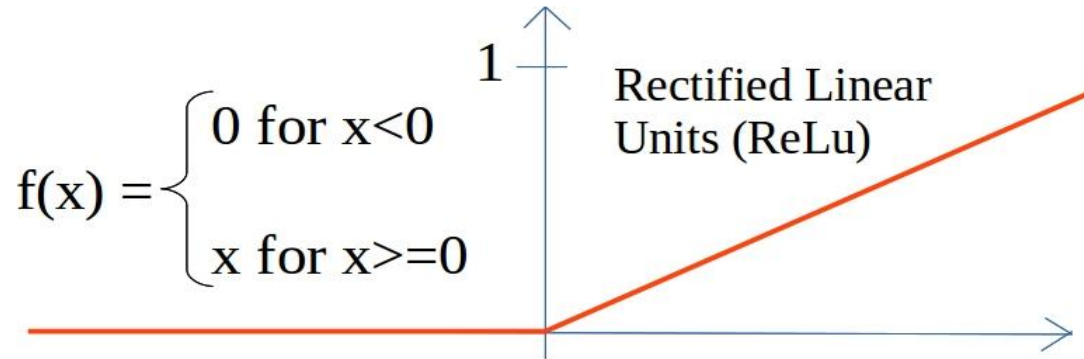
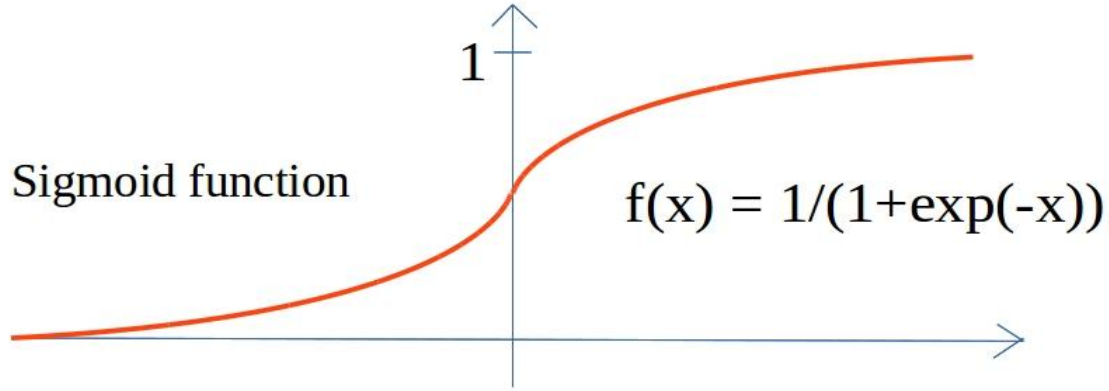
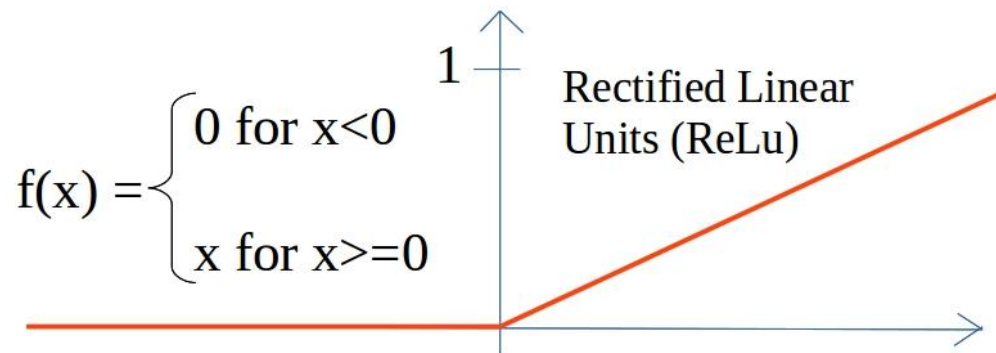


# Add-ons to Neural Networks

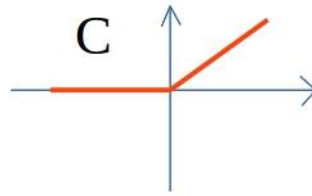
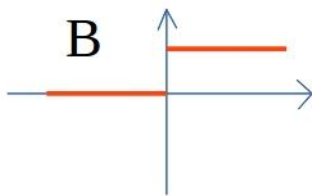
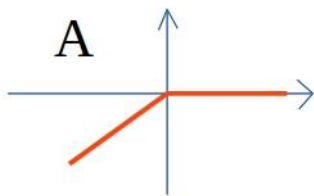
# Activation function



