



# Summer of Code

# **Artificial Intelligence**

## (Machine Learning & Deep Learning)

Instructor

**Wajahat Ullah**

- *Research Assistant* (DIP Lab)

Duration

**03 Months**

(September – November)



# Day 01 – Deep Learning (Convolutional Neural Networks)

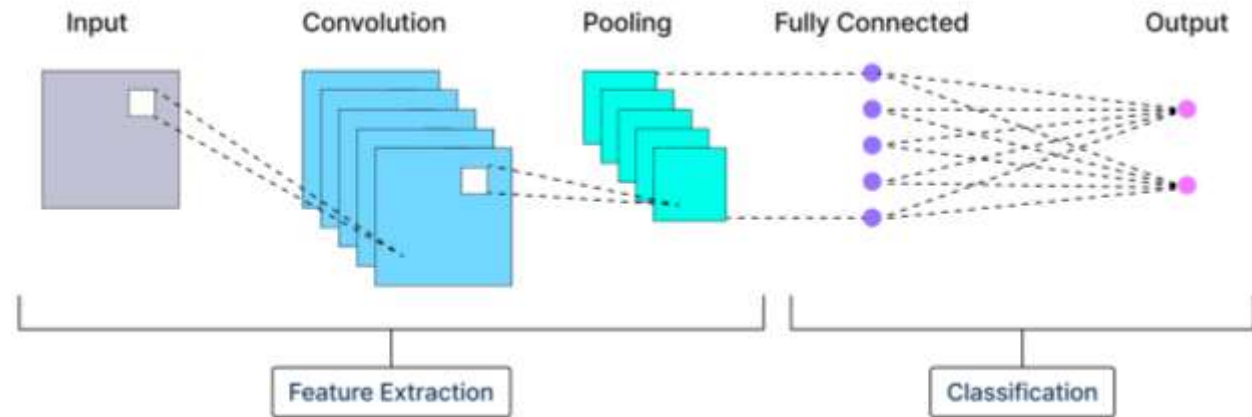
## Objectives:

- ❖ Convolution
- ❖ Pooling
- ❖ Convolutional Neural Networks

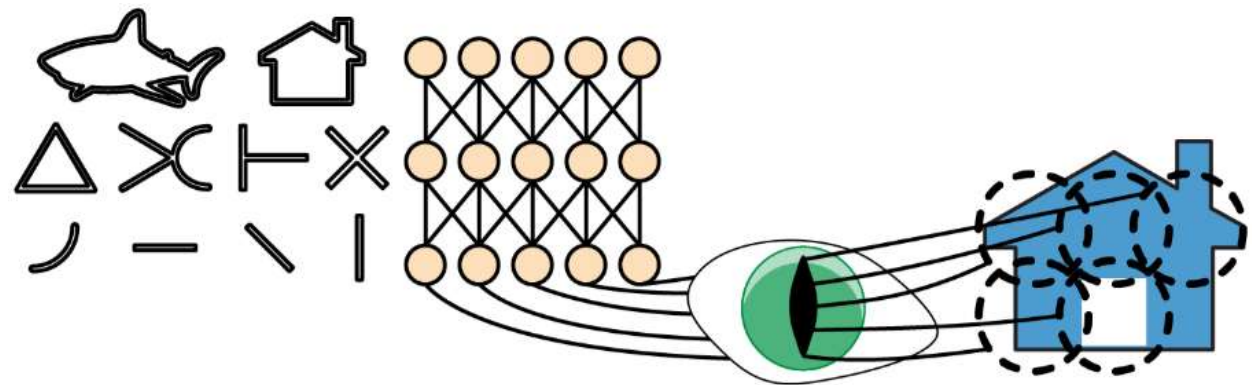
# Convolutional Neural Networks

- A class of neural networks primarily used for analyzing visual data such as images and videos.
- Learn spatial hierarchies of features through convolutional operations.
- The fundamental unit of such networks is a small bundle of computation called an artificial neuron.
- Modeled after the visual cortex of the human brain as neurons respond to specific regions of the visual field.

**CNNs**



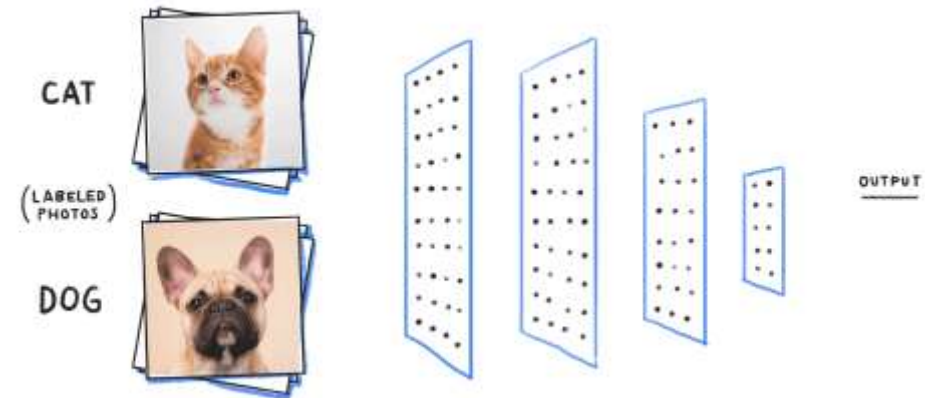
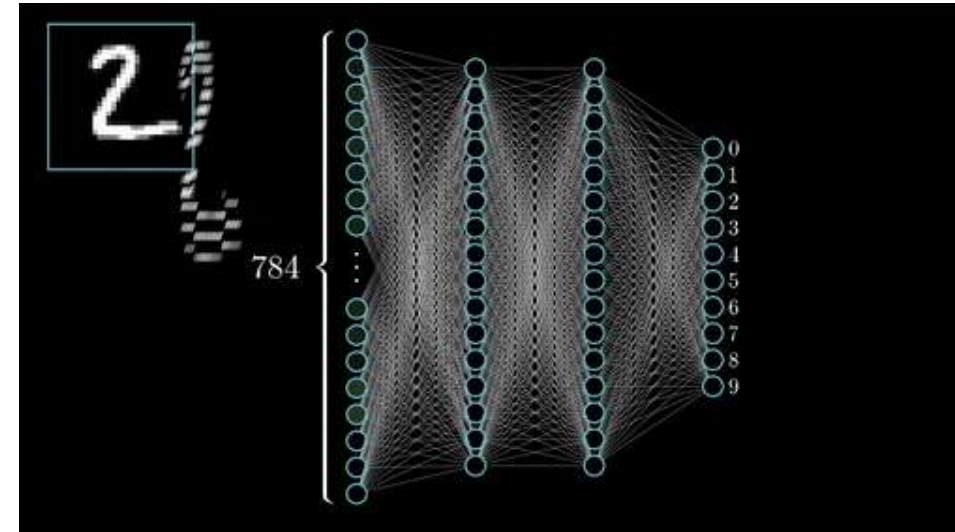
**Human Visual Cortex**





# Convolutional vs Fully Connected Layers

- Each neuron connected to a small range of input, instead of all the inputs.
- Performs the convolution operation to extract features.
- It has fewer parameters compared to fully connected layers because of weight sharing.
- Primarily used for feature extraction

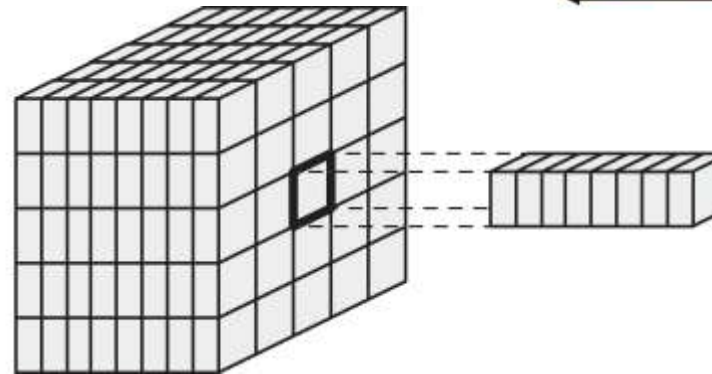
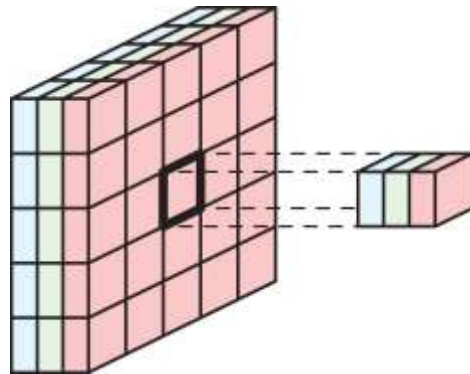
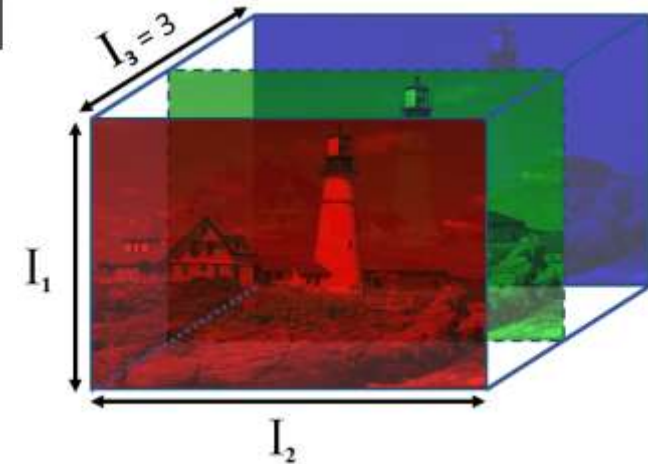


