# Lecture 19
# Convolutional Neural Networks

Syed Hasib Akhter Faruqui

Disclosure: The slides are adopted from Stanford CS231n and Andrew Ng's online Machine Learning Course.

# Research Questions: Visual Recognition

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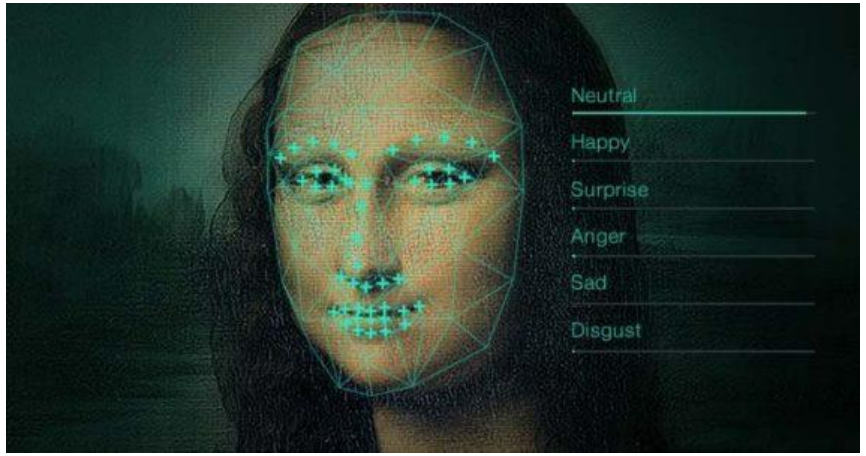
Emotion Detection

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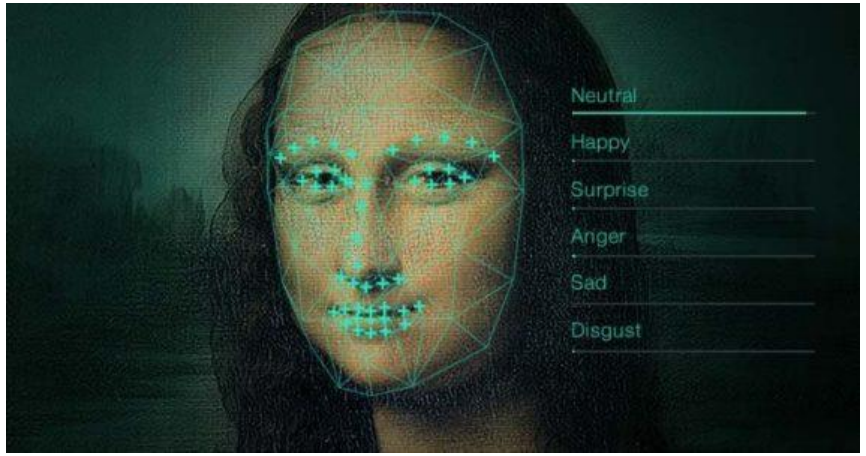


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Object Detection

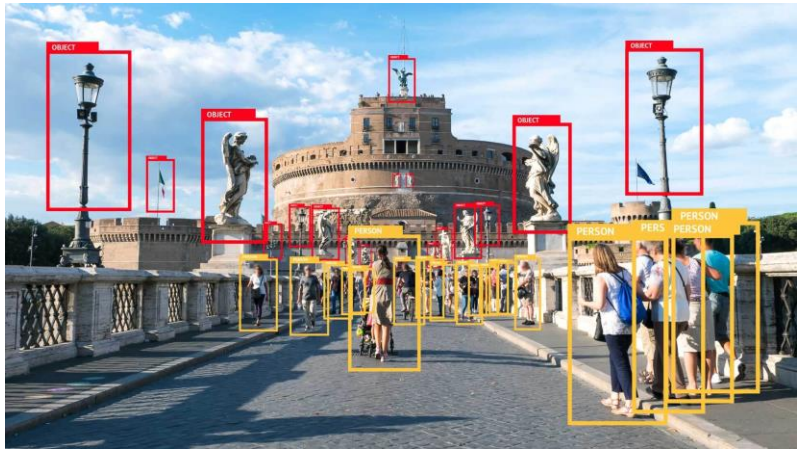


Image Source: https://martechtoday.com/how-visual-recognition-is-set-to-change-advertising-223719

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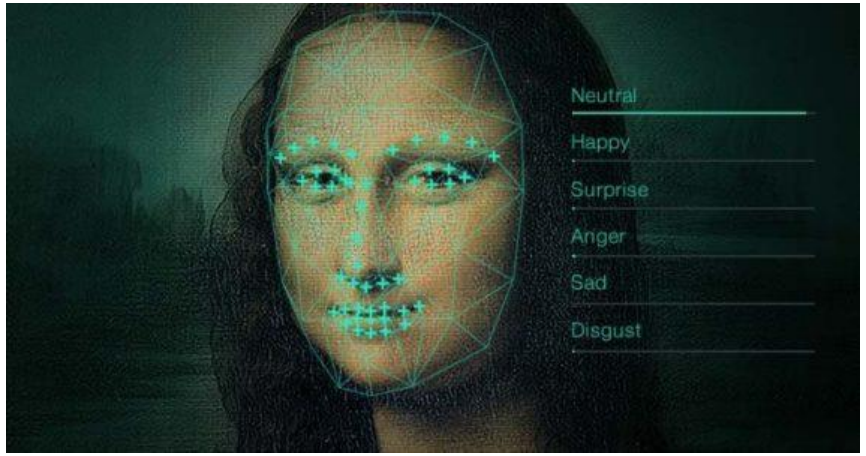


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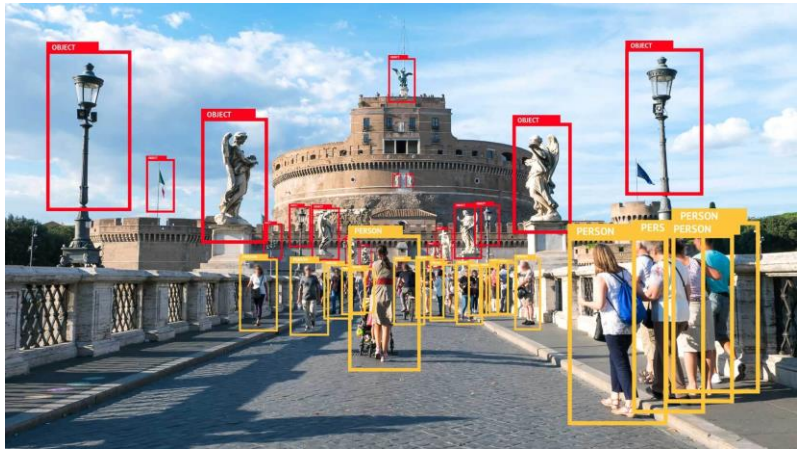


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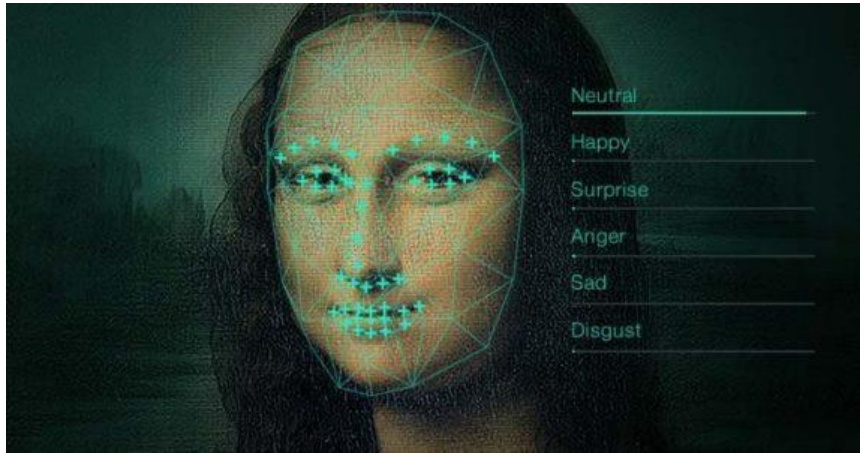


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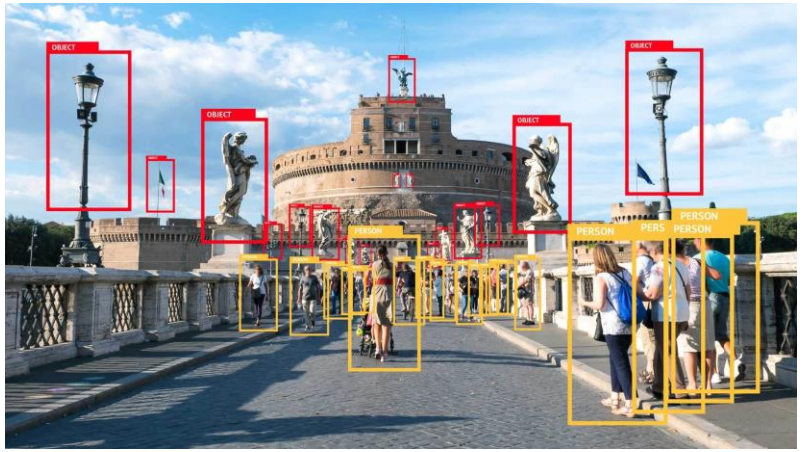

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"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

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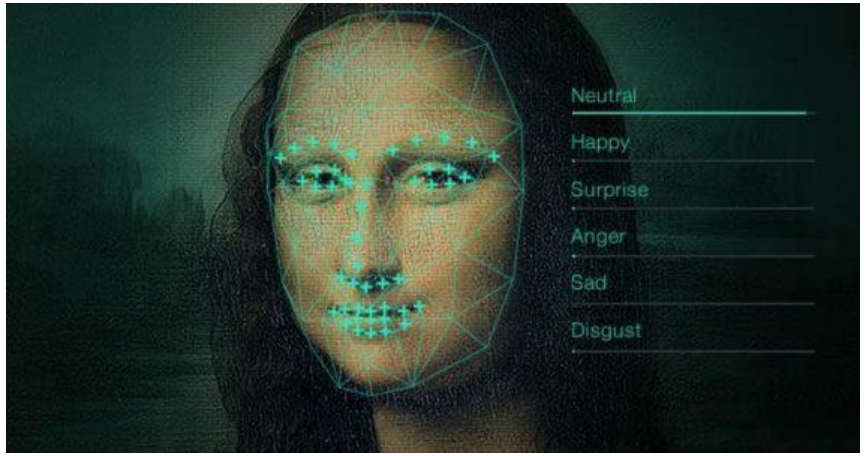


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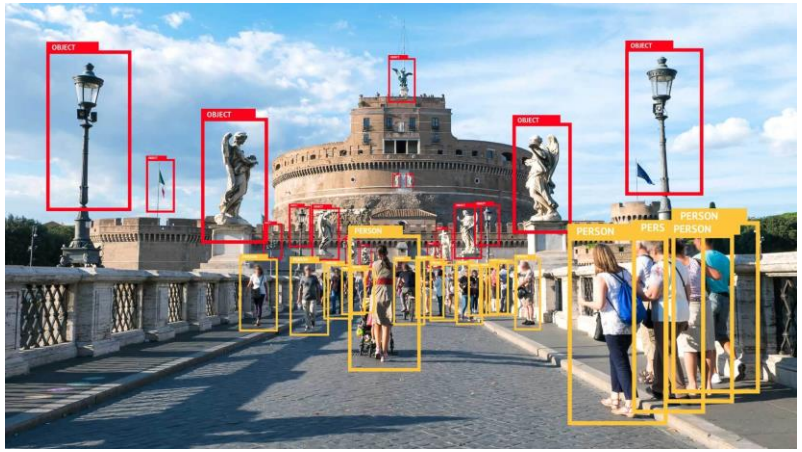

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## Pose Detection

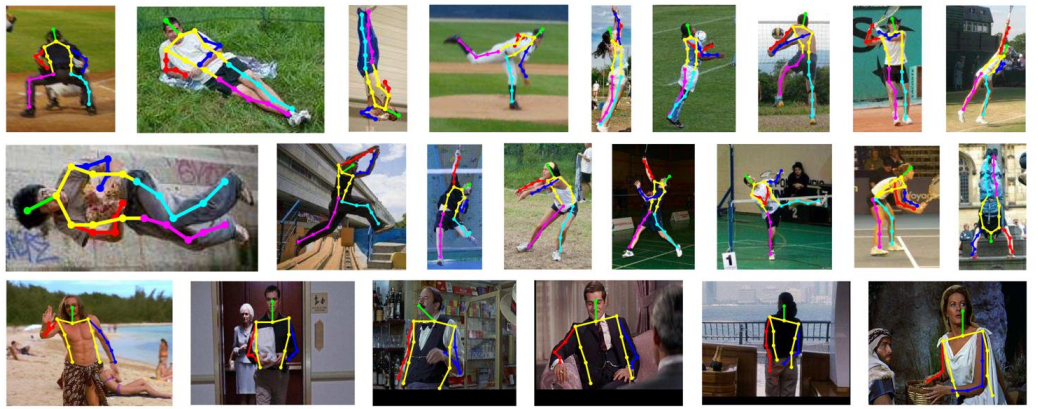
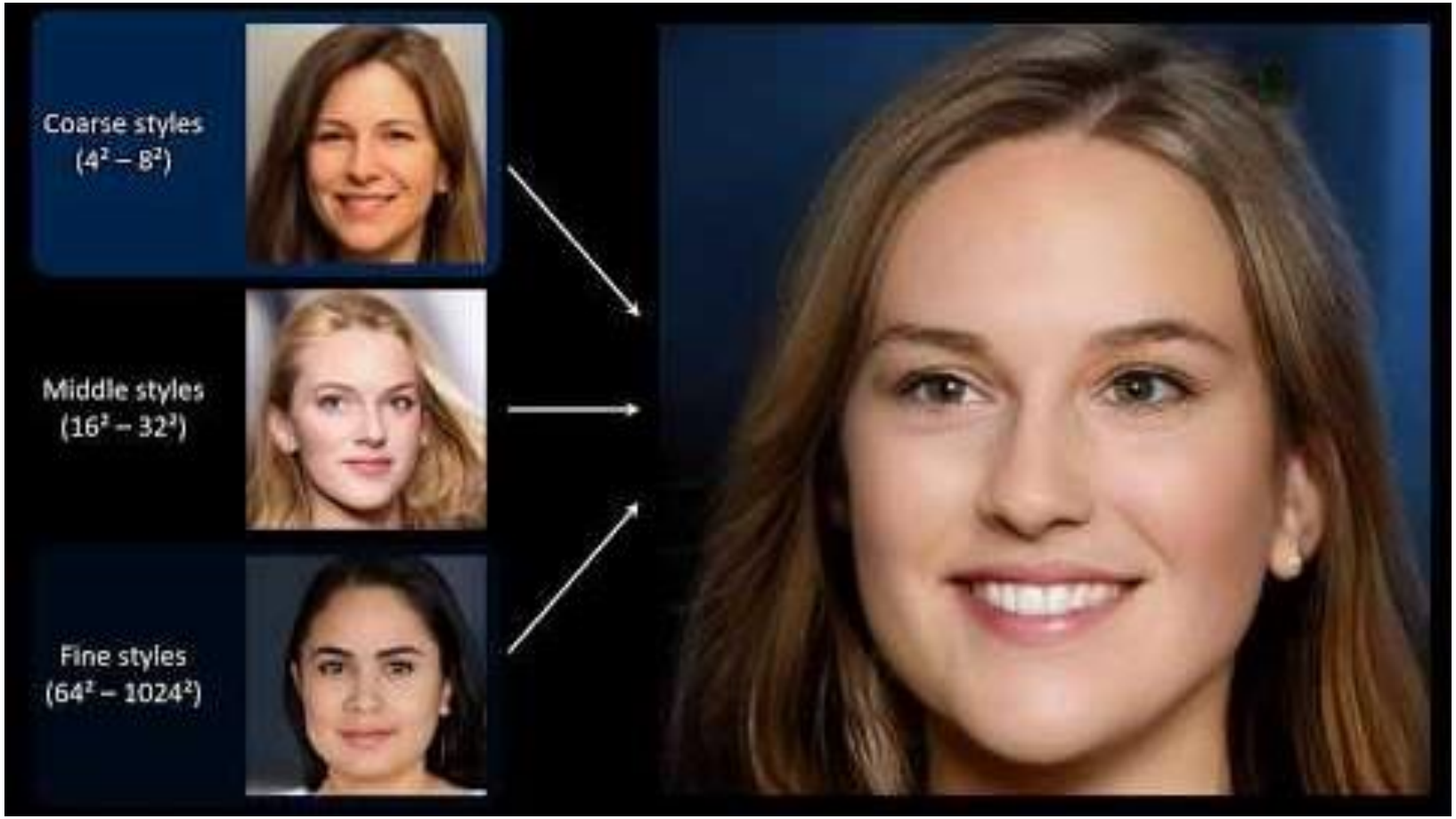


