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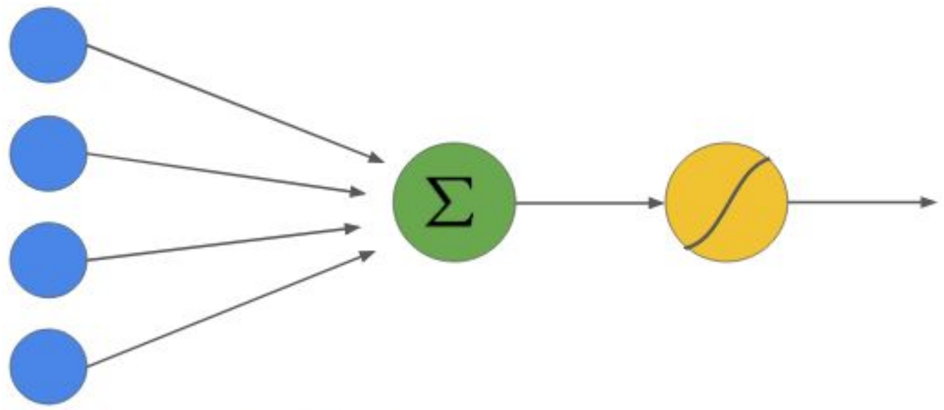
Intro to Deep Learning and Computer Vision

MIT GSL-PRO, Uruguay 2020

Week 3, Day 1

How Does Deep Learning Relate to Previous Models We've Covered?

- Let's revisit our **logistic regression** model:



- We can think of this as a **single unit neural network** with a **sigmoid activation**!

Neural Networks As Cascaded Groupings of Units

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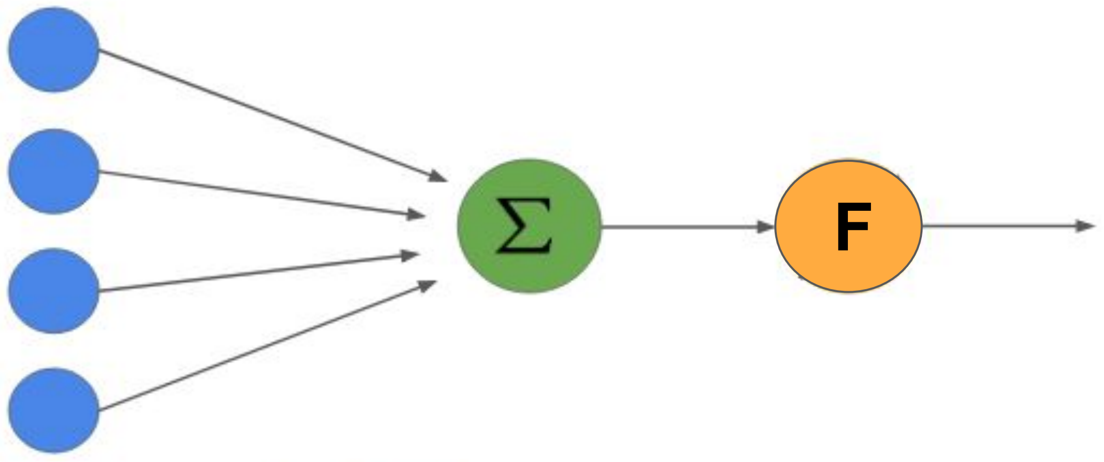
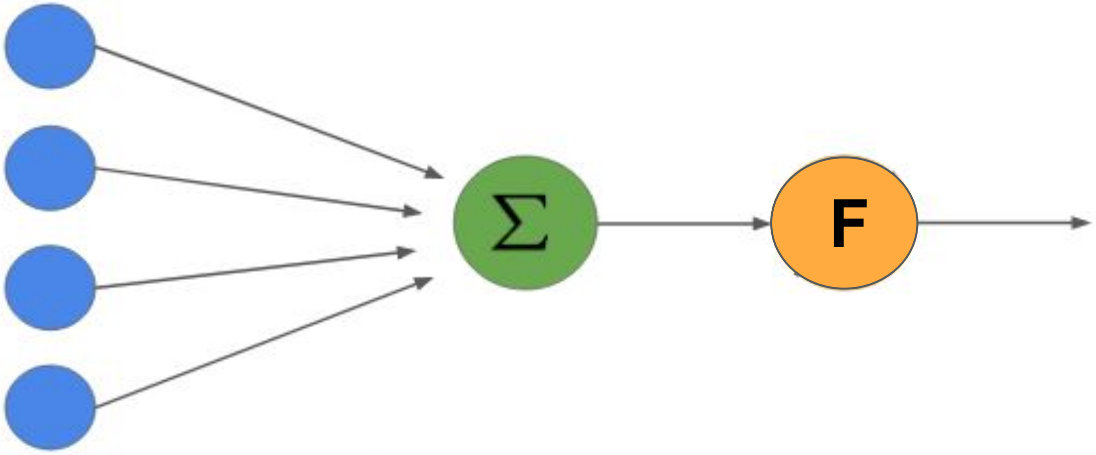
- When **F** is a **sigmoid**, this becomes logistic regression.
- When **F** is **linear**, this becomes linear regression.
- When the **F** is **cross-entropy**, this becomes binary/multiclass classification.



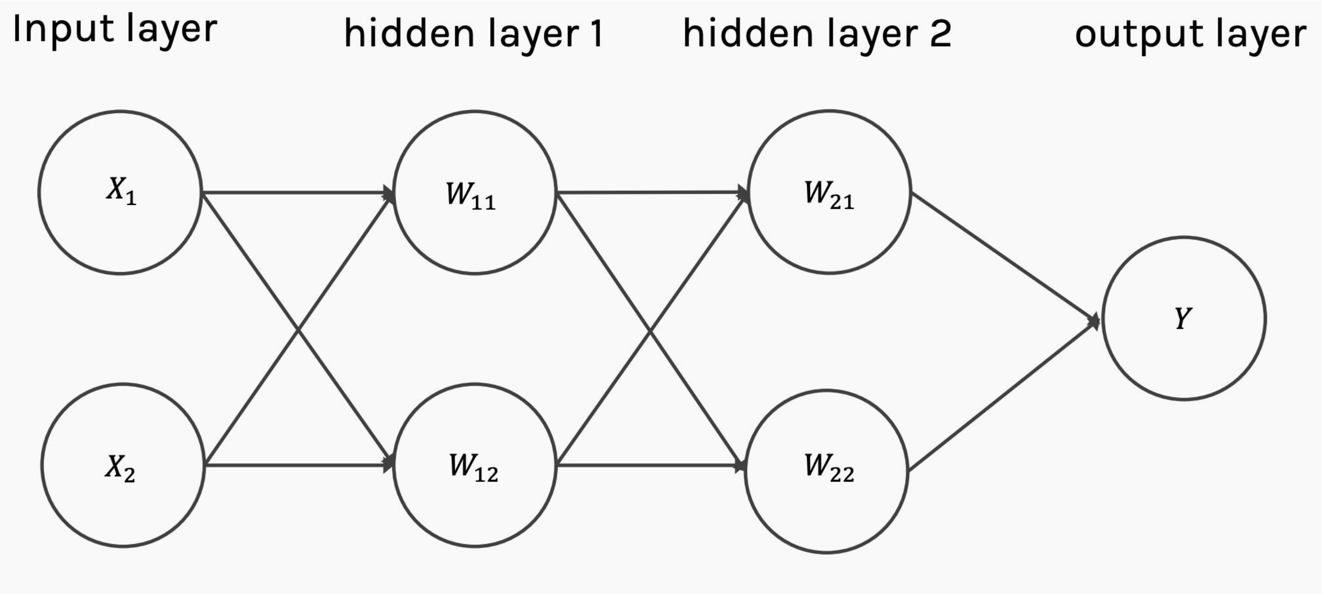
Neural Networks As Cascaded Groupings of Units

- This intuition will be helpful as we discuss how networks **make predictions**, and how they are **trained.**



Review from Last Week – Neural Networks

- Last week, we discussed **neural networks**, and how they can be used for **supervised learning**.
- In addition to **NLP** and **e-commerce**, neural networks can also be used to solve problems in **computer vision** and **healthcare**.

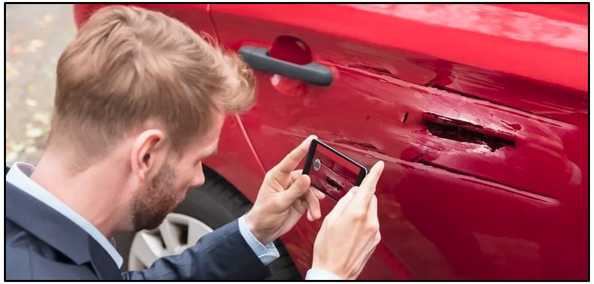


Applications of Neural Networks

Autonomous Vehicles

Google

Insurance Claims



Chatbots

Different Classes of Neural Networks

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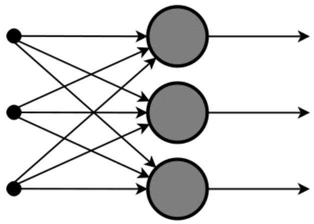
Many different kinds of neural networks:

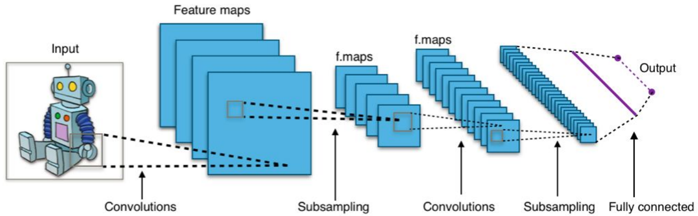
- **Feedforward**
- **Convolutional (CNNs)**
- Recurrent (RNNs)
- Graph
- Variational Autoencoders* (VAEs)
- Generative Adversarial Networks (GANs)

This course only analyzes the first two kinds of networks.

