}_i)$$

$$\frac{\partial}{\partial w^1_{k1}} C(\hat{Y}) = \sum_{i=1}^{n} \frac{\partial}{\partial w^1_{k1}} L(\hat{Y}_i)$$

$$\frac{\partial}{\partial w^0_{jk}} C(\hat{Y}) = \sum_{i=1}^{n} \frac{\partial}{\partial w^0_{jk}} L(\hat{Y}_i)$$

$$f(A)_{ij} = \frac{1}{1+e^{-a_{ij}}}$$

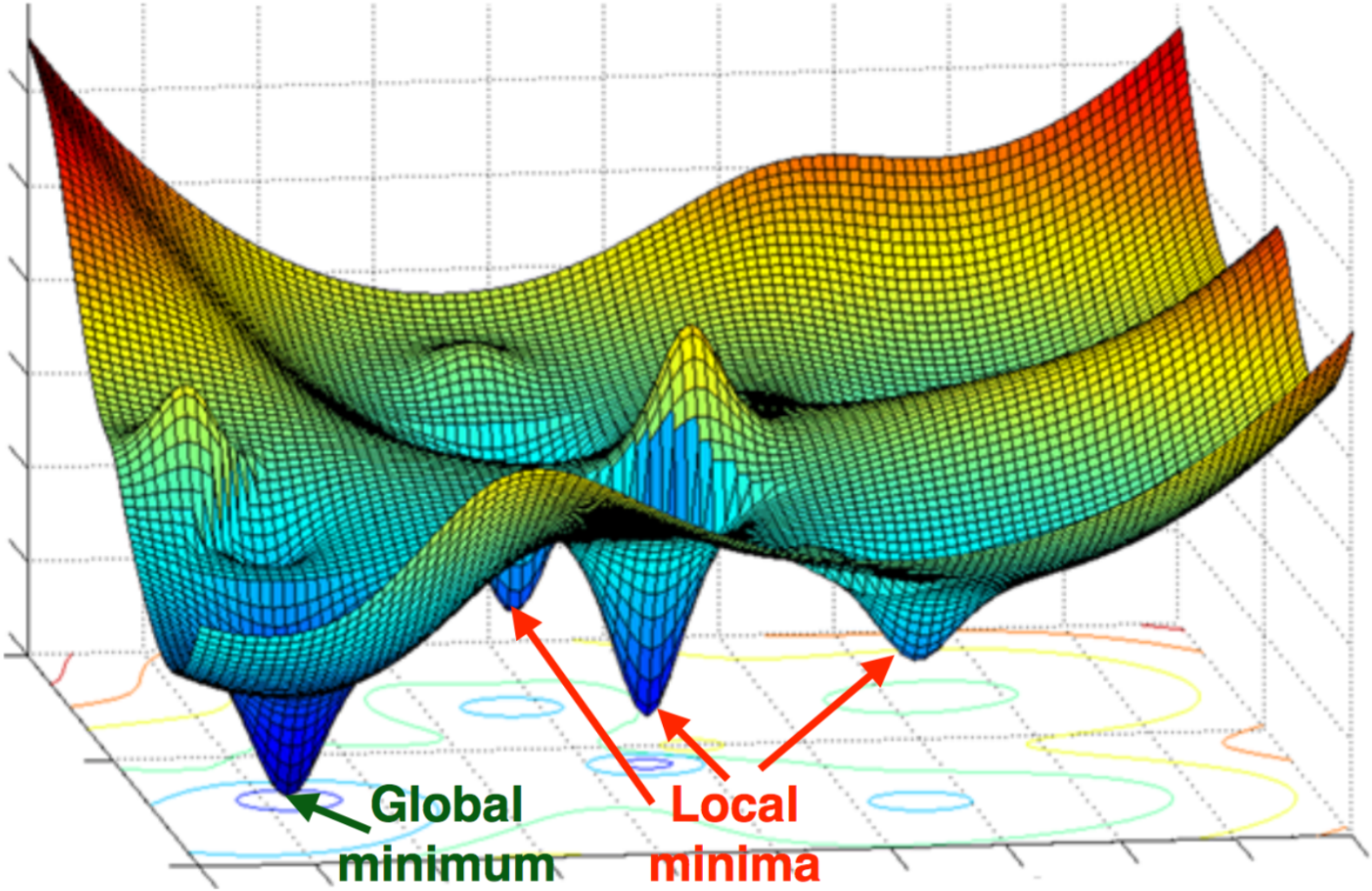
$$\eta^1_{ik} = f(x_{i\cdot}^T w^0_{\cdot k})$$

$$\hat{Y}_i = f\left(\sum_{k=1}^{p} f(x_{i\cdot}^T w^0_{\cdot k}) w^1_{k1}\right)$$

$$L(\hat{Y}_i) = (Y_i - \hat{Y}_i)^2$$

$$C(\hat{Y}) = \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$$

Sadly, backpropagation (GD) is very weak on Deep NN's



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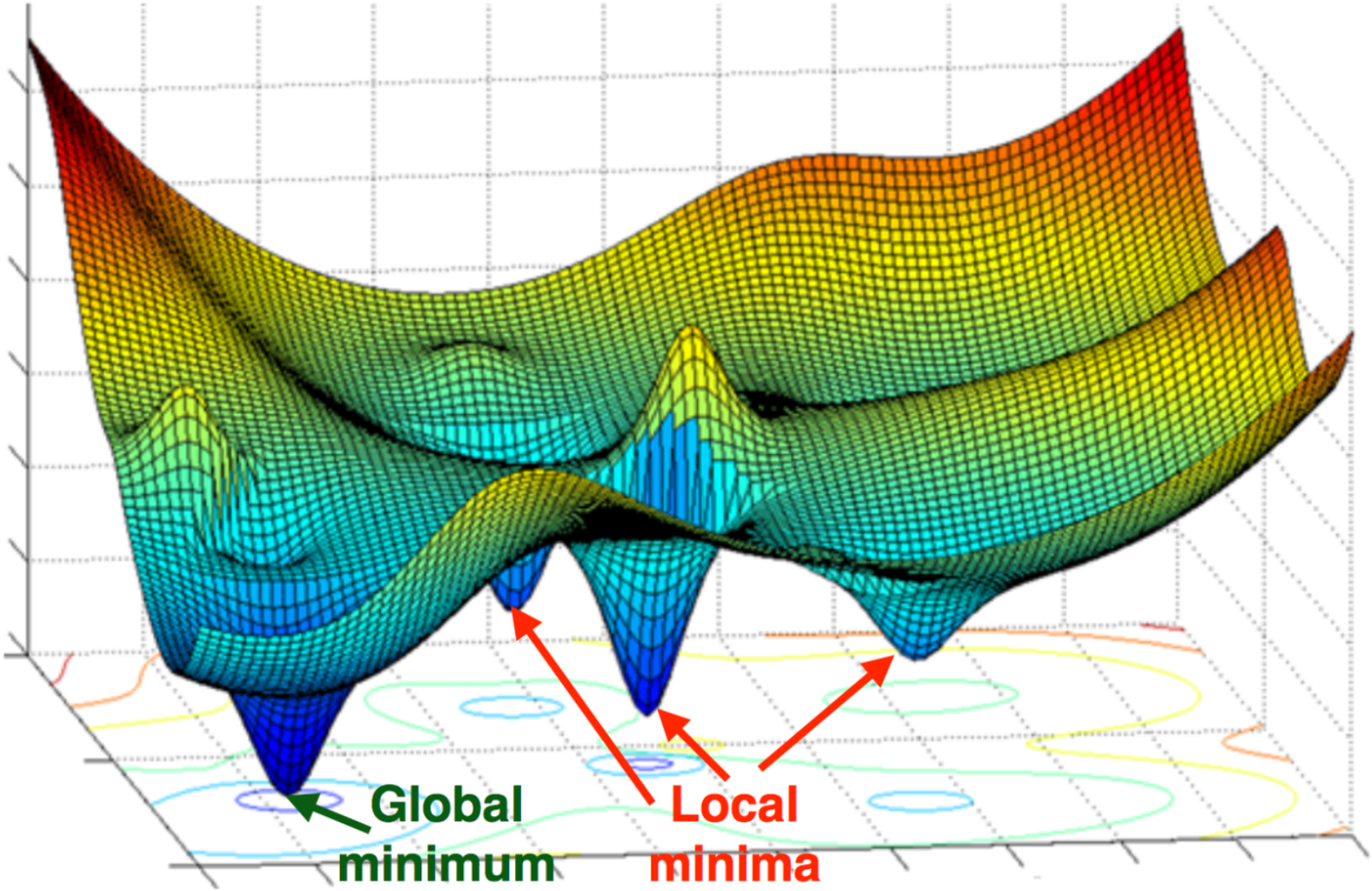
Because there's so, many w's... and thus so many local minima...



