Microsoft

Deep Learning

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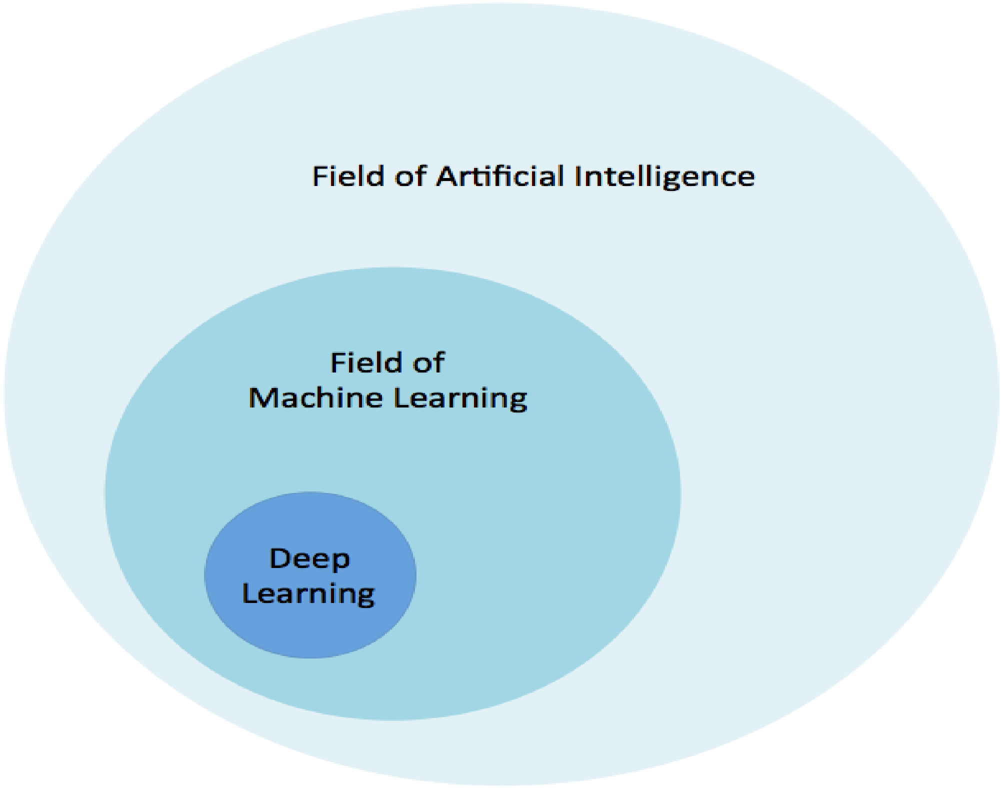
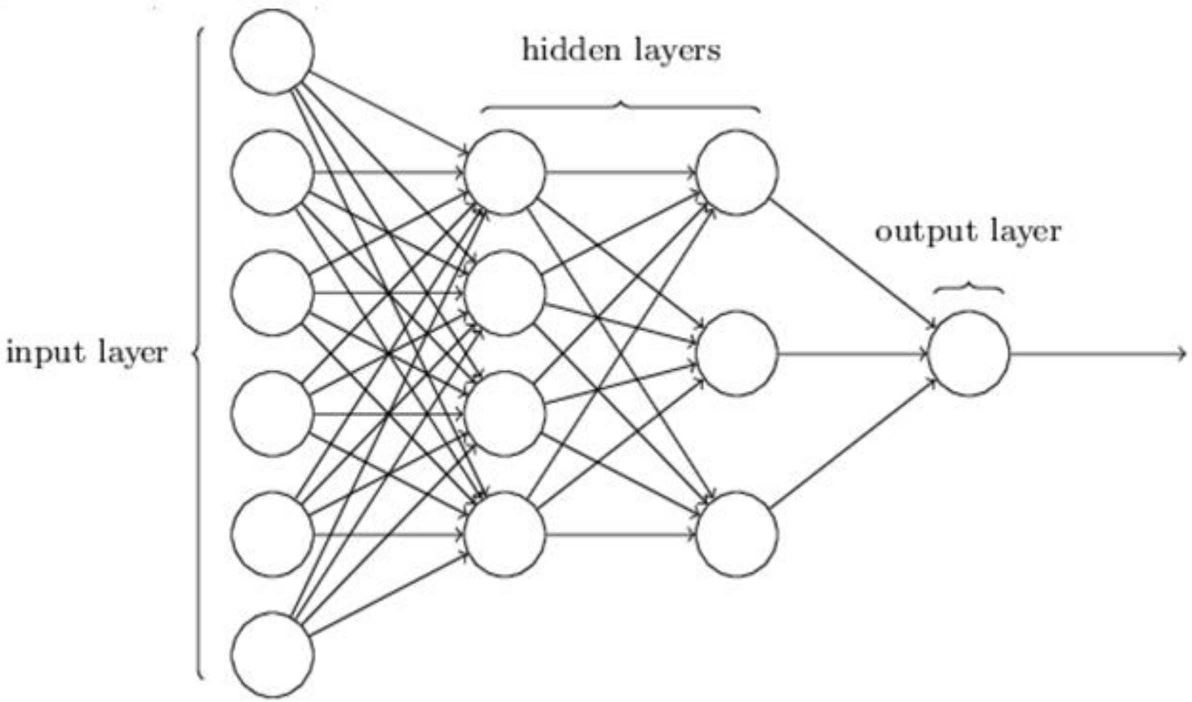
What Is Deep Learning?

1. Based on Algorithms that attempt to model high level abstractions in data
2. Deep learning is synonymous with artificial neural network (ANN)
3. The “deep” in deep learning refers to the depth of the network. An ANN can be very shallow





Deep Learning

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Uber to require selfie security check from drivers

Using Microsoft Cognitive Services, Uber hopes to make riders feel safer by verifying the ID of drivers before rides are given.

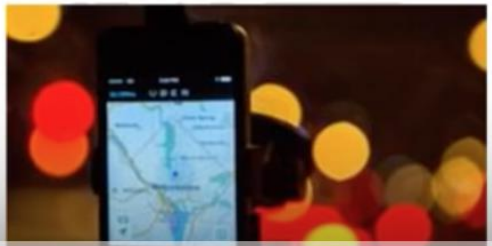
By Jake Smith for iGeneration | September 23, 2016 -- 19:59 GMT (03:59 GMT+08:00) | Topic: Innovation

f 23 in 3

Uber announced on Friday a new security feature called Real-Time ID Check that will require drivers to periodically take a selfie before starting their driving shift.

The feature, which begins rolling out to US cities on Friday, uses Microsoft Cognitive Services to reduce fraud and give riders an extra sense of security.

SHARING ECONOMY



Uber says Microsoft's feature instantly compares the selfie to

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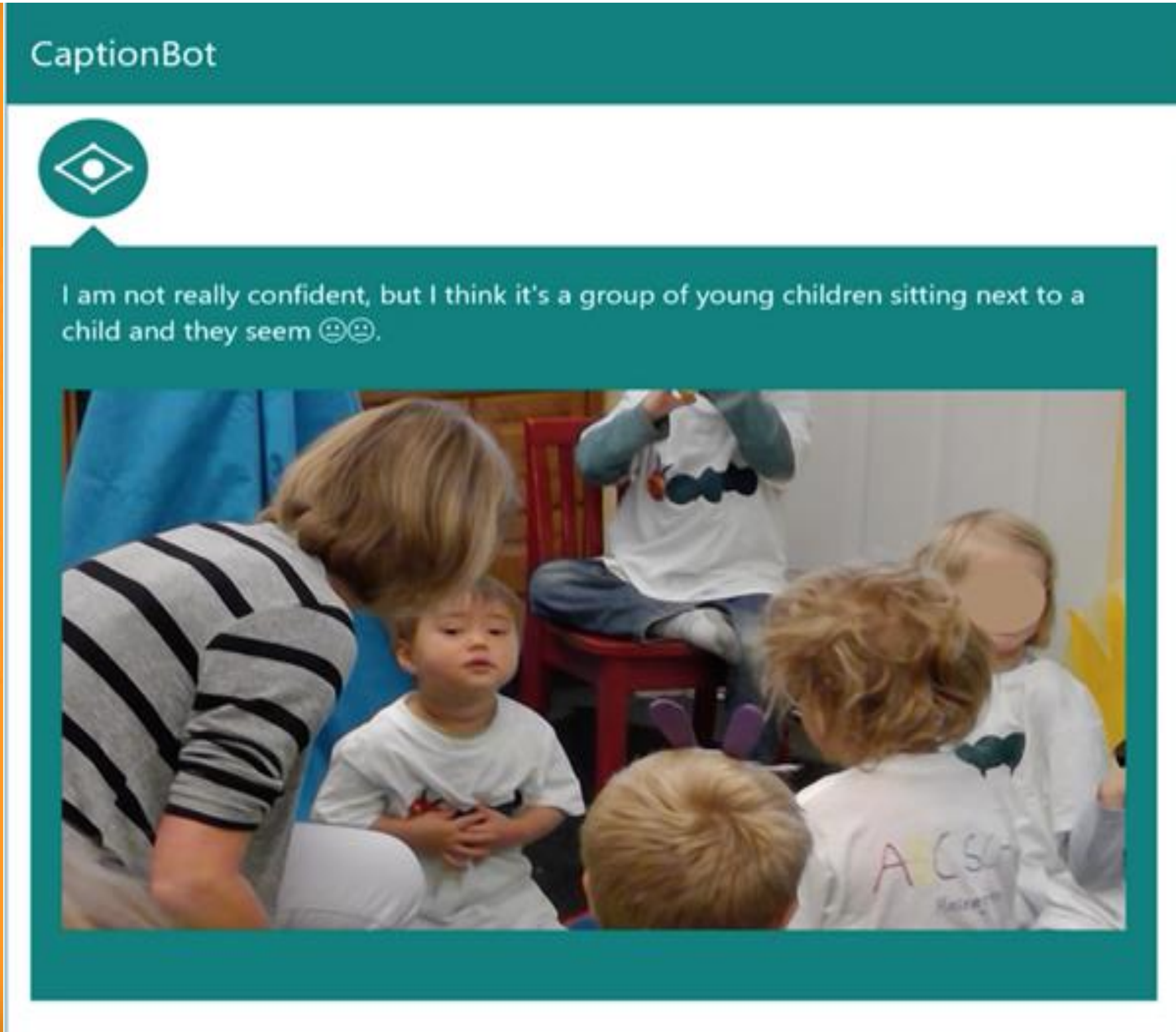

Deep Learning

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September 6, 2016

Microsoft and Liebherr together to make Refrigerators smart

Smart refrigerators, Cortana, Microsoft and Liebherr

When this joint venture of Microsoft and Liebherr will come into reality, it will be the next level of machine learning. SmartDeviceBox is nothing a communication module which fits into Liebherr refrigerators and freezers, connecting them to the internet. The modular units can be integrated and upgraded at any time in existing SmartDevice-ready appliances to create value and comfort for customers through new digital features and solutions.

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The underlying state-of-the-art deep learning algorithms themselves are also available within Microsoft's open source Computational Network Toolkit (CNTK) and can be used to build custom models for new use cases.

Microsoft states that it has already built a new image processing system to detect specific food items using the deep learning algorithms contained in CNTK.

Deep Learning

Microsoft’s historic speech breakthrough

- Microsoft 2016 research system for conversational speech recognition
- 5.9% word-error rate
- enabled by CNTK’s multi-server scalability

Historic Achievement: Microsoft researchers reach human parity in conversational speech recognition

Microsoft researchers from the Speech & Dialog research group include, from back left, Wayne Xiong, Geoffrey Zweig, Xuedong Huang, Dong Yu, Frank Seide, Mike Seltzer, Jasha Droppo and Andreas Stolcke. (Photo by Dan DeLong)

[W. Xiong, J. Droppo, X. Huang, F. Seide, M. Seltzer, A. Stolcke, D. Yu, G. Zweig: “Achieving Human Parity in Conversational Speech Recognition,” https://arxiv.org/abs/1610.05256]

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Microsoft Cognitive Toolkit

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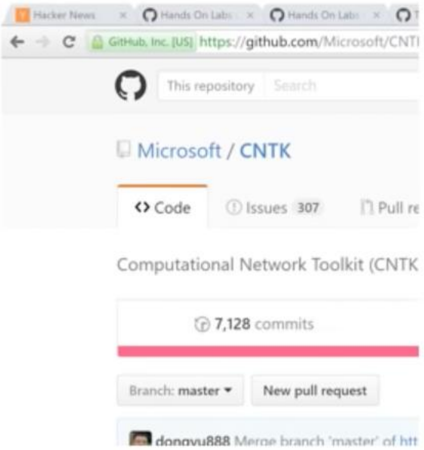
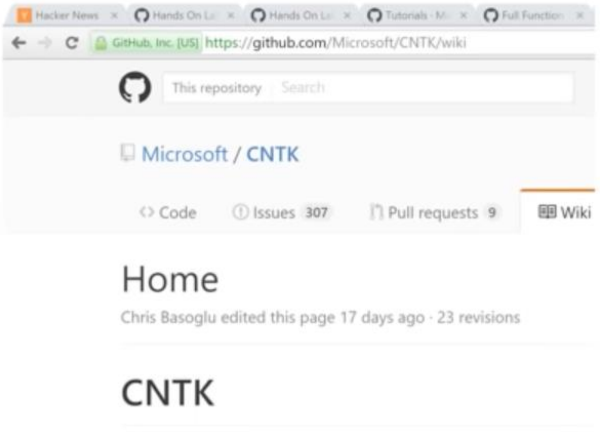
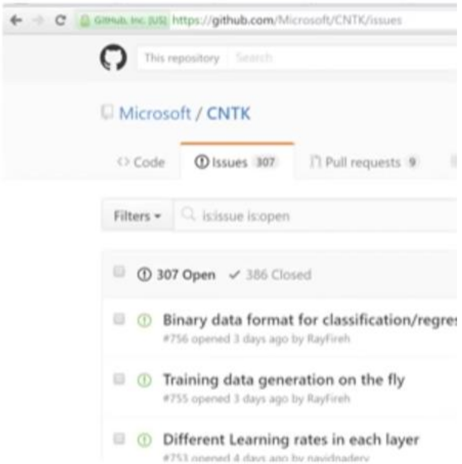
- Github: https://github.com/ Microsoft/CNTK
- Wiki: https://github.com/ Microsoft/CNTK/wiki
- Issues: https://github.com/ Microsoft/CNTK/issues







Why Is Deep Learning Popular?

- DL models has been here for a long time
  - Fukushima (1980) – Neo-Cognitron
  - LeCun (1989) – Convolutional Neural Network

- DL popularity grew recently
  - With growth of Big Data
  - With the advent of powerful GPUs

Motivation: Why Go Deep

- Deep Architectures can be representationally efficient
  - Fewer computational units for same function
- Deep Representations might allow for a hierarchy or representation
  - Allows non-local generalization
  - Comprehensibility
- Multiple levels of latent variables allow combinatorial sharing of statistical strength
- Deep architectures work well (vision, audio, NLP, etc.) !

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Different Levels Of Abstraction

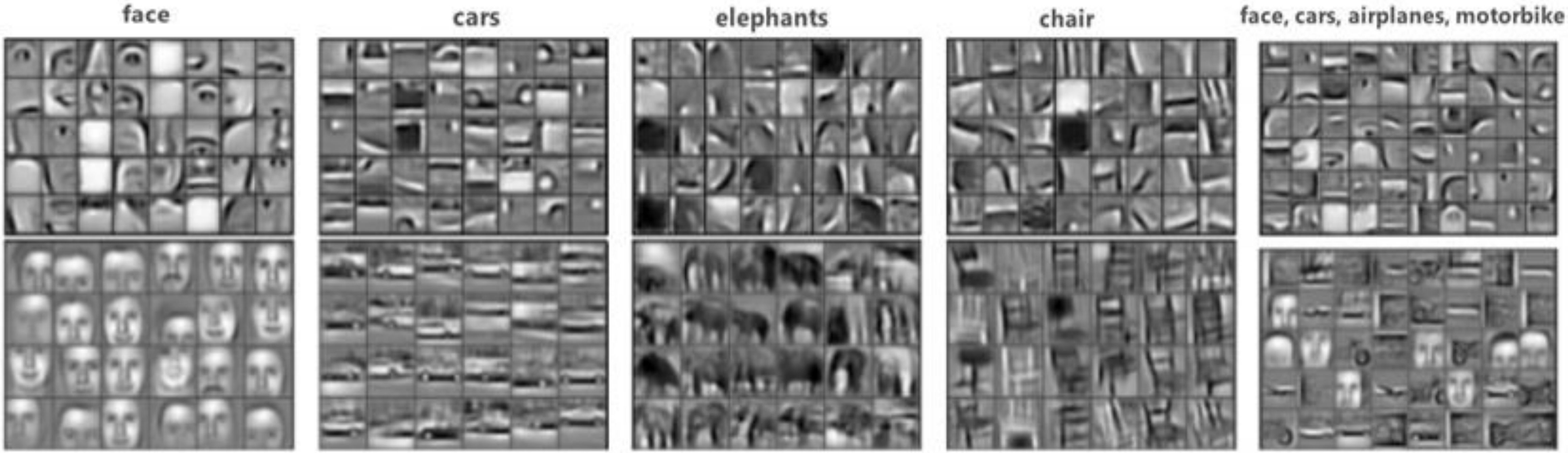
Hierarchical Learning

- Natural progression from low level to high level structure as seen in natural complexity
- Easier to monitor what is being learnt and to guide the machine to better subspaces
- A good lower level representation can be used for many distinct tasks

Compositional Data

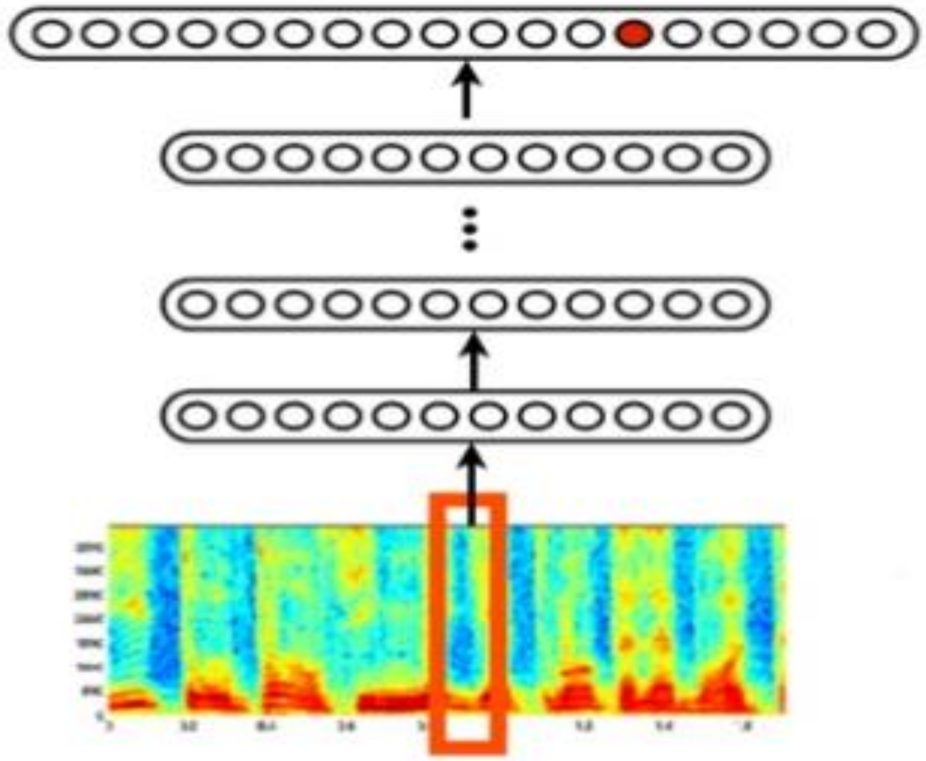
NATURAL DATA
IS COMPOSITIONAL.

Compositional Data

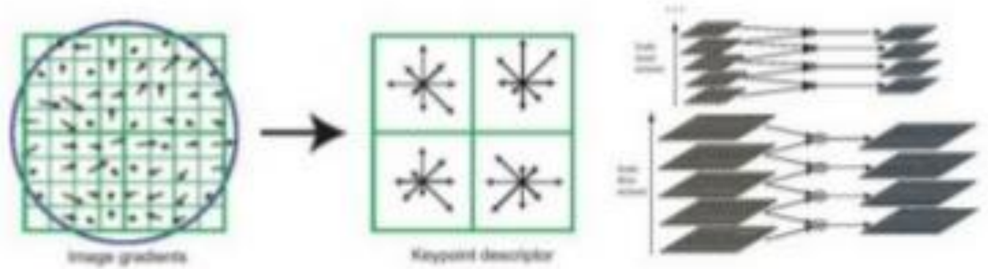


Compositional Data

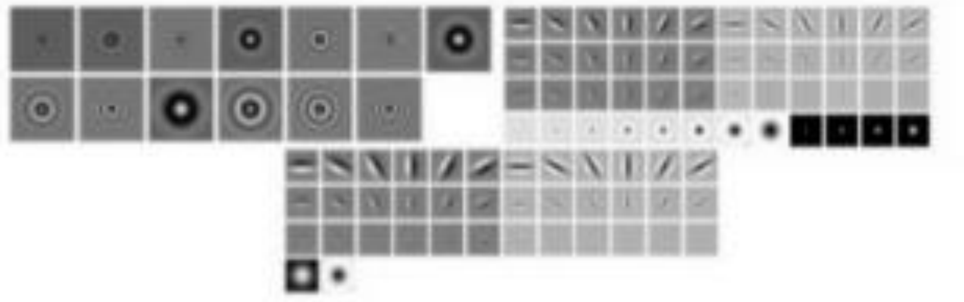
Sound



Traditional vs Deep Learning



SIFT



Textons

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Traditional vs Deep Learning

Feature extractors, required:

- Expert knowledge
- Time-consuming hand-tuning
- In industrial applications, this 90% of the time
- Sometimes are problem specific

But, what if we could learn feature extractors ?

Traditional vs Deep Learning

Traditional ML requires manual feature extraction/engineering

Deep learning can automatically learn features in data

Feature extraction for unstructured data is very difficult

Deep learning is largely a "black box" technique, updating learned weights at each layer

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Deep Learning Begins With A Little Function

It all starts with a humble linear function called a perceptron.

weight1 × input1
weight2 × input2
+ weight3 × input3

sum

Perceptron:
If sum > threshold: output 1
Else: output 0

Example: The inputs can be your data. Question: Should I buy this car?