# Images and Tensors

- A digital image is a grid of pixel values, each pixel containing intensity information.
- Grayscale images are represented as a 2D matrix of pixels (Height x Width), while color images have channels as well (Height, Width, Channels).
- Tensors are generalization of matrices to higher dimensions.



|        |        |        |        |        |        |        |
|--------|--------|--------|--------|--------|--------|--------|
| 0.2251 | 0.2563 | 0.2826 | 0.2826 | 0.4    |        |        |
| 0.5342 | 0.2051 | 0.2157 | 0.2826 | 0.3822 | 0.4391 | 0.4391 |
| 0.5342 | 0.1789 | 0.1307 | 0.1789 | 0.2051 | 0.3256 | 0.2483 |
| 0.4308 | 0.2483 | 0.2624 | 0.3344 | 0.3344 | 0.2624 | 0.2549 |
| 0.3344 | 0.2624 | 0.3344 | 0.3344 | 0.3344 | 0.3344 | 0.3344 |



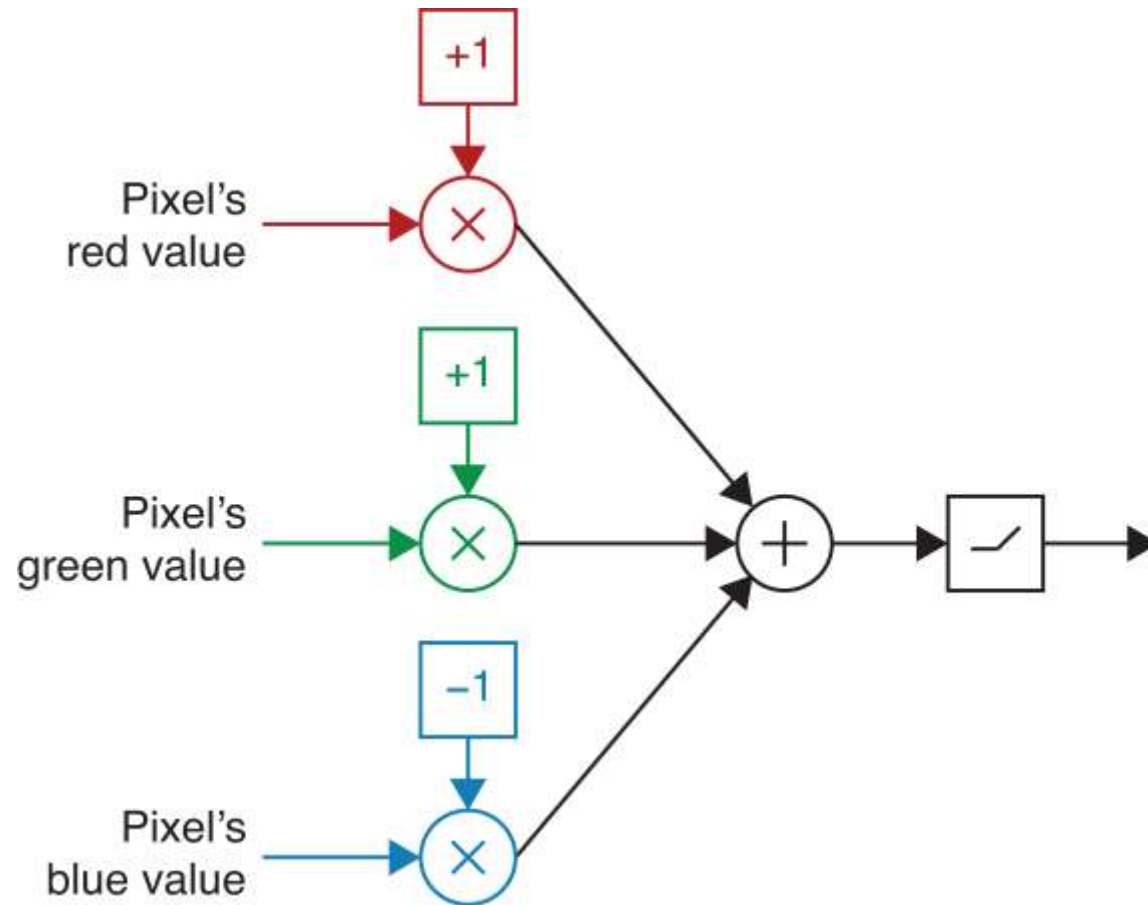
# Convolution

Let's say we want to detect the intensity of yellow color in each pixel



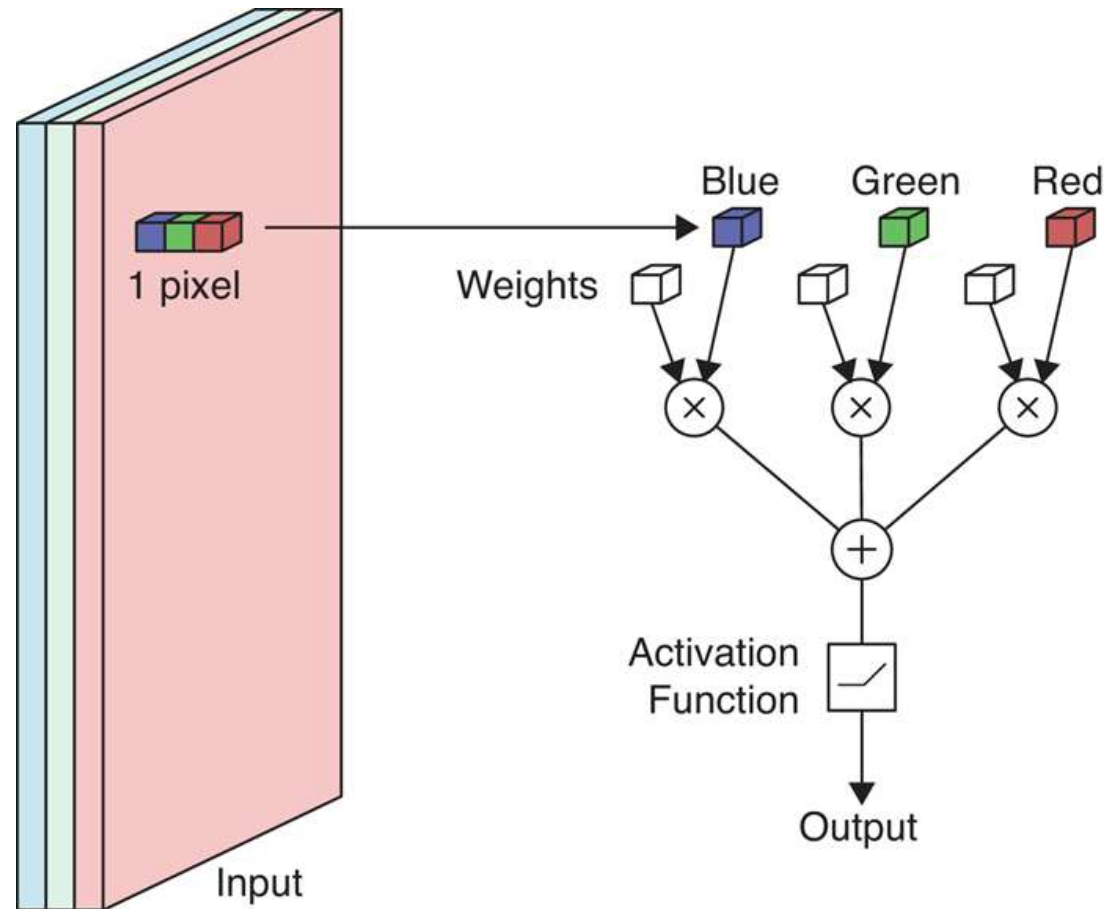