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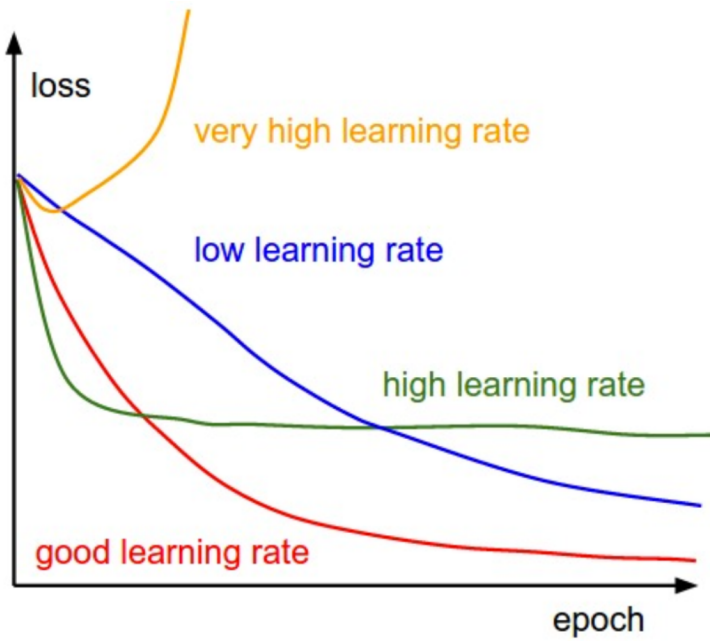
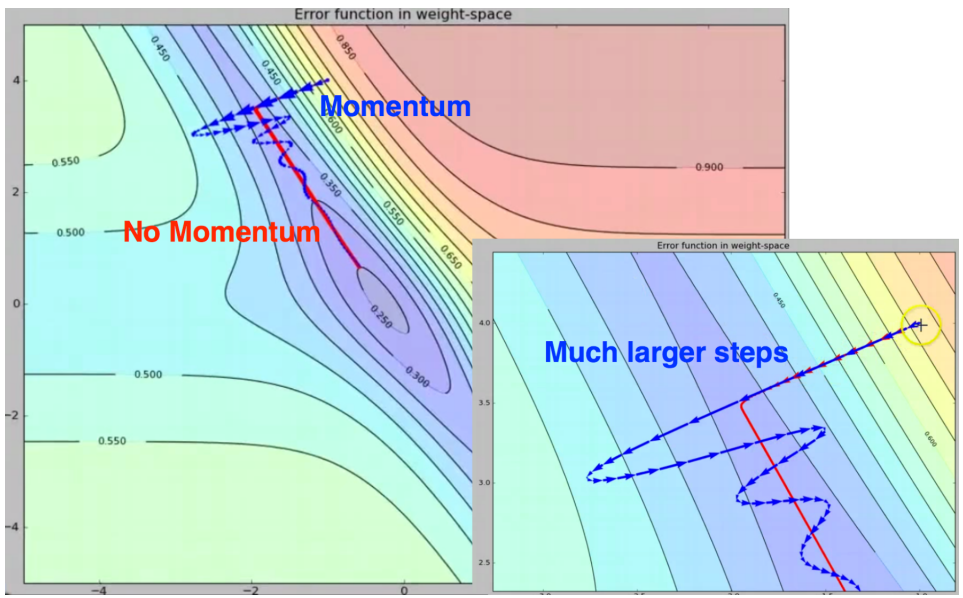
- But if you're gonna, then consider stochastic or mini-batch
- You'll be doing many *epochs* (iterations through the data)
- And you might wanna explore using momentum and velocity

$$V^{(t)} = \mu V^{(t-1)} - \alpha \nabla Cost(W^{(t-1)})$$
$$W^{(t)} = W^{(t-1)} + V^{(t)}$$





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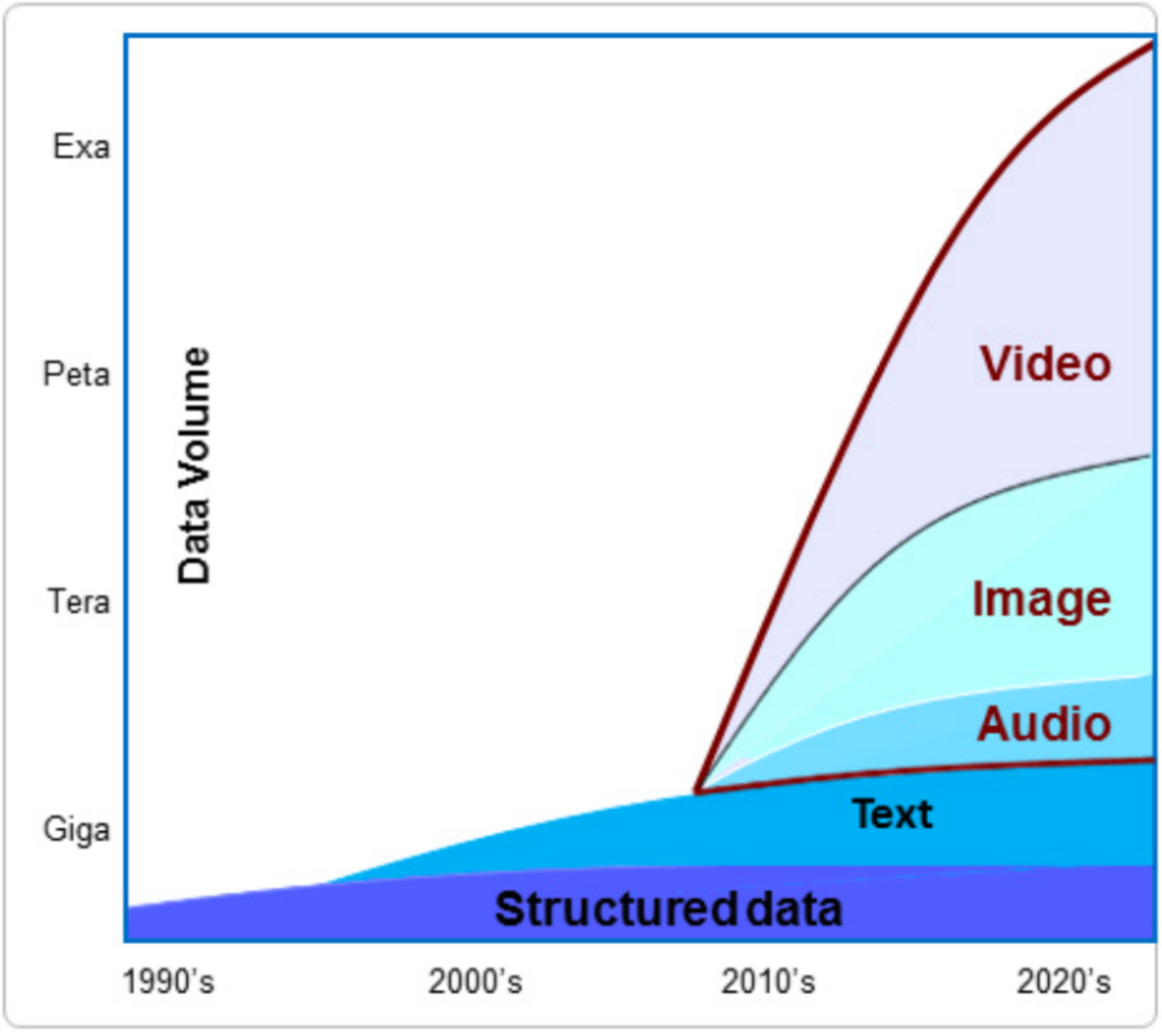
Here's what you'll actually do:
go find a NN paper that does *something* like what you're trying to do, get theirs to work, and then adapt it to your data

The new type of data



What data/information is contained in an image?