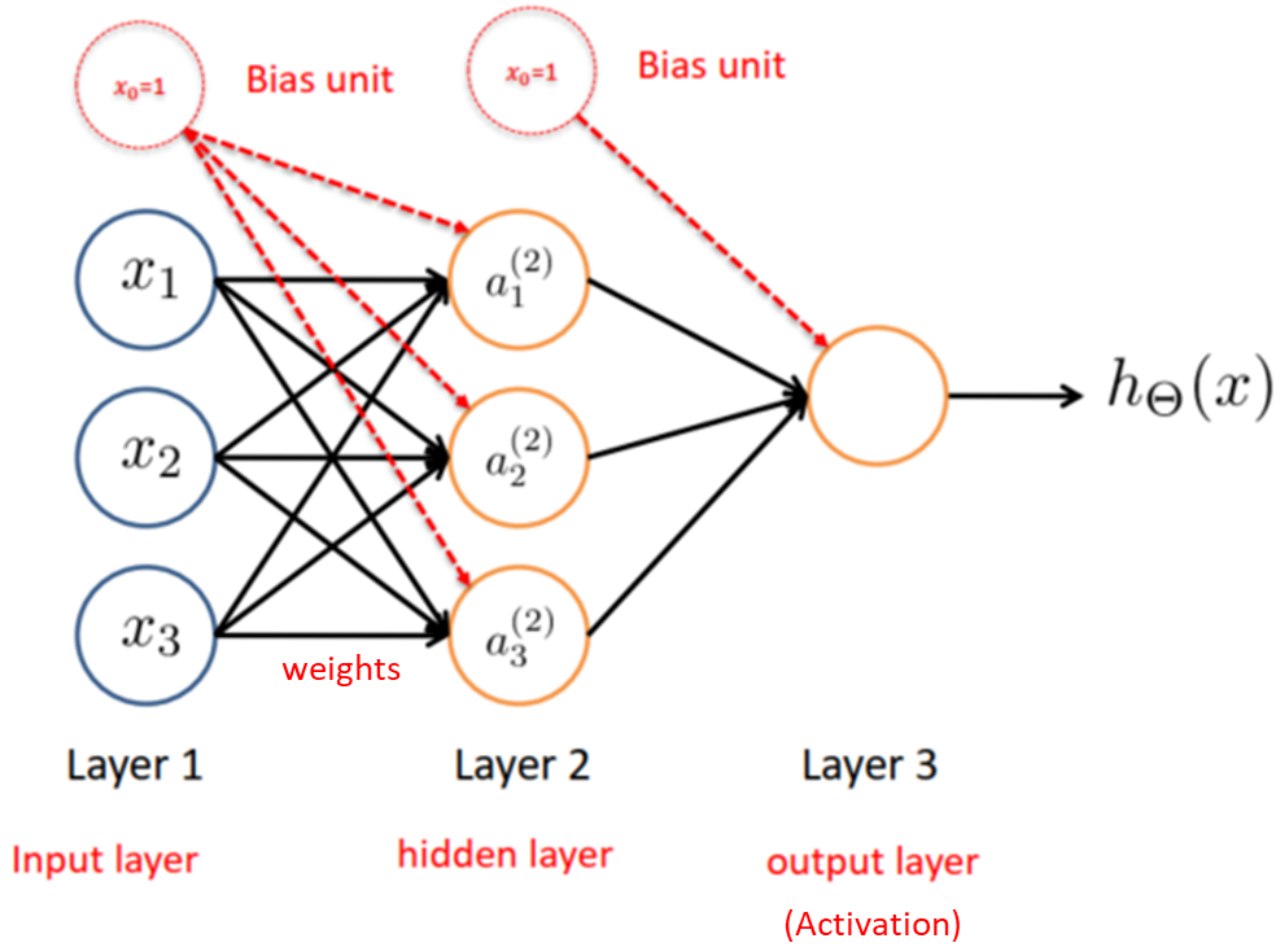
Image Source: https://nanonets.com/blog/human-pose-estimation-2d-guide/

# Research Questions: Image Generation




*Karras, Tero, Samuli Laine, and Timo Aila. "A style-based generator architecture for generative adversarial networks." In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 4401-4410. 2019.*

# Recall from last time



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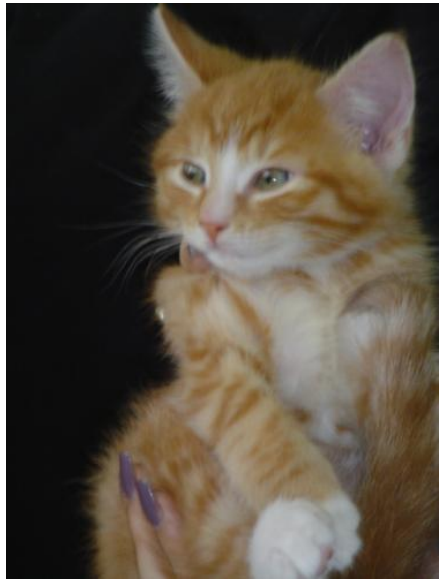

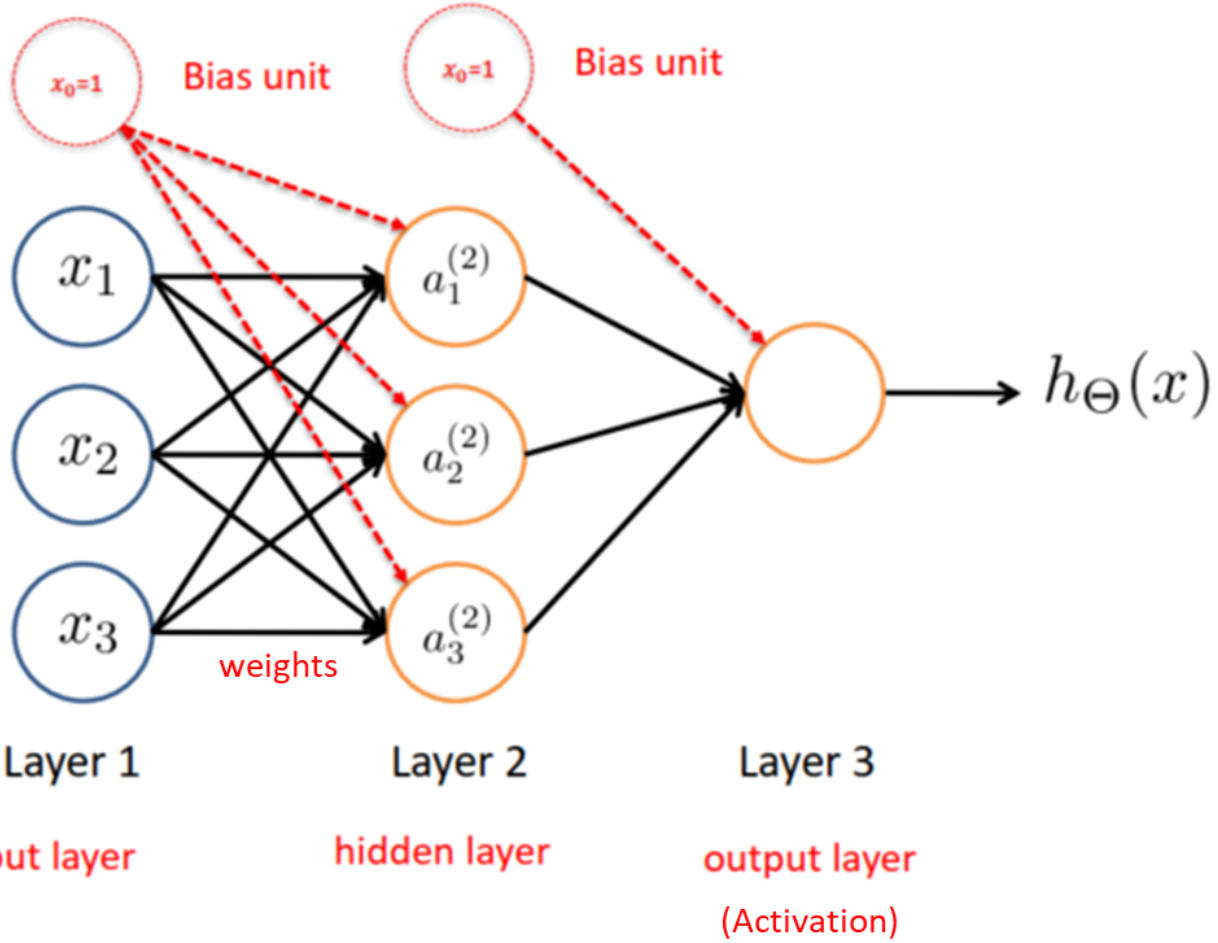

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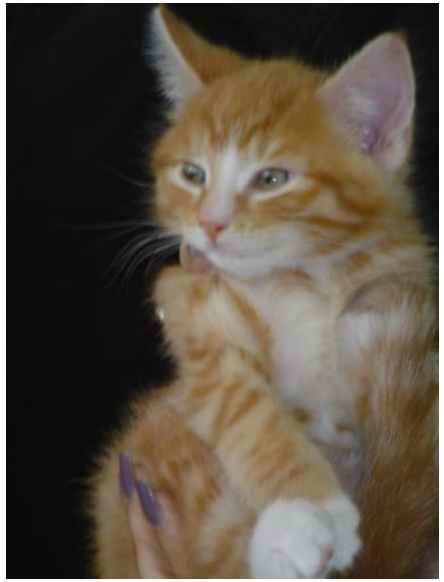
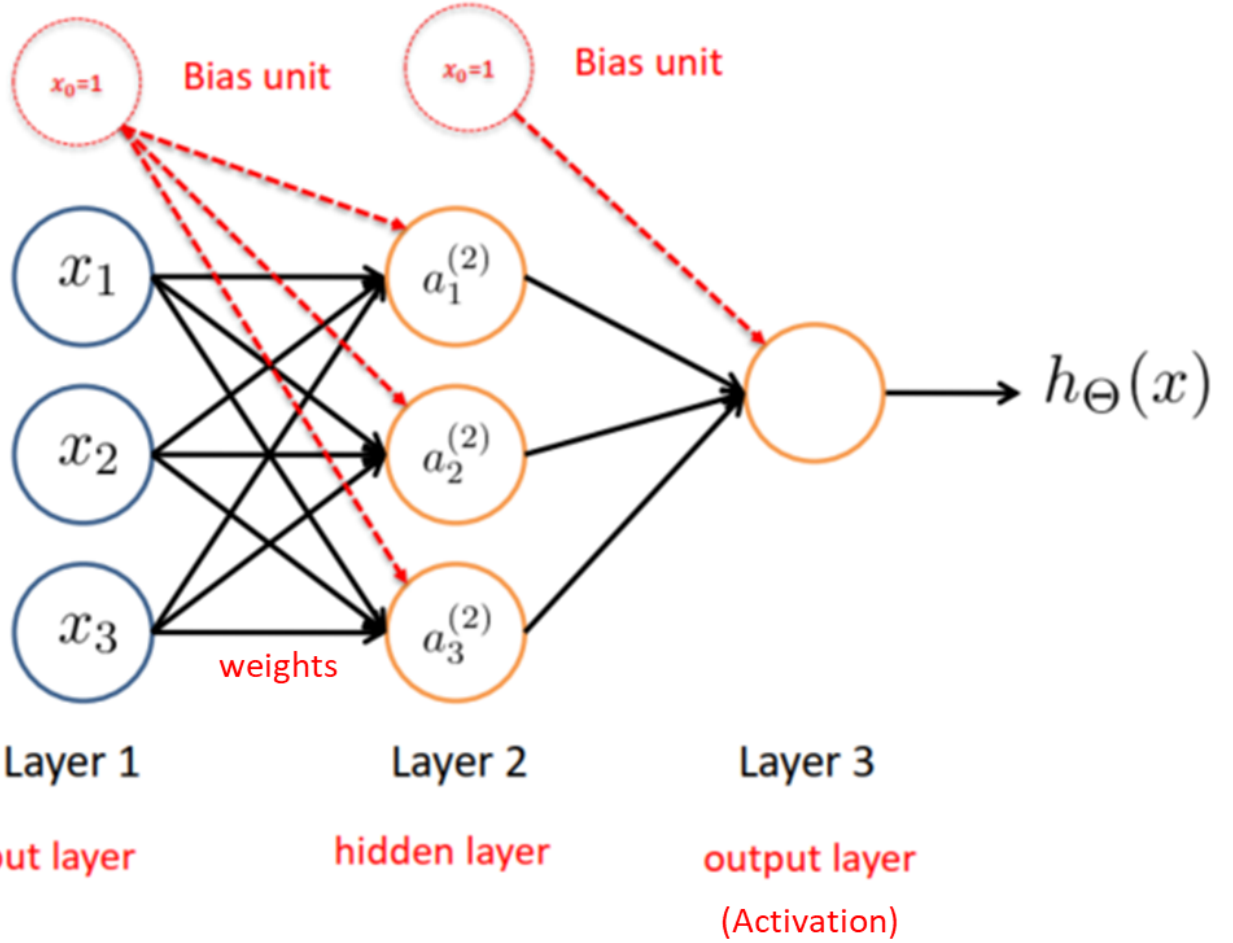
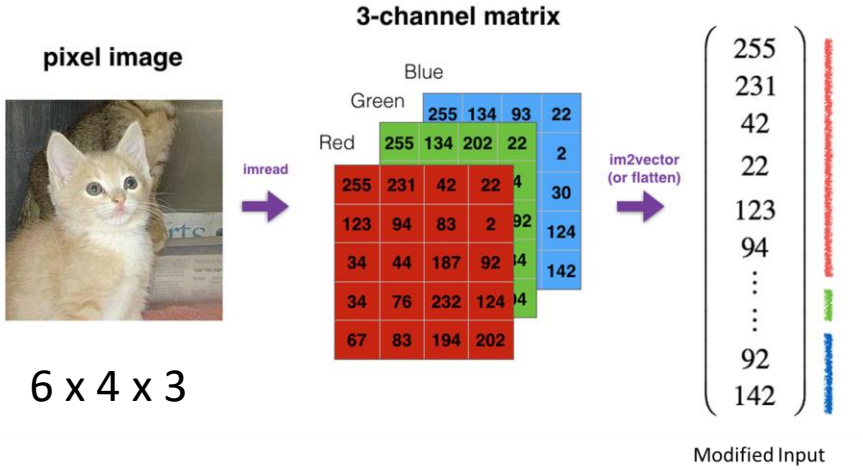
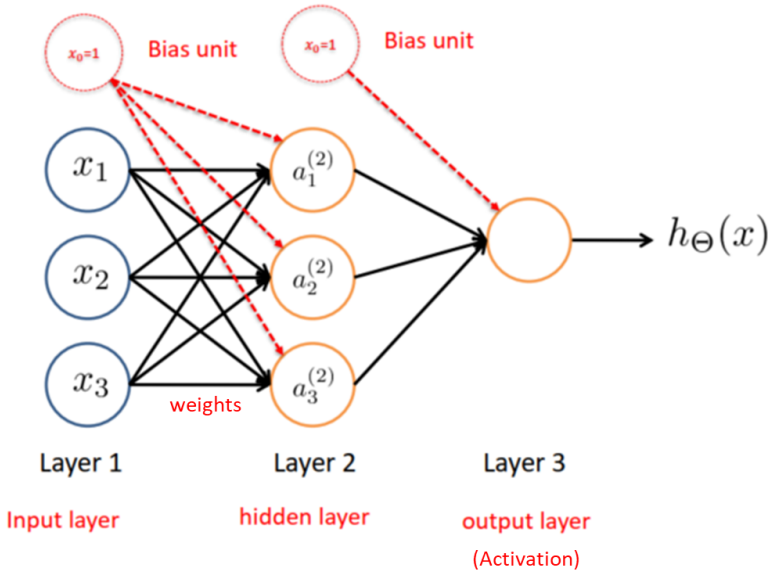





Cat

# Fully Connected Layers



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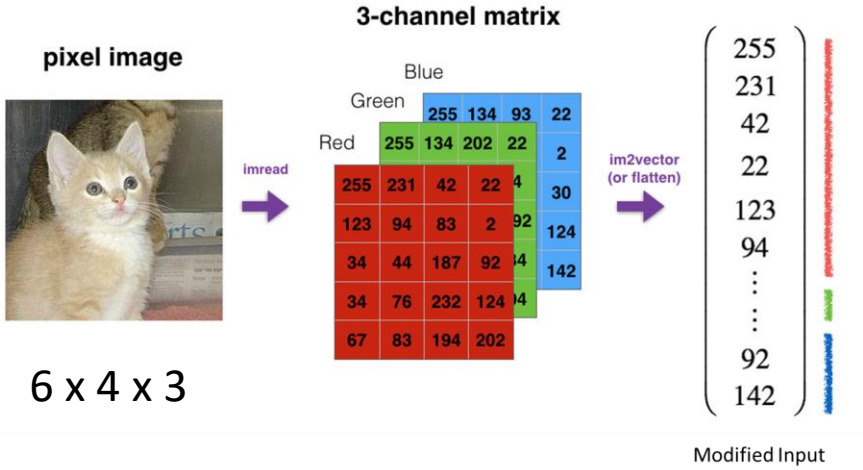
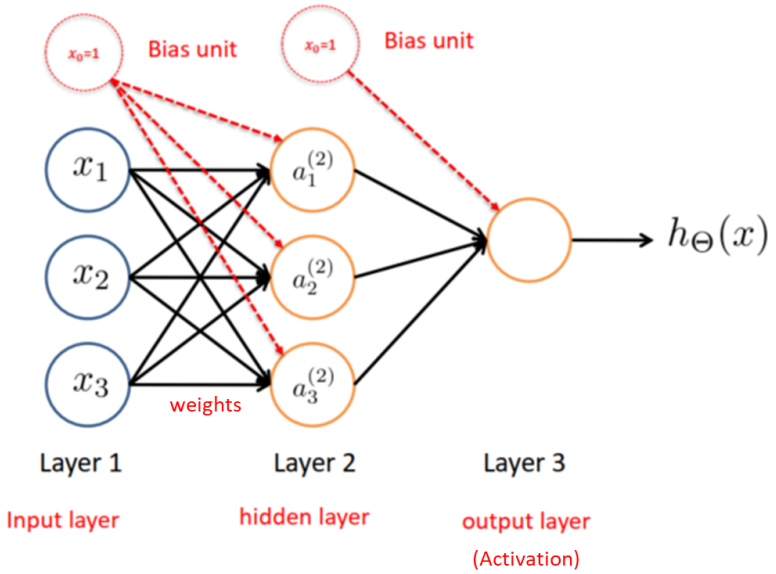
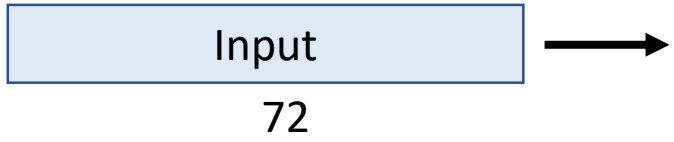