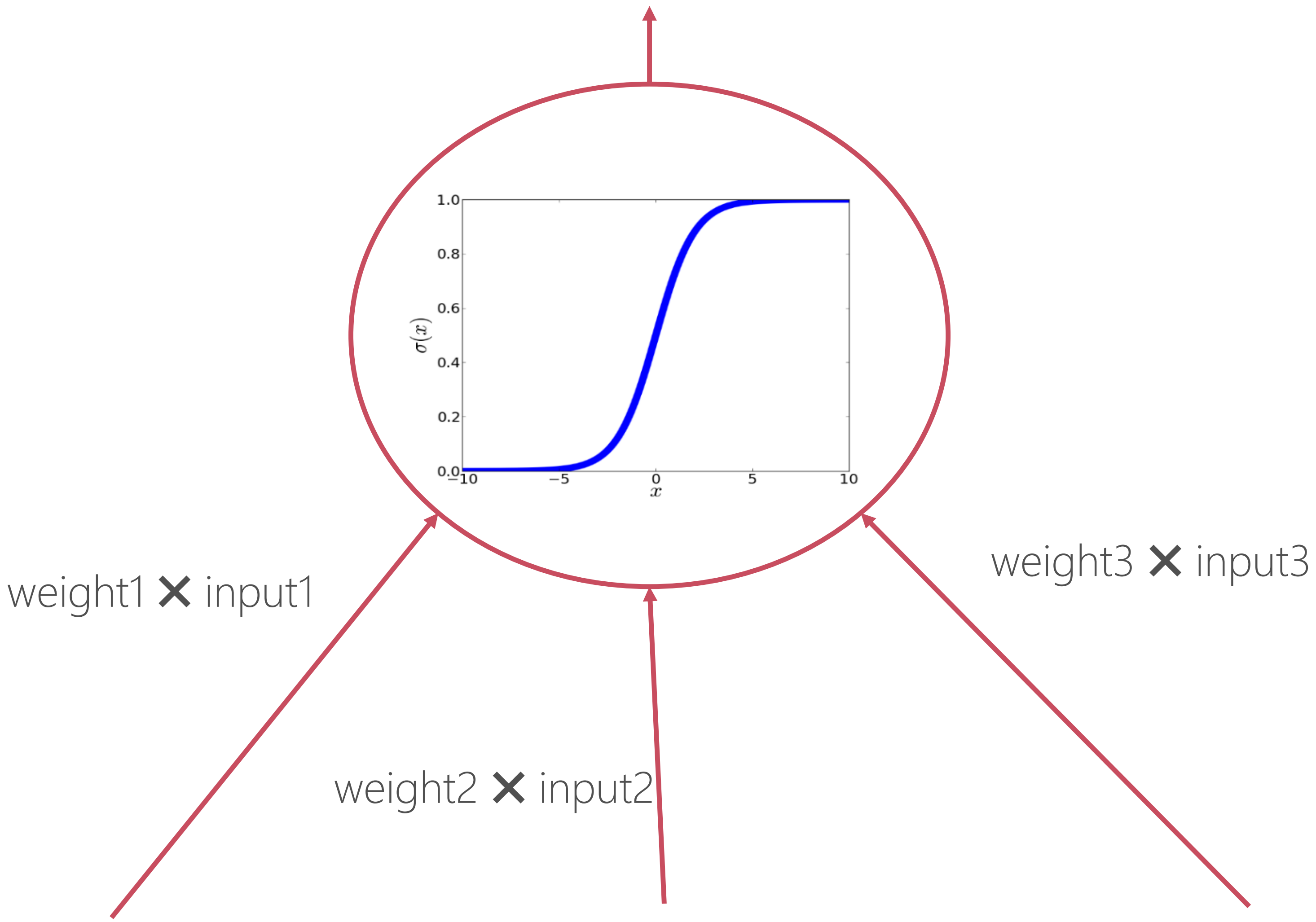
0.2 × gas mileage
0.3 × horsepower
+ 0.5 × num cup holders

sum

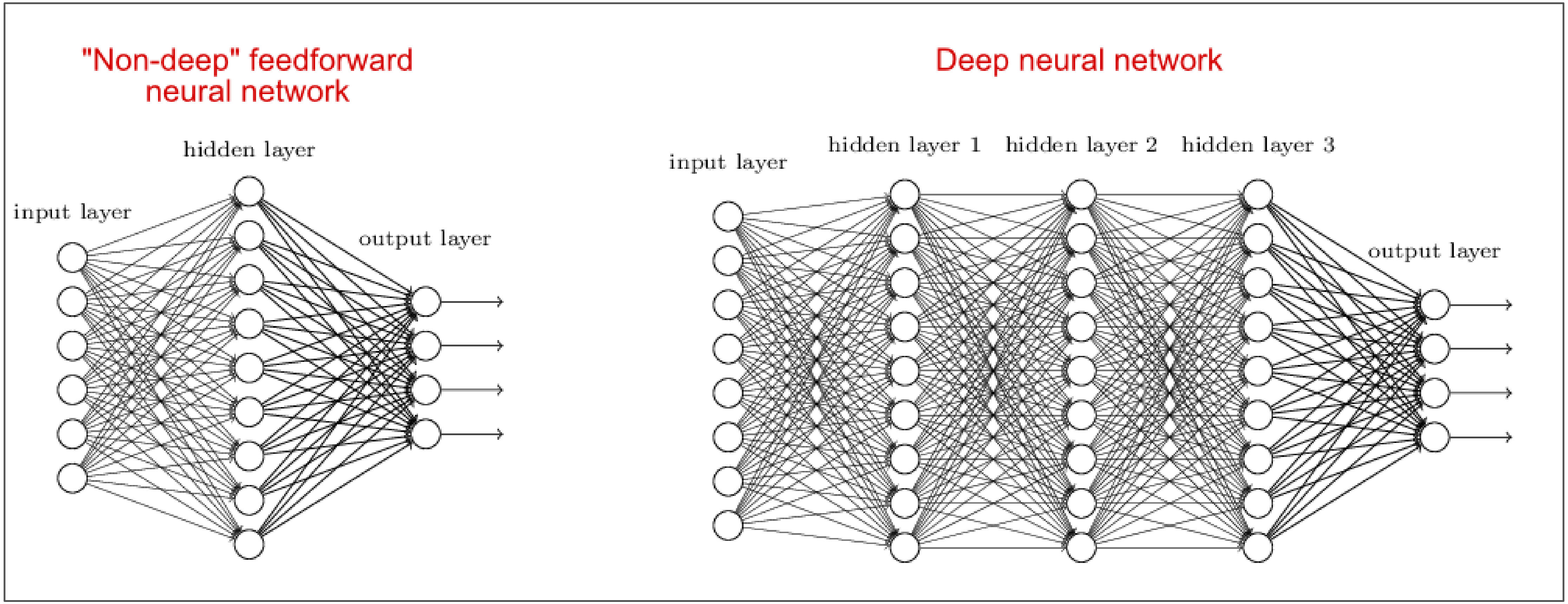
Perceptron:
If sum < threshold: buy
Else: walk

These Little Functions Are Chained Together

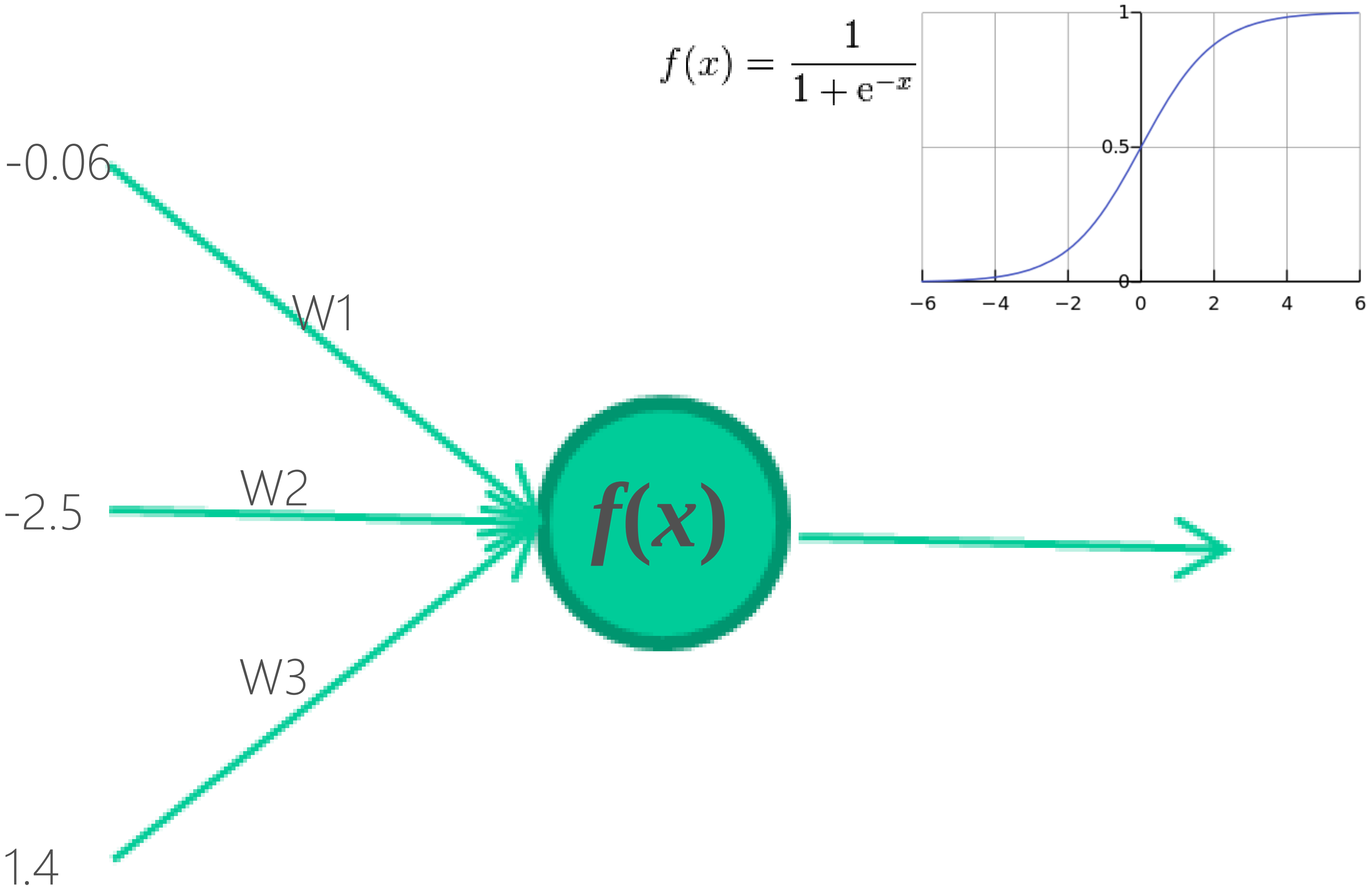
- Deep learning comes from chaining a bunch of these little functions together
- Chained together, they are called neurons



Deep Neural Network (DNN)



$$f(x) = \frac{1}{1 + e^{-x}}$$



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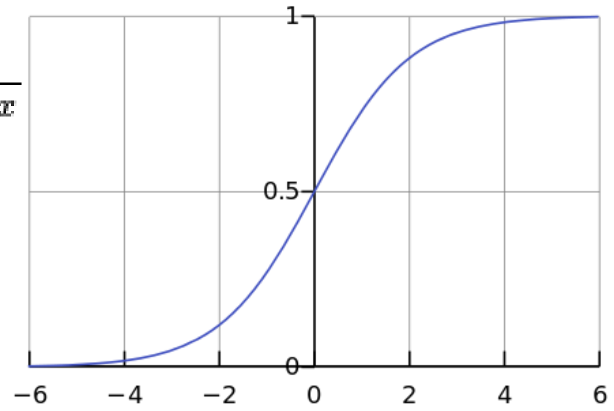

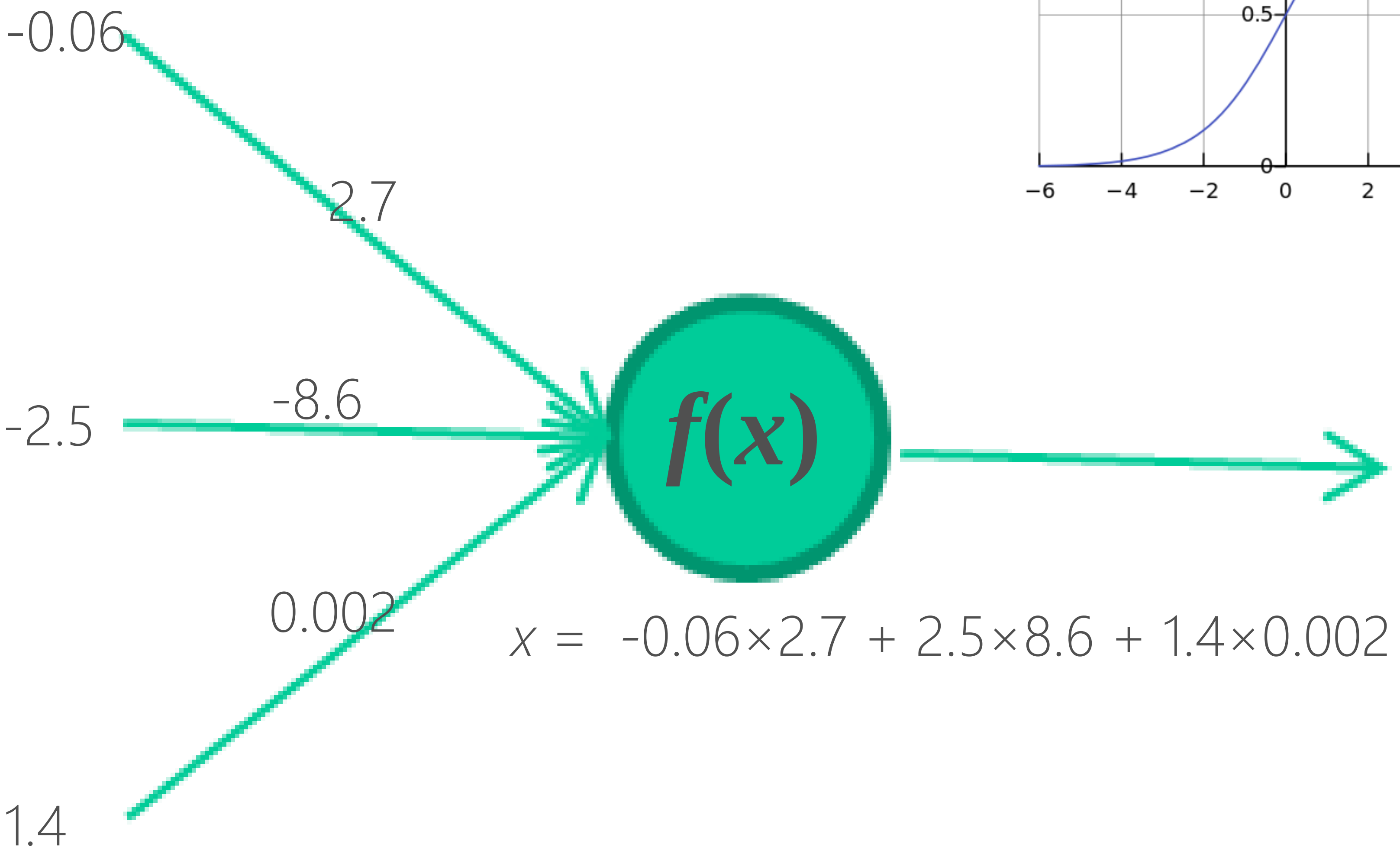

$$x = -0.06\times2.7 + 2.5\times8.6 + 1.4\times0.002 = 21.34$$

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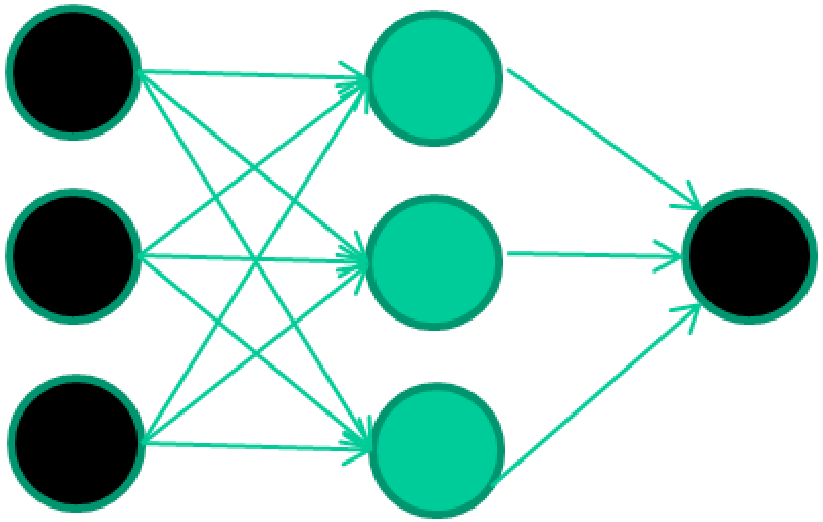
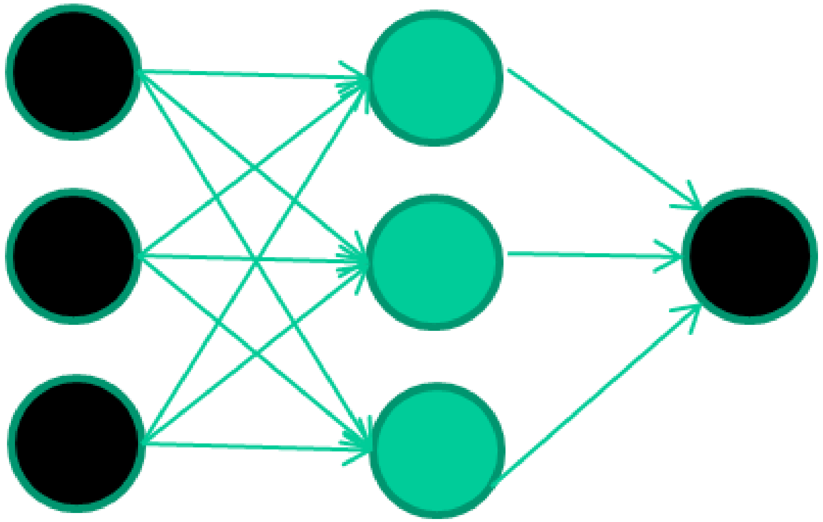
A dataset

Fields			*class*
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc ...			



Training the neural network

Fields			*class*
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc ...			



Training the neural network

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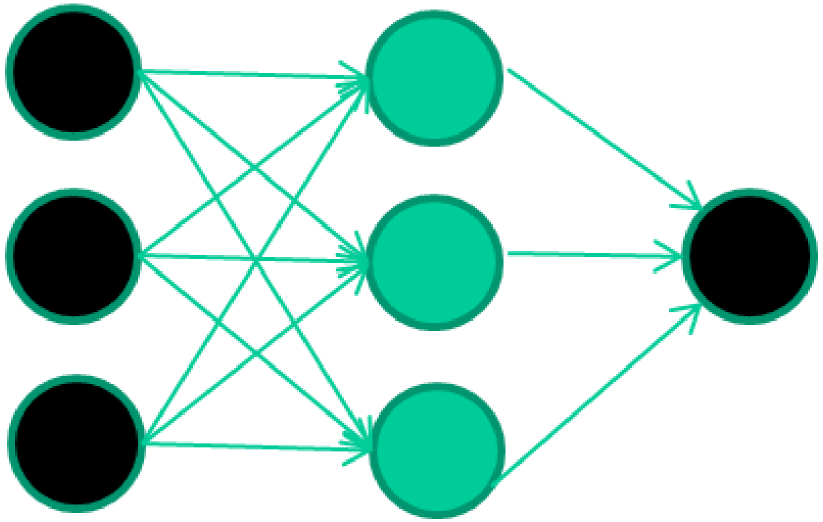
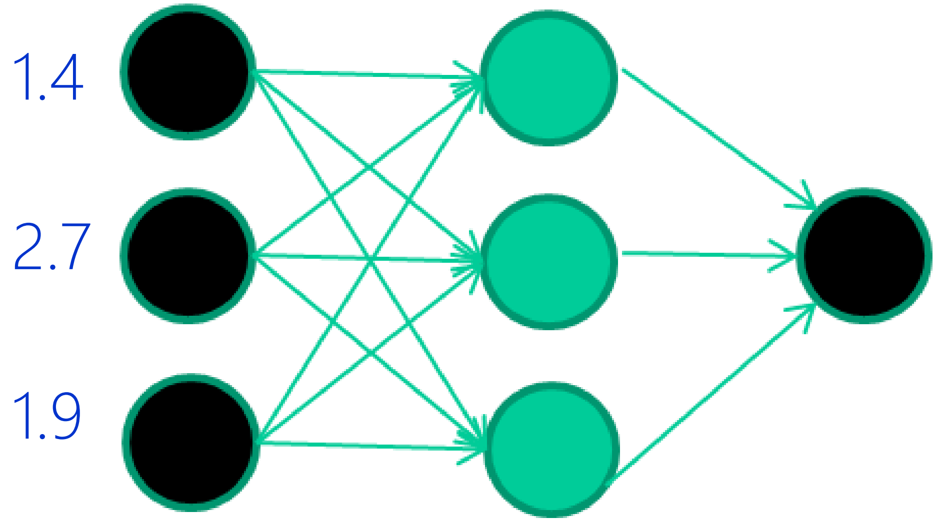
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

Initialise with random weights



Present a training pattern

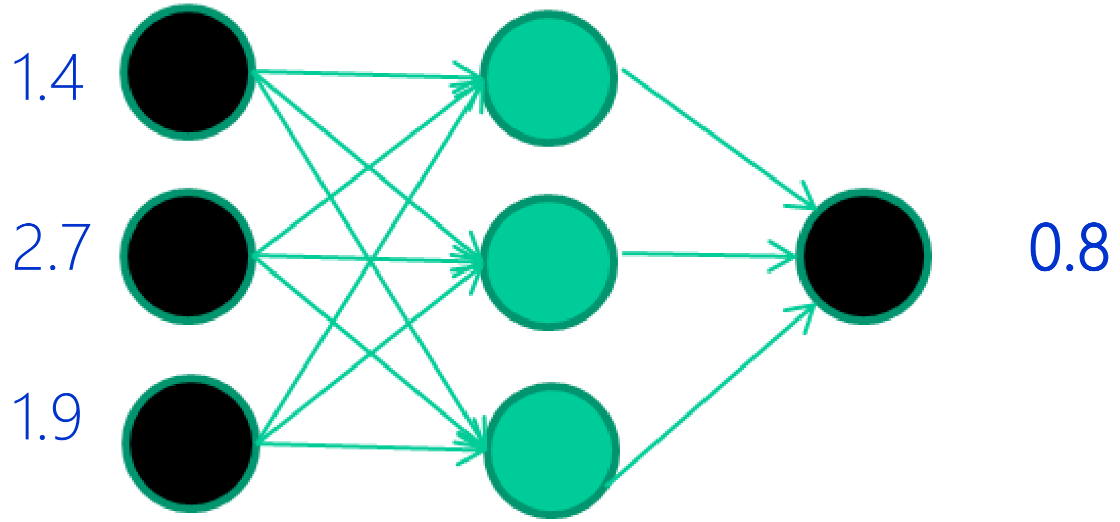
Fields			class
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc ...			



Feed it through to get output

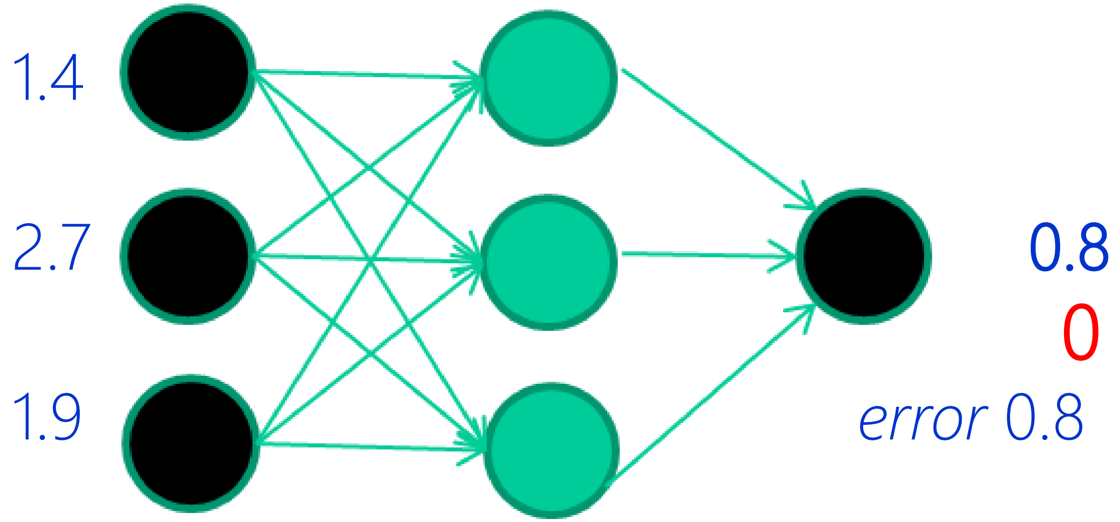
Fields			*class*
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0

etc ...



