Deep Learning Bootcamp

A hands-on intensive workshop covering neural fundamentals,
computer vision, and natural language processing using modern deep learning tools.

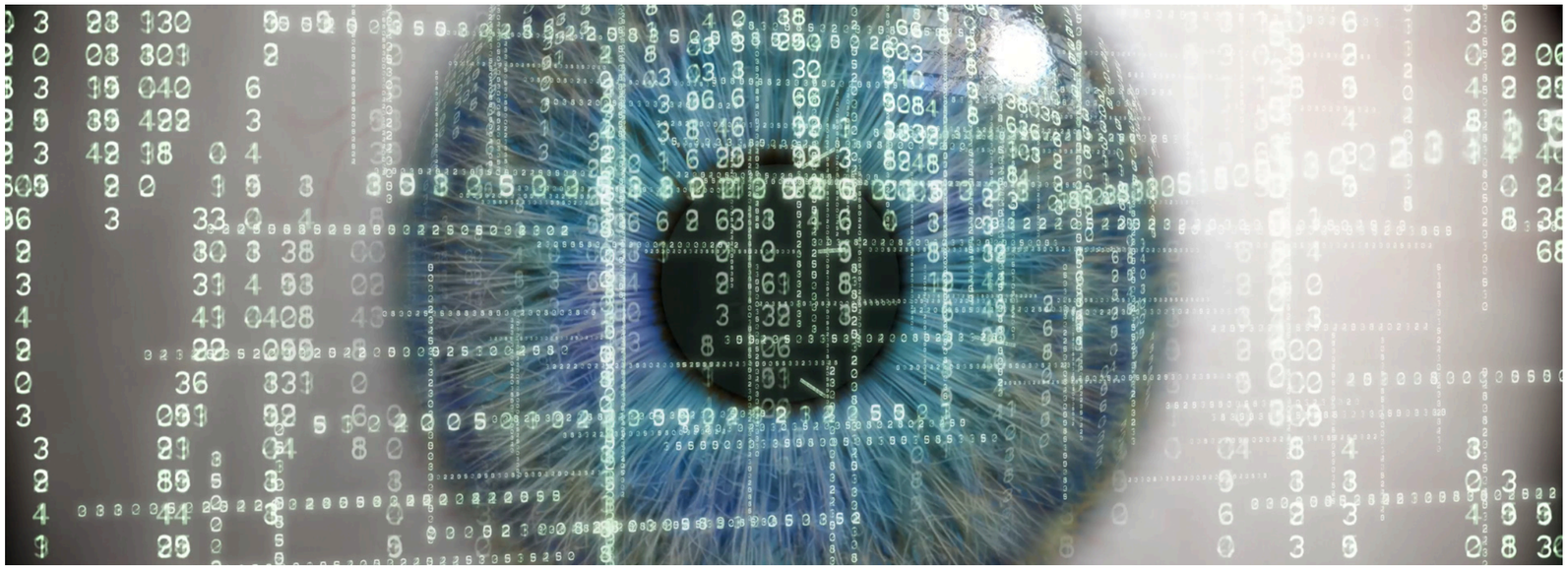
by: Lama Ayash

Day 2

Course Outlines

Computer Vision

Computer Vision (CV) enables machines to see, understand, and interpret the visual world. Inspired by how humans perceive and process visual information.



Computer Vision

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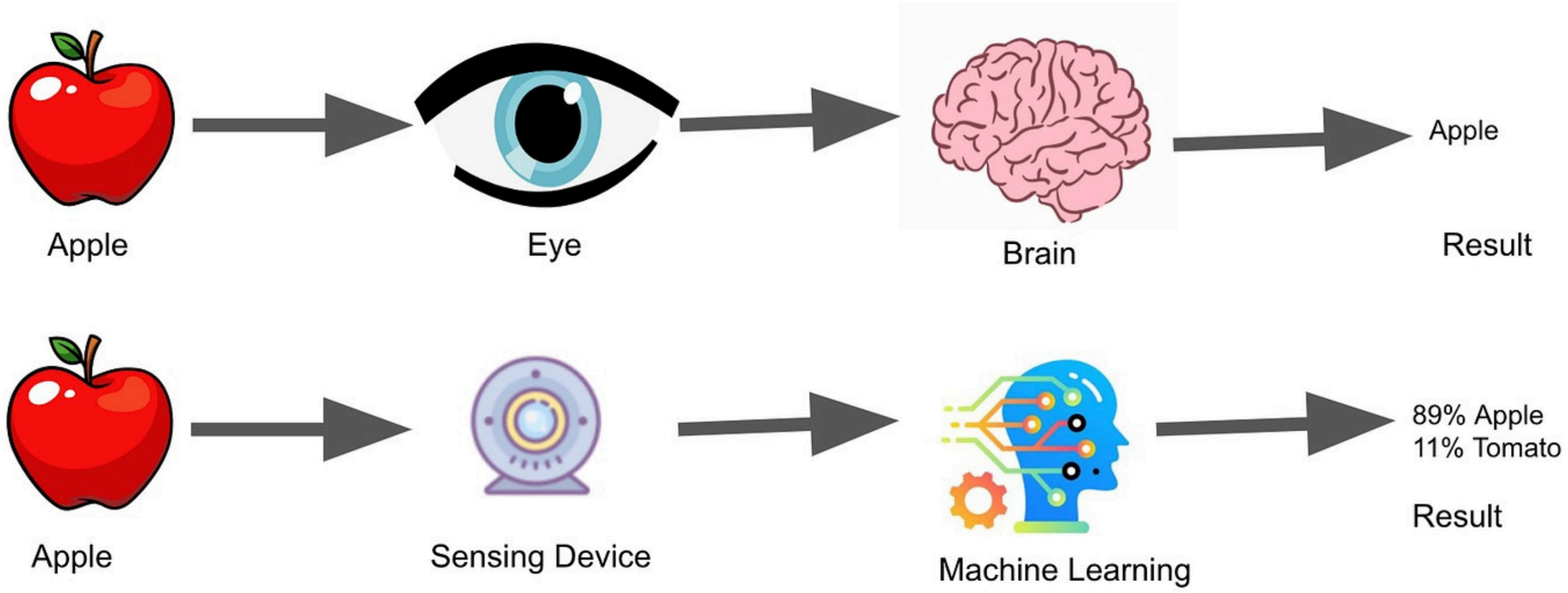


Computer Vision Tasks

- Image Classification

Classification is the simplest and most common task in computer vision.

The class in this case is a cat

The class in this case is a dog

Computer Vision Tasks

- Object Detection and Localization

  The goal is to detect and locate specific objects within a larger image.

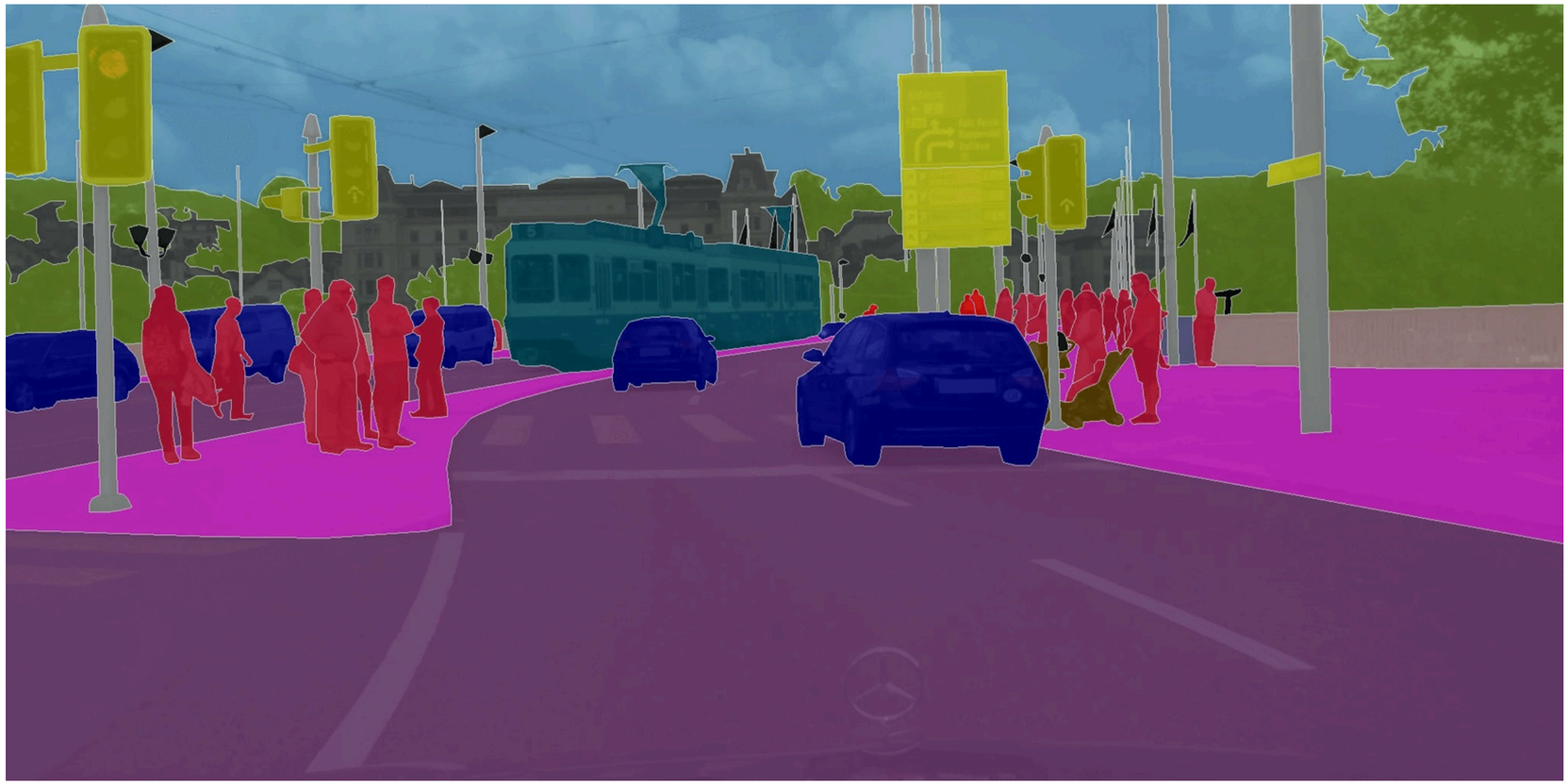
Class: No mask detected

Class: A mask is detected in the image

Computer Vision Tasks

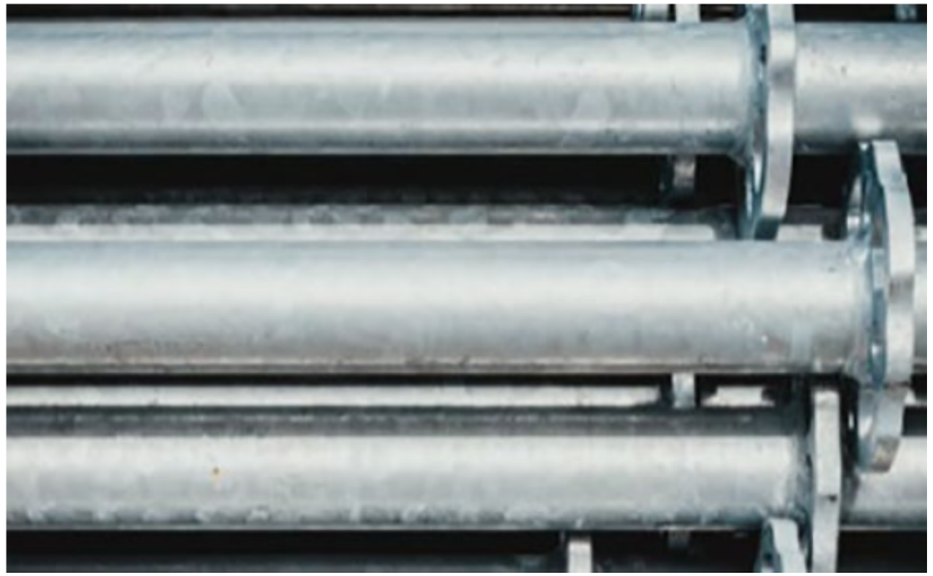
- Image Segmentation

  Segmentation divides an image into distinct regions or objects based on color, texture, and boundaries.



Computer Vision Tasks

- Anomaly Detection
  - Detects unusual patterns or defects in images by comparing them to normal reference data.



Perfect examples of steel pipes

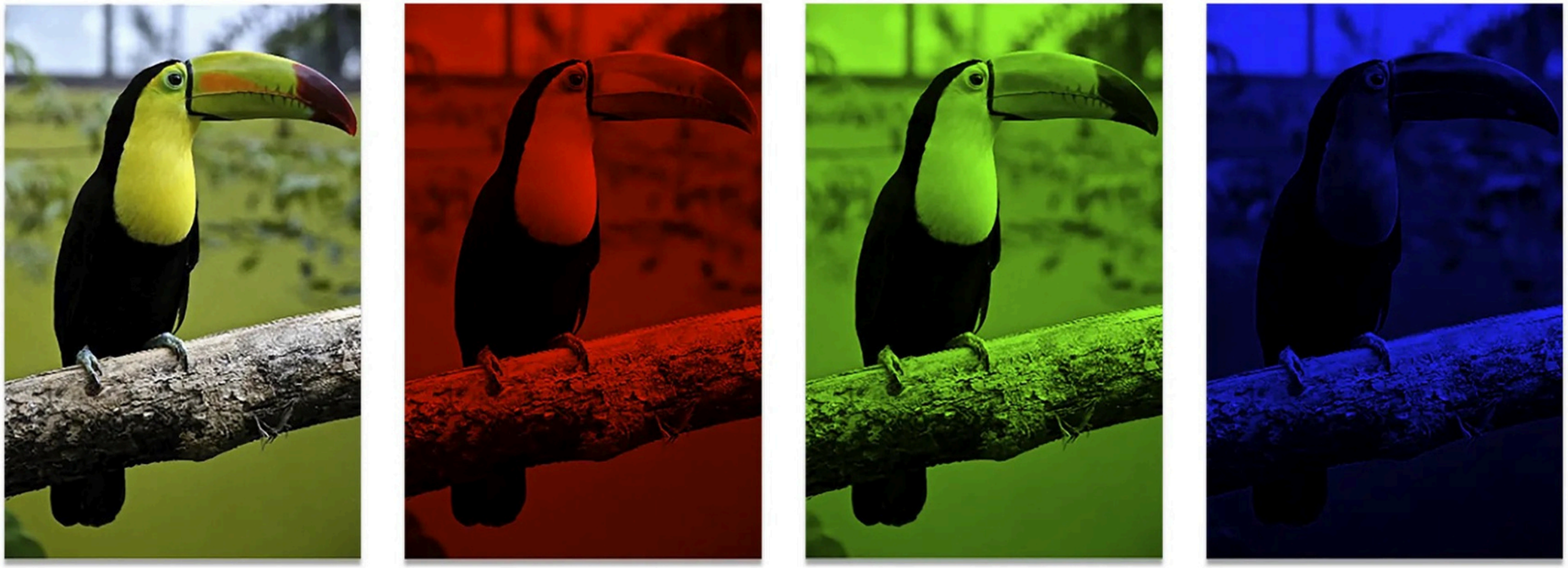
Channels

- A **channel** represents one dimension of color or intensity information in an image.

2	36	40	200
195	190	20	180
40	54	200	200
30	40	200	180

Channles

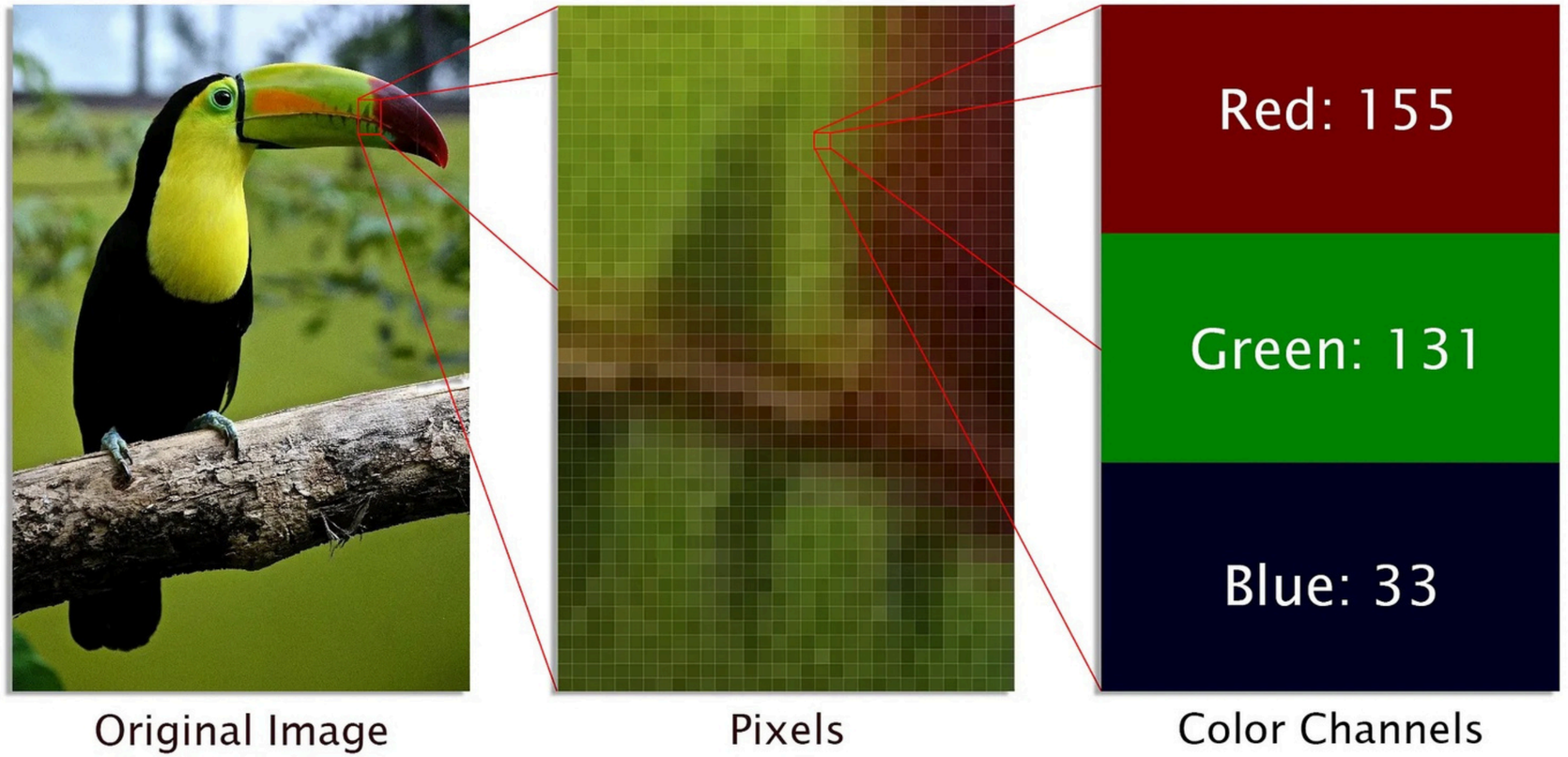
- A color image has three channels: Red, Green, and Blue (RGB).