6 x 4 x 3



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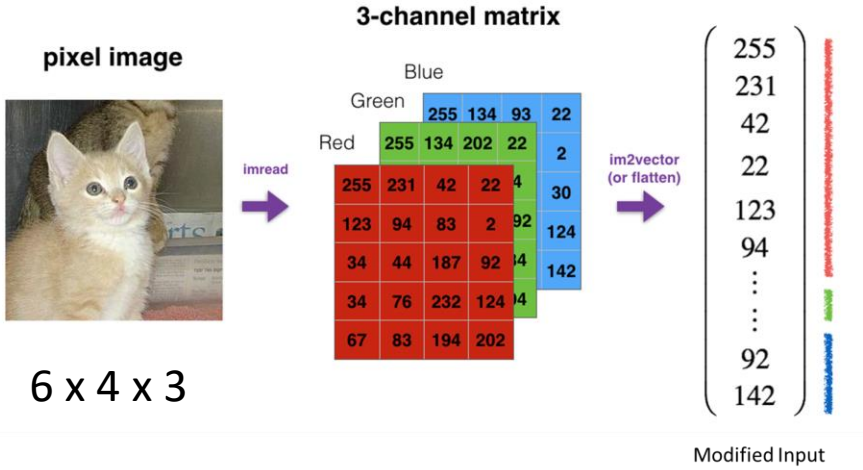
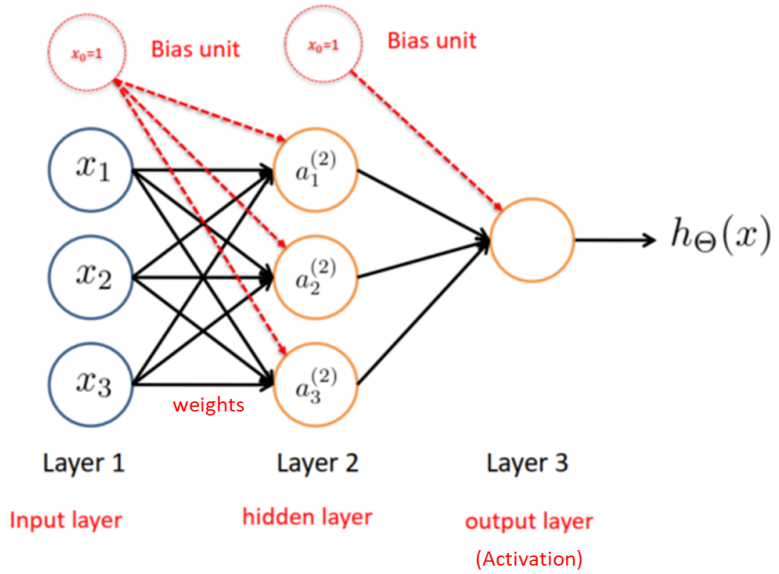


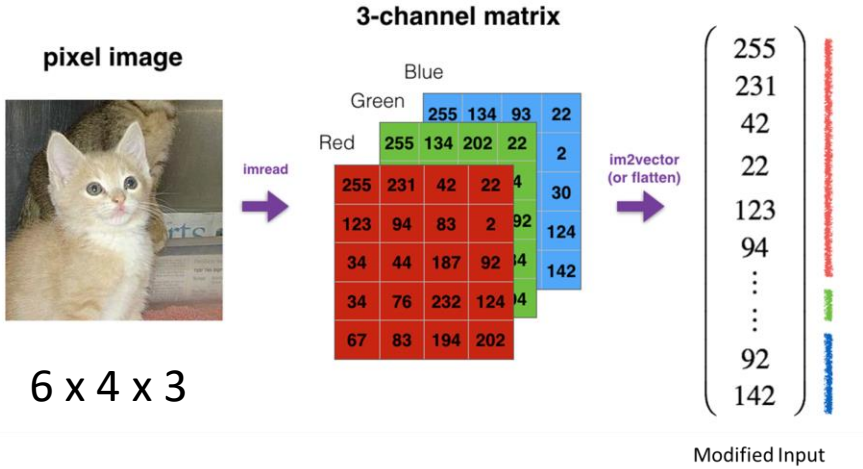

Input

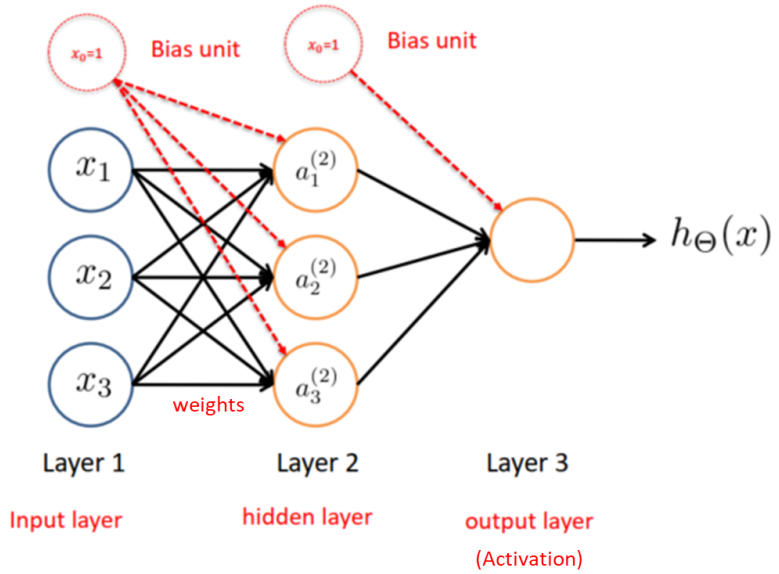
72

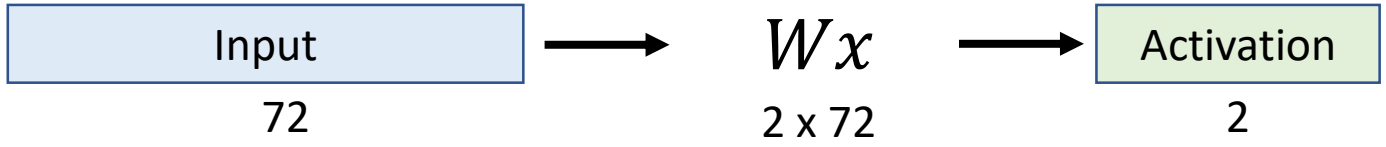
$$Wx$$

2 x 72

# Fully Connected Layers



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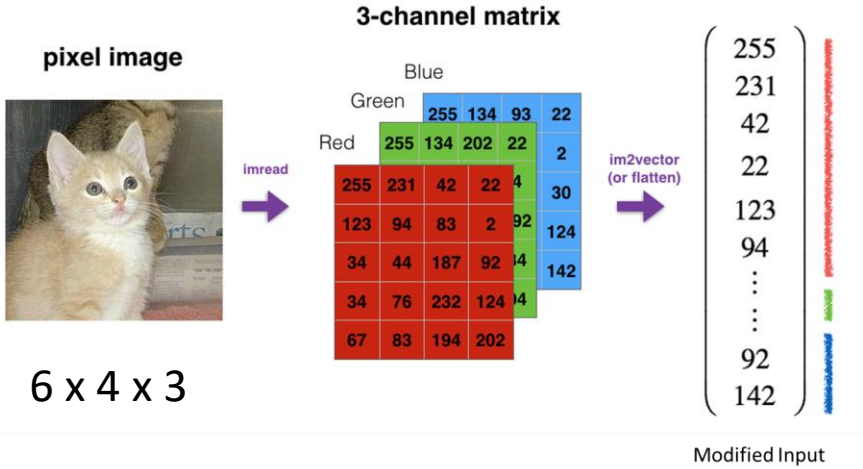


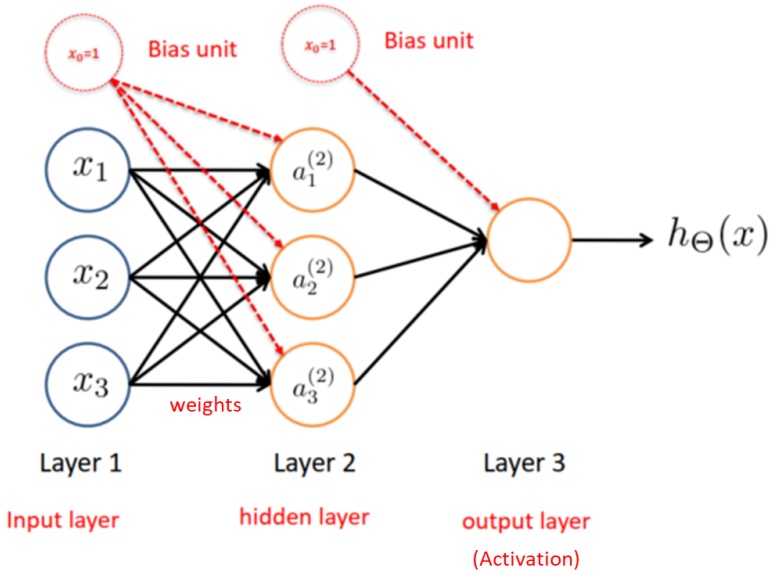


Input
72

$Wx$
2 x 72

Activation
2

**Output:** 1 Number
The result of taking a dot product between a row of W and the input
(a 72-dimensional dot product)

# Issues in Image Recognition using Fully Connected Networks

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1. *They don’t scale well to full images*

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32 x 32 x 3 = 3072 weights

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What if we have a color image of 500 x 500 x 3
(750000 Weights)

***For multiple layers, number of weights to calculate will Increase!***

# Issues in Image Recognition using Fully Connected Networks

*1. They don't scale well to full images*

32 x 32 x 3 = 3072 weights

Width x Height x Color Channel

What if we have a color image of 500 x 500 x 3
(750000 Weights)

***For multiple layers, number of weights to calculate will Increase!***

*2. Doesn't preserve the spatial structure*

# Convolution Neural Networks

- We use three main types of layers to build Convolution Neural Network architectures
  1. **Convolutional Layer (**combined with activation function),
  2. **Pooling Layer**, and
  3. **Fully-Connected Layer (Exactly NN)**

# Convolution Layer (Higher Level Overview)

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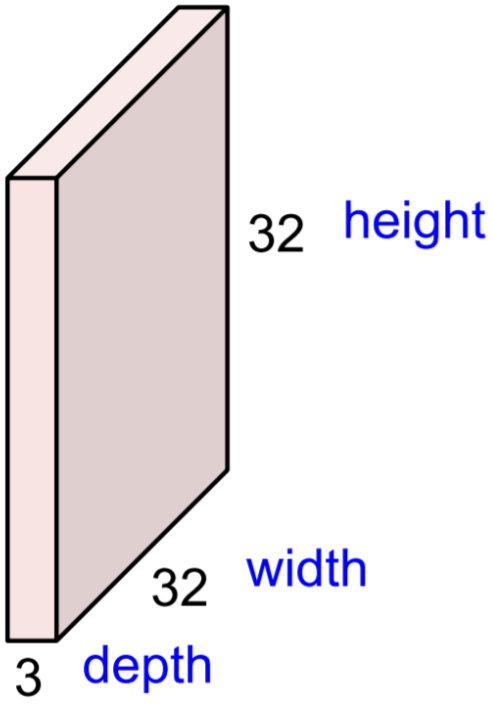


Input Image
32 x 32 x 3

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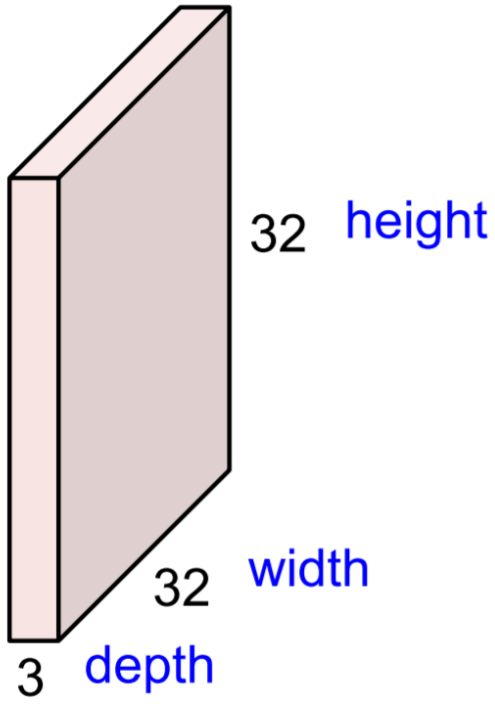


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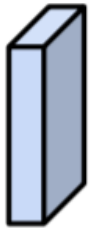

Filter
5 x 5 x 3

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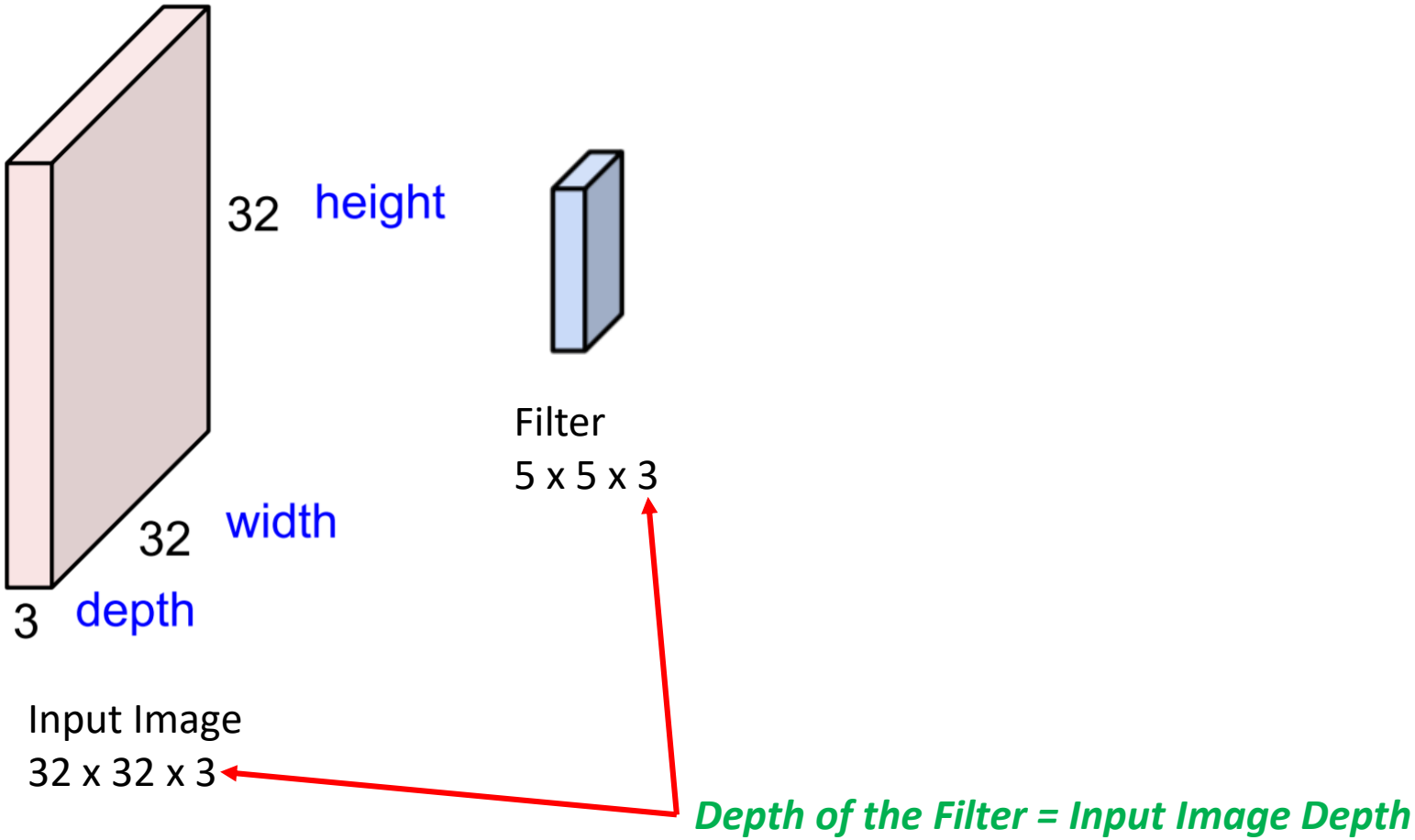

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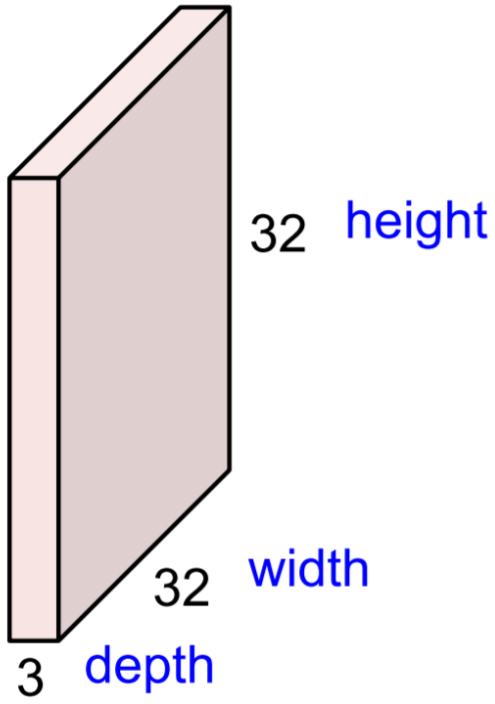