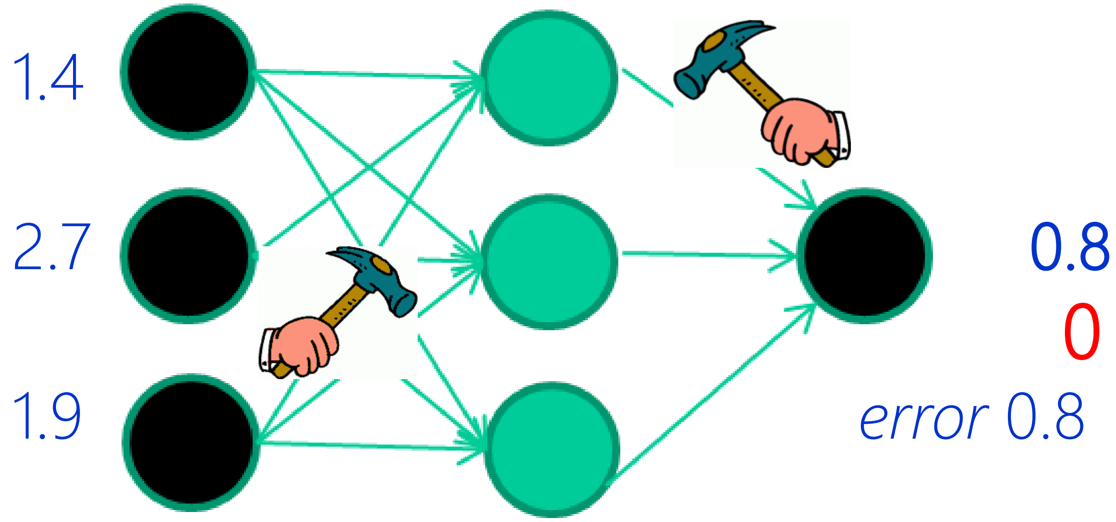
Compare with target output

Fields			*class*
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc ...			



Adjust weights based on error

Fields			*class*
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc ...			



Fields			class
1.4	2.7	1.9	0
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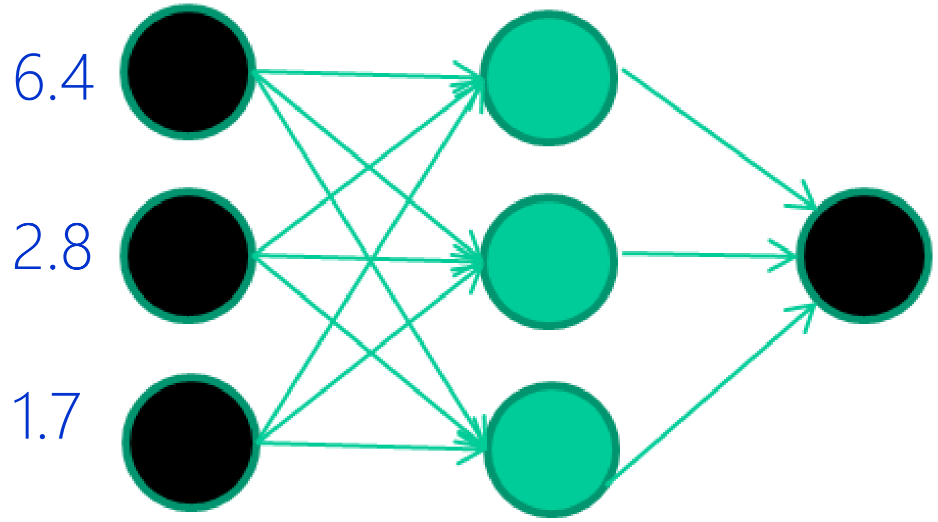
4.1	0.1	0.2	0
etc ...			

Present a training pattern



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Feed it through to get output

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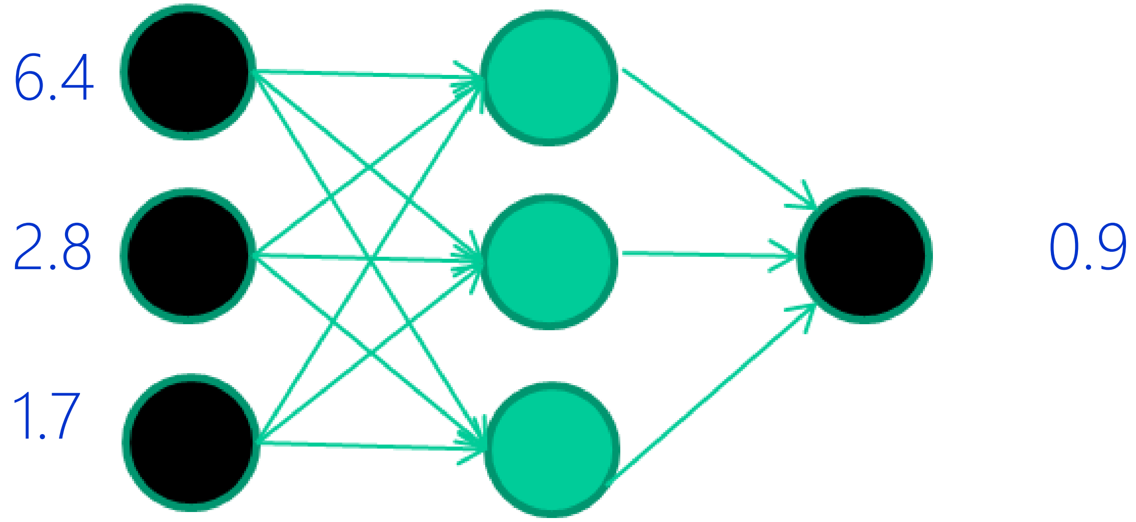

Fields			*class*
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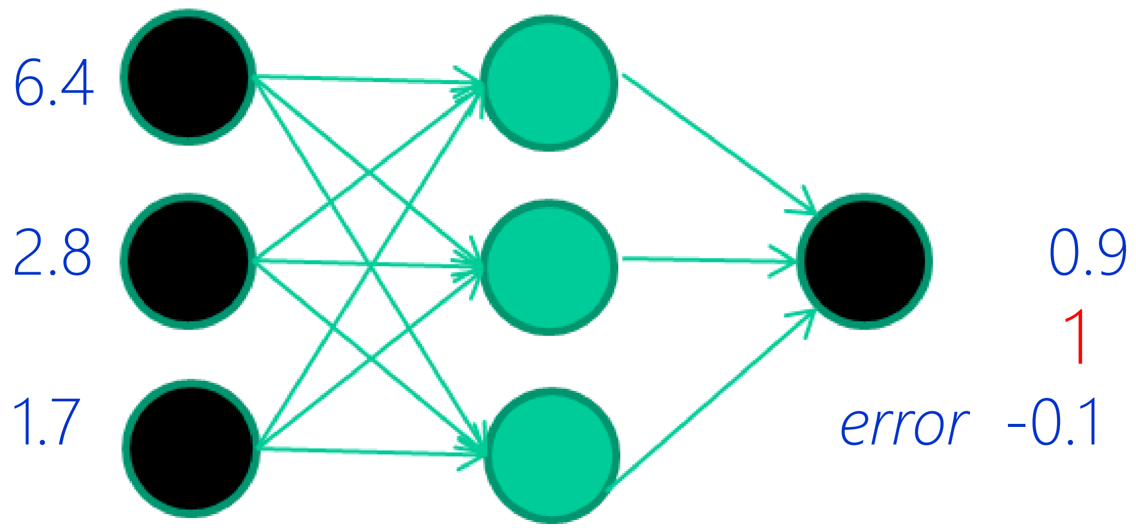
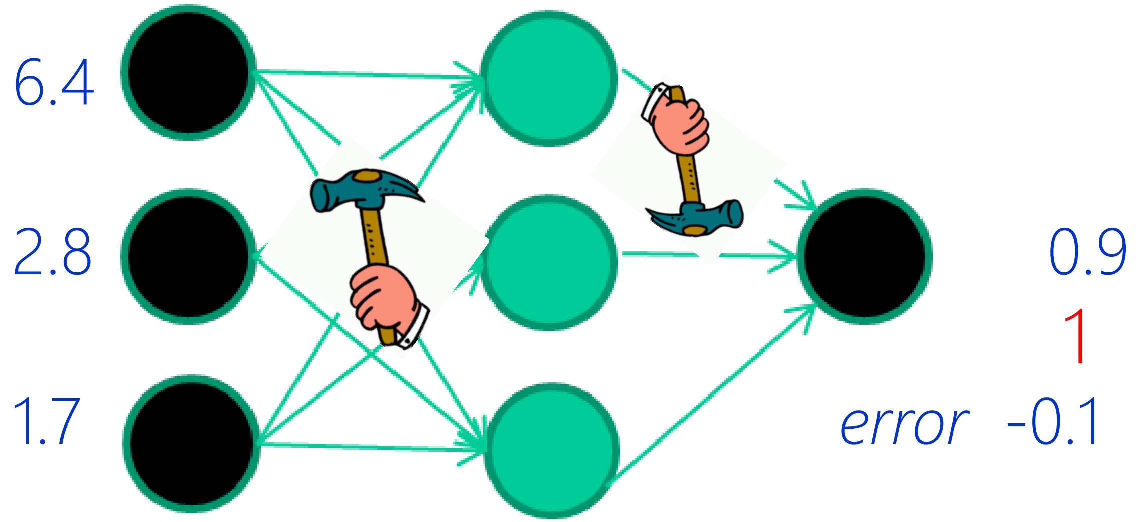
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc ...			

Compare with target output



And so on ....

Fields			*class*
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc ...			



Repeat this thousands, maybe millions of times – each time taking a random training instance, and making slight weight adjustments

Algorithms for weight adjustment are designed to make changes that will reduce the error

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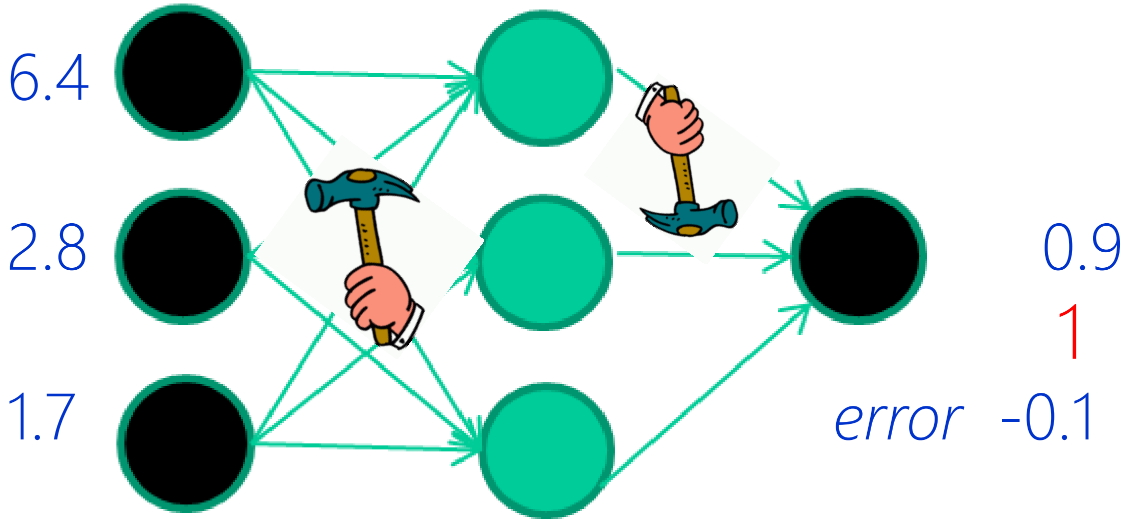
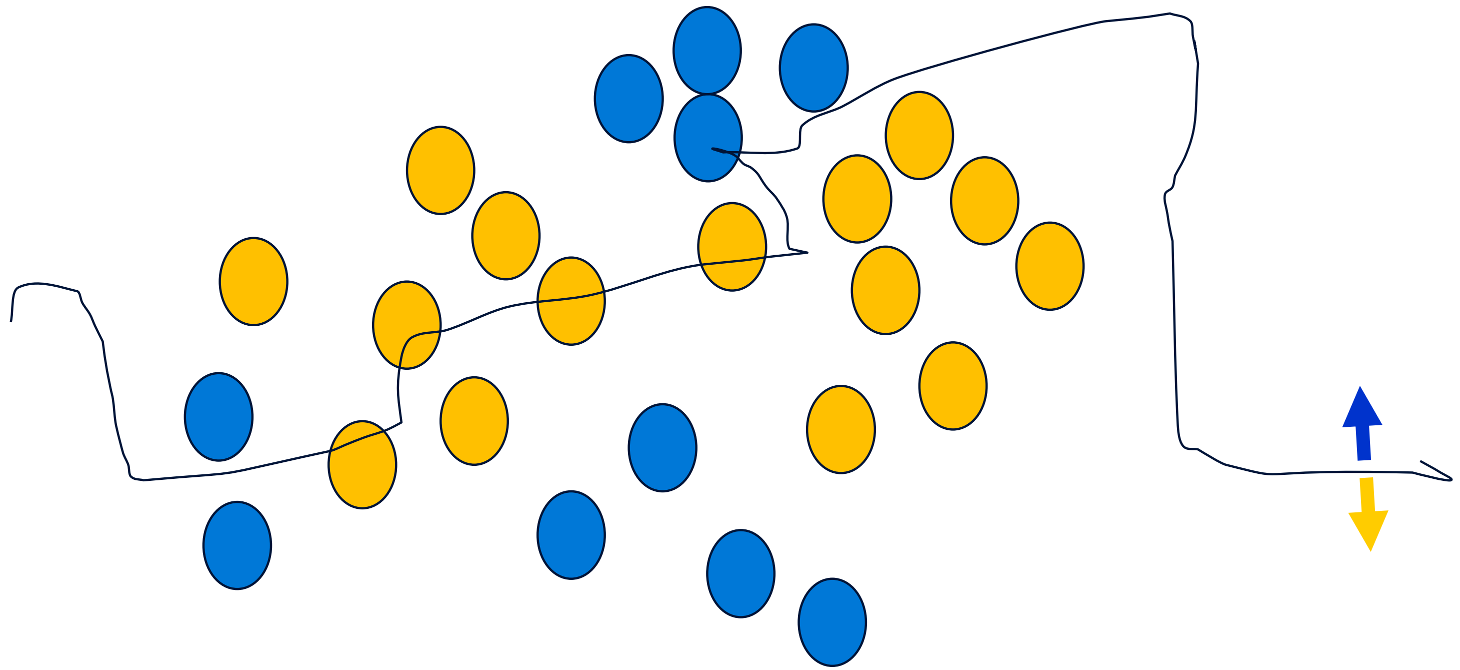
Adjust weights based on error

Fields			*class*
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc ...			



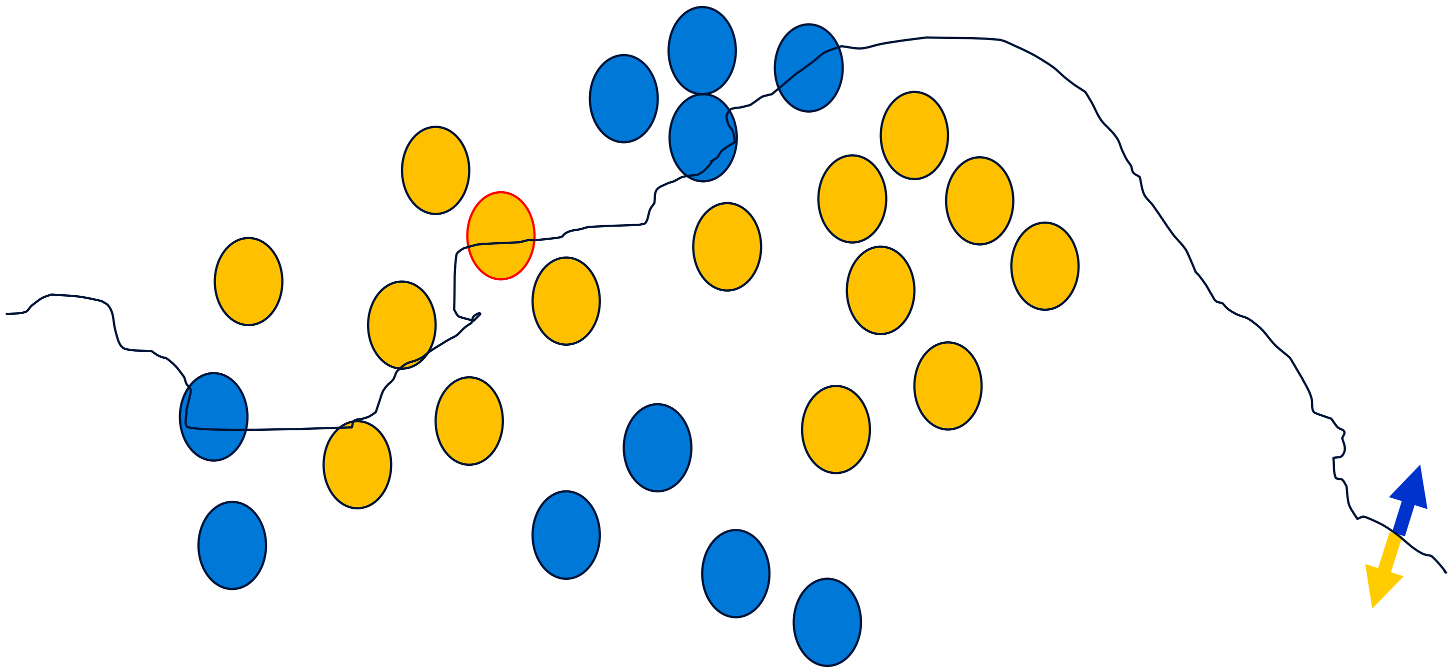
The Decision Boundary Perspective…

Initial random weights



The Decision Boundary Perspective…

Present a training instance / adjust the weights



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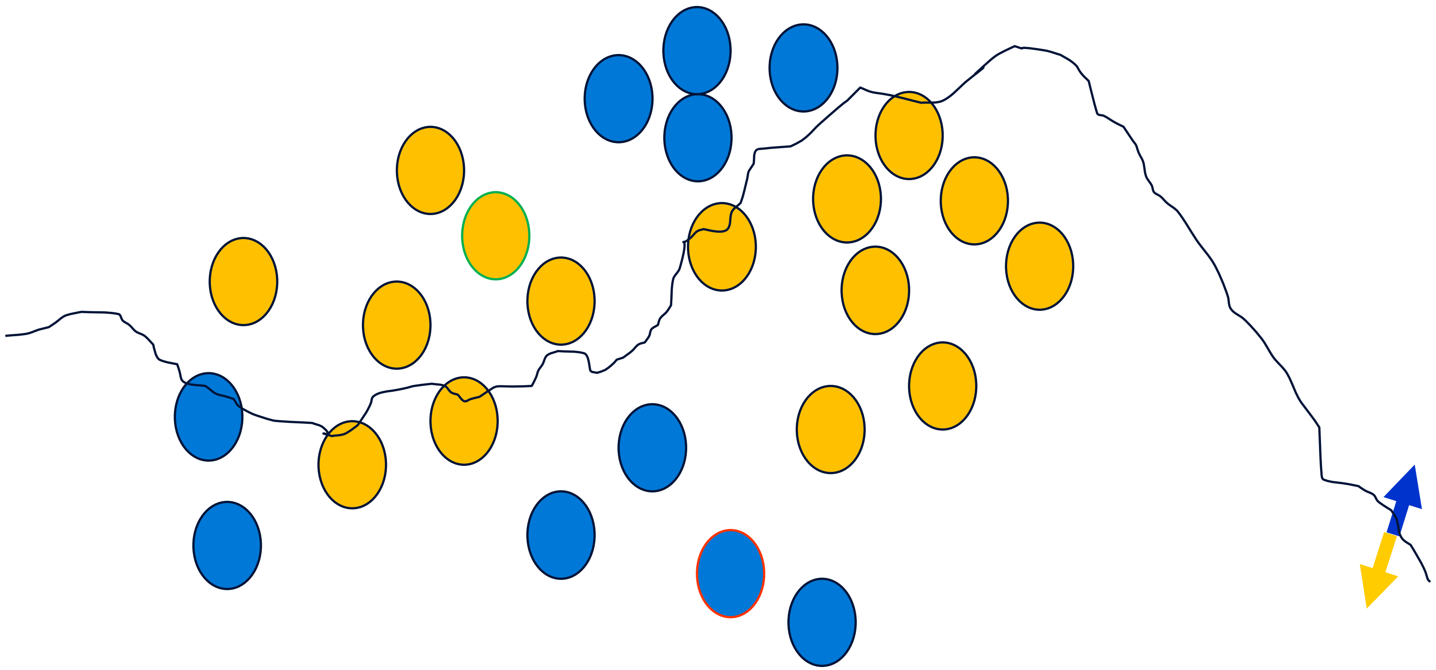
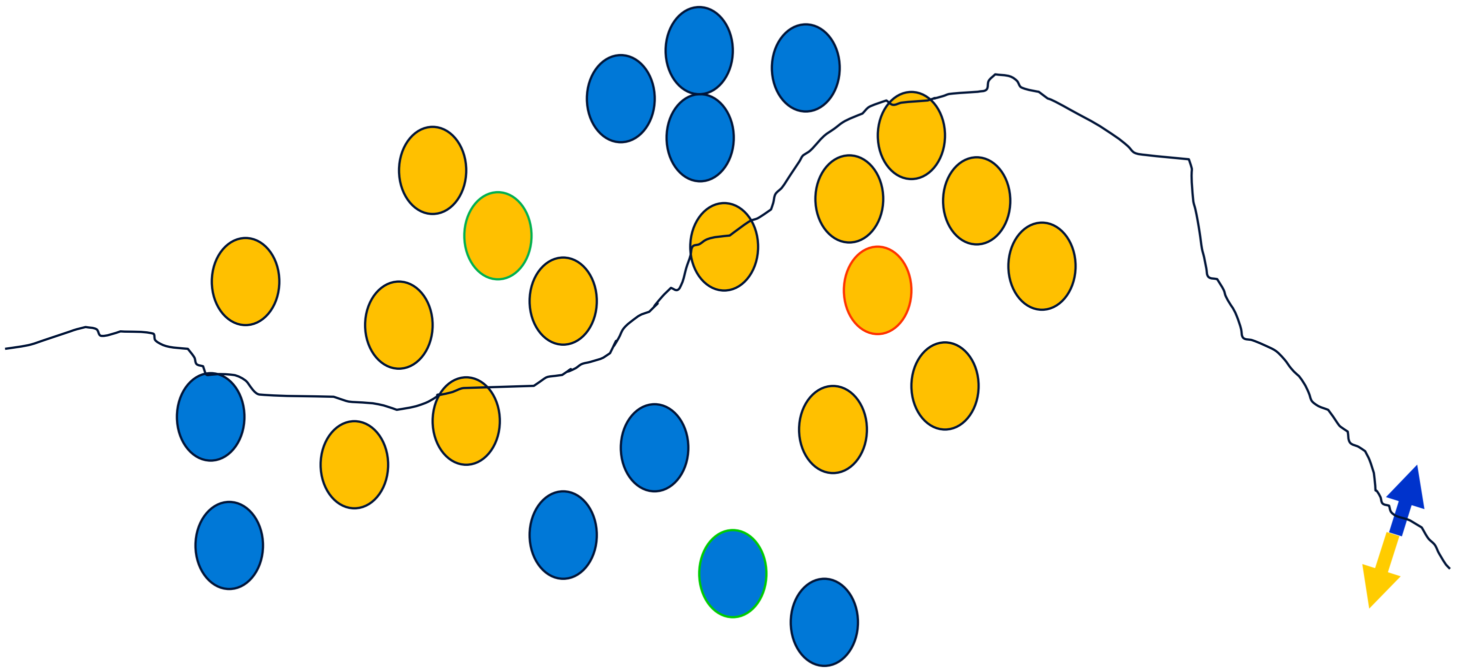
The Decision Boundary Perspective…

