CSE428: Image Processing

Lecture 12

Convolutional Neural Networks: Part 1

Image Classification Problem

Task: Write a computer program to differentiate between **cat** and **dog** images

- Solution 1

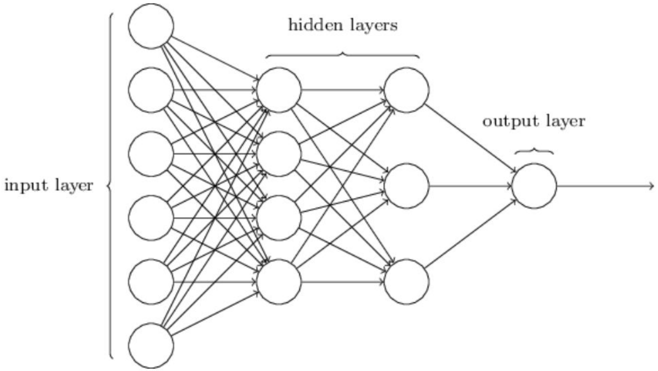
  Come up with a complicated function of pixels on your own

- Solution 2

  Have the computer come up with a complicated function

Feed Forward Neural Network / Multilayer Perceptron

Recall: A FFNN/MLP takes an input vector and predicts its label through a series of matrix multiplication and passing it through some nonlinearities!



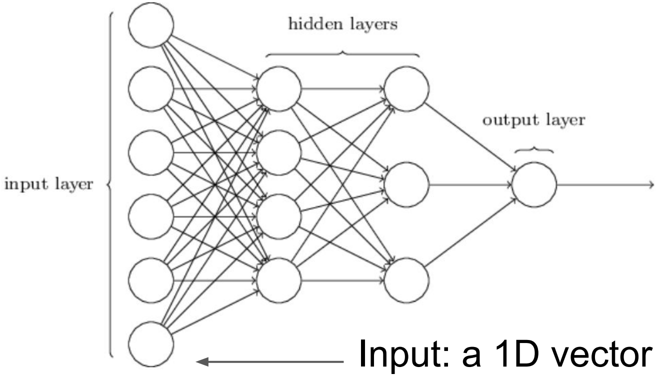
Powerful, but not well suited for image related computer vision tasks :(

Why not MLP?

For Computer Vision tasks feed forward fully connected neural networks (or multi layer perceptrons) are not suitable for mainly two reasons:

1. A lack of spatial reasoning
2. An explosive number of parameters

Image: a 3D volume
(height, width, depth)



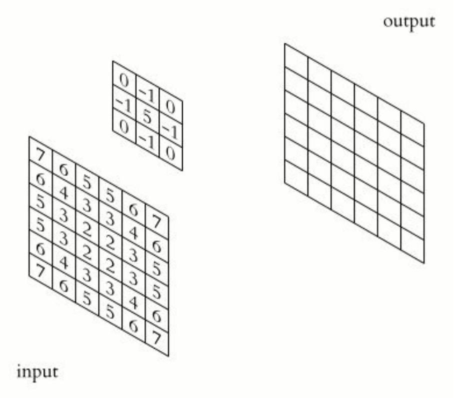
Prediction: 0 (Cat)
Prediction: 1 (Dog)

Input: a 1D vector
(features, 1)

Image Convolutions

Remember the convolution with kernels?

- Sliding kernel approach
- Had <u>*predefined*</u> kernels
- Works well for lower level vision tasks like edge detection
- Doesn't generalize well for higher level vision tasks like image classification



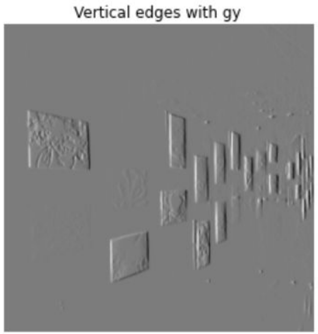


Image Convolutions

A higher level vision task is much more complicated than just detecting edges!

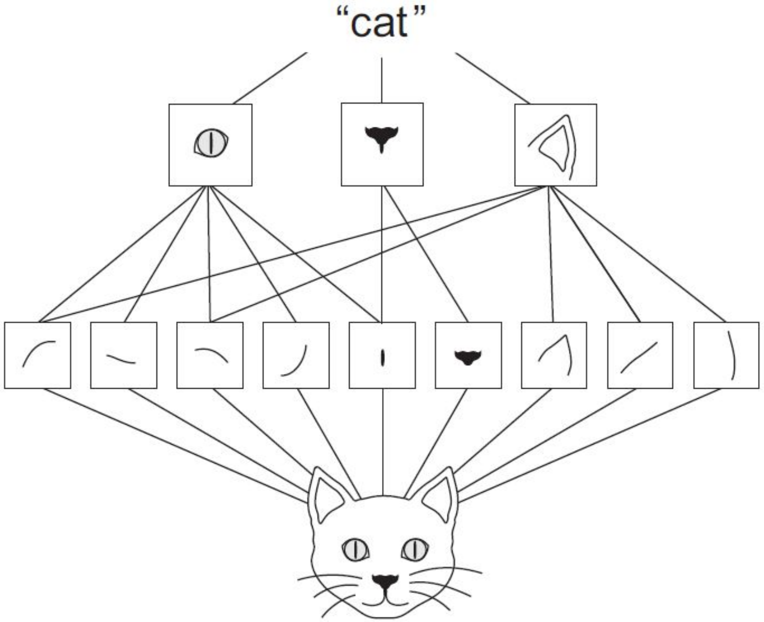
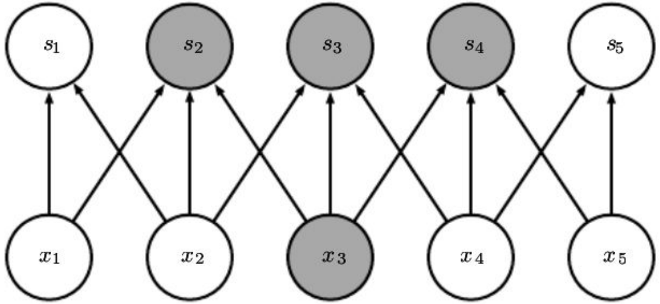
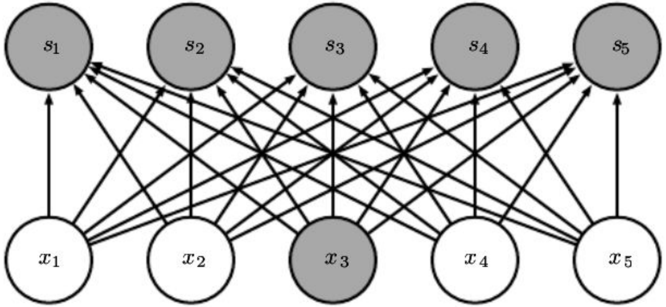


Image Convolutions

Image convolutions provide sparse connectivity as opposed to matrix multiplication in MLP, where the connection is no longer sparse.