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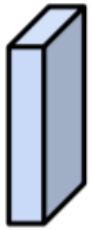

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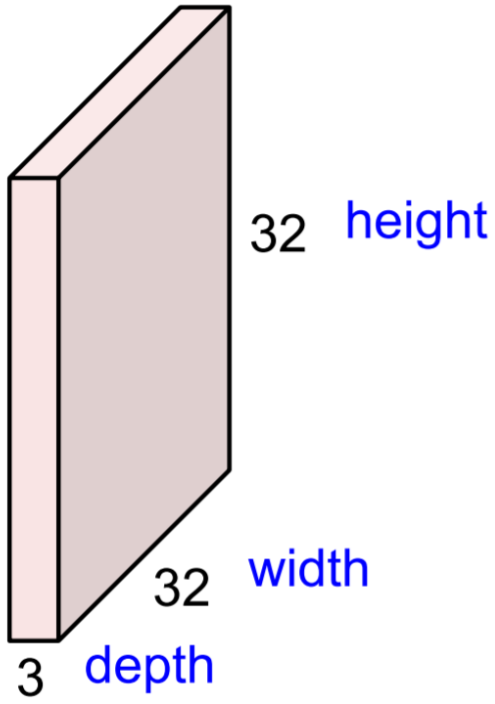


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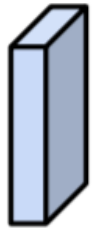

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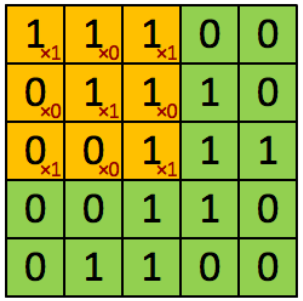
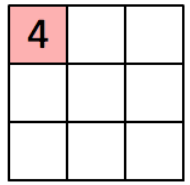



Image




Convolved
Feature

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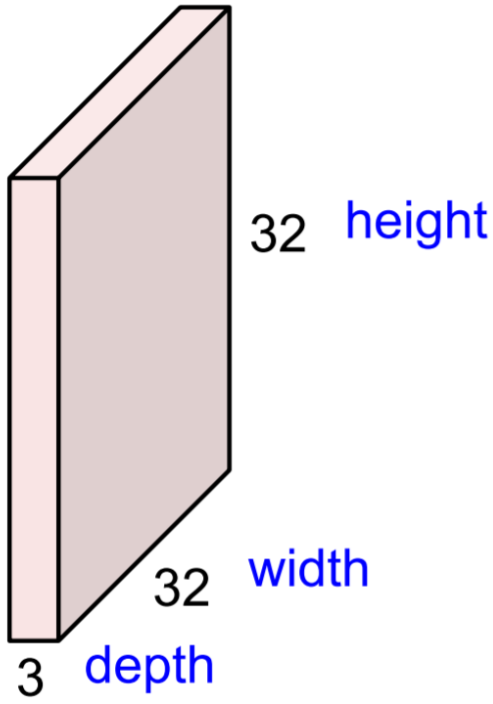


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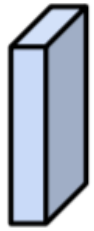
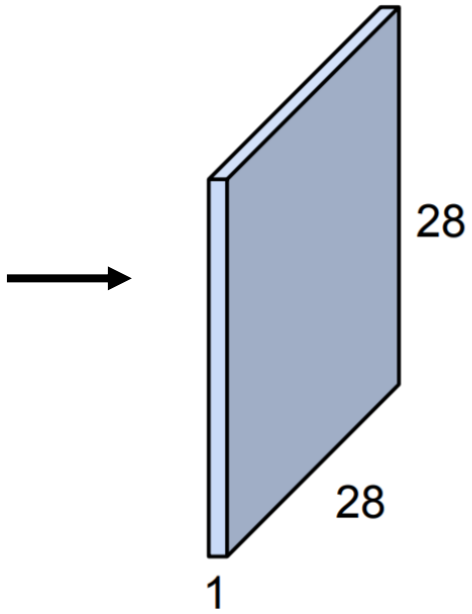


Filter
5 x 5 x 3




5 x 5 x 3 = 75-dimensional
dot product + bias

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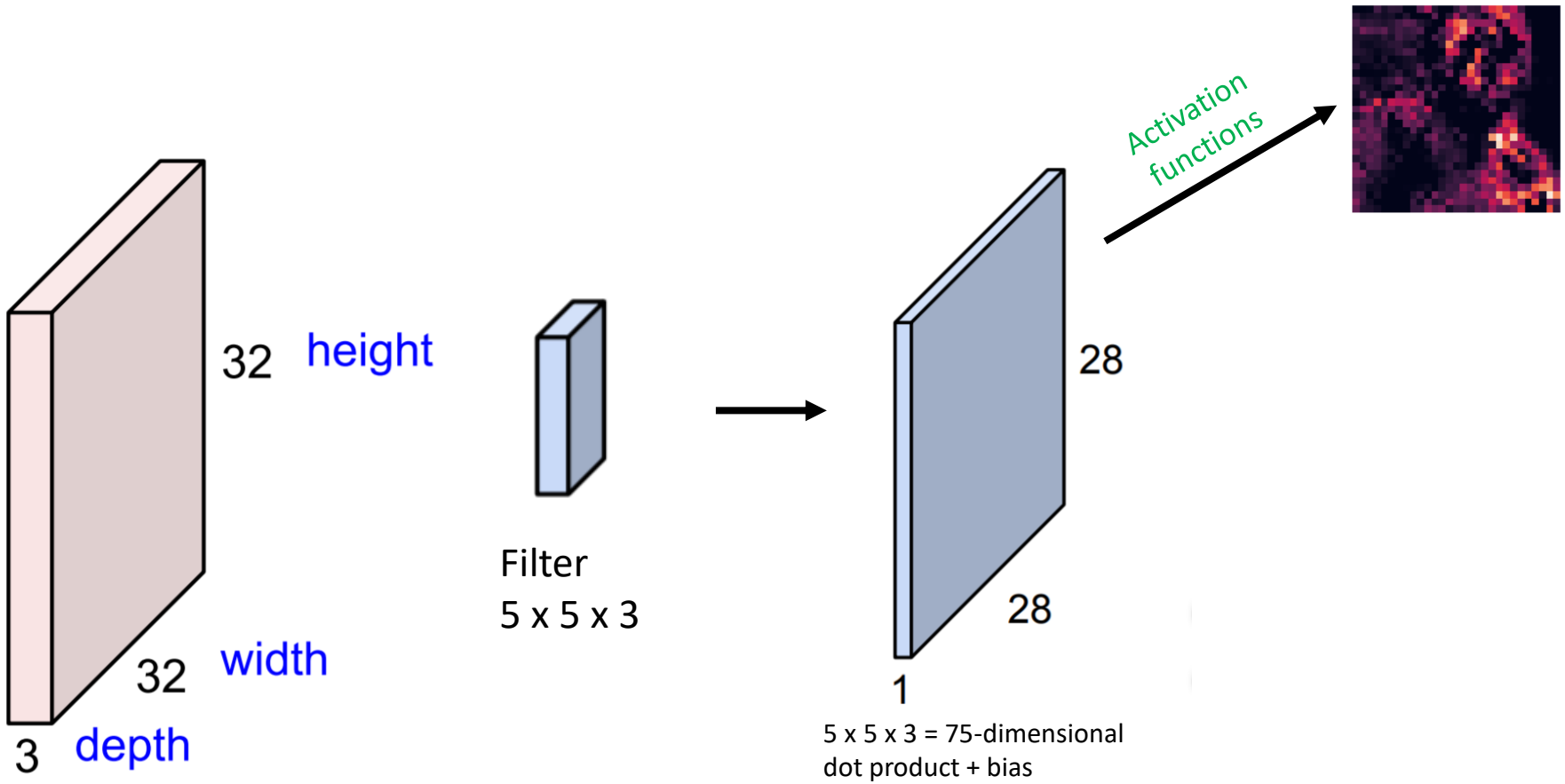

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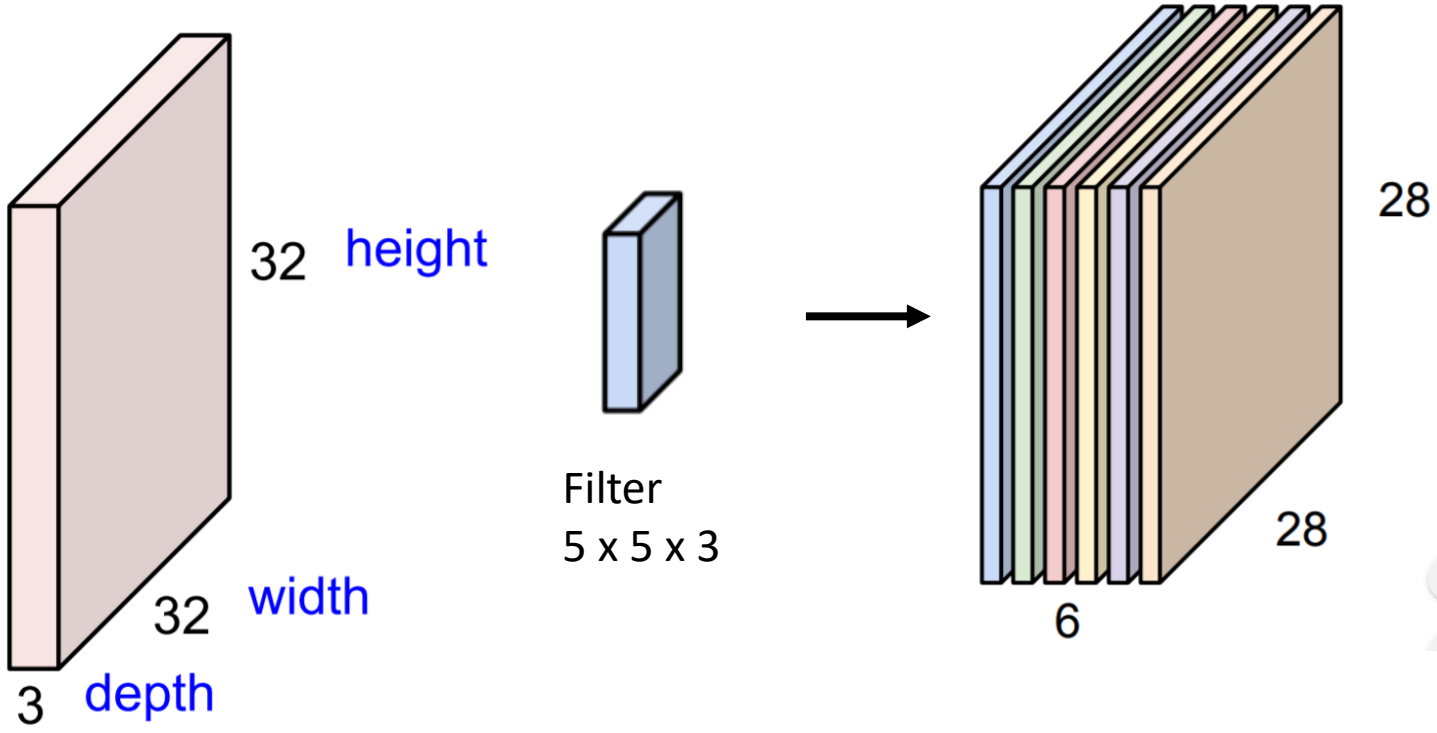


Input Image
32 x 32 x 3

If we had 6 5x5x3 filters
we will have 6 separate
activation function!

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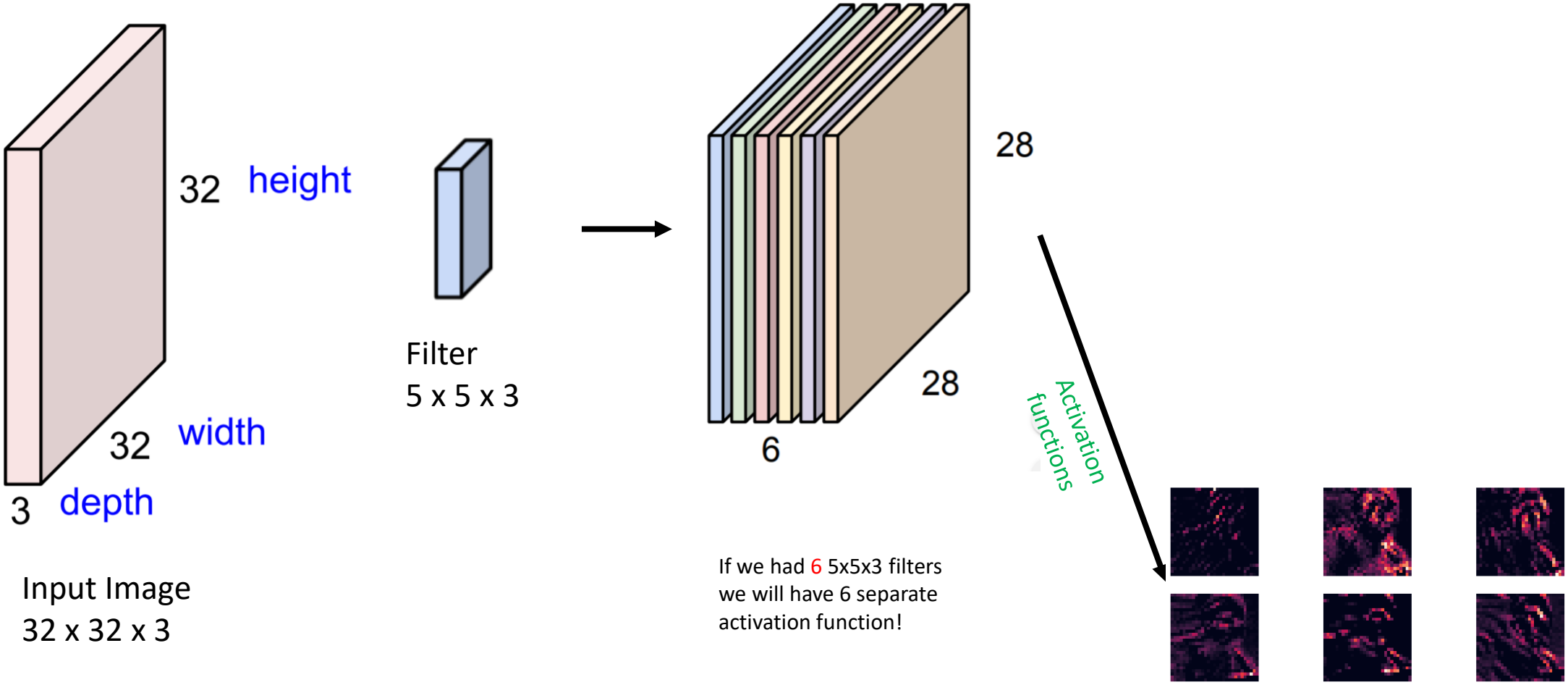

# Convolution Layer (Filter)

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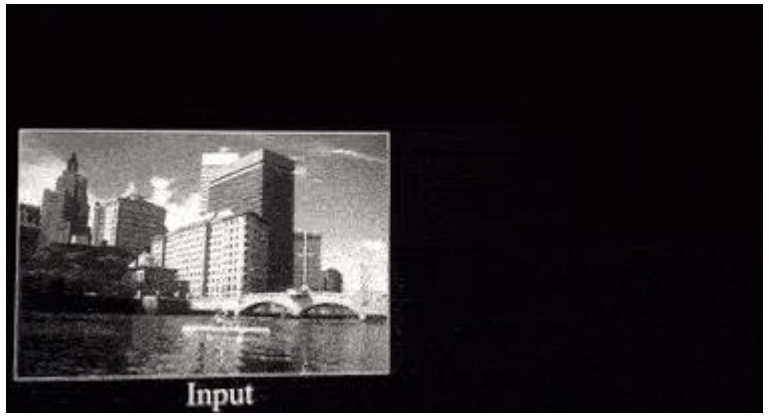
*How is it helping?*

*

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



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$*$

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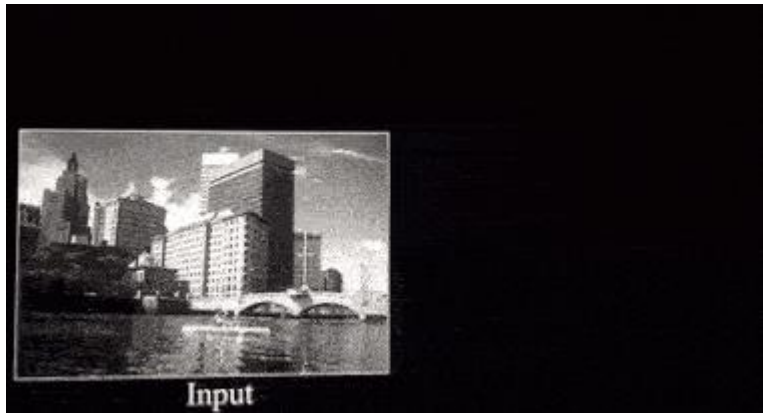


*Let's do an Example*

| | | |
|---|---|---|
| 1 | 3 | 1 |
| 0 | -1 | 1 |
| 2 | 2 | -1 |

input

$*$

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

kernel

flip(kernel)

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

*Multiply the window element by element with the flip(kernel), then sum the results*

