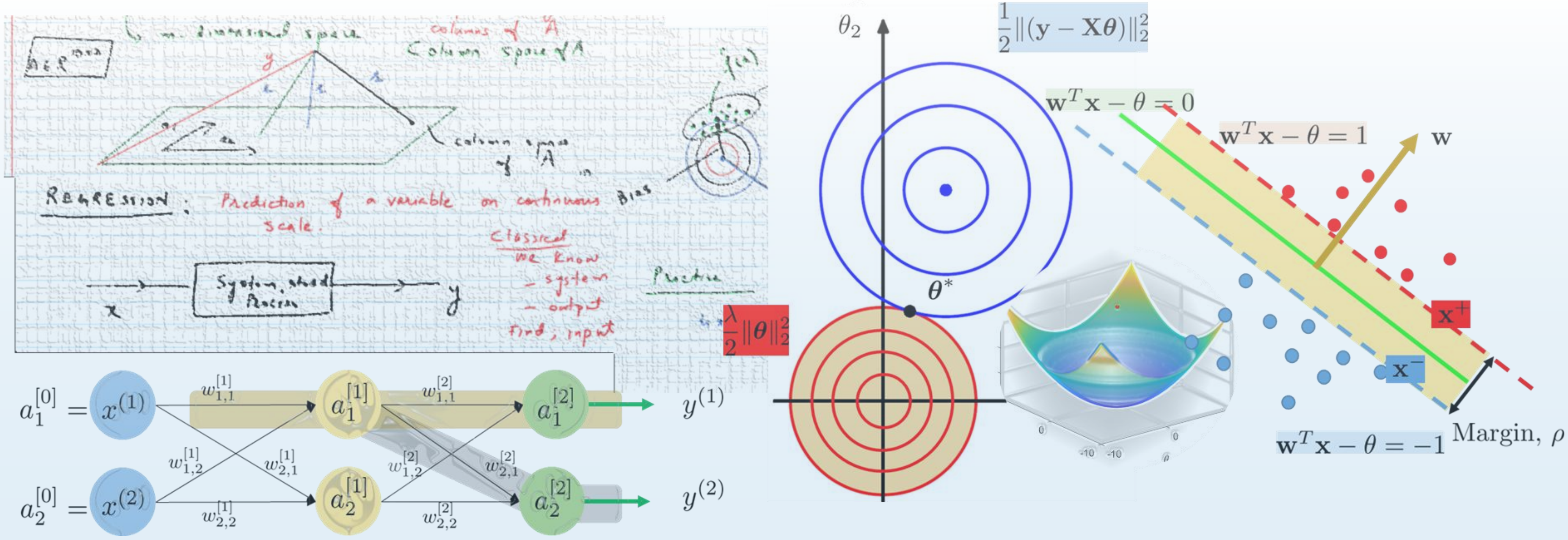

Machine Learning

Introduction to Deep Learning and Convolutional Neural Networks

School of Science and Engineering

https://www.zubairkhalid.org/ee514_2025.html

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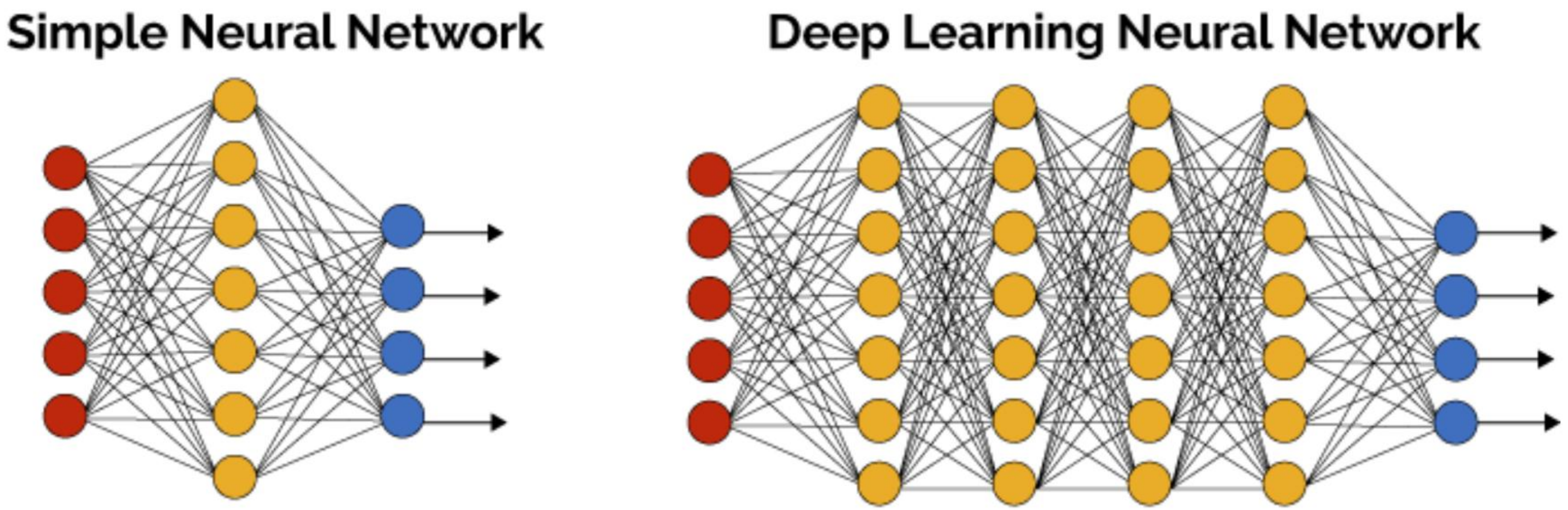
Outline

- Deep Learning Overview
- Convolutional Neural Networks

Deep Learning (DL)

Overview:

- We have already studied deep learning
- Deep Learning = Deep Neural Network
  - Using a neural network with **several layers** of nodes
- Deep: **high number of hidden layers**

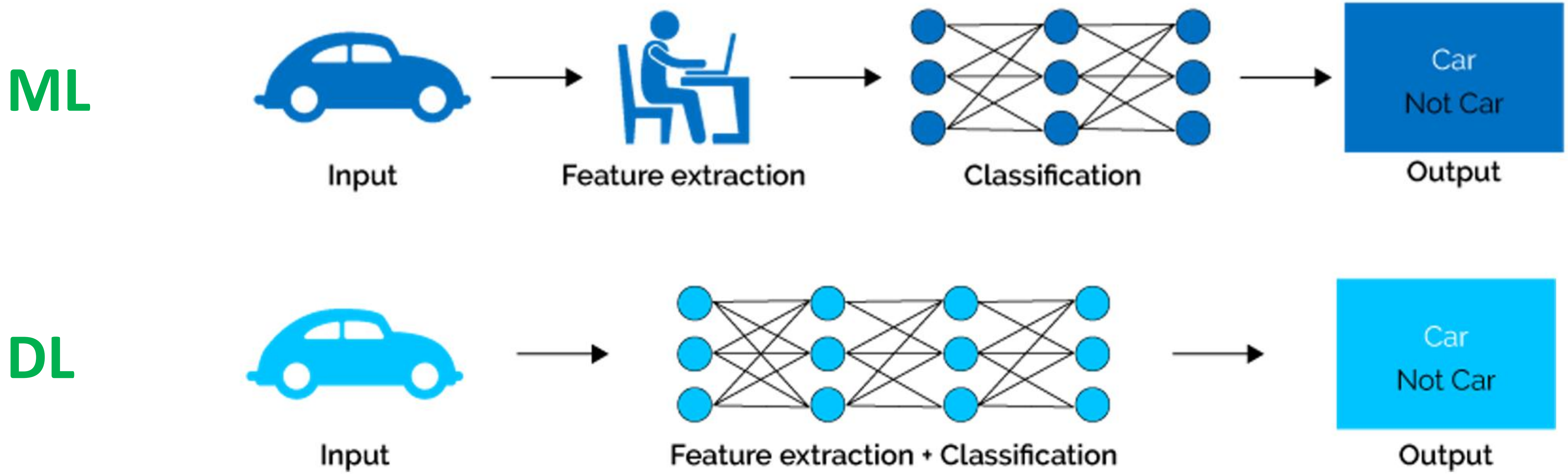


Deep neural network – generalizes very well as they are capable of learning the true underlying features.