Original Image | Red Channel | Green Channel | Blue Channel

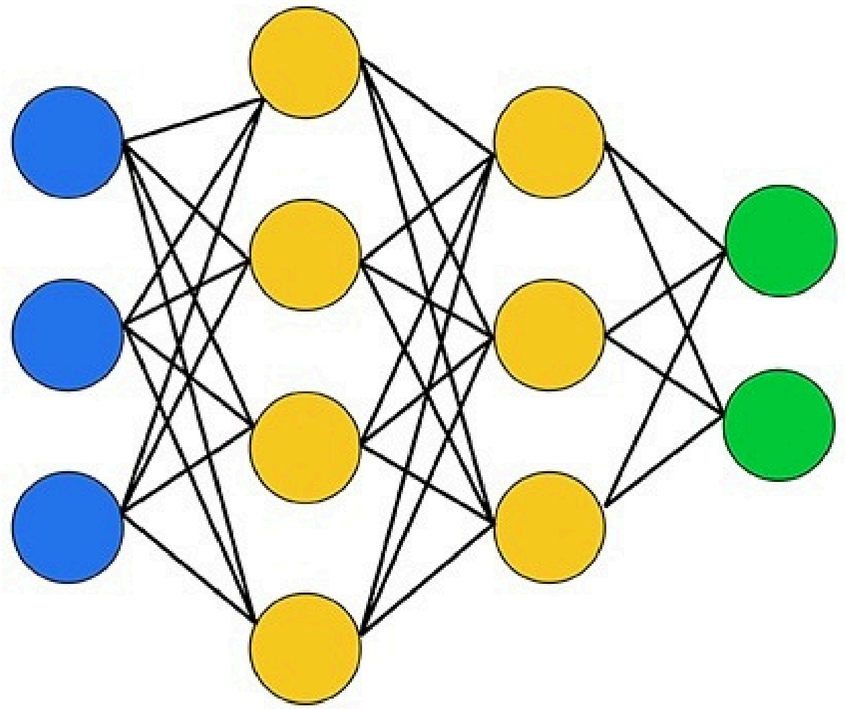
Channles

- A color image has three channels: Red, Green, and Blue (RGB).



Vision Models

- A color image has three channels: Red, Green, and Blue (RGB).



But can we apply the same approach to images?

Vision Models

Little or no invariance to shifting, scaling, and other forms of distortion

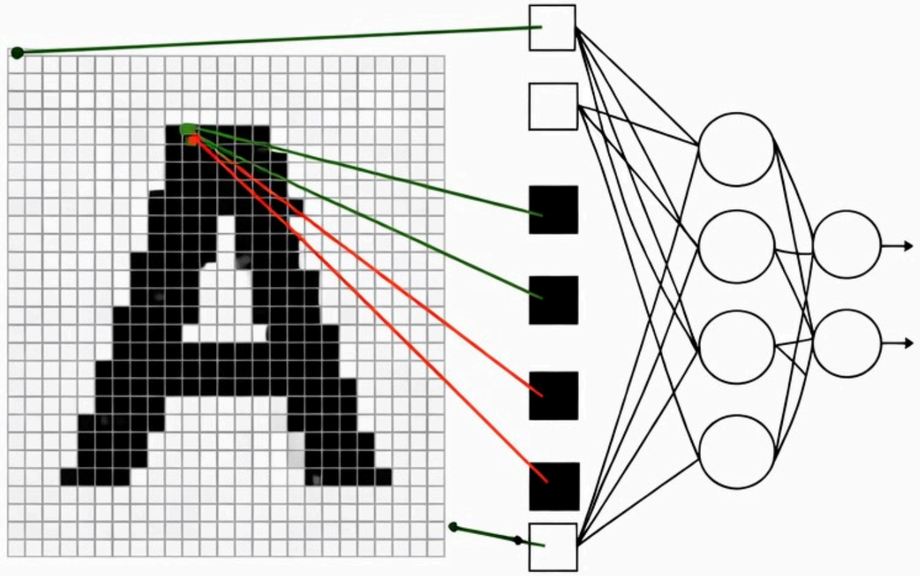


Figure 2: Original "A" character.

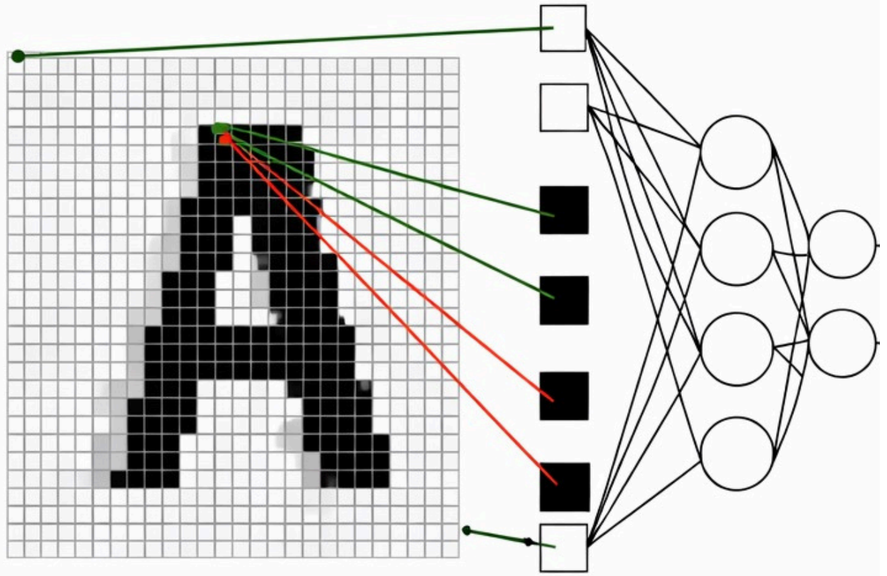
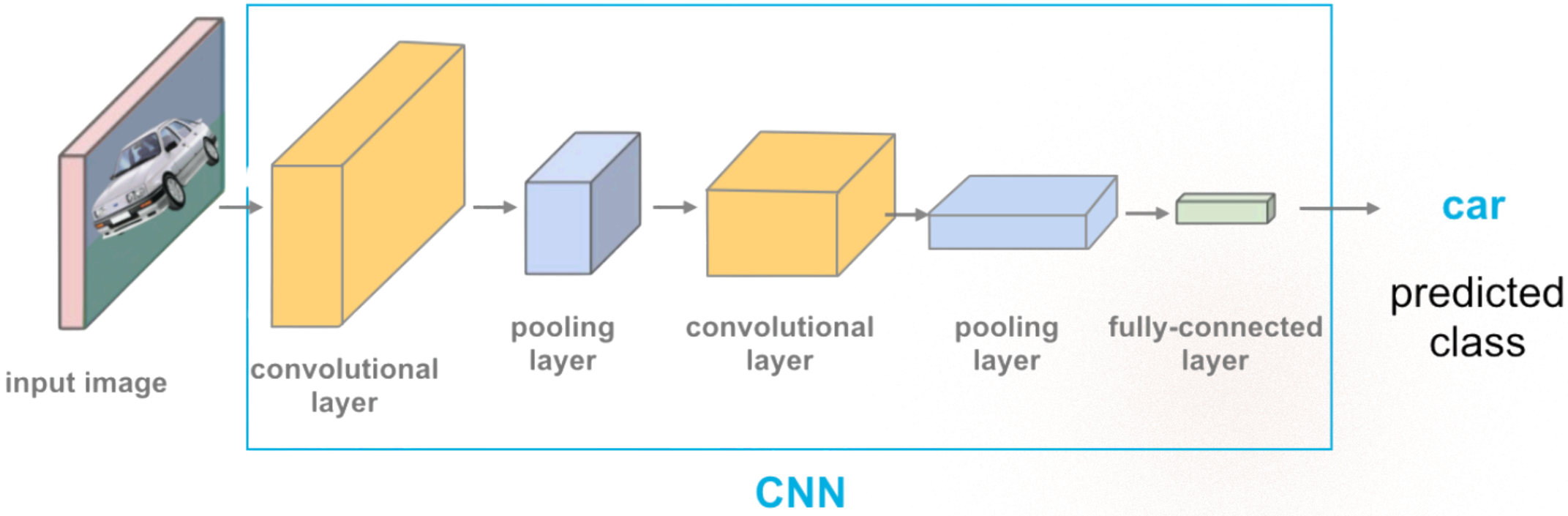


Figure 3: Shifted "A" character.

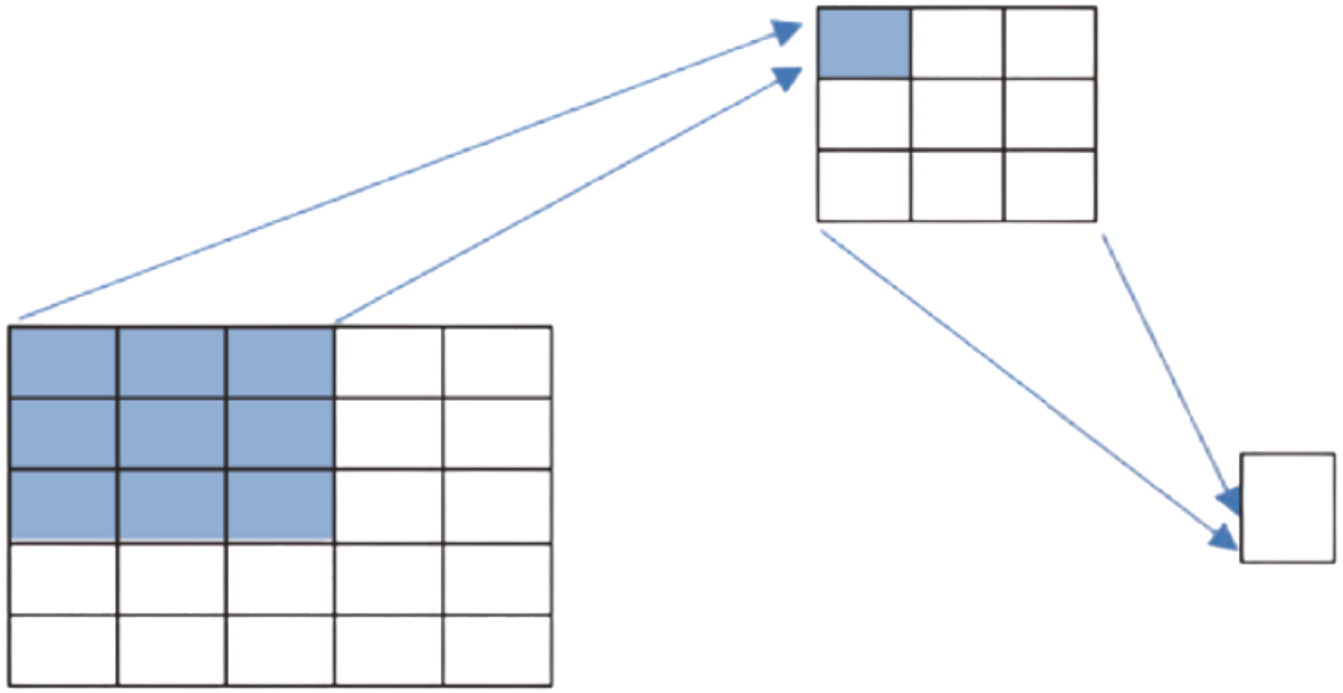
Convolutional Neural Networks

- A CNN is a deep network of neurons with learnable filters that perform convolution operations on inputs, usually images, to extract hierarchical features.



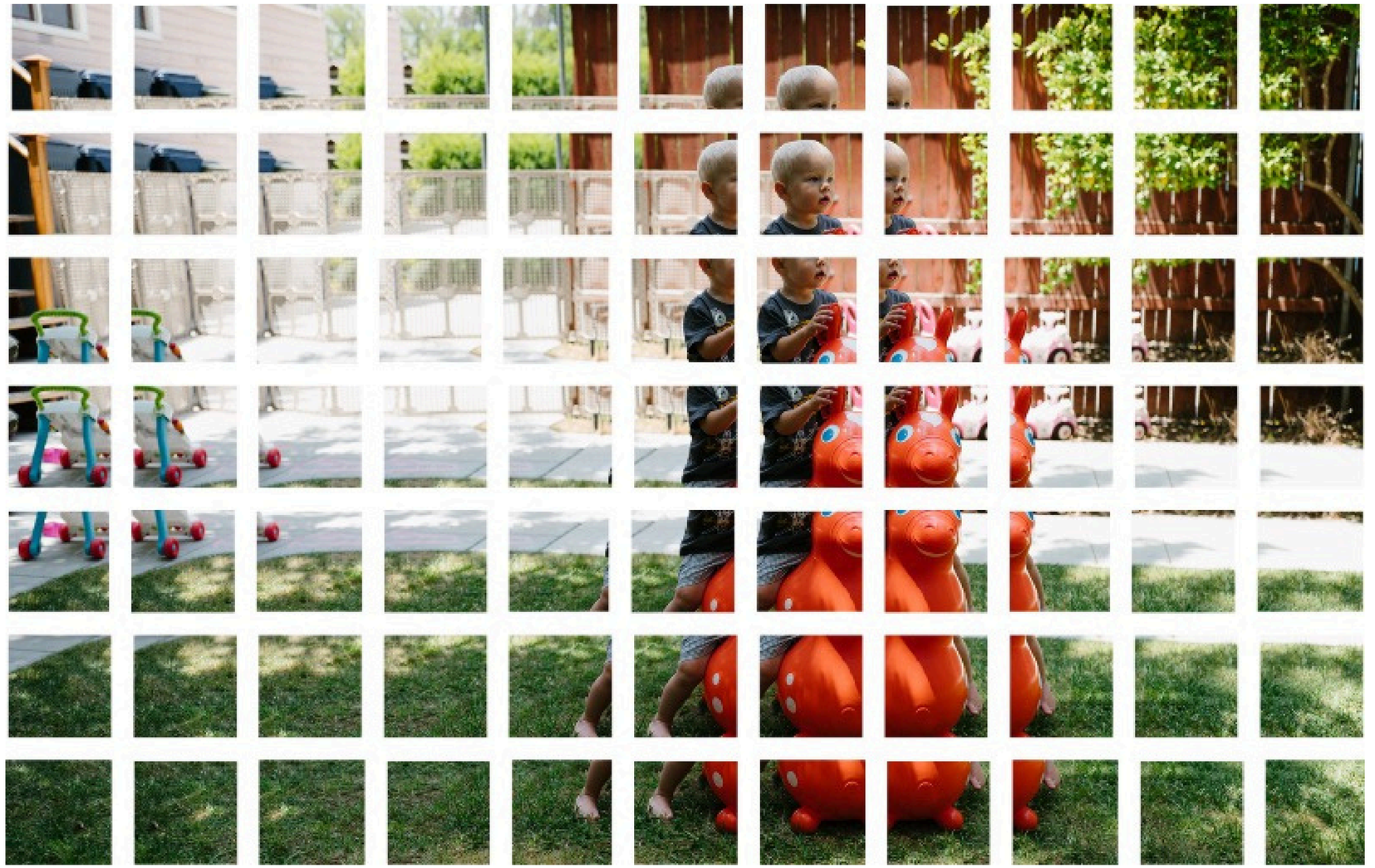
Convolutional Neural Networks

- It applies a set of learnable filters **(kernels)** that slide across the input, performing convolution operations to extract local patterns like edges, textures, and shapes.