# Convolution Layer (Filter)

*How is it helping?*

$*$

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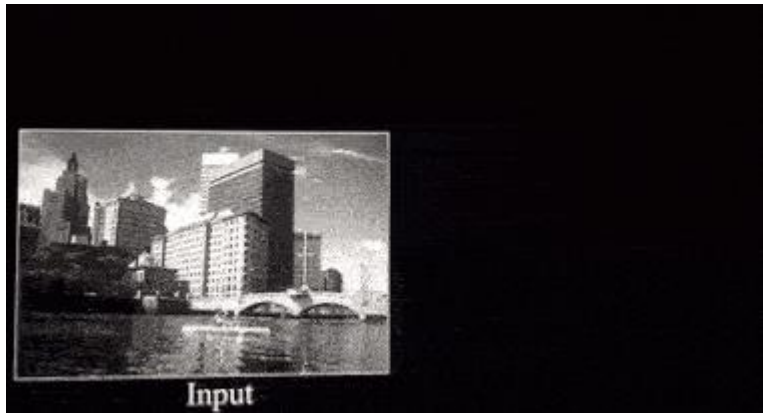



*Let's do an Example*

| | | |
|---|---|---|
| 1 | 3 | 1 |
| 0 | -1 | 1 |
| 2 | 2 | -1 |

input

$*$

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

kernel

flip(kernel)

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

*Multiply the window element by element with the flip(kernel), then sum the results*

| | | |
|---|---|---|
| **1** | **3** | 1 |
| **0** | **-1** | 1 |
| 2 | 2 | -1 |

=> 1(-1)+3(0)+0(2)-1(1) = -2

| | | |
|---|---|---|
| 1 | **3** | **1** |
| 0 | **-1** | **1** |
| 2 | 2 | -1 |

=> 3(-1)+1(0)-1(2)+1(1) = -4

| | | |
|---|---|---|
| 1 | 3 | 1 |
| **0** | **-1** | 1 |
| **2** | **2** | -1 |

=> 0(-1)-1(0)+2(2)+2(1) = 6

| | | |
|---|---|---|
| 1 | 3 | 1 |
| 0 | **-1** | **1** |
| 2 | **2** | **-1** |

=> -1(-1)+1(0)+2(2)-1(1) = 4

result(valid)

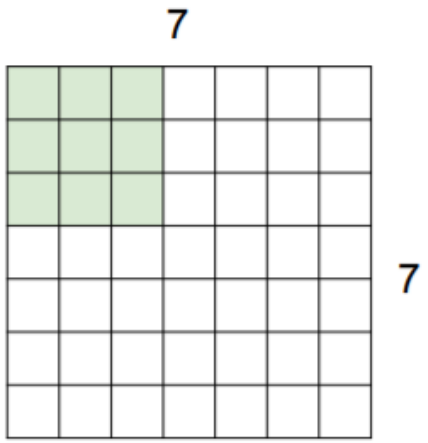
| | |
|---|---|
| -2 | -4 |
| 6 | 4 |

# Convolution Layer

- While convoluting so far, we have shown a sliding window of 1. This is called a ***STRIDE.***

# Convolution Layer

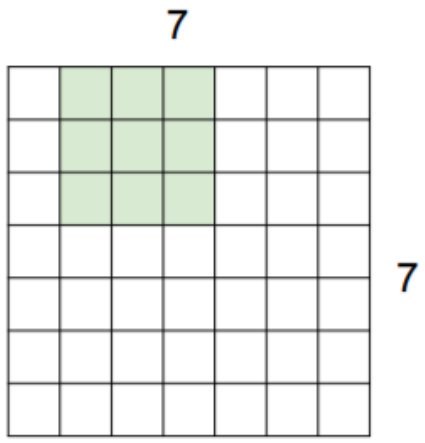
- While convoluting so far, we have shown a sliding window of 1. This is called a ***STRIDE.***




**Stride :** 1

# Convolution Layer

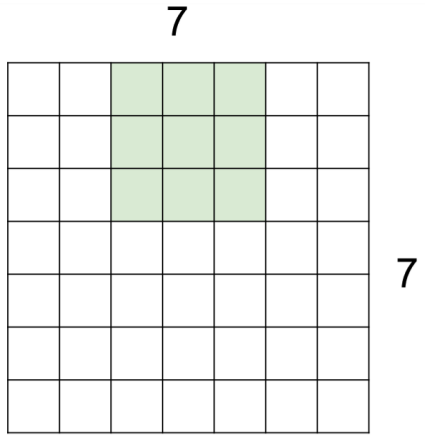
- While convoluting so far, we have shown a sliding window of 1. This is called a ***STRIDE.***




**Stride :** 1

# Convolution Layer

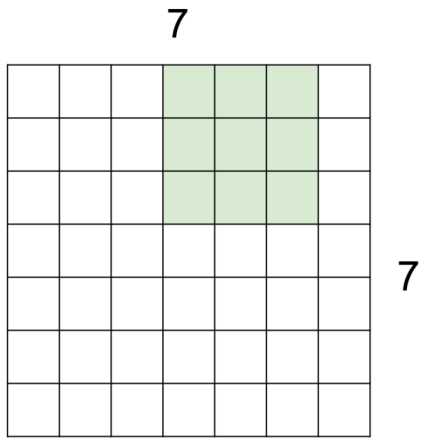
- While convoluting so far, we have shown a sliding window of 1. This is called a ***STRIDE.***




**Stride :** 1

# Convolution Layer

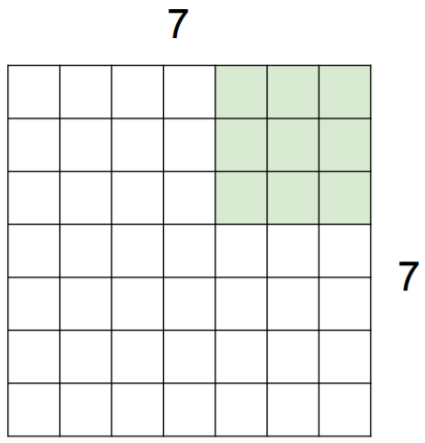
- While convoluting so far, we have shown a sliding window of 1. This is called a ***STRIDE.***




**Stride :** 1

# Convolution Layer

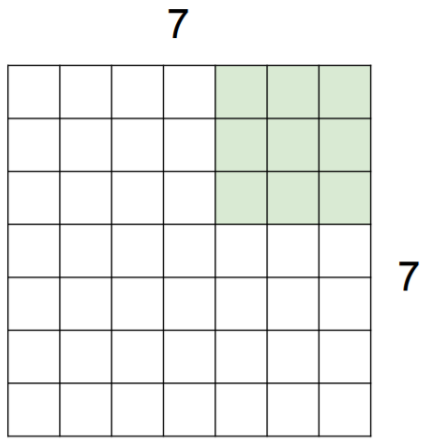
- While convoluting so far, we have shown a sliding window of 1. This is called a ***STRIDE.***




**Stride :** 1

# Convolution Layer

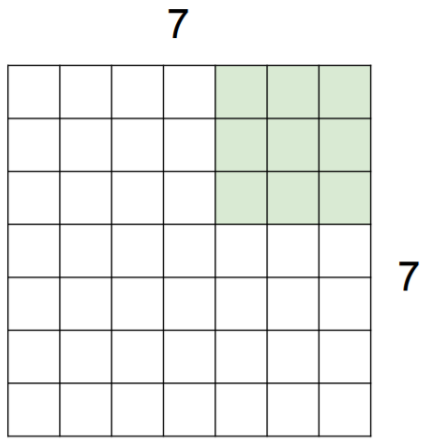
- While convoluting so far, we have shown a sliding window of 1. This is called a ***STRIDE.***
- Do you think we can change the strides?




**Stride :** 1

# Convolution Layer

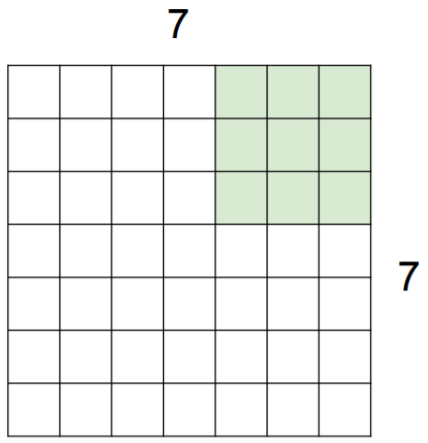
- While convoluting so far, we have shown a sliding window of 1. This is called a ***STRIDE.***
- Do you think we can change the strides? **Yes!**



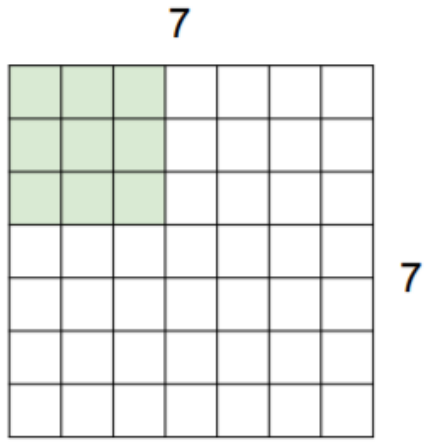

**Stride :** 1

# Convolution Layer

- While convoluting so far, we have shown a sliding window of 1. This is called a ***STRIDE.***
- Do you think we can change the strides? **Yes!**



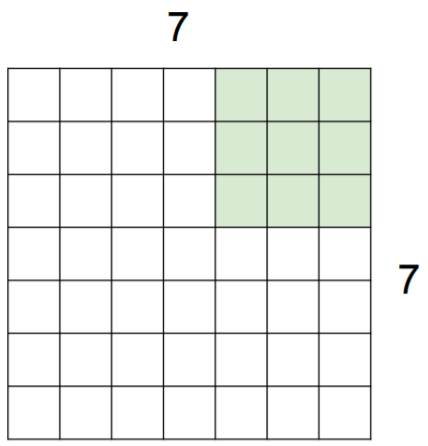

**Stride :** 1



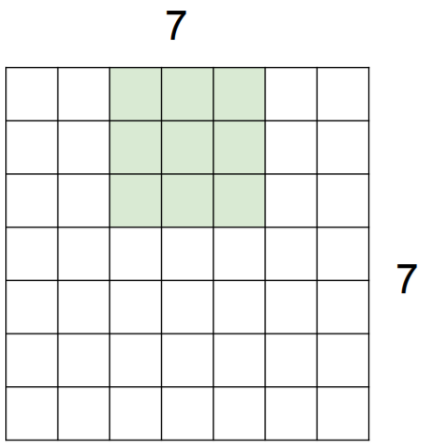

**Stride :** 2

# Convolution Layer

- While convoluting so far, we have shown a sliding window of 1. This is called a ***STRIDE.***
- Do you think we can change the strides? **Yes!**



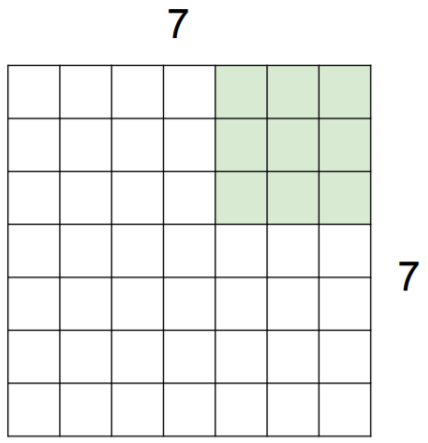

**Stride :** 1



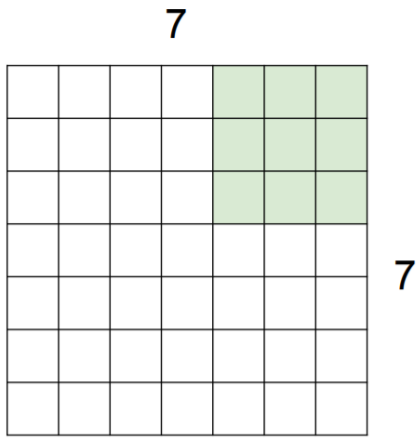

**Stride :** 2

# Convolution Layer

- While convoluting so far, we have shown a sliding window of 1. This is called a ***STRIDE.***
- Do you think we can change the strides? **Yes!**



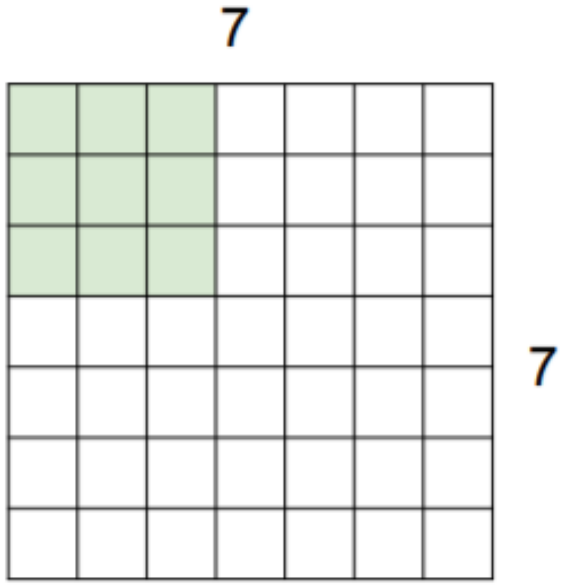

**Stride :** 1




**Stride :** 2

# Convolution Layer

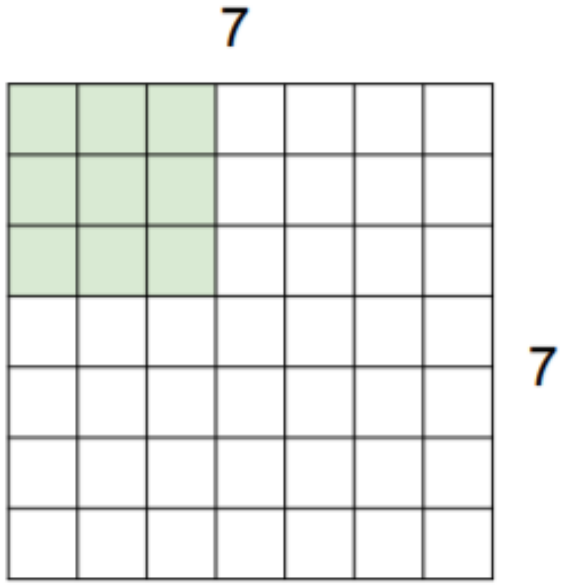
- What is the dimension of the transformed image?




**Input Dimension (N):** 7x7 (spatially)
**Filter Dimension (F) :** 3x3 (assume)
**Stride :** 1

# Convolution Layer

- What is the dimension of the transformed image?

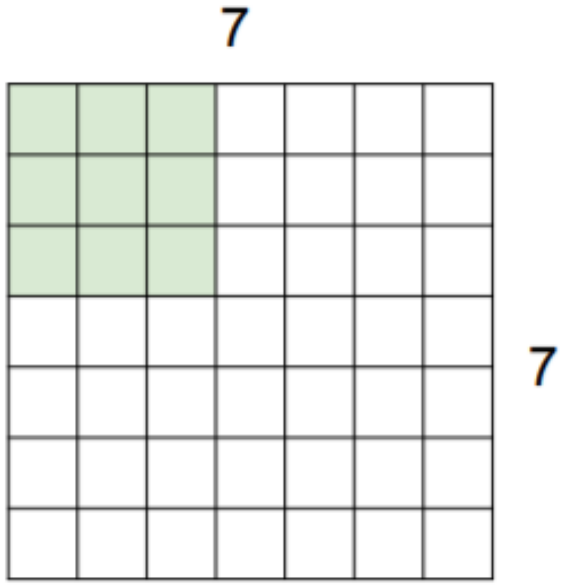



**Input Dimension (N):** 7x7 (spatially)
**Filter Dimension (F) :** 3x3 (assume)
**Stride :** 1

Output Dimension: $\frac{N-F}{Stride} + 1$

# Convolution Layer

- What is the dimension of the transformed image?

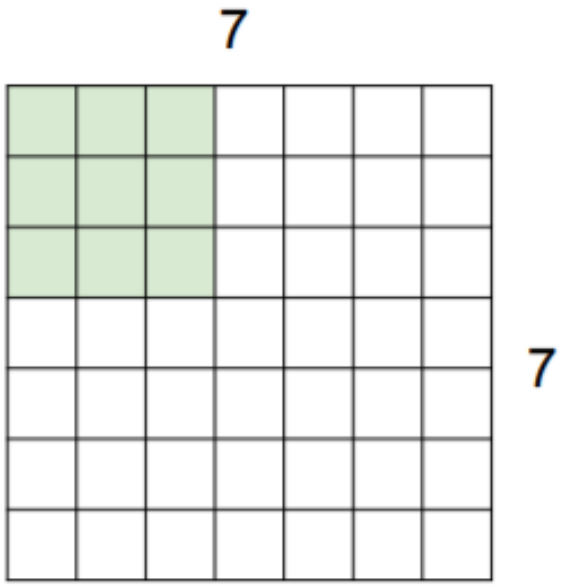



**Input Dimension (N):** 7x7 (spatially)
**Filter Dimension (F) :** 3x3 (assume)
**Stride :** 1
**Output Dimension:** 5x5 (output)

Output Dimension: $\frac{N-F}{Stride} + 1$

# Convolution Layer

- What is the dimension of the transformed image?

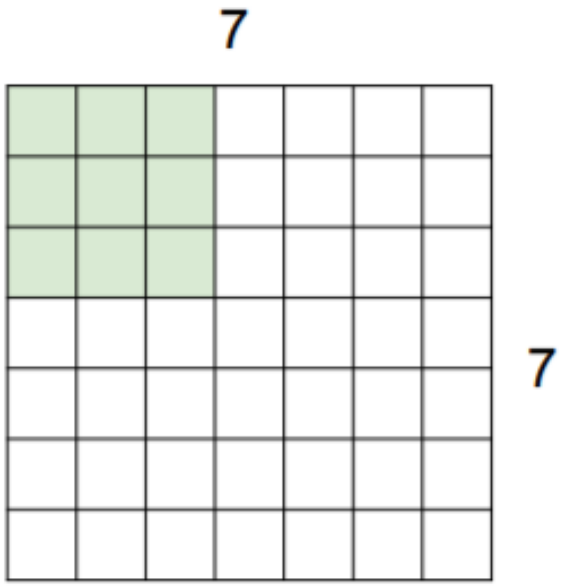



**Input Dimension (N):** 7x7 (spatially)
**Filter Dimension (F) :** 3x3 (assume)
**Stride :** 2

Output Dimension: $\frac{N-F}{Stride} + 1$

# Convolution Layer

- What is the dimension of the transformed image?

