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# Deep Learning Applications for Computer Vision

Lecture 16: More Hyperparameters and  
Pooling Layers



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# Parameters vs Hyperparameters

1. Parameters: weights and bias values

*Learned parameters*

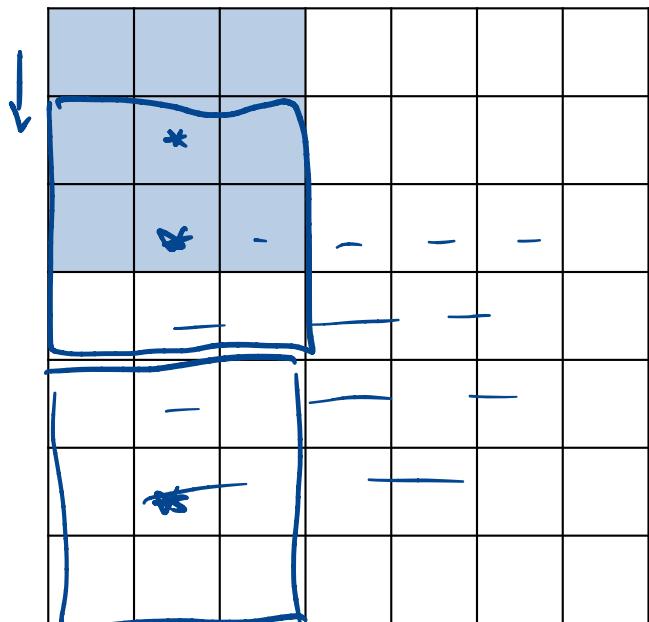
2. Hyperparameters:

- For all NN:
  - number of hidden layers, number of neurons
  - optimizer, activation function
- Specific to CNNs:
  - Number of filters in a convolutional block
  - Window size (F) :  $11 \times 11$  ,  $7 \times 7$  , ... ,  $3 \times 3$  ,  $1 \times 1$
  - Stride (S)
  - Zero-padding (P)