Deep Learning (DL)

Difference between ML and DL:

- High number of layers in deep neural network enables
  - feature identification
  - processing in a series of stages



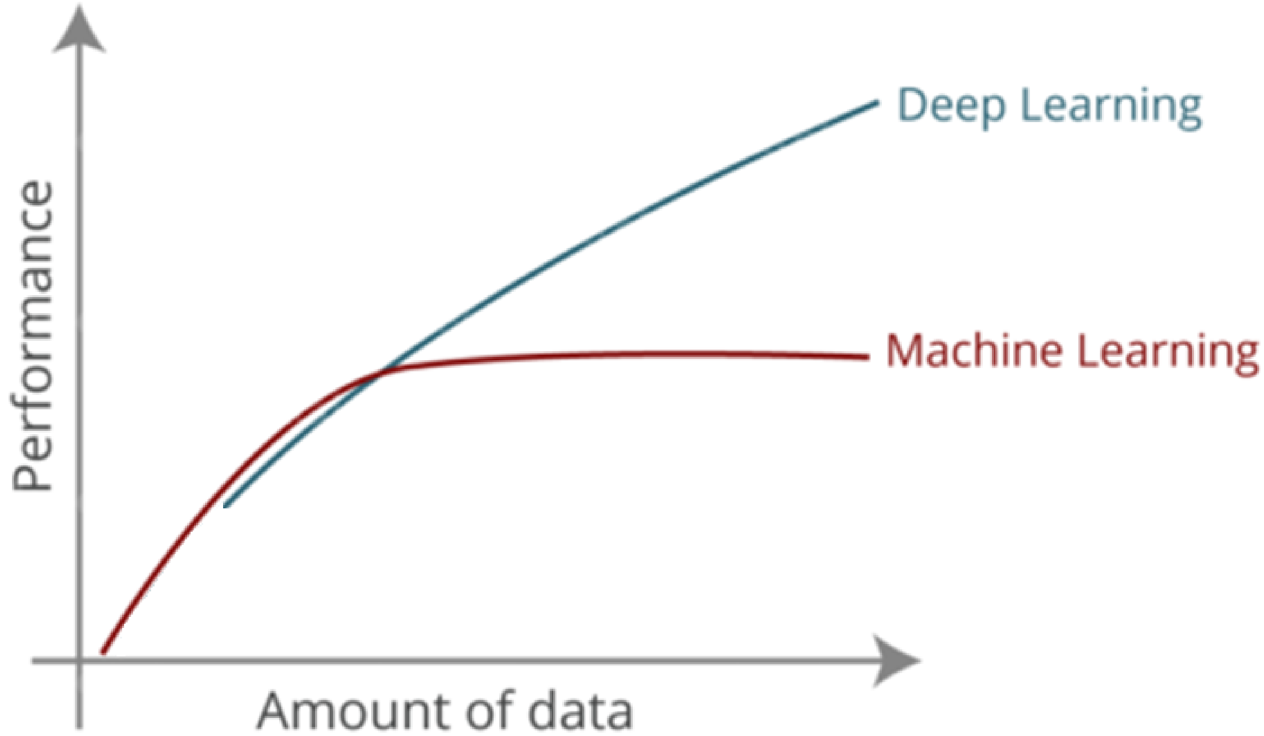
Multi-layer networks have been around but what has changed recently?

Deep Learning (DL)

Difference between ML and DL:

Now we have more

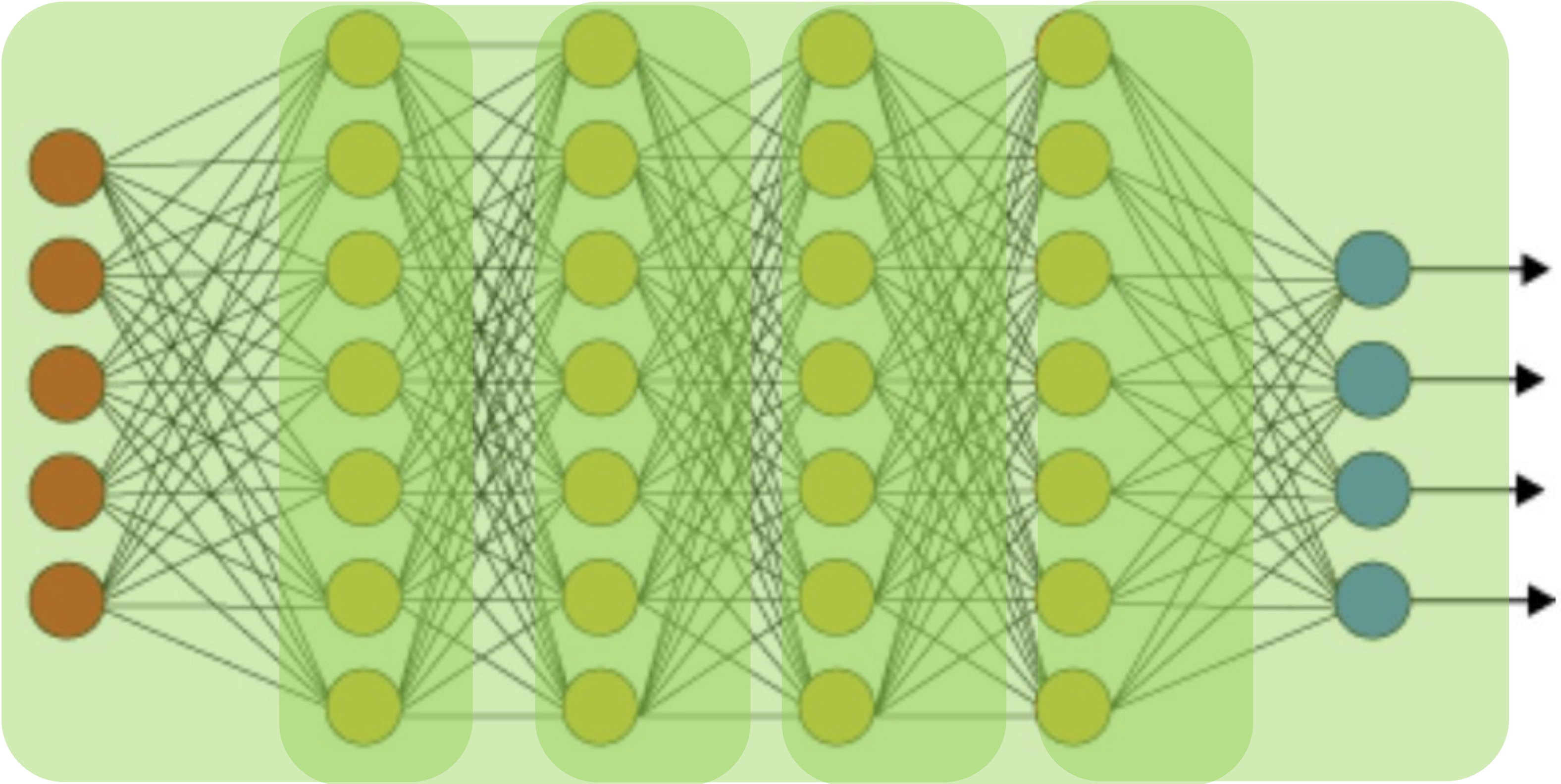
- Data; deep learning needs more data
- Computing power (availability of GPUs, parallel processing)
- New tricks to learn the weights of the network



Deep Learning (DL)

New way to train Deep Neural Networks:

We train layers of the network sequentially



First, train this layer

Then this layer

Then this layer

Then this layer

Then this layer

We train each of the non-output layer to act as an autoencoder.