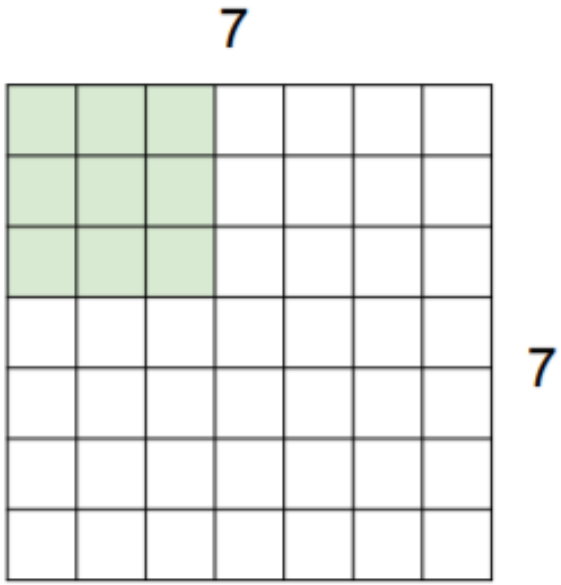



**Input Dimension (N):** 7x7 (spatially)
**Filter Dimension (F) :** 3x3 (assume)
**Stride :** 2
**Output Dimension:** 3x3 (output)

Output Dimension: $\frac{N-F}{Stride} + 1$

# Convolution Layer

- What is the dimension of the transformed image?

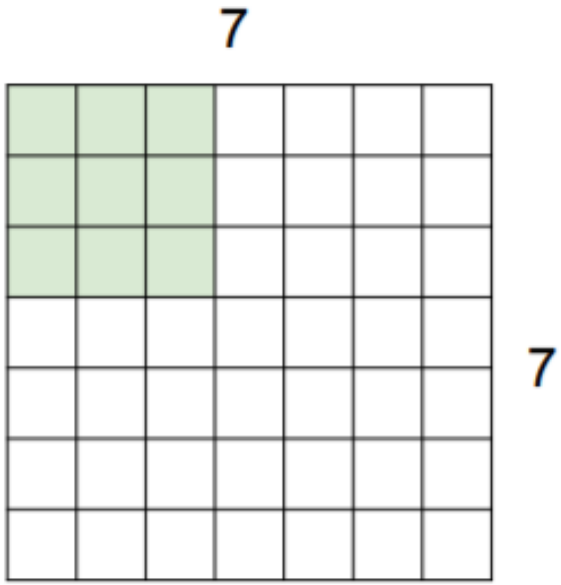



**Input Dimension (N):** 7x7 (spatially)
**Filter Dimension (F) :** 3x3 (assume)
**Stride :** 3
**Output Dimension:** ?

Output Dimension: $\frac{N-F}{Stride} + 1$

# Convolution Layer

- What is the dimension of the transformed image?



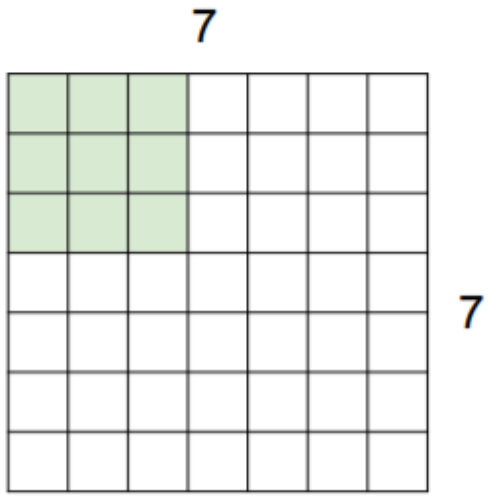

**Input Dimension (N):** 7x7 (spatially)
**Filter Dimension (F) :** 3x3 (assume)
**Stride :** 3
**Output Dimension:** ?

Output Dimension: $\frac{N-F}{Stride} + 1$

**Doesn't fit!**

# Convolution Layer

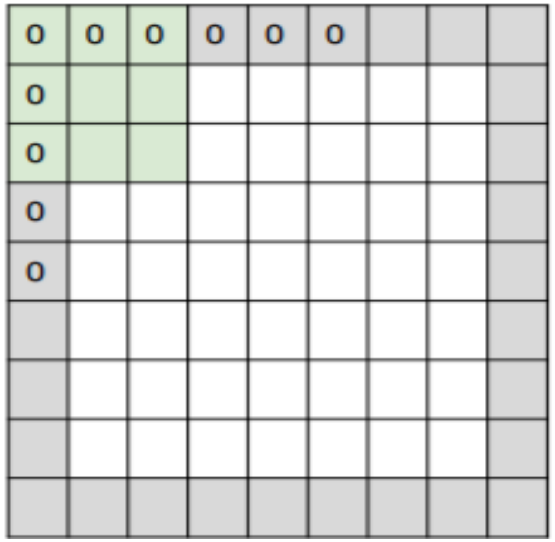
- What is the dimension of the transformed image?



# Convolution Layer

- What is the dimension of the transformed image?

In practice: Common to zero pad ($Z$) the border!

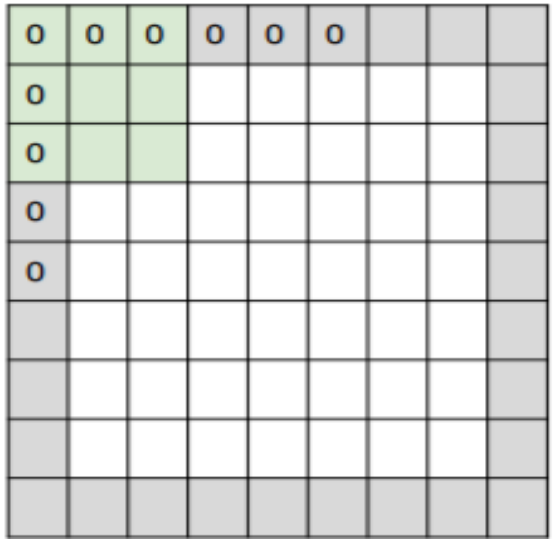



**Pad with 1 pixel**

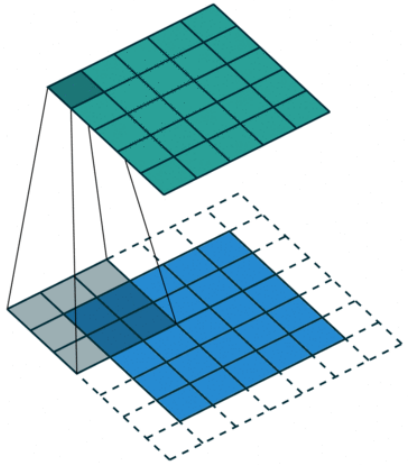
# Convolution Layer

- What is the dimension of the transformed image?

In practice: Common to zero pad ($Z$) the border!




**Pad with 1 pixel**

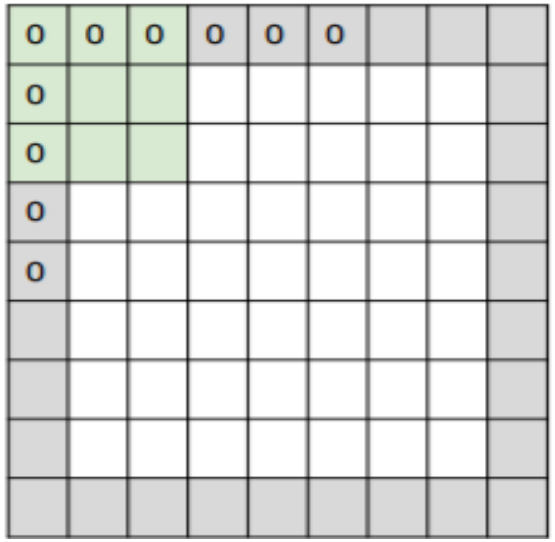


**Padding (P):** 1

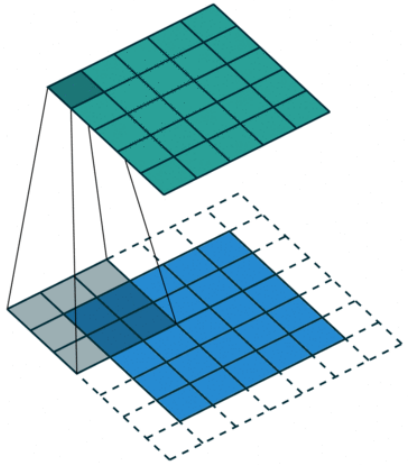
# Convolution Layer

- What is the dimension of the transformed image?

In practice: Common to zero pad ($Z$) the border!




**Pad with 1 pixel**

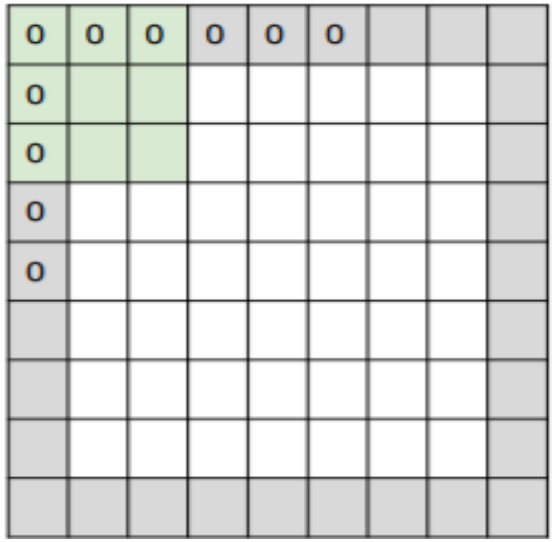


**Padding (P):** 1

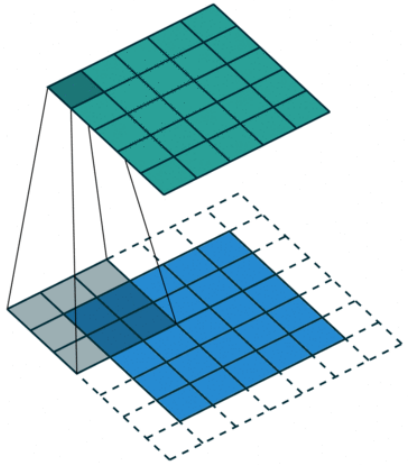
# Convolution Layer

- What is the dimension of the transformed image?

In practice: Common to zero pad ($Z$) the border!




**Pad with 1 pixel**



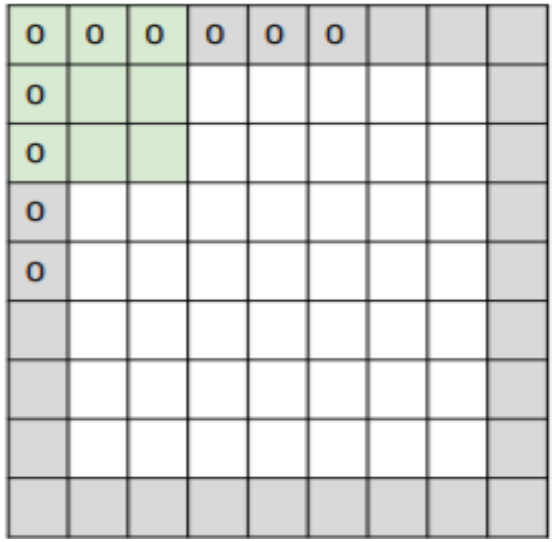
Output Dimension: $\frac{N-F+2P}{Stride}+1$

**Padding (P):** 1

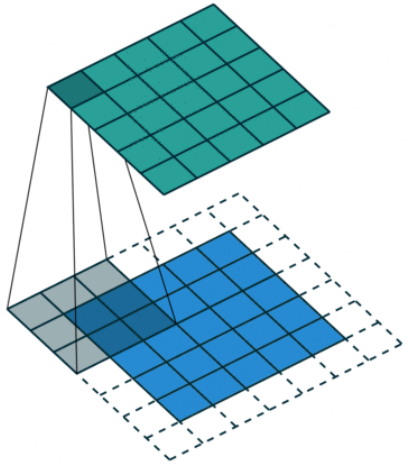
# Convolution Layer

- What is the dimension of the transformed image?

In practice: Common to zero pad ($Z$) the border!




**Pad with 1 pixel**



Output Dimension: $\frac{N-F+2P}{Stride}+1$

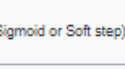
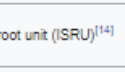
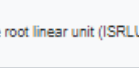
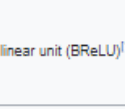
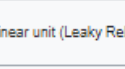
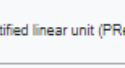
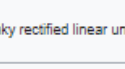
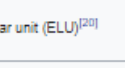
**Padding (P):** 1
**Output Dimension:** 3 x 3

# Convolution Layer

- In summary, we have ***four*** important hyper-parameters:
  1. Number of Filters, $K$
  2. Size of the Filter, $F$
  3. Stride, $S$
  4. Zero Padding, $Z$

# Activation Function

- A value passed through the function will be transformed within a range.

| Name | Plot | Equation |
|---|---|---|
| Identity |  | |
| Binary step |  | $f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$ |
| Logistic (a.k.a. Sigmoid or Soft step) |  | $f(x) = \sigma(x) = \frac{1}{1+e^{-x}}$ [1] |
| TanH |  | $f(x) = \tanh(x) = \frac{(e^{x} - e^{-x})}{(e^{x} + e^{-x})}$ |
| SQNL[9] | | $f(x) = \begin{cases} 1 & : x > 2.0 \\ x - \frac{x^2}{4} & : 0 \leq x \leq 2.0 \\ x + \frac{x^2}{4} & : -2.0 \leq x < 0 \\ -1 & : x < -2.0 \end{cases}$ |
| ArcTan |  | $f(x) = \tan^{-1}(x)$ |
| ArSinH | | $f(x) = \sinh^{-1}(x) = \ln\left(x + \sqrt{x^2 + 1}\right)$ |
| ElliotSig[10][11] Softsign[12][13] |  | $f(x) = \frac{x}{1 + \lvert x \rvert}$ |
| Inverse square root unit (ISRU)[14] |  | $f(x) = \frac{x}{\sqrt{1 + \alpha x^2}}$ |
| Inverse square root linear unit (ISRLU)[14] |  | $f(x) = \begin{cases} \frac{x}{\sqrt{1+\alpha x^2}} & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$ |
| Rectified linear unit (ReLU)[15] |  | $f(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ x & \text{for } x > 0 \end{cases}$ |
| Bipolar rectified linear unit (BReLU)[16] |  | $f(x_i) = \begin{cases} ReLU(x_i) & \text{if } i \bmod 2 = 0 \\ -ReLU(-x_i) & \text{if } i \bmod 2 \neq 0 \end{cases}$ |
| Leaky rectified linear unit (Leaky ReLU)[17] |  | $f(x) = \begin{cases} 0.01x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$ |
| Parameteric rectified linear unit (PReLU)[18] |  | $f(\alpha, x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$ |
| Randomized leaky rectified linear unit (RReLU)[19] |  | $f(\alpha, x) = \begin{cases} \alpha x & \text{for } x < 0 \text{ [3]} \\ x & \text{for } x \geq 0 \end{cases}$ |
| Exponential linear unit (ELU)[20] |  | $f(\alpha, x) = \begin{cases} \alpha(e^x - 1) & \text{for } x \leq 0 \\ x & \text{for } x > 0 \end{cases}$ |
| Scaled exponential linear unit (SELU)[21] | | $f(\alpha, x) = \lambda \begin{cases} \alpha(e^x - 1) & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$ with $\lambda = 1.0507$ and $\alpha = 1.67326$ |
| S-shaped rectified linear activation unit (SReLU)[22] | | $f_{t_l, a_l, t_r, a_r}(x) = \begin{cases} t_l + a_l(x - t_l) & \text{for } x \leq t_l \\ x & \text{for } t_l < x < t_r \\ t_r + a_r(x - t_r) & \text{for } x \geq t_r \end{cases}$ $t_l, a_l, t_r, a_r$ are parameters. |
| Adaptive piecewise linear (APL)[23] | | $f(x) = \max(0, x) + \sum_{s=1}^{S} a_i^s \max(0, -x + b_i^s)$ |

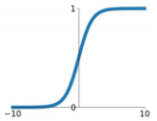
https://en.wikipedia.org/wiki/Activation_function

# Activation Function

- A value passed through the function will be transformed within a range.