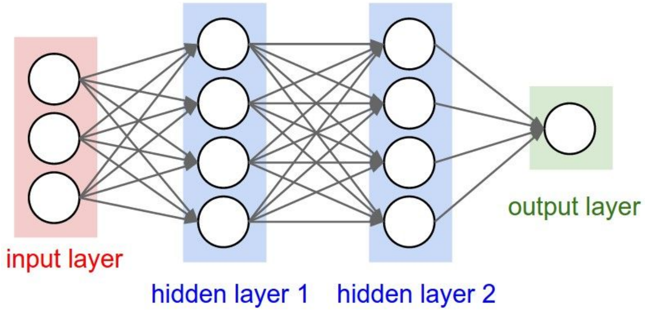
Convolution



Matrix multiplication

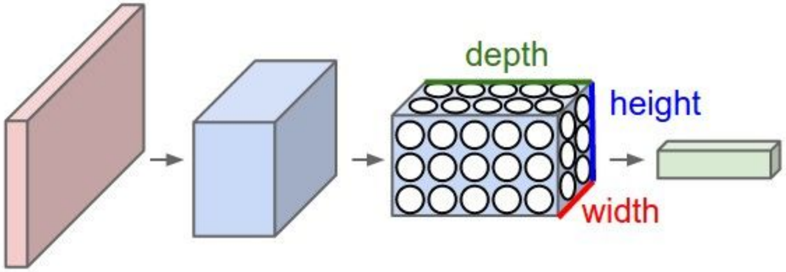
Image Convolutions

Proposal: have this ***convolution operation*** integrated with the multi layer perceptron or the feedforward neural networks!



MLP

Input to each layer: 1D “vector”
Output of each layer: 1D “vector”

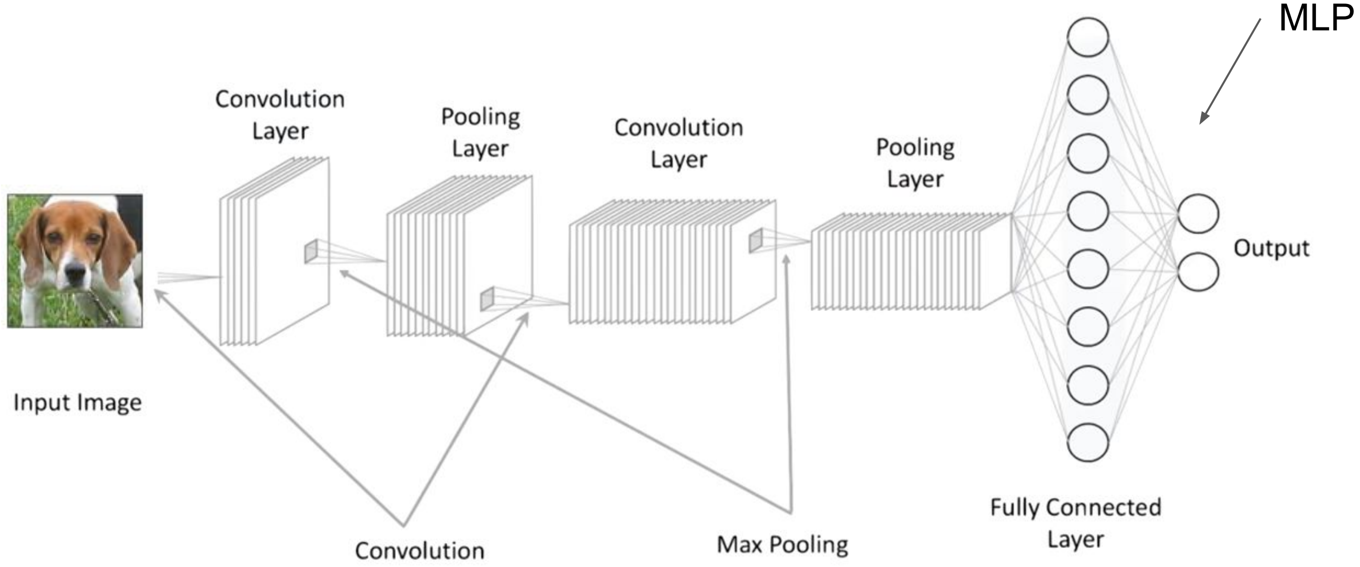


CNN

Input to each layer: 3D “volume”
Output of each layer: 3D “volume”

Convolutional Neural Networks (CNNs / ConvNets)

Key idea: have this convolution operation integrated with the feedforward neural network by treating the kernel entries as weights!

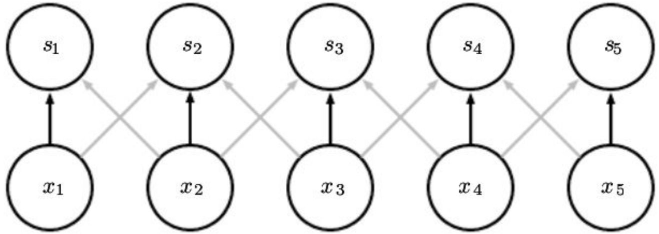


Advantages of CNNs

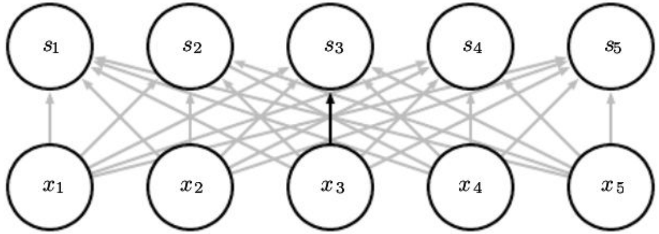
CNNs have many advantages for image related vision tasks:

1. Spatial Arrangement
    a. Focuses on local regions
2. Parameter Sharing
    a. Very few params per layer!

CNN



MLP



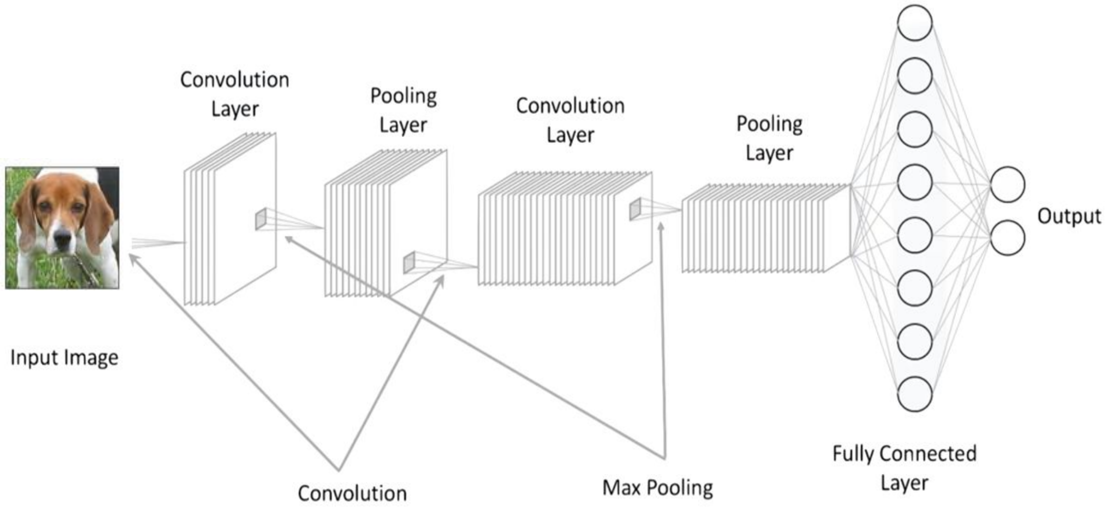
Visualize CNN on your browser:

https://www.cs.ryerson.ca/~aharley/vis/conv/

CNN Layers

Typically, a CNN has

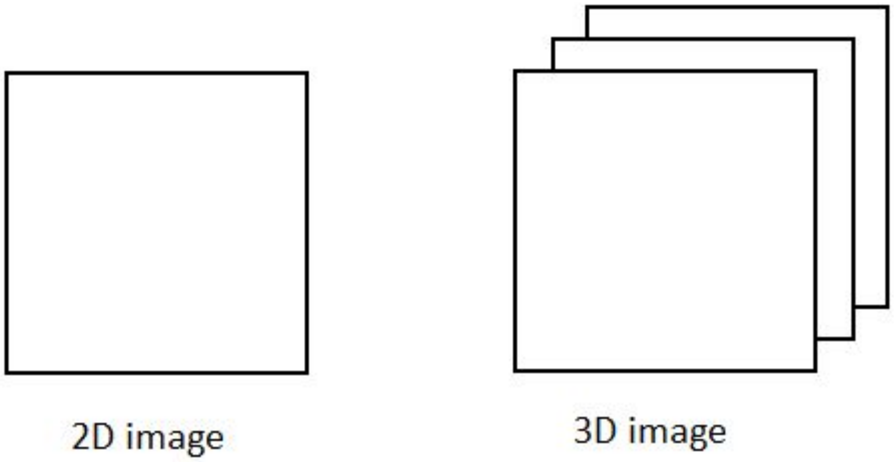
1. Input Layer
2. Convolution Layers
3. Pooling Layers
4. Fully Connected Layer
5. Output Layer



Input Layer

The Image!

- Grayscale Image
  - Shape: (H x W x 1)
- RGB Image
  - Shape: (H x W x 3)



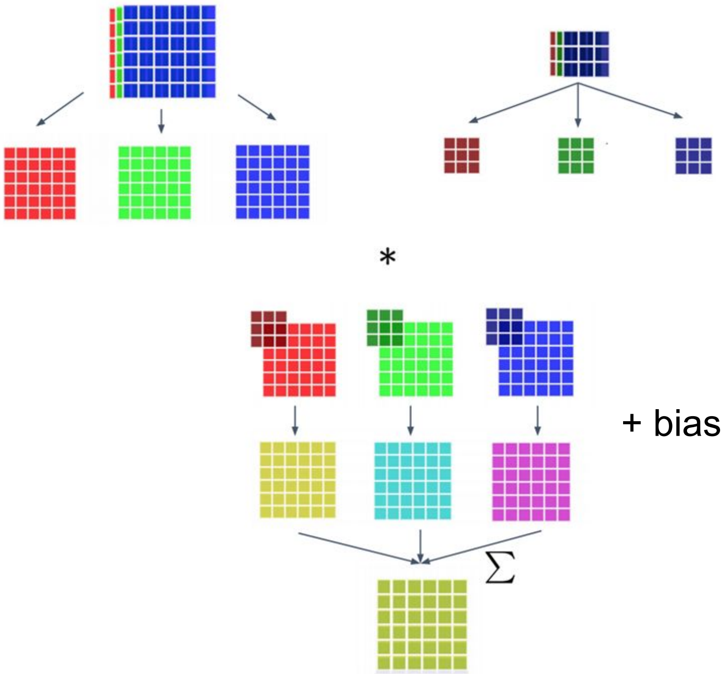
Concept: 3D Convolution (Convolution over Volume)