# Convolution

We can create a yellow detector as an artificial neuron like so



# Convolution

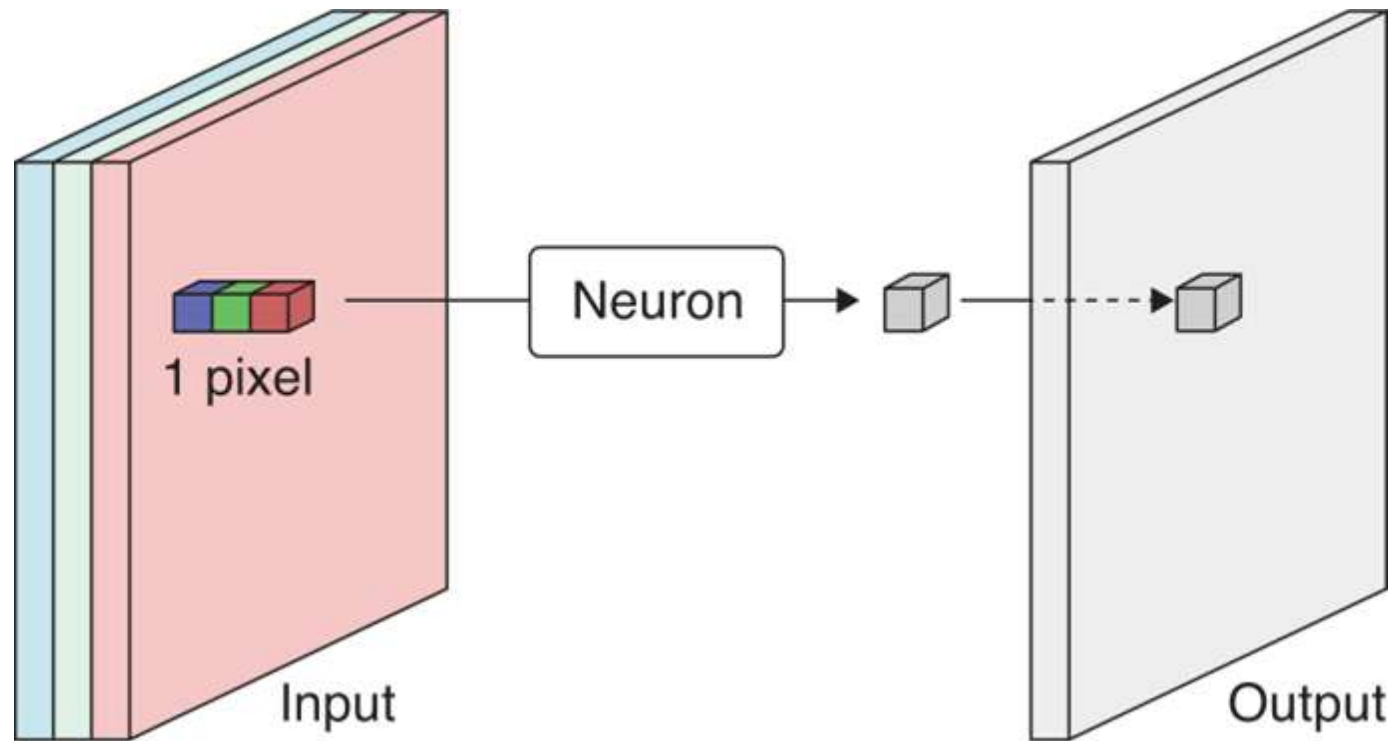
We can apply the yellow detector to every pixel in the color input image





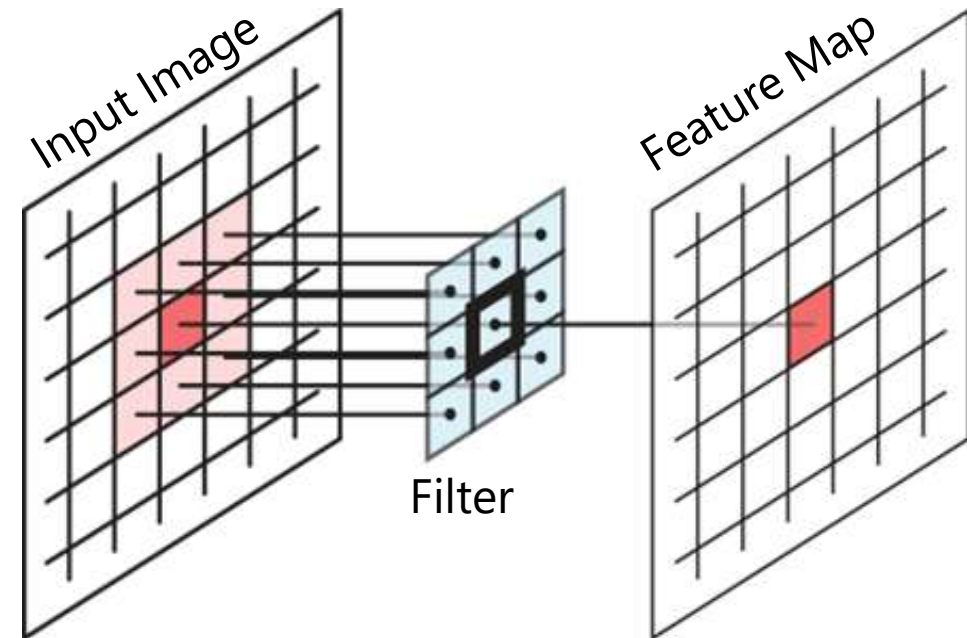
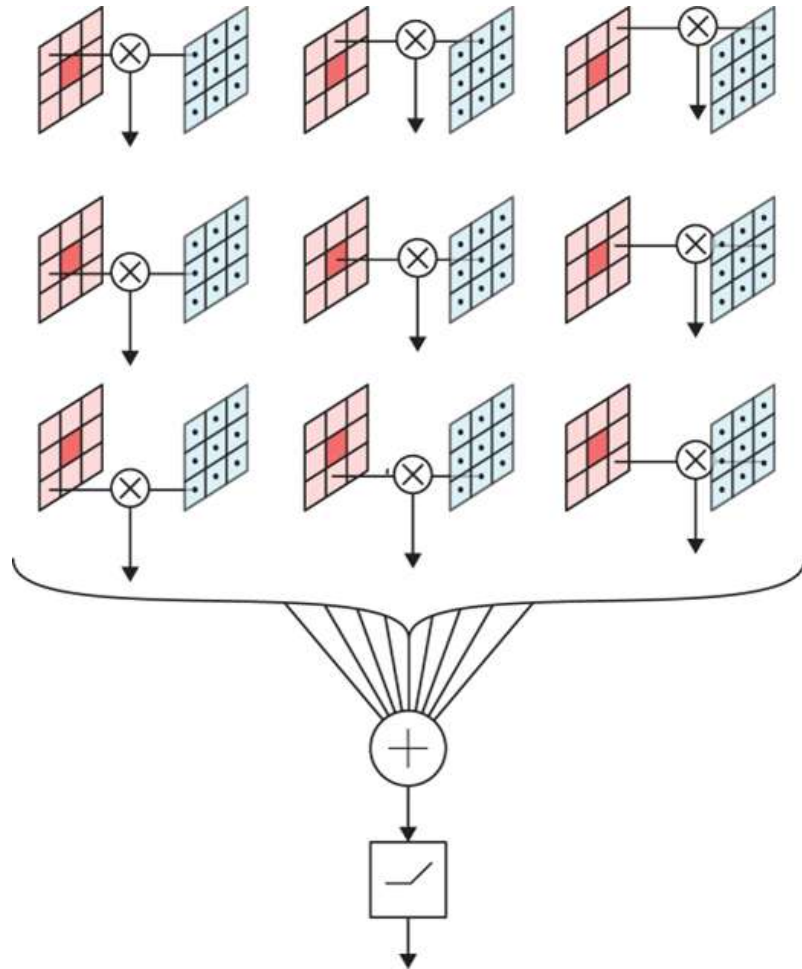
# Convolution

As a result, we get a grayscale image where each pixel corresponds to the intensity of yellow color in the input image



# Convolution

Instead of processing a single pixel at a time, we can process a small region around the pixel



# Convolution as Feature Extractor

We sweep the filter across the entire image to detect these different patterns as

Blur

|   |   |   |
|---|---|---|
| 1 | 1 | 1 |
| 1 | 1 | 1 |
| 1 | 1 | 1 |



Horizontal  
Edges

|    |    |    |
|----|----|----|
| 1  | 1  | 1  |
| 0  | 0  | 0  |
| -1 | -1 | -1 |



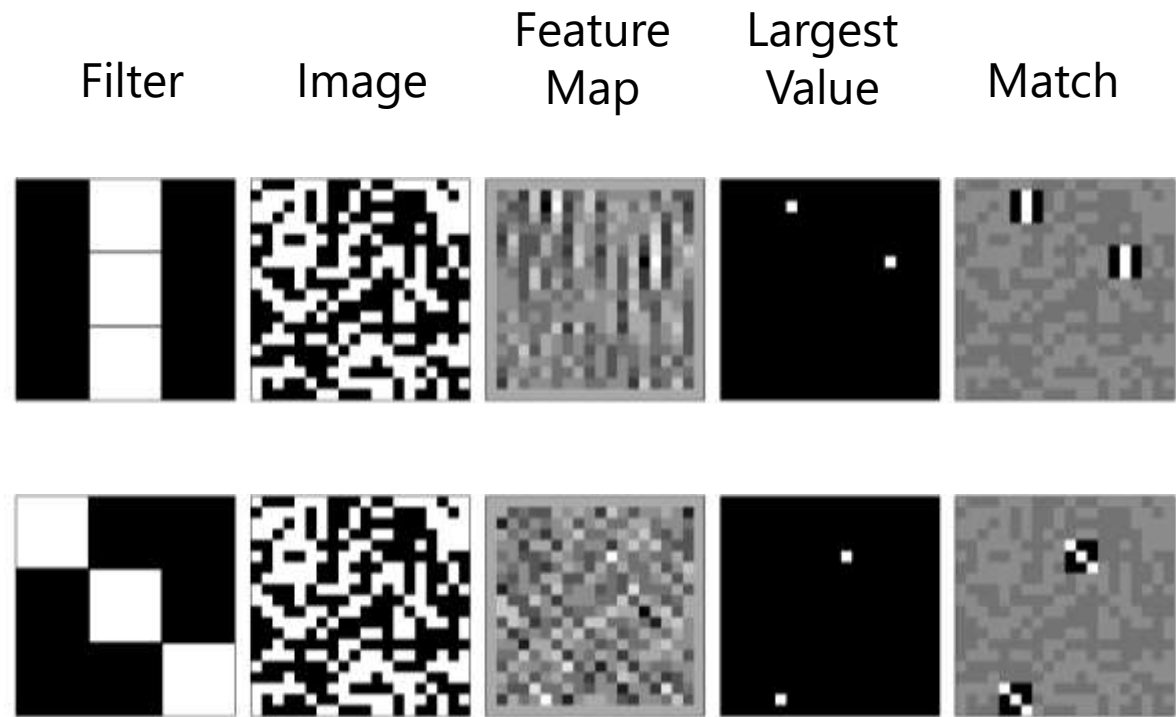
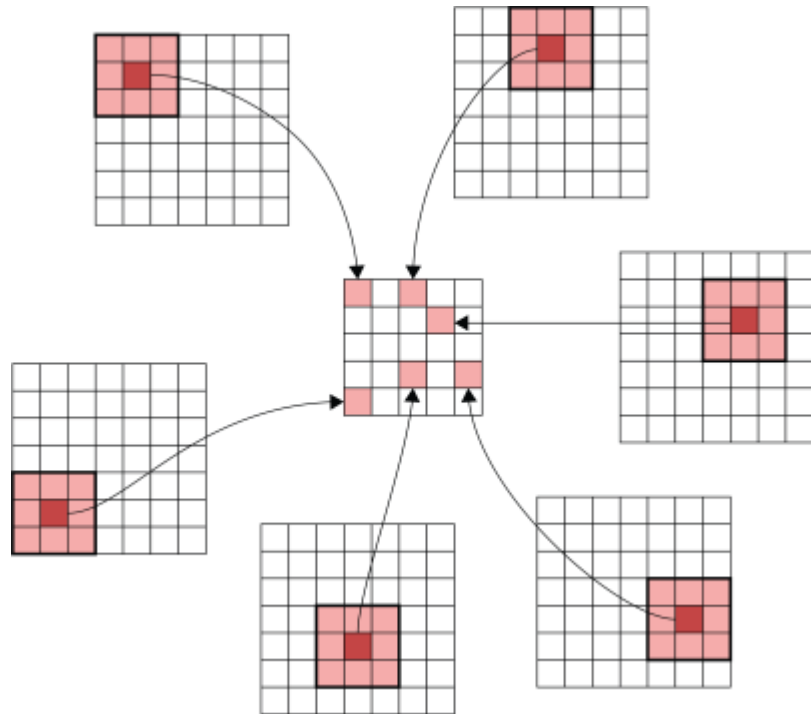
Vertical  
Edges