Present a training instance / adjust the weights



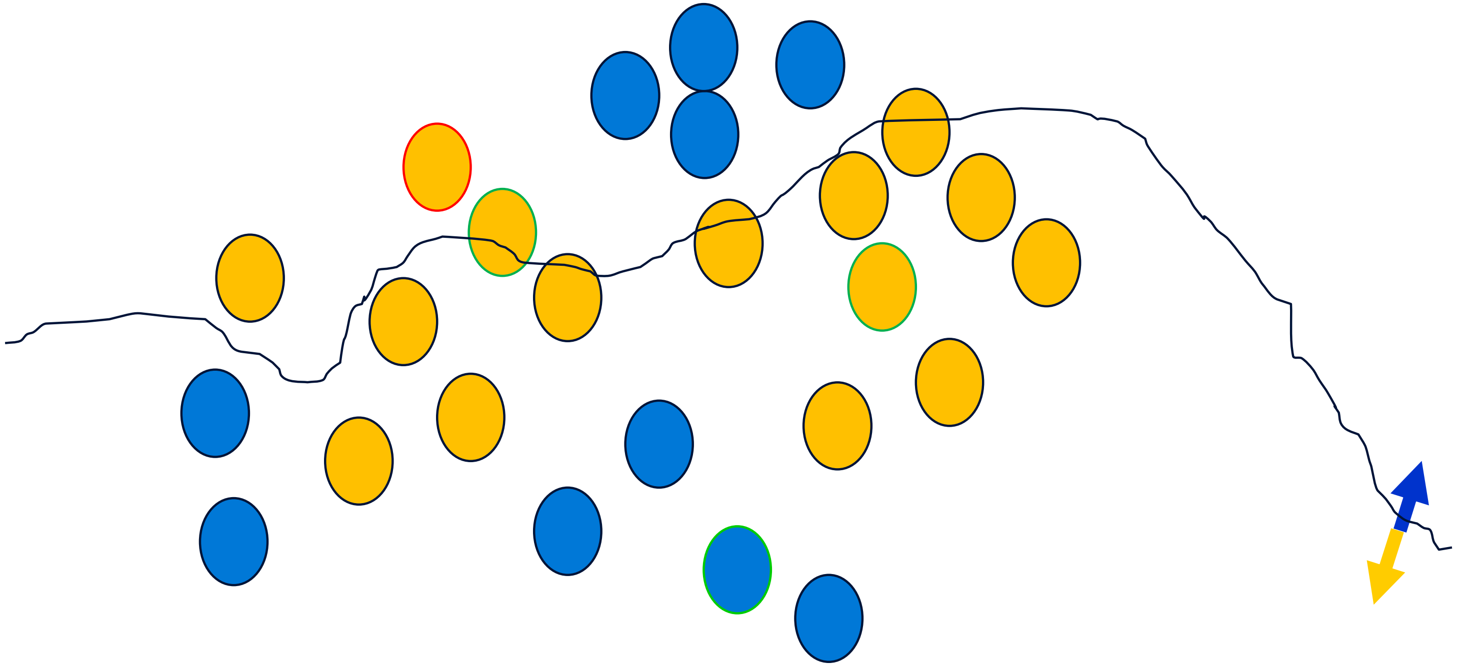
The Decision Boundary Perspective…

Present a training instance / adjust the weights



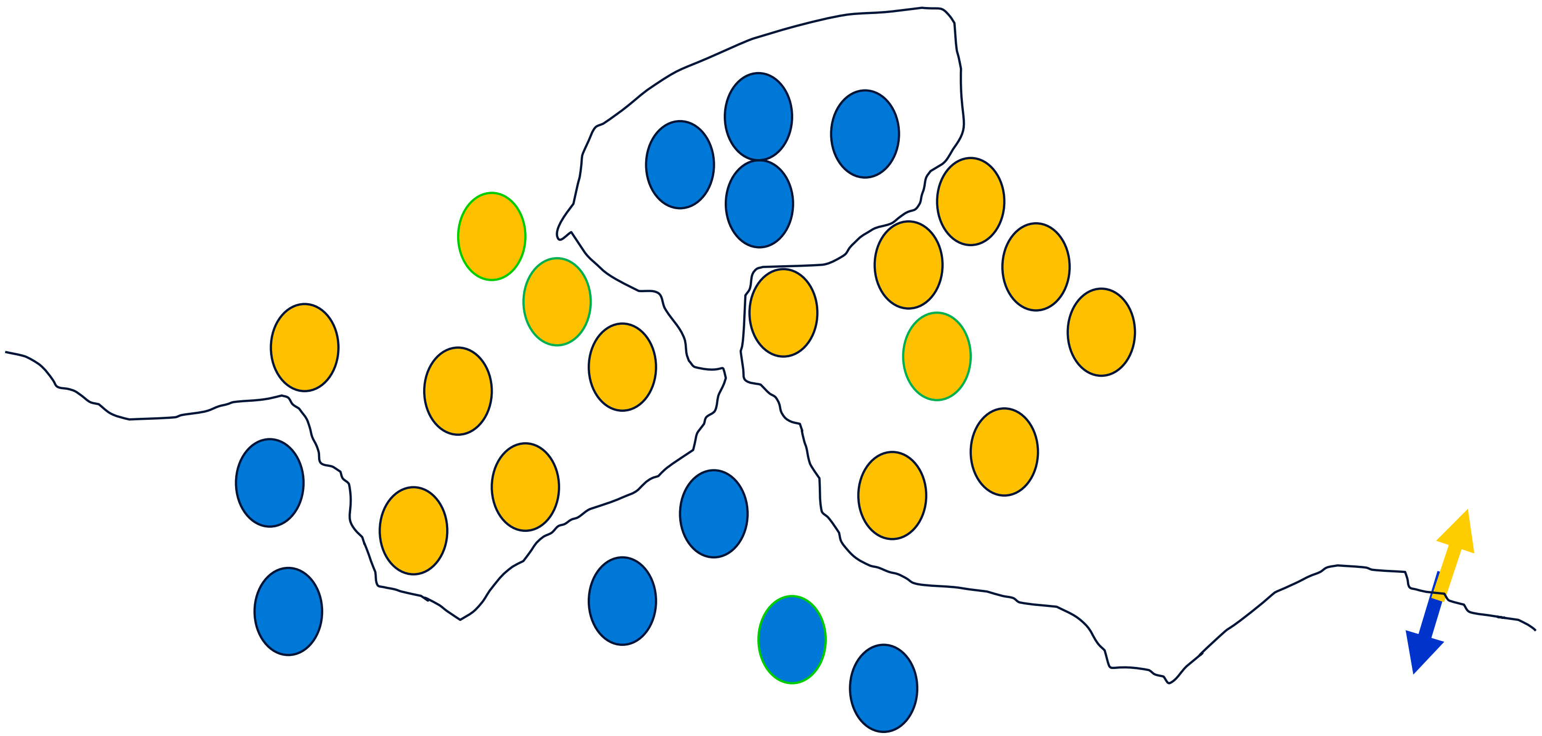
The Decision Boundary Perspective…

Present a training instance / adjust the weights



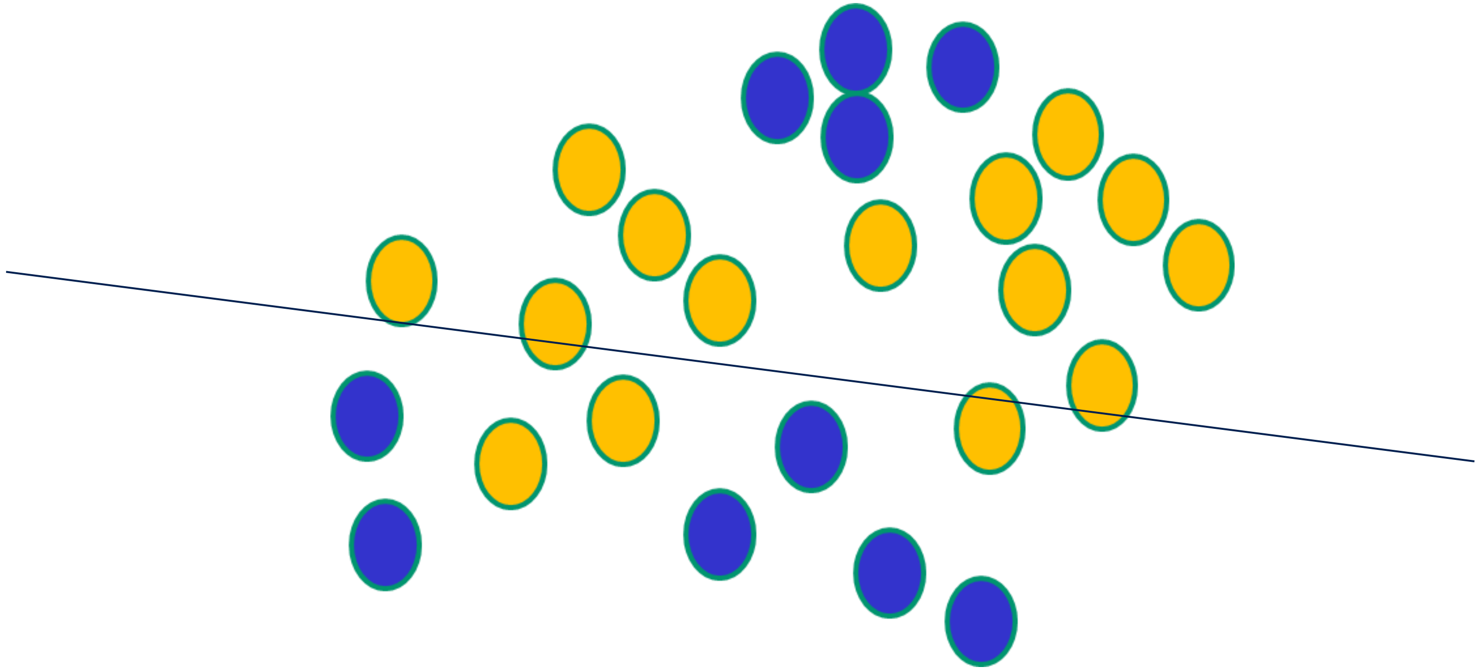
The Decision Boundary Perspective…

Eventually ....



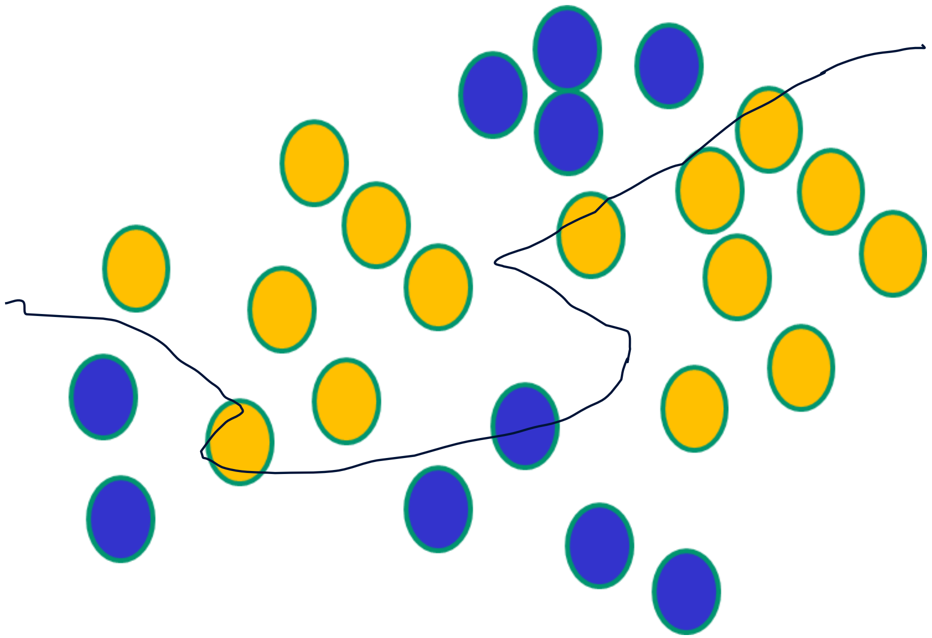
Some Other 'By The Way' Points

If $f(x)$ is linear, the NN can **only** draw straight decision boundaries (even if there are many layers of units)



Some Other 'By The Way' Points

NNs use nonlinear $f(x)$ so they can draw complex boundaries, but keep the data unchanged



Some Other 'By The Way' Points

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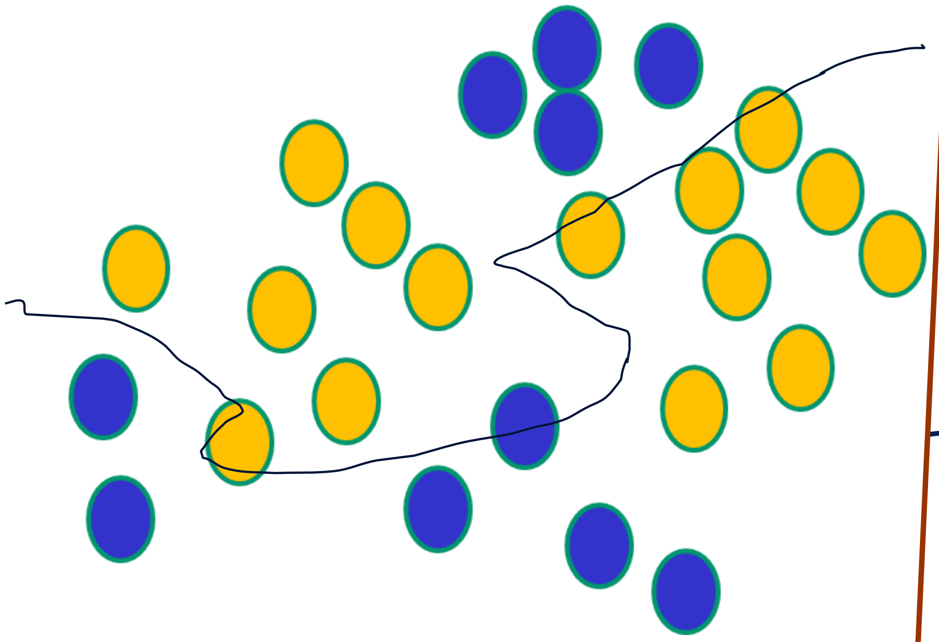
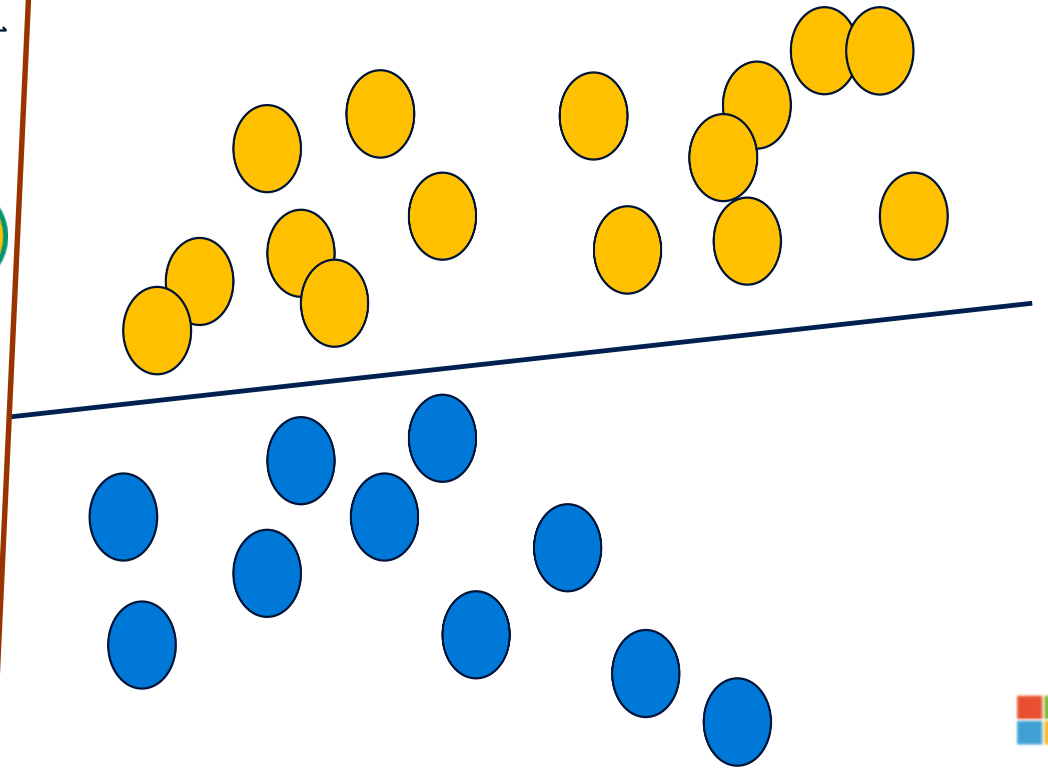
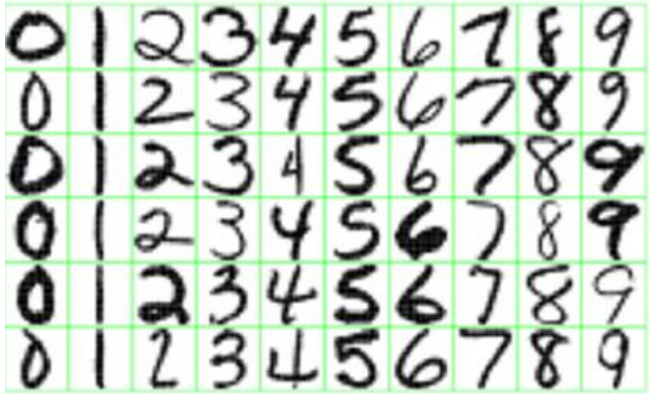
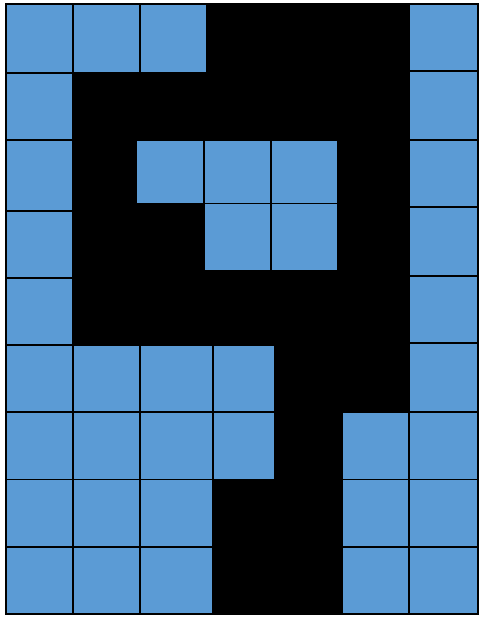


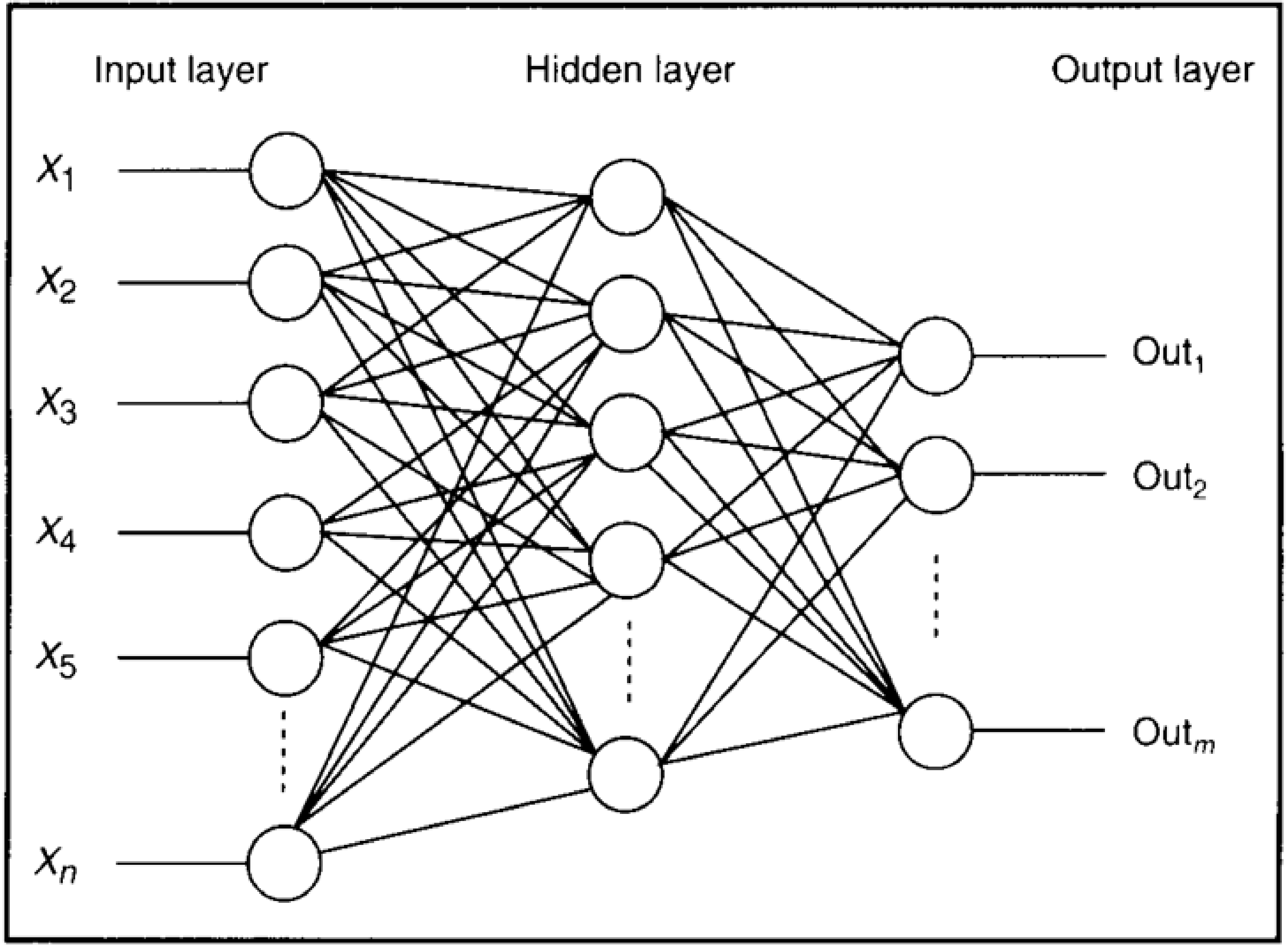
SVMs only draw straight lines, but they transform the data first in a way that makes that OK