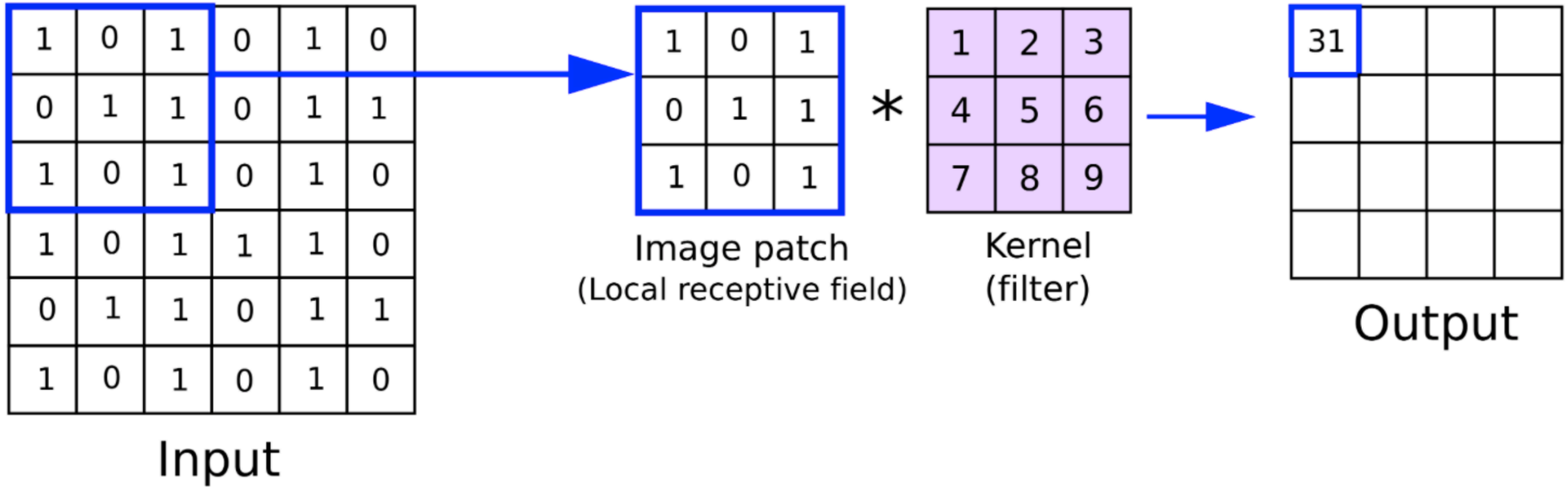
Convolutional Neural Networks

Convolutional Neural Networks



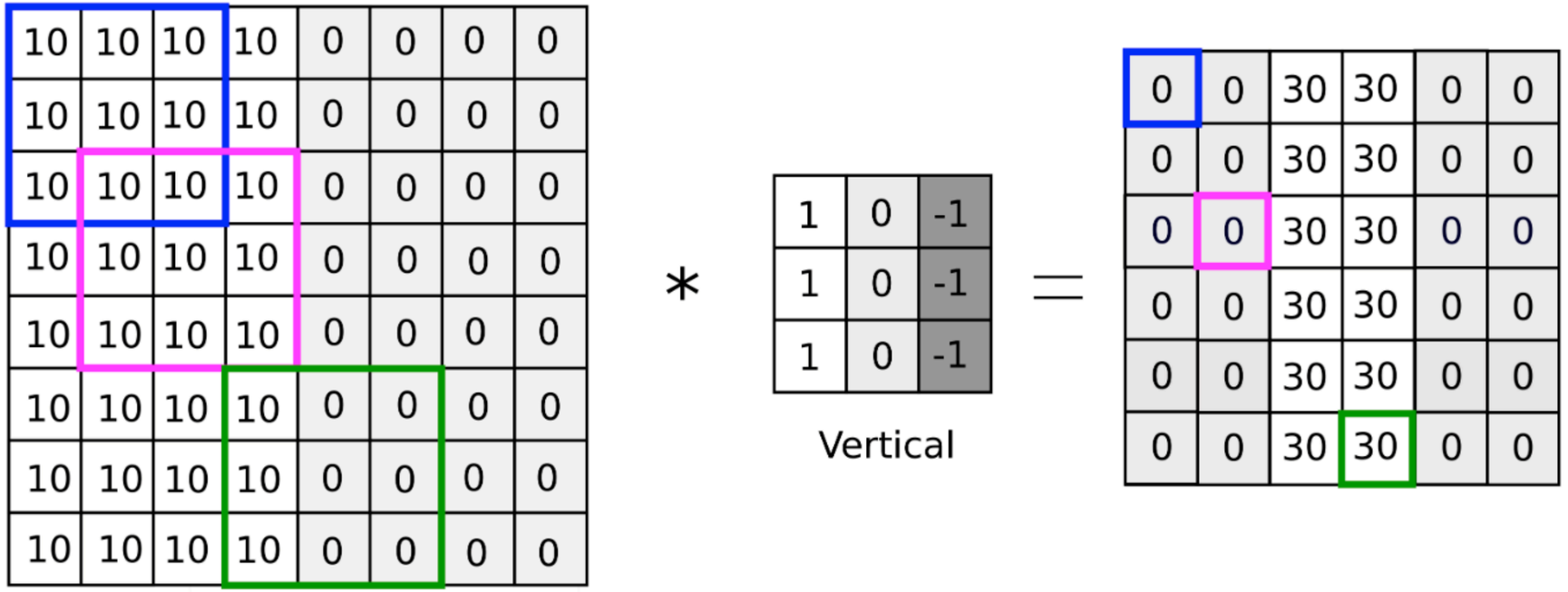
Convolution Layer

- Convolution involves applying a kernel (filter) over an image to extract features.
- A kernel is a small matrix (like: 3×3, 5×5).



Convolution Layer

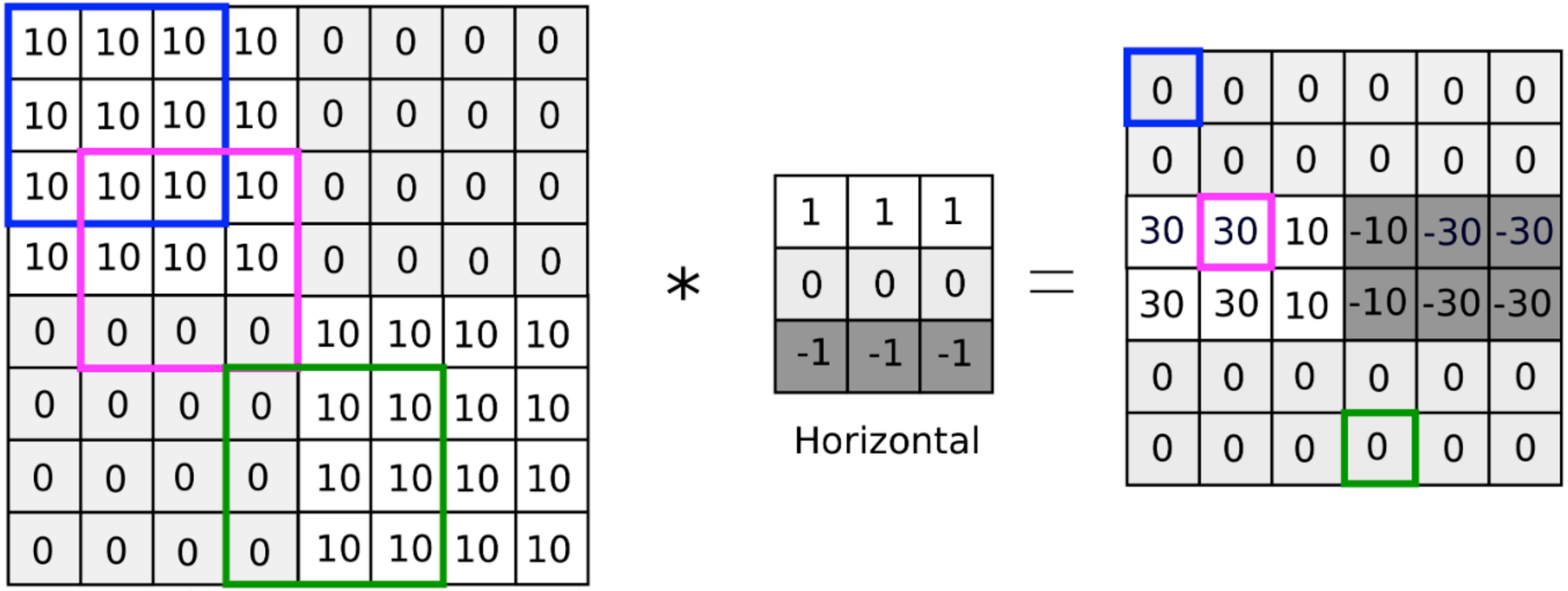
- Edge detection is an example of the usefulness of convolution in identifying the regions in an image where there is a sharp change in colors or intesntiy.



An example of vertical edge detection

Convolution Layer

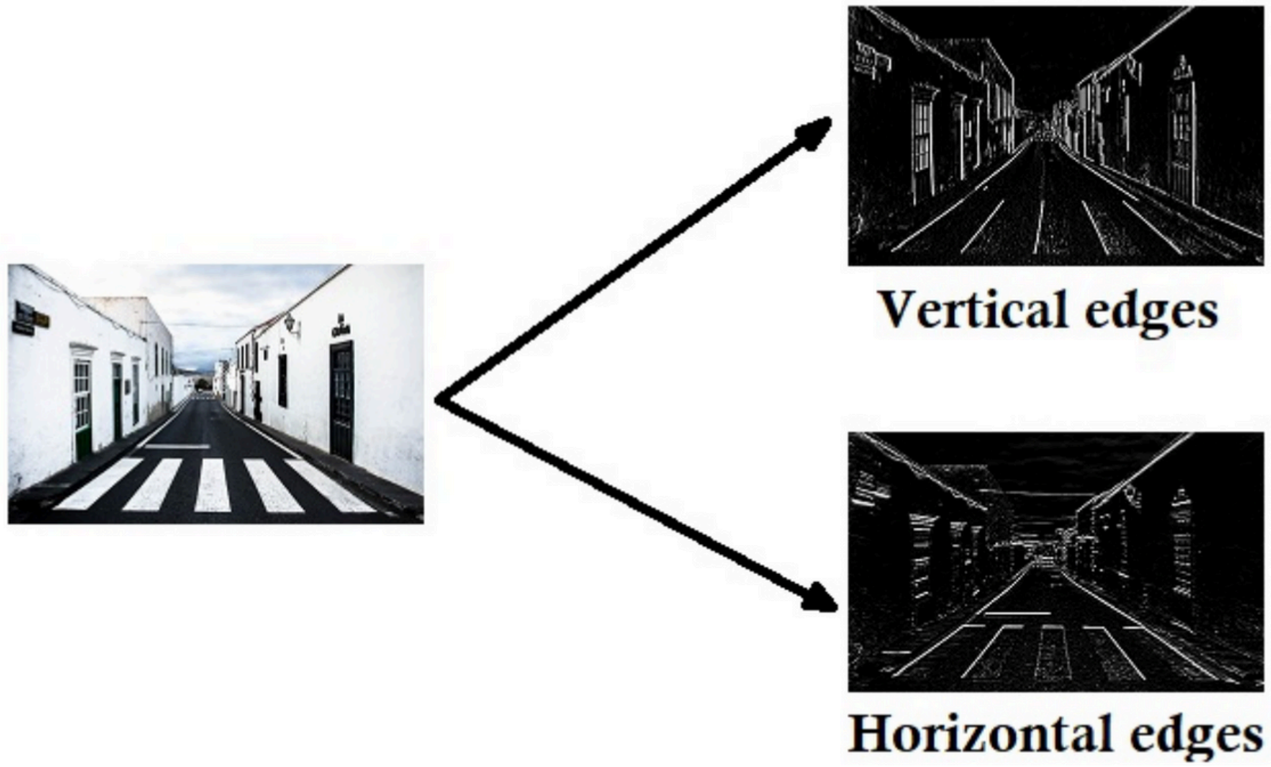
- Edge detection is an example of the usefulness of convolution in identifying the regions in an image where there is a sharp change in colors or intesntiy.



An example of horizontal edge detection

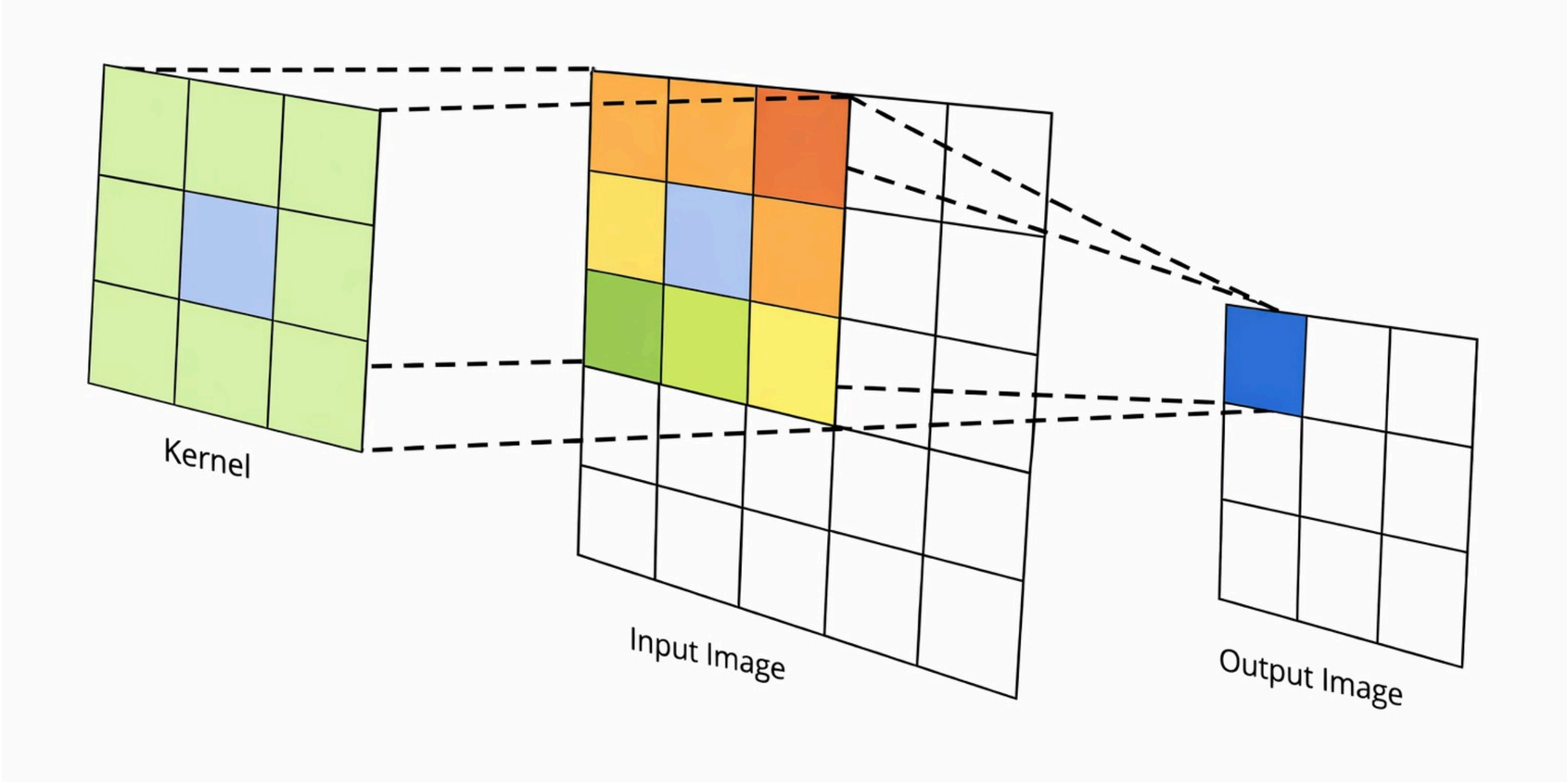
Convolution Layer

- Edge detection is an example of the usefulness of convolution in identifying the regions in an image where there is a sharp change in colors or intesntiy.



Convolution Layer

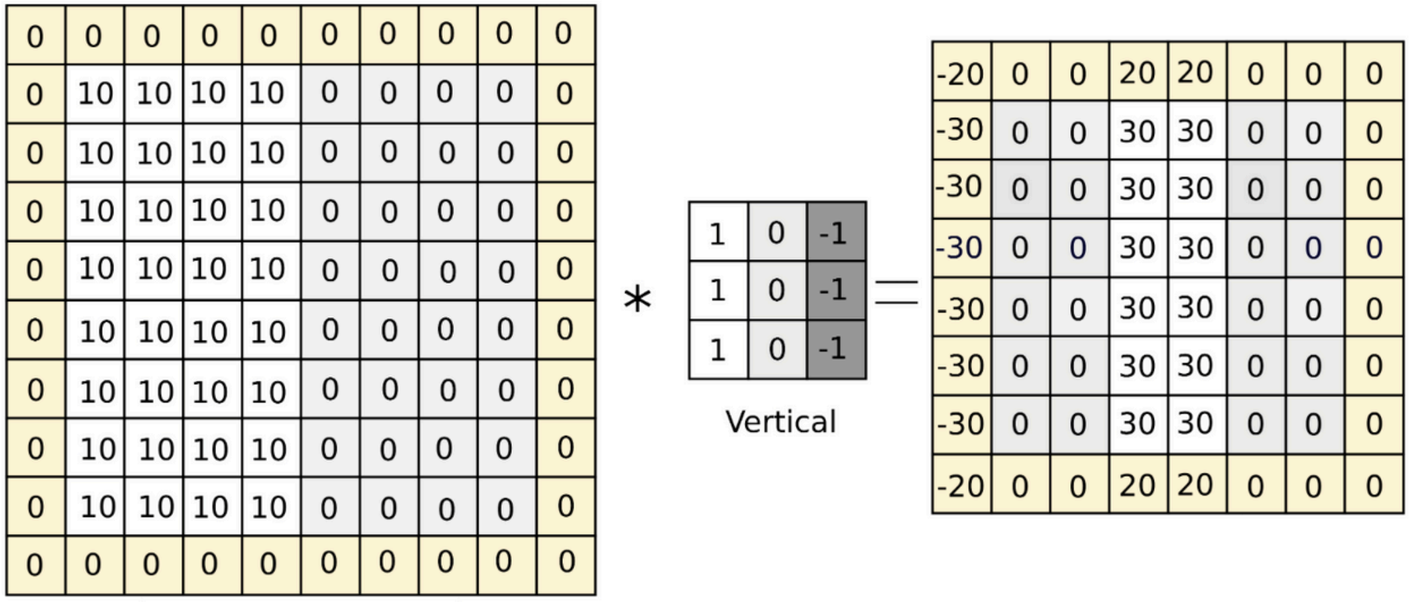
- The kernel is slid across the image, computing a dot product with local regions at each position.