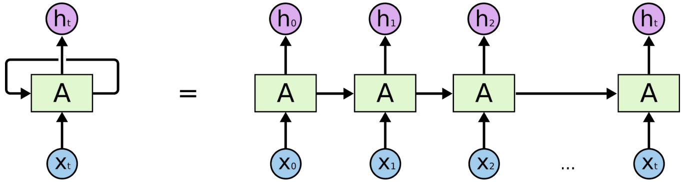
[1] **Feedforward** network class



[2] **Convolutional** network class



[3] **Recurrent** network class

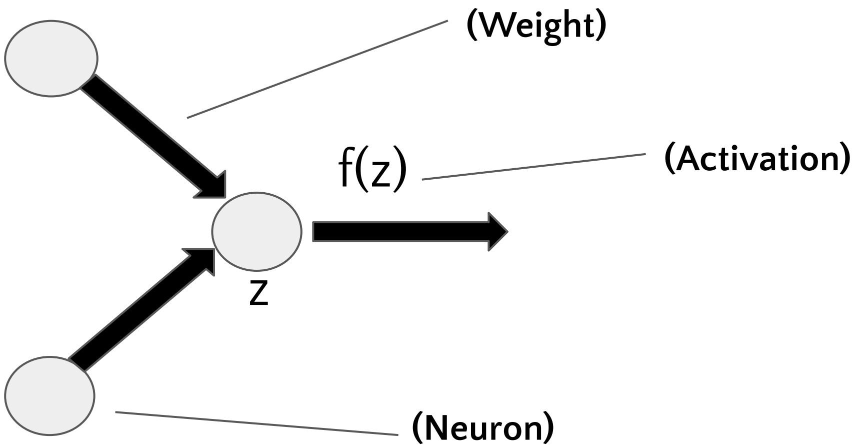


* VAEs are actually unsupervised! They are part of a class of algorithms known as **deep generative models.**

Anatomy of a Feedforward Neural Network

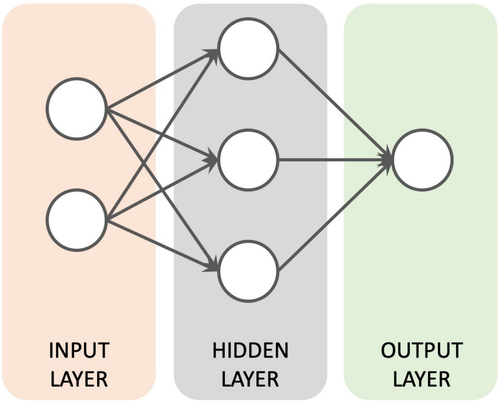
Feedforward neural networks have 3 basic elements:

- **Neurons**
- **Weights**
- **Activations**



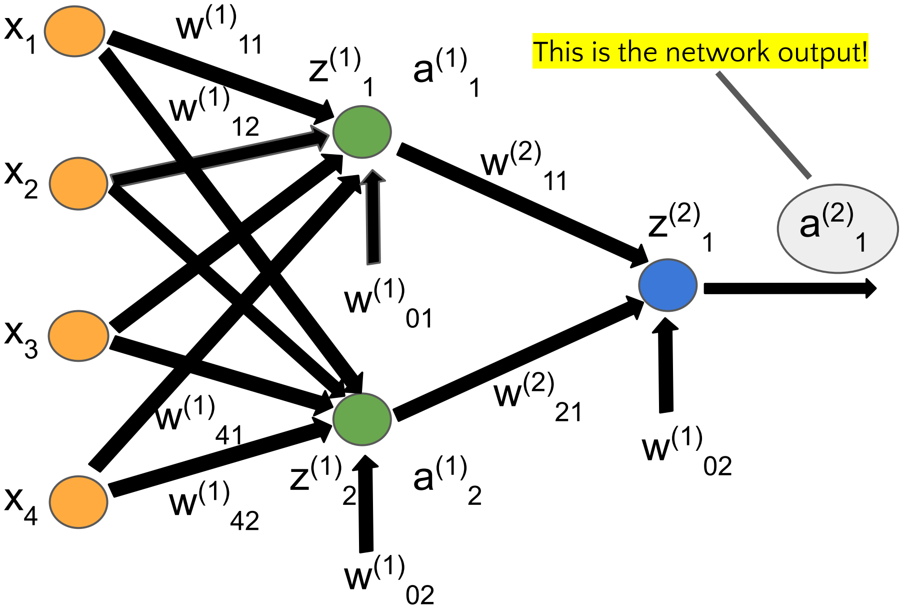
Feedforward networks are composed of **cascaded layers** of neurons, weights, and activations

- **Input** layer
- **Hidden** layer(s)
- **Output** layer



How Neural Networks Make Predictions

- Input is propagated through the network with the **forward** algorithm
- At each layer:
  - Neuron **activations** from previous layer are multiplied by layer **weights**, and **summed** together.
  - Activation function is applied to the **sum**.



[1] Weighted sum of activations:

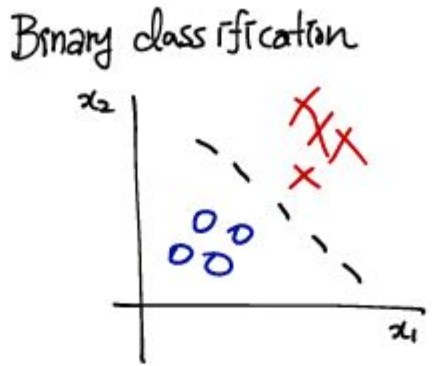
$$z^{(L)}_i = \sum x_j w^{(L-1)}_{ji} + w^{(L-1)}_{0i}$$

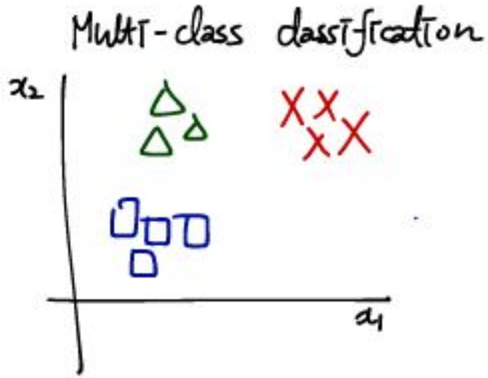
[2] Activation of sum:

$$a^{(L)}_i = f(z^{(L)}_i)$$

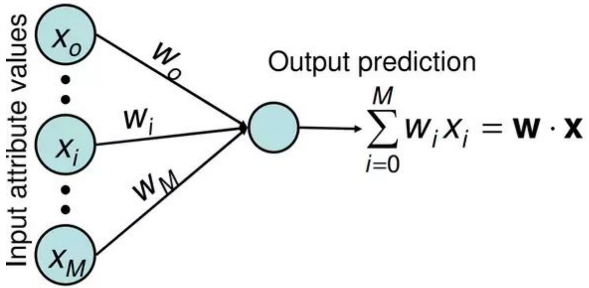
Intuition for Neural Network Predictions

- Trained neural networks learn “when activations should be **high** or **low**”
- Output layers typically reflect what the network is used for:
  - Any real number output → **Regression**
  - {1, 0} output → **Binary Classification**
  - {1, 2, 3, ..., 10} output → **Multiclass Classification**





Linear Regression with Neural Networks!



Output Activation Functions and their Applications

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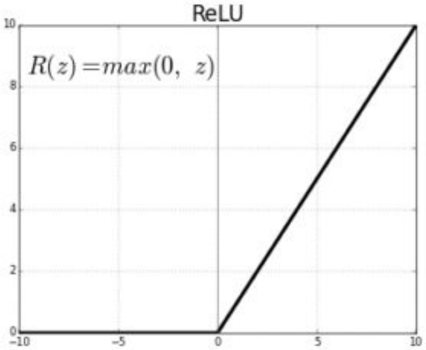
[1] Regression:

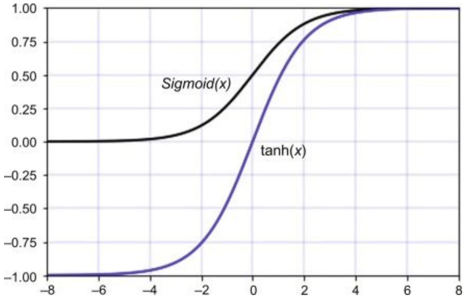
- Linear: **f(x) = x,** varies from **(-∞,∞)**
- Rectified Linear Unit (ReLU): **ReLU(x),** varies from **(0,∞)**



[1]

[2] Logistic Regression/Binary Classification:

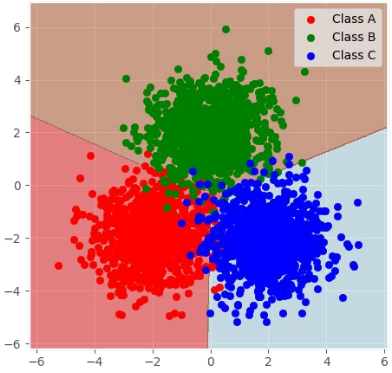
- Sigmoid: **σ(x),** varies from **(0,1)**
- Hyperbolic Tangent: **tanh(x),** varies from **(-1,1)**



[2]

[3] Multiclass Classification

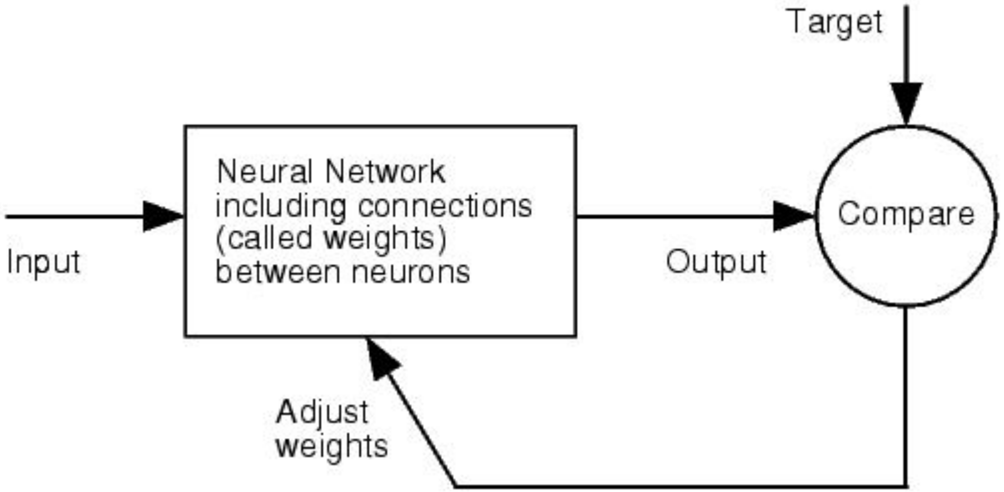
- SoftMax: **SM(x_i),** varies from **(0,1)**



[3]

Training Neural Networks – Overview

- For neural networks to be useful, we need to **train** them
- Neural networks can be trained by **optimizing** their **weights**.
    - This is how neural networks "**learn**"!
    - Different **weights** lead to different **predictions**
- These weights are "learned" through the **backpropagation** algorithm.

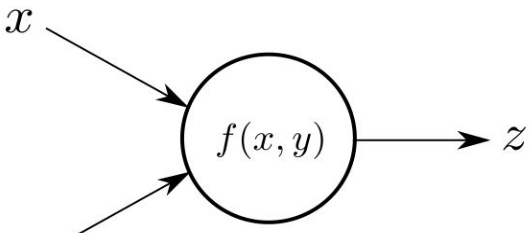


The Backpropagation Algorithm

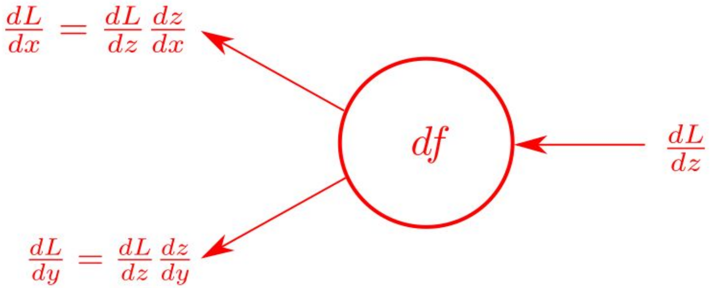
Algorithm composed of two stages:

1. **Forward pass:** Network makes prediction with labeled training data.
2. **Backward pass:** Network weights are updated according to how "wrong" the prediction is.