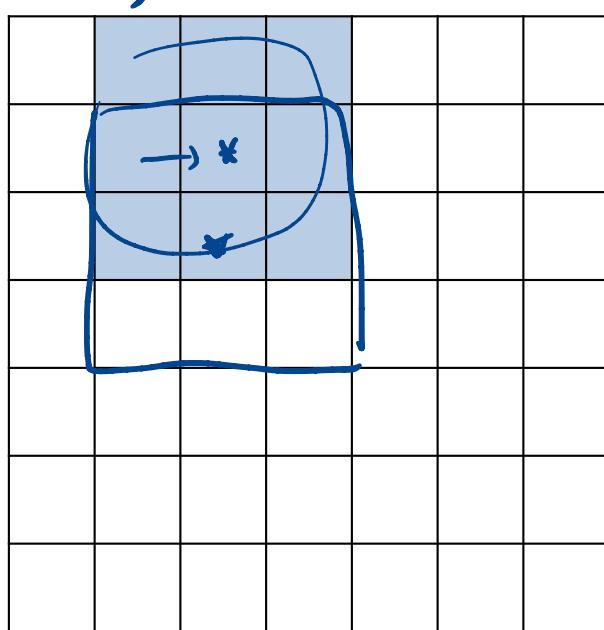


# Stride

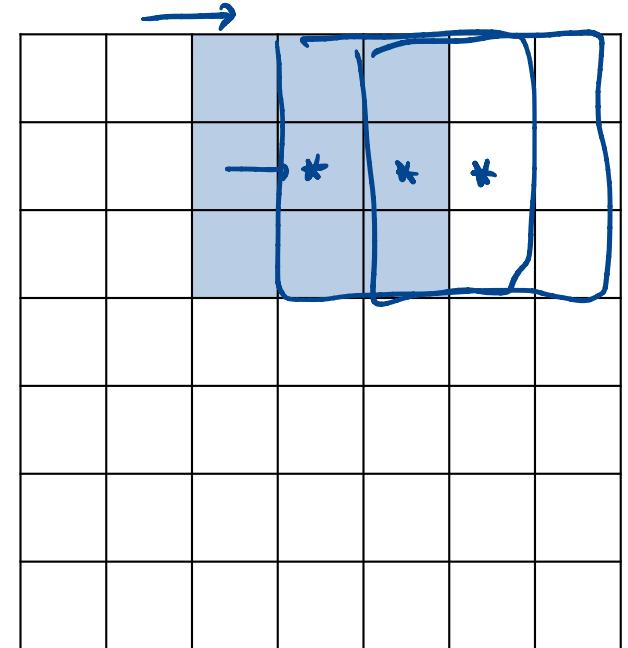
- Could be 1. Often is larger.