Padding

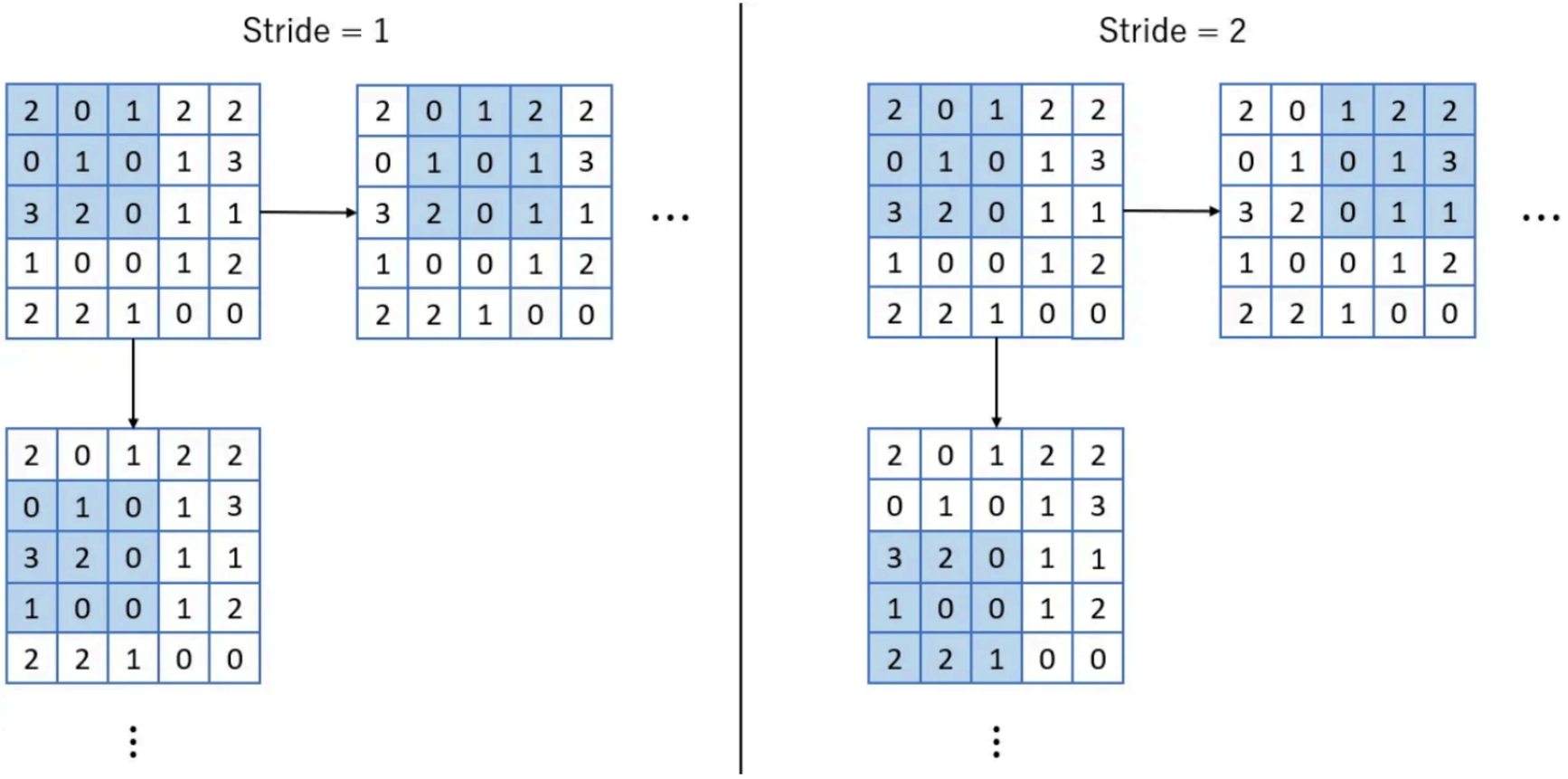
- Padding means adding extra layers of zeros around the image borders.
- If padding size = p, new input dimension becomes:

$$(n + 2p) \times (n + 2p)$$



Stride

- Stride refers to the speed at which a filter translates across an image.



Output Dimensions in Convolution

$$n_{\text{out}} = \left\lfloor \frac{n_{\text{in}} + 2p - k}{s} \right\rfloor + 1$$

n_{in} : number of input features

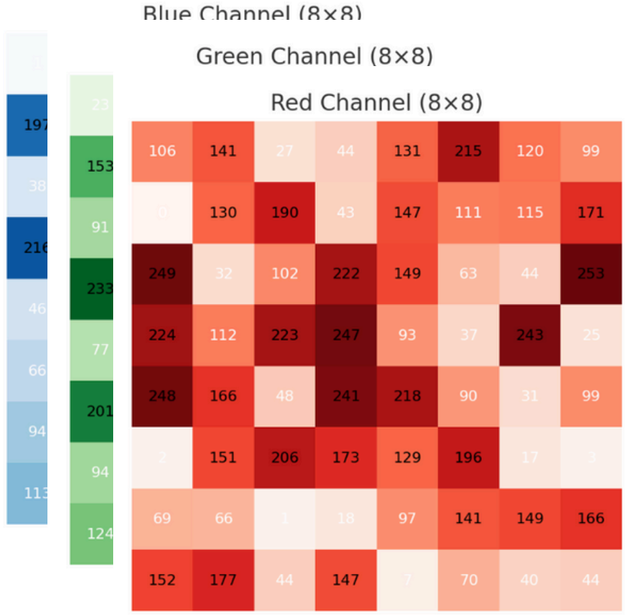
n_{out} : number of output features

k : convolution kernel size

p : convolution padding size

s : convolution stride

Output Dimensions in Convolution



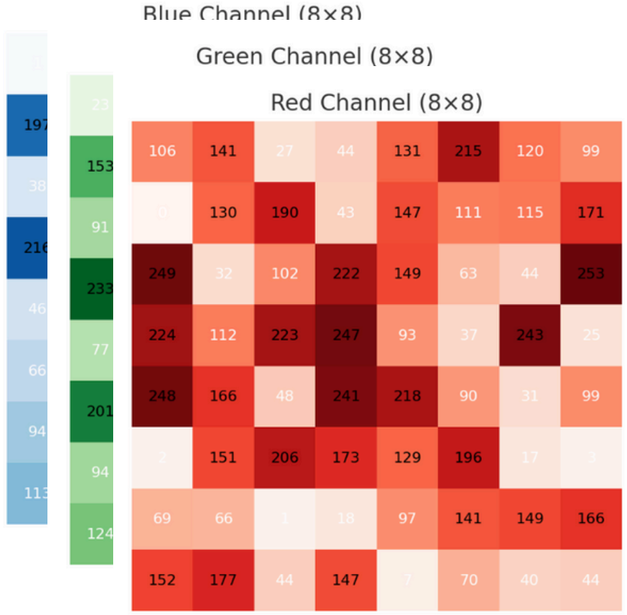
Hight=8

Width=8

Depth=3

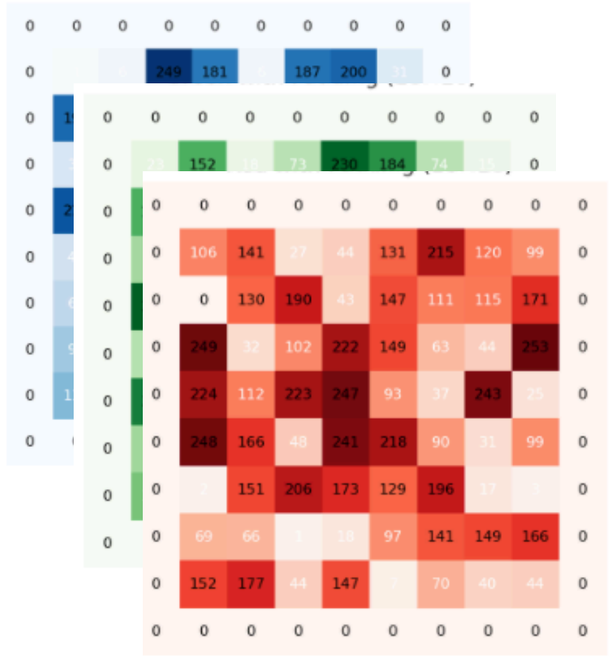
Output Dimensions in Convolution

Input size:



(8*8*3)

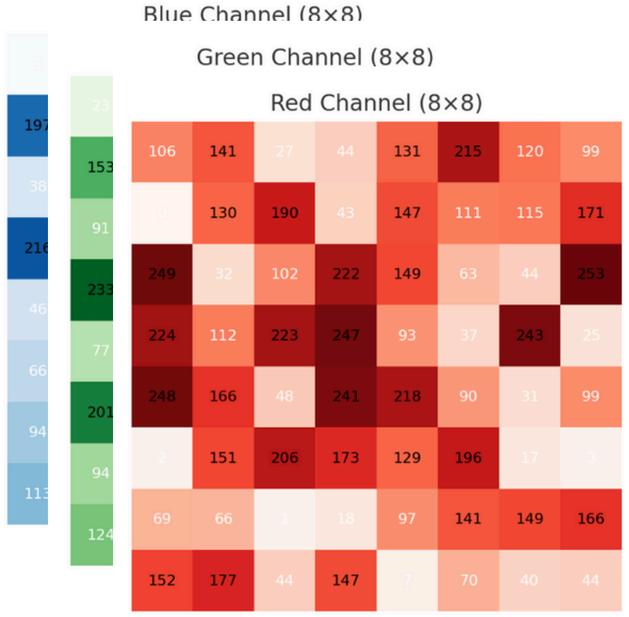
Padding:



(1)

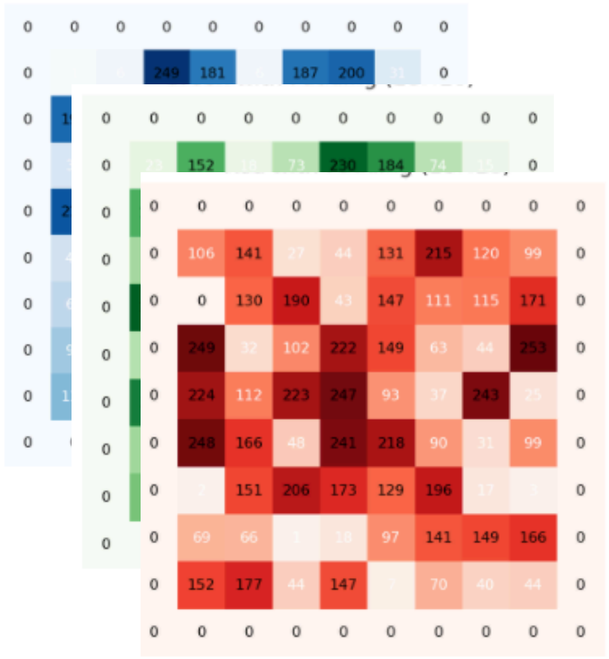
Output Dimensions in Convolution

Input size:



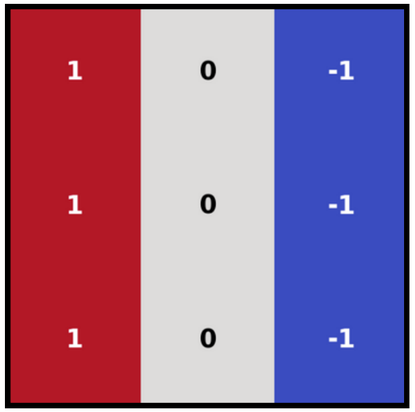
(8*8*3)

Padding:



(1)

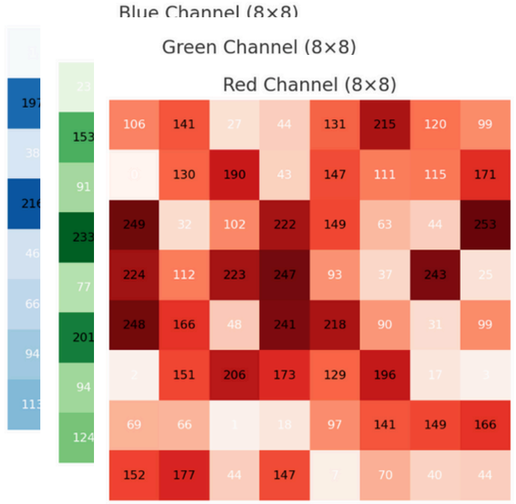
Kernel size:



(3*3)

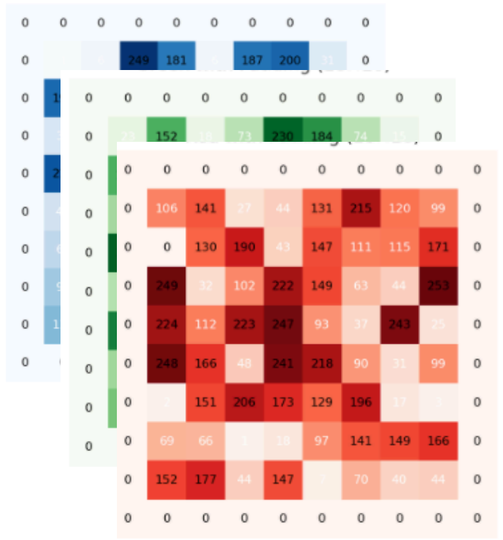
Output Dimensions in Convolution

Input size:



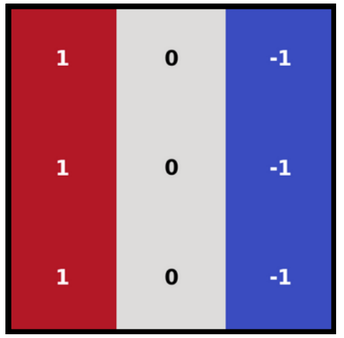
(8*8*3)

Padding:



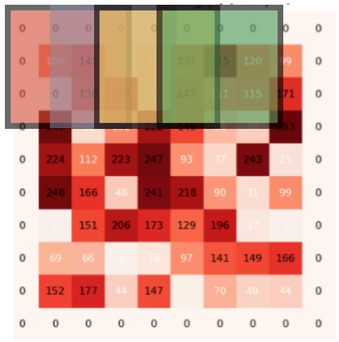
(1)

Kernel size:



(3*3)

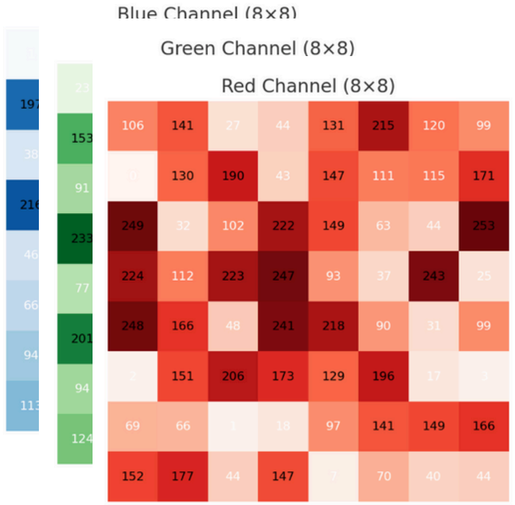
Stride:



(1)

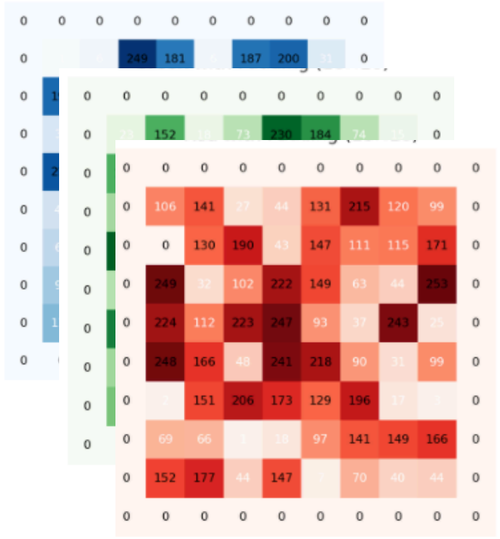
Output Dimensions in Convolution

Input size:



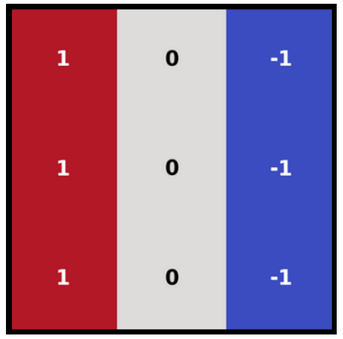
(8*8*3)

Padding:



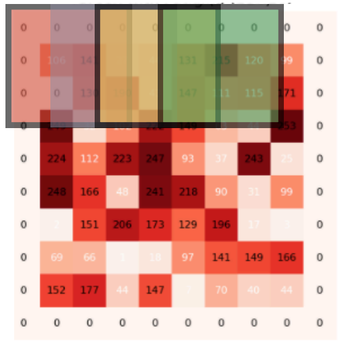
(1)

Kernel size:



(3*3)

Stride:



(1)

$$n_H[l] = \frac{n_H[l-1] + 2p[l] - f[l]}{s[l]} + 1$$

$$n_{out} = \frac{8 + 2(1) - 3}{1} + 1 = \frac{7}{1} + 1 = 8$$

Output Dimensions in Convolution

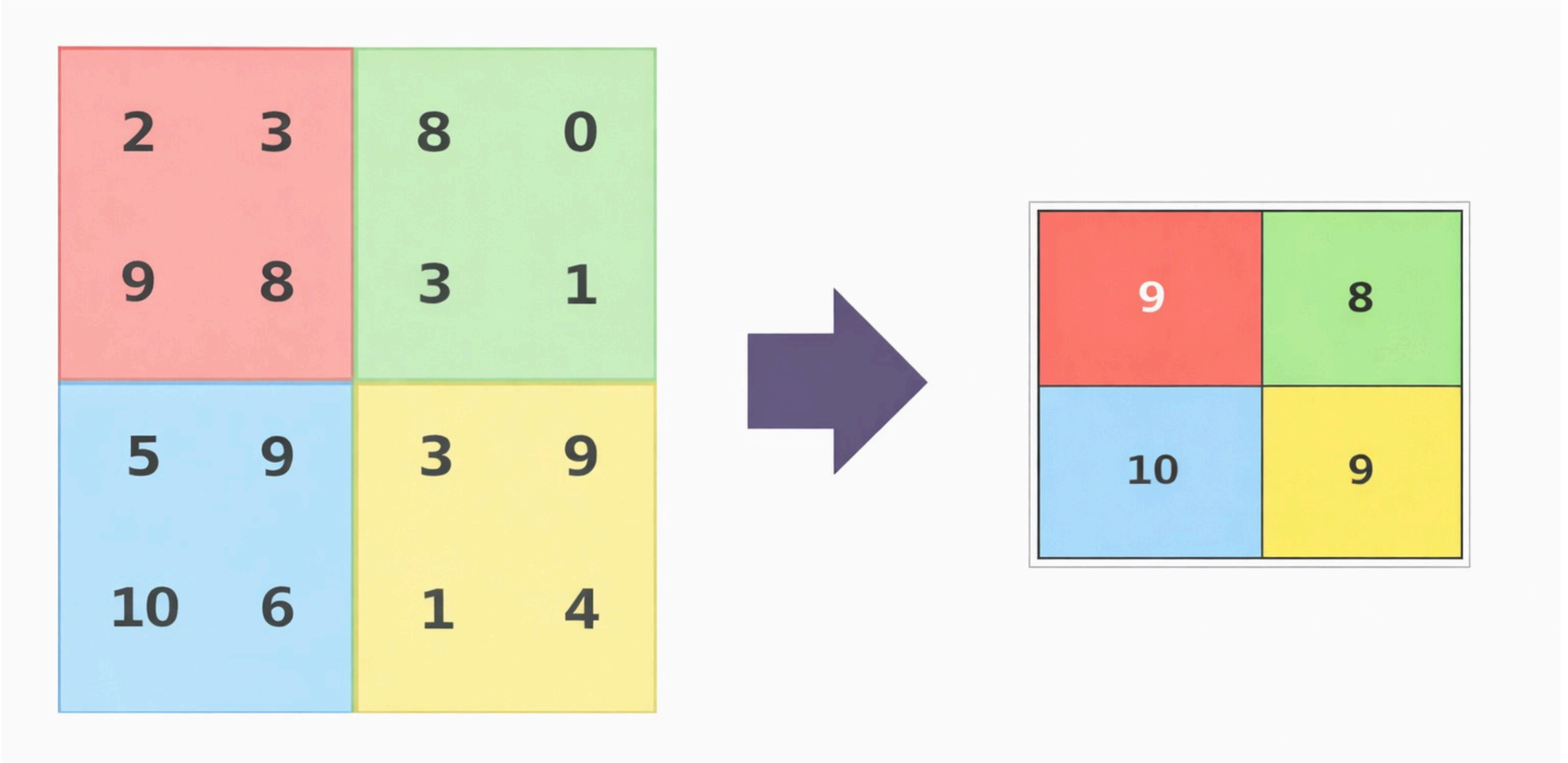
Input image size: 10 × 10 × 3
Kernel size: 5 × 5
Padding: 2
Stride: 2
Number of filters: 16

$$n_{\text{out}} = \left\lfloor \frac{n_{\text{in}} + 2p - k}{s} \right\rfloor + 1$$

Pooling Layer

- Pooling is used for dimensionality reduction in CNNs.
  It reduces the spatial size of feature maps while keeping important information.

- Max Pooling



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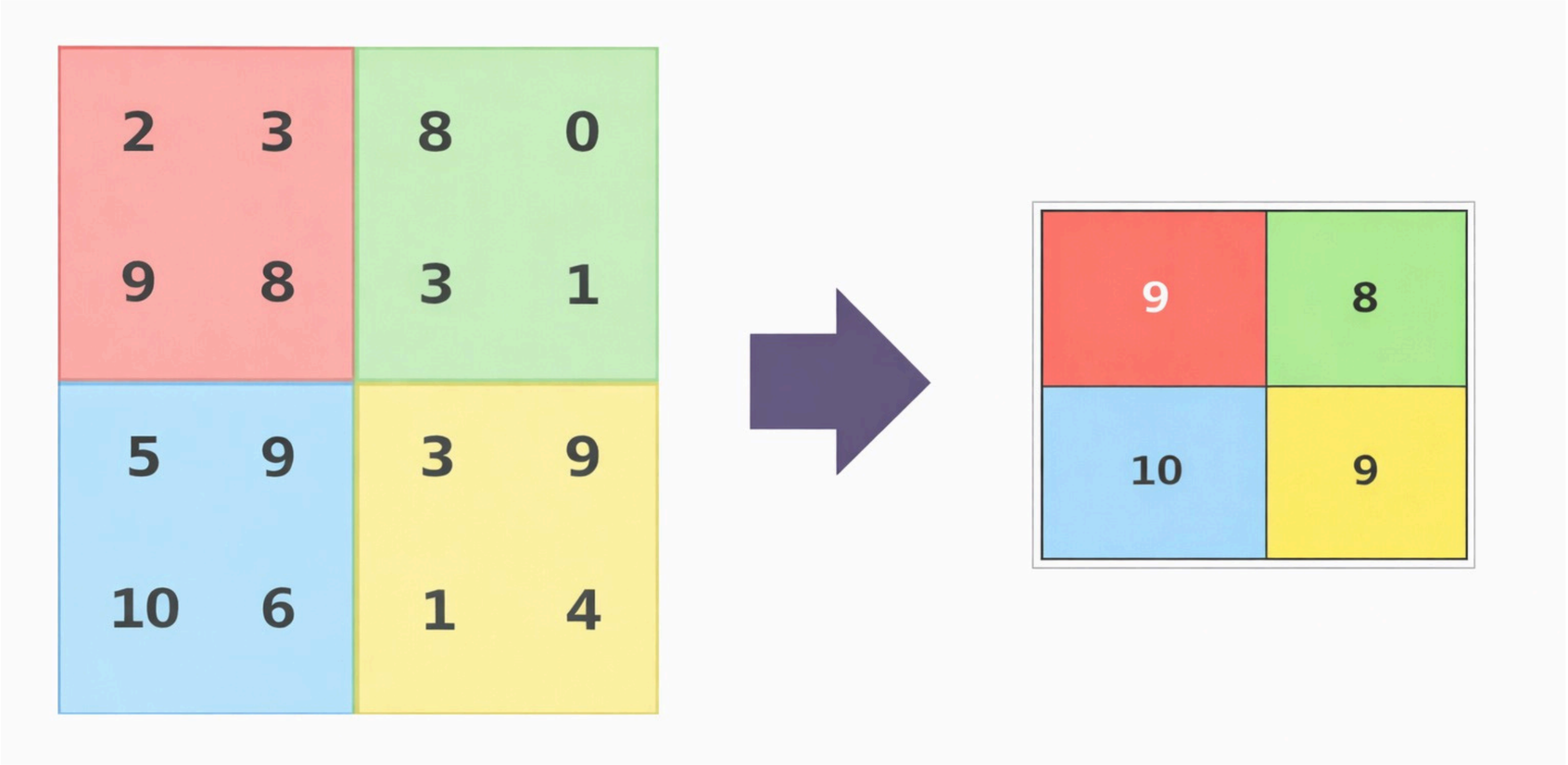
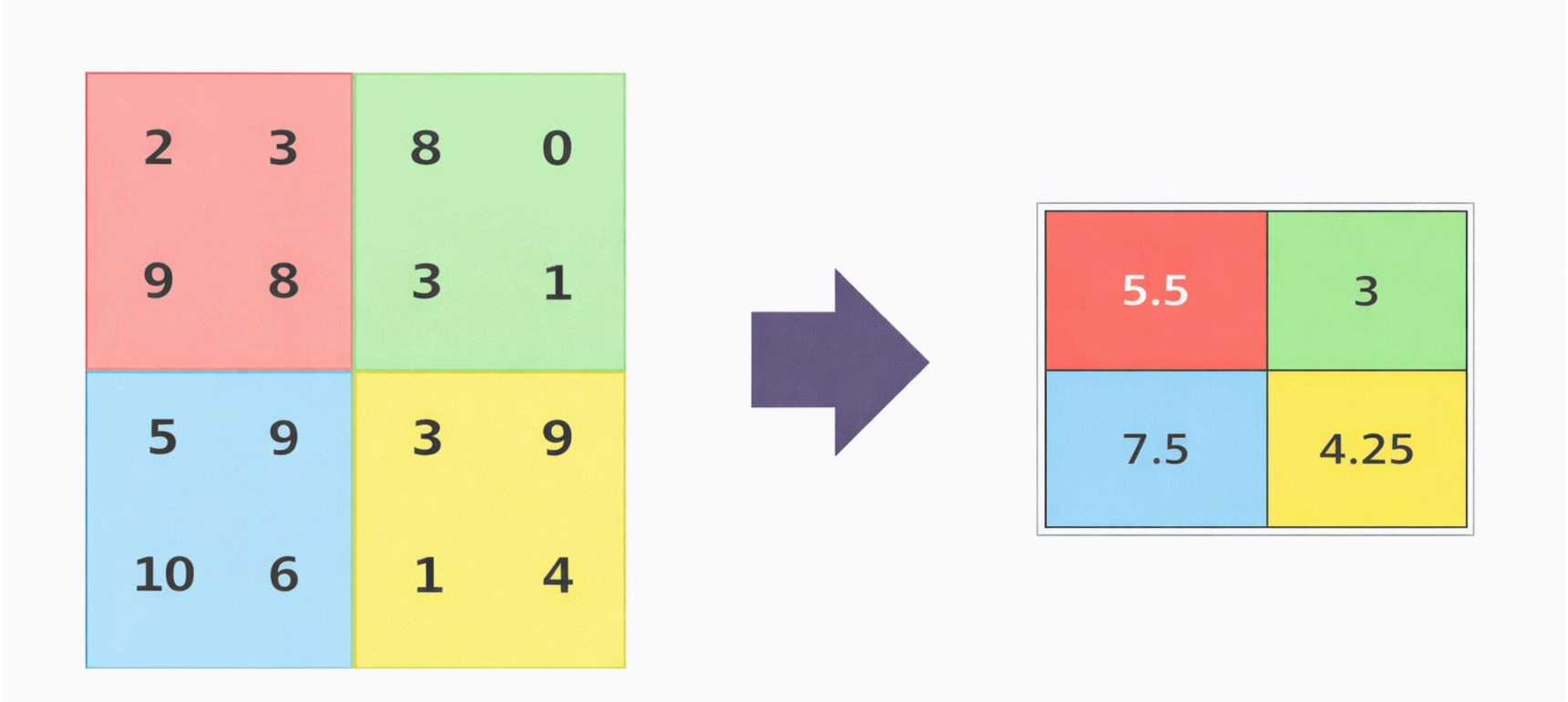


Pooling Layer

- Pooling is used for dimensionality reduction in CNNs.
  It reduces the spatial size of feature maps while keeping important information.

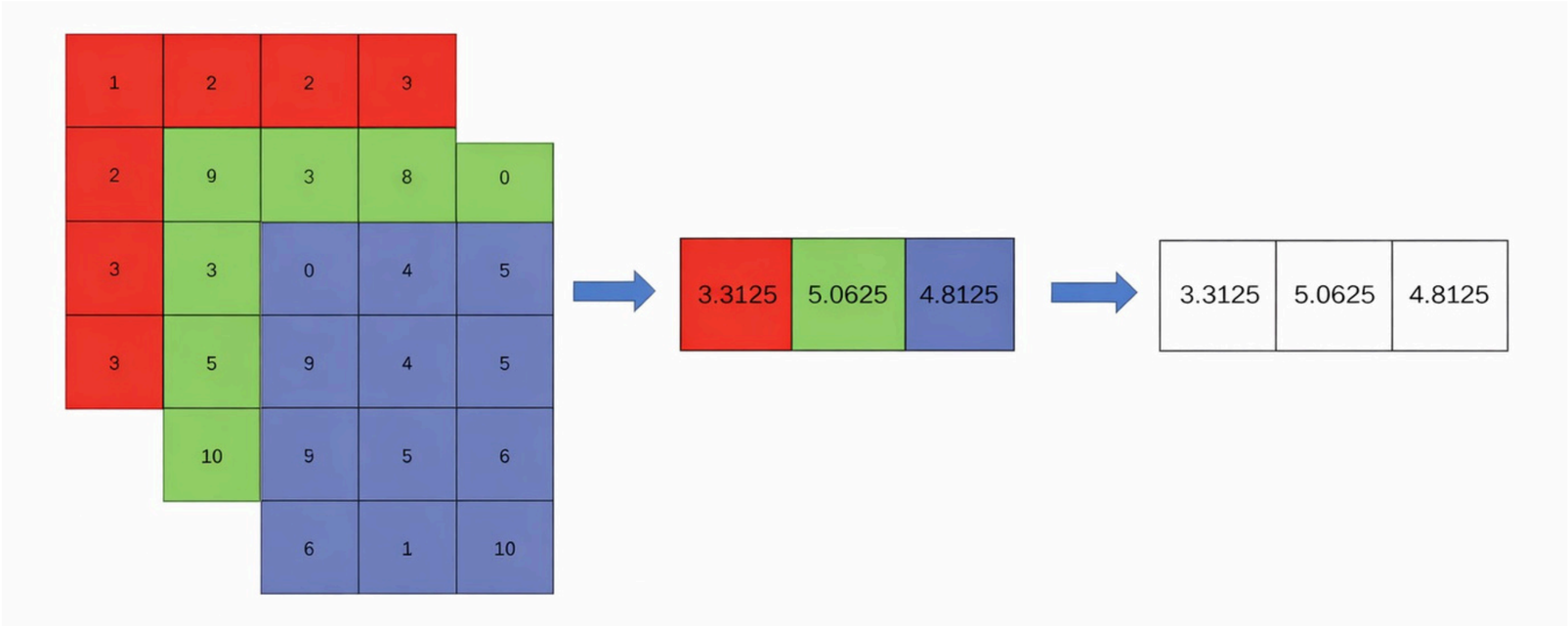
- Average Pooling



Pooling Layer

- Pooling is used for dimensionality reduction in CNNs.
  It reduces the spatial size of feature maps while keeping important information.