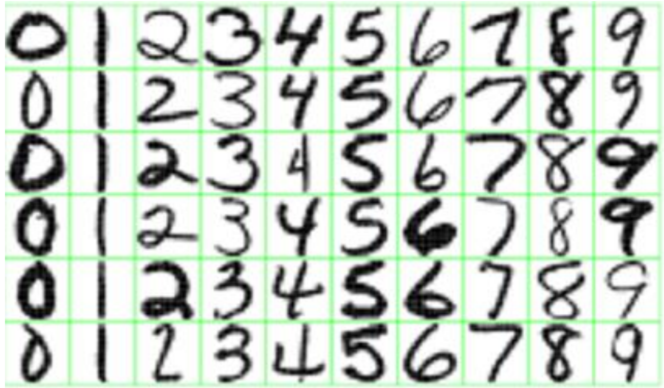
Feature Detectors

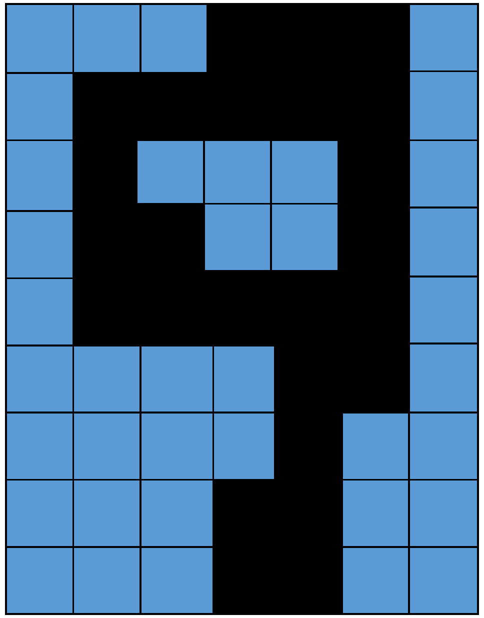


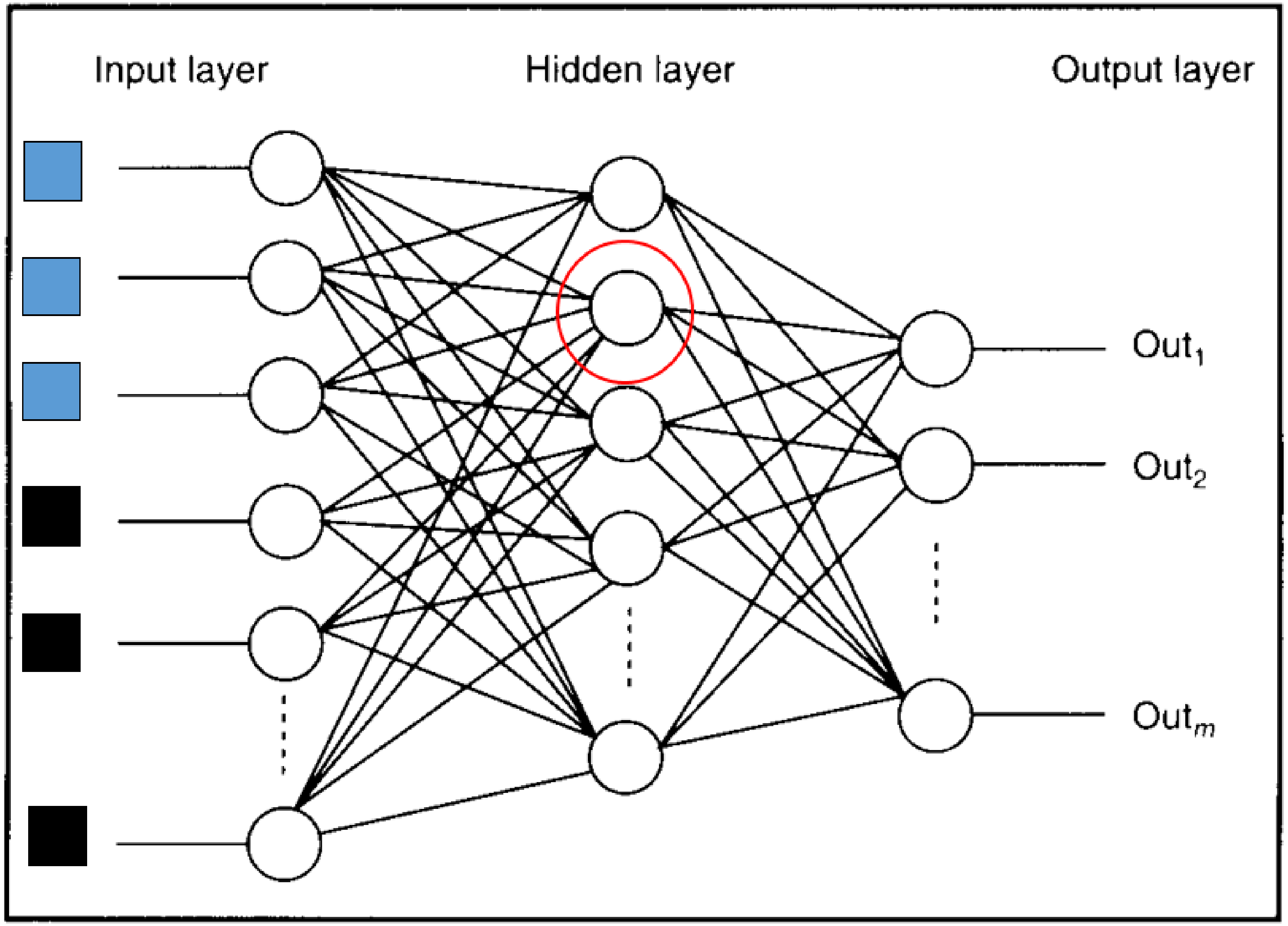




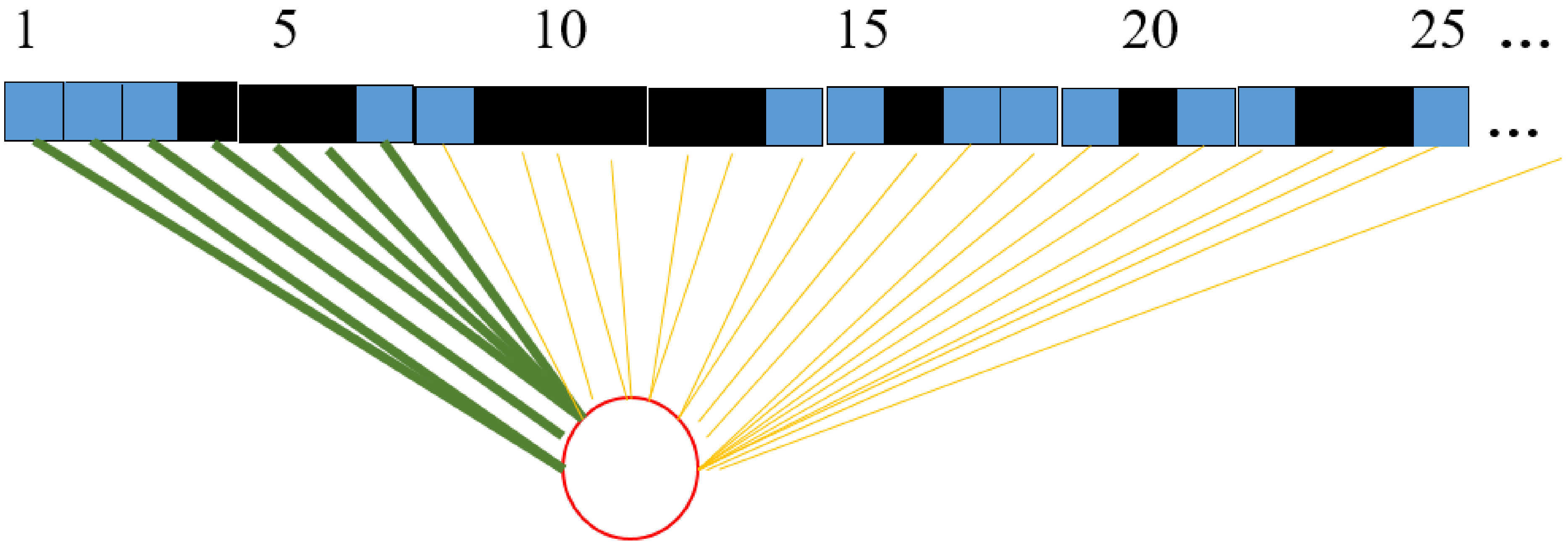
What Is This Unit Doing?

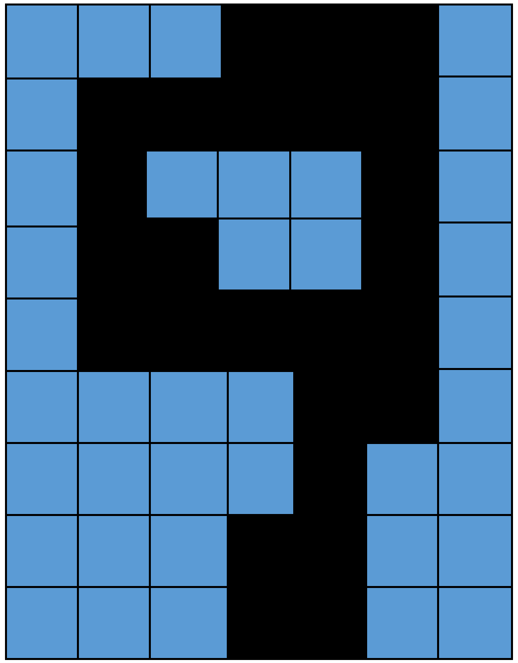




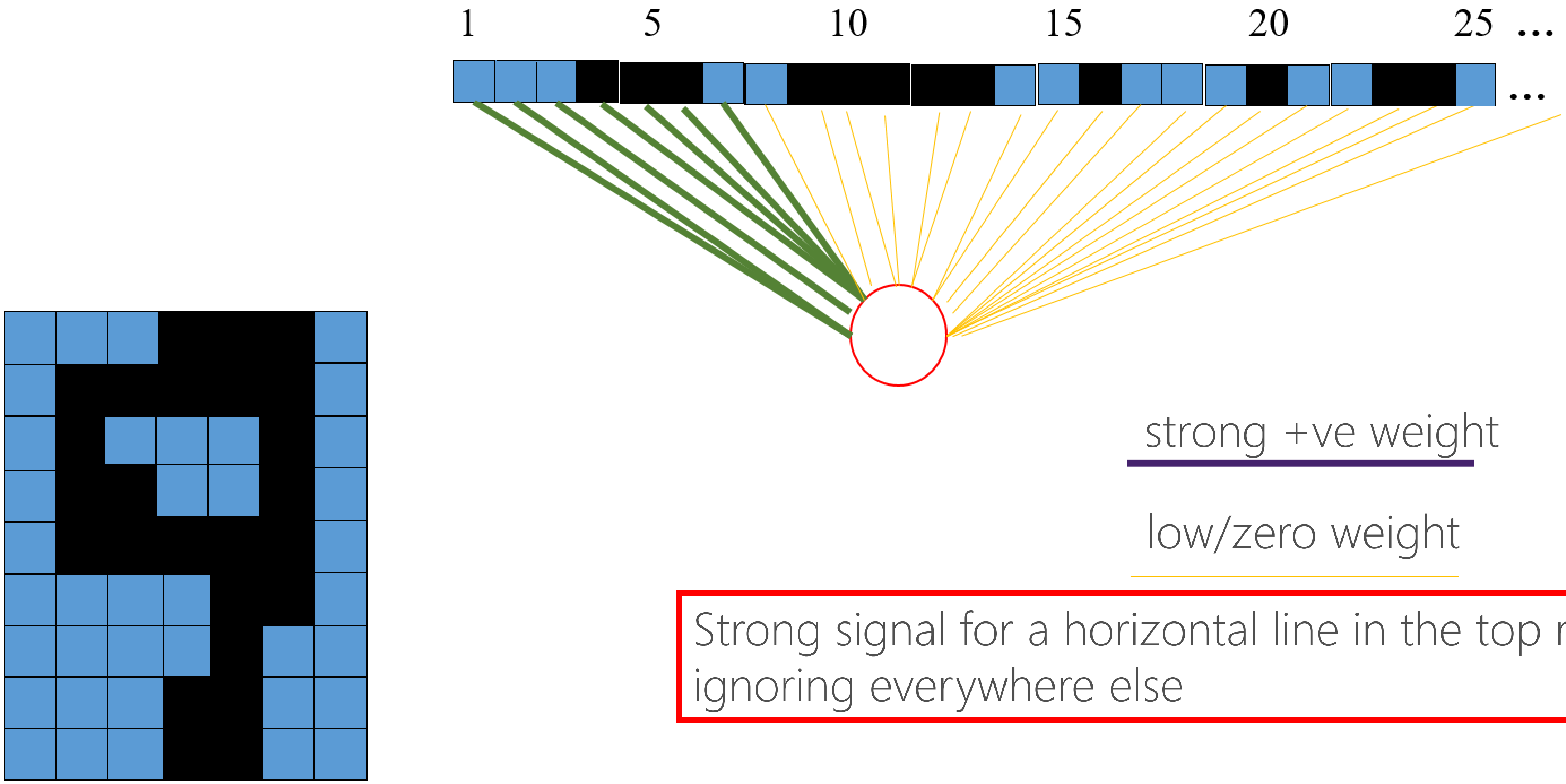


Hidden Layer Units Become Self-Organised Feature Detectors



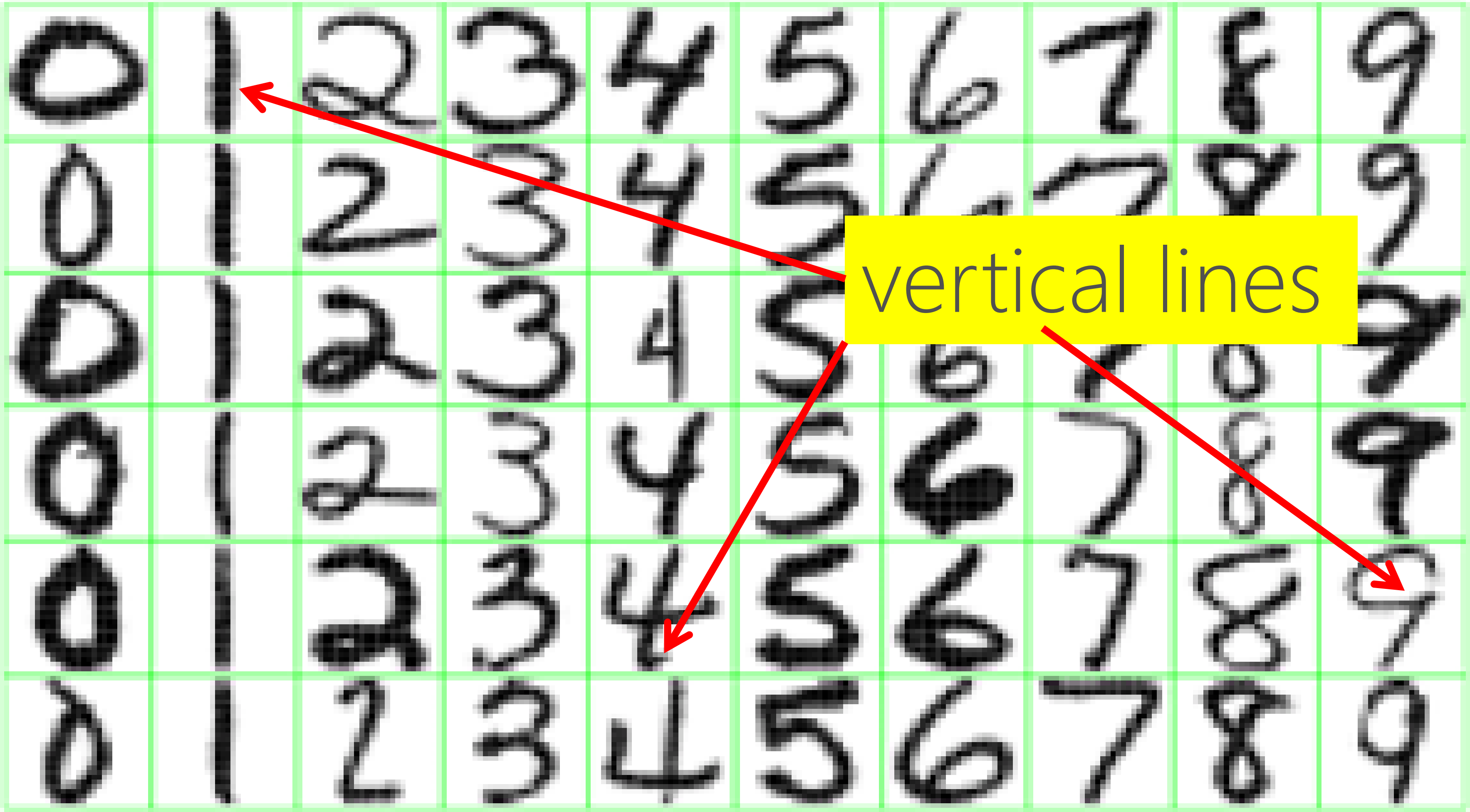


What Does This Unit Detect?

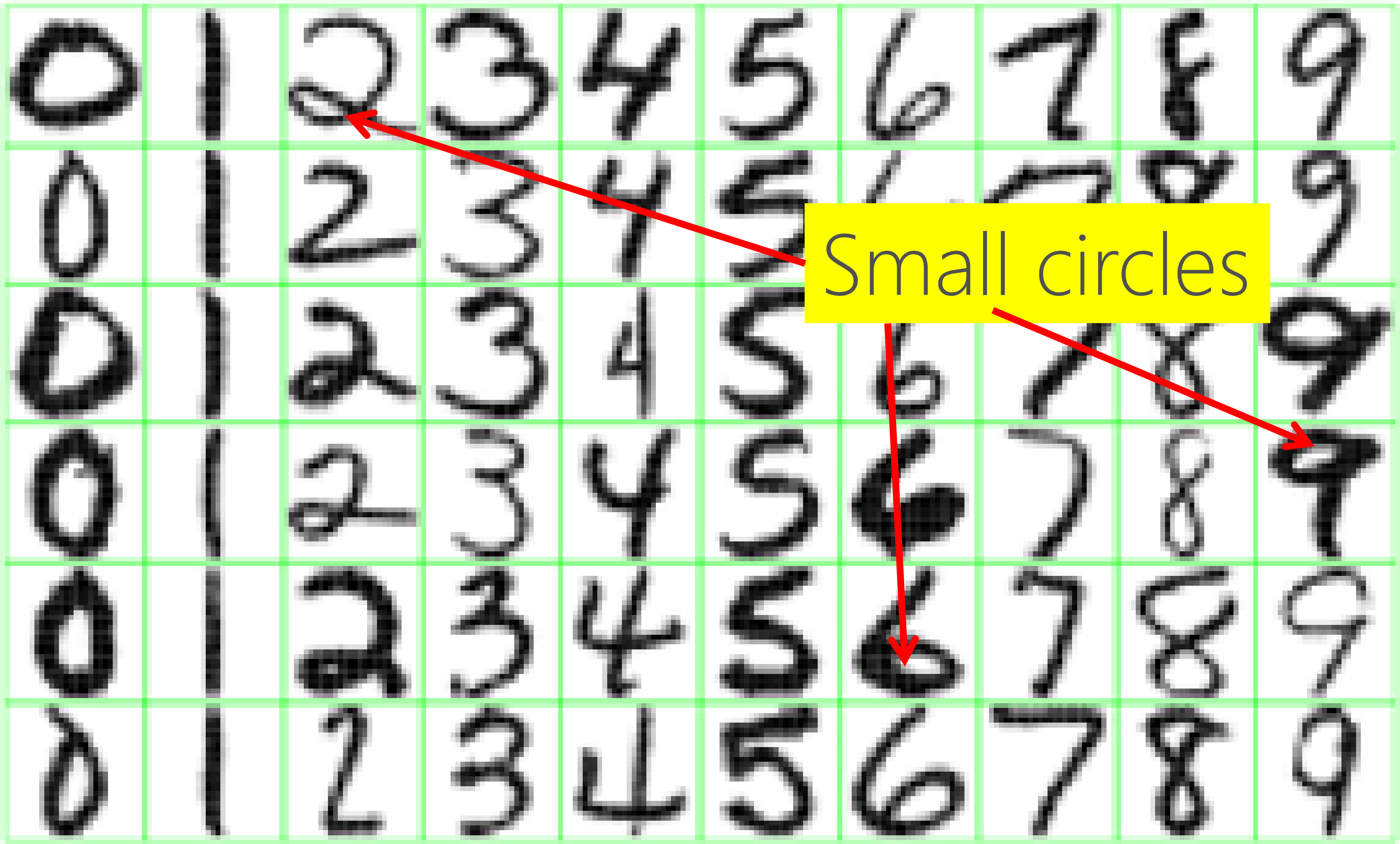


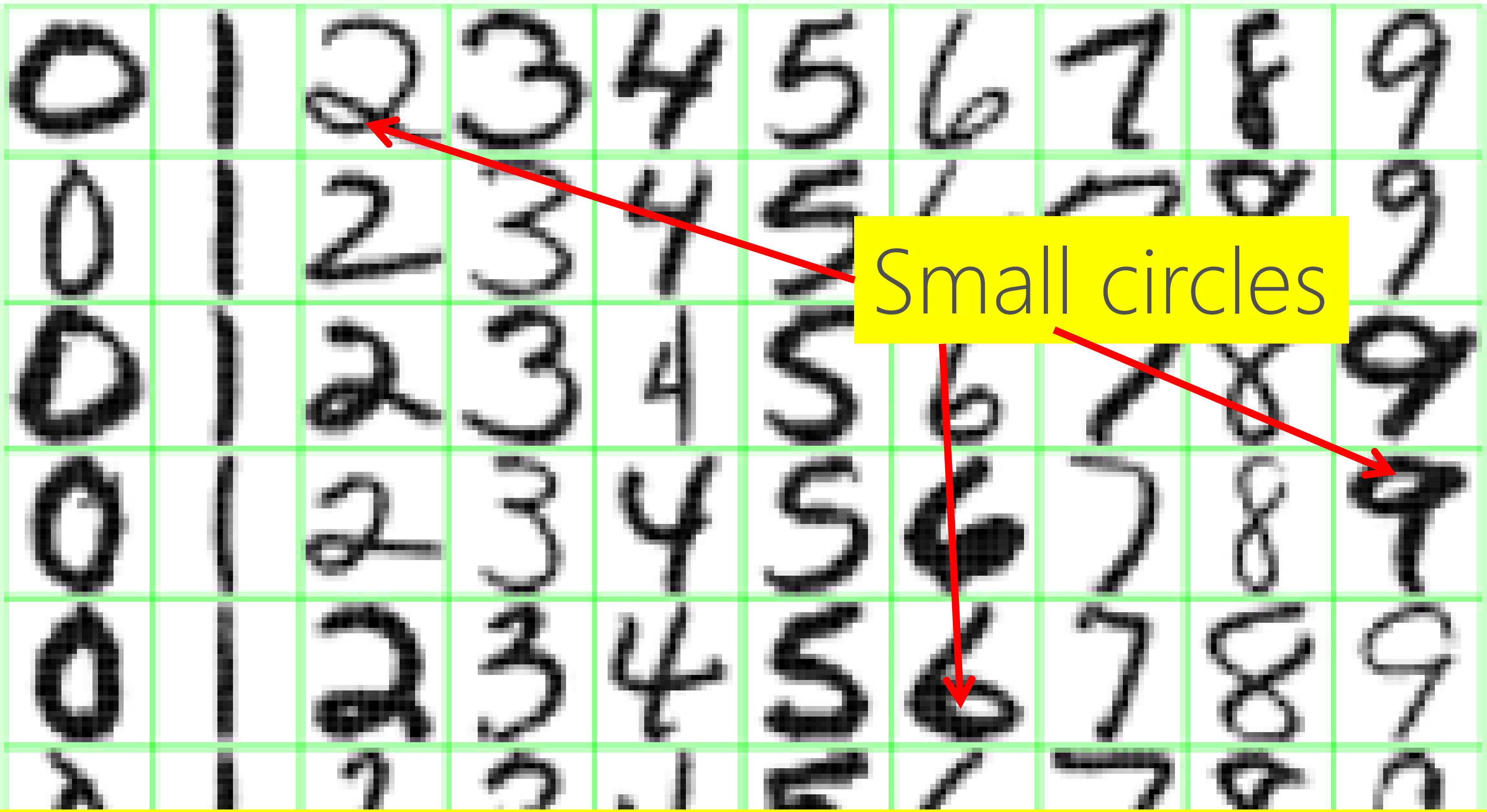
Strong signal for a horizontal line in the top row, ignoring everywhere else

What features might you expect a good NN to learn, when trained with data like this?


vertical lines


Horizontal lines


Small circles



But what about position invariance ???
our example unit detectors were tied to specific parts of the image