$S=1$



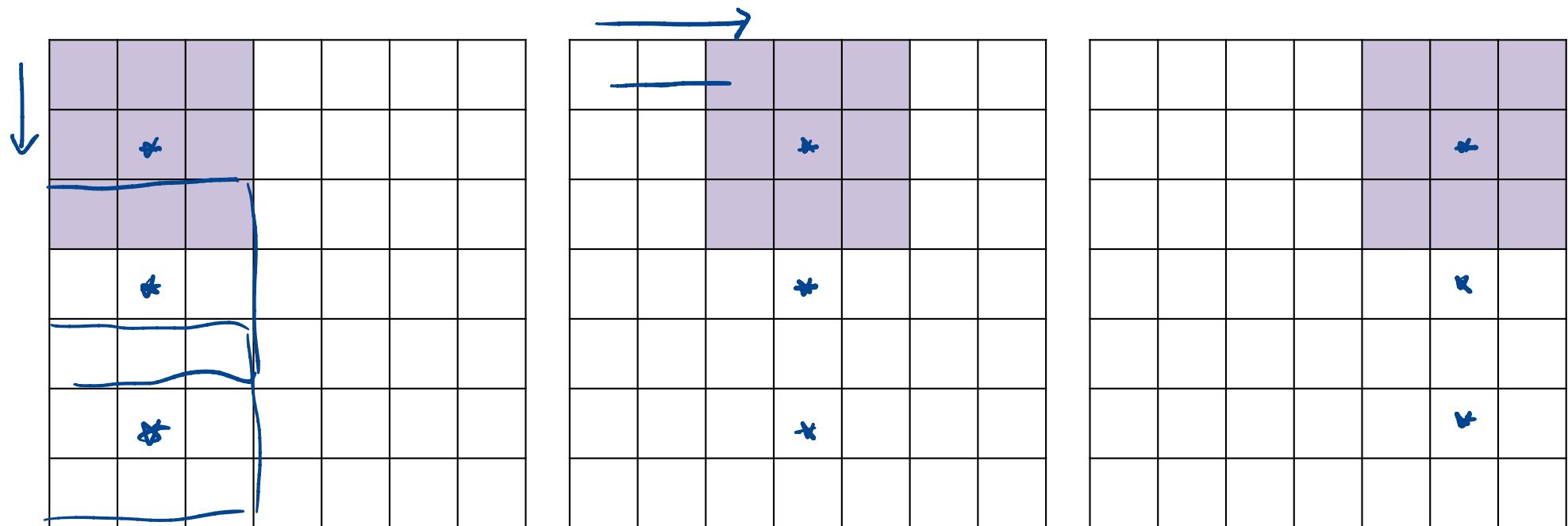
Horizontally , Vertically



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# Stride

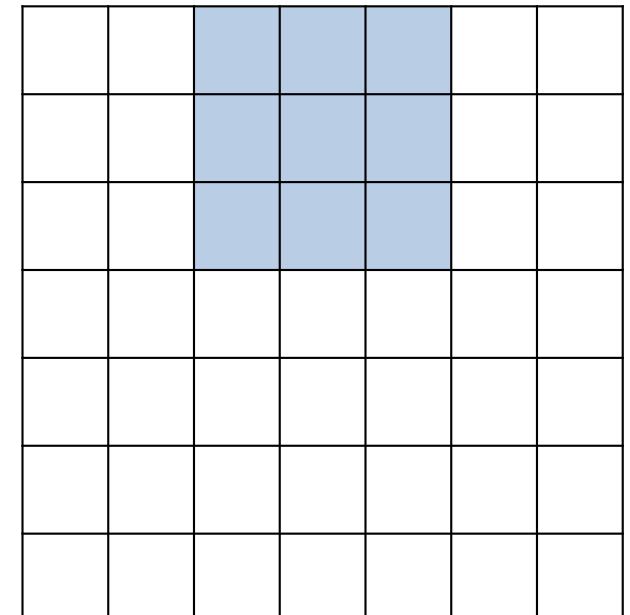
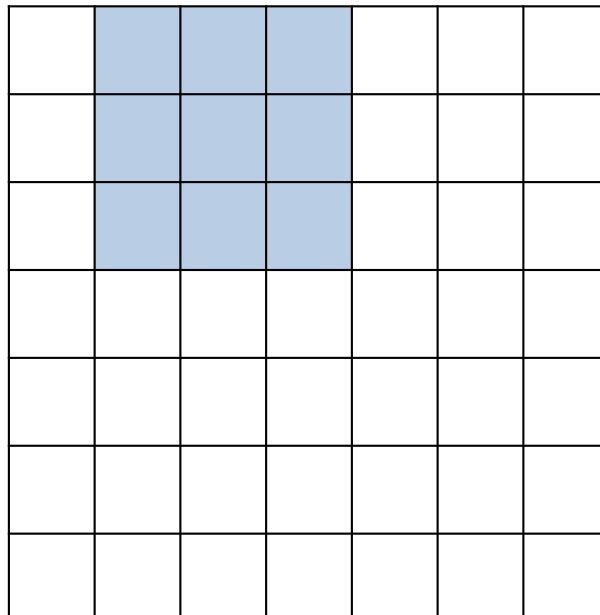
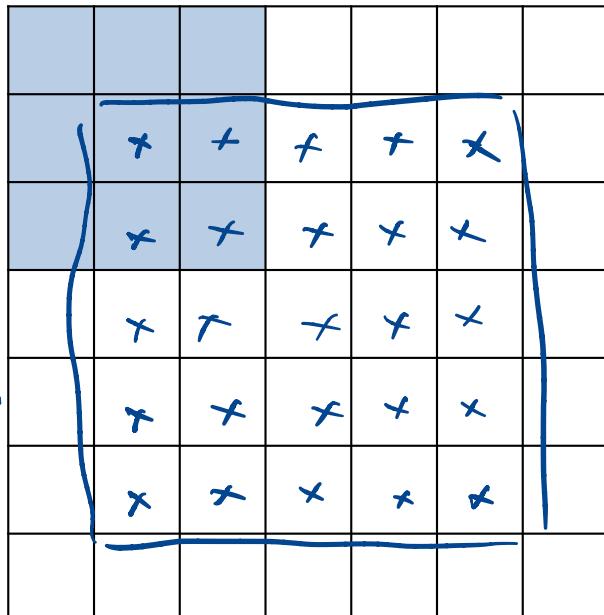
- Stride = 2



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# Output size

- Stride affects the size of the output (activation maps)