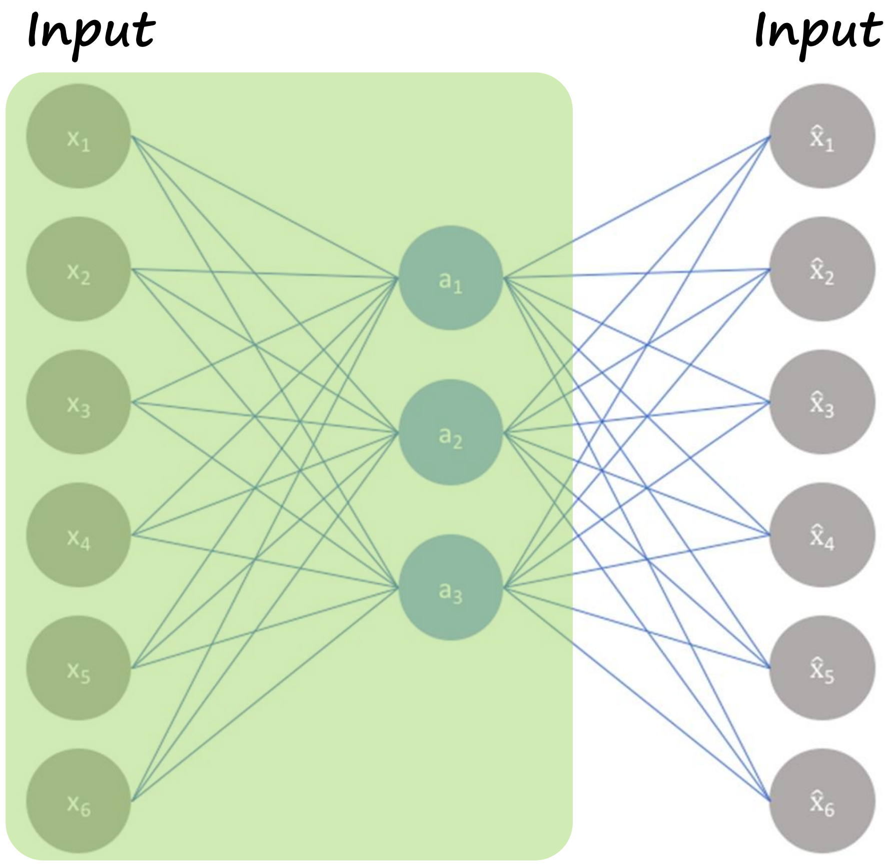
Deep Learning (DL)

AutoEncoders:

- A type of neural network that is used to learn **data encodings** (unsupervised).
- In general, autoencoder has three parts;
  - **Encoder**
  - **bottleneck (code, latent representation)**
  - **Decoder**

- A simple example:

An auto-encoder (one hidden layer network) is trained to reproduce the input using standard learning algorithm.



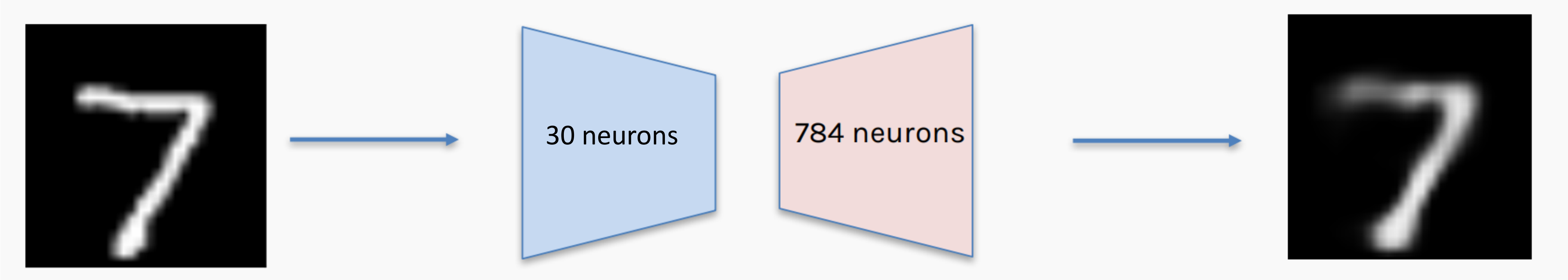
Idea:

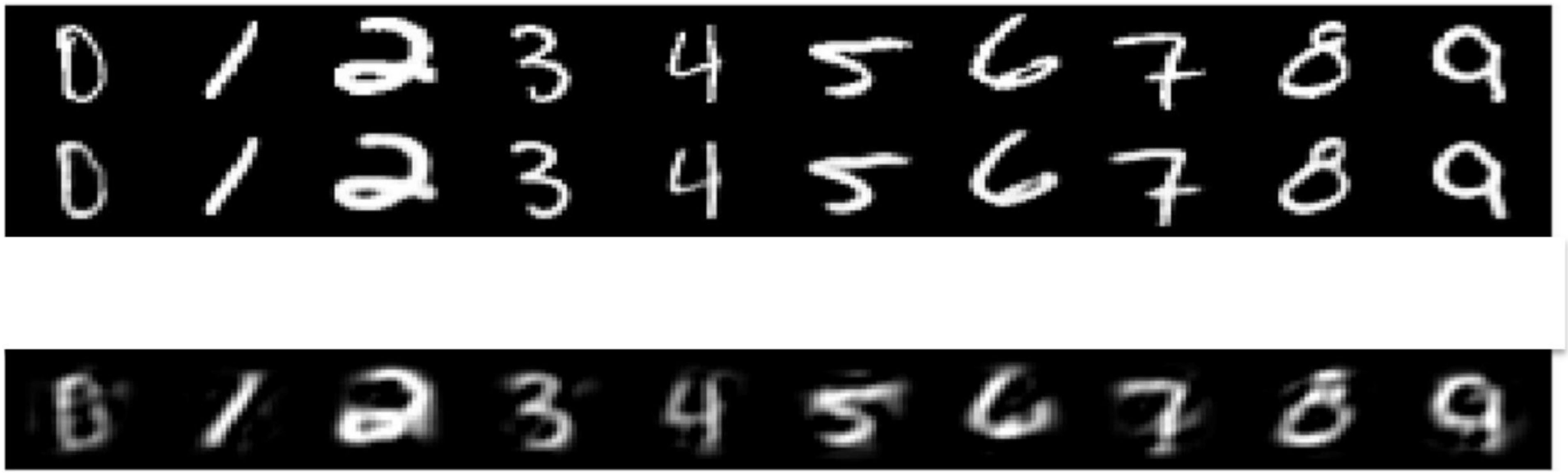
- Learn a lower-dimensional representation (encoding) for a higher-dimensional data.
- Capture the most important parts of the input.

In other words, training autoencoder forces the 'hidden layer' units to become good feature detectors.

Deep Learning (DL)

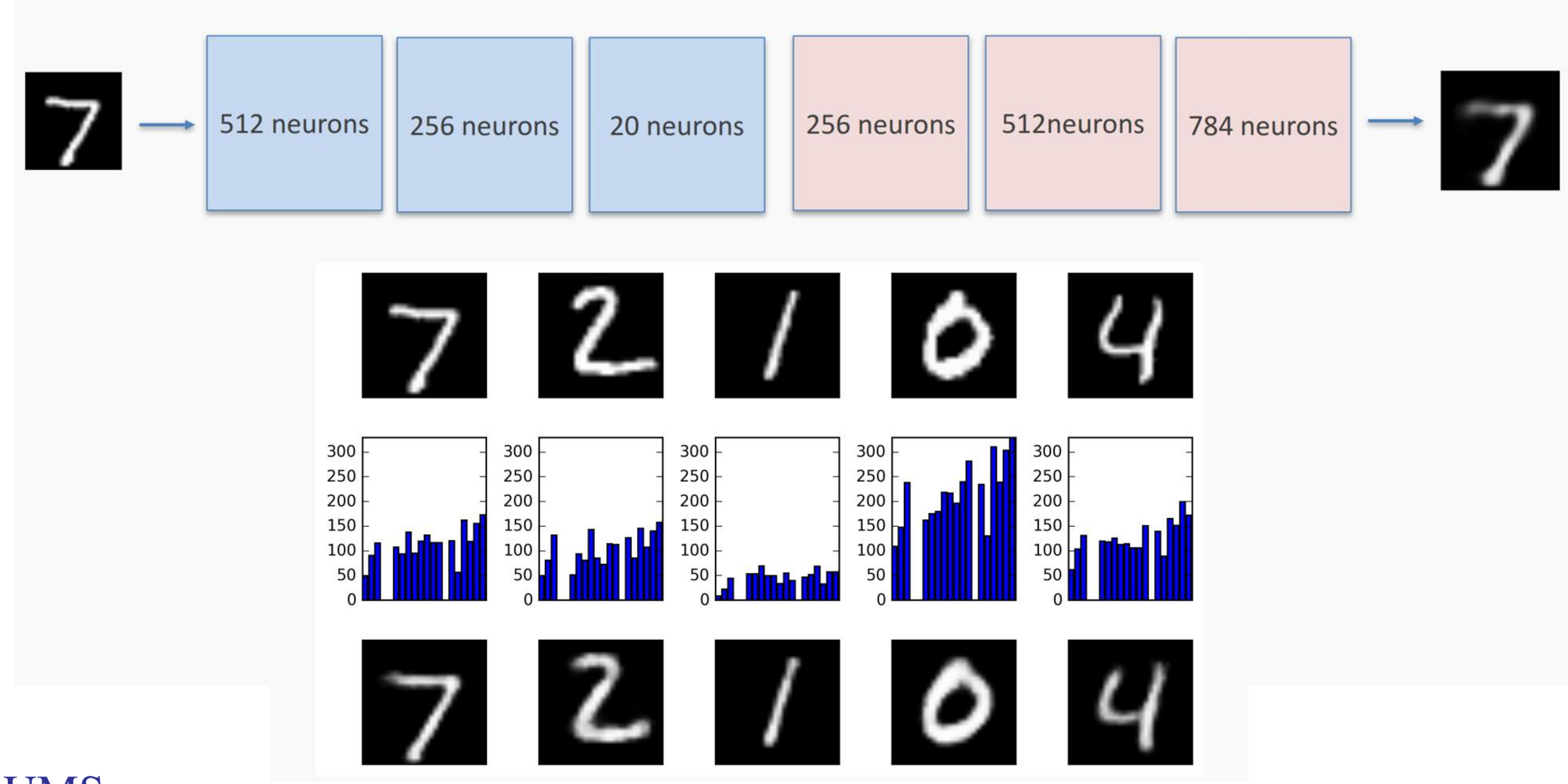
AutoEncoders – Representation Example; Linear (PCA) vs non-linear :