[1] Forwardpass



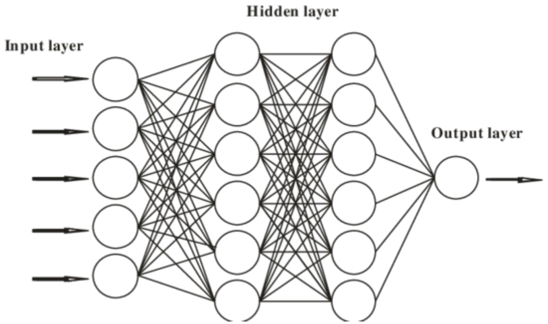
[2] Backwardpass

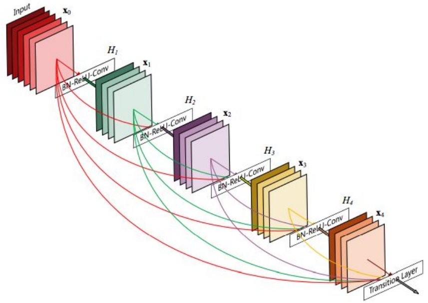


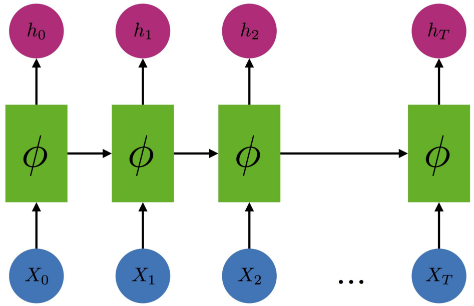
Overview – Deep Learning

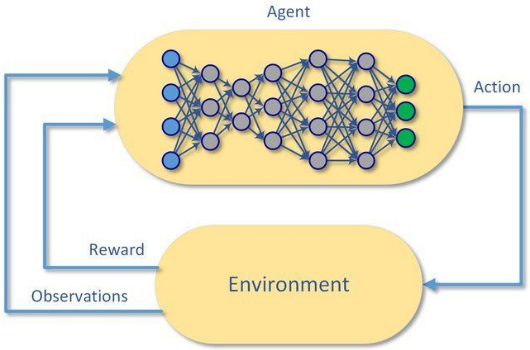
Field of **Deep Learning** uses **Deep Neural Networks (DNNs),** which can learn remarkably complicated tasks, given sufficient data and training. Some examples include:

- Object **detection** and **classification**
- Speech and image **generation**
- High-dimensional **predictions**
- **Recommendation** systems
- **Decision-making** for agents







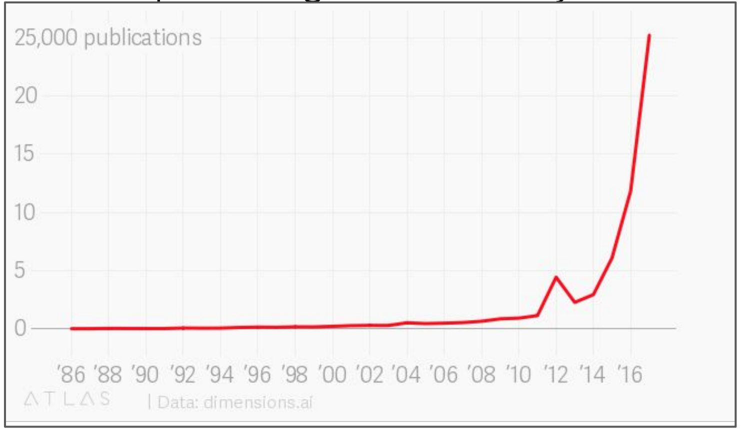


Deep Learning Is A Very New Field

Field has seen a lot of advances in recent years from development of better **CPUs** and graphical/tensor processing units (**GPUs/TPUs**).

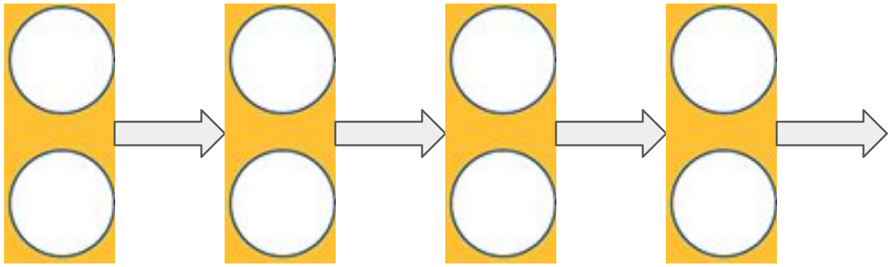
Advances are quite literally happening every day!

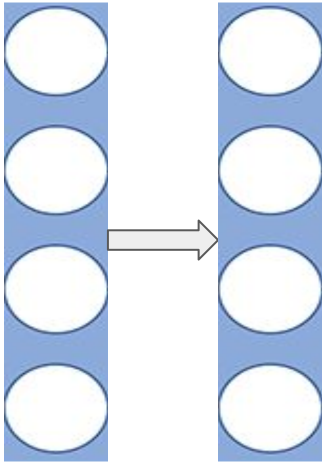
Deep Learning Publications by Year



Deeper, Not Wider, Neural Networks*

more layers with **less weights** > **less layers** with **more weights**

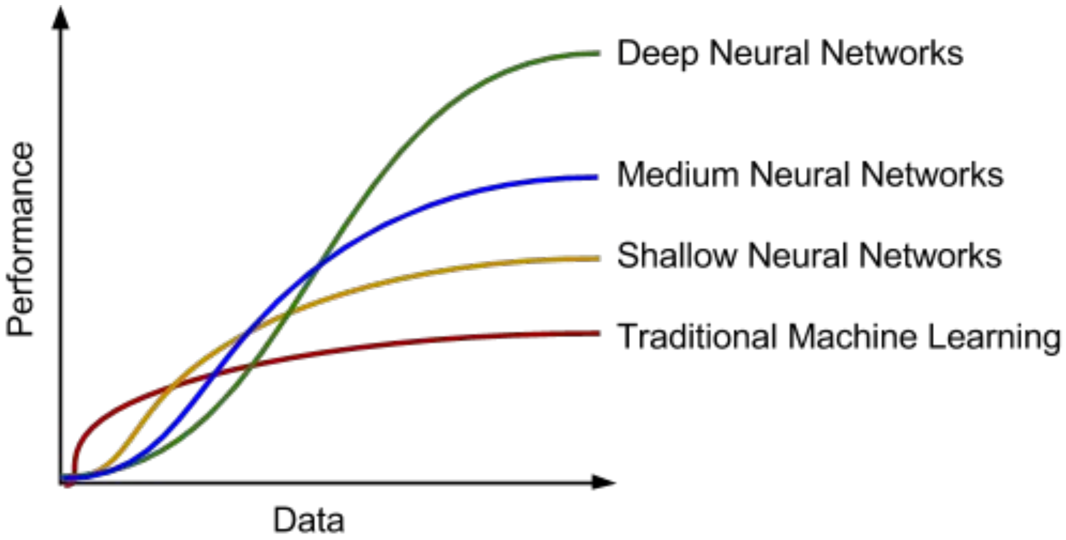




*For More Information on this: Stack Overflow Post.

Why Deep Learning?

- Why should we even consider deep learning when we already have machine learning models that can solve our problems?
- Deep learning can often achieve **higher performance** than other models
- Caveat: **Need more data** in order to achieve **higher performance**



Models we've studied so far

Deep Learning Packages in Python

These packages allow us to implement, train, and evaluate million-parameter neural networks in **less than 15 lines of code!**

Main deep learning package we will use in this class: **Keras.**

Other packages to explore:

- TensorFlow
- PyTorch
- Caffe
- Chainer
- FastAI

Week 3, Day 2
Intro to Computer Vision

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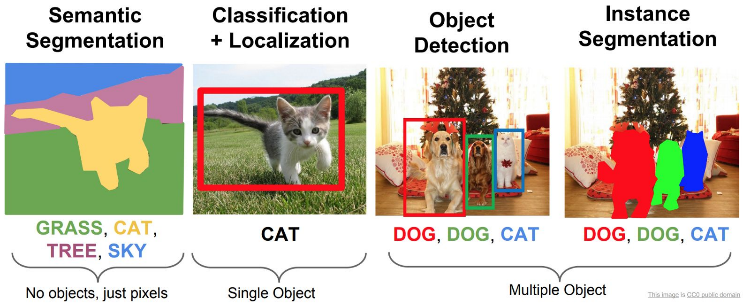
Overview – Computer Vision

- **Computer Vision** is a subset of artificial intelligence primarily concerned with understanding **spatial and imagery** data. Typical applications include:
    - Image blurring, sharpening, and edge detection
    - Capturing motion
    - Image classification/object detection and classification/scene segmentation
    - Image and video generation
- This field developed independently of deep neural networks, but has improved substantially over the last decade through integration of these deep network frameworks.



Computer Vision as Filtering

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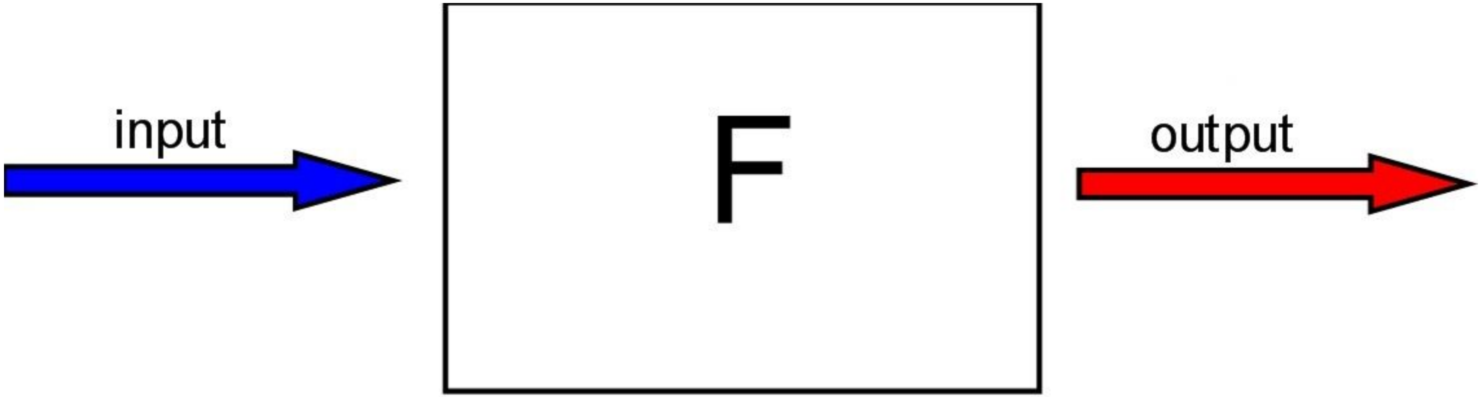
- **Filtering** is the most central idea in **computer vision.**

- Intuitive idea behind filtering: A **system F transforms** an **input** into an **output.**



Filtering – Convolutions

- Filtering is done through **convolution** and **kernels**
- **Convolution** is a mathematical operation that computes a **sum of linear combinations of the input**

$$x[n] * h[n] = \sum_{\mathbf{K}=-\infty}^{\infty} x[n-\mathbf{K}] \cdot h[\mathbf{K}]$$

Input

Filter/Kernel

- **Kernels** are matrices* which we **convolve** our **input** with to **filter!**

* For discrete problems, kernels can be matrices. For continuous problems, they take the more general form of an inner product of a function applied to the two inputs. Link HERE.