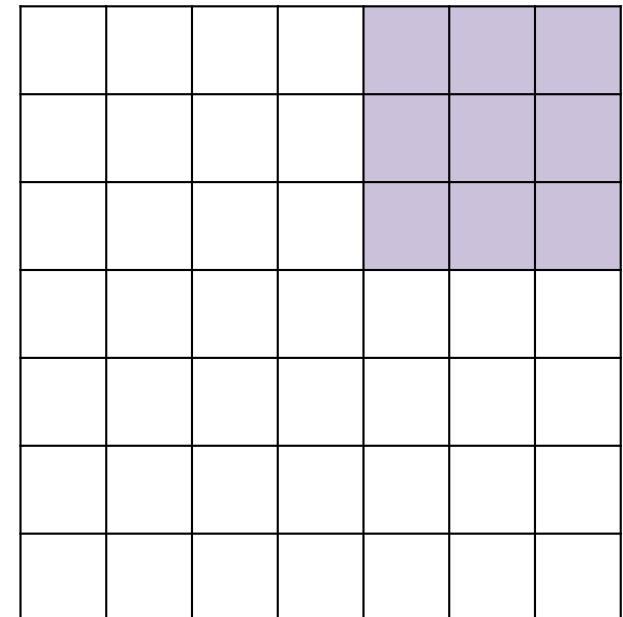
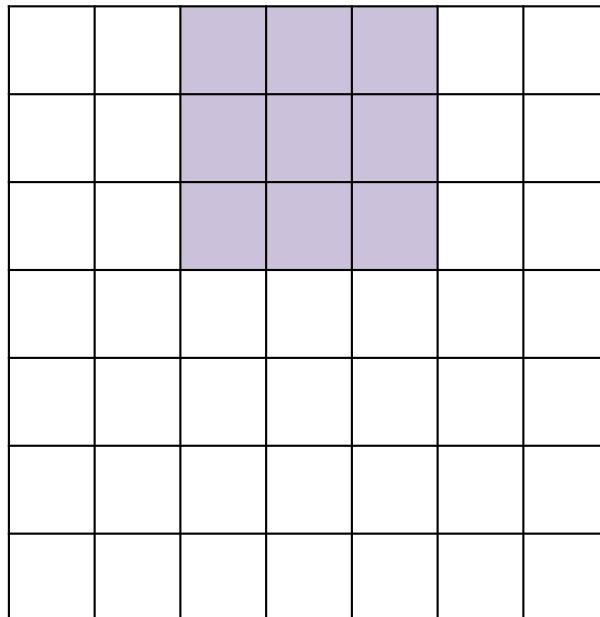
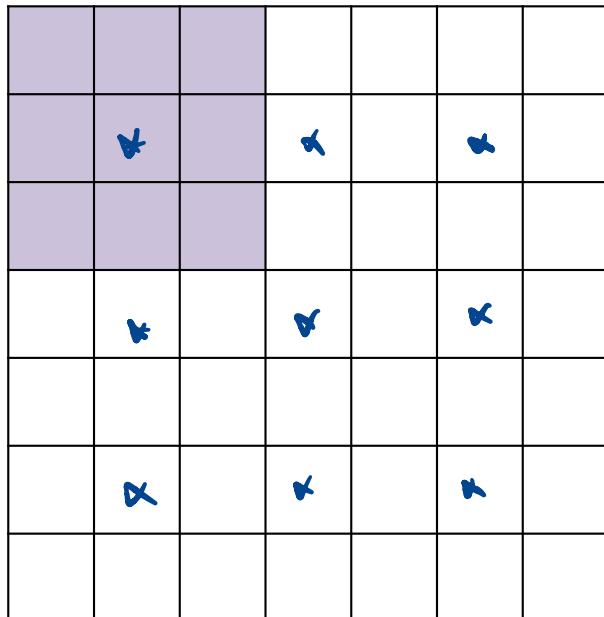
$$\begin{aligned} S &= 1 \\ \text{Input: } & \left[ \begin{array}{c|c} W = 7 & H = 7 \end{array} \right] \\ F &= 3 \end{aligned} \quad \Rightarrow \quad \text{Output size} = [S \times 5]$$



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# Output size

- Stride affects the size of the output (activation maps)