Deep Learning (DL)

AutoEncoders – Representation Example; Deeper:



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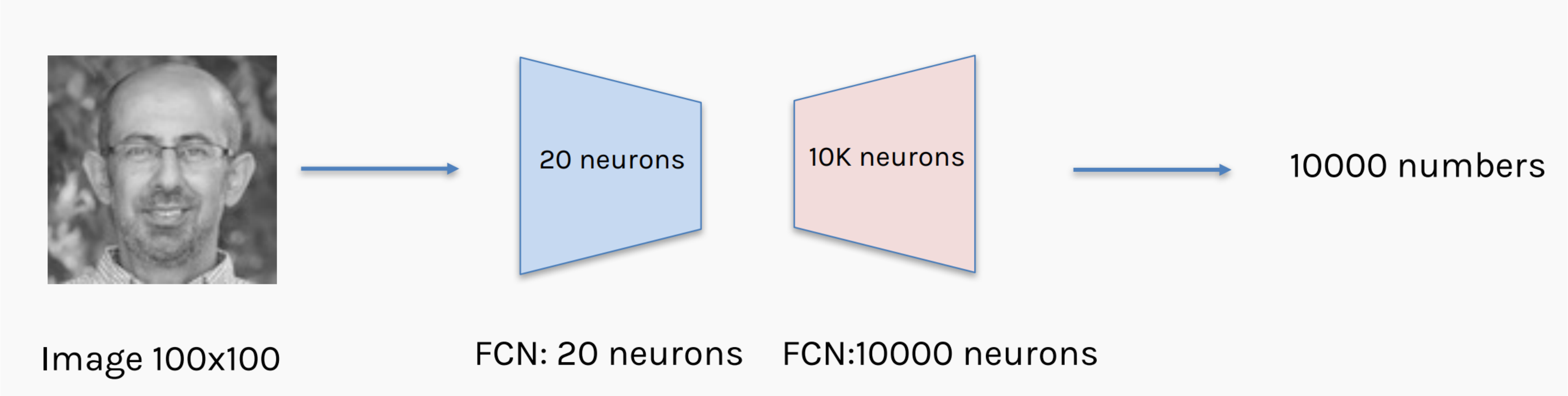
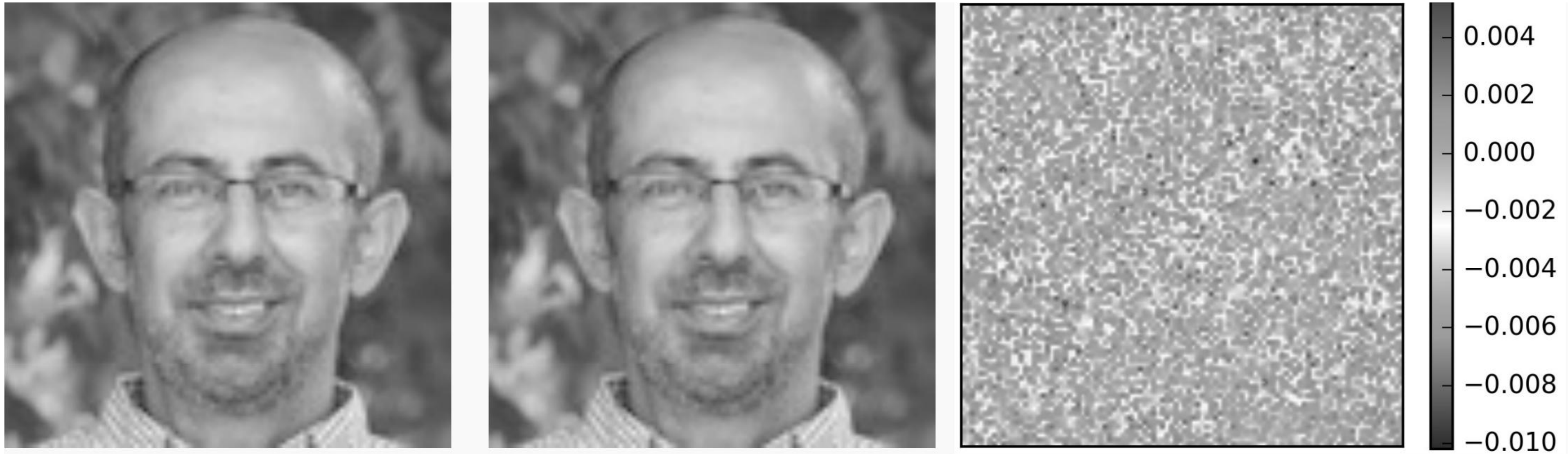
Deep Learning (DL)

AutoEncoders – Compression Example:





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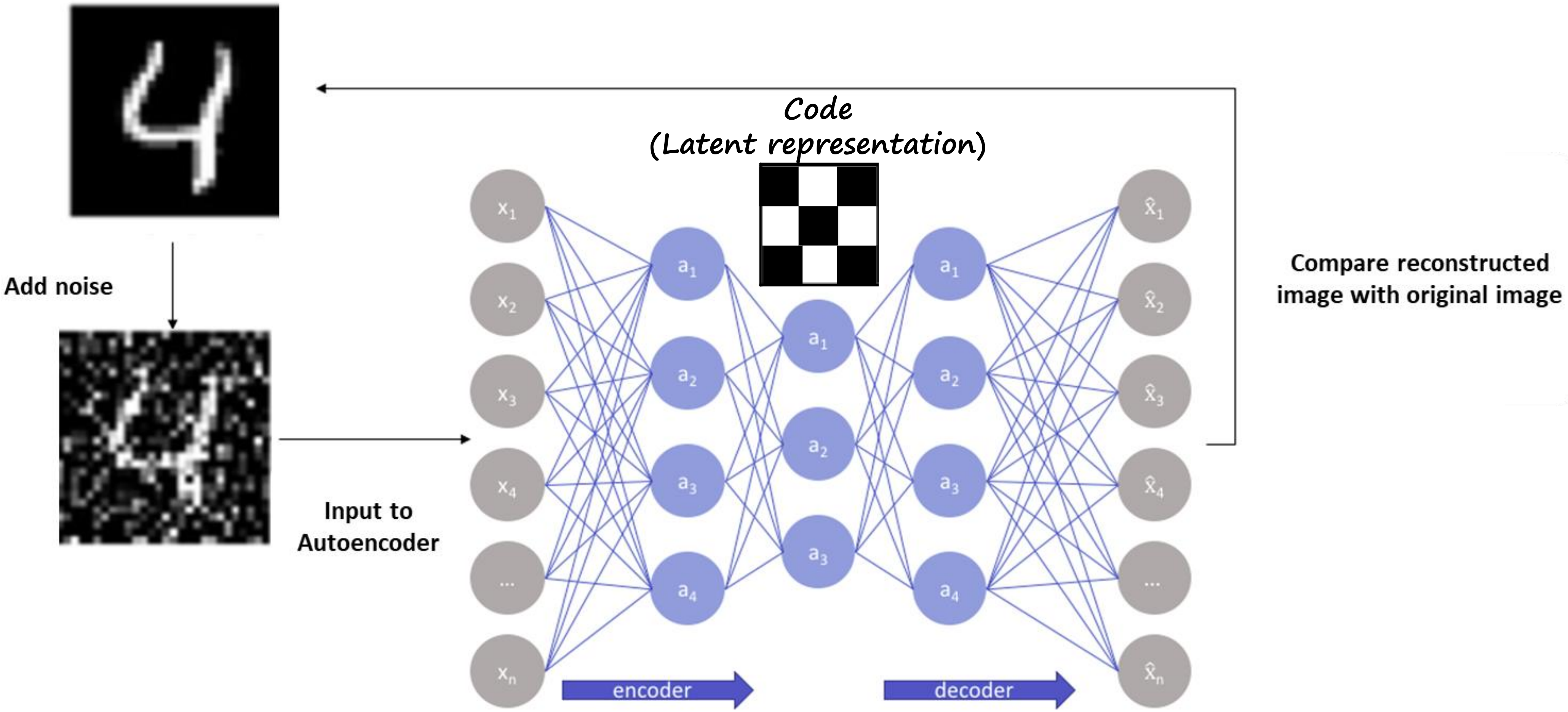
Deep Learning (DL)