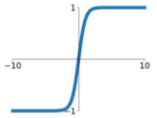
**Sigmoid**

$\sigma(x) = \frac{1}{1+e^{-x}}$



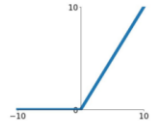
**tanh**

$\tanh(x)$



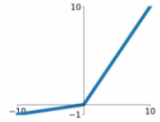
**ReLU**

$\max(0, x)$



**Leaky ReLU**

$\max(0.1x, x)$

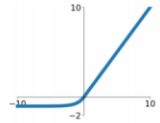


**Maxout**

$\max(w_1^T x + b_1, w_2^T x + b_2)$

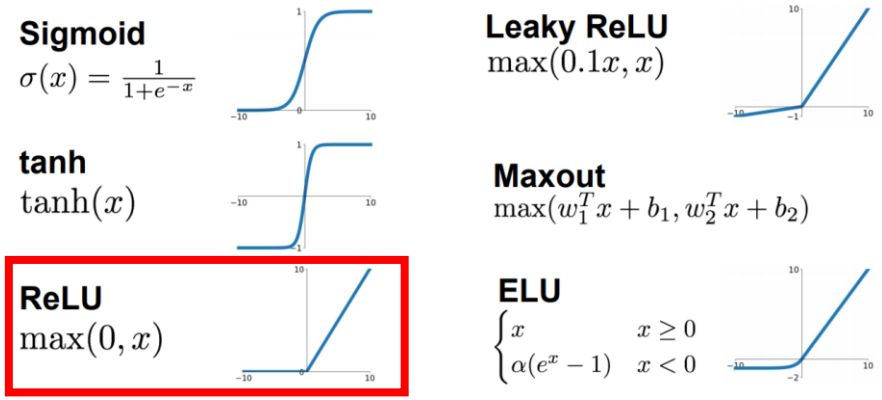
**ELU**

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



# Activation Function

- A value passed through the function will be transformed within a range.
- The most used activation function in CNNs is the ReLU (Rectified Linear Unit).



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| | | | |
|---|---|---|---|
| 1 | 14 | -9 | 4 |
| -2 | -20 | 10 | 6 |
| -3 | 3 | 11 | 1 |
| 2 | 54 | -2 | 80 |

ReLU

| | | | |
|---|---|---|---|
| 1 | 14 | 0 | 4 |
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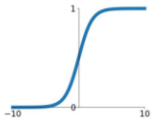
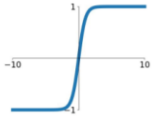
| 0 | 3 | 11 | 1 |
| 2 | 54 | 0 | 80 |

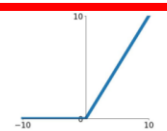
**Sigmoid**
$\sigma(x) = \frac{1}{1+e^{-x}}$



**tanh**
$\tanh(x)$



**ReLU**
$\max(0, x)$



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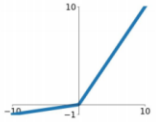

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$\max(w_1^T x + b_1, w_2^T x + b_2)$

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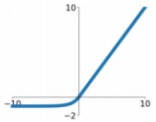

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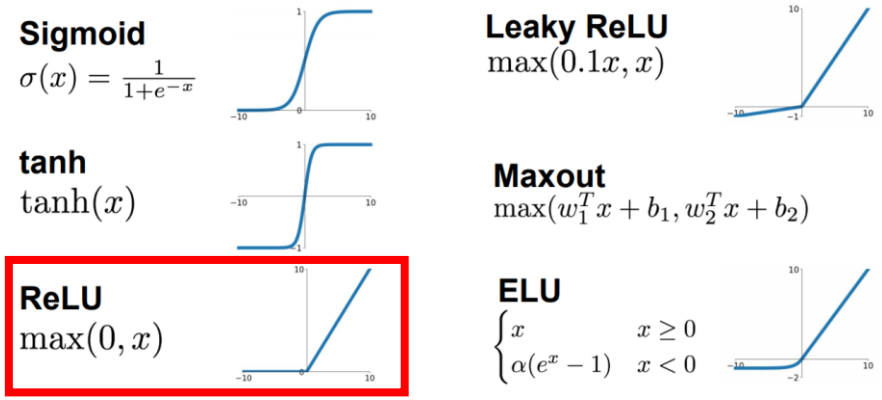
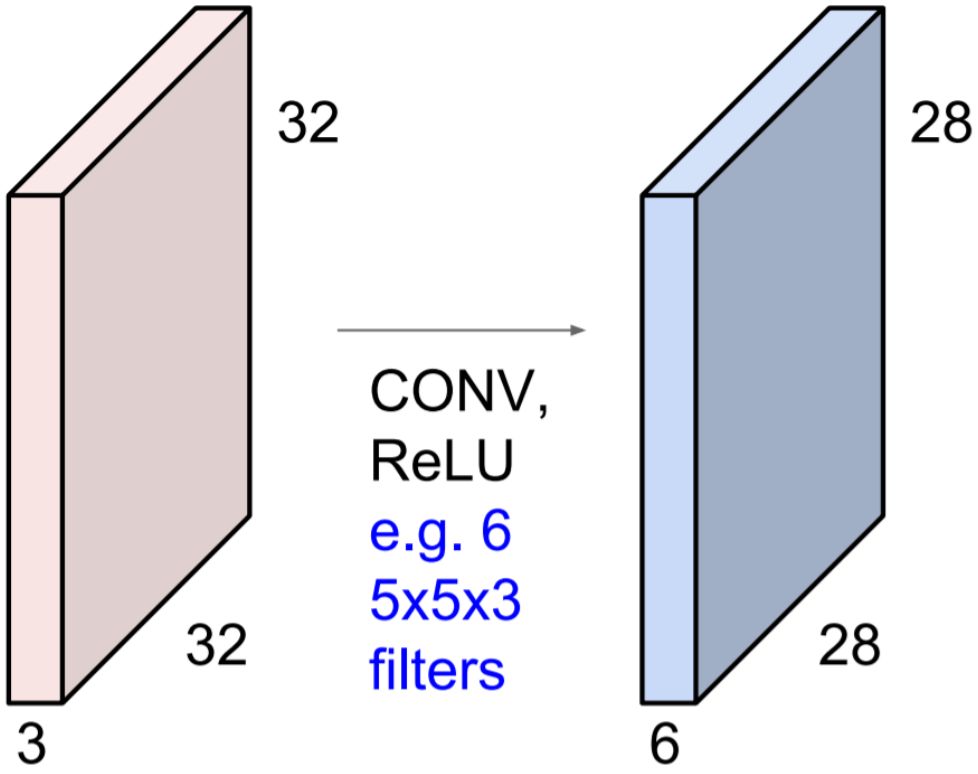
ReLU

| | | | |
|---|---|---|---|
| 1 | 14 | 0 | 4 |
| 0 | 0 | 10 | 6 |
| 0 | 3 | 11 | 1 |
| 2 | 54 | 0 | 80 |

- While using **ReLU**, be careful with your selection of **learning rate!**



# Convolution + Activation Layer



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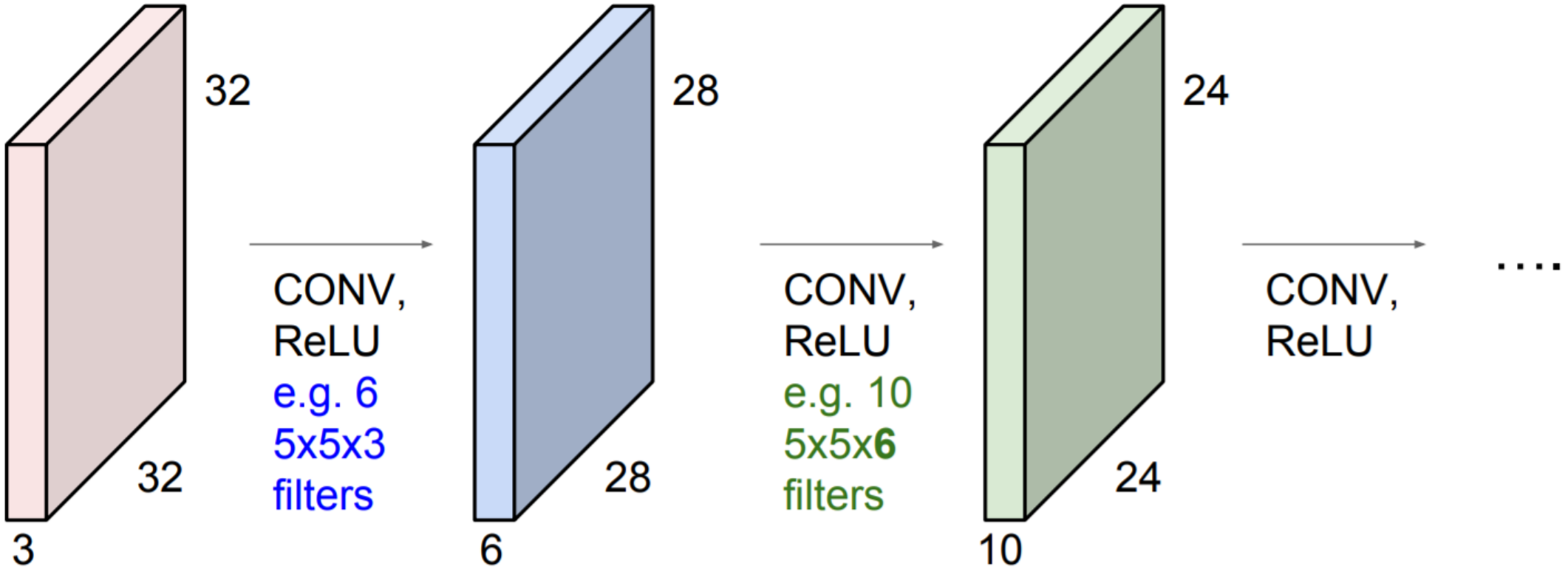
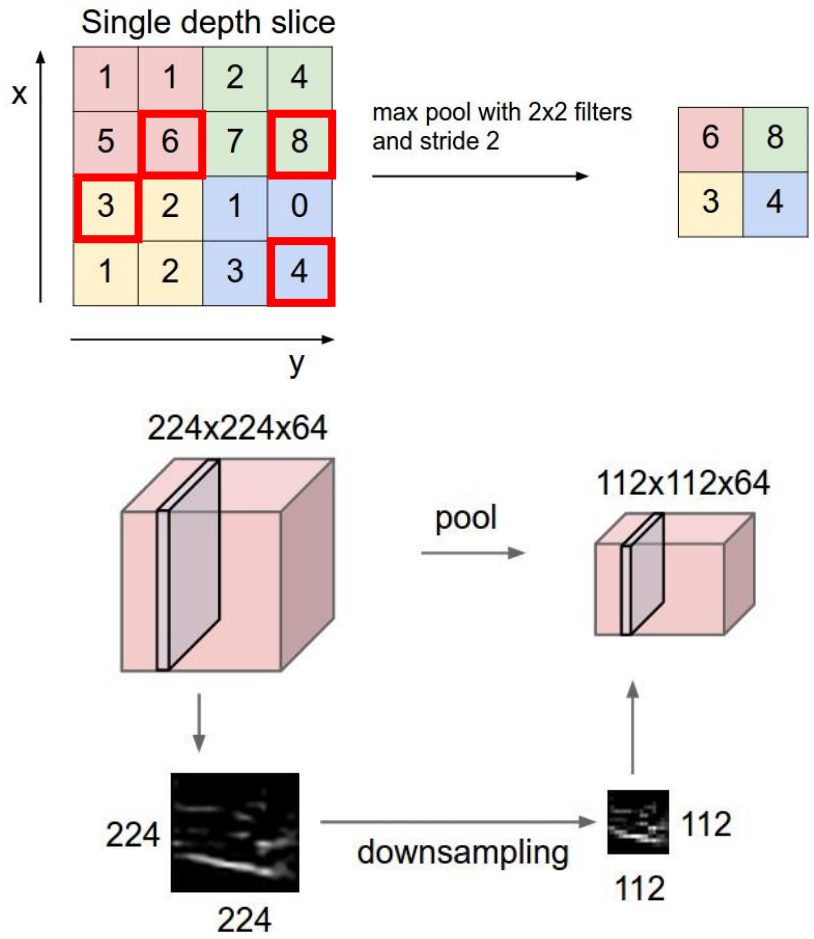


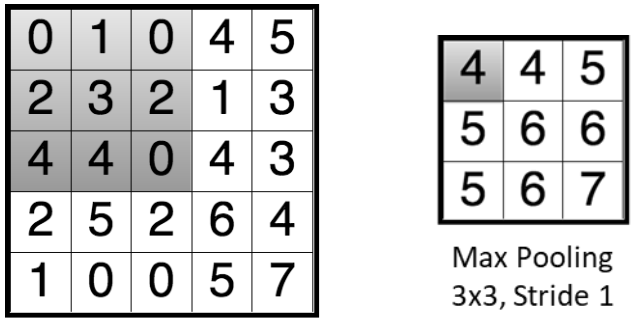
# Pooling Layers

- Pooling in a CNN is a subsampling step
  - Replaces the output to summary statistics of nearby outputs!
- It is common to periodically insert a Pooling layer in-between successive Conv layers
- Operates over each activation map independently
- Pooling is performed for two reasons
  1. Dimensionality reduction.
  2. Invariance to transformations of rotation and translation (*If we translate the input by a small amount values of most of the outputs does not change*). This is important *to identify if a feature is present rather than where exactly it is.*



# Pooling Layers

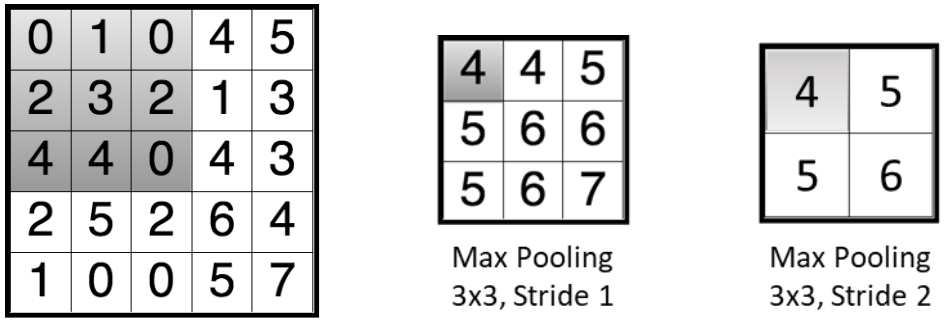
Similar to Convolution layer the strides can be changed!




1. norm of a rectangular neighborhood
2. Weighted average based on the distance from the central pixel

# Pooling Layers

Similar to Convolution layer the strides can be changed!



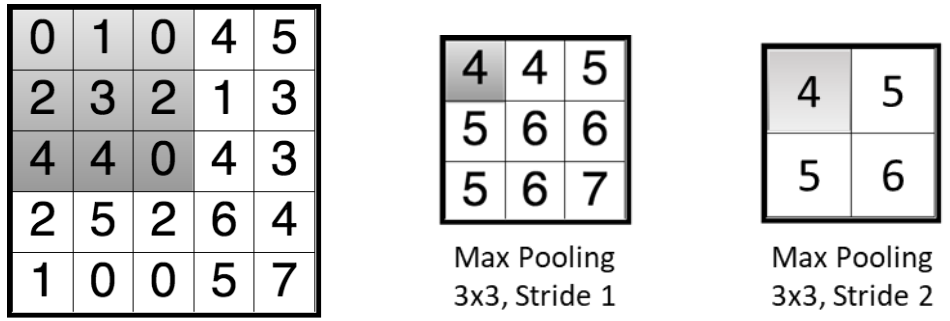

1. norm of a rectangular neighborhood
2. Weighted average based on the distance from the central pixel

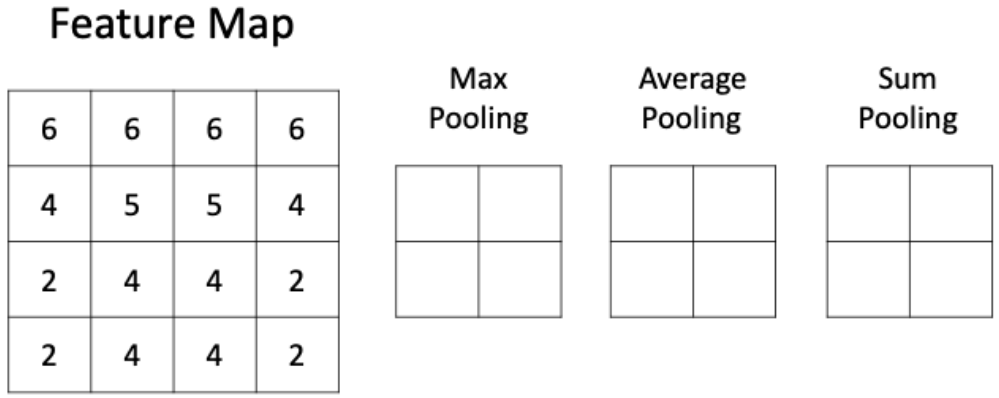
# Pooling Layers

$L\,2$ norm of a rectangular neighborhood

Similar to Convolution layer the strides can be changed!