Convolution operation with 1 kernel of size ***F***

Input (image)
Volume : W_{in} x H_{in} x C_{in}

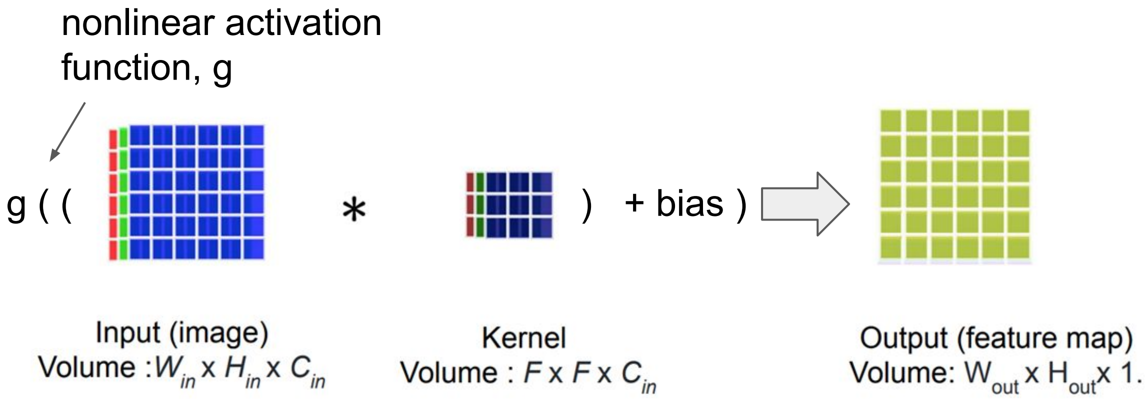
Kernel
Volume : F x F x C_{in}

Note: here, $C_{in(Image)} = C_{in(Kernel)}$ i.e. kernels always extend the full depth of the input volume,



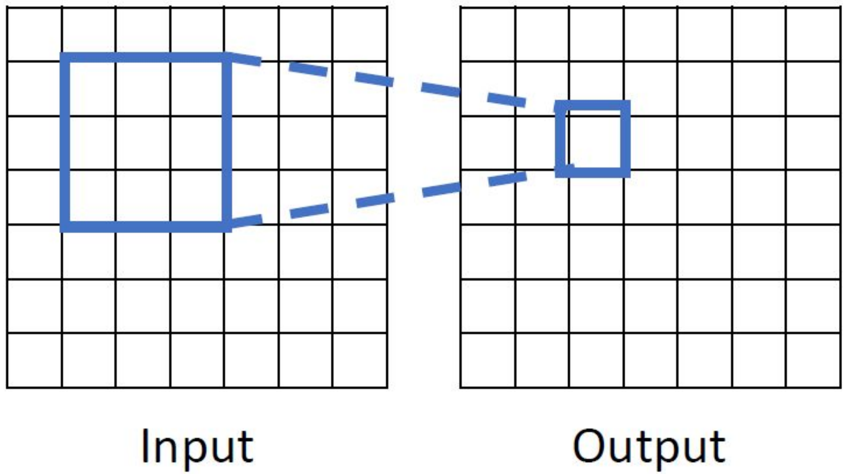
Concept: 3D Convolution (Convolution over Volume)

3D Convolution with a *single* kernel produces *one* 2D "feature map"



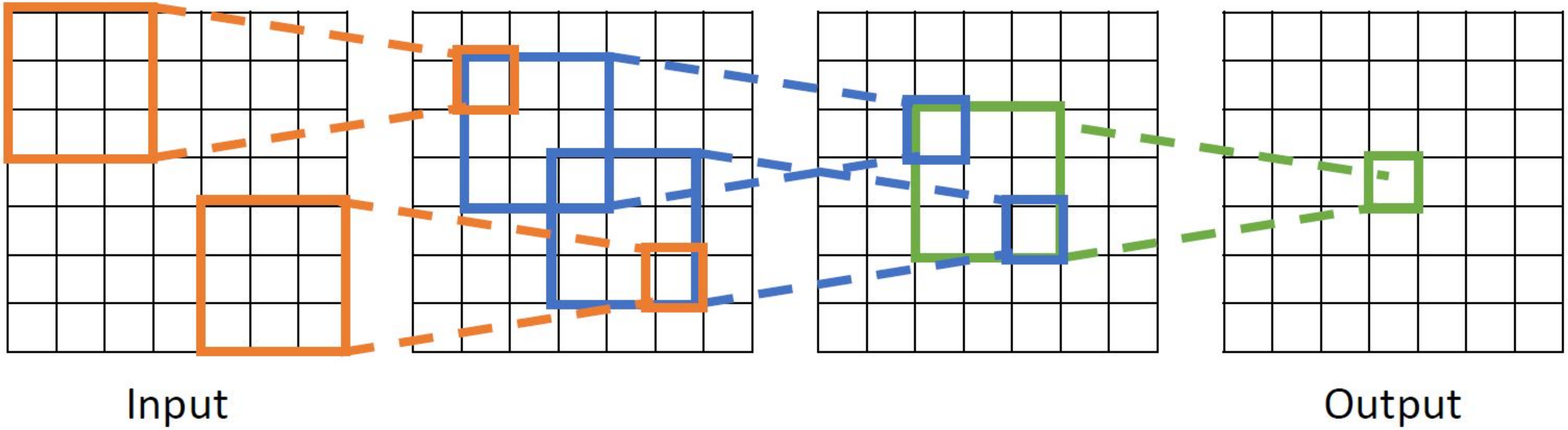
Concept: Receptive Field

Each element in the output is the result of a ***F*** x ***F*** "receptive field" of the input



Concept: Receptive Field

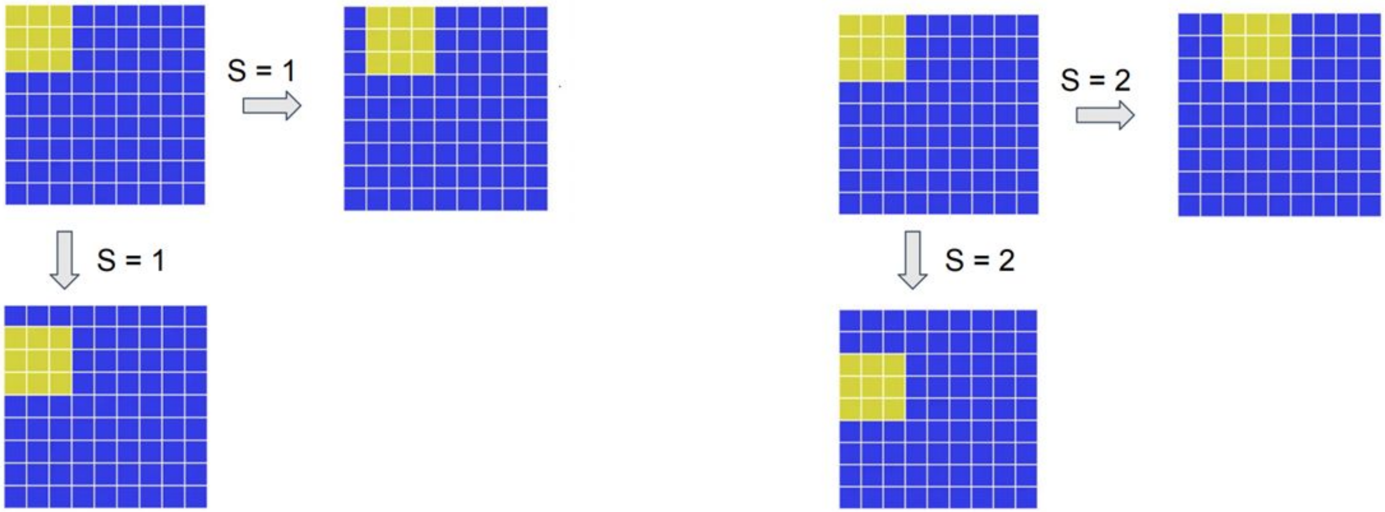
Successive convolution layer increases the apparent “receptive field” of the output