# ReLu function

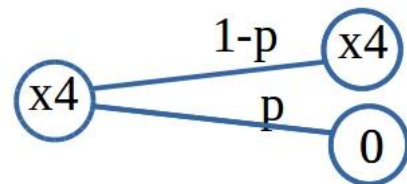
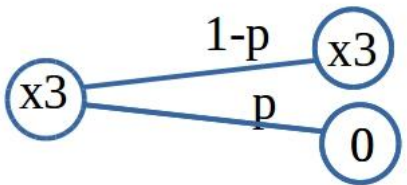
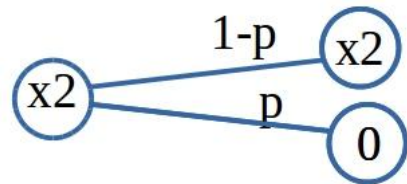
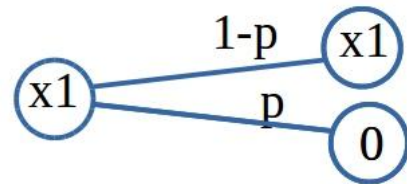


Derivative:



# Dropout

Method to prevent overfitting



$$P(x_i \rightarrow 0) = p$$

# Dropout

Method to prevent overfitting

$$\begin{aligned}w_{111}x_1 + w_{112}x_2 + w_{113}x_3 + w_{114}x_4 &= w_{111}x_1 + w_{112}x_2 \\w_{121}x_1 + w_{122}x_2 + w_{123}x_3 + w_{124}x_4 &= w_{121}x_1 + w_{122}x_2 \\w_{131}x_1 + w_{132}x_2 + w_{133}x_3 + w_{134}x_4 &= w_{131}x_1 + w_{132}x_2 \\w_{141}x_1 + w_{142}x_2 + w_{143}x_3 + w_{144}x_4 &= w_{141}x_1 + w_{142}x_2\end{aligned}$$

$$\begin{aligned}w_{111}x_1 + w_{112}x_2 + w_{113}x_3 + w_{114}x_4 &= w_{112}x_2 + w_{113}x_3 \\w_{121}x_1 + w_{122}x_2 + w_{123}x_3 + w_{124}x_4 &= w_{122}x_2 + w_{123}x_3 \\w_{131}x_1 + w_{132}x_2 + w_{133}x_3 + w_{134}x_4 &= w_{132}x_2 + w_{133}x_3 \\w_{141}x_1 + w_{142}x_2 + w_{143}x_3 + w_{144}x_4 &= w_{142}x_2 + w_{143}x_3\end{aligned}$$

$$\begin{aligned}w_{111}x_1 + w_{112}x_2 + w_{113}x_3 + w_{114}x_4 &= w_{112}x_2 + w_{114}x_4 \\w_{121}x_1 + w_{122}x_2 + w_{123}x_3 + w_{124}x_4 &= w_{122}x_2 + w_{124}x_4 \\w_{131}x_1 + w_{132}x_2 + w_{133}x_3 + w_{134}x_4 &= w_{132}x_2 + w_{134}x_4 \\w_{141}x_1 + w_{142}x_2 + w_{143}x_3 + w_{144}x_4 &= w_{142}x_2 + w_{144}x_4\end{aligned}$$

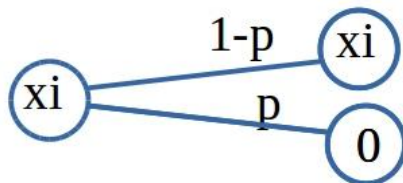
Same  
input

Different  
redundant  
representations

# Dropout

Method to prevent overfitting

What happens with  $p$  if training is over and we use the model for prediction?



A We set  $p = 1$

B We take same  $p$  as in training

C We set  $p = 0.5$

D We set  $p = 0$

# Dropout

Method to prevent overfitting



© istockphoto.com/karlasmitt

$$\begin{aligned} &w_{111}x_1 + w_{112}x_2 + w_{113}x_3 + w_{114}x_4 \\ &w_{121}x_1 + w_{122}x_2 + w_{123}x_3 + w_{124}x_4 \\ &w_{131}x_1 + w_{132}x_2 + w_{133}x_3 + w_{134}x_4 \\ &w_{141}x_1 + w_{142}x_2 + w_{143}x_3 + w_{144}x_4 \end{aligned}$$