|    |   |   |
|----|---|---|
| -1 | 0 | 1 |
| -1 | 0 | 1 |
| -1 | 0 | 1 |



# Convolution as Feature Extractor

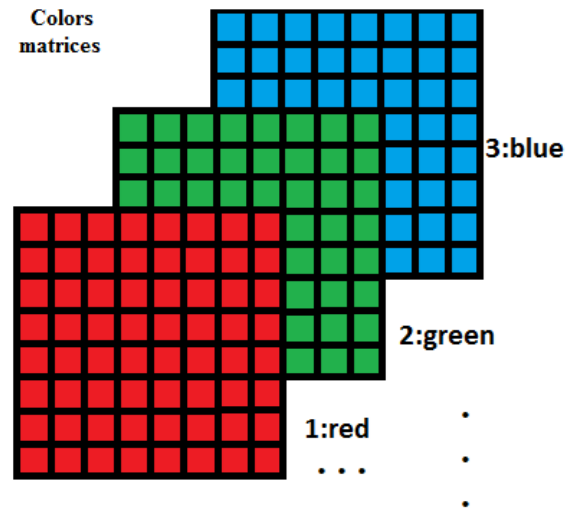
This Process of sweeping the filter across the image and getting a feature map is called convolution



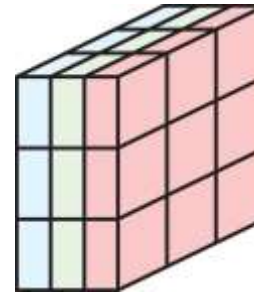


# Multichannel Convolution

While performing convolution on input with more than one channel, our filter must also have the same number of channels