Concept: Stride

Stride is the number of pixels the kernel moves at each step, denoted by “S”

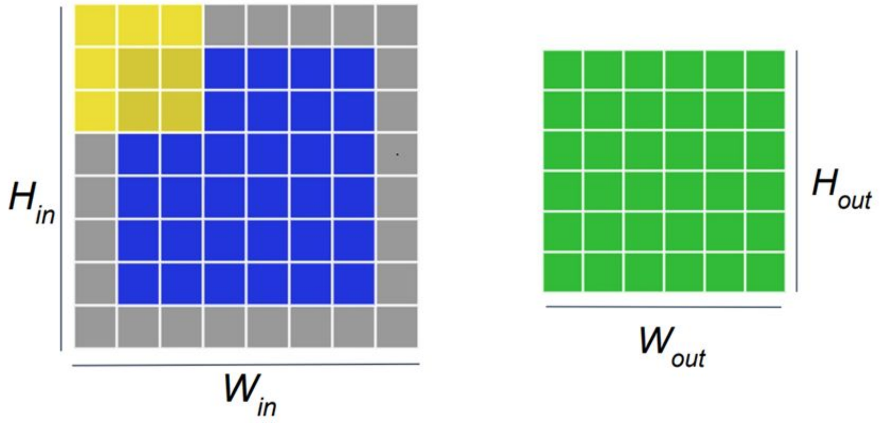
Higher value of stride increases the receptive field much faster

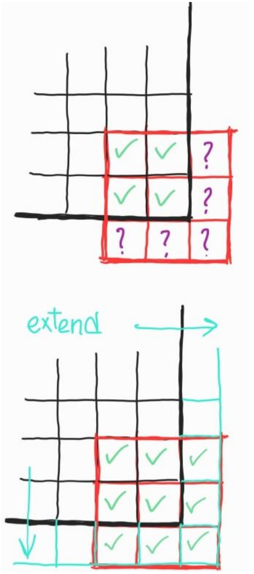


Concept: Padding

Padding: extend the borders of the original image by “P” pixels on each side:

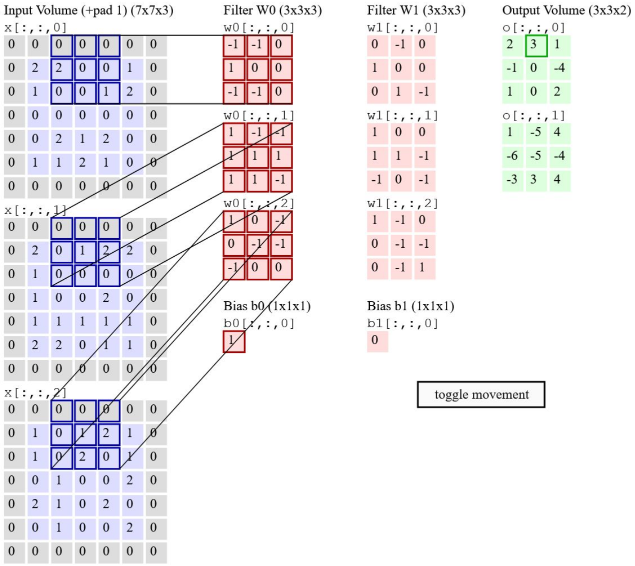
1. To keep the output image the same size as the original image
2. To achieve any arbitrary output shape

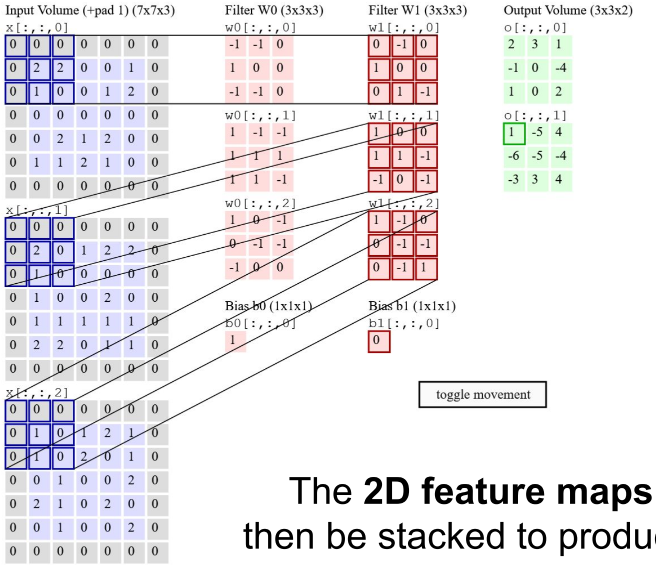




Concept: 3D Convolution with multiple Kernels

3D convolution with <u>*multiple* kernels</u> produces <u>*multiple* 2D "feature maps"</u> (/kernel)