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A color image is a *tensor*: a matrix of vectors

$$\begin{bmatrix} RGB & RGB & \cdots & RGB \\ RGB & RGB & \cdots & RGB \\ \vdots & \vdots & \ddots & \vdots \\ RGB & RGB & \cdots & RGB \end{bmatrix}$$

image.shape = (width, height,3)

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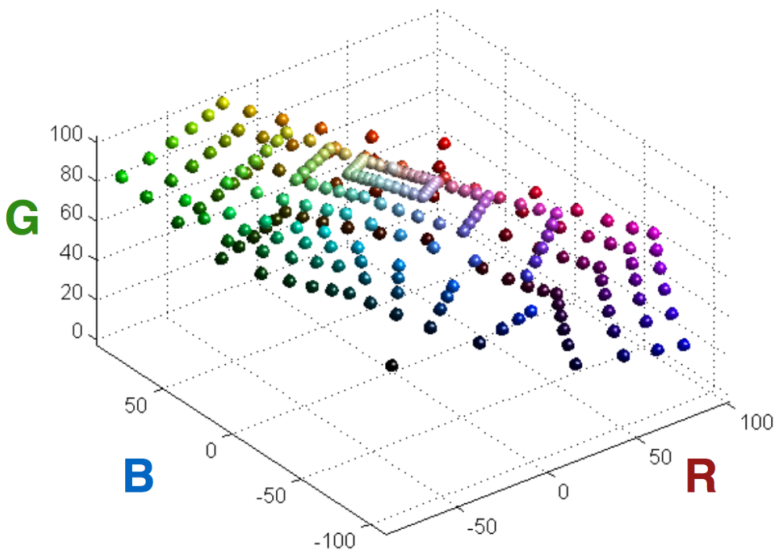

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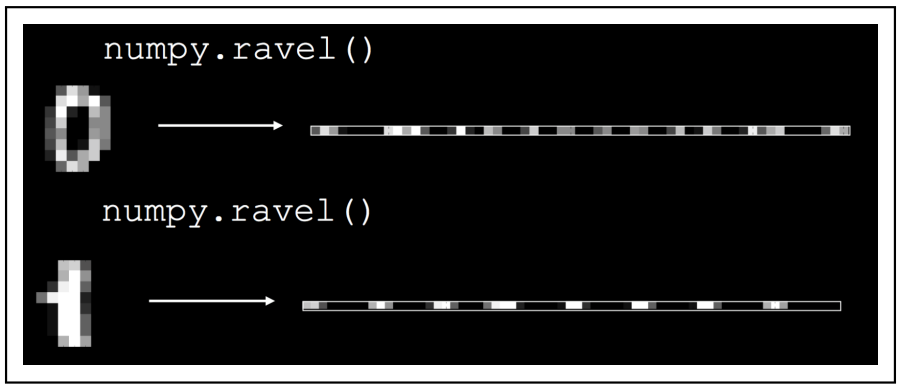

featurized.shape = (width·height·3,1)

What data/information is contained in an image?

$$\begin{array}{c} \\ \text{image 1} \\ \text{image 2} \\ \vdots \\ \text{image n} \end{array} \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix} \xRightarrow{\text{Predict}} \begin{array}{c} \text{Image Label} \\ \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} \end{array}$$

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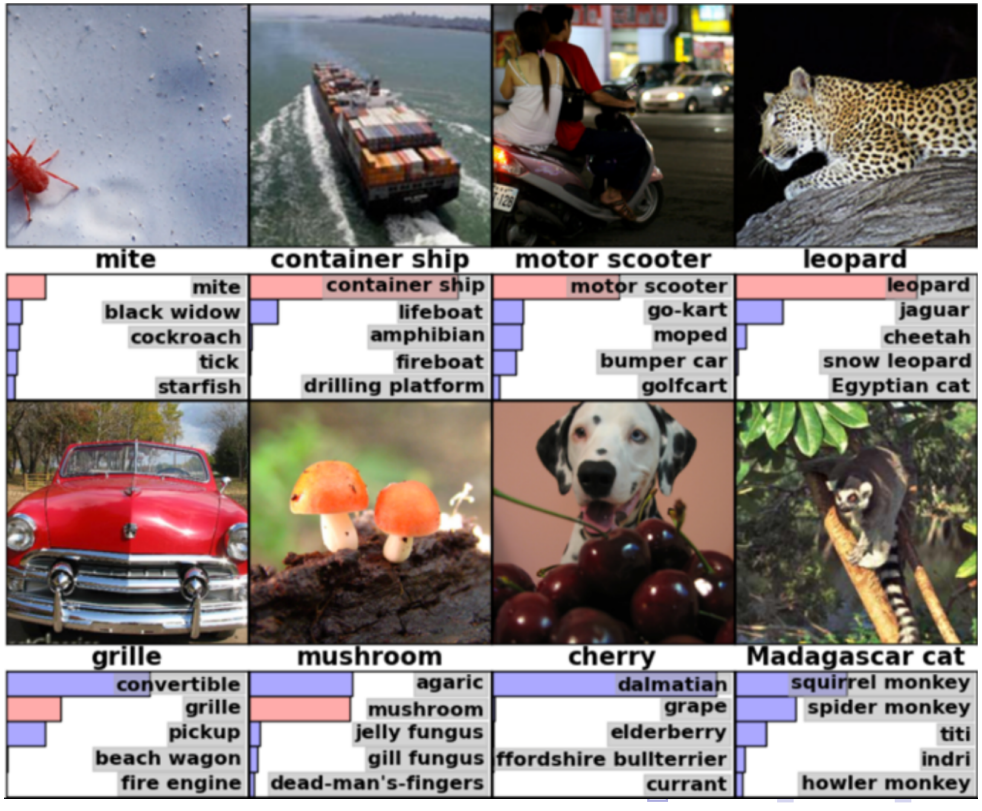

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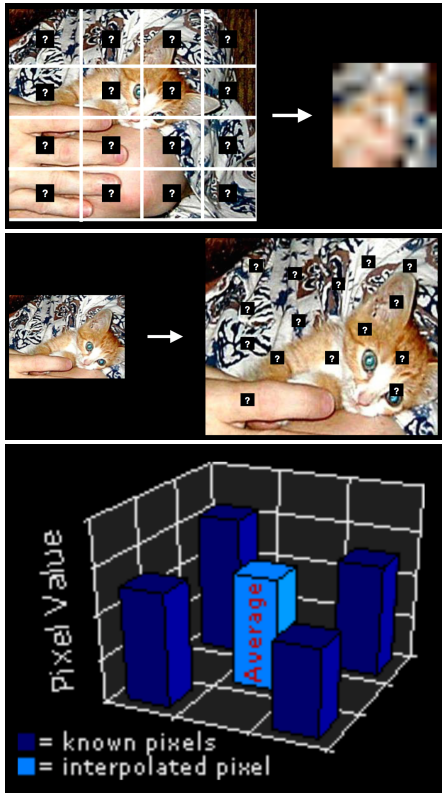
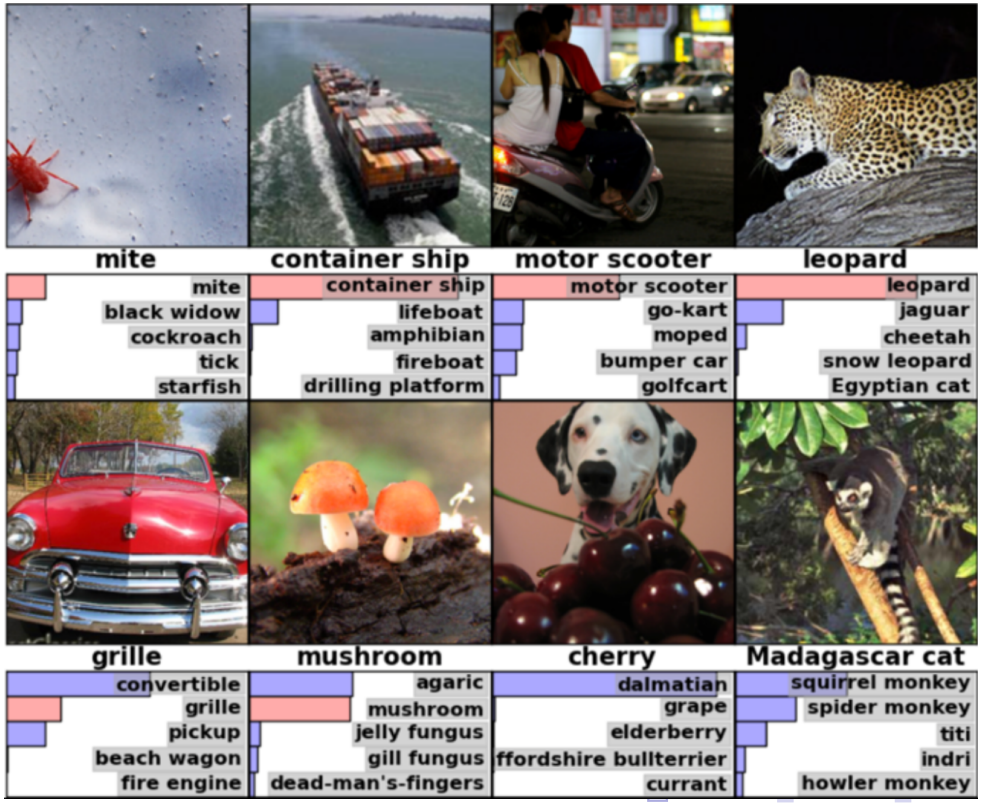
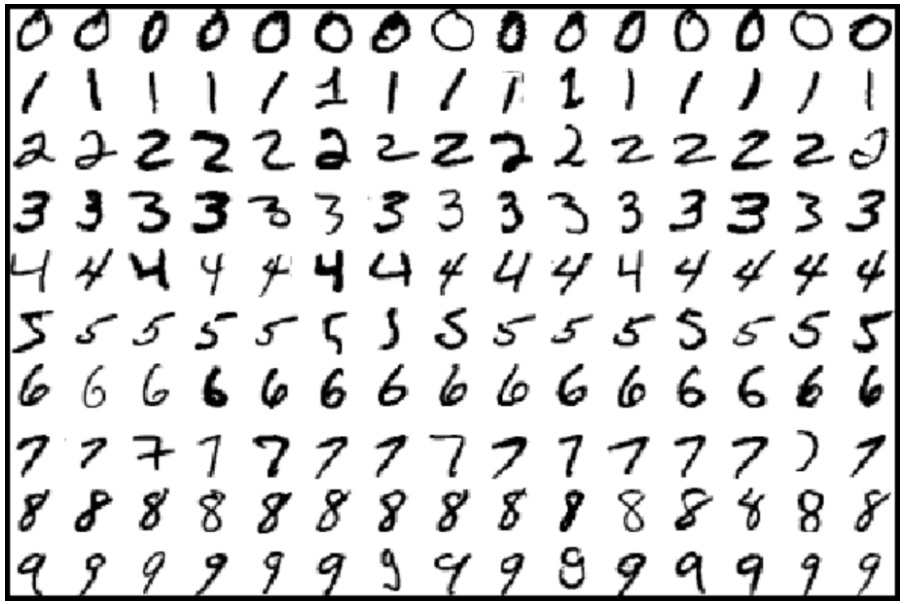