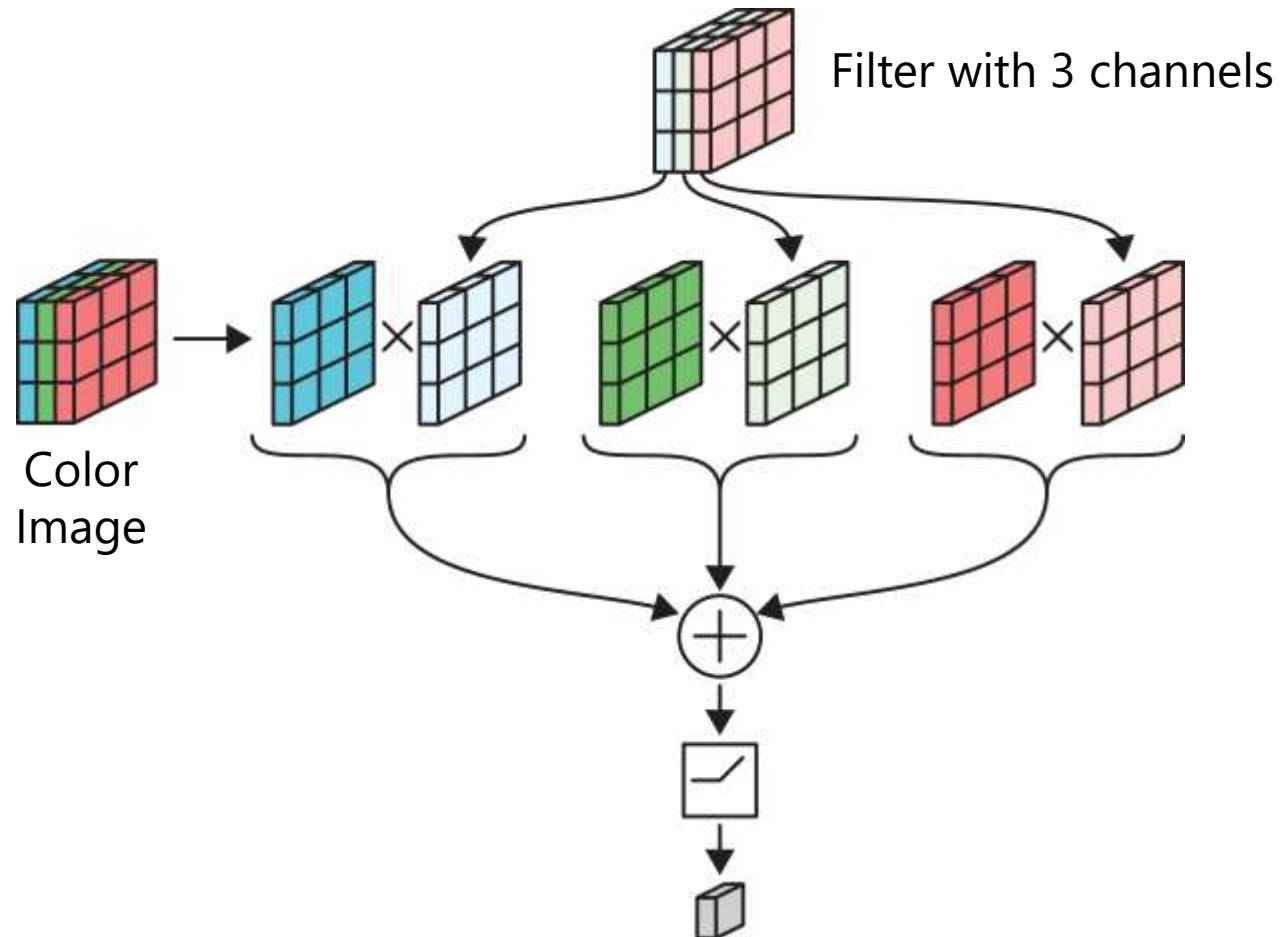
Color Image



Filter with 3 channels

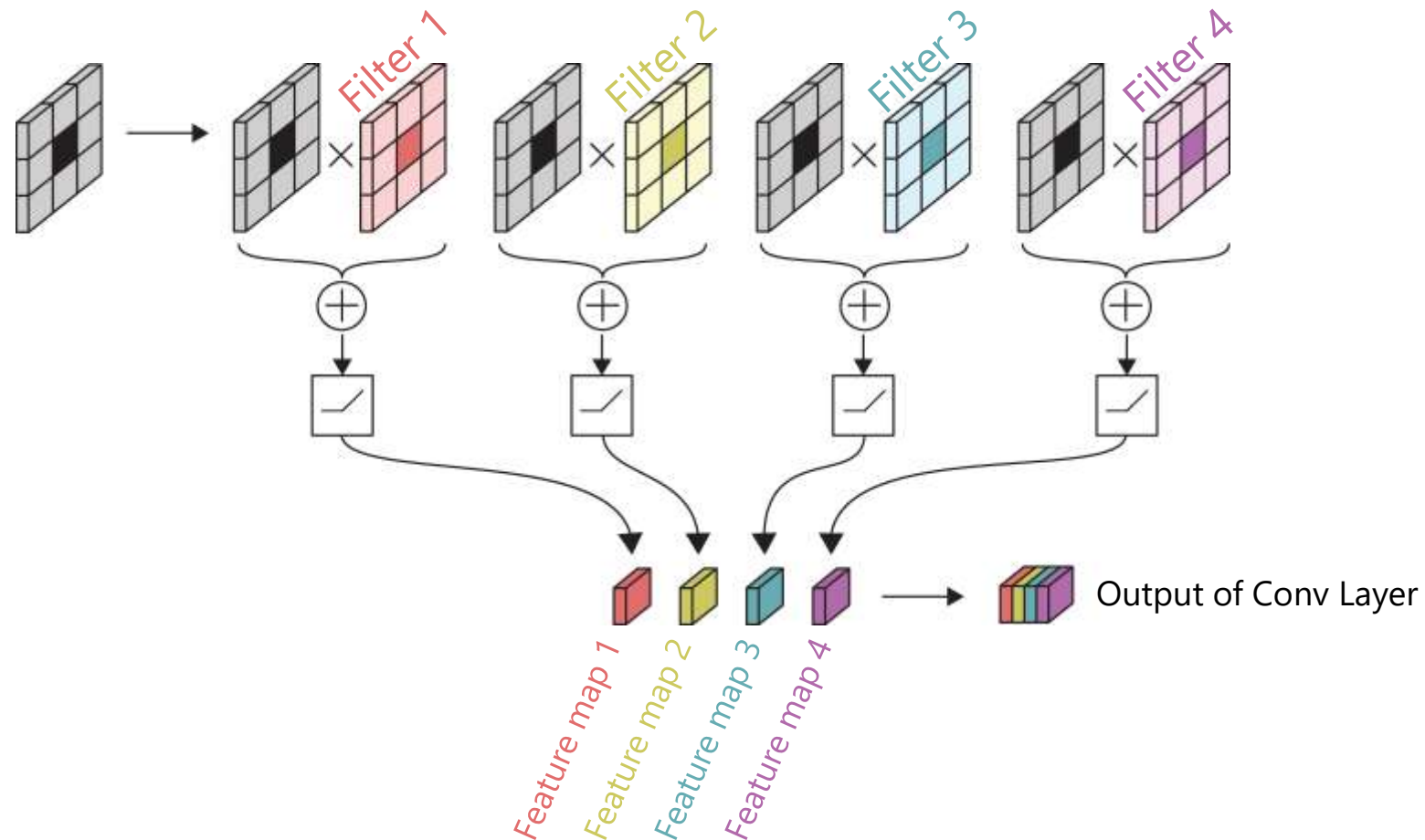
# Multichannel Convolution

Each filter will then apply to the corresponding channel and results are added together



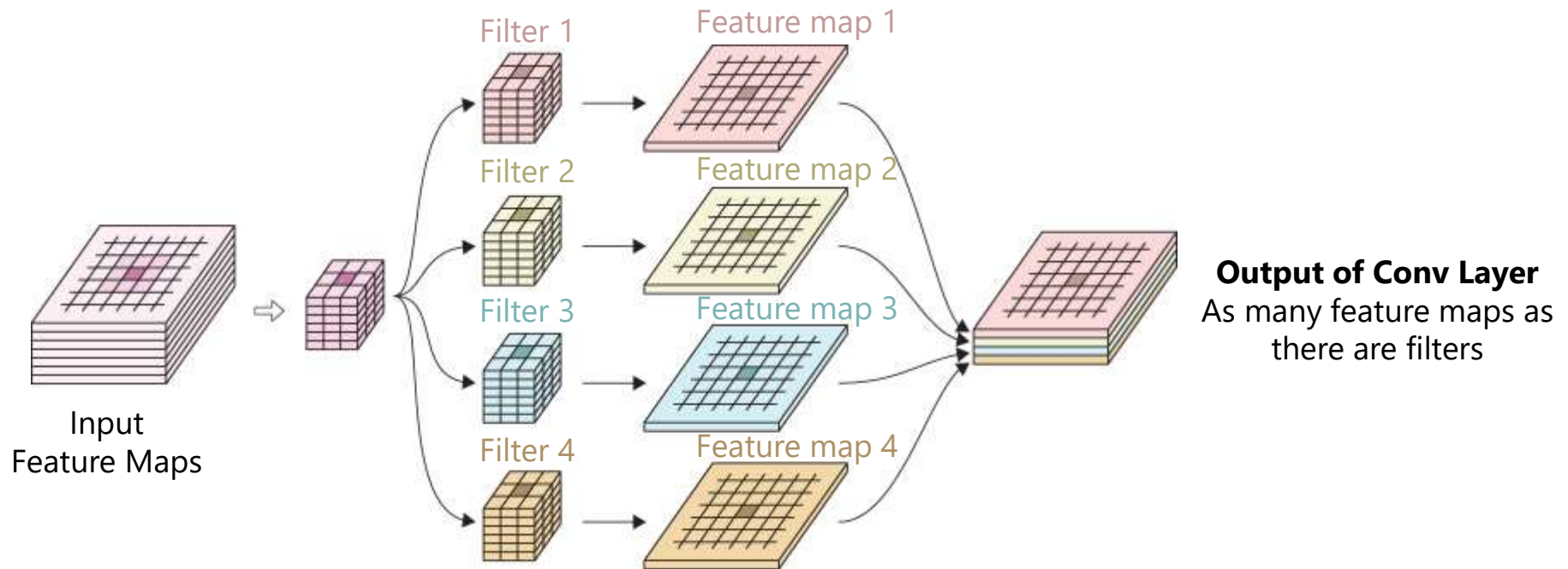
# Convolutional Layer

We bundle up multiple filters together, each looking for a different pattern, forming a convolutional layer



# Convolutional Layer

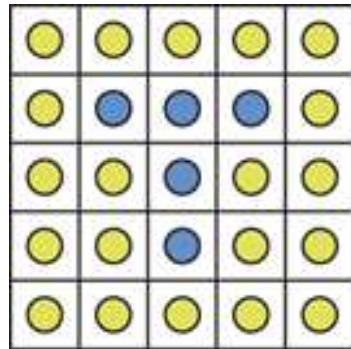
A convolutional layer can have many filters, but each one will produce a single feature map



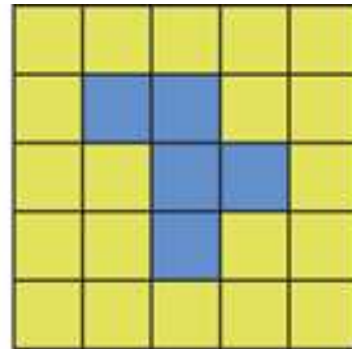


# Pooling Layer

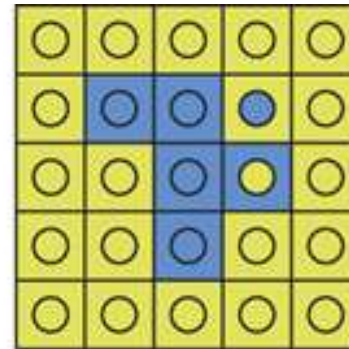
The convolutional filters look for exact match, so a slight change in the input will result in mismatch



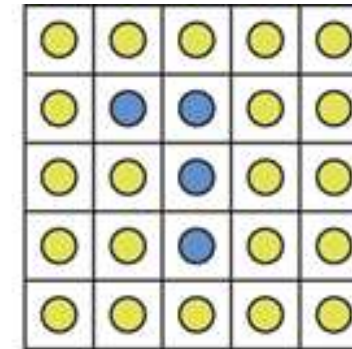
perfect  
filter



perfect  
image



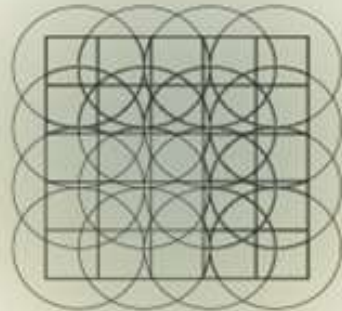
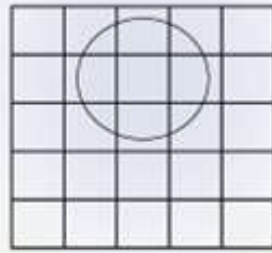
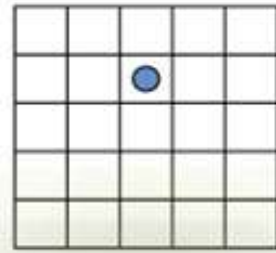
overlay



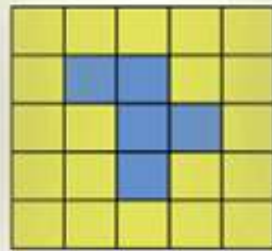
filter result

# Pooling Layer

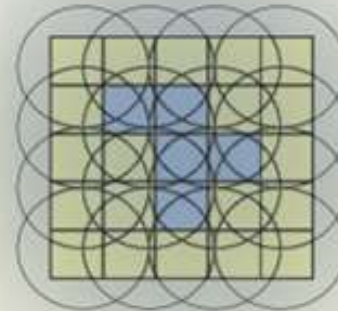
Is there a way for our filters to match the input despite slight translations?  
we can make the filters look in its surrounding as well