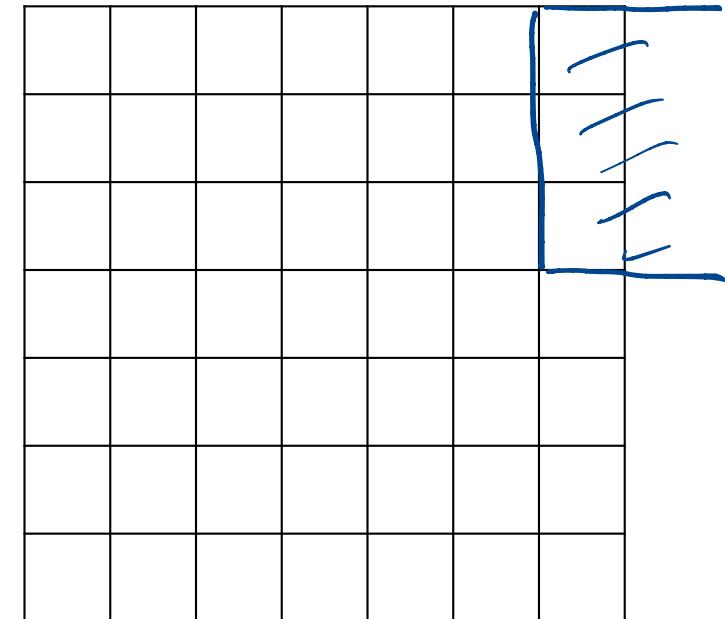
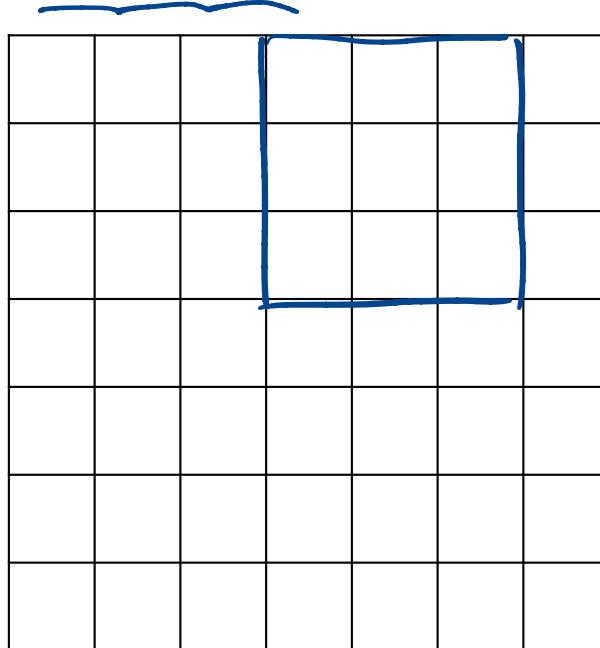
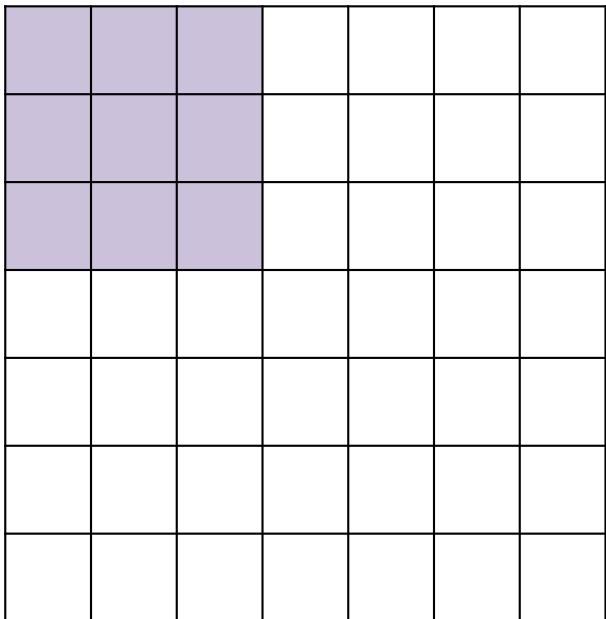
$$\left. \begin{array}{l} S = 2 \\ |x| = 7, H = 7 \\ F = 3 \end{array} \right\} \text{Output size} = 3 \times 3$$



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# Output size

- Stride = 3?