NNs are the best at identifying patterns in complex data



Classifier	Test Error Rate
Large and Deep Convolutional Network	0.33%
SVM with degree 9 polynomial kernal	0.66%
Gradient boosted stumps on Haar features	0.87%

Neural networks can recognize patterns from complex, heavy-tailed inputs such as image, audio, video, text, and human speech data

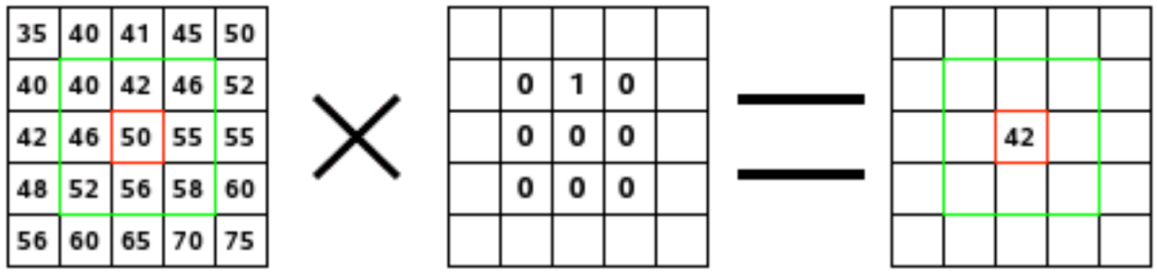
Image Processing

- Remove unnecessary details to allow for better generalization of images to image classes

$$x_i \to y_i : \underset{\boldsymbol{y}}{\operatorname{argmin}} \quad \frac{1}{2}\underbrace{\sum (x_i - y_i)^2}_{\textit{Fidelity}} + \lambda \underbrace{\sum |y_{i+1} - y_i|}_{\textit{Variation}}$$

Convolutional Kernel

- Spatial proximity *and pixel agreement (bi-lateral)*



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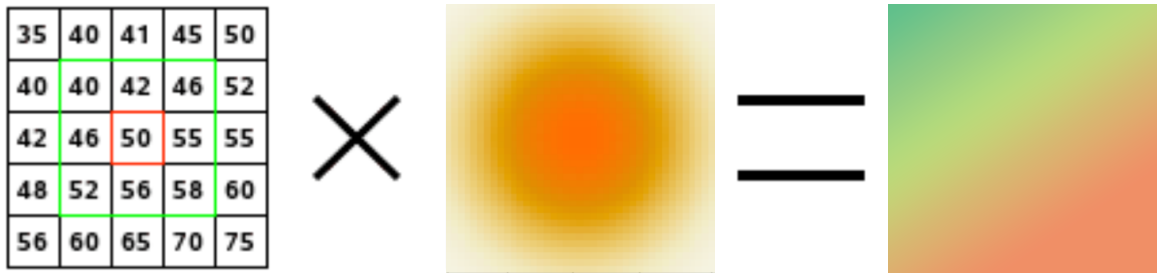

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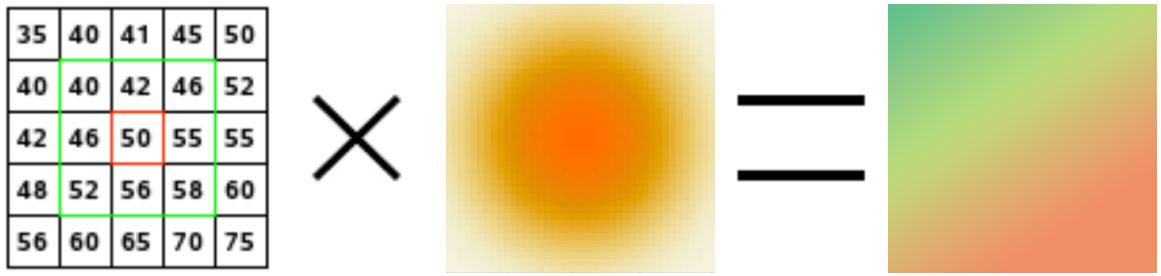
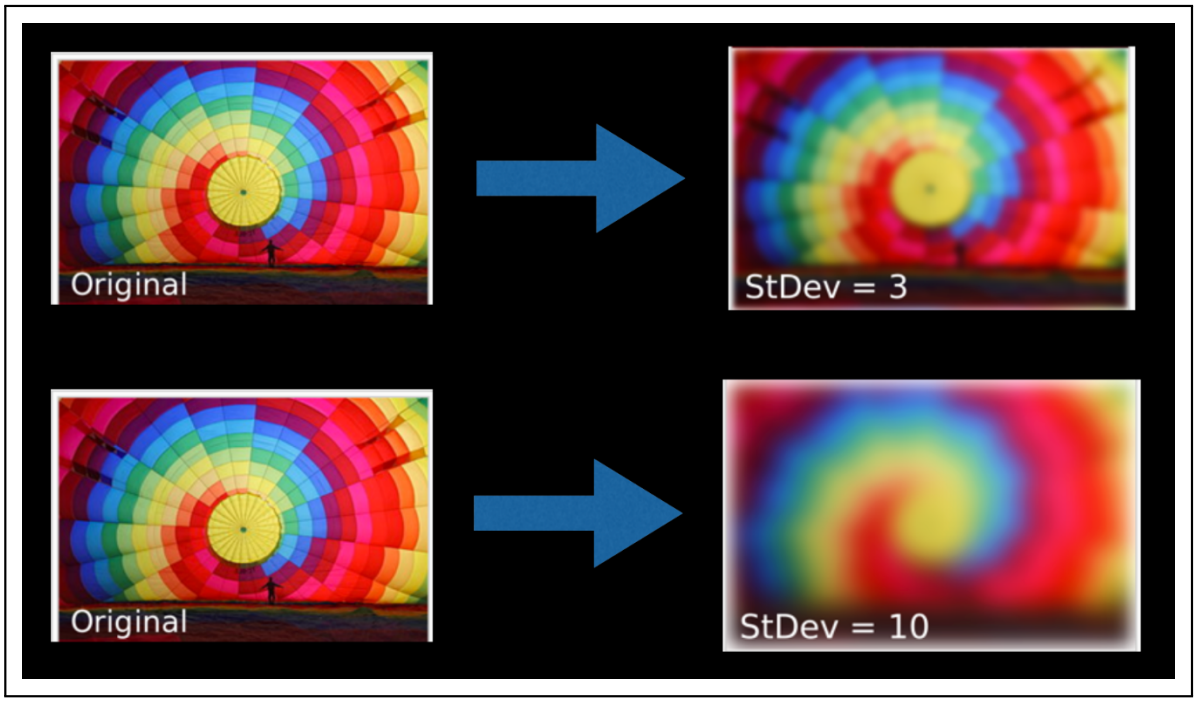
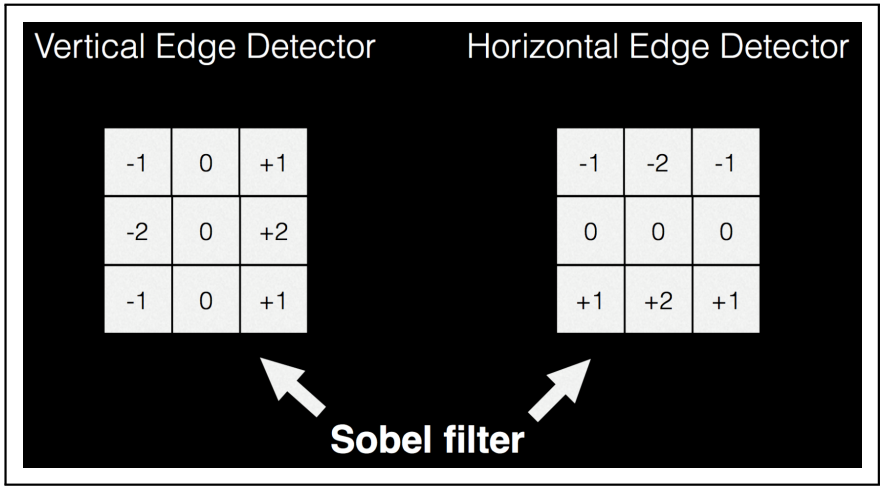
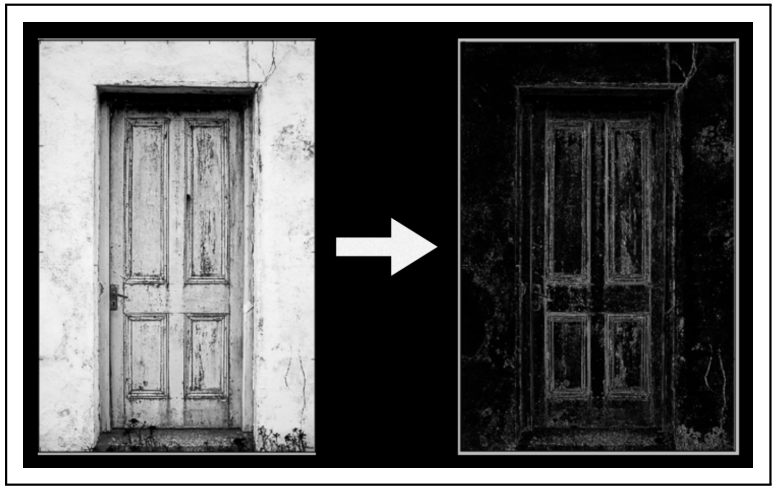