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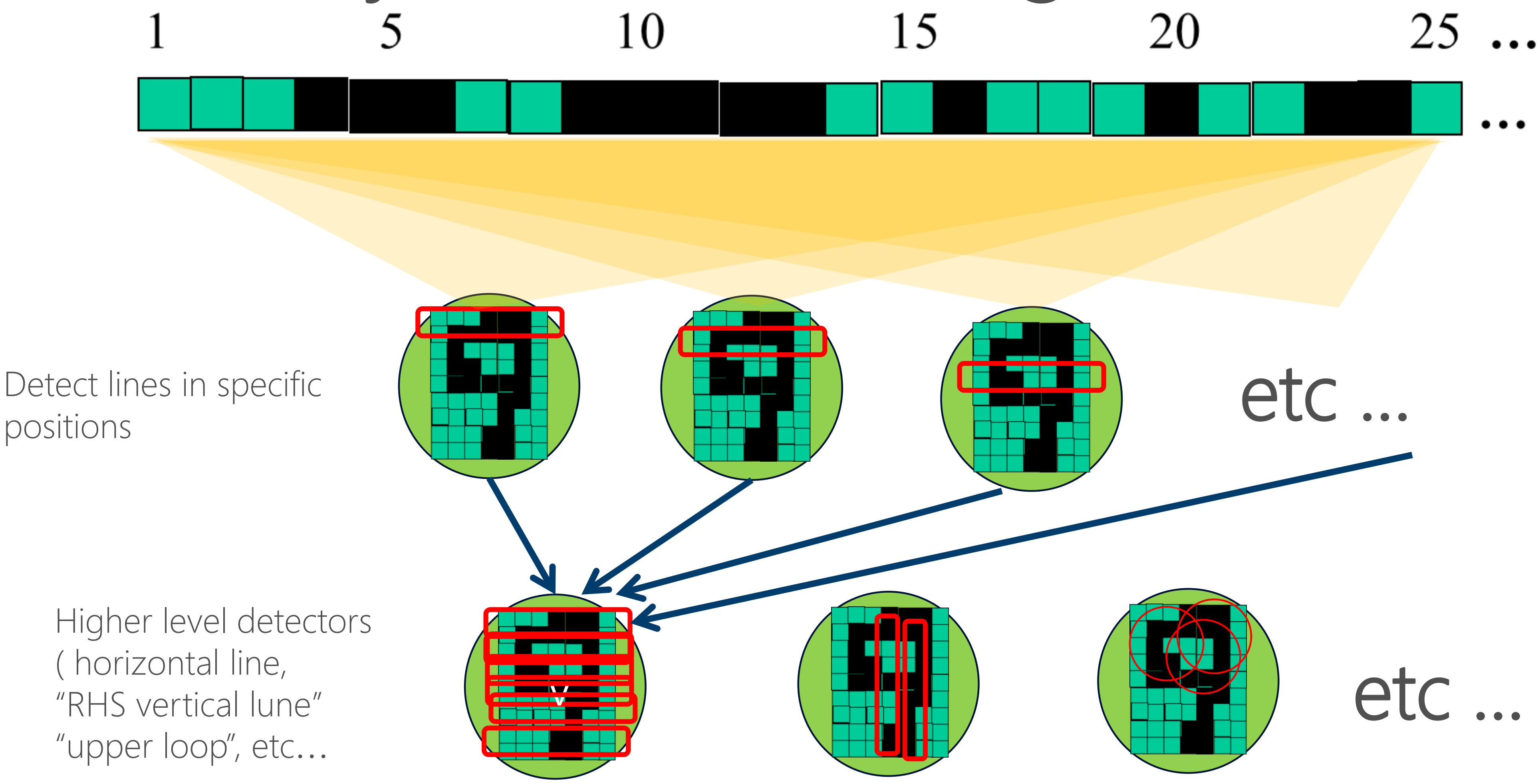
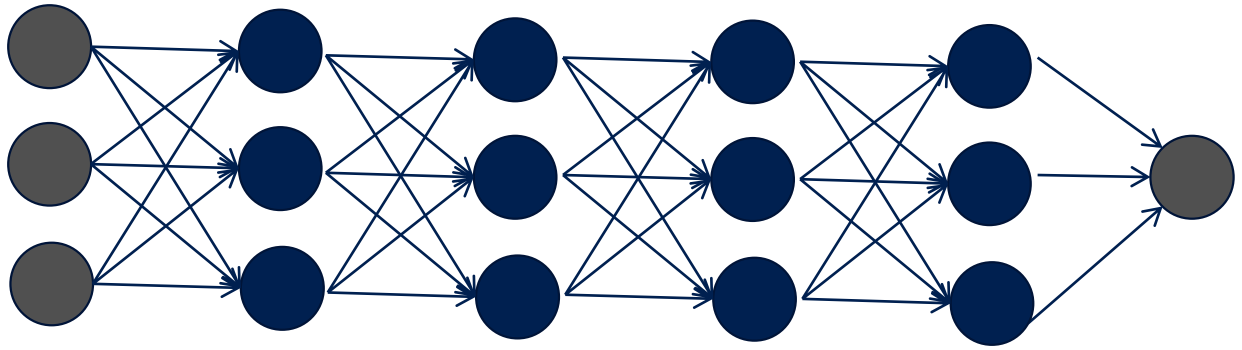
Successive Layers Can Learn Higher-Level Features

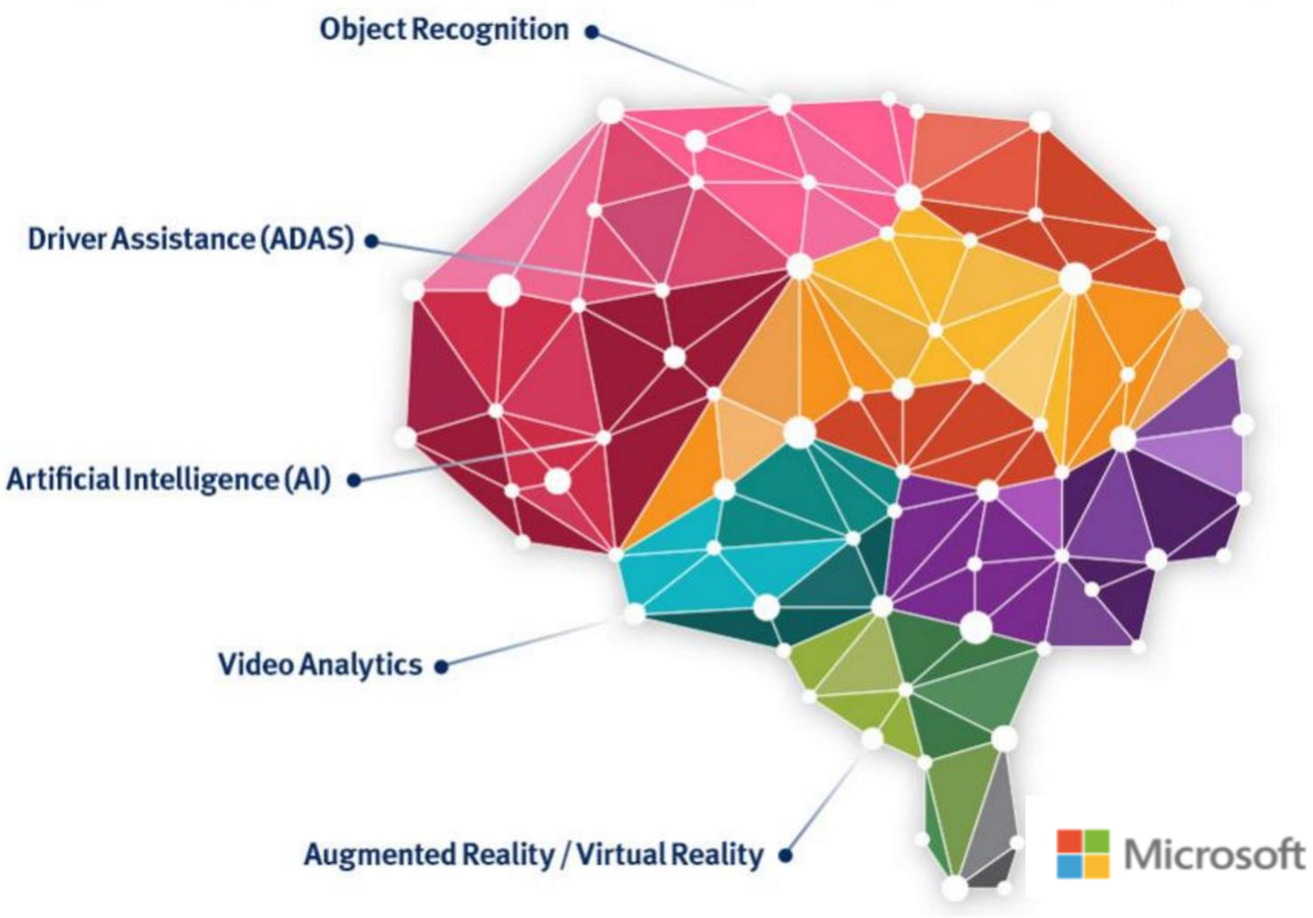


Multiple Layers Make Sense



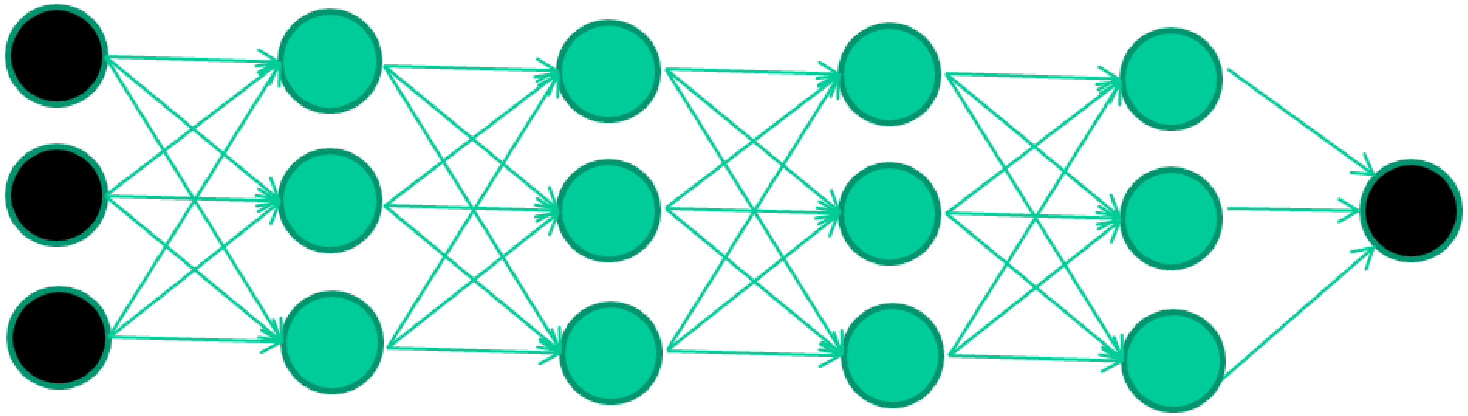
Multiple Layers Make Sense

- Deep Learning = Brain “inspired”
- Audio / Visual Cortex has multiple stages = Hierarchical

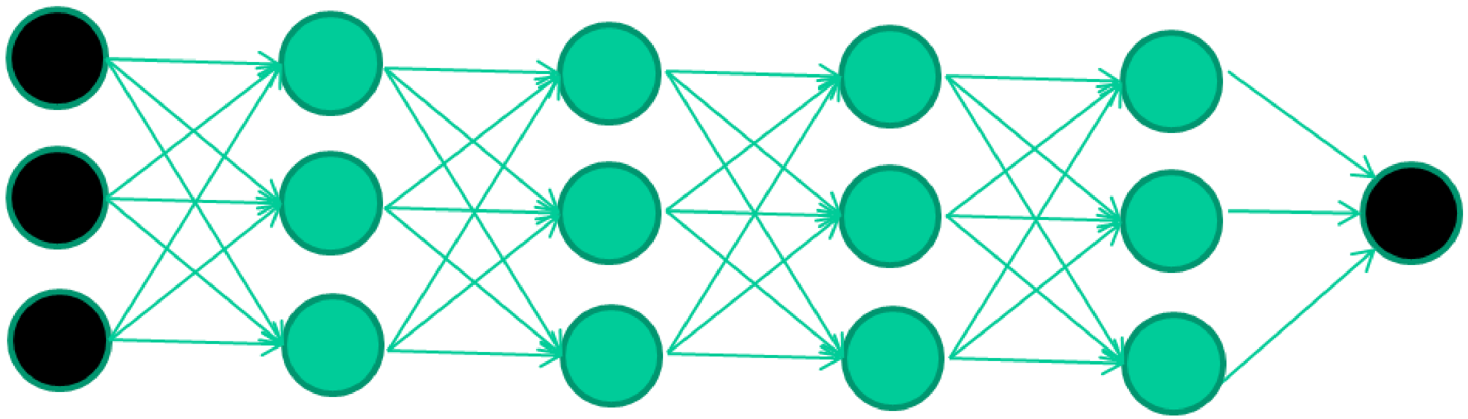


Multiple Layers Make Sense

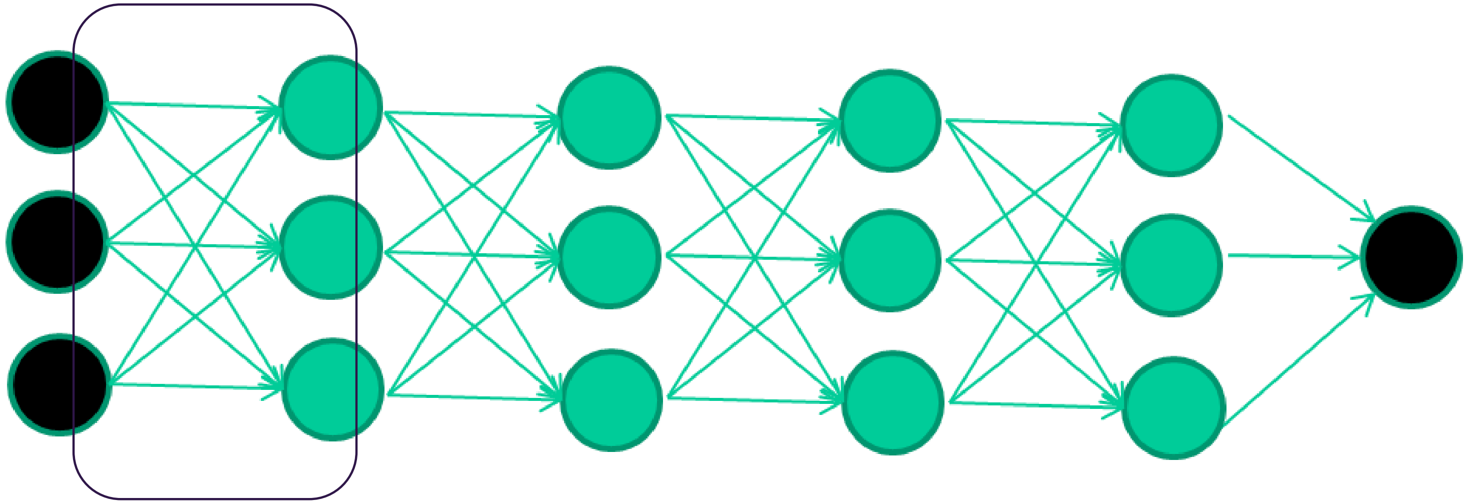
Many-layer neural network architectures should be capable of learning the true underlying features and 'feature logic', and therefore generalise very well …



The New Way To Train Multi-Layer NNs…

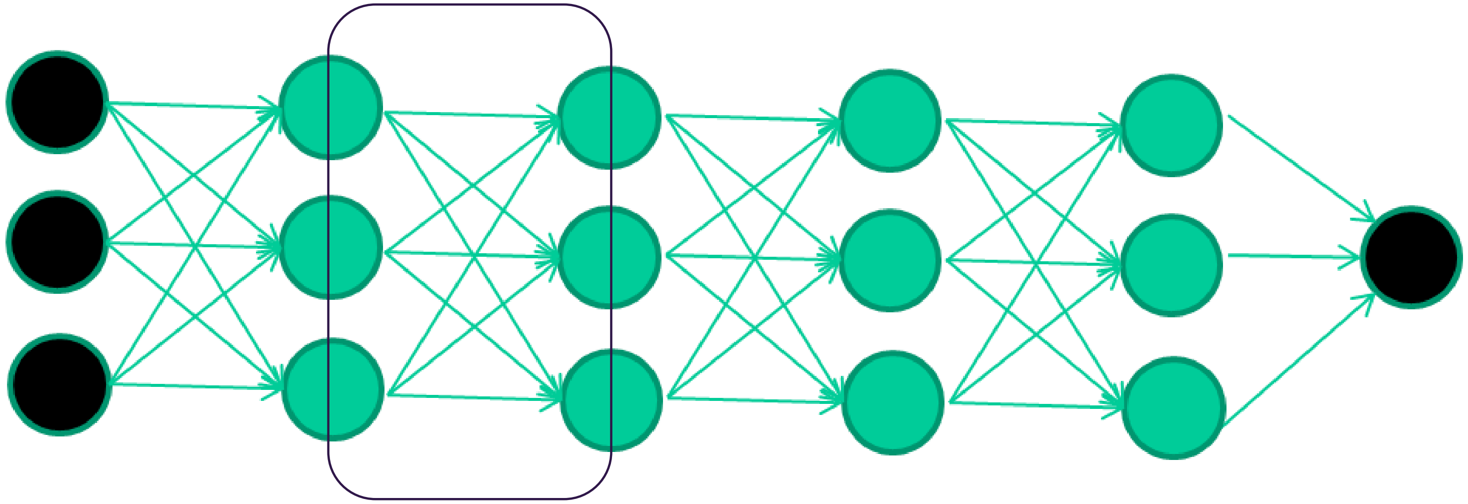


The New Way To Train Multi-Layer NNs…



Train this layer first

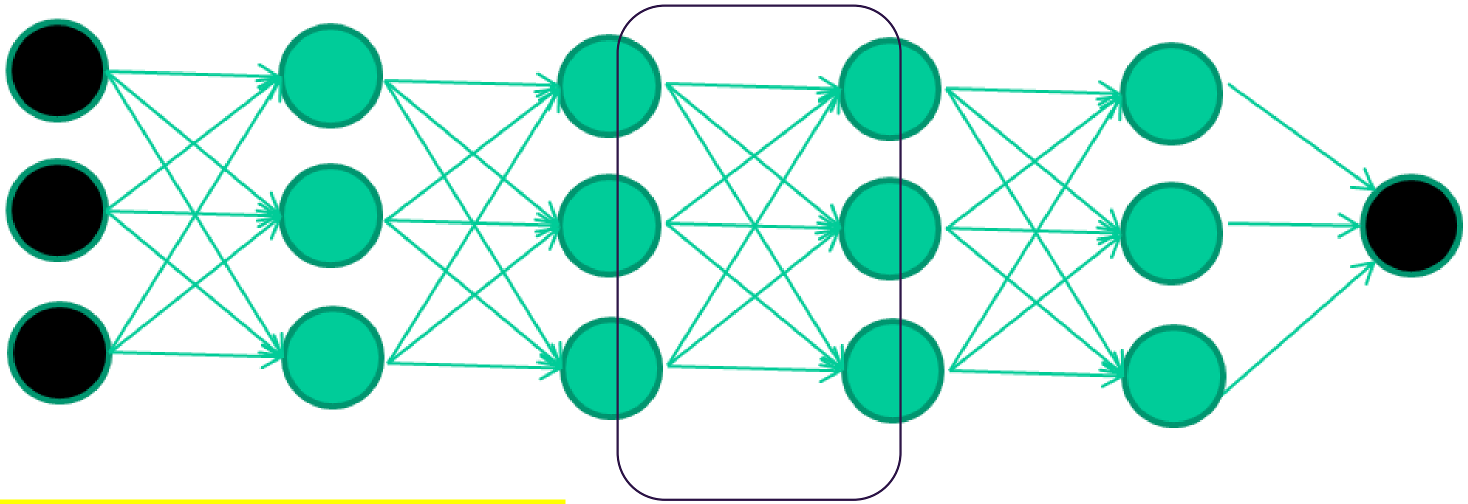
The New Way To Train Multi-Layer NNs…



Train this layer first

then this layer

The New Way To Train Multi-Layer NNs...



Train this layer first

then this layer

then this layer

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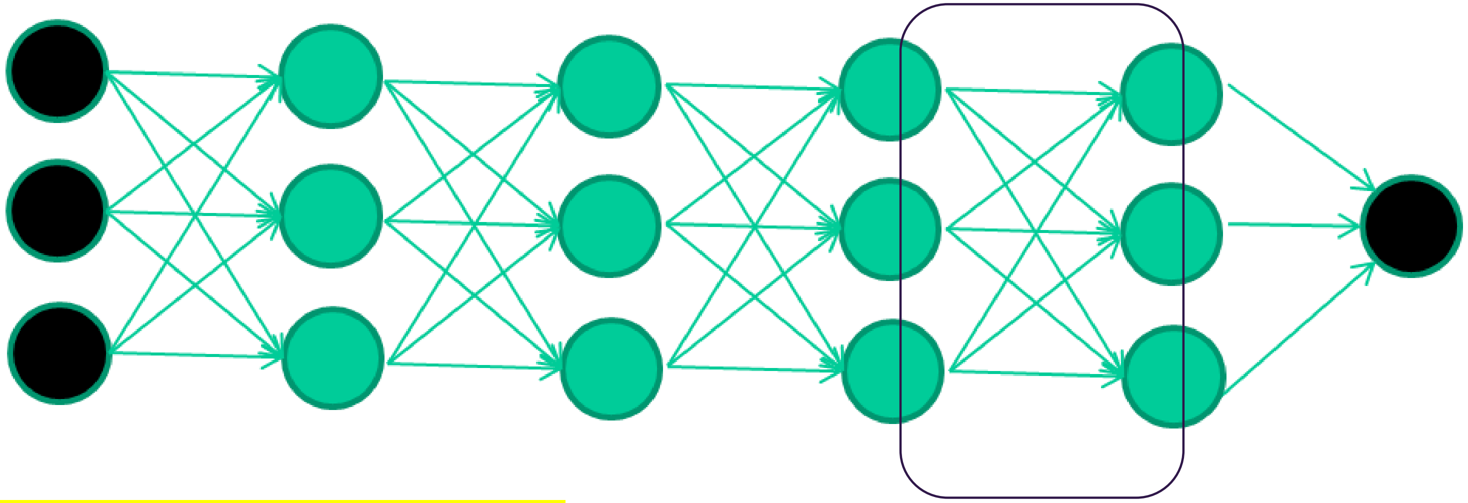
The New Way To Train Multi-Layer NNs...