Convolution* – Building Intuition

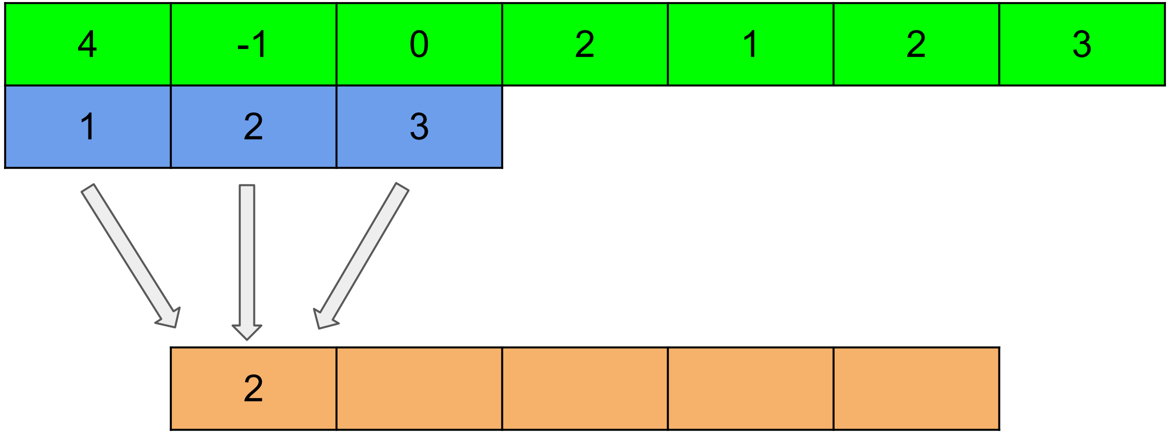
- Think of convolution as **sliding a filter** across the **input**, and computing the product between the **filter/kernel** and **input** for each input value
- This concept is illustrated on the next slides

4	-1	0	2	1	2	3	x[n] (Input)

1	2	3	h[n] (Filter)

* Technically, this is **correlation**, not **convolution.** They are both closely related, with just a simple change of sign. If interested, see the link HERE.

Convolution – 1D Example

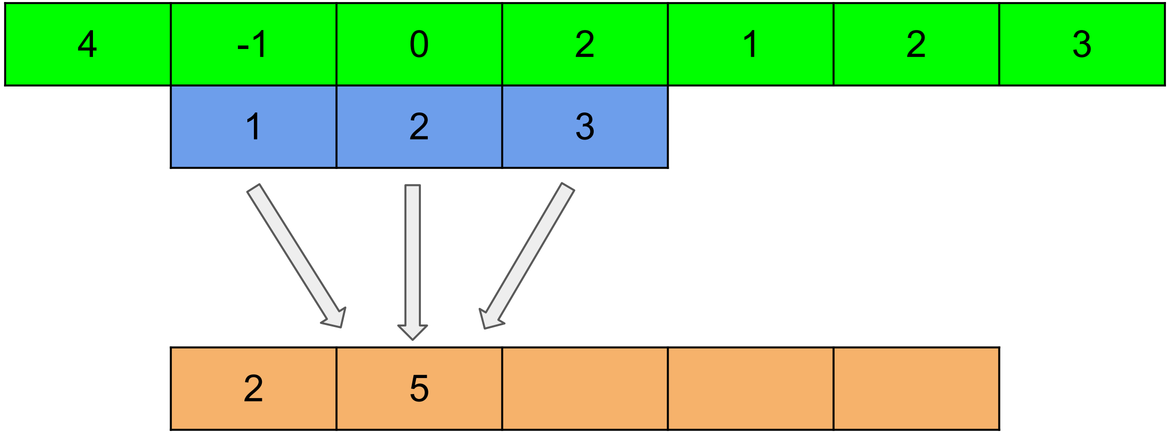


x[n] (Input)

h[n] (Filter)

$y[n] = x[n] * h[-n]$

Convolution – 1D Example



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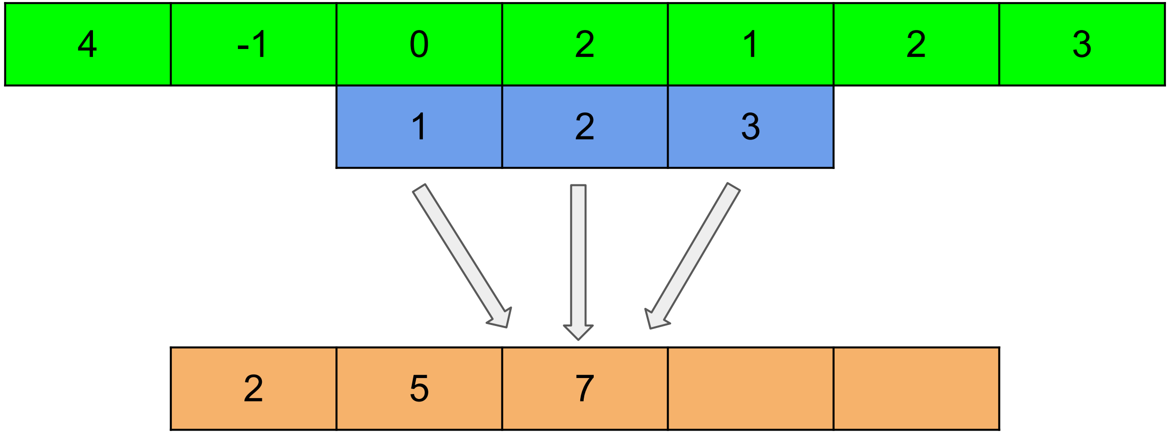

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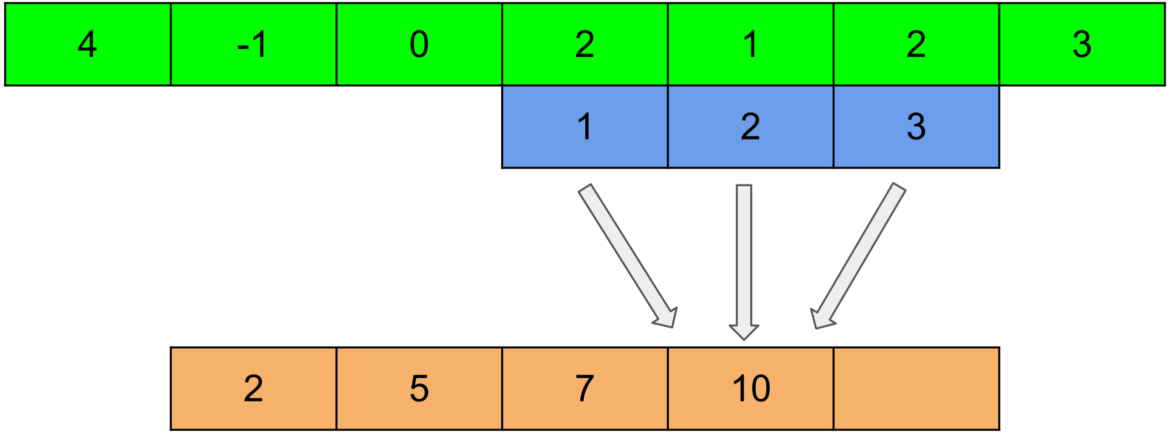

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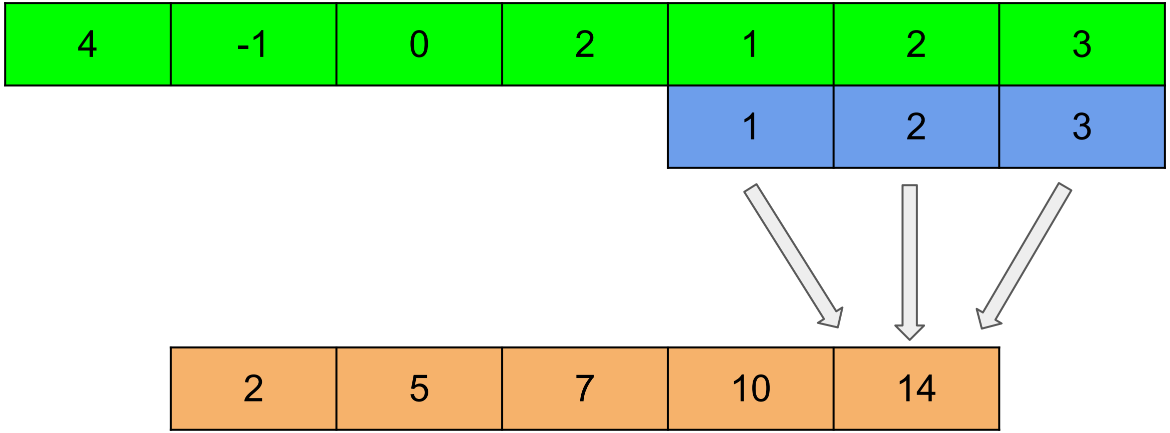


x[n] (Input)

h[n] (Filter)

$y[n] = x[n] * h[-n]$

Filtering – "Padding" Techniques

- What do we do if we want the output to be the same size as input?
  - We can use **padding**!
- Different Types of Padding:
  - **Valid padding** – Do nothing (does not fix size problem)

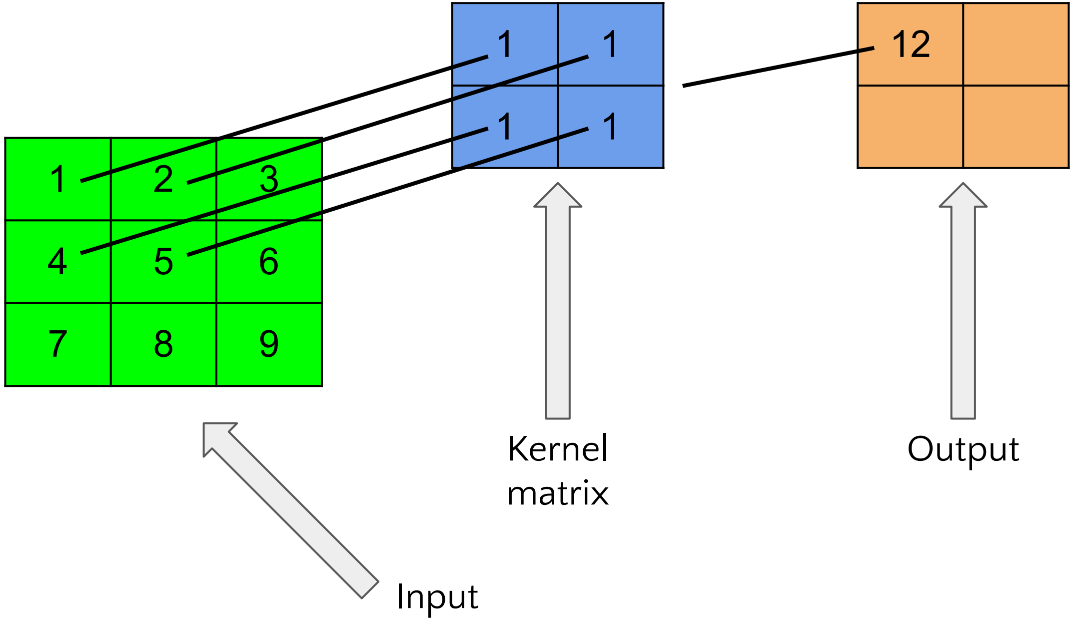
4	-1	0	2	1	2	3

  - **Zero padding** – Add **0**'s to the edges of the input

0	4	-1	0	2	1	2	3	0

Convolution – 2D Example

- In 2D, we use **matrices** for our **kernels**



Convolution – 2D Example

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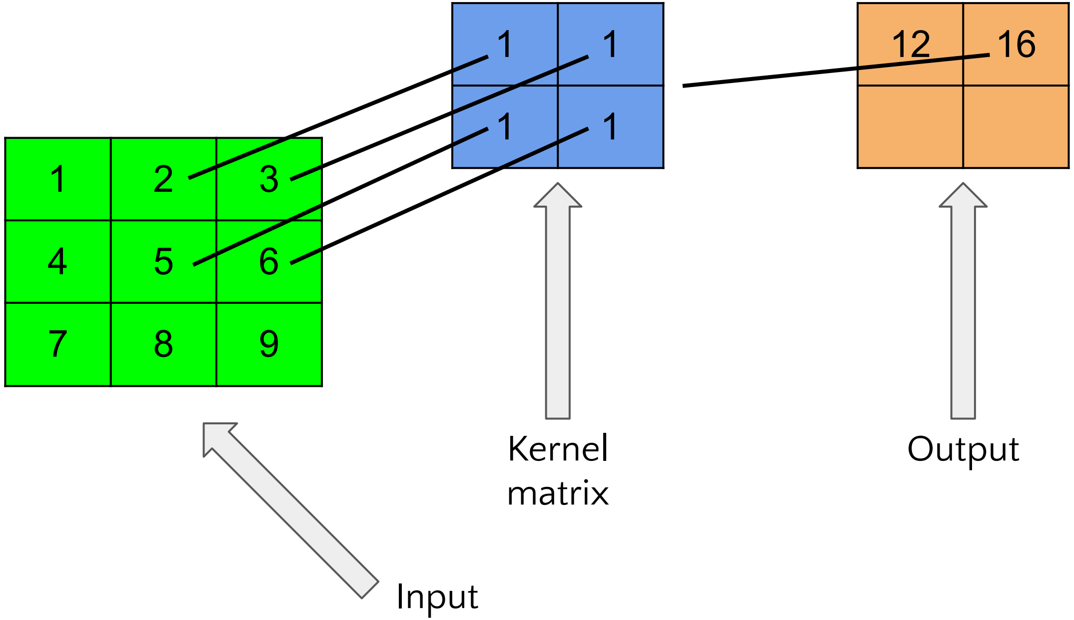