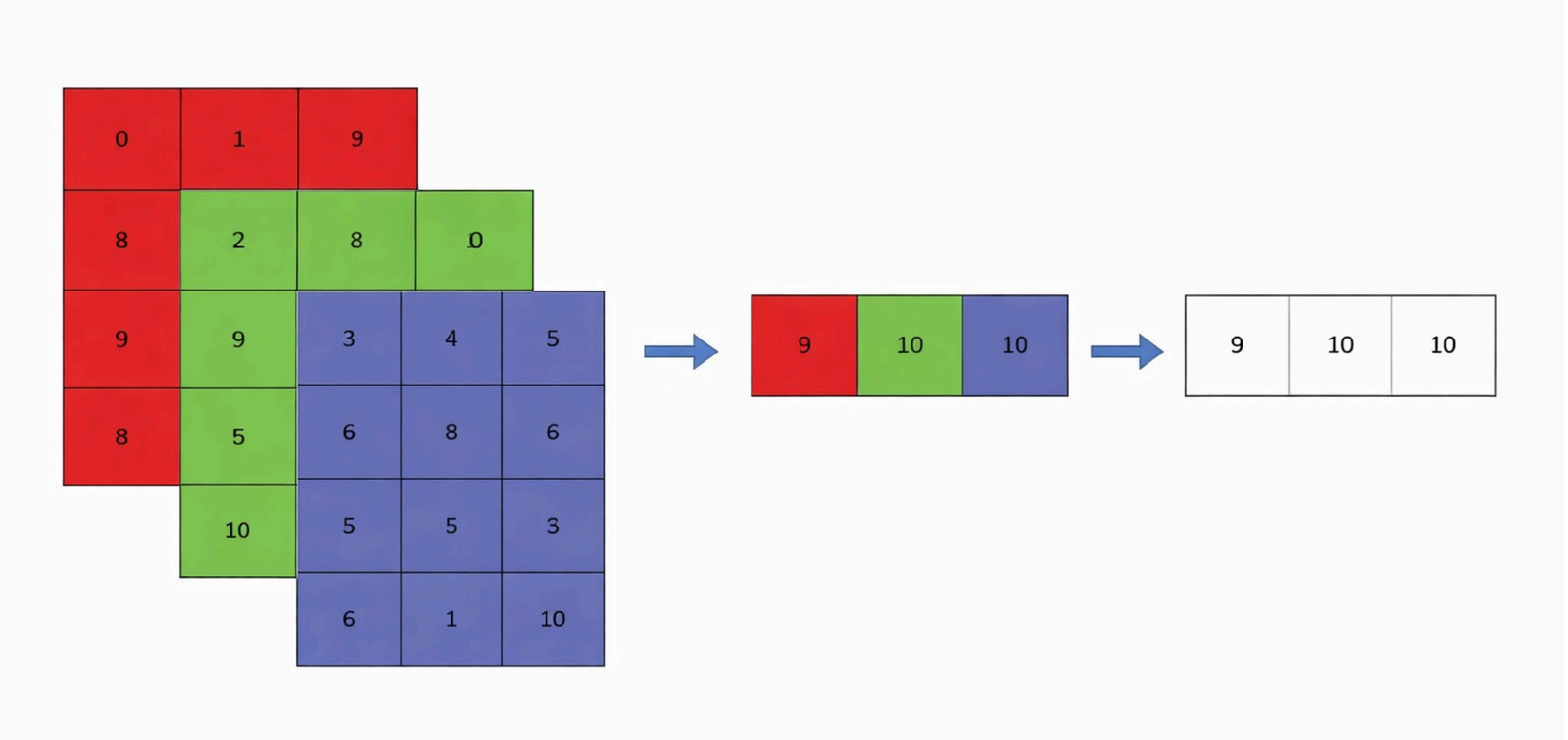
- Global Average Pooling



Pooling Layer

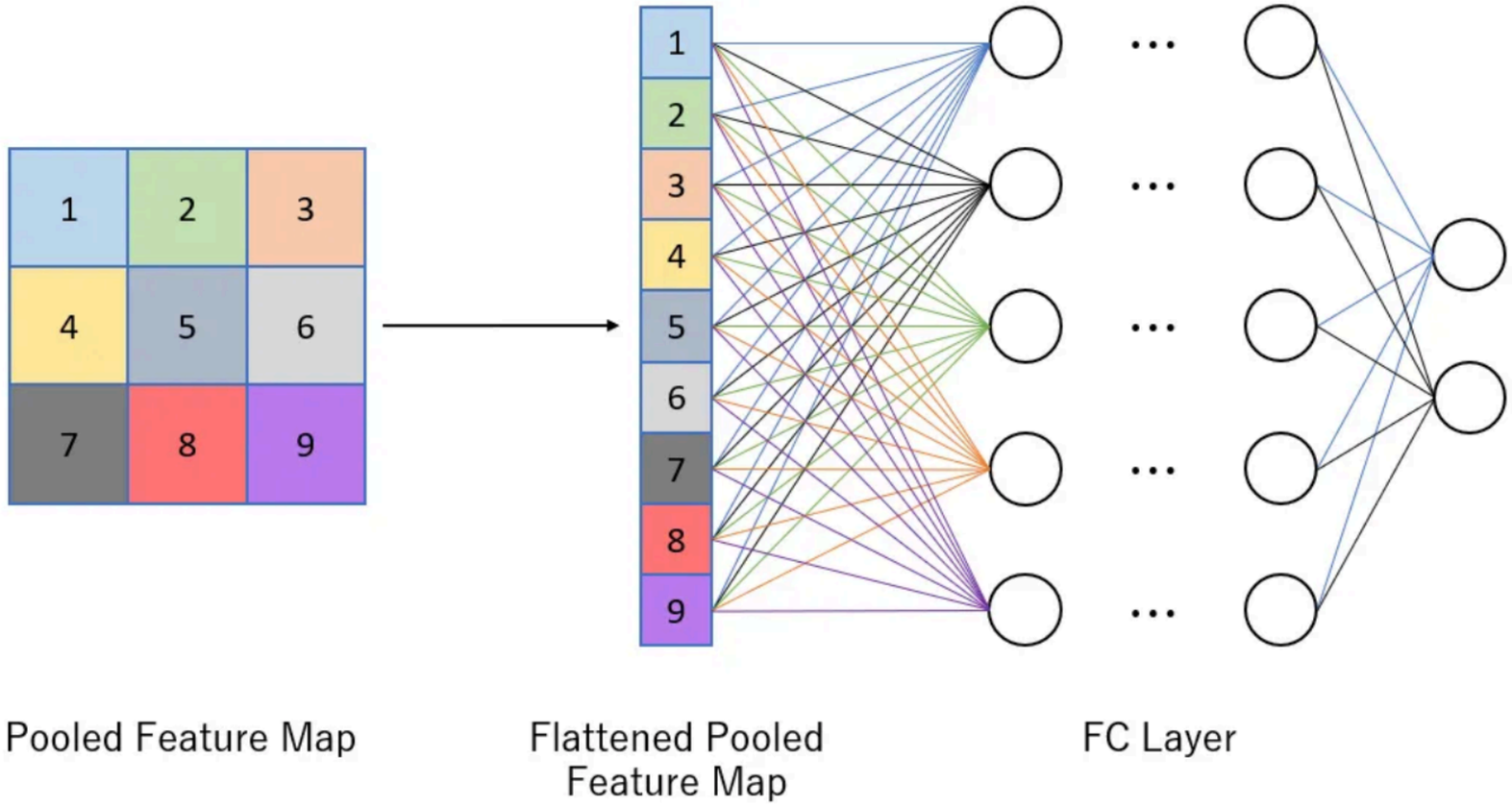
- Pooling is used for dimensionality reduction in CNNs.
  It reduces the spatial size of feature maps while keeping important information.

- Global Max Pooling



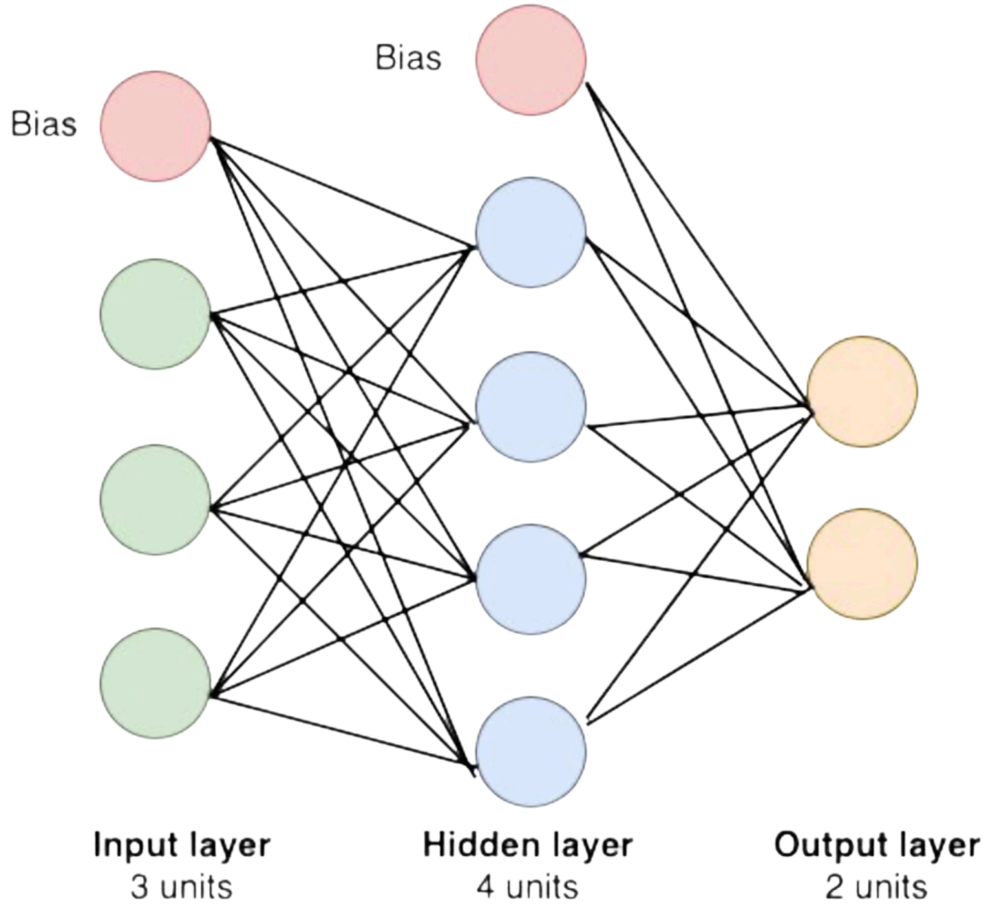
Dense Layer

- It combines the features learned by earlier convolutional and pooling layers to perform high-level reasoning or classification.



Learnable Parameters in NN

Learnable Parameters in a Neural Network: $= (n_{\text{in}} \times n_{\text{out}}) + n_{\text{out}}$



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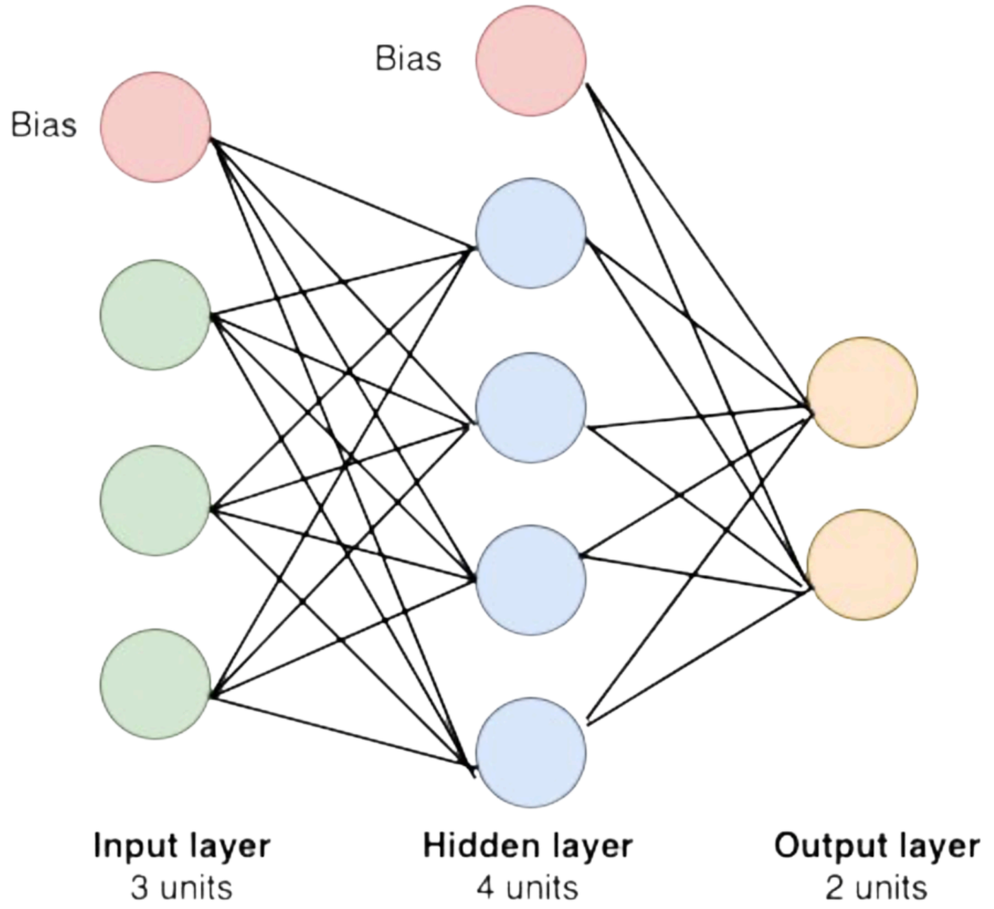


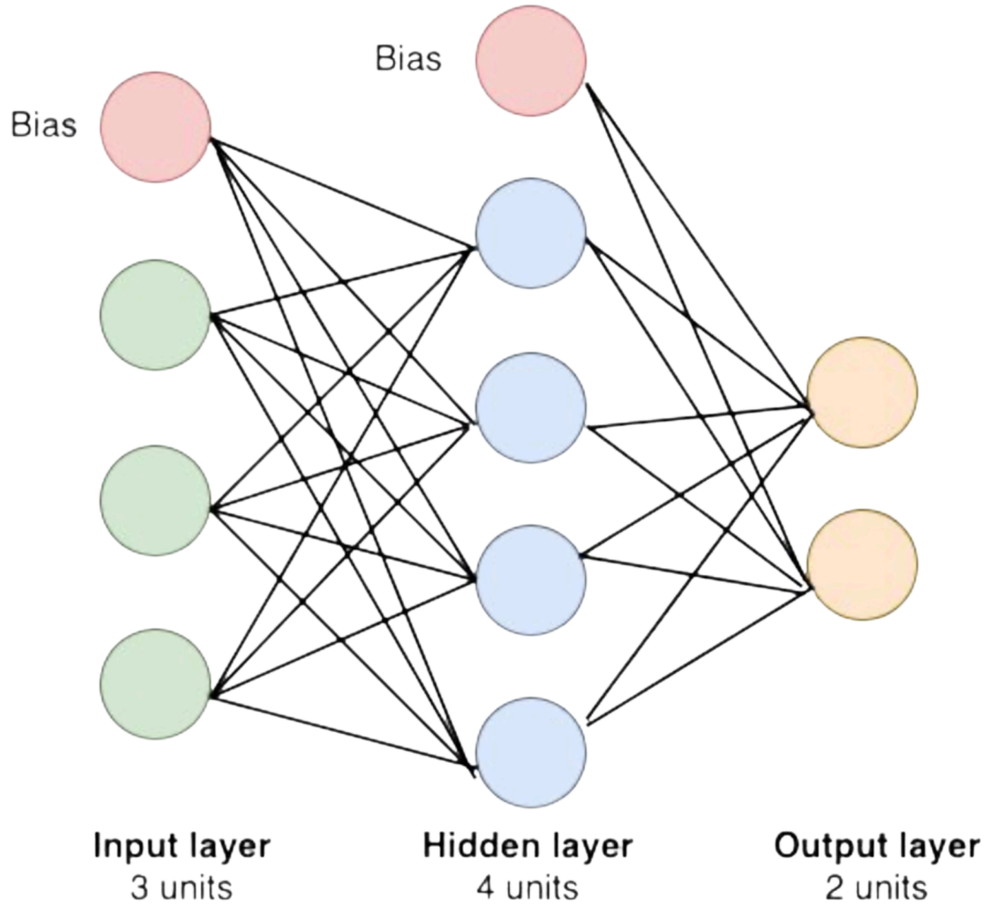
$$\text{Weights} = 3 \times 4 = 12$$

$$\text{Biases} = 4$$

$$\text{Total}_{\text{IH}} = 12 + 4 = \mathbf{16}$$

Learnable Parameters in NN

Learnable Parameters in a Neural Network: $= (n_{\text{in}} \times n_{\text{out}}) + n_{\text{out}}$



$$\text{Weights} = 3 \times 4 = 12$$

$$\text{Biases} = 4$$

$$\text{Total}_{\text{IH}} = 12 + 4 = \mathbf{16}$$

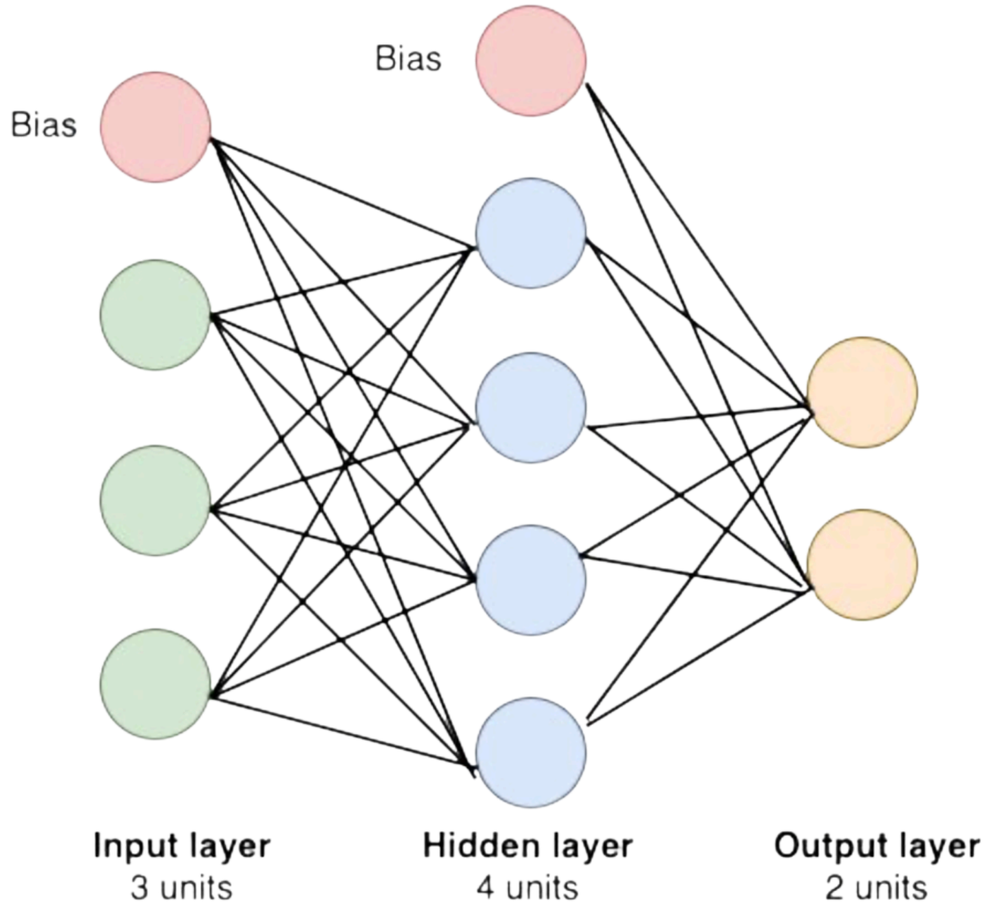
$$\text{Weights} = 4 \times 2 = 8$$

$$\text{Biases} = 2$$

$$\text{Total}_{\text{HO}} = 8 + 2 = \mathbf{10}$$

Learnable Parameters in NN

Learnable Parameters in a Neural Network: $= (n_{\text{in}} \times n_{\text{out}}) + n_{\text{out}}$



$$\text{Weights} = 3 \times 4 = 12$$

$$\text{Biases} = 4$$

$$\text{Total}_{\text{IH}} = 12 + 4 = \mathbf{16}$$

$$\text{Weights} = 4 \times 2 = 8$$

$$\text{Biases} = 2$$

$$\text{Total}_{\text{HO}} = 8 + 2 = \mathbf{10}$$

$$\text{Total} = 16 + 10 = \mathbf{26}$$

Learnable Parameters in CNN

Learnable Parameters in a CNN:

$$\textbf{Params} = (K_h \times K_w \times C_{in} + 1) \times C_{out}$$

A convolution layer with:

- Kernel size: 3×3
- Input channels: 3 (RGB)
- Output channels: 16 filters

Learnable Parameters in CNN

Learnable Parameters in a CNN:

$$\textbf{Params} = (K_h \times K_w \times C_{in} + 1) \times C_{out}$$

A convolution layer with:

- Kernel size: 3×3
- Input channels: 3 (RGB)
- Output channels: 16 filters

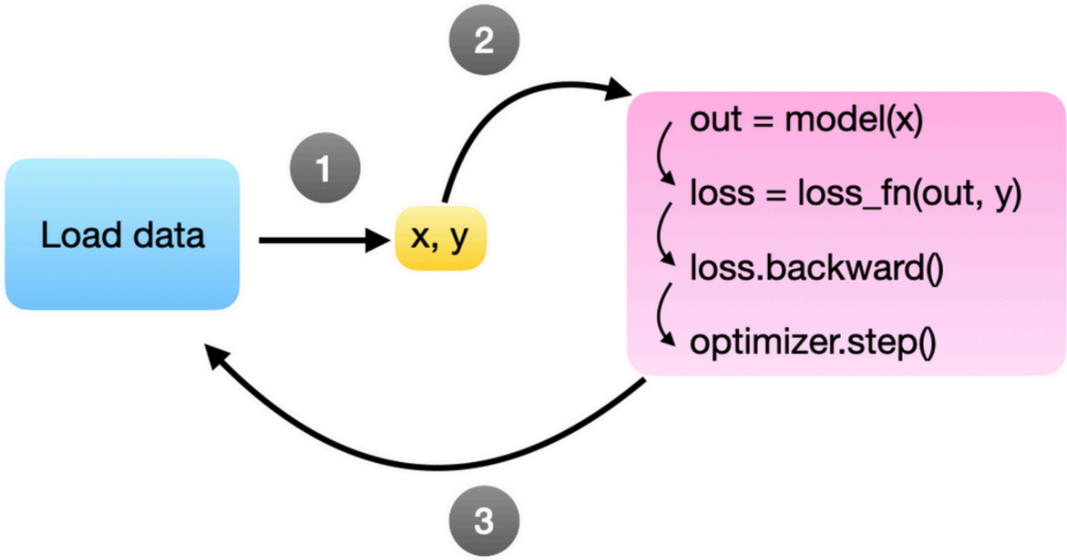
$$(3 \times 3 \times 3 + 1) \times 16$$

$$28 \times 16 = 448$$

Efficient Data Loading

- Training speed depends not only on the model
- GPU should never wait for data

```
for epoch in range(num_epochs):
    inputs = []
    for f in filename_minibatch:
        img = Image.open(os.path.join(img_dir, f))
        img_tensor = o_tensor(img).to('cuda')
        inputs.append(img_tensor)
    inputs = torch.cat(inputs)
    logits = model(inputs)
    loss.backward()
    optimizer.step()
```

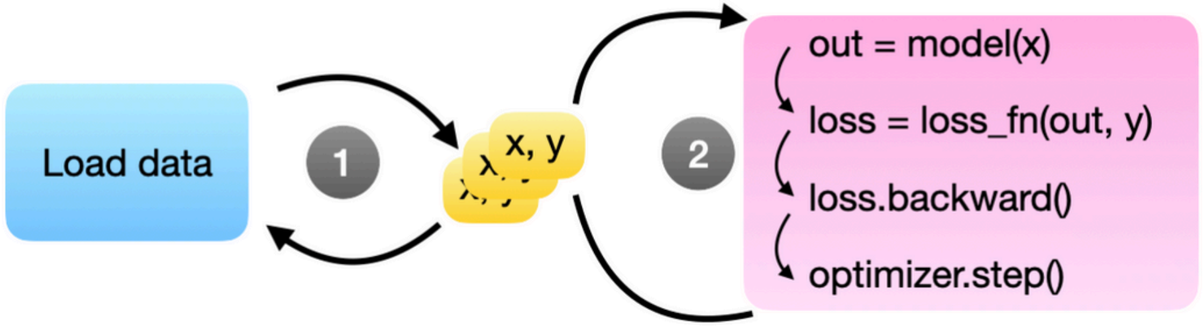


Efficient Data Loading

- Load next mini-batch in background
- Supports multiple worker processes
- Automatic shuffling, batching, and collation

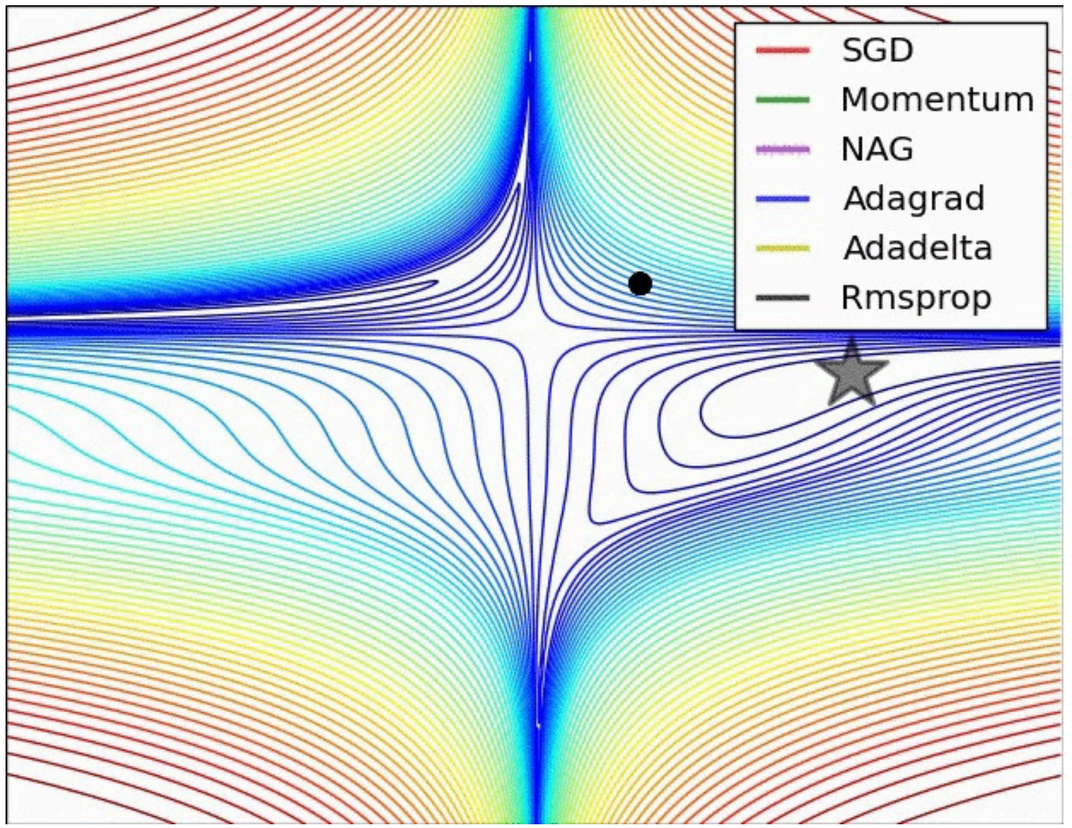
```
from torch.utils.data import Dataset, DataLoader

train_loader = DataLoader(dataset, batch_size=64,
                          shuffle=True, num_workers=4)
```



Optimization

- Optimizers are algorithms that update a model's parameters in order to minimize the loss function during training.

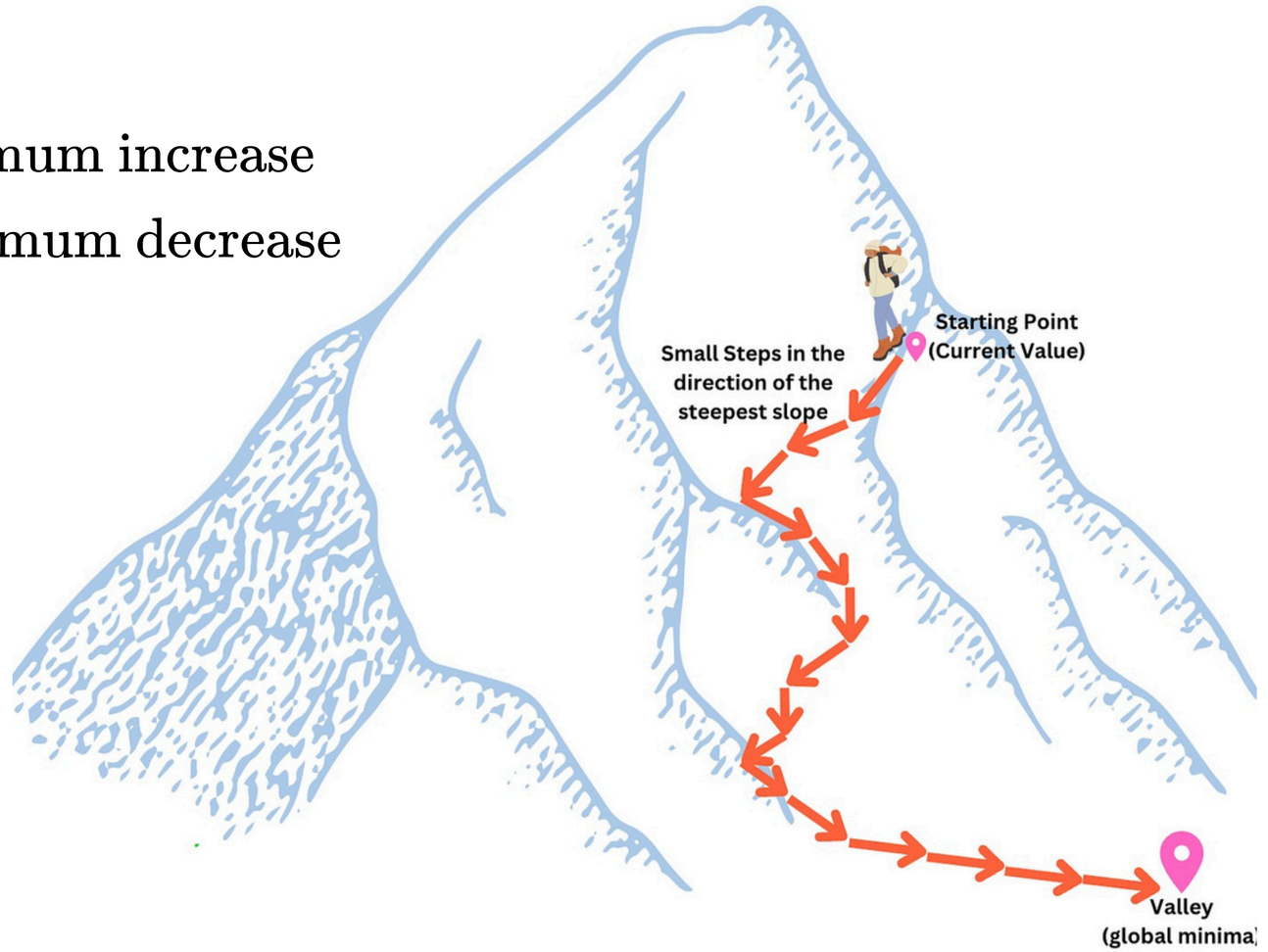


Batch Gradient Descent

- Direction of Maximum Increase and Decrease

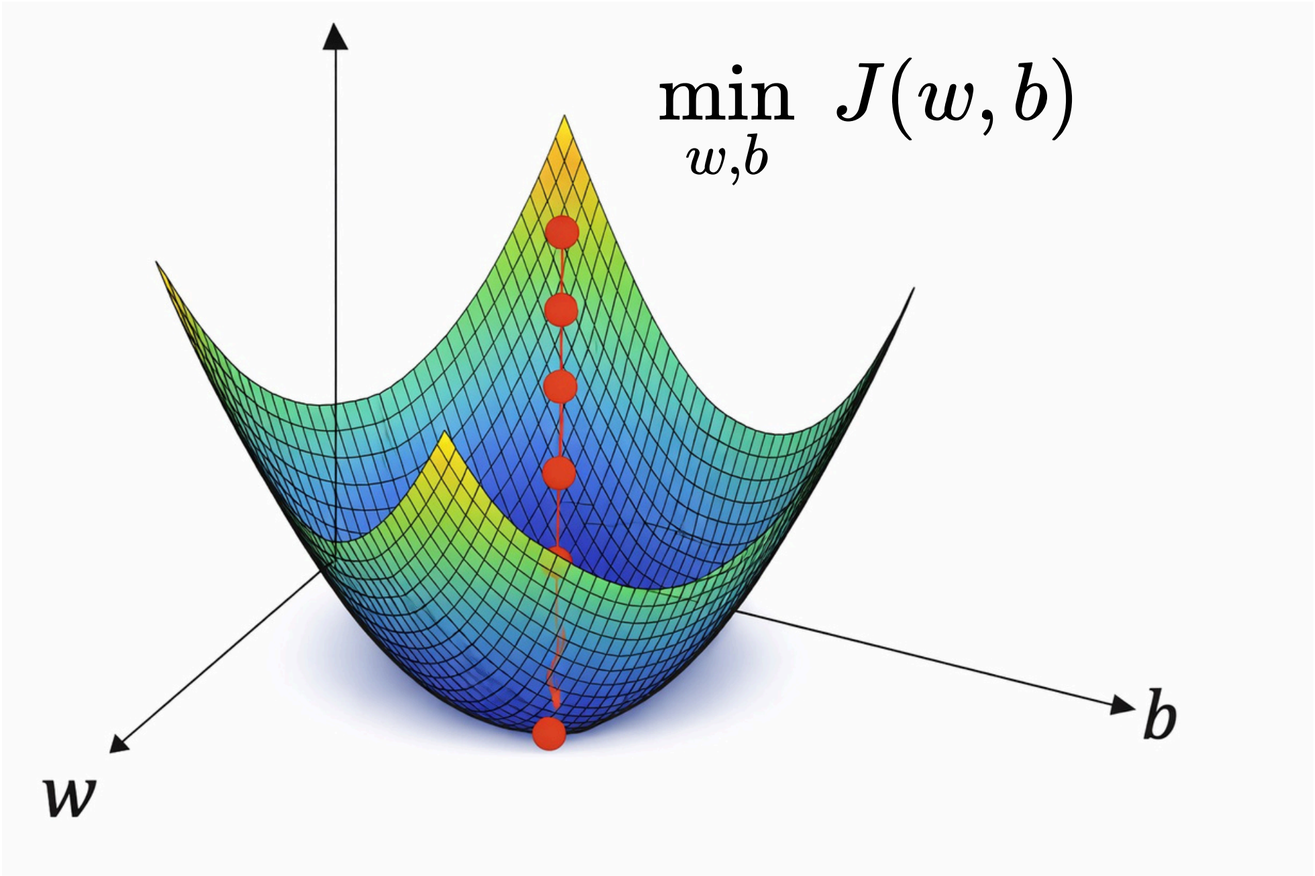
$\nabla f(x)$: direction of maximum increase

$-\nabla f(x)$: direction of maximum decrease



Gradient Descent

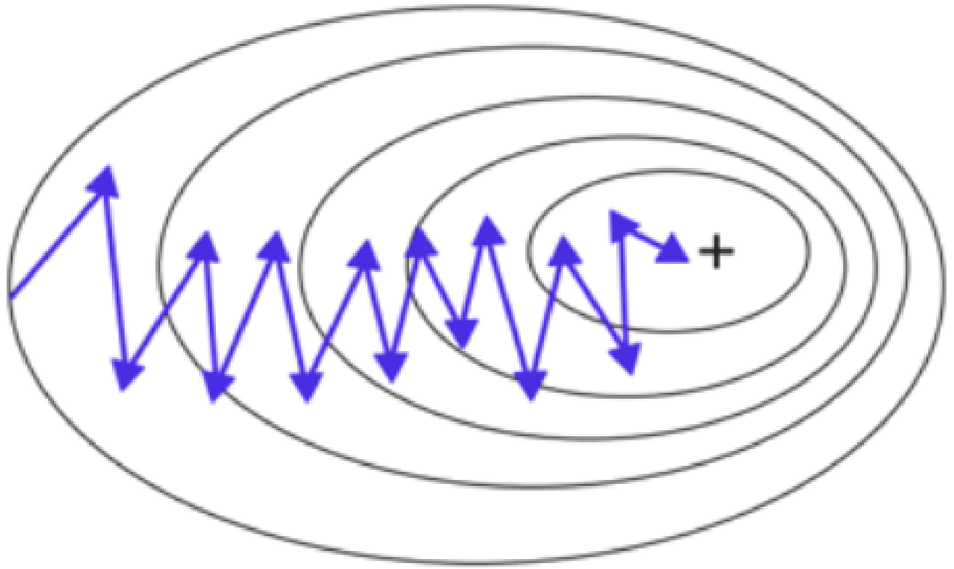
- Moving in the direction of steepest loss decrease



Stochastic Gradient Descent

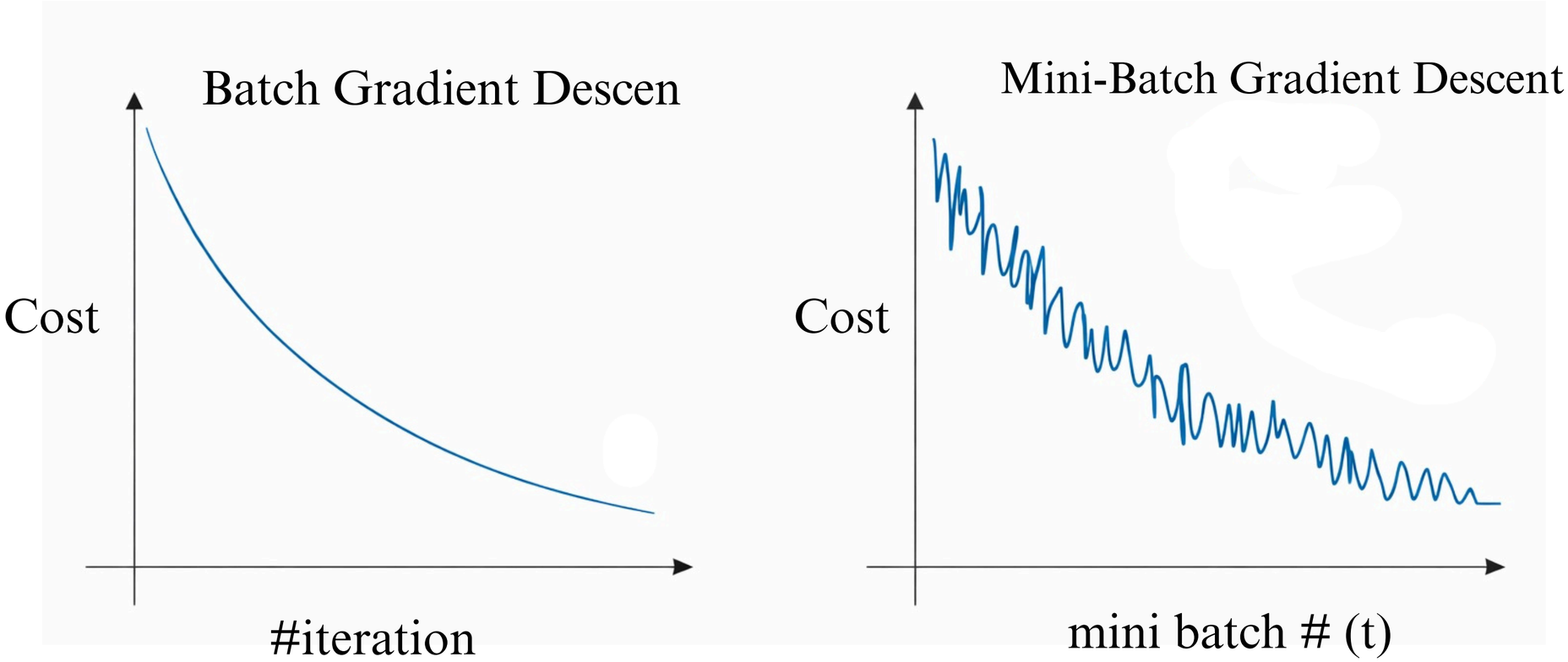
- Updates model parameters using one training sample at a time

$$\theta = \theta - \eta \cdot \nabla L(x_i, y_i)$$



Mini-Batch Gradient Descent

- Instead of using all training examples or just one, we update parameters using a small batch of samples.