Convolutional Kernel

It may be easier to identify objects if we just consider the edges





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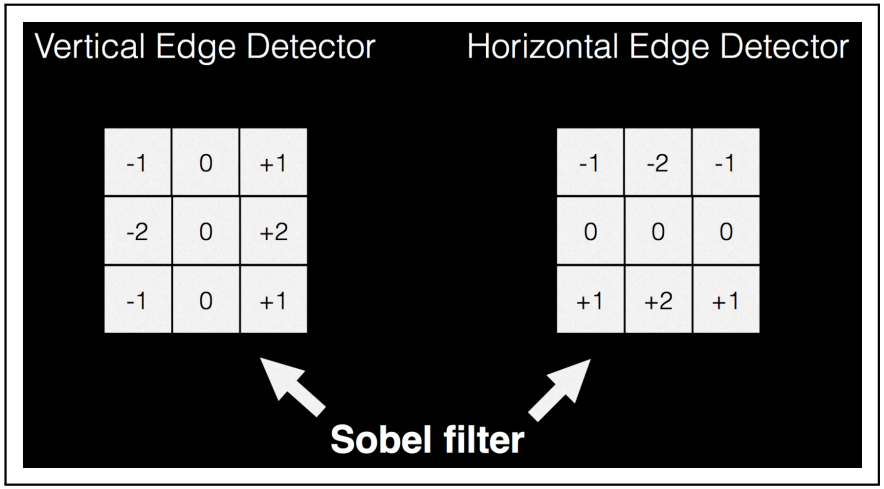
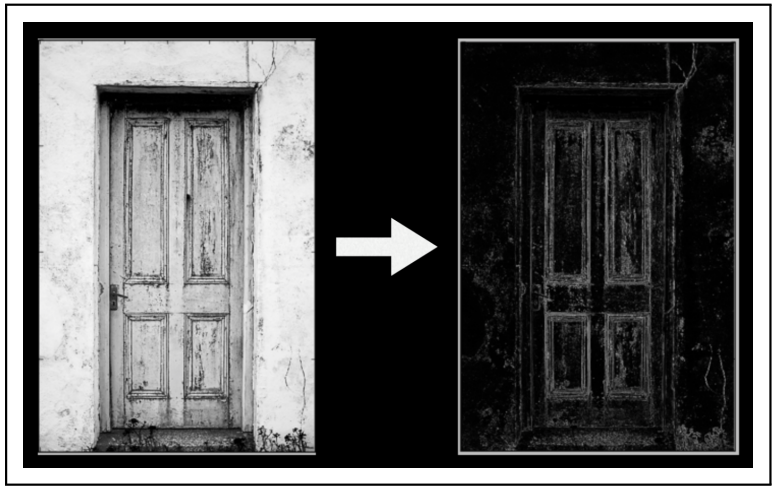




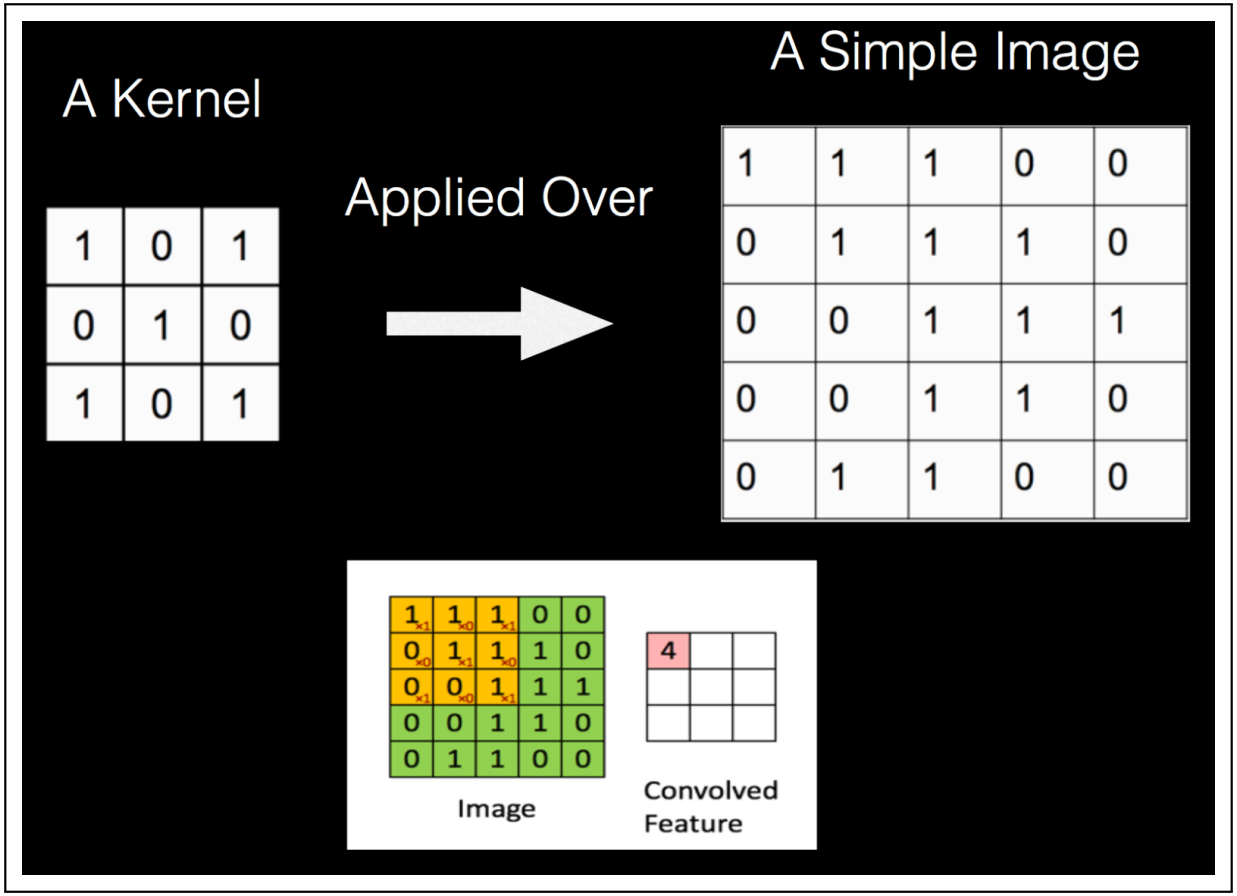
Canny Filter

Sobel Filter

Convolutional Kernel

Convolutional Kernel

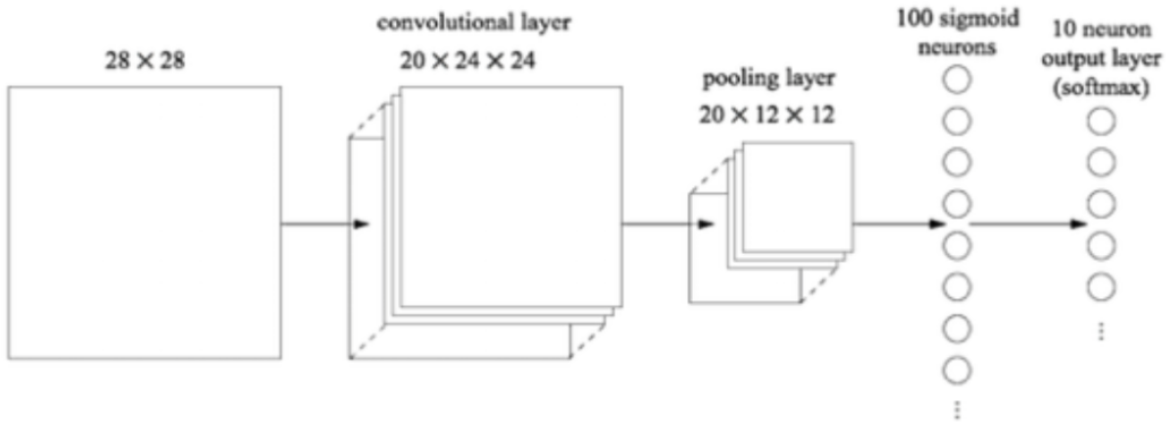
Recall that a convolution matrix (or kernel or mask) in image processing is a small matrix that can be used to blur, sharpen, emboss, detect edges, etc. through *convolutions* with an image