Convolution – 2D Example

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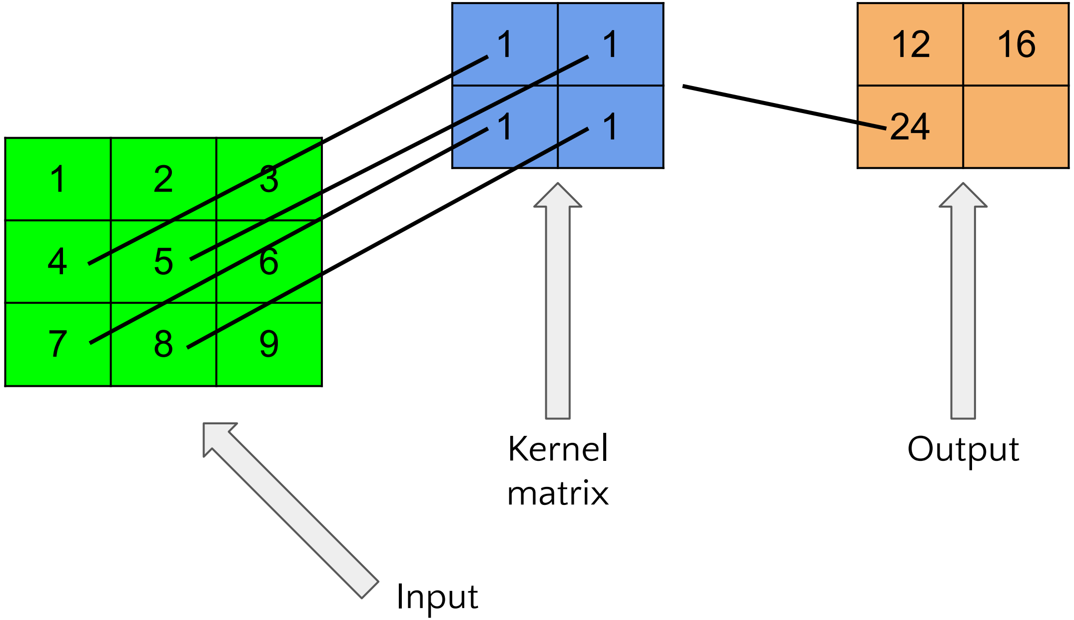

Convolution – 2D Example

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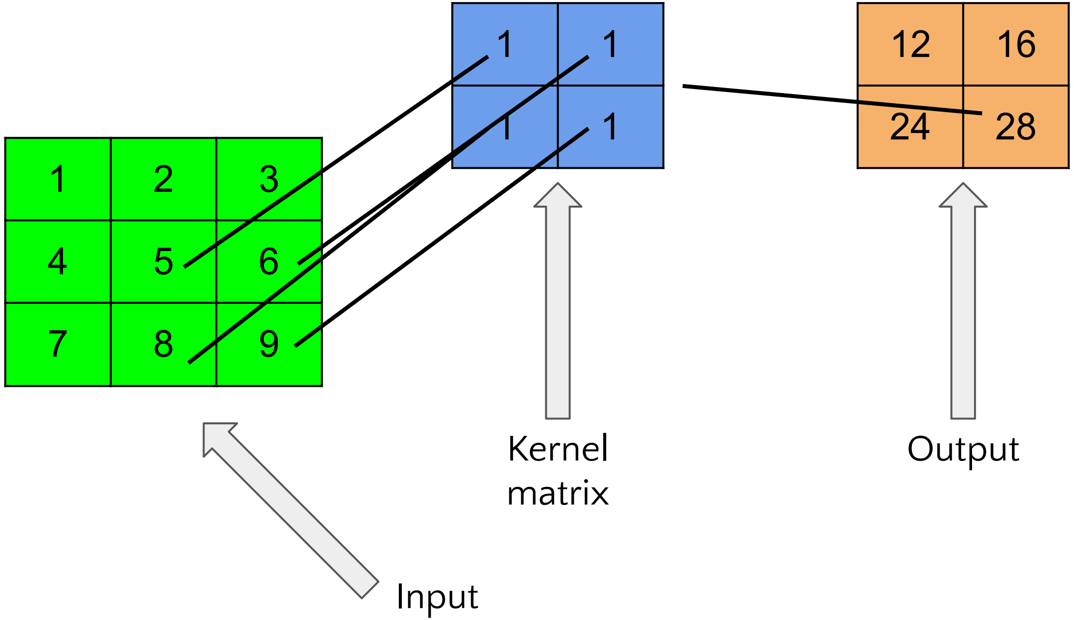
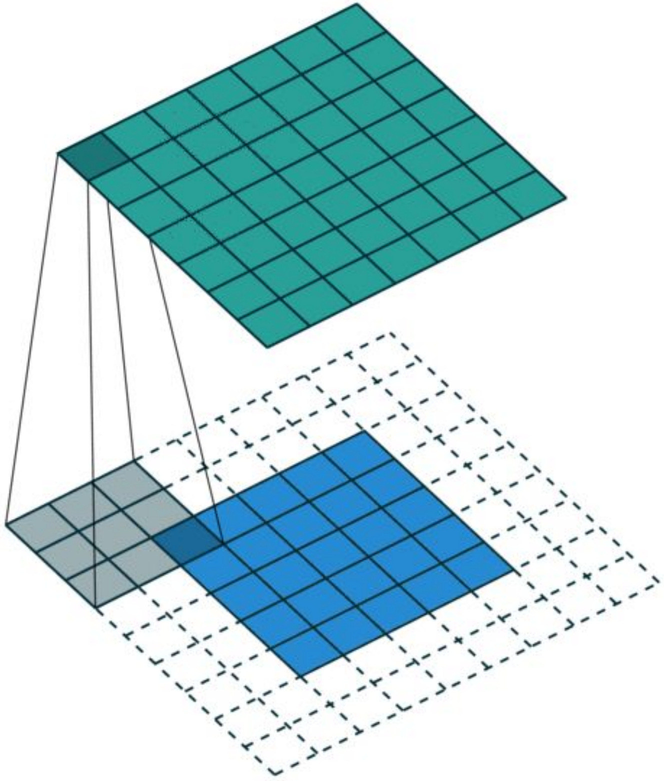


2D Convolution with Padding

- In 2D, we use **matrices** for our **kernels**

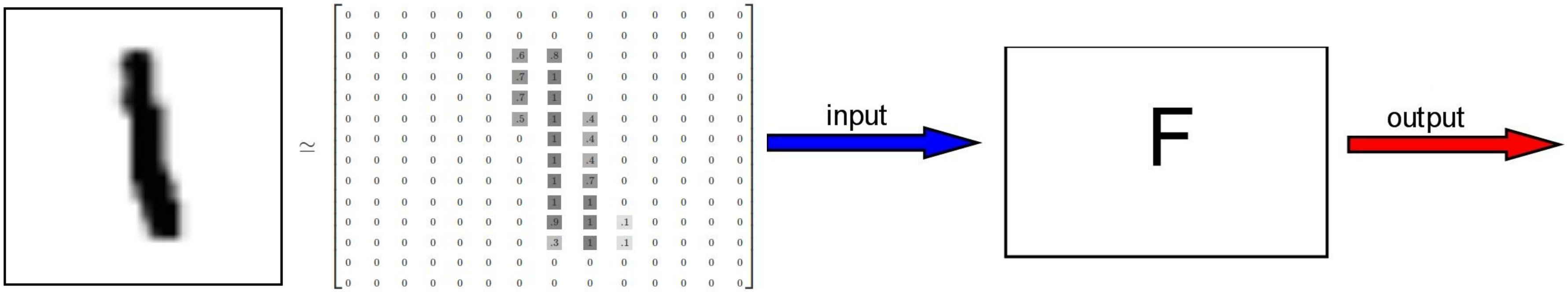
- **Padding with zeros** ensures the output is the same size as the input

- Notice how we do the same sum of products between elements of the kernel and input as we saw before!



Filtering for Images

- Filtering primarily used in the image domain
- Can use filters for a variety of tasks, such as:
    - **Blurring**
    - **Sharpening**
    - **Edge detection**
    - **Corner Detection**



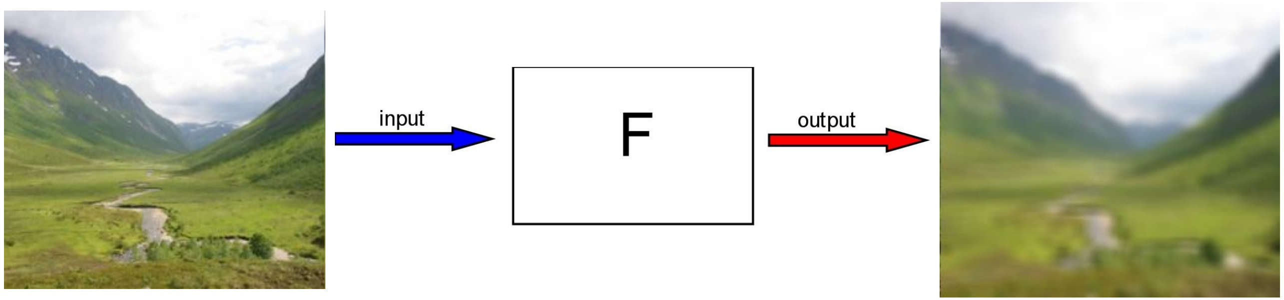
Filtering – Types of Kernels

- Blurring

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

- Gaussian Blurring

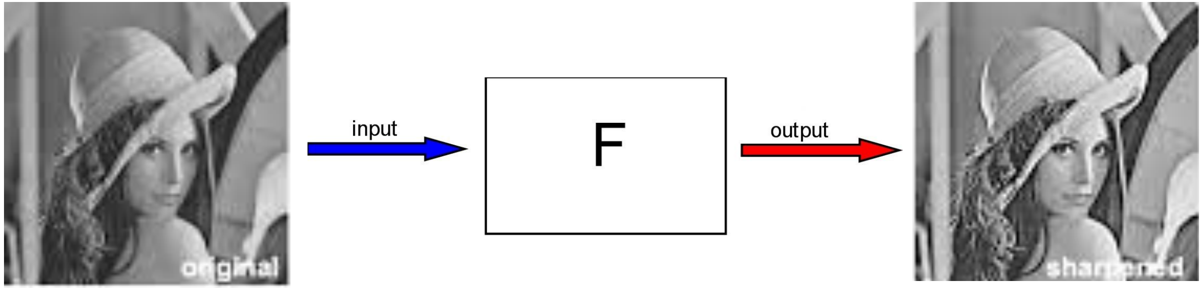
$$\frac{1}{209}\begin{bmatrix} 16 & 26 & 16 \\ 26 & 41 & 26 \\ 16 & 26 & 16 \end{bmatrix}$$