Denoising AutoEncoders:

Idea: The denoising autoencoder gets rid of noise by learning a representation of the input where the noise can be filtered out easily.



Deep Learning (DL)

Overview:

- This is the overall idea!
- There are many types of deep neural networks, different architectures, different types of autoencoder, and different training algorithms
- Fast growing research in the area!

Convolutional Neural Networks (CNNs)

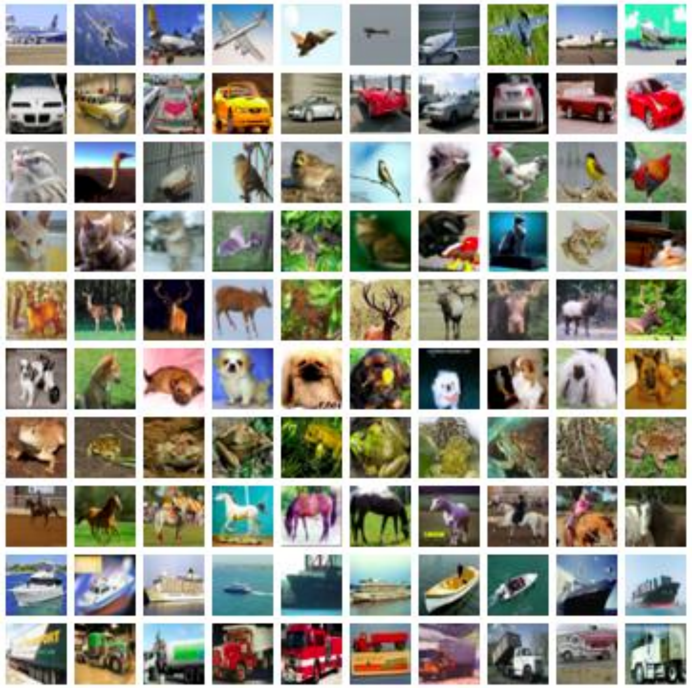
Overview:

Motivation:

Consider an object detection (classification) problem from images using neural network.

For example: CIFAR-10 dataset

- 10 classes, Input image is 32x32x3 = 3072



Fully connected neural network

- Treats input as a vector
- **Each** neuron in the first layer will have 3072 weights

For 400x400x3 image, each neuron has 480,000 weights

Very large number of parameters!

Why? Regular Neural Network treats input as a vector

Solution: Exploit the structure in the input data

Convolutional Neural Networks (CNNs)

Overview:

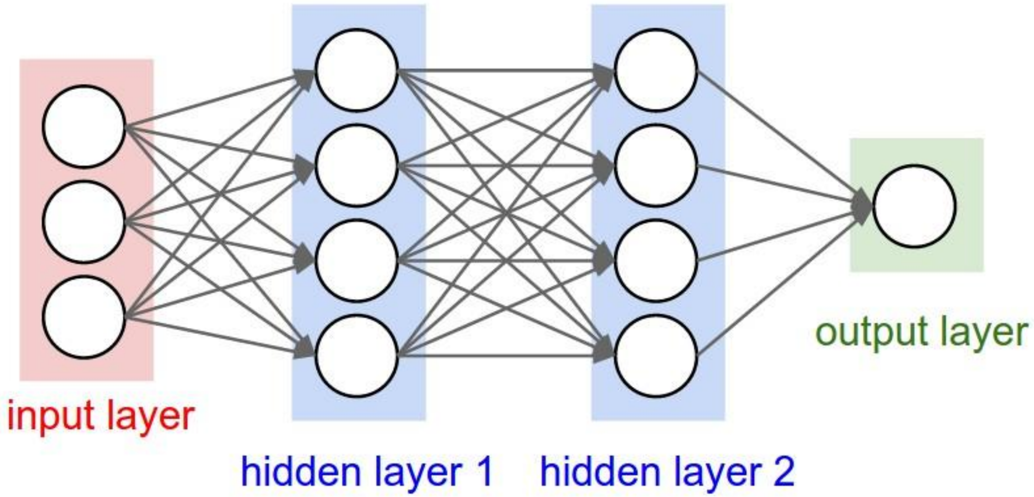
- Convolutional Neural Networks exploits the structure in the input, that is, a fact that the input consists of images.

- Instead of treating image as an input vector and each layer as a column of neurons, we
  - take image as an input
  - arrange neurons in 3 dimensions: width, height and depth in each layer

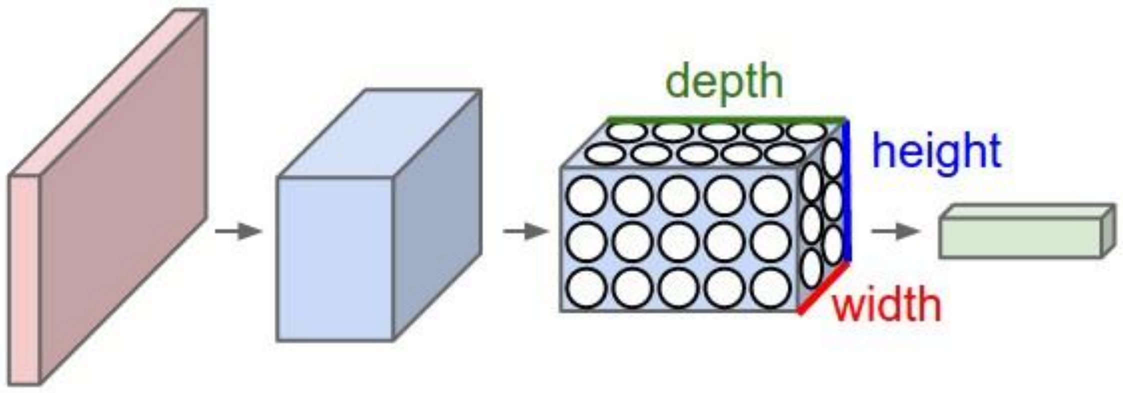
- Each layer transforms an input volume (3D) to an output 3D volume.

Convolutional Neural Networks (CNNs)

Overview:



Regular Neural Network



Convolutional Neural Network (CNN)

In CNNs, the structure of image is exploited, and each layer transforms a volume of activations to an output volume through differentiable function that may or may not have parameters.