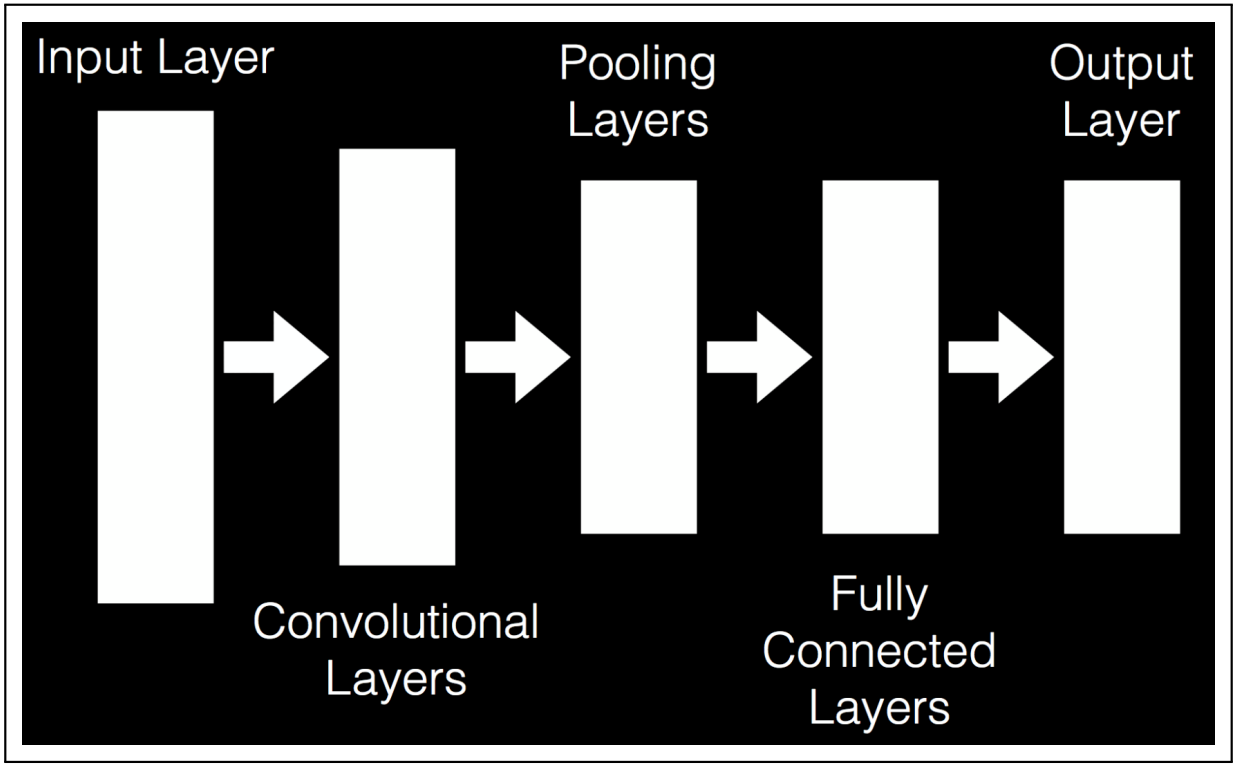
Can NN's learn their own convolution matrices?

idea: *denovo* kernels

Can NN's learn their own convolution matrices? Yep.

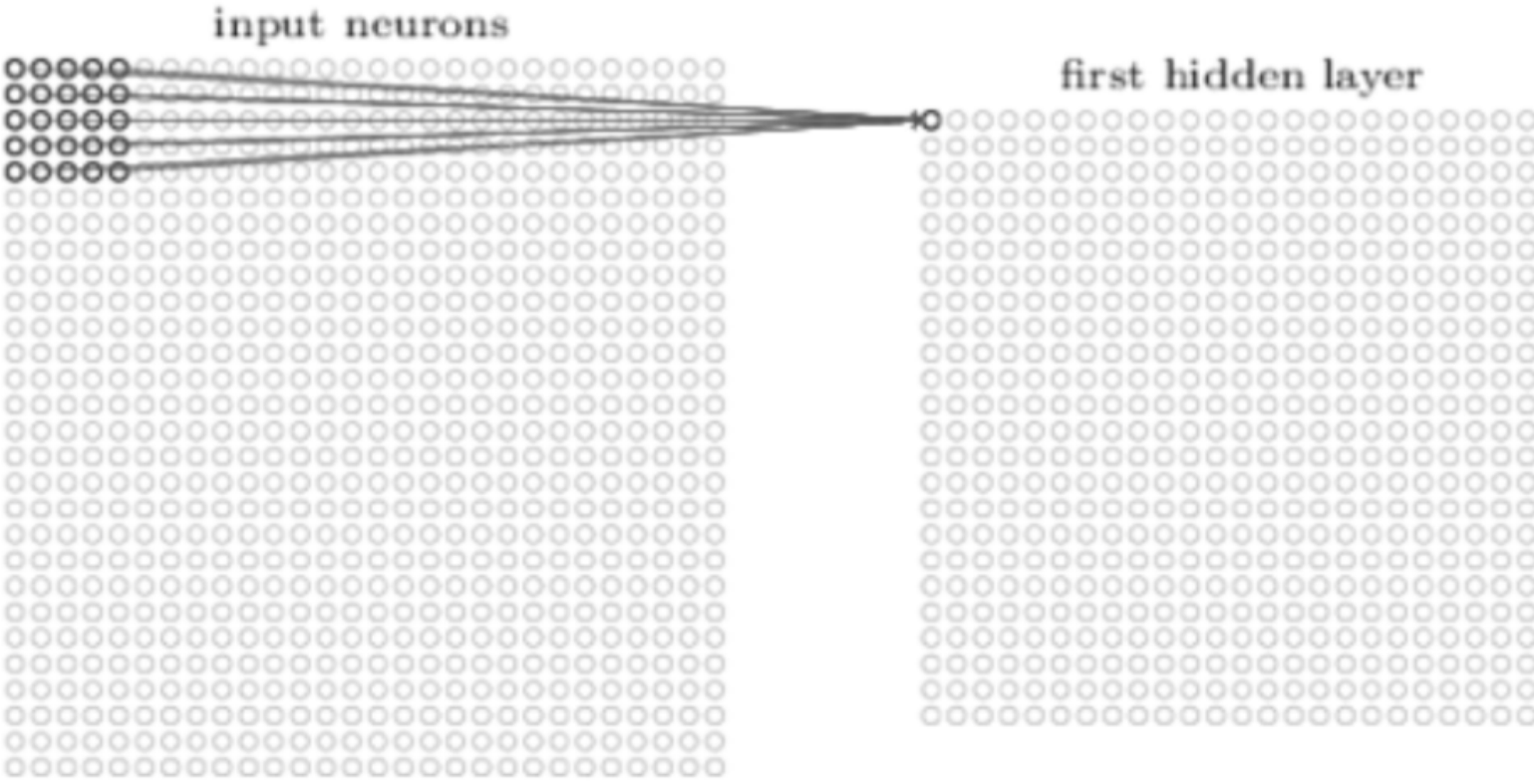


Convolutional Neural Network (CNN)



There are three key features that make this CNN structure actually work: (1) local receptive fields, (2) shared weights, and (3) pooling

1. Local Receptive Field



- A group of pixes are a *local receptive field*
- Defined by the size of the kernel
- The image is transformed into the set of local receptive fields