Filtering – Types of Kernels

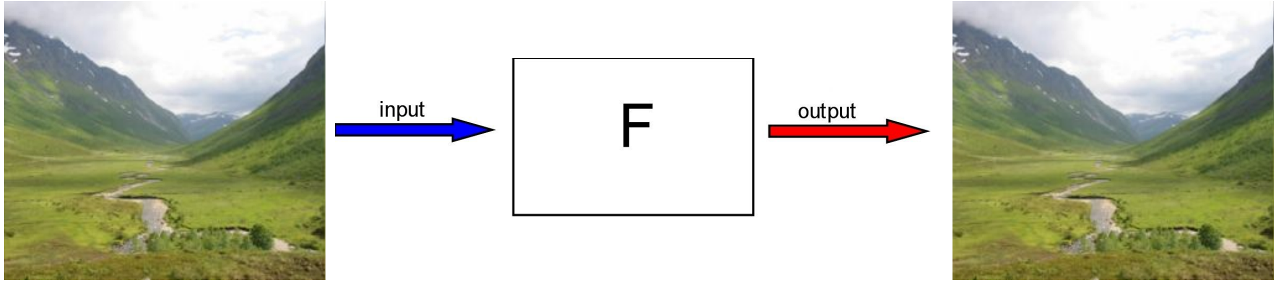
- Sharpening

-1	0	1
-2	0	2
-1	0	1



- Identity

0	0	0
0	1	0
0	0	0



Computer Vision with Deep Learning – CNNs

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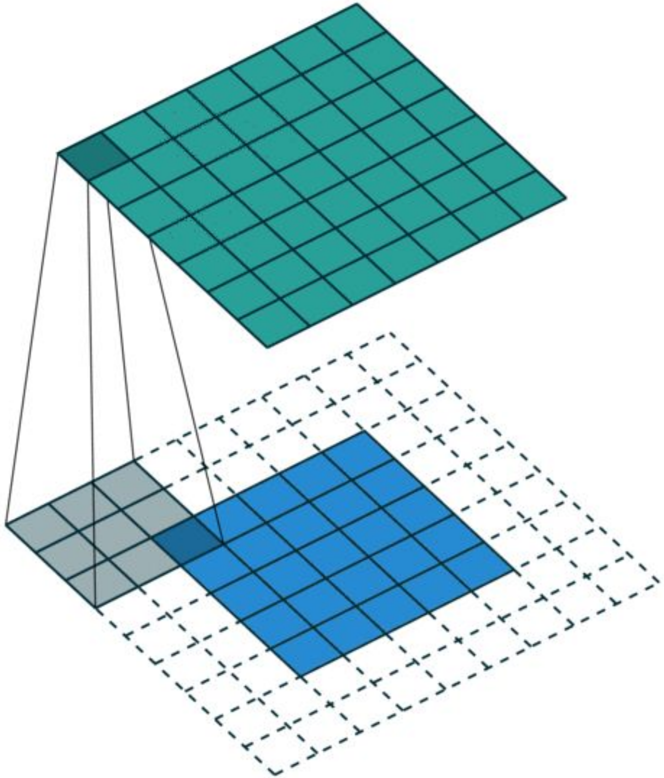
- Computer Vision connected to Deep Learning primarily through **Convolutional Neural Networks (CNNs)**.
- These networks use **convolutional layers**
    - Finds **local features** in an image
    - But can find features **anywhere** in an image (**translation invariance**)
- Convolutional layers use the same **convolution*** operation that we saw for filtering!



* Technically, this is **correlation**, not **convolution.** They are both closely related, with just a simple change of sign. If interested, see the link HERE.

Anatomy of a Convolutional Neural Network (CNN)

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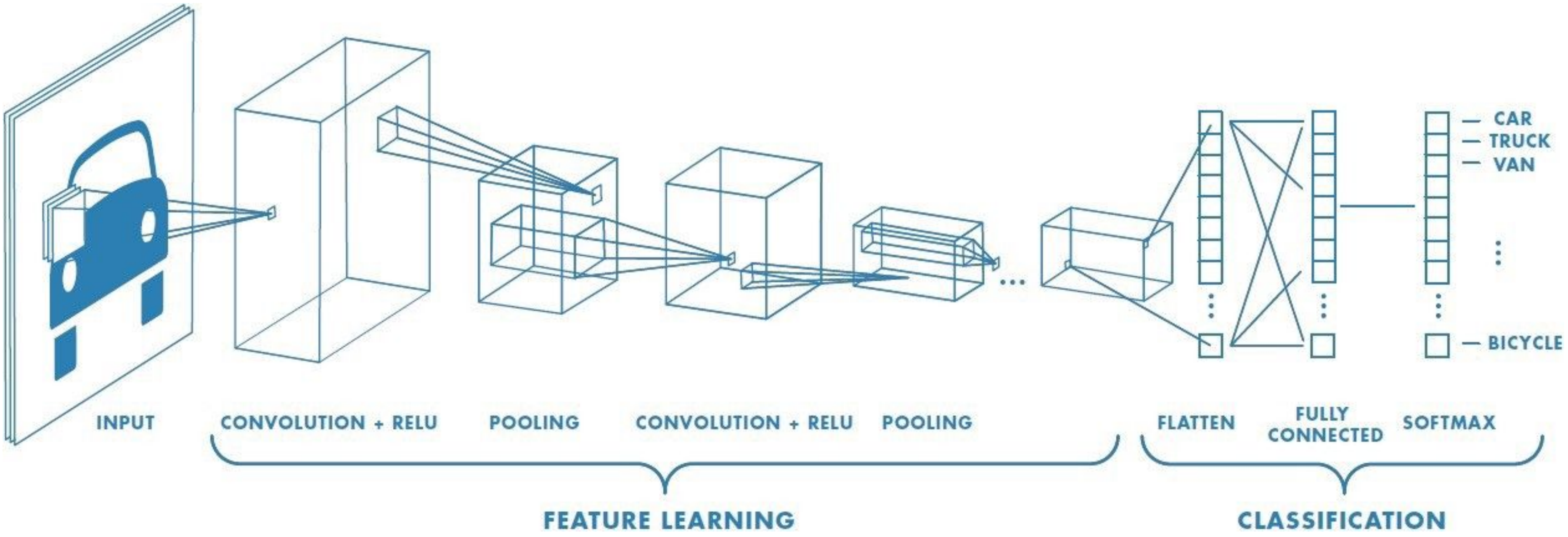
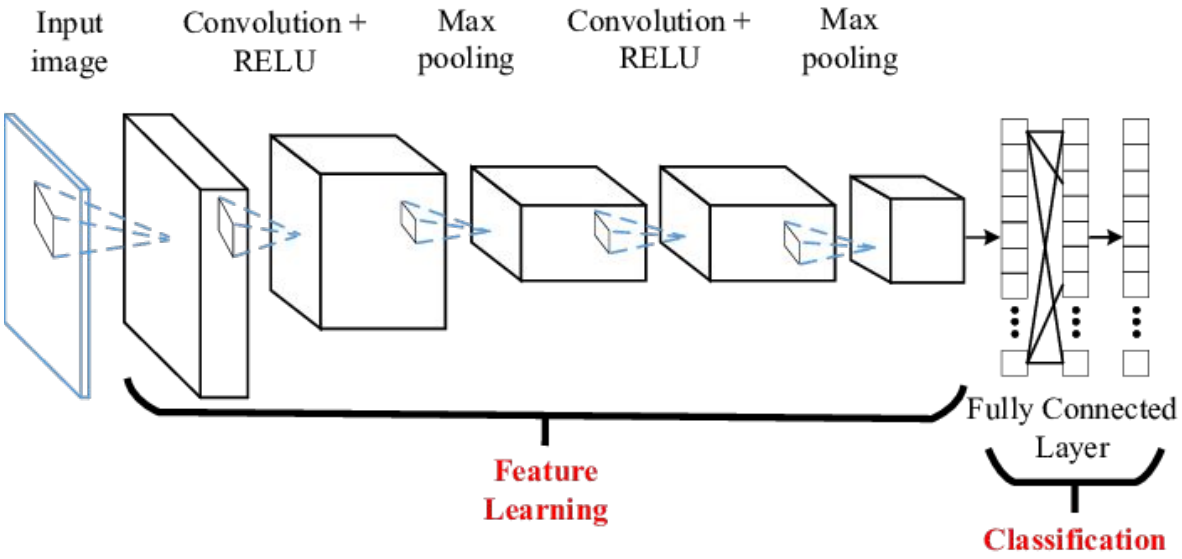


Core Elements of CNNs

- Input "layer"
- Convolutional layers
- Max pooling layers
- Flattening layer*
- Fully Connected layers*
- Output layers



*Some neural networks, such as Fully Convolutional Neural Networks, don't use these elements.

Introducing Non-Linearities in CNNs: Max Pooling

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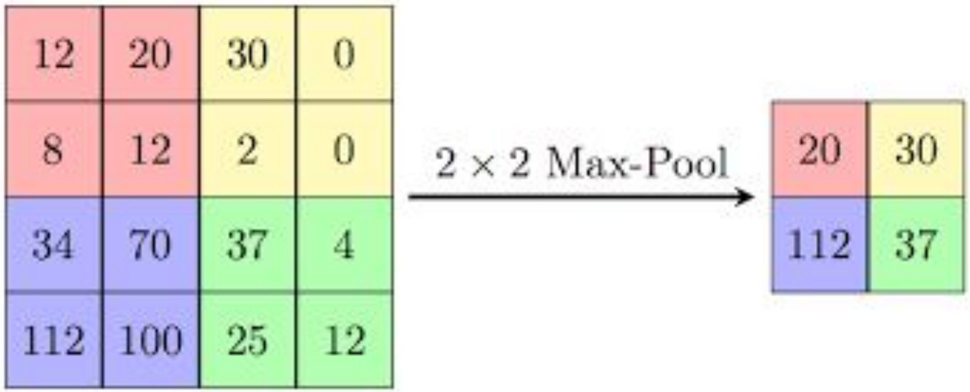
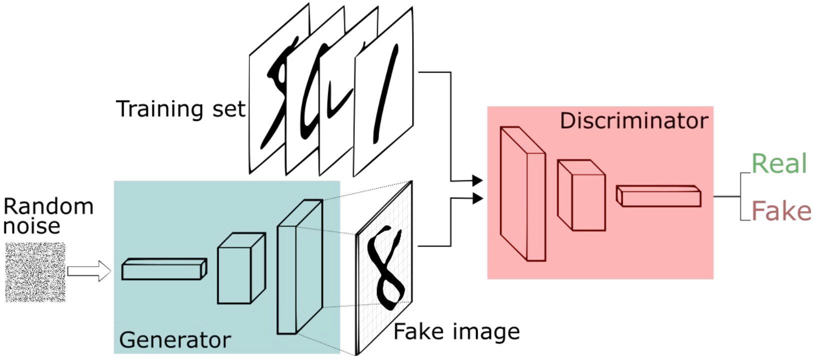
- Recall with feedforward networks that we primarily used **ReLU** as a means to introduce non-linearities into our neural networks.
- In CNNs, we will introduce non-linearity as well – through **max pooling** functions.