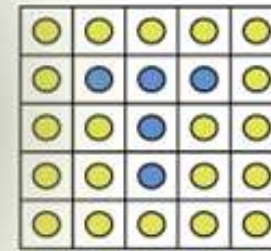
blurry  
filter



perfect  
image



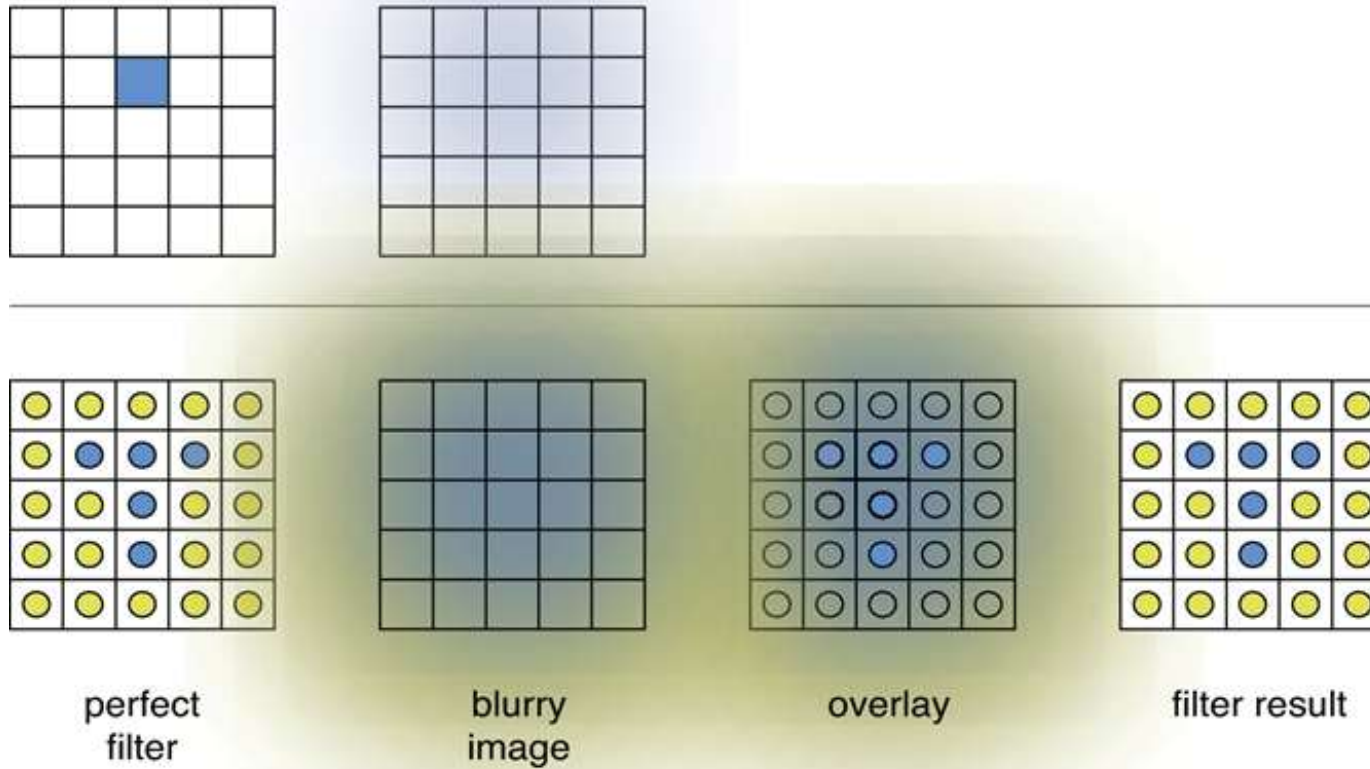
overlay



filter result

# Pooling Layer

A better way would be to blur the input based on small regions. This is called pooling



# Pooling Layer

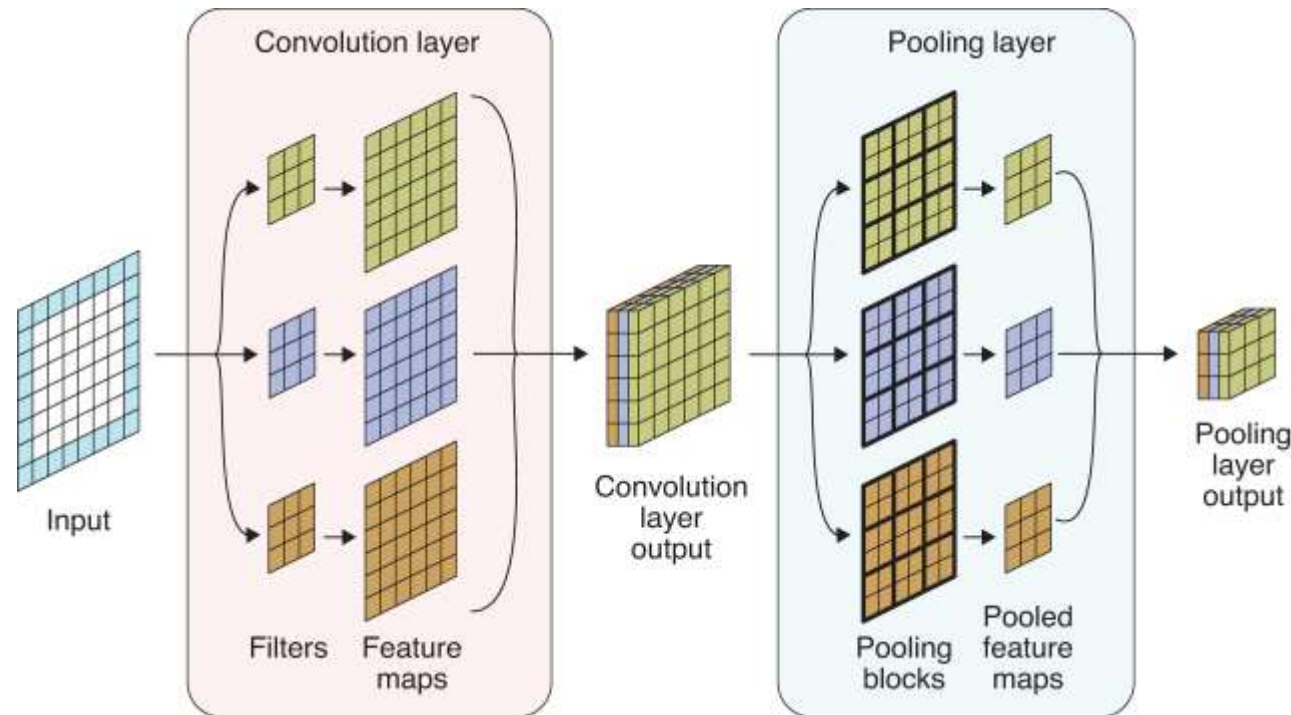
Pooling frees our filters to be precisely in the right place and also reduce the feature map size

|    |     |    |   |
|----|-----|----|---|
| 3  | 2   | -3 | 2 |
| 1  | 6   | 20 | 5 |
| 4  | -13 | 2  | 6 |
| -2 | 3   | 9  | 3 |

|    |     |    |   |
|----|-----|----|---|
| 3  | 2   | -3 | 2 |
| 1  | 6   | 20 | 5 |
| 4  | -13 | 2  | 6 |
| -2 | 3   | 9  | 3 |

|    |   |
|----|---|
| 3  | 6 |
| -2 | 5 |

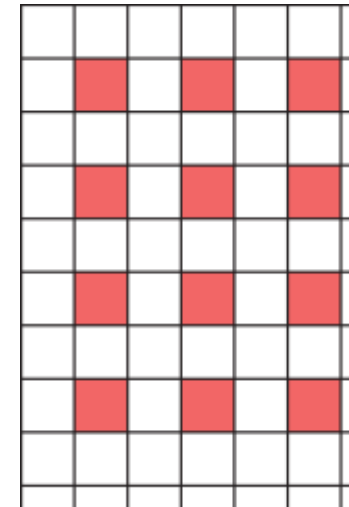
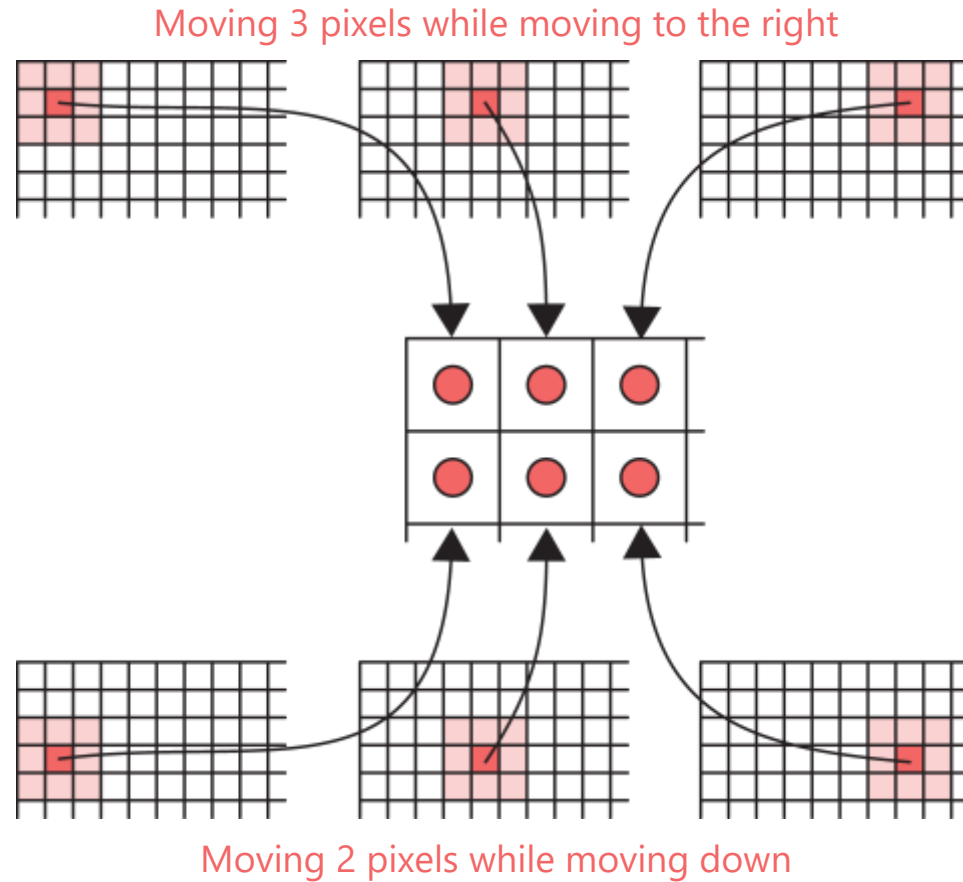
|   |    |
|---|----|
| 6 | 20 |
| 4 | 9  |

| Average | Max |


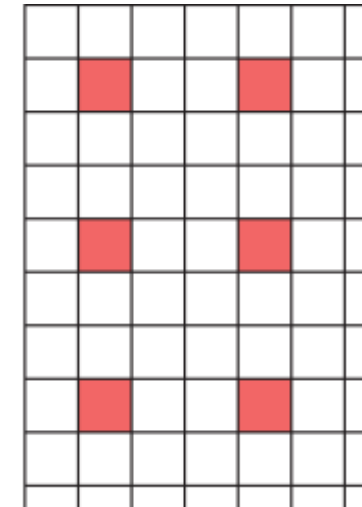


# Striding

Instead of sweeping our filters over one pixel at a time, we can move more than one pixel