In CNN, we use three main types of layers to build network architecture:

- Convolutional layer
- Pooling layer
- Fully-connected layer

Convolutional Neural Networks (CNNs)

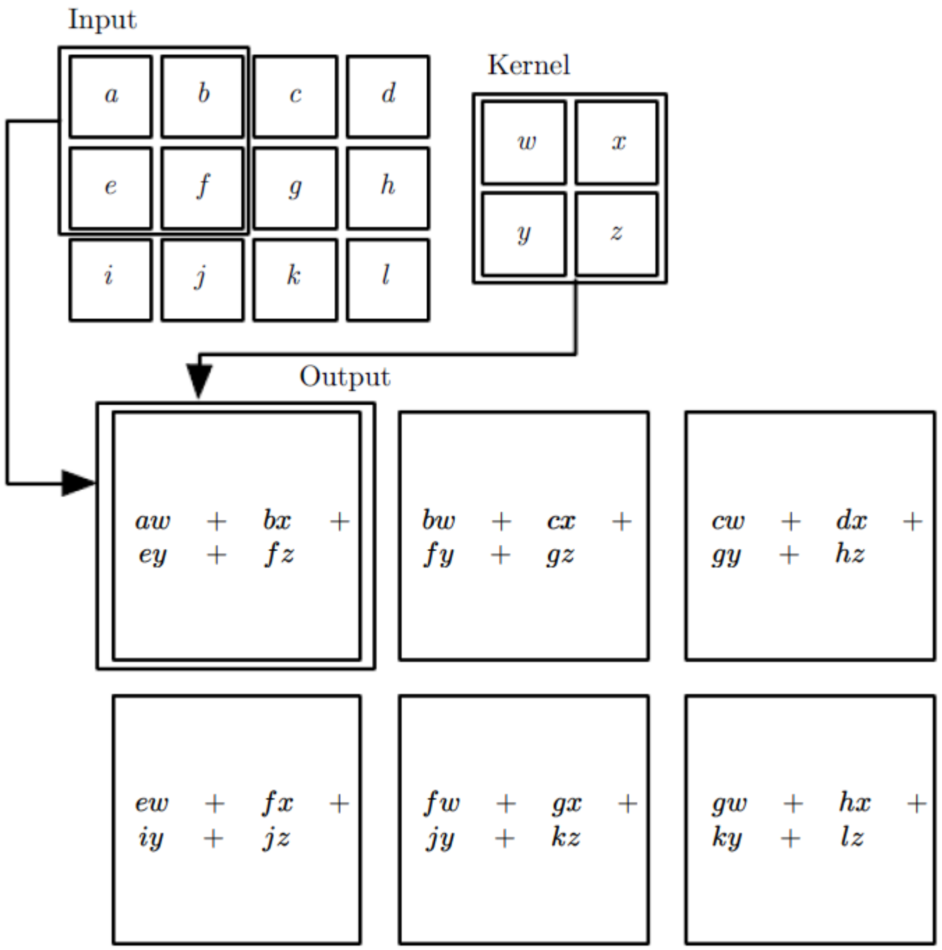
Convolutional Layer:

- Convolution Operation:

Convolutional Neural Networks (CNNs)

Convolutional Layer:

- Convolution in 2D:



Convolution leverages three important ideas that can help improve a machine learning system:

- **Sparse interactions**
  - Kernel smaller than the input
- **Parameter sharing**
- **Equivariant Representations**
  - Equivariance to translations

Convolutional Neural Networks (CNNs)

Convolutional Layer:

- Convolutional layer parameters consists of a set of learnable filters.

- Intuitively, network learn filters that activate when they see some type of visual feature e.g.,
  - an edge of some orientation or boundary of the shape on the first layer
  - wheel like patterns on higher layers of network

- Each filter in a set of filters produces a separate 2-dimensional activation map.

- These 2D maps are stacked along the depth dimension to produce output volume.

Convolutional Neural Networks (CNNs)

Convolutional Layer:

- Instead of connecting each neuron to all the neurons in the previous volume, CNN connects the neuron to a local region in the input volume controlled by hyperparameter referred to as **receptive field** (denoted by F).

- Extent of this connectivity is always equal to the depth of input volume.
  - Connections are local along height and width but always full along the depth of input volume.

Convolutional Neural Networks (CNNs)

Convolutional Layer:

Example:

Input: 32x32x3 image

Receptive field: 5x5

Each neuron in the convolutional layer will connect to 5x5x3 region in input volume.

Total weights: 76 = 5x5x3 weights + 1 bias parameter

Convolutional Neural Networks (CNNs)

Convolutional Layer:

Spatial Arrangement of Neurons in the Output Volume:

- 3 hyper-parameters control the arrangement of neurons in the output volume
  - Depth
  - Stride
  - Zero-padding

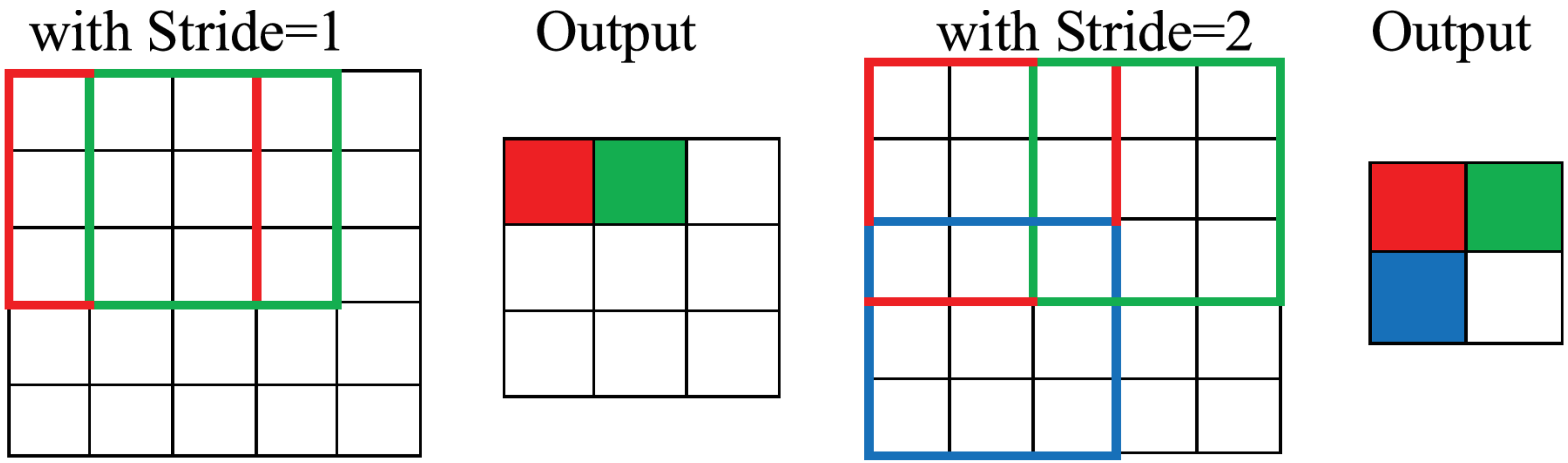
- Depth (denoted by k):
  - It is equal to the number of filters we want to use.
  - Each filter is assumed to reveal something different in the input.
  - The neurons that are all looking at the same region of the input as a depth column.

Convolutional Neural Networks (CNNs)

Convolutional Layer:

Spatial Arrangement of Neurons in the Output Volume:

- Stride (denoted by S):
  - Controls the amount of translation in the convolution operation.
  - Stride=1: filter is translated (moved) one pixel when we slide the filter.
  - Stride=2: filter is translated (moved) two pixel when we slide the filter.
  - Stride=2 produces smaller output volume as compared to stride=1.



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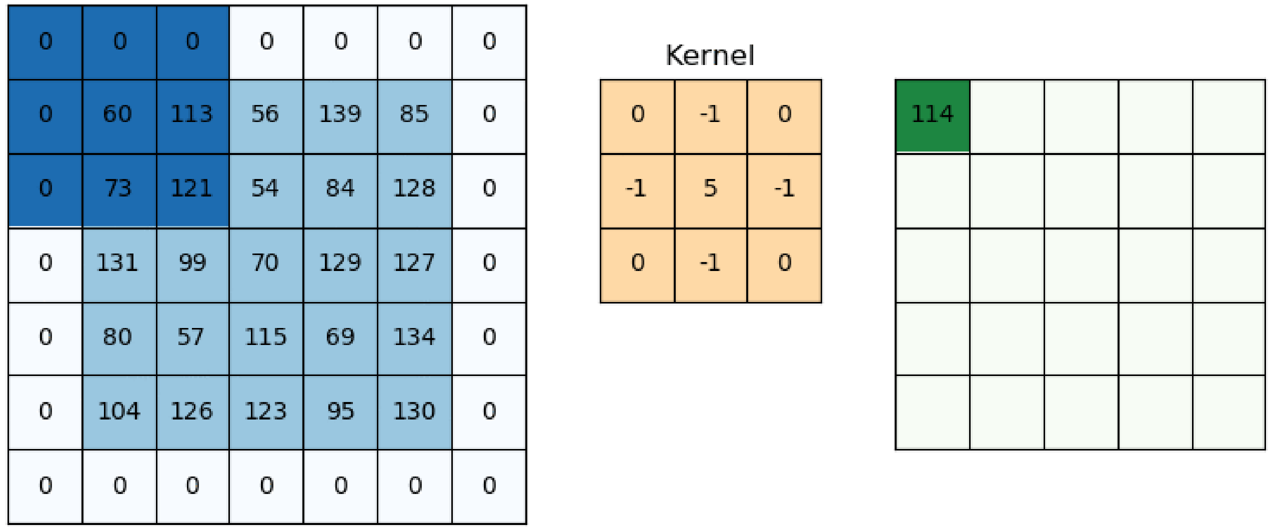
Convolutional Neural Networks (CNNs)

Convolutional Layer:

Spatial Arrangement of Neurons in the Output Volume:

- Zero-padding (denoted by P):
  - To handle the convolution along the boundary points, we zero-pad input around the borders. The amount of zero-padding controls the spatial size of the output volume.