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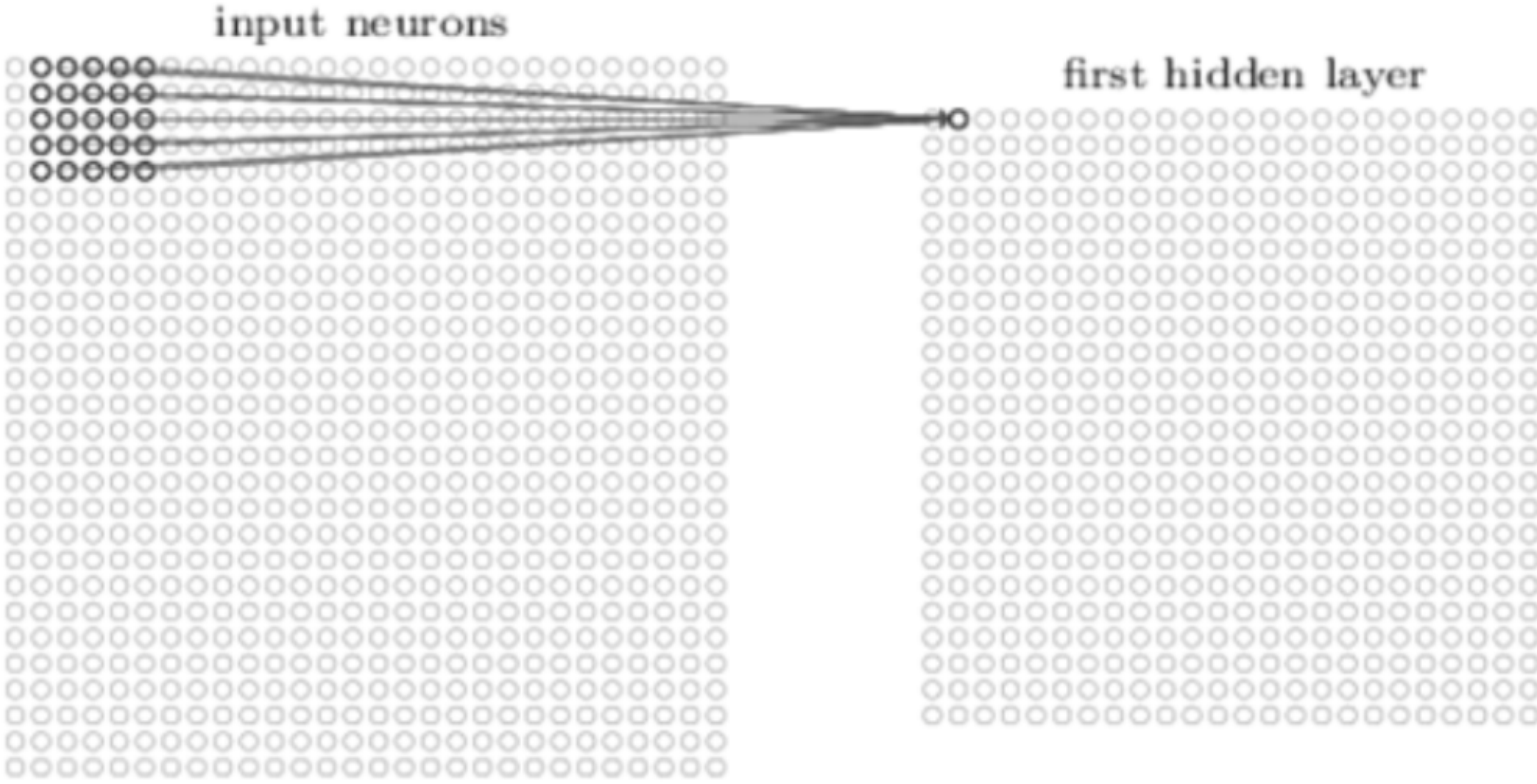

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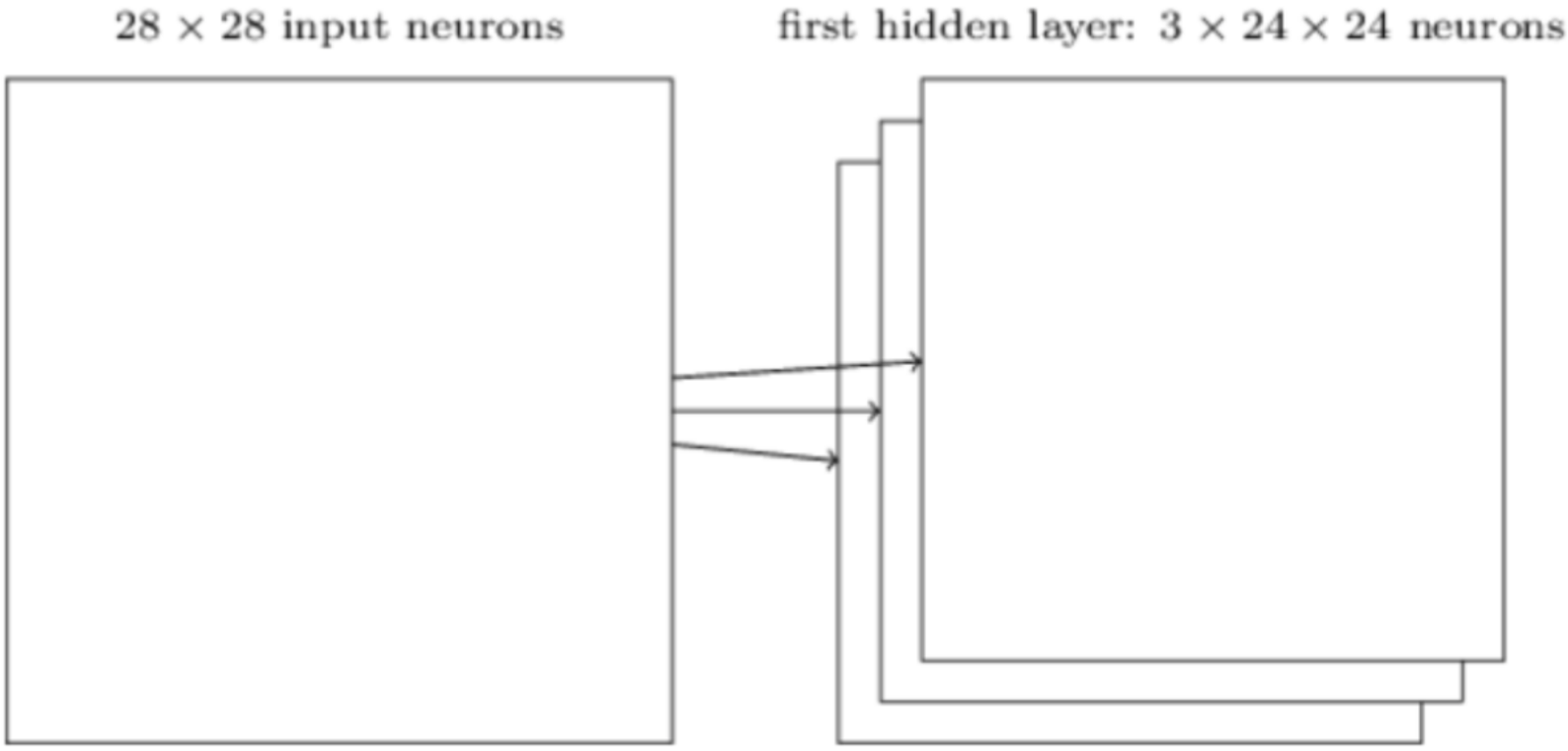
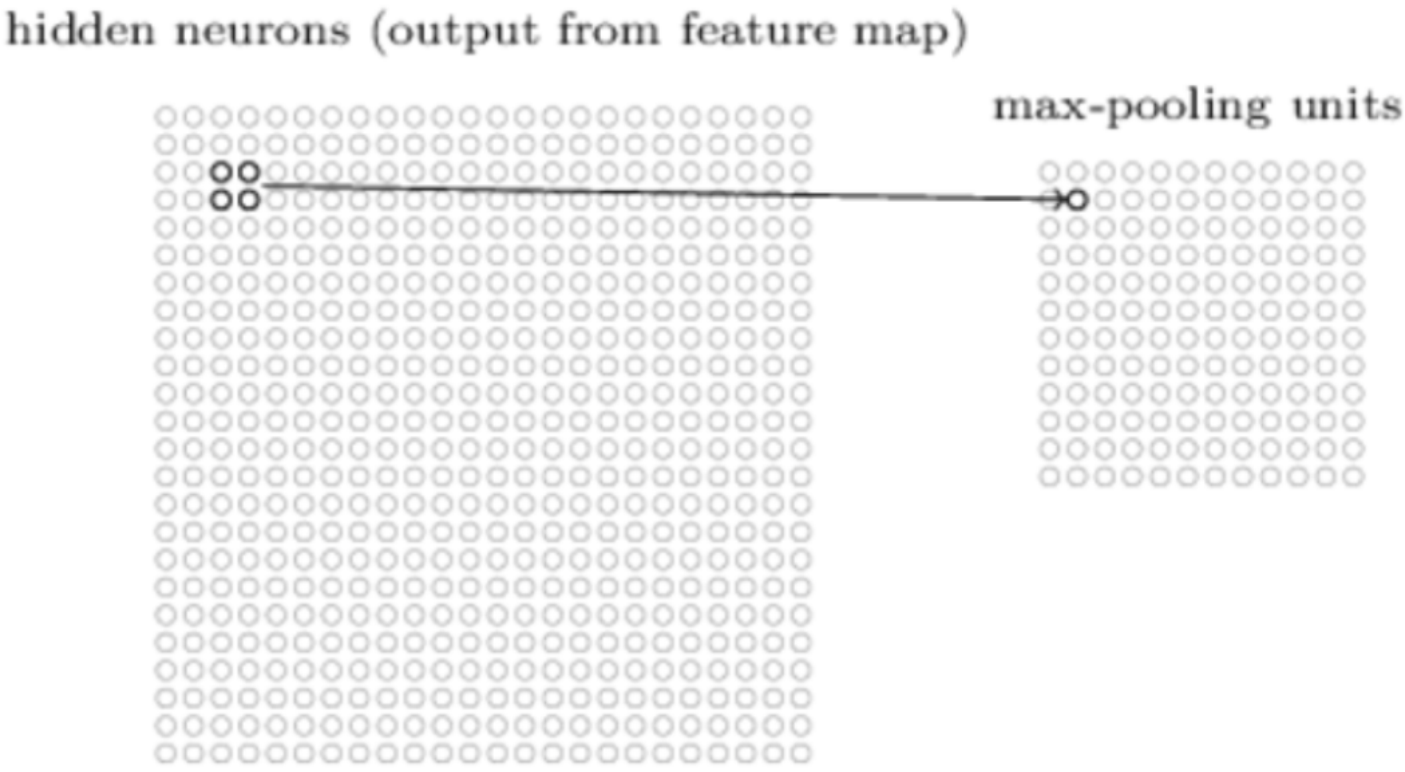
2. Shared Weights