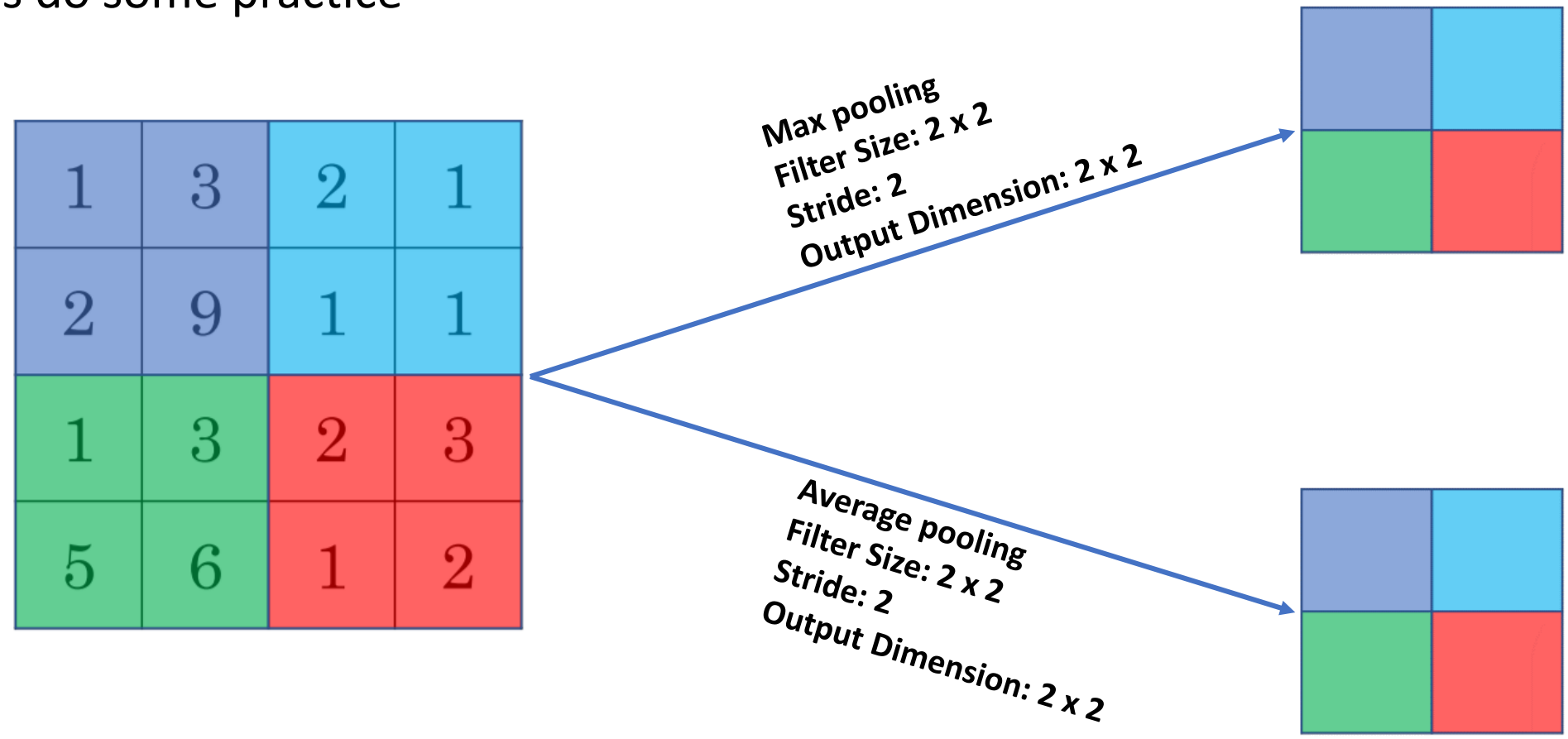
- Popular pooling functions:
  1. Max pooling operation reports the maximum output within a rectangular neighborhood
  2. Average of a rectangular neighborhood
  3. Sum pooling
  4. Weighted average based on the distance from the central pixelWeighted average based on the distance from the central pixel



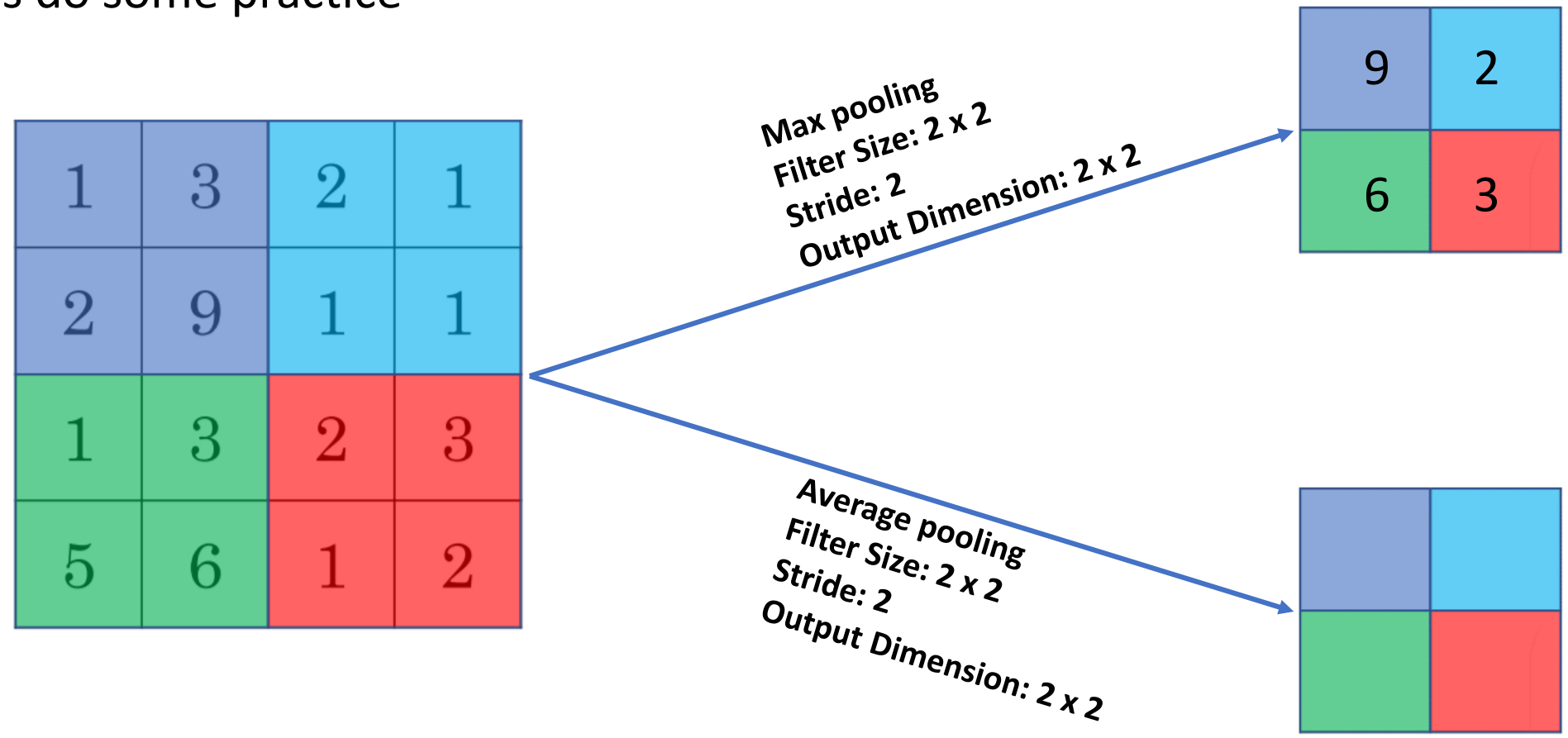
# Pooling Layers

- Let's do some practice



# Pooling Layers

- Let's do some practice



# Pooling Layers

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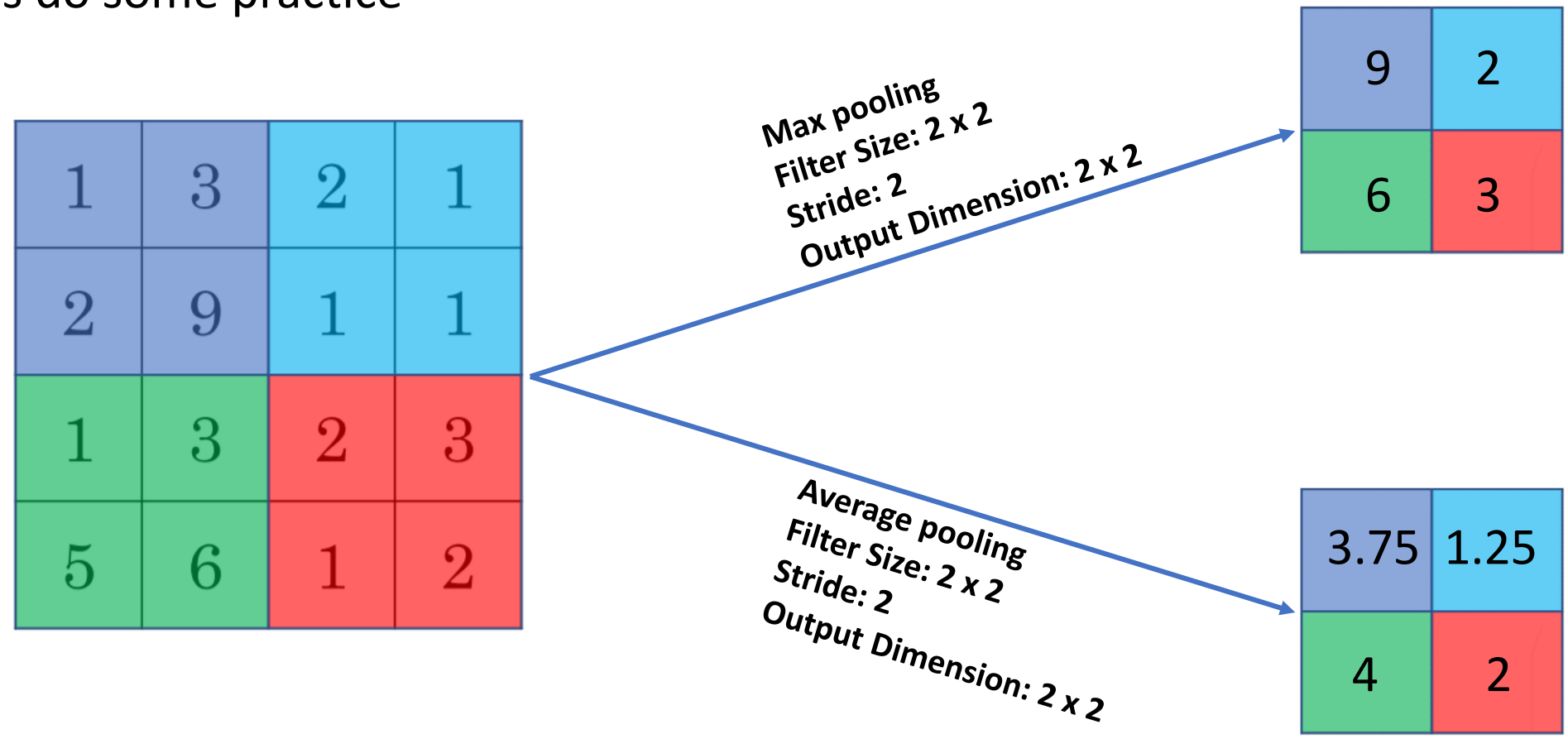
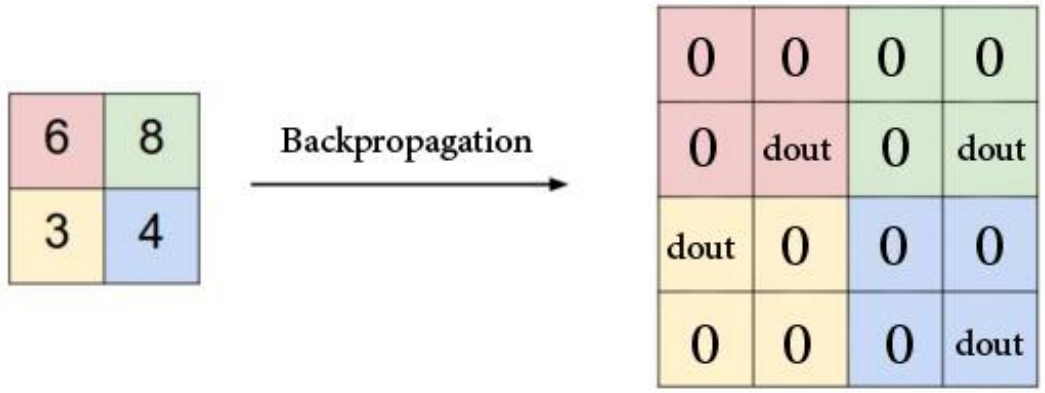


# Pooling Layers

- In summary, we have ***three*** important hyper-parameters:
  1. Filters Size, $F$
  2. Stride, $S$
  3. Zero Padding are rarely used
- Max pooling or Average pooling popularly are used

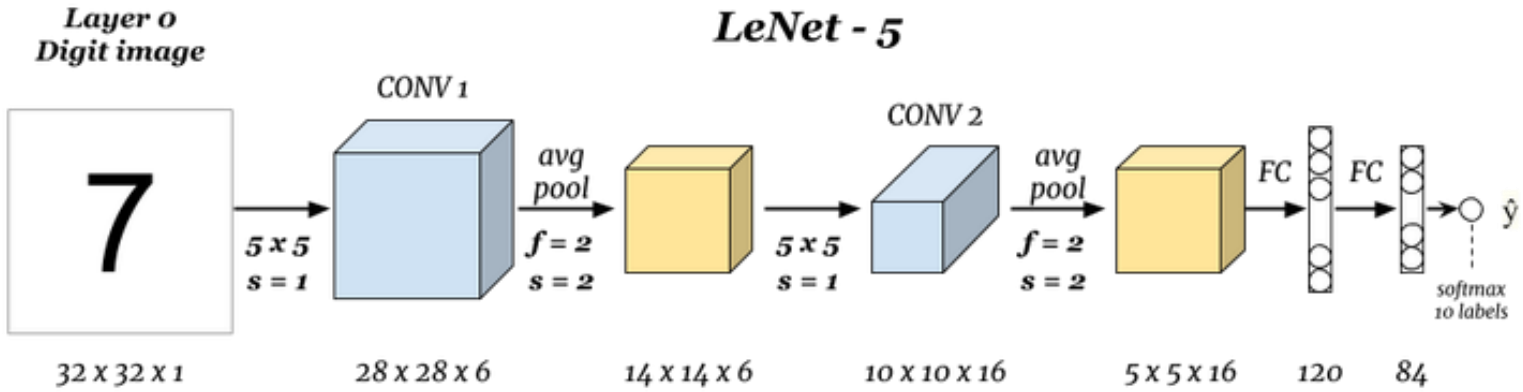
# Un-Pooling Layers

- While backpropagating we only preserve the max nodes:



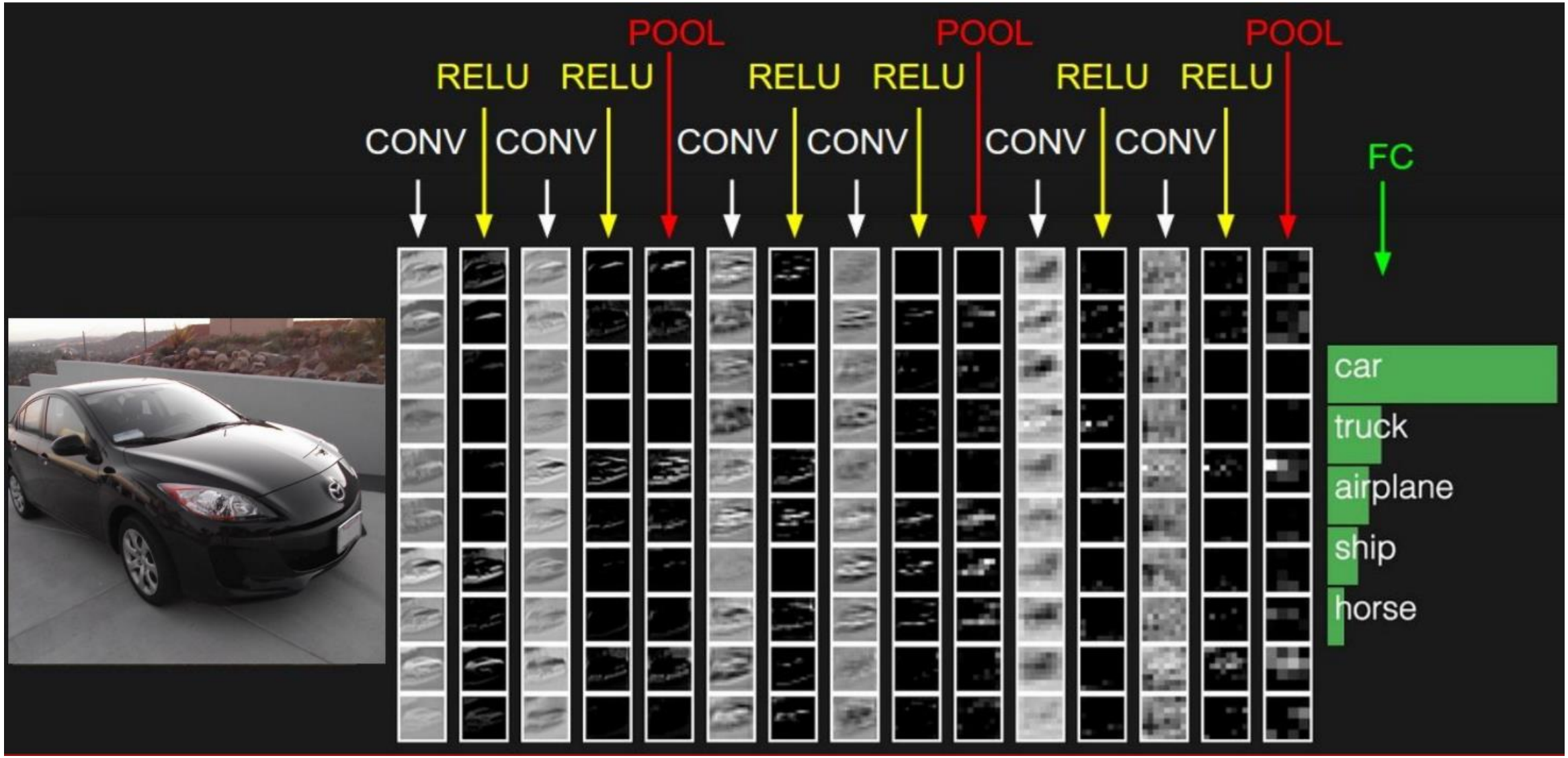
# Example 1 (Classic LeNet – 5)

- This model was published in 1998. The last layer wasn't using softmax back then.
- Used for digit recognition.
- The dimensions of the image decreases as the number of channels increases.
- It has *60k* parameters.




LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278-2324.

# Example 2


POOL
POOL
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FC
car
truck
airplane
ship
horse