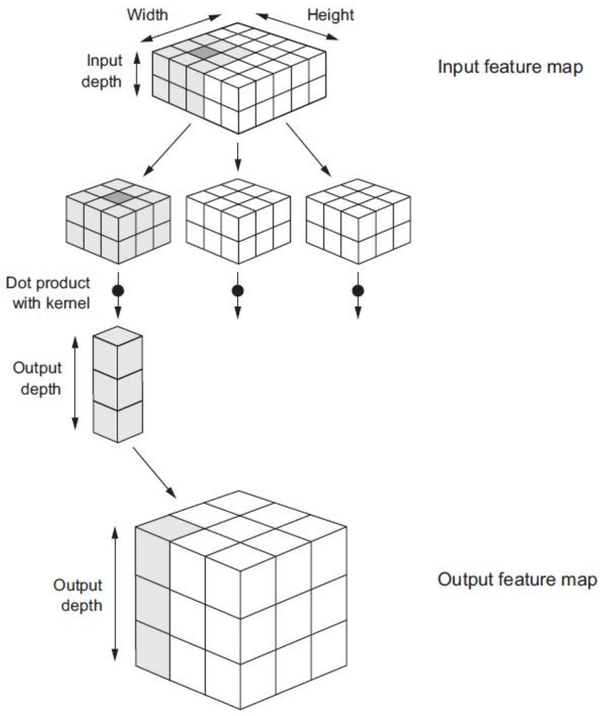
The **2D feature maps** can then be stacked to produce a **3D volume of feature maps**

Convolution Layer

A convolution layer or conv layer in CNN takes a 3D volume as an input and produces another 3D volume output of feature maps

By performing convolution over the input volume using some kernels which extend the full depth of the input volume & passing it through a nonlinearity

- Input *volume*: $\boldsymbol{H_{in}}$ x $\boldsymbol{W_{in}}$ x $\boldsymbol{C_{in}}$
- Output *volume*: $\boldsymbol{H_{out}}$ x $\boldsymbol{W_{out}}$ x $\boldsymbol{C_{out}}$

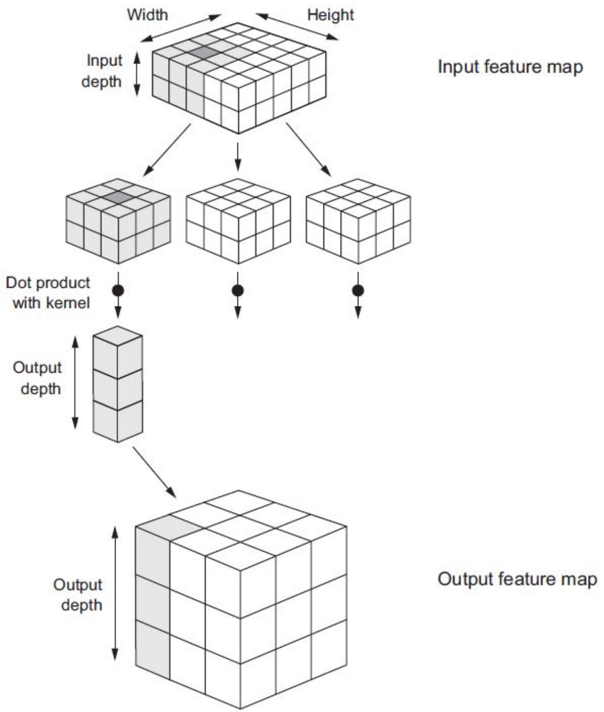


Convolution Layer

In general for a convolution layer

- Input *volume*: $\boldsymbol{H_{in}}$ x $\boldsymbol{W_{in}}$ x $\boldsymbol{C_{in}}$
- Kernel *volume (of* size ***F***): ***F*** x ***F*** x $\boldsymbol{C_{in}}$
- Number of kernels: $\boldsymbol{C_{out}}$
- Padding: ***P***
- Strinde: ***S***
- Then output *volume*: $\boldsymbol{H_{out}}$ x $\boldsymbol{W_{out}}$ x $\boldsymbol{C_{out}}$

$$H_{out} = \frac{H_{in} - F + 2P}{S} + 1 \; ; \; W_{out} = \frac{W_{in} - F + 2P}{S} + 1$$



tf.keras.layers.Conv2D

```
tf.keras.layers.Conv2D(
    filters, kernel_size, strides=(1, 1), padding='valid',
    data_format=None, dilation_rate=(1, 1), groups=1, activation=None,
    use_bias=True, kernel_initializer='glorot_uniform',
    bias_initializer='zeros', kernel_regularizer=None,
    bias_regularizer=None, activity_regularizer=None, kernel_constraint=None,
    bias_constraint=None, **kwargs
)
```

Convolution Layer Example

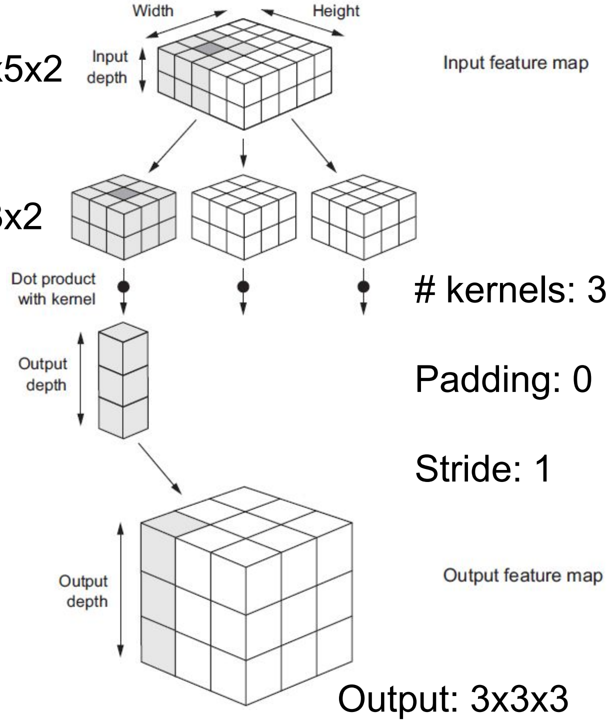
Example 1

- Input *volume*: $\boldsymbol{H_{in}}$ x $\boldsymbol{W_{in}}$ x $\boldsymbol{C_{in}}$
- Kernel *volume (of* size ***F***): ***F*** x ***F*** x $\boldsymbol{C_{in}}$
- Number of kernels: $\boldsymbol{C_{out}}$
- Padding: ***P***
- Strinde: ***S***
- Then output *volume*: $\boldsymbol{H_{out}}$ x $\boldsymbol{W_{out}}$ x $\boldsymbol{C_{out}}$

$$H_{out} = \frac{H_{in} - F + 2P}{S} + 1 \; ; \; W_{out} = \frac{W_{in} - F + 2P}{S} + 1$$