Tasks in CV + DL

- Recent advances in automated tasks have been achieved through recent advances in CV and DL:
  - Object detection
  - Semantic segmentation
  - Image classification
  - Image and video generation



Applications: Using CNNs for Vision in Healthcare

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[1] Pneumonia Prediction:

This week, we'll be using Convolutional Neural Networks to predict whether a patient has pneumonia using chest x-ray imagery.

[2] Breast Cancer Prediction:

A hybrid Deep Learning and Logistic Regression model yielded substantial improvement in breast cancer diagnosis over only the Logistic Regression model. Paper HERE.

[3] Automated Detection of Diabetic Retinopathy and Diabetic Macular Edema:

Uses CNNs; named by JAMA as one of the best papers of the decade. Paper HERE.

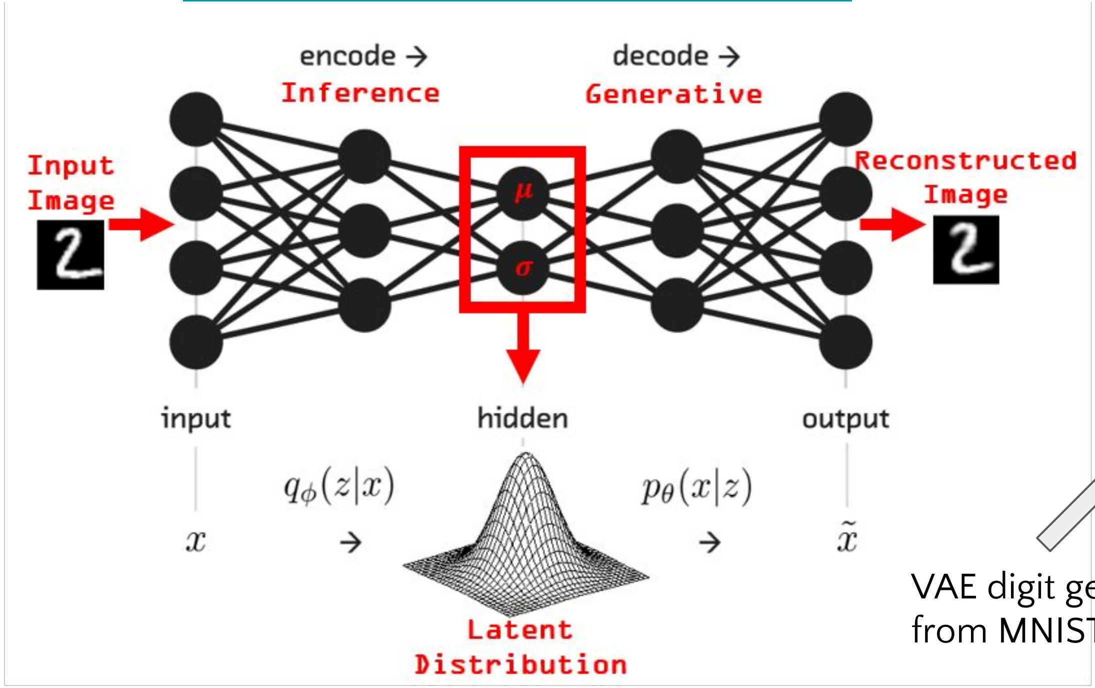
ADDITIONAL SLIDES

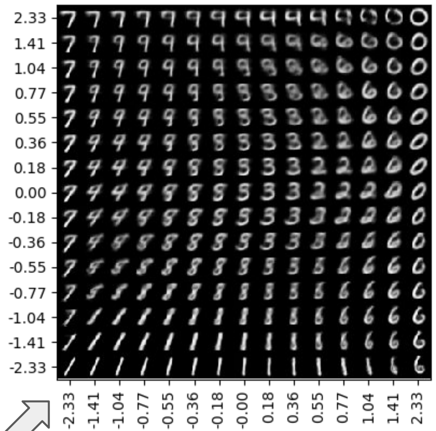
(for students' reference)

Variational Autoencoders (VAEs) – NNs for Unsupervised Learning

- Variants of neural networks that don't require **labeled data:**

[Variational Autoencoders (VAEs)]





VAE digit generation from MNIST data!

Generative Adversarial Neural Networks (GANs)

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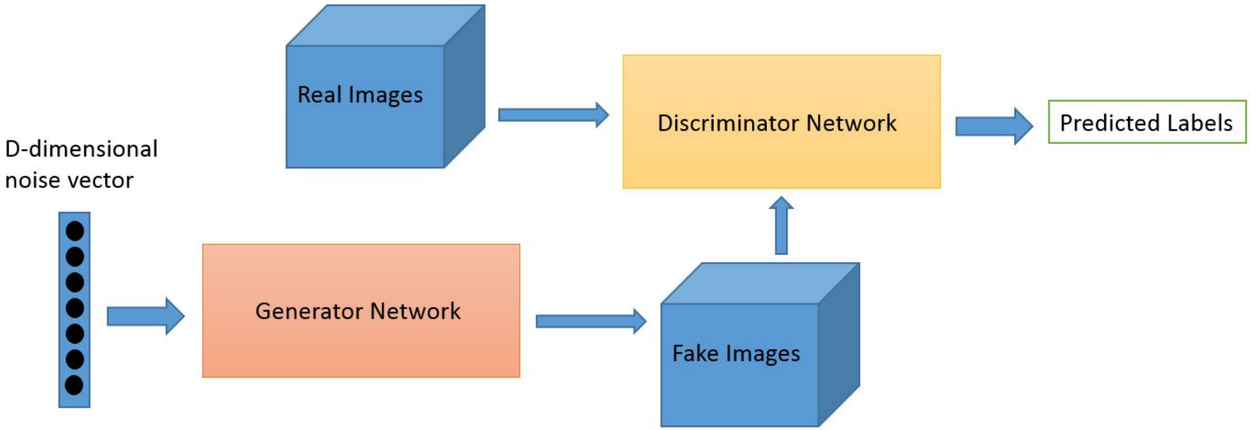
- Composed of **generator** and **discriminator** networks.
- **Generator** is given random noise, and tries to output fake images to fool the discriminator.
- **Discriminator** is trained on real and fake images, and tries to learn how to spot fake images.
- Practical note: Proper training of these networks is quite difficult, and requires careful tuning.



GANs + CV: Deep Convolutional GANs (DCGAN)

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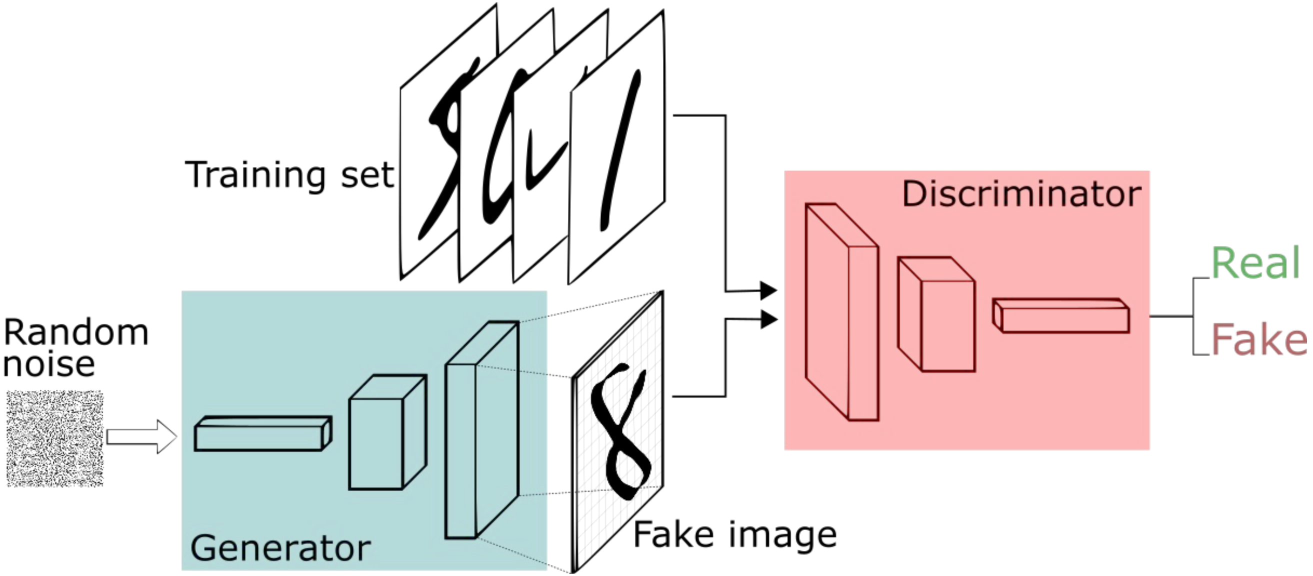
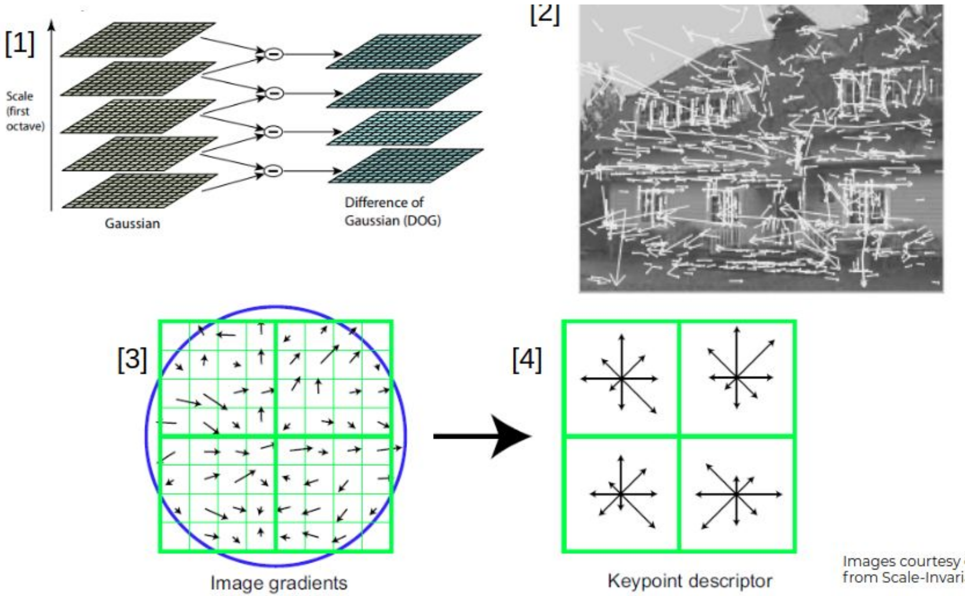
- Useful link for tutorial here: [TensorFlow]

- This architecture can be used for real-world image generation!



Classical CV Object Detection: Scale-Invariant Feature Transform (SIFT)

- CV technique for object detection that doesn't use deep learning
- Original paper can be found HERE, code can be found HERE



SIFT (Scale-Invariant Feature Transform)

[1] Find extremes

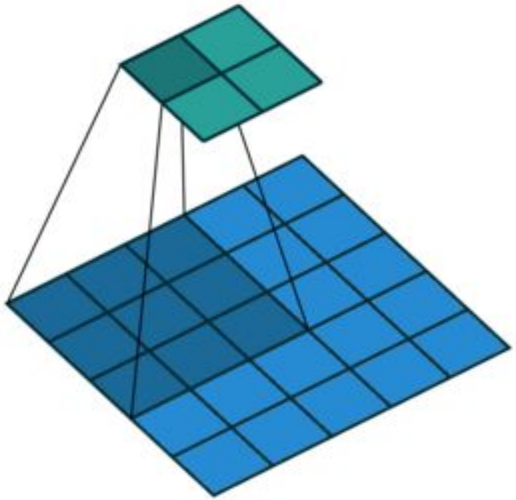
[2] Detect keypoints

[3] Assign orientations

[4] Assign keypoint descriptors

Images courtesy of David G. Lowe, "Distinctive Image Features from Scale-Invariant Keypoints."