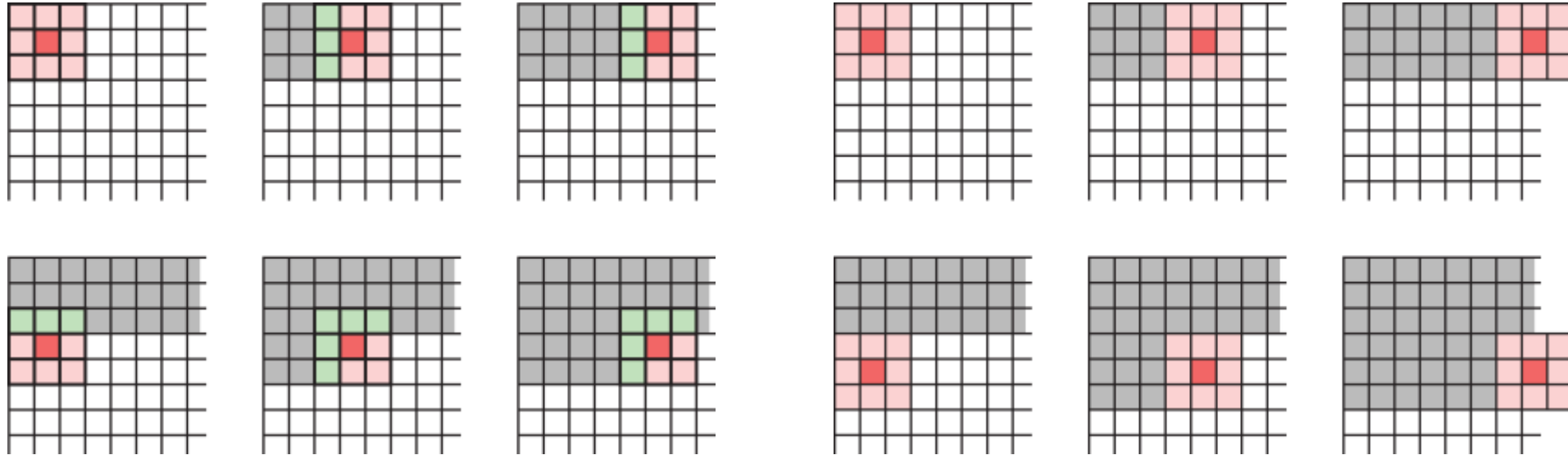
Stride = 2  
Center Filter over  
every other pixel



Stride = 3  
Center Filter over  
every third pixel

# Striding

Instead of sweeping our filters over one pixel at a time, we can move more than one pixel

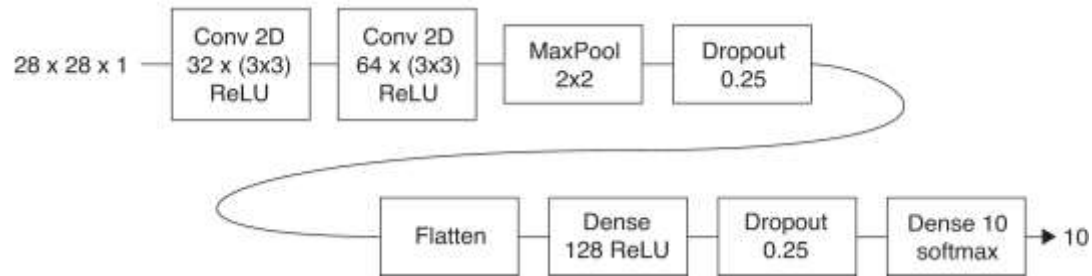


Stride = 2  
Center Filter over every other pixel

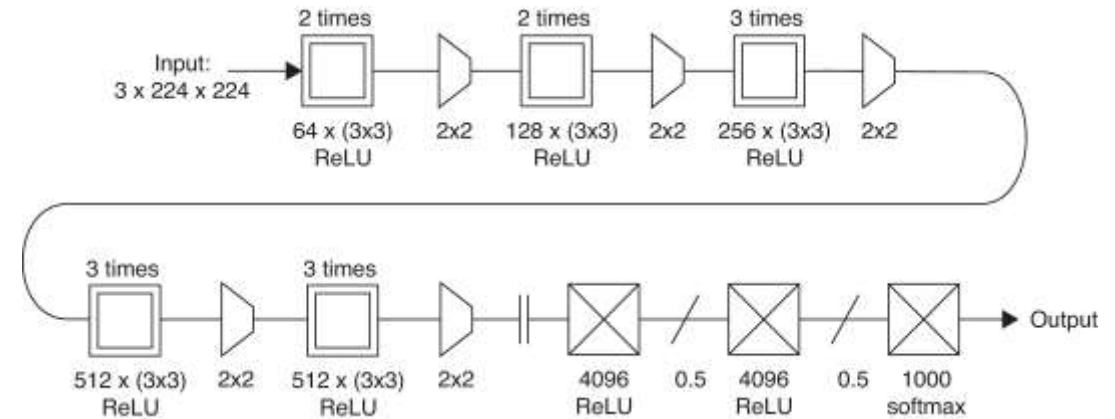
Stride = 3  
Center Filter over every third pixel

# Convnets in Practice

Convolutional Neural Networks (CNNs) are made of convolutional layers and pooling layers (along with others)