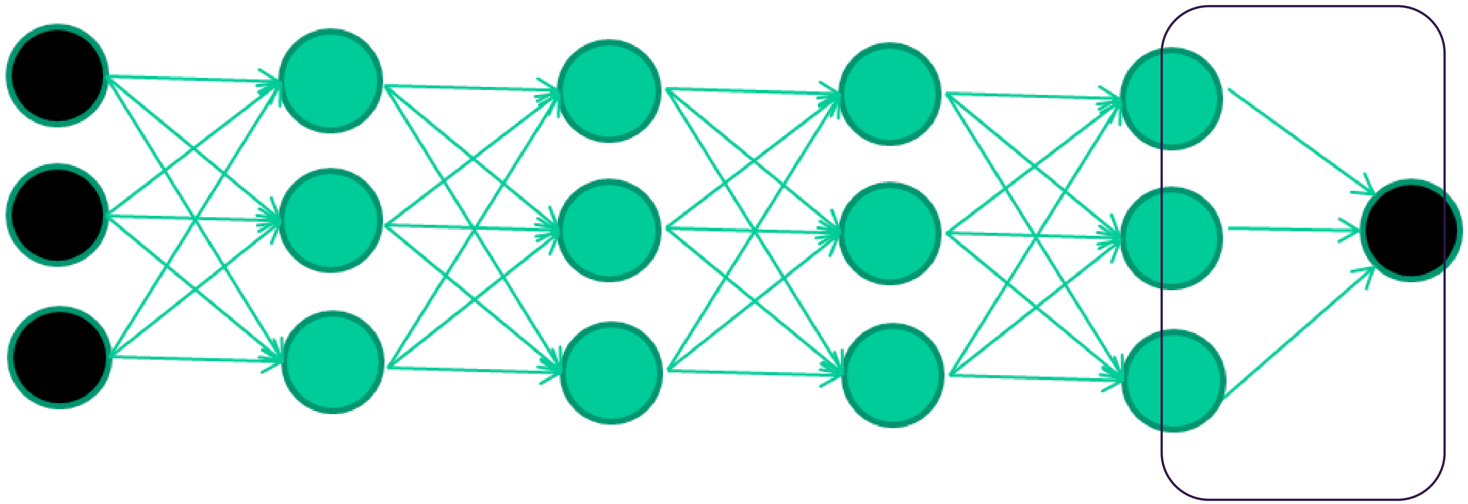
Train this layer first

then this layer

then this layer

then this layer

The New Way To Train Multi-Layer NNs…



Train this layer first

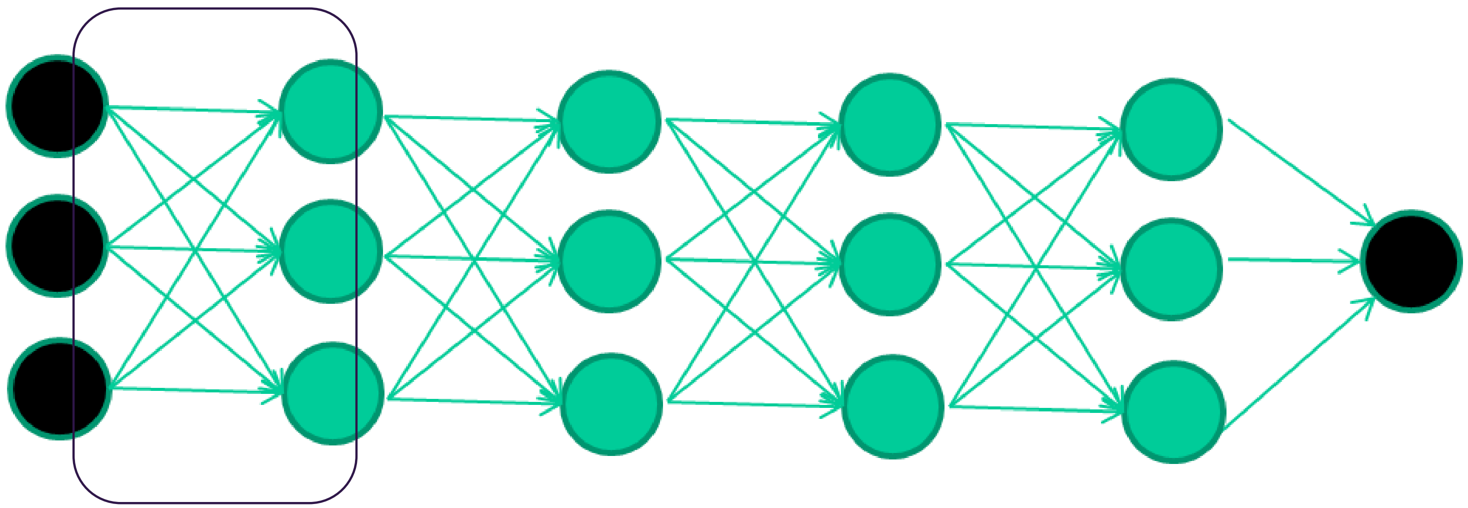
then this layer

then this layer

then this layer

finally this layer

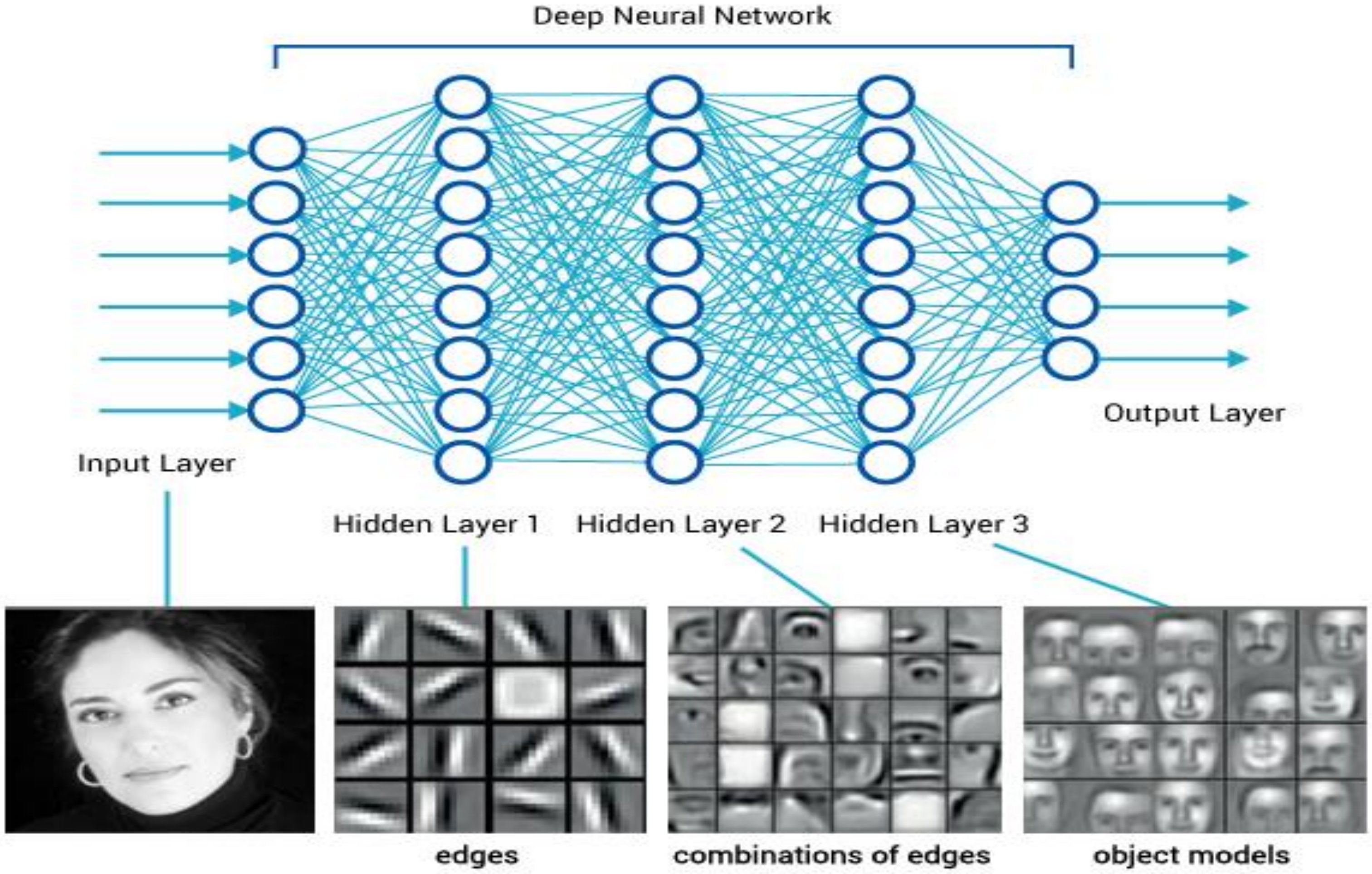
The New Way To Train Multi-Layer NNs…



Each layer can be thought of as a set of features

Idea Behind Deep Learning

- There are many types of deep learning
- Different kinds of autoencoder, variations on architectures and training algorithms, etc.
- It's a growing area



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Common DNNs

- Deep Convolutional Neural Network (DCNN)
  - To extract representation from images
- Recurrent Neural Network (RNN)
  - To extract representation from sequential data
- Deep Belief Neural Network (DBN)
  - To extract hierarchical representation from a dataset
- Deep Reinforcement Learning (DQN)
  - To prescribe how agents should act in an environment in order to maximize future cumulative reward (e.g., a game score)

We will cover DCNN today

Open Source Deep Learning Frameworks

DL4J

- JVM-based
- Distrubted
- Integrates with Hadoop and Spark

Theano

- Very popular in Academia
- Fairly low level
- Interfaced with via Python and Numpy

Torch

- Lua based
- In house versions used by Facebook and Twitter
- Contains pretrained models

Microsoft

Open Source Deep Learning Frameworks

TensorFlow

- Google written successor to Theano
- Interfaced with via Python and Numpy
- Highly parallel
- Can be somewhat slow for certain problem sets

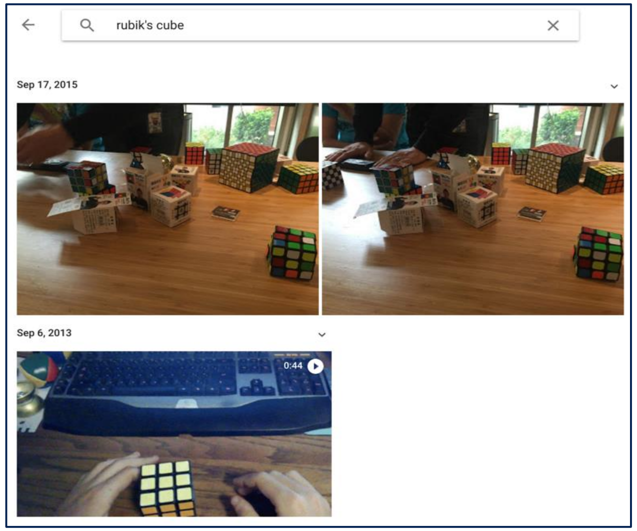
Caffe

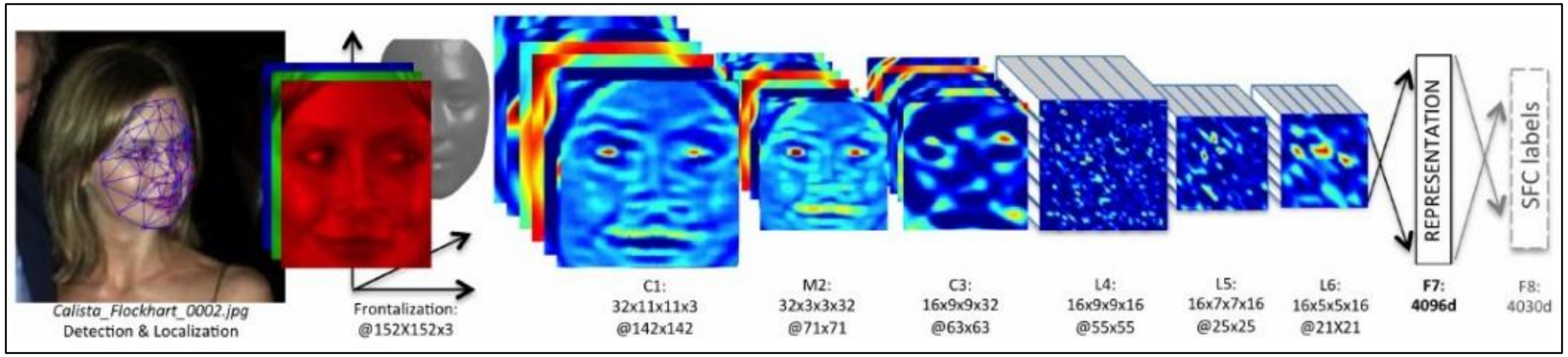
- Not general purpose. Focuses on machine-vision problems
- Implemented in C++ and is very fast
- Not easily extensible
- Has a Python interface

Microsoft

Deep Learning And Computer Vision

ConvNet





Face Verification, Taigman et al. 2014 (FAIR)

e.g. Google Photos search

[Goodfellow et al. 2014]

Self-driving cars

Image Classification

- Task of taking an input image and outputting a class
- Probability of classes that best describes the image
- For humans, effortless task

What We See

08	02	22	97	38	15	00	40	00	75	04	05	07	78	52	12	50	77	91	08
49	49	99	40	17	81	18	57	60	87	17	40	98	43	69	48	04	56	62	00
81	49	31	73	55	79	14	29	93	71	40	67	53	88	30	03	49	13	36	65
52	70	95	23	04	60	11	42	69	24	68	56	01	32	56	71	37	02	36	91
22	31	16	71	51	67	63	89	41	92	36	54	22	40	40	28	66	33	13	80
24	47	32	60	99	03	45	02	44	75	33	53	78	36	84	20	35	17	12	50
32	98	81	28	64	23	67	10	26	38	40	67	59	54	70	66	18	38	64	70
67	26	20	68	02	62	12	20	95	63	94	39	63	08	40	91	66	49	94	21
24	55	58	05	66	73	99	26	97	17	78	78	96	83	14	88	34	89	63	72
21	36	23	09	75	00	76	44	20	45	35	14	00	61	33	97	34	31	33	95
78	17	53	28	22	75	31	67	15	94	03	80	04	62	16	14	09	53	56	92
16	39	05	42	96	35	31	47	55	58	88	24	00	17	54	24	36	29	85	57
86	56	00	48	35	71	89	07	05	44	44	37	44	60	21	58	51	54	17	58
19	80	81	68	05	94	47	69	28	73	92	13	86	52	17	77	04	89	55	40
04	52	08	83	97	35	99	16	07	97	57	32	16	26	26	79	33	27	98	66
88	36	68	87	57	62	20	72	03	46	33	67	46	55	12	32	63	93	53	69
04	42	16	73	38	25	39	11	24	94	72	18	08	46	29	32	40	62	76	36
20	69	36	41	72	30	23	88	34	62	99	69	82	67	59	85	74	04	36	16
20	73	35	29	78	31	90	01	74	31	49	71	48	86	81	16	23	57	05	54
01	70	54	71	83	51	54	69	16	92	33	48	61	43	52	01	89	19	67	48

What Computers See

Input Image

- An image is an an array of pixel values
- A JPG color image with size 480 x 480:
  - The representative array will be 480 x 480 x 3. Each number is given a value from 0 to 255 which is the pixel intensity
- Grey scale image contains a single sample (intensity value) for each pixel
- Image Classification:
  - Given an array of numbers, produce probabilities of the image being a certain class

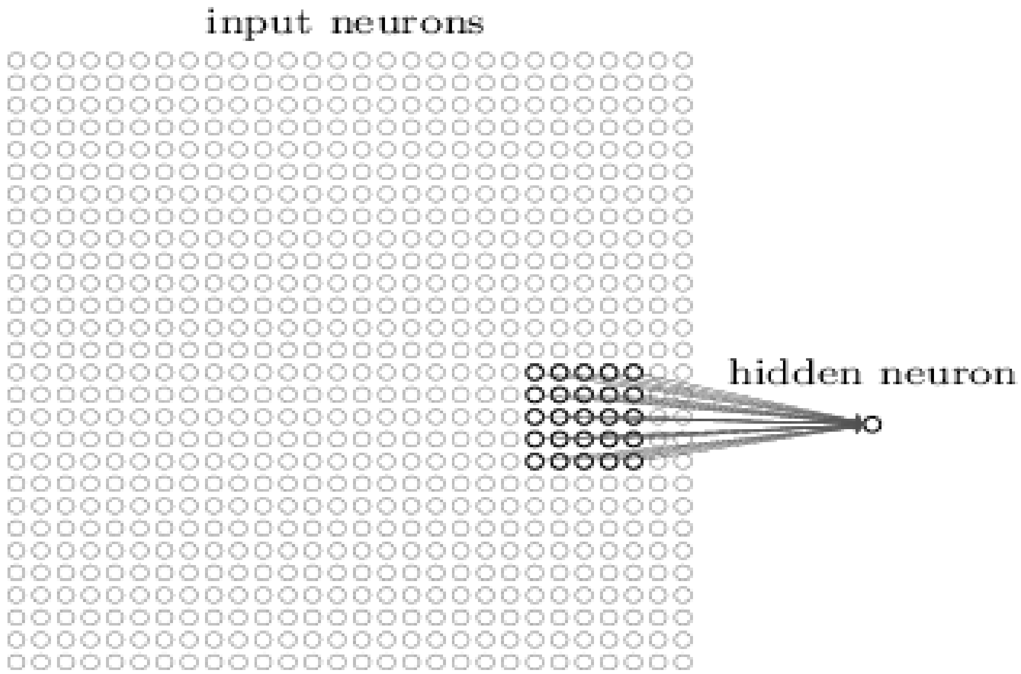
Convolutional Neural Networks

Three basic ideas:

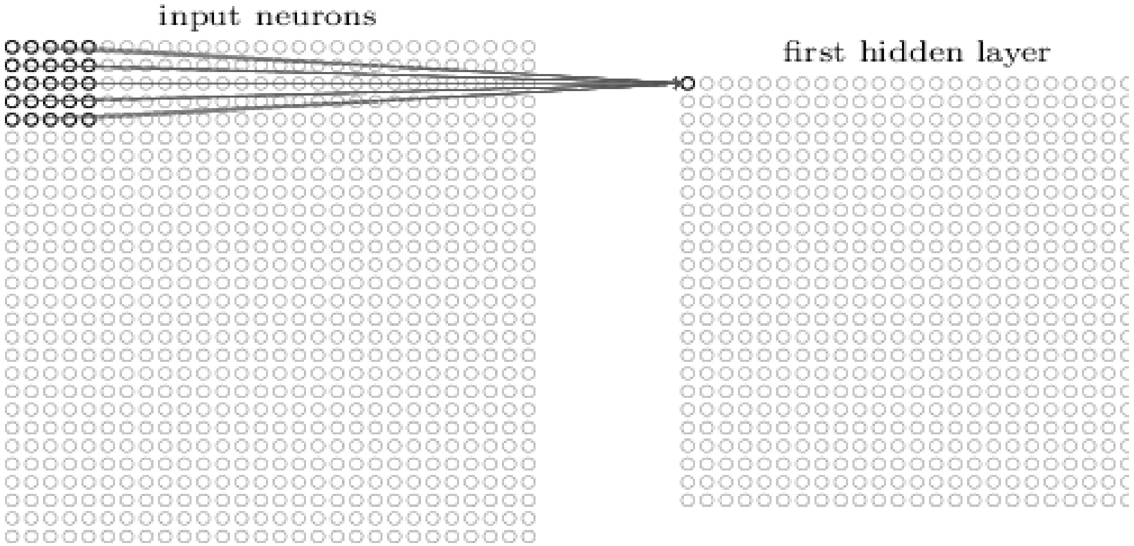
- Local receptive fields
- Shared weights
- Pooling

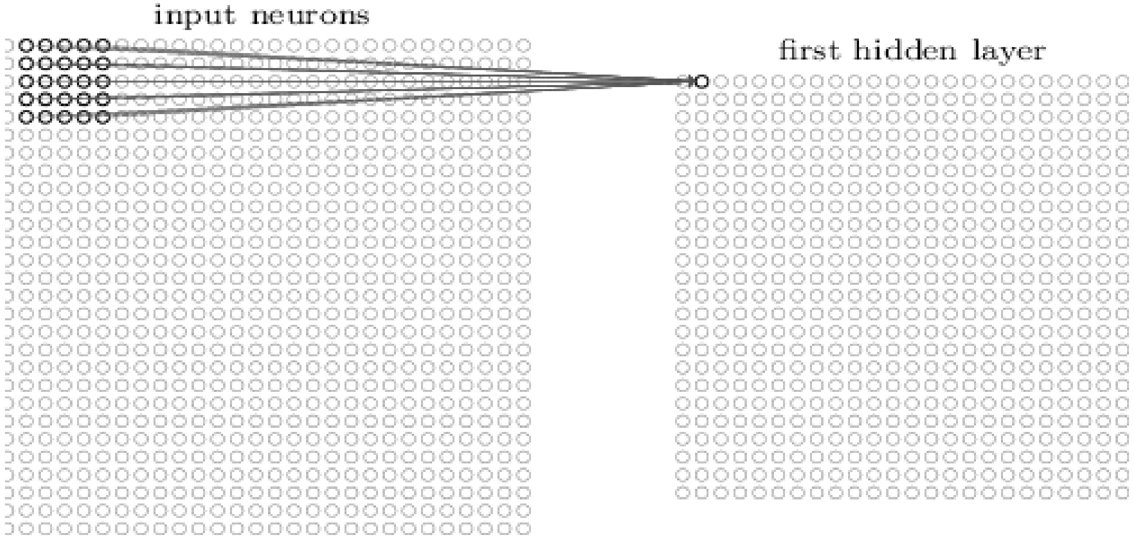
Local Receptive Fields

- Connections are from small, localized regions of the input image to hidden layers
- A little window on the input pixels
- Each neuron in the first hidden layer is connected to a small region of the input neurons. For example, a 5x5 region



Local Receptive Fields



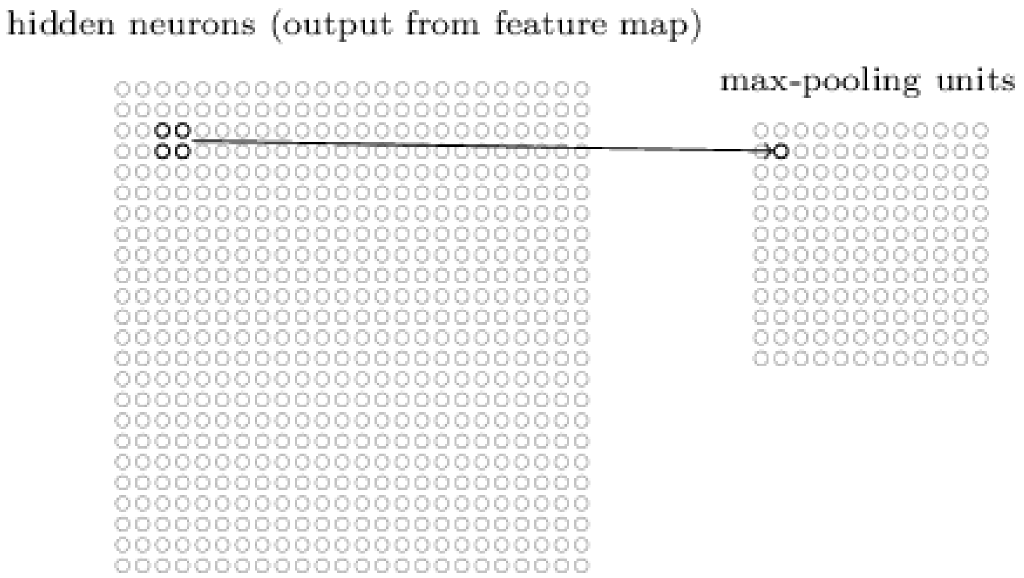


Pooling Layers

Often used immediately after convolutional layers

- Simplify the information in the output from the convolutional layer
- Takes each feature map output from the convolutional layer and prepares a condensed feature map
- Max-pooling:

  A pooling unit simply outputs the maximum activation in the $p \times p$ region



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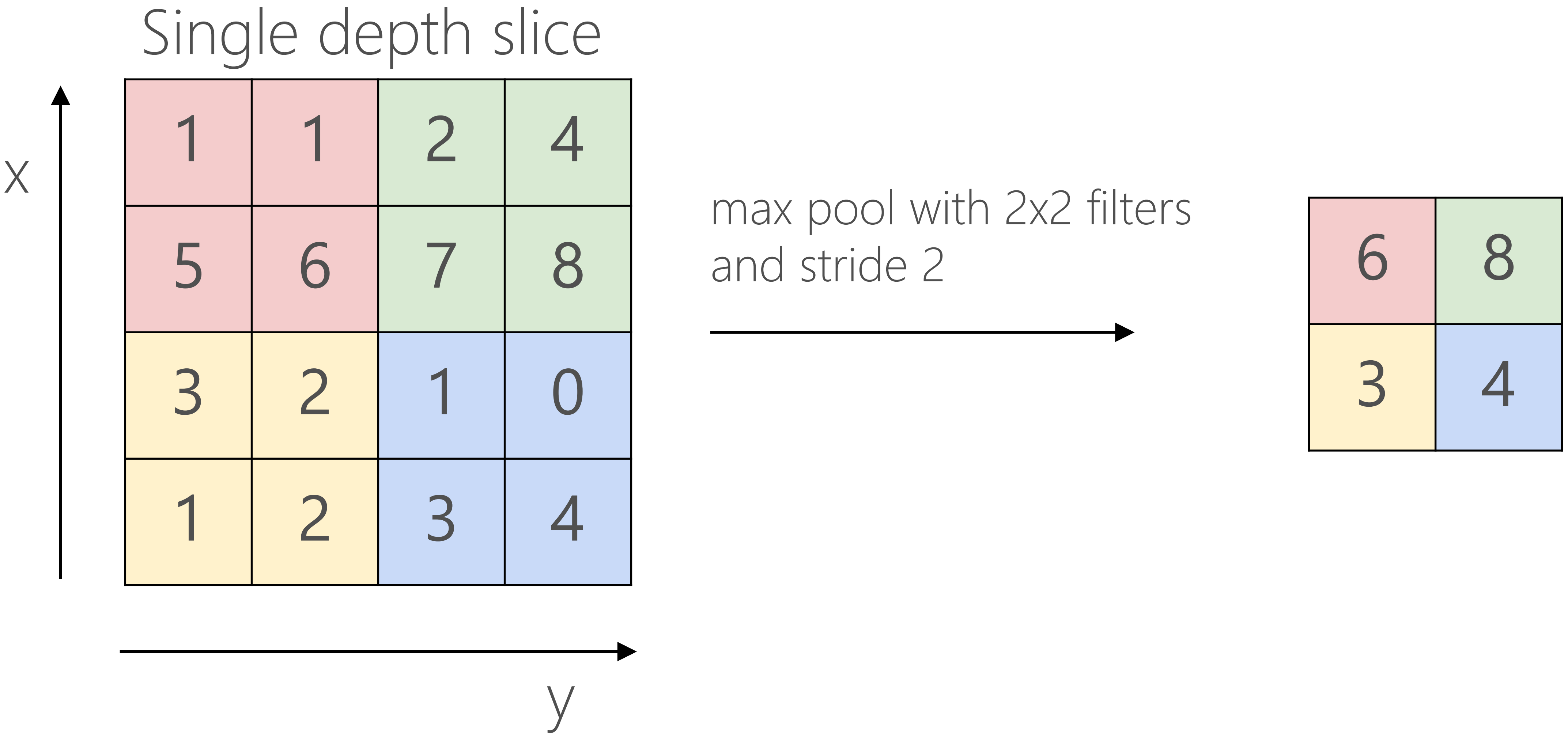
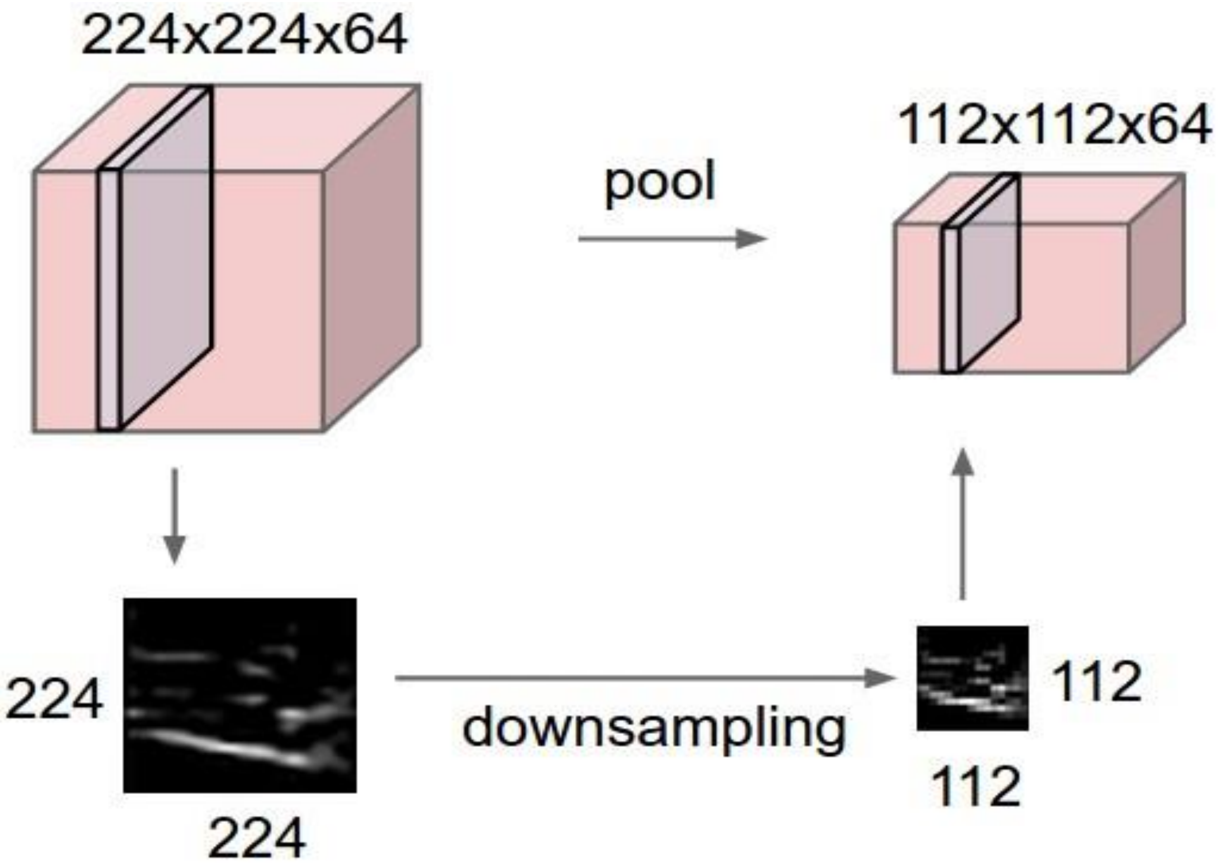
Max Pooling



Single depth slice
x
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
y
max pool with 2x2 filters
and stride 2
6 8
3 4

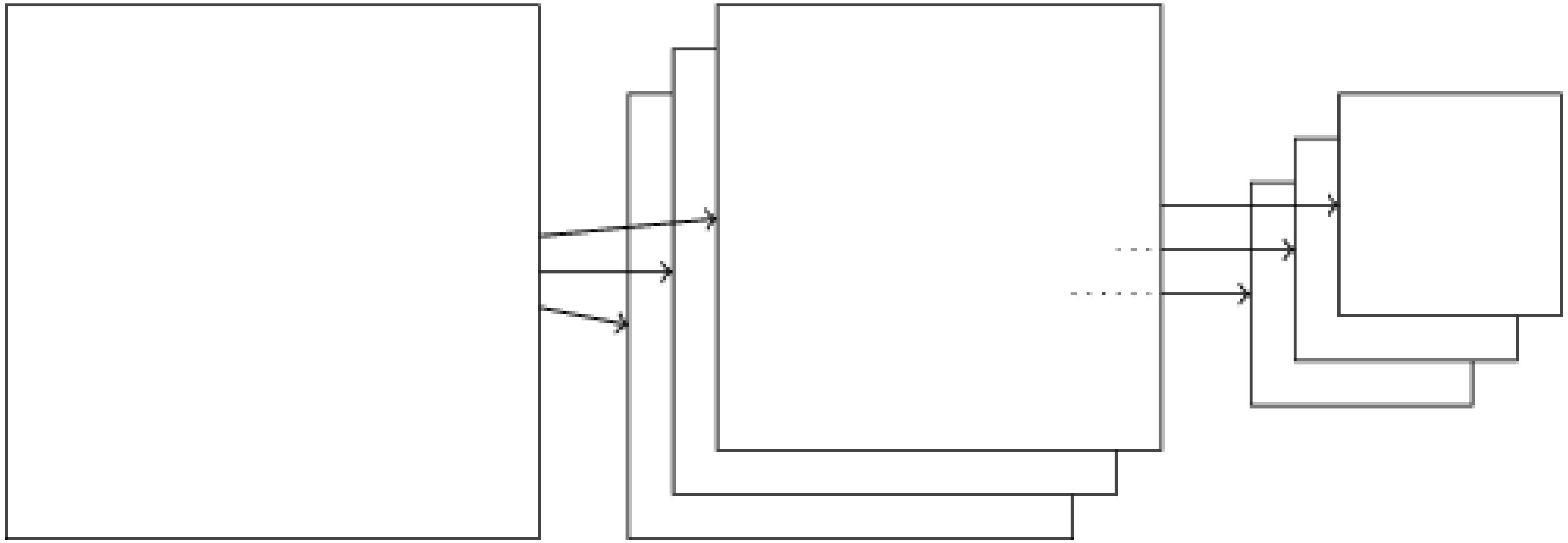
Pooling Layers

- Smaller representations and more manageable
- Operates over each activation map independently



Pooling Layers

Combined convolutional and max-pooling layers:



Shared Weights And Biases

1. Each hidden neuron has a bias and pxp weights connected to its local receptive field
2. The same weights and bias for each of the hidden neurons
3. In other words, for the $j,\ k^{th}$ hidden neuron, the output is:

$$\sigma(b + \sum_{l=0}^{n} \sum_{m=0}^{n} w_{l,m} a_{j+l,k+m})$$

where σ is the neural activation function - perhaps the sigmoid function
b is the shared value for the bias
$w_{l,m}$ is a $n \times n$ array of shared weights
$a_{x,y}$to denote the input activation at position x, y

Microsoft

Shared Weights And Biases

- Convolutional networks are well adapted to the translation invariance of images
- Greatly reduces the number of parameters involved in a convolutional network $(p \times p + b)$

Terminology

Feature map/Activation map	Map from the input layer to the hidden layer
Shared weights	Weights defining the feature map
Shared bias	Bias defining the feature map
Kernel/Filter	Shared weights and bias

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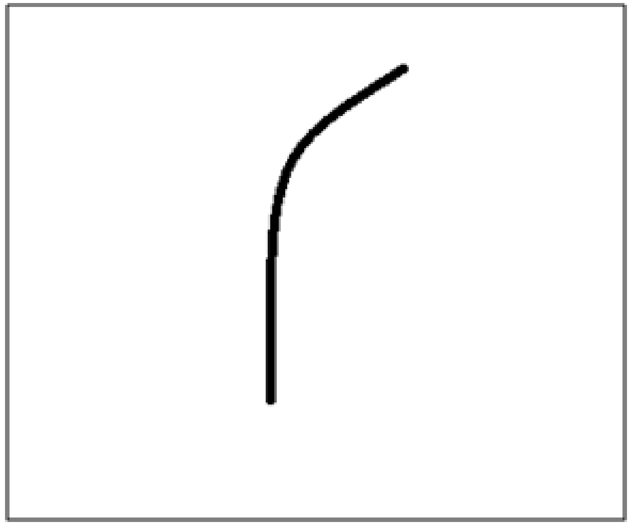
First Layer – High Level Perspective

- Filters can be thought of as feature identifiers (straight edges, simple colors, and curves)
- In the simple case of a one filter convolution and a curve detector filter, activation map results in regions that are most likely curves in the picture

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter



Visualization of a curve detector filter

- More filters mean greater the depth of the activation map
- This results in more information about the input

Going Deeper Through The Network

- Many layers are interspersed between convolution layers (example: ReLu and Dropout)
- Introduction of nonlinearities
- Improve the robustness of the network and control overfitting

Input -> Conv -> ReLU -> Conv -> ReLU -> Pool -> ReLU -> Conv -> ReLU -> Pool ->Fully Connected

RelU

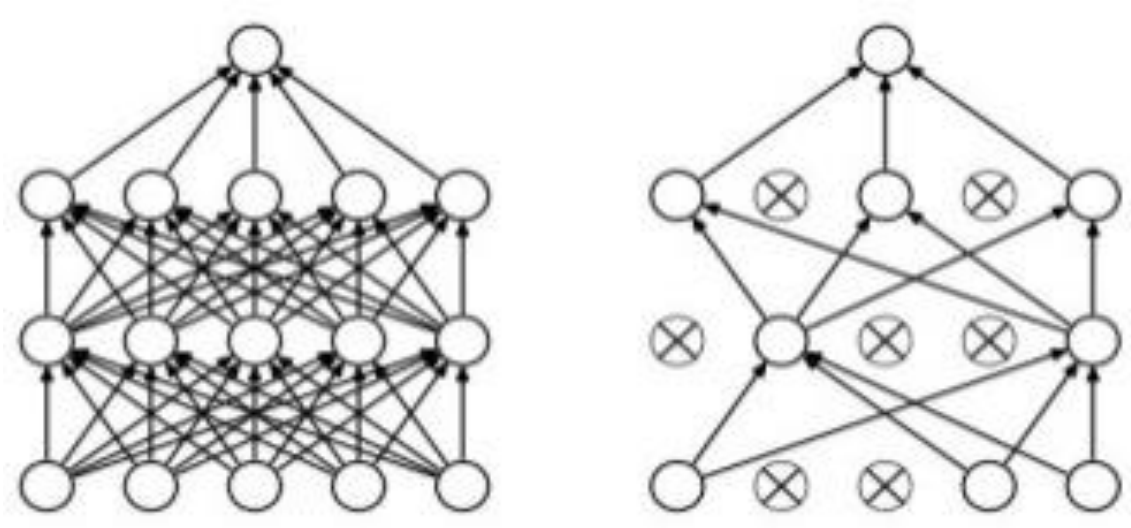
- The Rectified Linear Unit has become very popular recently

$$f(x) = \max(0, x)$$

- Activation is simply thresholded at zero
- It was found to greatly accelerate (Krizhevsky et al.) the convergence of stochastic gradient descent compared to the sigmoid/tanh functions
- Compared to tanh/sigmoid neurons that involve expensive operations (exponentials, etc.), the ReLU is simply thresholding

Dropout

- A form of ensemble learning
- Avoids overfitting (by preventing inter-dependencies from emerging between nodes)
- Dropout - an extreme version of bagging
- At each training step, the dropout procedure creates a different network by removing some neurons randomly



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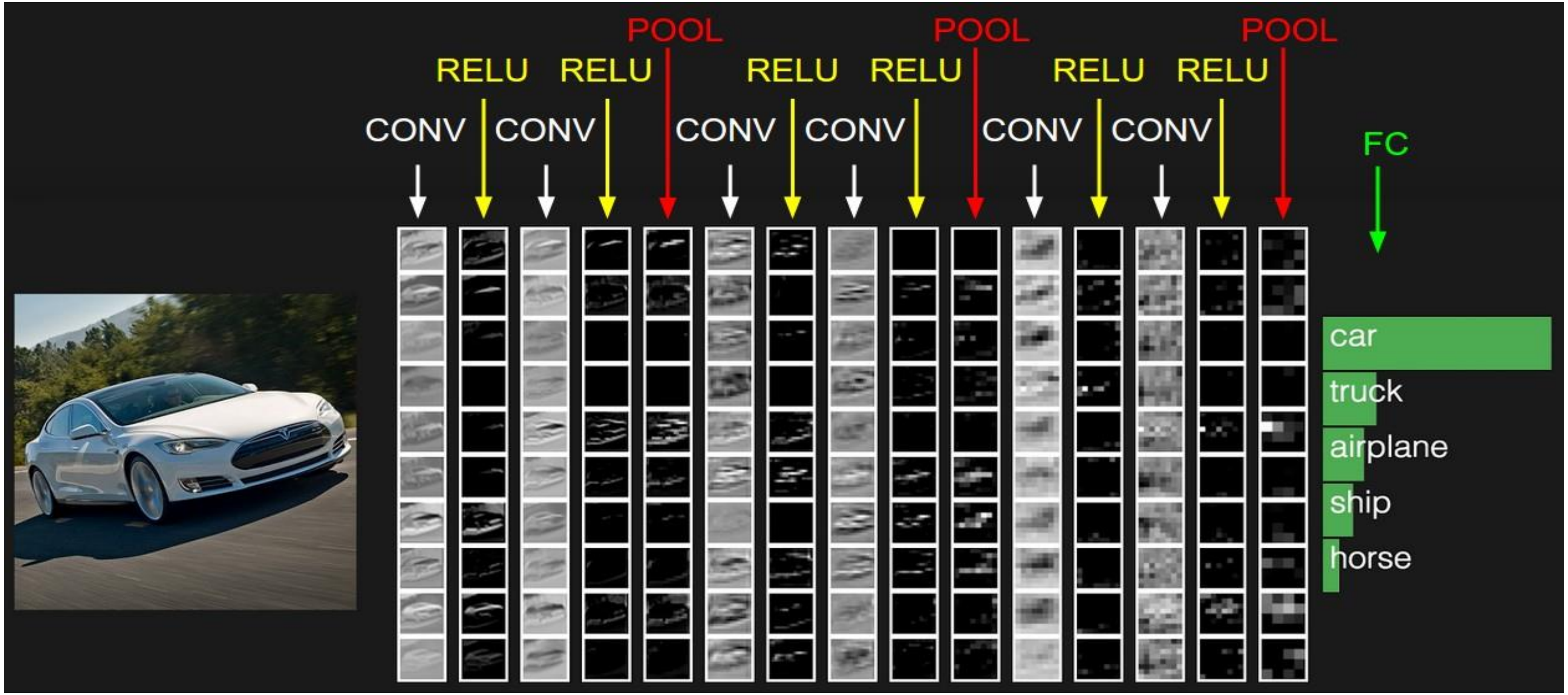
Fully Connected Layer (FC layer)



Deep Learning And NLP

CNNs for NLP

- CNNs were responsible for major breakthroughs in Image Classification and are the core of most Computer Vision systems today, from Facebook's automated photo tagging to self-driving cars.

- More recently, CNNs are also applied to problems in Natural Language Processing.

- The intuitions behind CNNs are easier to understand for the Computer Vision use case.

CNNs for NLP

- Instead of image pixels, the input to most NLP tasks are sentences or documents represented as a matrix.

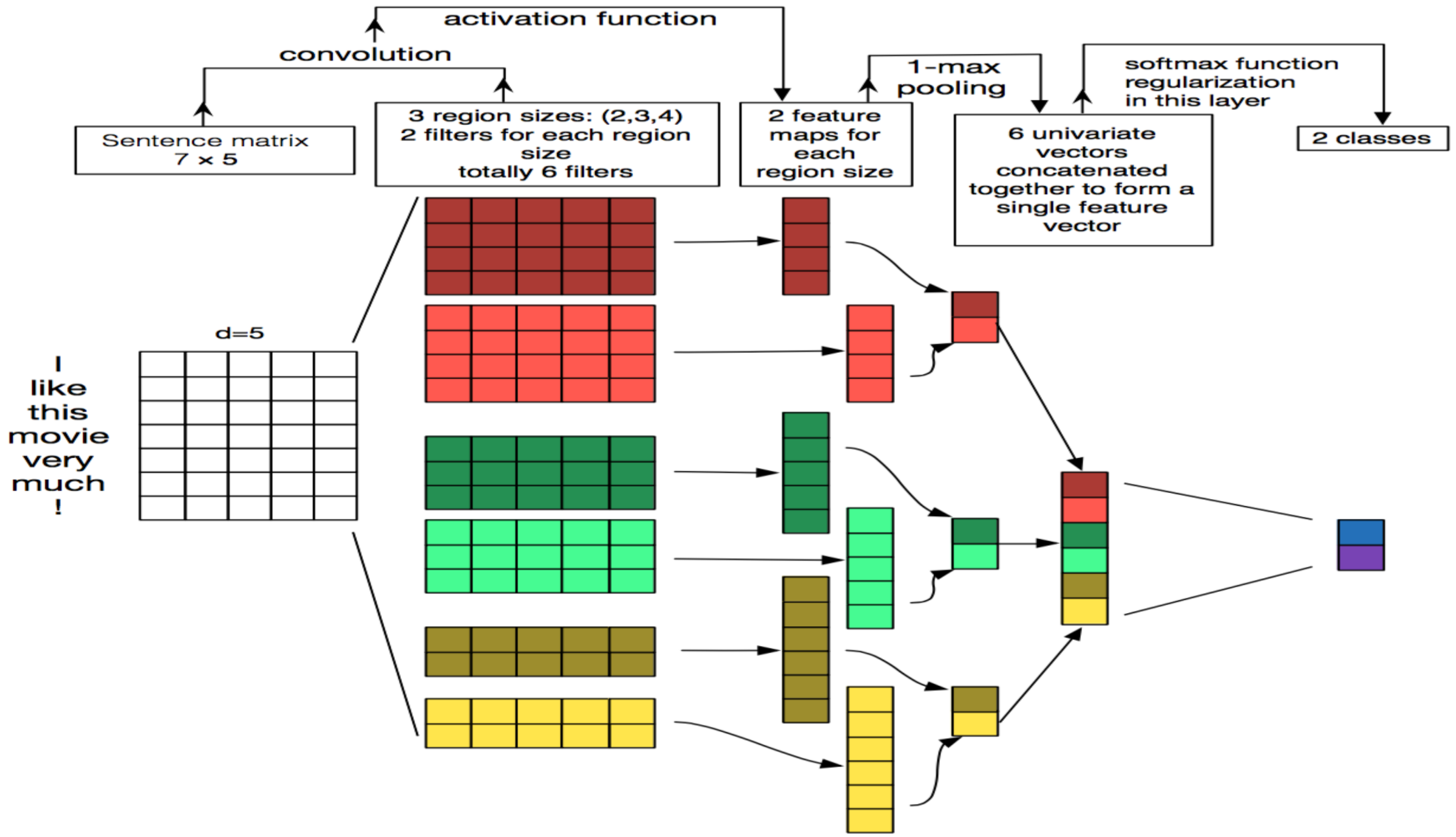
- Each row of the matrix corresponds to one token, typically a word, but it could be a character. That is, each row is vector that represents a word.

- Typically, these vectors are word embeddings, but they could also be one-hot vectors that index the word into a vocabulary.

- For a 10 word sentence using a 100-dimensional embedding we would have a 10×100 matrix as our input. That's our "image".

CNNs for NLP

- In vision, filters slide over local patches of an image, but in NLP, filters slide over full rows of the matrix (words).
- The height, or region size, may vary, but sliding windows over 2-5 words at a time is typical.
- Example of Convolutional Neural Network for NLP:



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What about the nice intuitions we had for Computer Vision?

- With text, you probably do care a lot where in the sentence a word appears.
- Pixels close to each other are likely to be semantically related (part of the same object), but the same isn’t always true for words.
- In many languages, parts of phrases could be separated by several other words.
- Words compose in many ways: an adjective modifying a noun, but how exactly this works and what higher level representations actually “mean” isn’t as obvious as in the Computer Vision case.

What about the nice intuitions we had for Computer Vision?

- Given all this, it seems like CNNs wouldn't be a good fit for NLP tasks.

- Recurrent Neural Networks make more intuitive sense. The are similar to how we process language: Reading sequentially from left to right.

- Fortunately, this doesn't mean that CNNs don't work.

CNNs work for NLP!

- The simple Bag of Words model is an obvious oversimplification and can lead to pretty good results.
- A big argument for CNNs is that they are fast. Very fast.
- Convolutions are a central part of computer graphics and typically, implemented on GPUs.
- Compared to something like n-grams, CNNs are efficient with representation. With a large vocabulary, computing anything more than 3-grams can quickly become expensive.
- Even Google doesn’t provide anything beyond 5-grams. Convolutional Filters learn good representations automatically, without needing to represent the whole vocabulary.
- Possibly, many of the learned filters in the first layer capture feature similar to n-grams, but represent them in a more compact way.

Microsoft