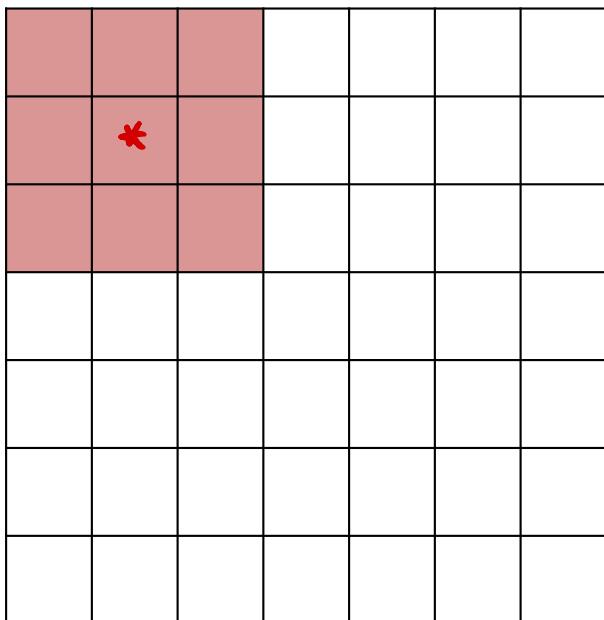
$\Rightarrow$  We cannot have  $S=3$



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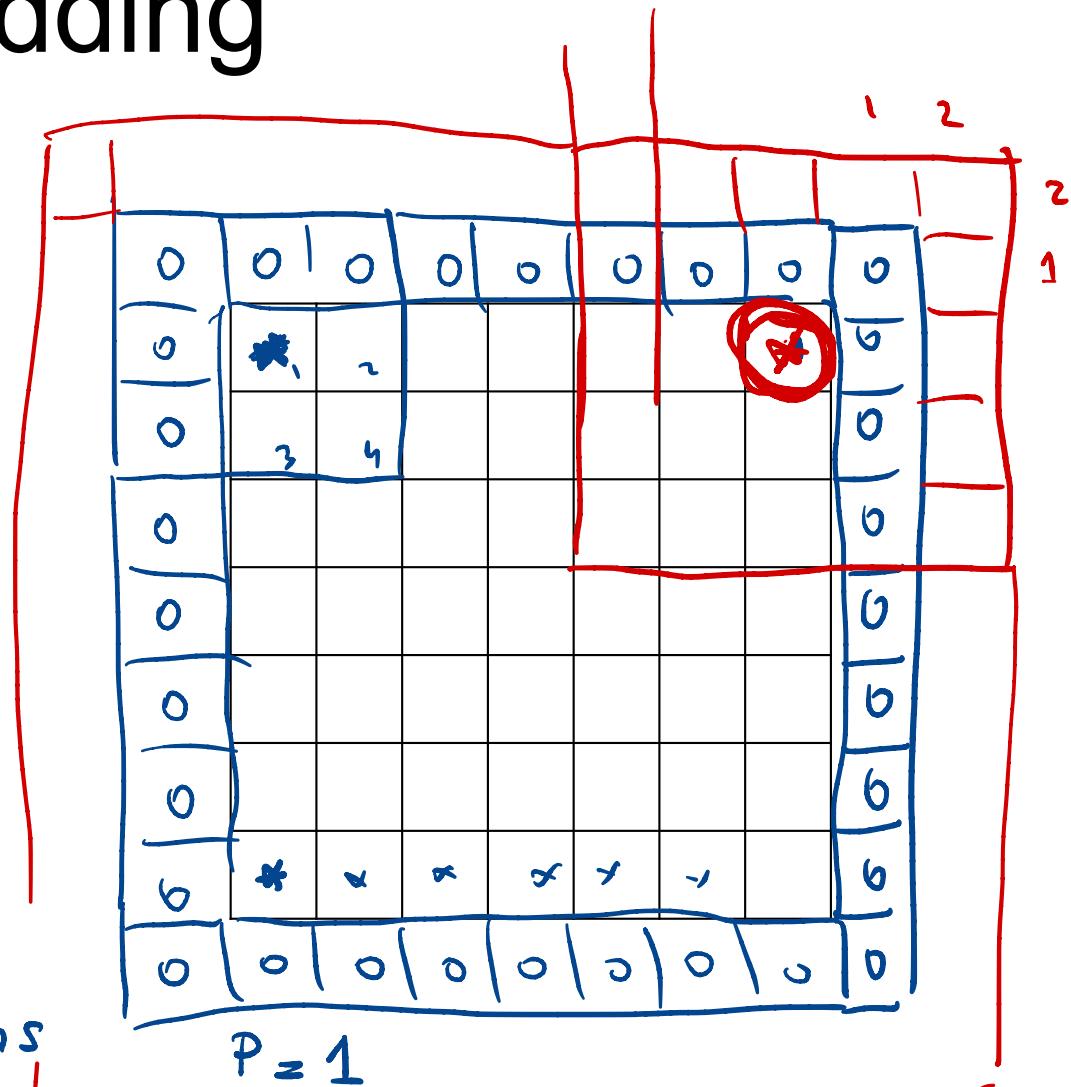
# Padding