LeNet Architecture



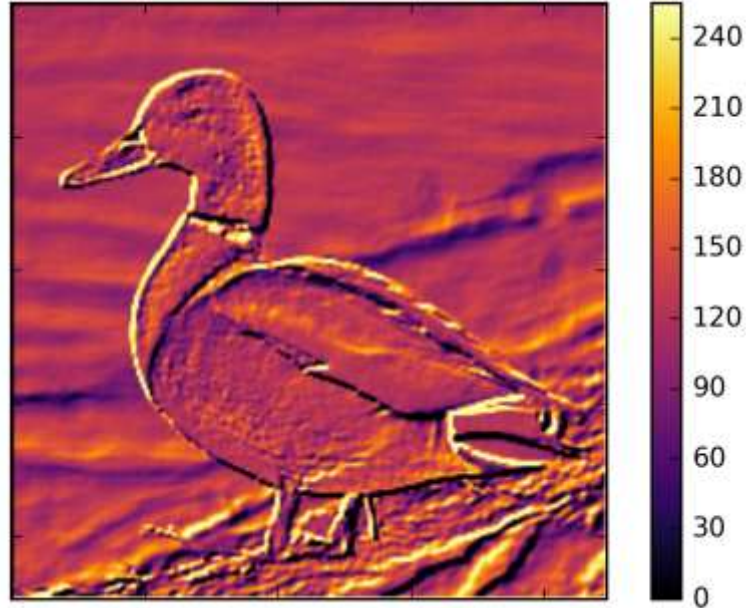
VGG16 Architecture

# Visualizing Feature Maps

Let's visualize the feature maps obtained from various CNN blocks of VGG16



Input Image



Feature map of a single filter



# Visualizing Feature Maps

Let's visualize the feature maps obtained from various CNN blocks of VGG16



Input Image

block1\_conv1



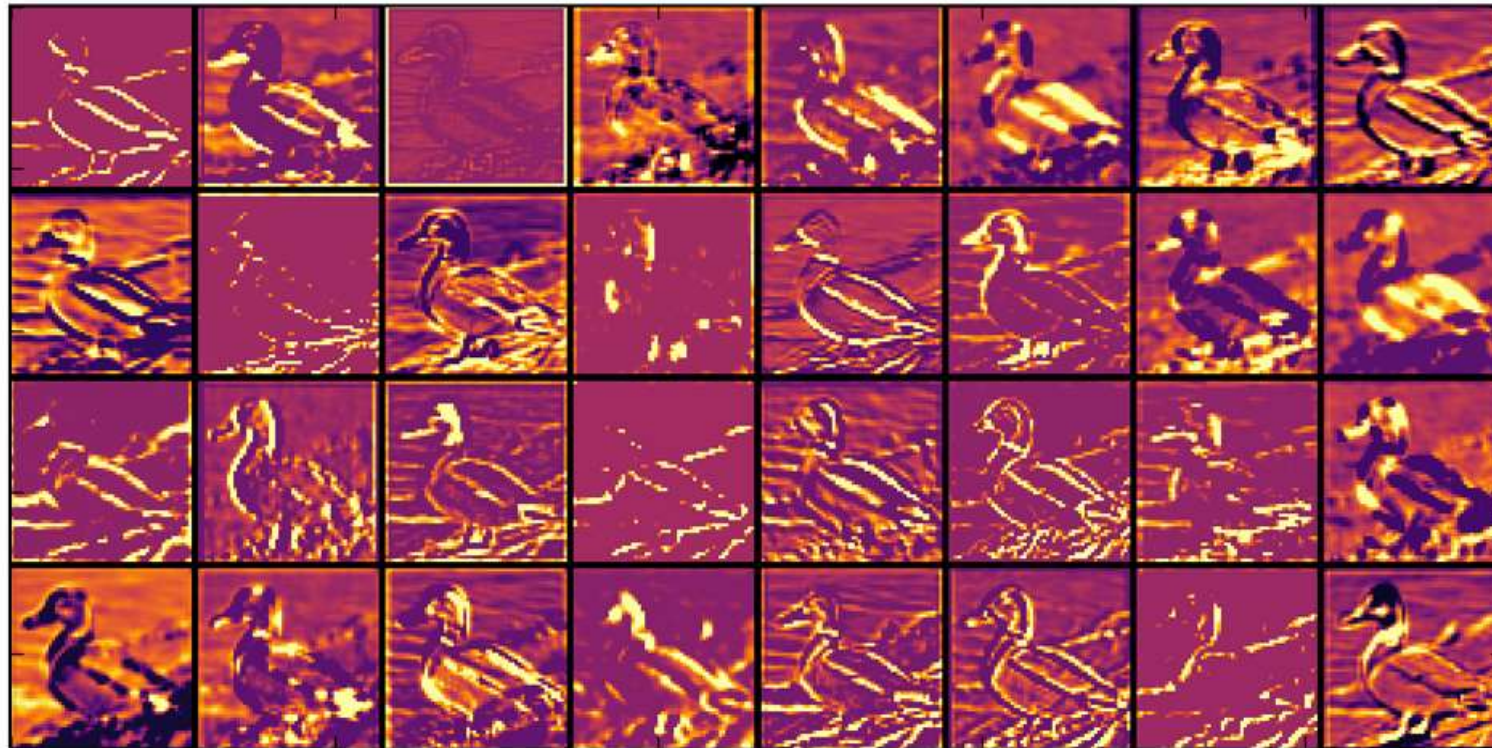
# Visualizing Feature Maps

Let's visualize the feature maps obtained from various CNN blocks of VGG16



Input Image

block3\_conv1





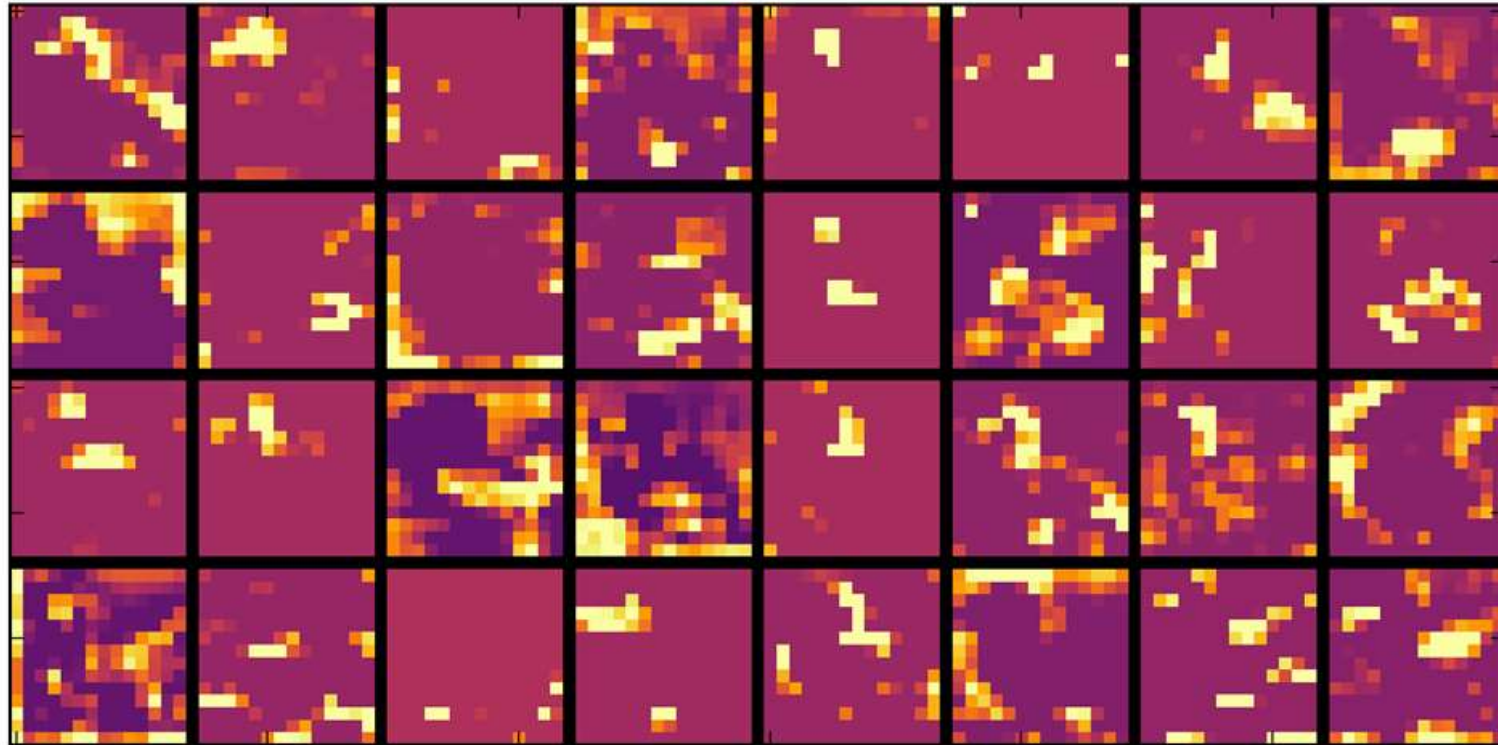
# Visualizing Feature Maps

Let's visualize the feature maps obtained from various CNN blocks of VGG16



Input Image

block5\_conv1



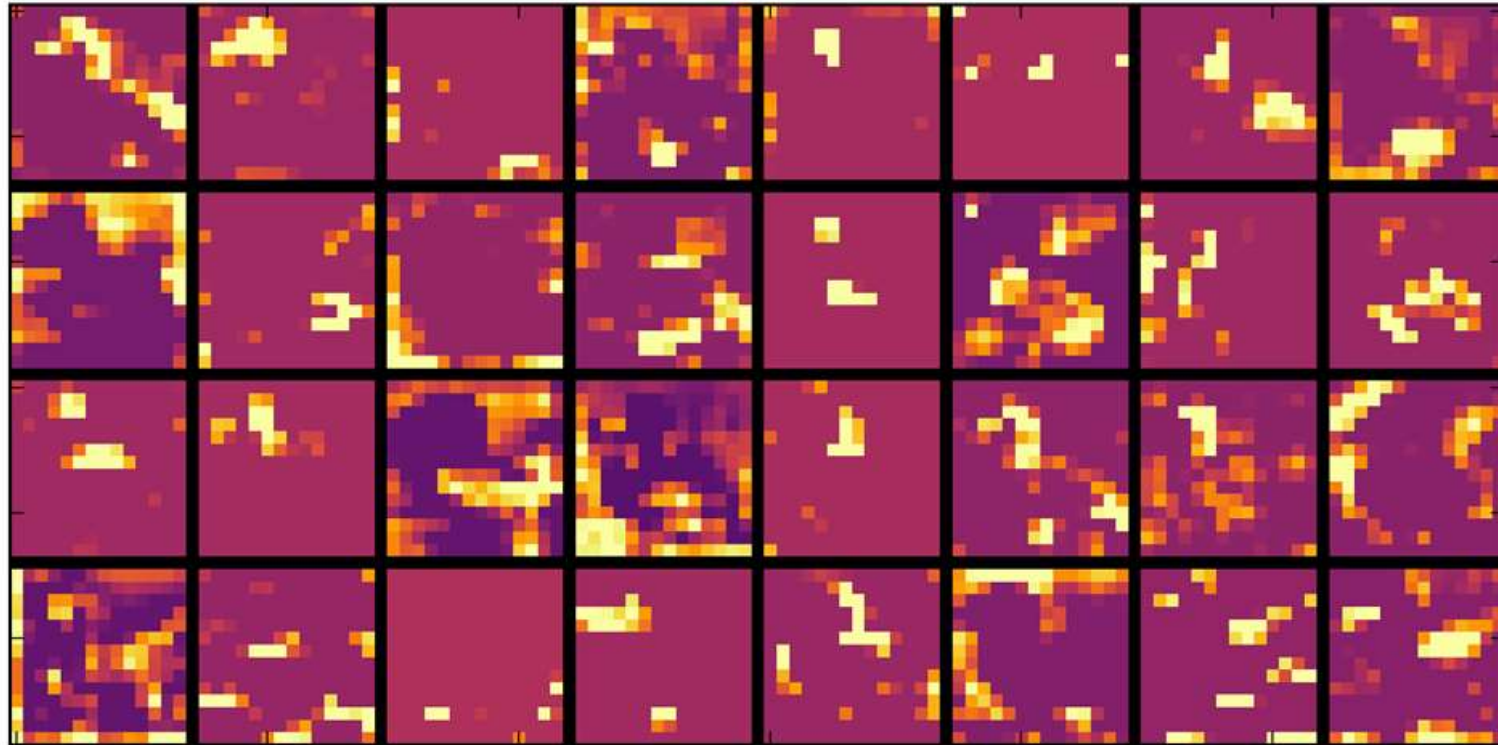
# Visualizing Feature Maps

Let's visualize the feature maps obtained from various CNN blocks of VGG16



Input Image

block5\_conv1



Thank You