Input: 5x5x2

Kernel: 3x3x2



kernels: 3

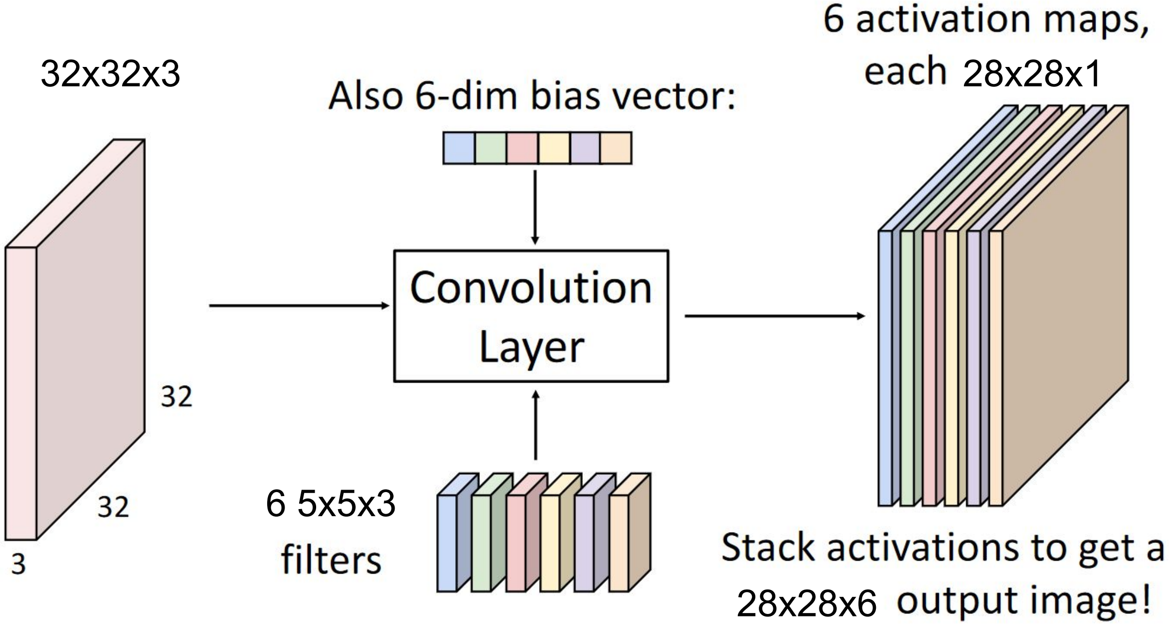
Padding: 0

Stride: 1

Output: 3x3x3

Convolution Layer Example

Example 2



Convolution Layer Parameters

Hyperparameters:

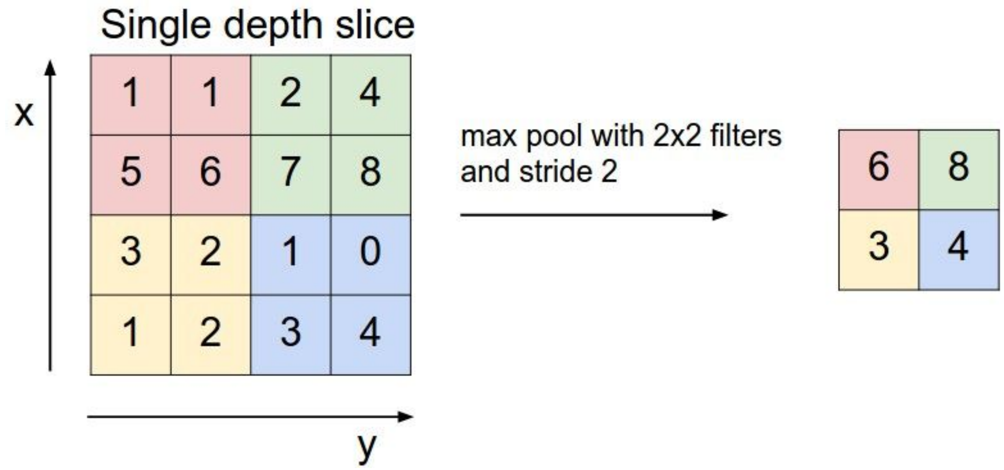
- Kernel size: $\boldsymbol{F}$
- Number of kernels: $\boldsymbol{C_{out}}$
- Padding: $\boldsymbol{P}$
- Strinde: $\boldsymbol{S}$

Learnable parameters:

- Kernel weights: $\boldsymbol{C_{out}} \times \boldsymbol{F} \times \boldsymbol{F} \times \boldsymbol{C_{in}}$
- Kernel biases: $\boldsymbol{C_{out}}$

Pooling Layer

- Pooling layers are inserted between successive Conv layers
- Progressively reduce the spatial size while keeping the depth constant
- Operates independently on each channel or “depth” over some ***F*** x ***F*** region

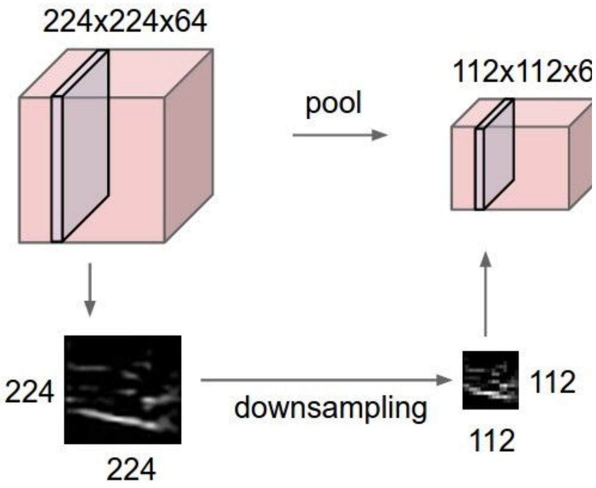


Pooling Layer

In general for a pooling layer

- <u>Input *volume*</u>: $\boldsymbol{H_{in}}$ x $\boldsymbol{W_{in}}$ x $\boldsymbol{C_{in}}$
- Kernel size: ***F***
- Strinde: ***S***
- Pooling function: MAX, Avg
- Then <u>output *volume*</u>: $\boldsymbol{H_{out}}$ x $\boldsymbol{W_{out}}$ x $\boldsymbol{C_{in}}$

$$H_{out} = \frac{H_{in} - F}{S} + 1 \ ; \ W_{out} = \frac{W_{in} - F}{S} + 1$$



tf.keras.layers.MaxPooling2D

```
tf.keras.layers.MaxPool2D(
    pool_size=(2, 2), strides=None, padding='valid', data_format=None,
    **kwargs
)
```