- Pad with zeros



F:  $3 \times 3 \rightarrow$  Add 2 rows, 2 columns

$F: S \times S \rightarrow \text{Add } 4 \text{ rows, } 4 \text{ columns}$



# Output Size - Formula

- H, W, D: Height, Width and Depth of the input volume
- F: Filter size (assume square filter)
- P: Amount of Zero Padding (assume same row, col)
- S: Stride

$$W_o = \frac{W_i + 2P - F}{S} + 1$$

$$H_o = \frac{H_i + 2P - F}{S} + 1$$



# Example

$$W_o = \frac{W_i + 2P - F}{S} + 1$$

$$H_o = \frac{H_i + 2P - F}{S} + 1$$

We cannot have  
S=3 in this situation

$$32 \times 32$$

$$H_i = 32$$

$$W_i = 32$$

$$\begin{matrix} F = 3 \\ P = 1 \end{matrix}$$

$$S = 1$$

$$W_o = \frac{32+2-3}{1} + 1 = \underline{\underline{32}}$$

$$H_o = 32$$

$$H=32, W=32, \cancel{S=3}, P=1, F=3$$

$$W_o = \frac{32+2-3}{3} + 1 = 10.33 + 1 = 11.33$$

$$H=32, W=32, S=3, F=5, P=0$$

$$W_o = \frac{32+0-5}{3} + 1 = \underline{\underline{10}}$$



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# Pooling Layers

- Occur after a Convolutional Layer
- Role:
  - condense the information from the input
  - the size of the output will be reduced (*downsampling*)
  - model – invariant to small transformations

1	4	2	6	1	8
3	8	4	0	3	7
2	5	3	6	5	3
1	9	7	2	1	2

MAX

8	6	8
9	7	5

SUM

16	12	19
17	18	11



# Pooling Layers – Output Size

1	4	2	6	1	8
3	8	4	0	3	7
2	5	3	6	5	3
1	9	7	2	1	2

$$F=2$$

$$S=2$$

$$4 \times 6$$

non-overlapping windows

8	6	8
9	7	7

$$2 \times 3$$

Pooling layers do not have learned parameters!  
Hyperparameters:  $F, S$

1	4	2	6	1	8
3	8	4	0	3	7
2	5	3	6	5	3
1	9	7	2	1	2

$$4 \times 6$$

$$F=2$$

$$S=1$$

8	8	6	6	8
8	8	6	6	7
9	9	7	6	5

$$3 \times 5$$

$S < F \Rightarrow$  overlapping windows



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