Template Matching: When Invariance Is Not Important



GIF courtesy of Towards Data Science

Template Matching

[1] Slide template over image using correlation or least square metric.

[2] Return peak by finding min or max point of metric.

[3] Draw bounding box using min/max point as top left corner.

CNNs in 3D: Volumetric CNNs

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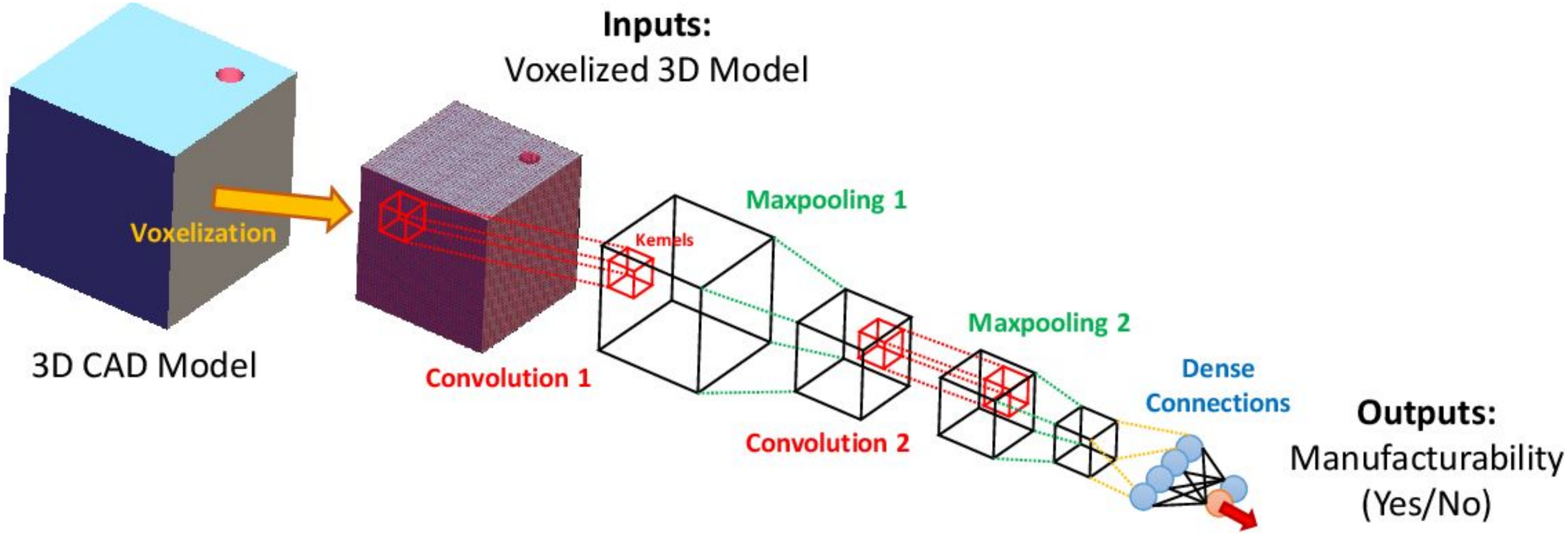
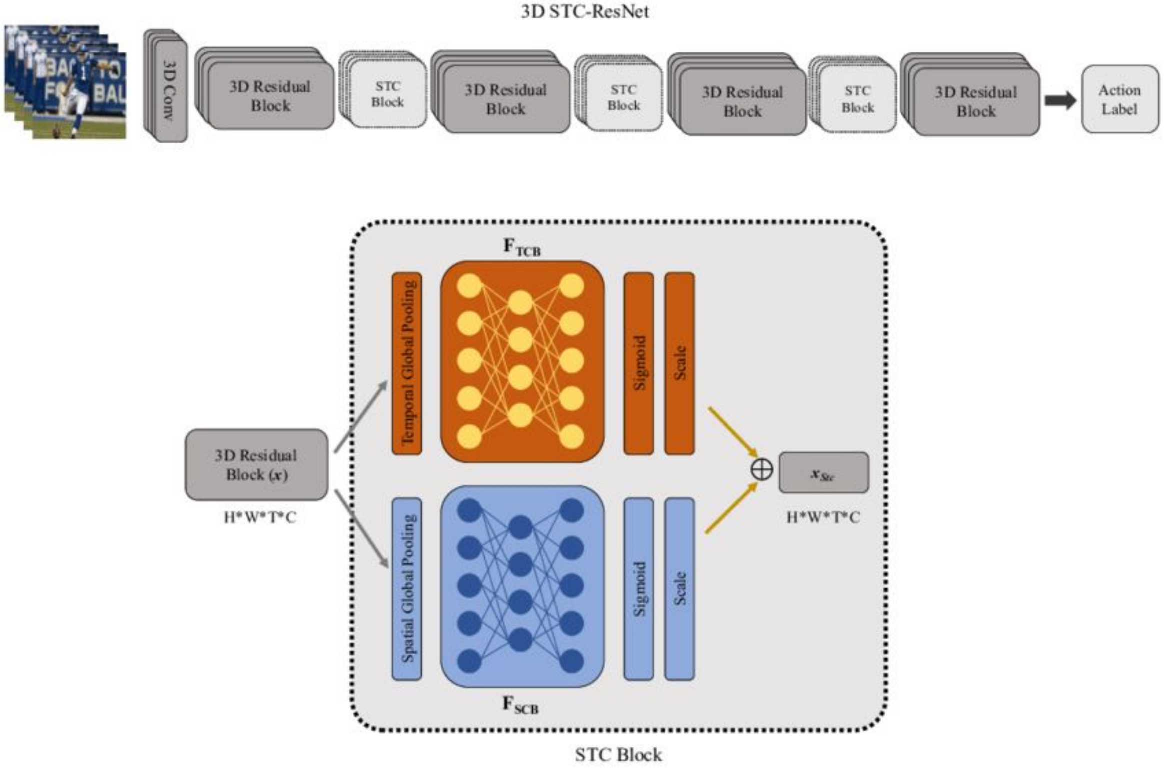
Link to GitHub repository **HERE**



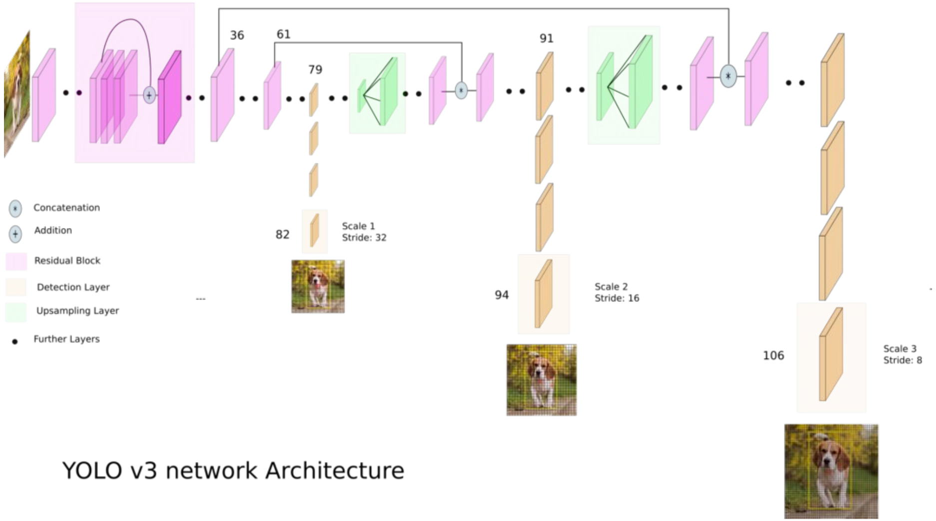
CNNs over Time: Video Classification CNNs

Link to GitHub repository [HERE]

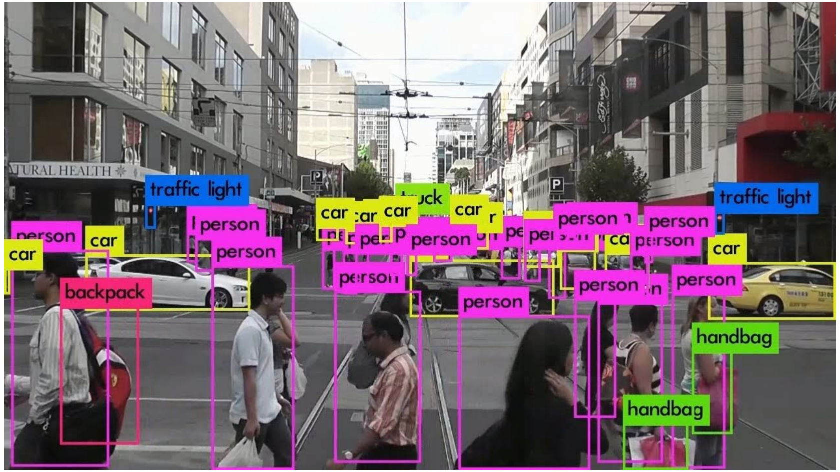


CNNs for Self-Driving Cars: YOLO-v3

Link to GitHub repository [HERE]

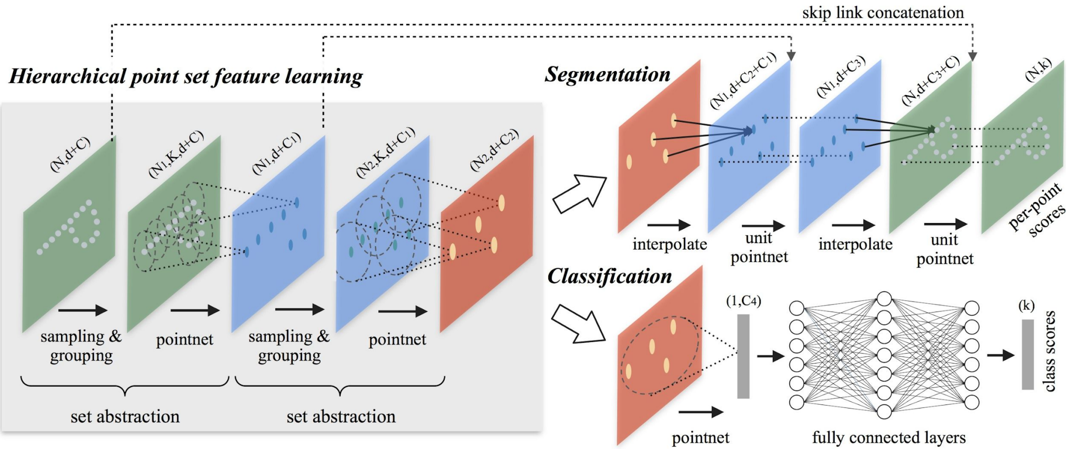


YOLO v3 network Architecture



CNNs for Self-Driving Cars: PointNet++

Link to GitHub repository [HERE]



(Some) Neural Network Architectures for Computer Vision

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[ResNet](#) – Residual neural network for image classification

[VGG-16](#)/[SegNet](#) – Fully convolutional encoder-decoder networks (FCNNs)

[Inception](#) – Image classification

[AlexNet](#) – Original network for MNIST digit classification

[YOLOv3](#) – Real-time object detection and classification

[CycleGAN](#) – Image translation using GANs

[MeshCNN](#) – 3D convolutional neural networks

[PointNet++](#) – Lidar Point Cloud Object Segmentation