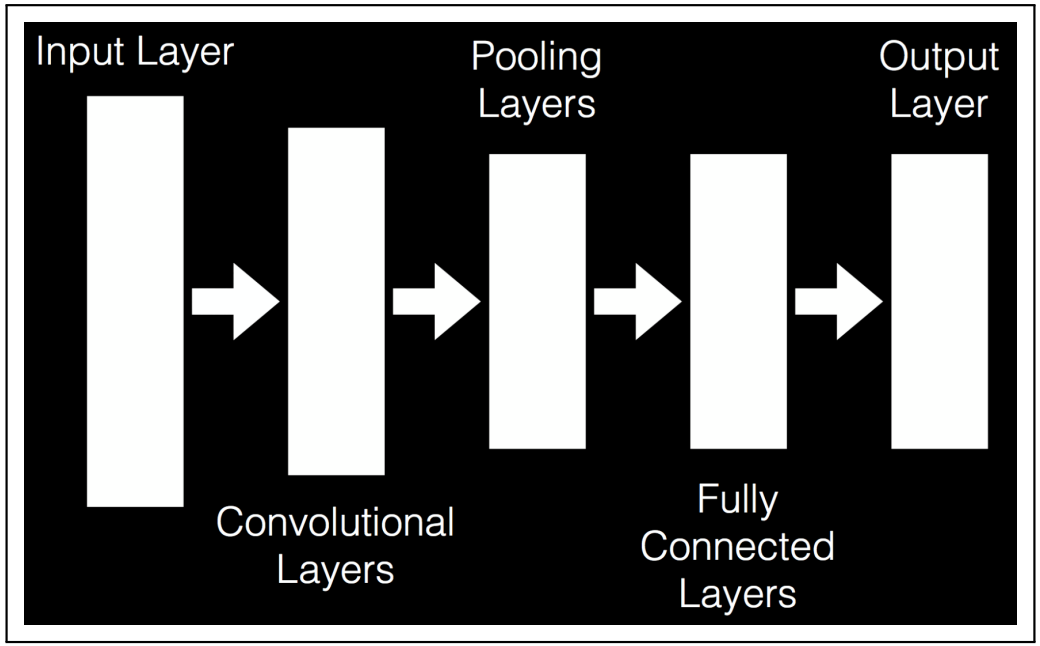
- Multiple convolutions are learned/used
- Weights within a convolution are (obviously) shared

3. Pooling



- Convolutional layers are simplified using, e.g., *max pooling*
- This reduces computational complexity in downstream layers
- In addition it provides a form of translational invariance

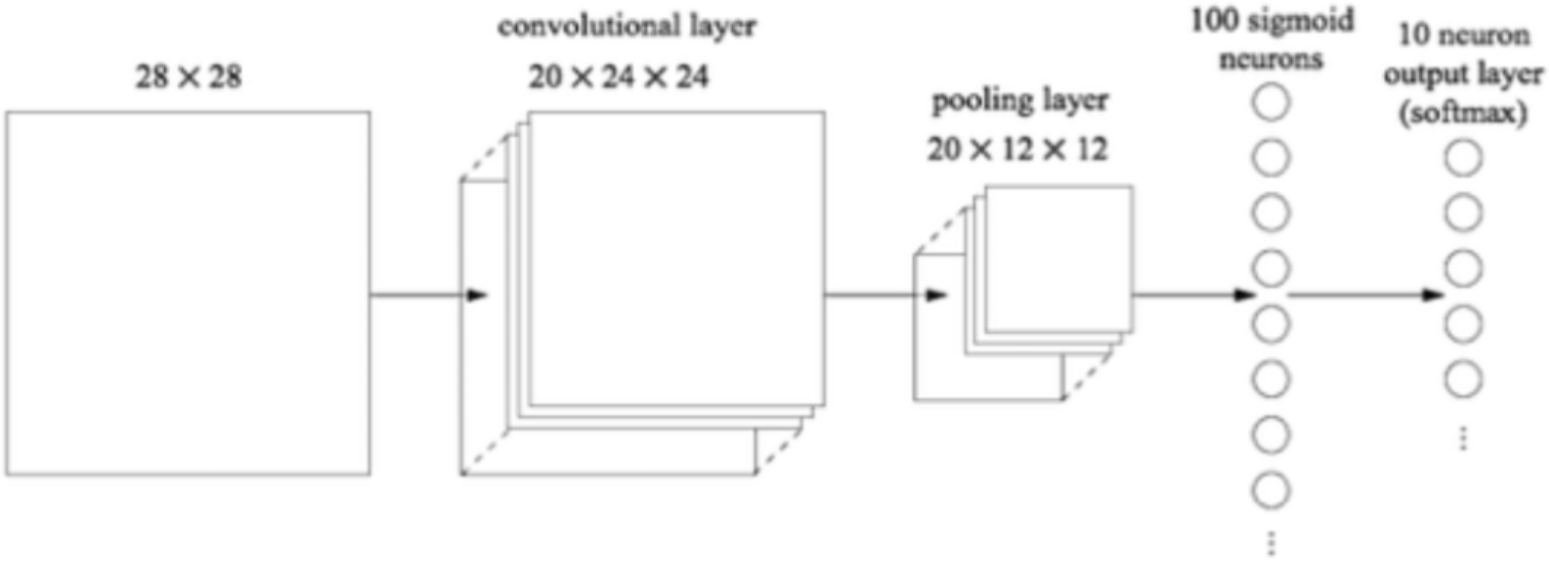
Fully Connected and Output Layers



- Fully connected layers hierarchically aggregate learned features – they produces higher order features in standard NN manner
- Softmax can be applied to the output layer $\eta_k, k = 1, \cdots K$ to estimate the one-versus-all class probabilities of K classes:

$$\frac{e^{\eta_k}}{\sum_{k'=1}^{K} e^{\eta_{k'}}}$$

So a final CNN might look something like this...



Recurrent Neural Network (RNN)

- A RNN is a NN where a hidden layer feeds back into itself
- This allows the NN to exhibit dynamic temporal behavior
- RNN's provide "internal memory" for sequence processing
- They are very applicable to handwriting/speech recognition

`https://github.com/SirDudeness/BassGenerator`

Mores

github.com/sallamander/neural-networks-intro
[Provides introductions in NumPy, Theano, Tensorflow, & Keras]
neuralnetworksanddeeplearning.com [General introduction]
cs231n.github.io/ [Convolution NN's for visual recognition]
deeplearning.net/tutorial/lenet.html [Mathematics]
arxiv.org/abs/1503.02531 [Interpretation detractions]
[Projects]
lasagne.readthedocs.org/en/latest/index.html
(also, see nolearn for an scikit learn type of interface)
cbinsignts.com/blog/python-tools-machine-learning
deeplearning.net/tutorial/lenet.html
deeplearning4j.org
caffe.berkeleyvision.org
"How does deep learning work and how is it different from normal neural net works applied with SVM" on quora.com differentiates deep learning from other methods. Hinton's 2007 Google talk "The Next Generation of Neural Networks" introduces deep learning

Fine

NN's do not **currently** make machine learning any *easier*...