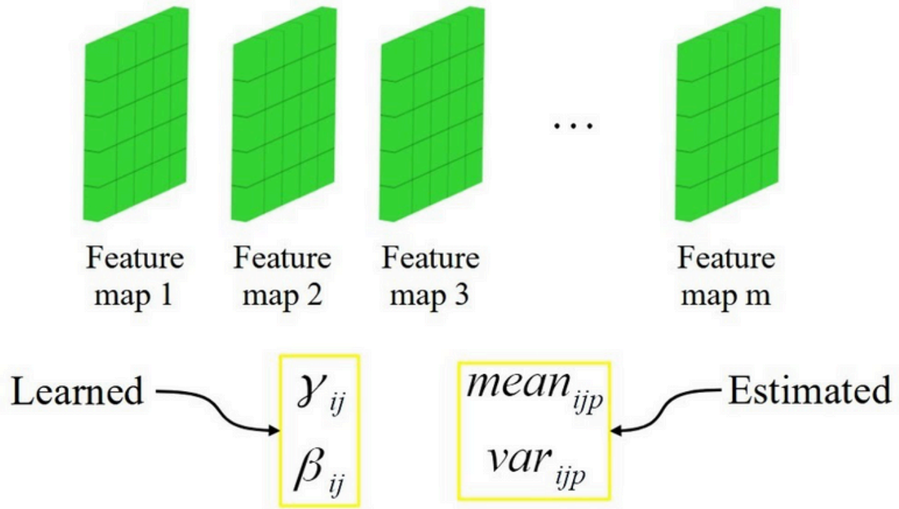
Common mini-batch sizes are 32/64/128 examples


Mini-batch gradient descent
Batch gradient descent
Stochastic gradient descent

Batch Normalization

- Uses batch statistics: mean (μ) and variance (σ^2) of the current mini-batch
- has 2 learnable parameters:
    - γ (gamma) controls the scale (how stretched the distribution is)
    - β (beta) controls the shift (moves the center left or right)

$$\hat{x} = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}} \qquad y = \gamma\hat{x} + \beta$$



Batch Normalization

$$\hat{x} = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}}$$

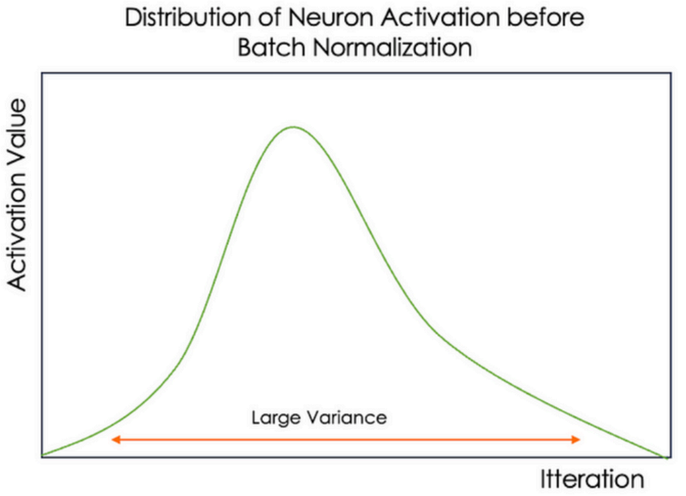
$$x = [2,\ 4,\ 6,\ 8]$$

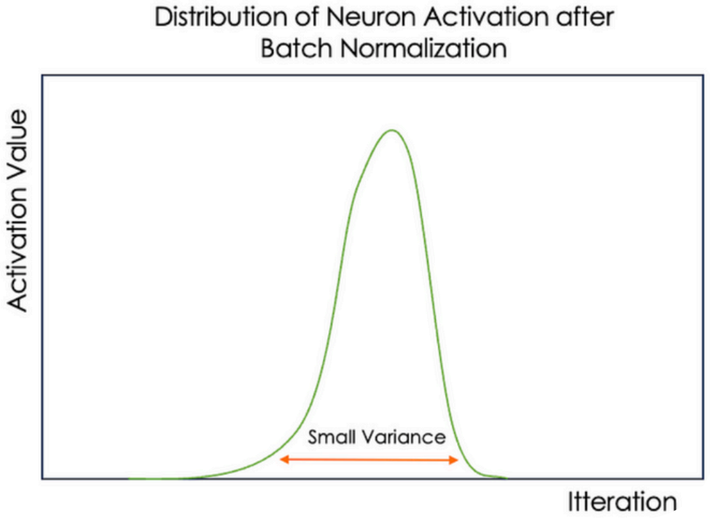
$$\mu = \frac{2 + 4 + 6 + 8}{4} = 5$$

$$\sigma^2 = \frac{(2-5)^2 + (4-5)^2 + (6-5)^2 + (8-5)^2}{4} = \frac{9 + 1 + 1 + 9}{4} = 5$$

$$\hat{x} = [-1.342,\ -0.447,\ 0.447,\ 1.342]$$

$$\mu_{\hat{x}} = 0 \qquad \sigma^2_{\hat{x}} = 1$$





Batch Normalization

$$y = \gamma \hat{x} + \beta$$

$$\gamma = 2,\ \beta = 1$$

$$y = 2 \cdot \hat{x} + 1$$

$$y = [-1.684,\ 0.106,\ 1.894,\ 3.684]$$

$$Var(y) = \gamma^2 = 4$$

- Applying γ (scale) stretches the distribution.
- Applying β (shift) moves the entire distribution left/right.
- The distribution is now 4× wider than before scaling
- β does not affect variance only shifts the mean

*BatchNorm learns statistics during training and reuses them during inference.

Dropout

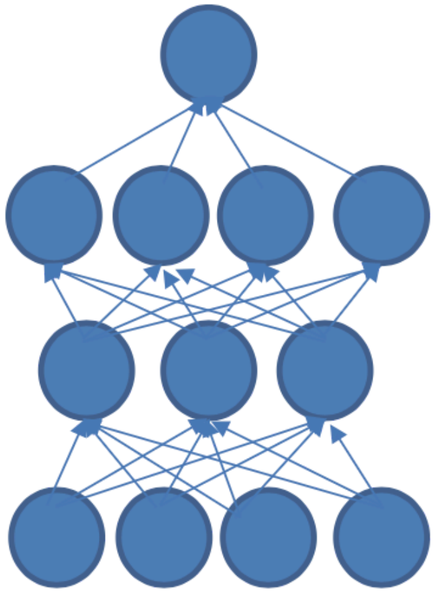
Input x = {1, 2, 3, 4, 5},

Dropout p = 0.2, keep probability = 0.8.

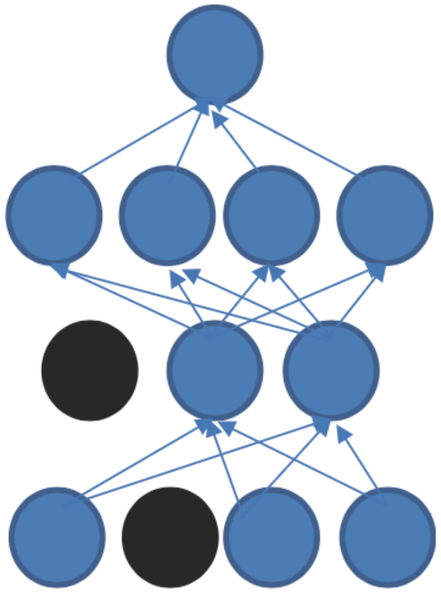
Randomly dropped version may be

{1, 0, 3, 4, 5} or {1, 2, 0, 4, 5}.

Hidden layer example: 1000 neurons, p = 0.5 → 500 neurons removed each iteration.

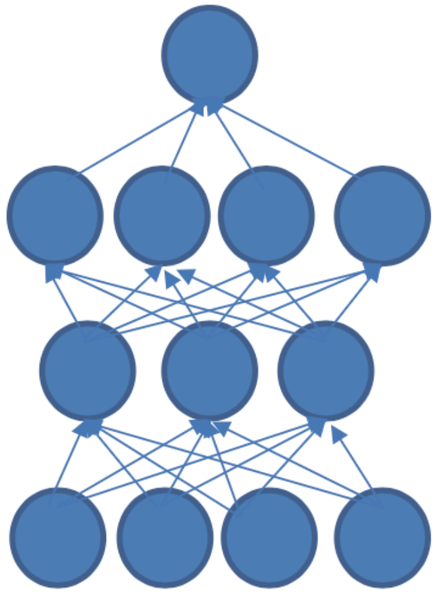


Architecture without dropouts

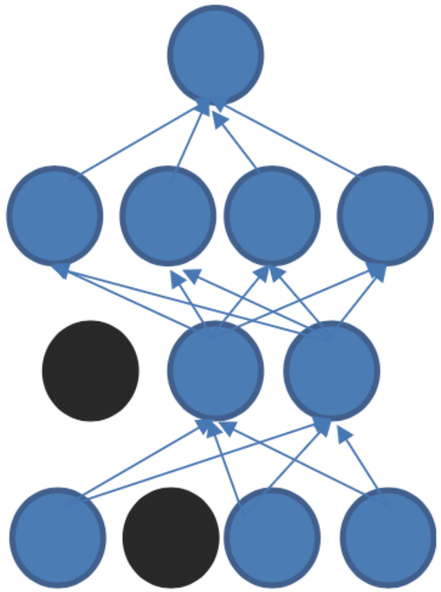


Architecture with dropouts

Dropout



Architecture without dropouts



Architecture with dropouts

$$x = [2,\ 4,\ 6,\ 8]$$

$$w = [1,\ 2,\ 3,\ 4]$$

$$y = x \cdot w^T = (2)(1) + (4)(2) + (6)(3) + (8)(4)$$

$$y = 2 + 8 + 18 + 32 = 60$$

$$p = 0.5$$

Dropout

Training

$$r = [1,\ 0,\ 1,\ 0]$$

$$x_{\text{drop}} = x \odot r = [2,\ 0,\ 6,\ 0]$$

$$y_{\text{train}} = (2)(1) + (0)(2) + (6)(3) + (0)(4)$$

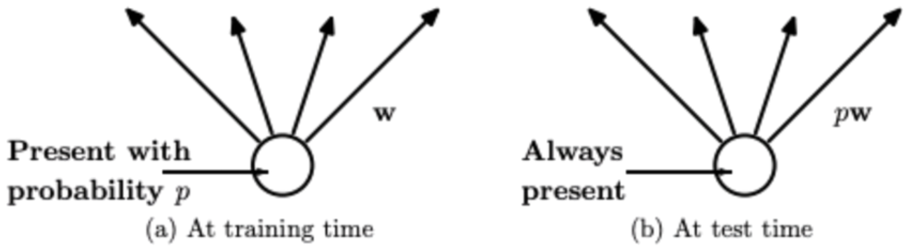
$$= 2 + 0 + 18 + 0 = 20$$

Inference

$$w' = p \cdot w = [0.5,\ 1,\ 1.5,\ 2]$$

$$y_{\text{test}} = x \cdot w'^{T} = (2)(0.5) + (4)(1) + (6)(1.5) + (8)(2)$$

$$y_{\text{test}} = 1 + 4 + 9 + 16 = 30$$

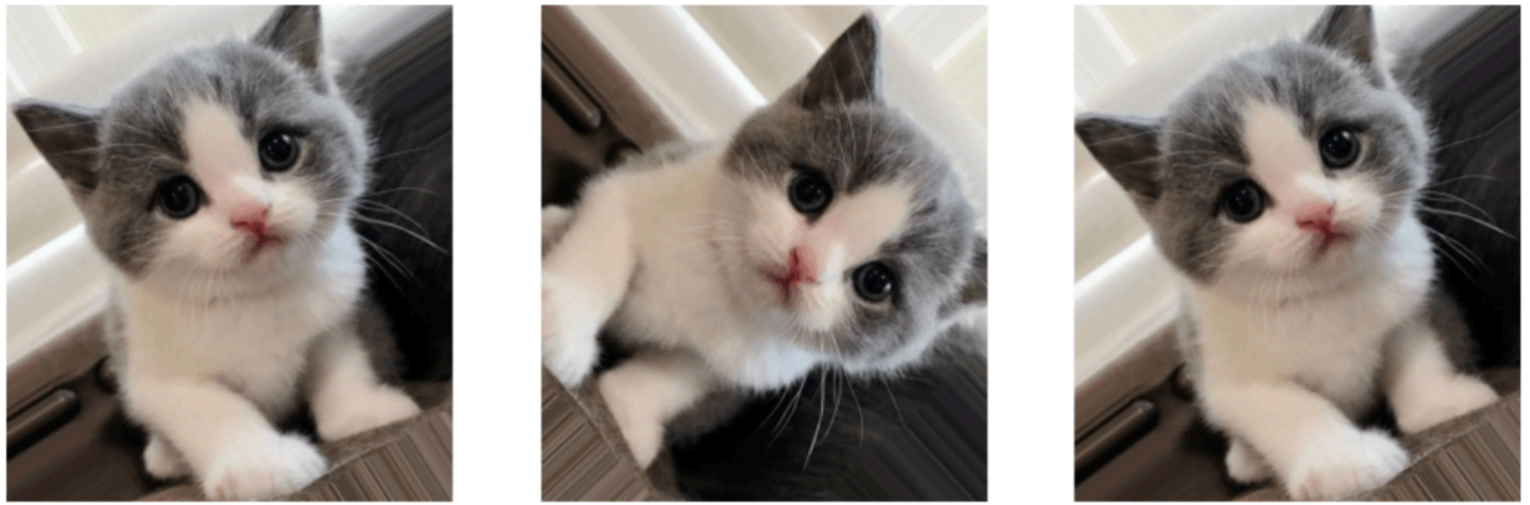


(a) At training time (b) At test time

- Training avg = 30, Testing = 30

Data Augmentation

Random Rotation



Rotation technique

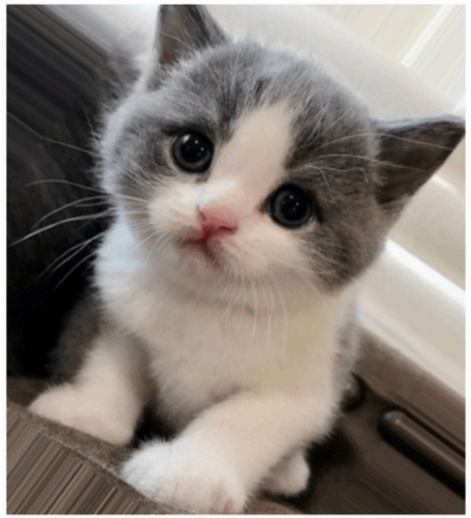
Data Augmentation

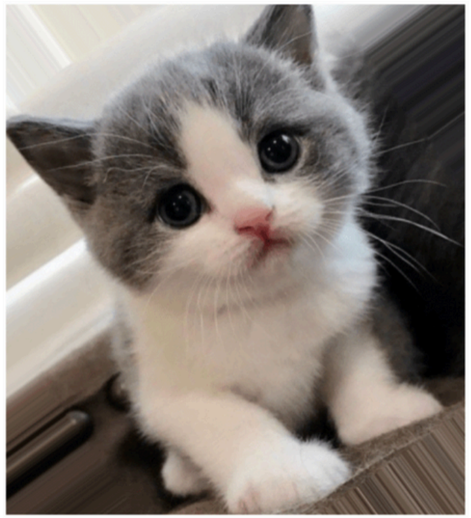
Brightness



Data Augmentation

Flip





Horizontal flip technique

Vertical flip technique

Data Augmentation

Zoom

Zoom technique

Random Shift

Width shift technique


Q
A

Thank You