Source: https://medium.com/@draj0718/zero-padding-in-convolutional-neural-networks-bf1410438e99

Convolutional Neural Networks (CNNs)

Convolutional Layer:

Spatial Arrangement of Neurons in the Output Volume:

For

- F – receptive field size, S – stride, P – amount of zero padding and W – Input volume size
    - Output volume slice size: 1 + (W-F+2P)/S

- ***Example:***
- 7x7 input, 3x3 filter, 0 padding and 1 stride
    - 1 + (W-F+2P)/S = 5
    - 5x5 output

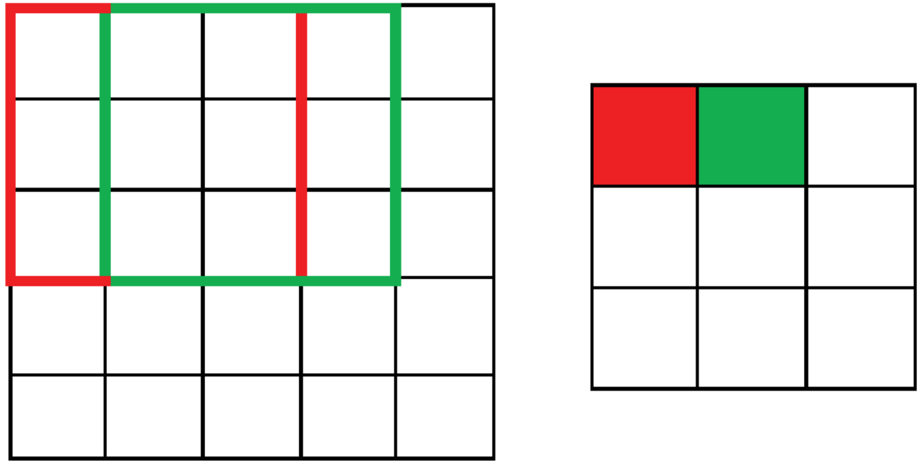
- With 2 stride
    - 1 + (W-F+2P)/S = 3
    - 3x3 output

Convolutional Neural Networks (CNNs)

Convolutional Layer:

Parameter Sharing

- Number of parameters can be further reduced by parameter sharing.
- Idea:
  - Neurons at each depth slice share the same weights and a bias.
  - At each depth level, we have a 2D slice and we use same parameters for every neuron at each depth level.



Convolutional Neural Networks (CNNs)

Convolutional Layer:

Parameter Sharing - Example

- Input: 227x227x3
- First convolutional layer: F=11, S=4, P=0, depth=96
- Output slice size: 1+(W−F+2P)/S = 55
- Without parameters sharing:
  - Number of parameters per depth slice: 55x55x(11x11x3+1)
- With parameters sharing:
  - Number of parameters per depth slice: 11x11x3+1

Convolutional Neural Networks (CNNs)

Convolutional Layer:

Parameter Sharing

- Q: What is the benefit of parameter sharing?
- A: 1) Significant reduction in the number of parameters.

  2) Convolutional layer output can be computed by simply convolving filter with an input.

- Each neuron of the depth slice has same parameters which means
  - Shared weights can be interpreted as a filter.
  - The depth slice output is simply a convolution of the filter and the input.

- Parameter sharing is also intuitive because if the filter is detecting an edge at some spatial position, we also want to detect the edge in a similar way at all other positions.

Convolutional Neural Networks (CNNs)

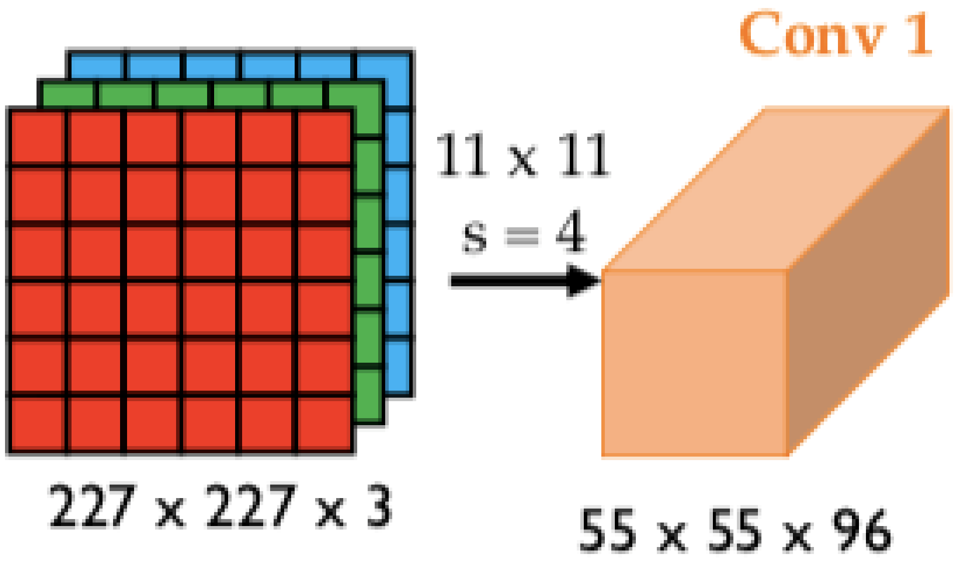
Convolutional Layer:

Summary:

- Accepts a volume of size $W_1 X H_1 X D_1$
- 4 Hyper-parameters define the convolutional layer
  - Number of filters, k
  - Spatial extent of each filter, F
  - Stride, S
  - Zero-padding, P
- Produces a volume of size $W_2 X H_2 X D_2$
  - $W_2 = 1 + (W_1 - F + 2P)/S$
  - $H_2 = 1 + (H_1 - F + 2P)/S$
  - $D_2 = k$ (depth)
- With parameters sharing, the number of parameters are $FxFxD_1$ weights and 1 bias per depth slice and $FxFxD_1xk$ weights and k biases overall
- The d-th depth slice output is given by the convolution of d-th filter and the input volume.

Convolutional Neural Networks (CNNs)

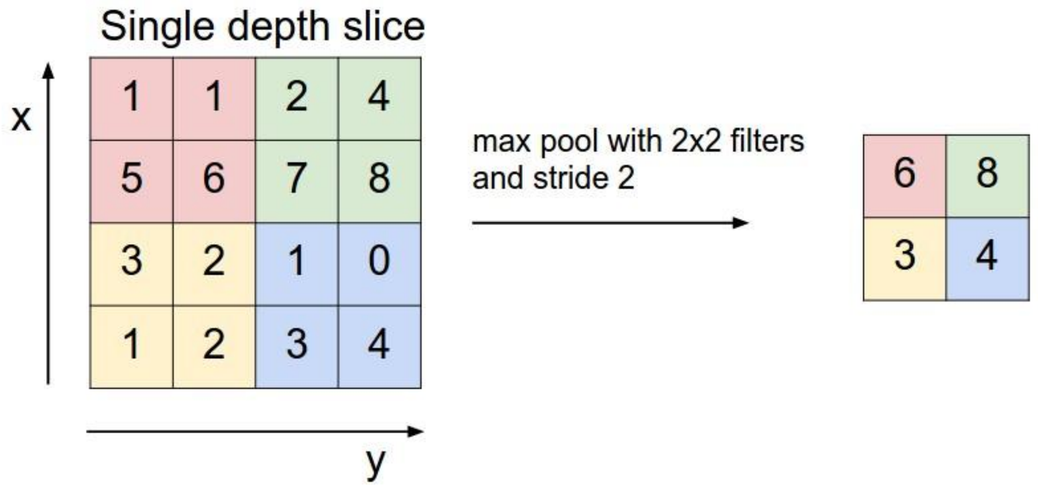
AlexNet:



Convolutional Neural Networks (CNNs)

Pooling Layer:

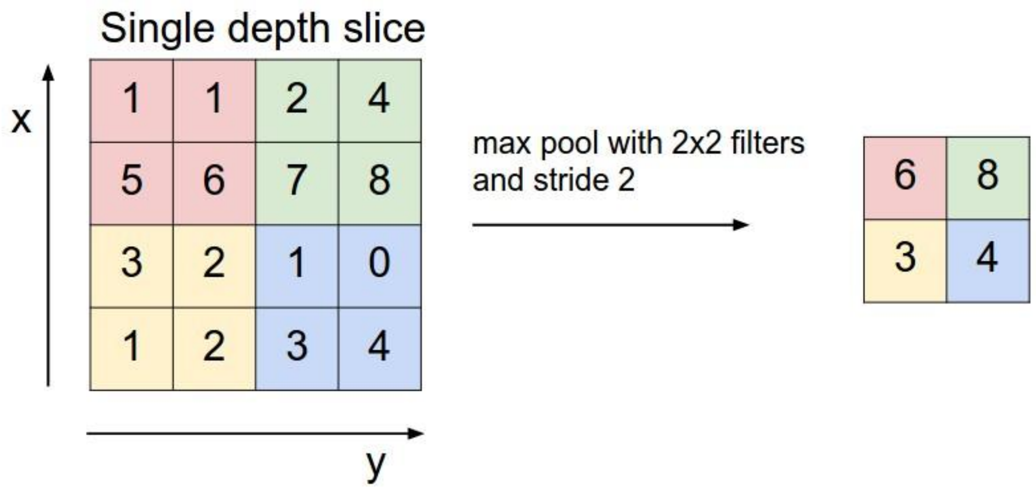
- We usually use pooling layer between the convolutional layers in CNNs.
- The role of pooling layer is to progressively reduce the spatial size of the volume to reduce
  - the number of parameters
  - computation time
- **Idea:** The pooling layer operates independently on every depth slice of the input and resizes it spatially using the 'Max' operation.
- Example:

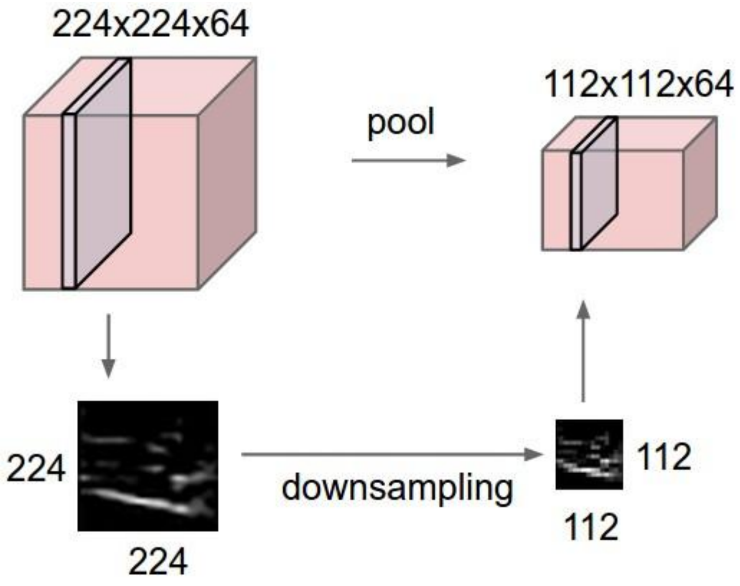


Convolutional Neural Networks (CNNs)

Pooling Layer:

- Pooling layer is defined by two hyper-parameters
    - Spatial extent – F
    - Stride – S
- In the example, F=2 and S=2
- Input: a volume of size $W_1 X H_1 X D_1$
- Output: a volume of size $W_2 X H_2 X D_2$
    - $W_2 = 1 + (W_1 - F)/S$
    - $H_2 = 1 + (H_1 - F)/S$
    - $D_2 = D_1$ (same depth)
- Pooling layer does not have any parameters.





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Convolutional Neural Networks (CNNs)

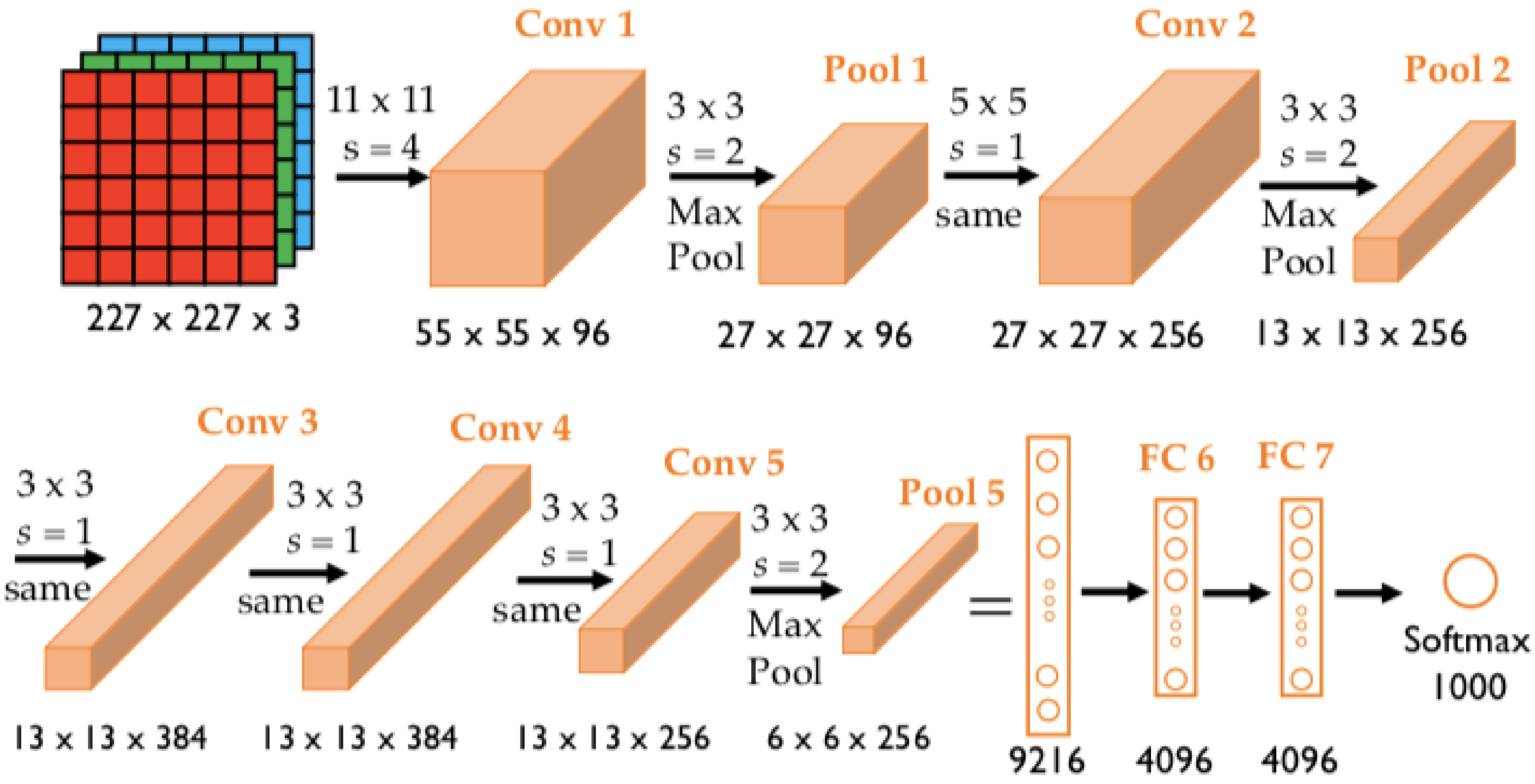
Pooling Layer:

- Instead of Max-Pooling, other pooling techniques are also adopted such as
  - average pooling
  - L_2 norm pooling

- These days, research has suggested to use bigger strides at the convolutional layer level instead of frequent pooling layers.

Convolutional Neural Networks (CNNs)

AlexNet:



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