Pooling Layer

Hyperparameters:

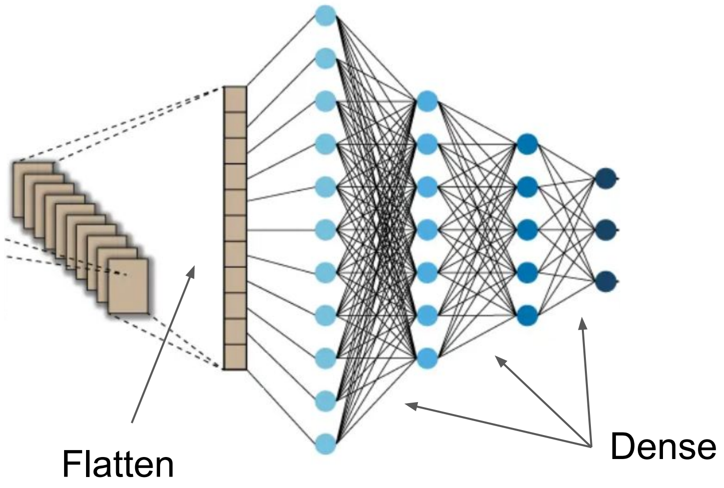
- Kernel size: ***F***
- Strinde: ***S***
- Pooling function: ***MAX, Average***

Learnable parameters:

- Zero!

Fully Connected Layer

A fully connected layer in CNN first flatens or unravels a 3D volume into a 1D vector and does similar computations like an MLP



tf.keras.layers.Flatten

```
tf.keras.layers.Flatten(
    data_format=None, **kwargs
)
```

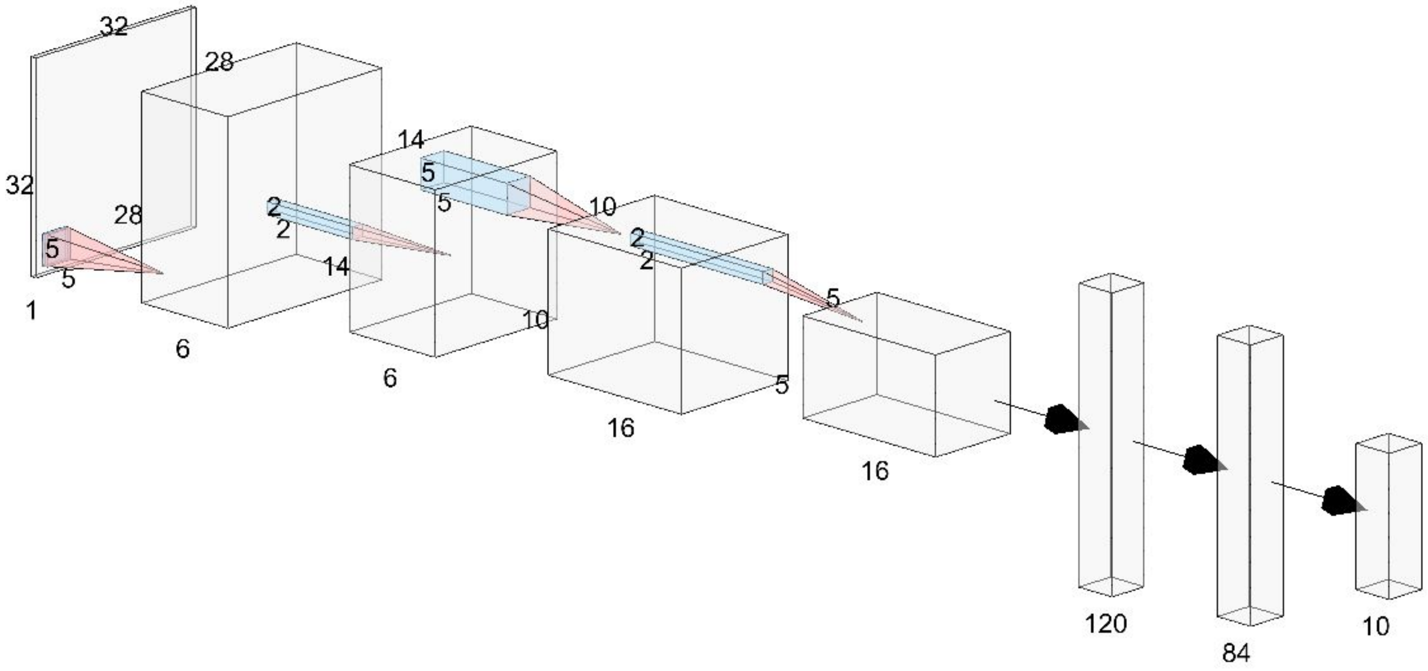
tf.keras.layers.Dense

```
tf.keras.layers.Dense(
    units, activation=None, use_bias=True,
    kernel_initializer='glorot_uniform',
    bias_initializer='zeros', kernel_regularizer=None,
    bias_regularizer=None, activity_regularizer=None, kernel_constraint=None,
    bias_constraint=None, **kwargs
)
```

The LeNet-5 CNN Architecture

Layers:

1. Input
2. Conv-1
3. Pool-1
4. Conv-2
5. Pool-2
6. FC-1
7. FC-2
8. Output



Resources

1. https://cs231n.github.io/convolutional-networks/
2. https://web.eecs.umich.edu/~justincj/teaching/eecs498/FA2020/
3. https://www.tensorflow.org/api_docs/python/tf/keras
4. Deep Learning with Python Book by François Chollet
5. https://www.deeplearningbook.org/
6. Hands-on Computer Vision with TensorFlow 2 by Eliot Andres & Benjamin Planche (Packt Pub.)

Colab Notebooks

1. NN Demo

   https://colab.research.google.com/drive/1Zrb2f_xNSfZ1QXASa9vnbFFub56J9opI?usp=sharing

2. CNN Demo

   https://colab.research.google.com/drive/1w0ELsNal47SszoBKUGa736V7JWFeYIzJ?usp=sharing