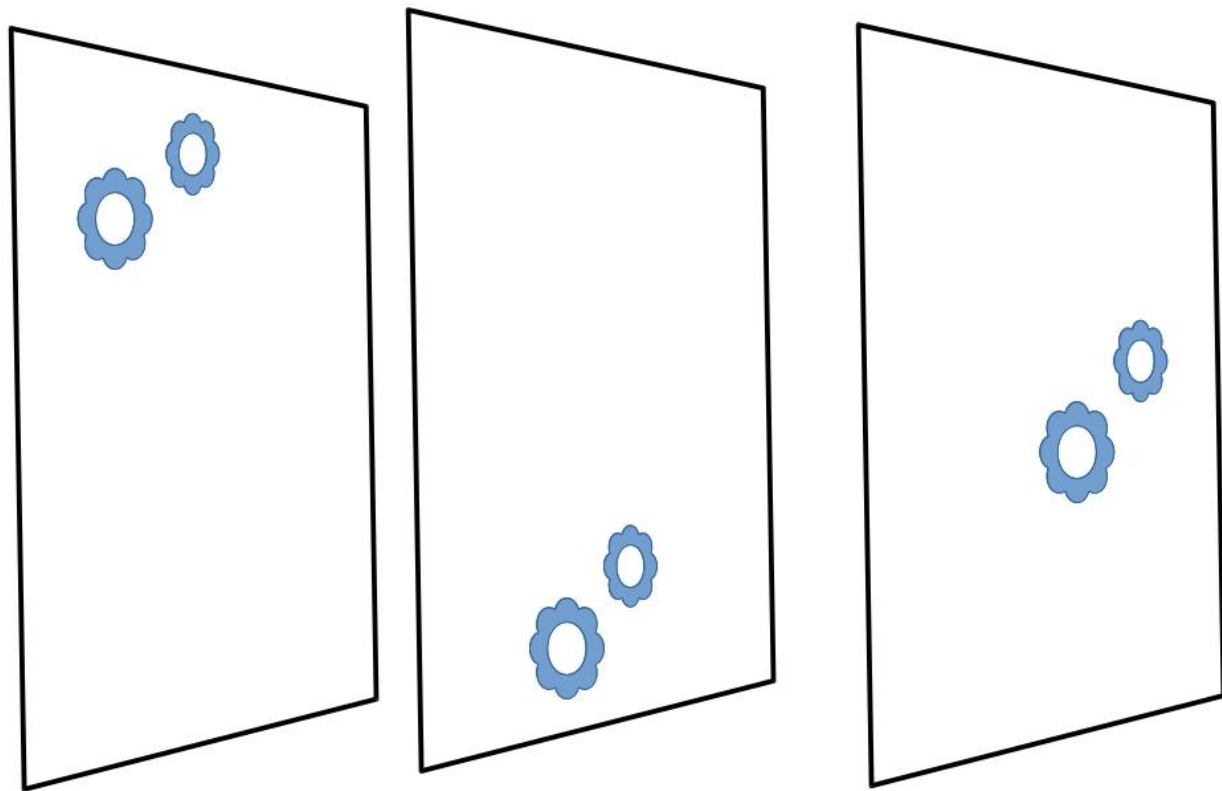
It's a hamster

I agree

Me too!

Clearly not a cat

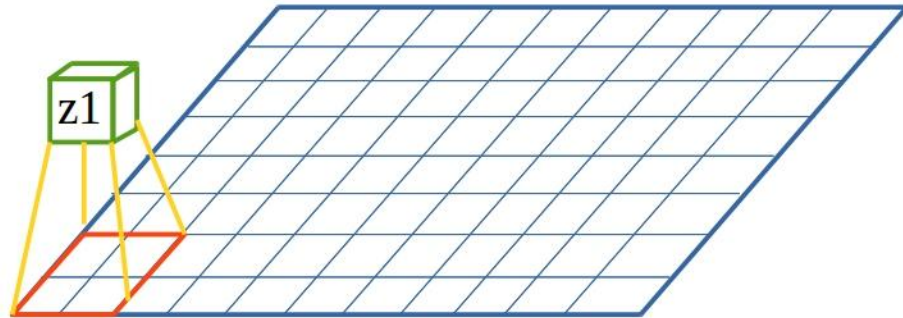
# Convolutions





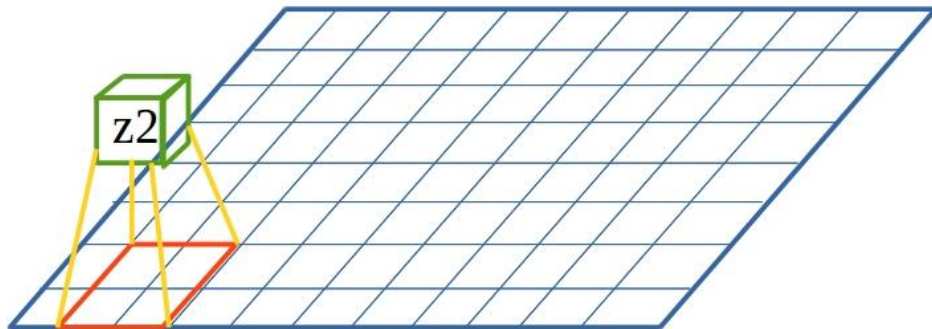
# Convolutions

$$z1 = w1*x1 + w2*x2 + w3*x3 + w4*x4$$

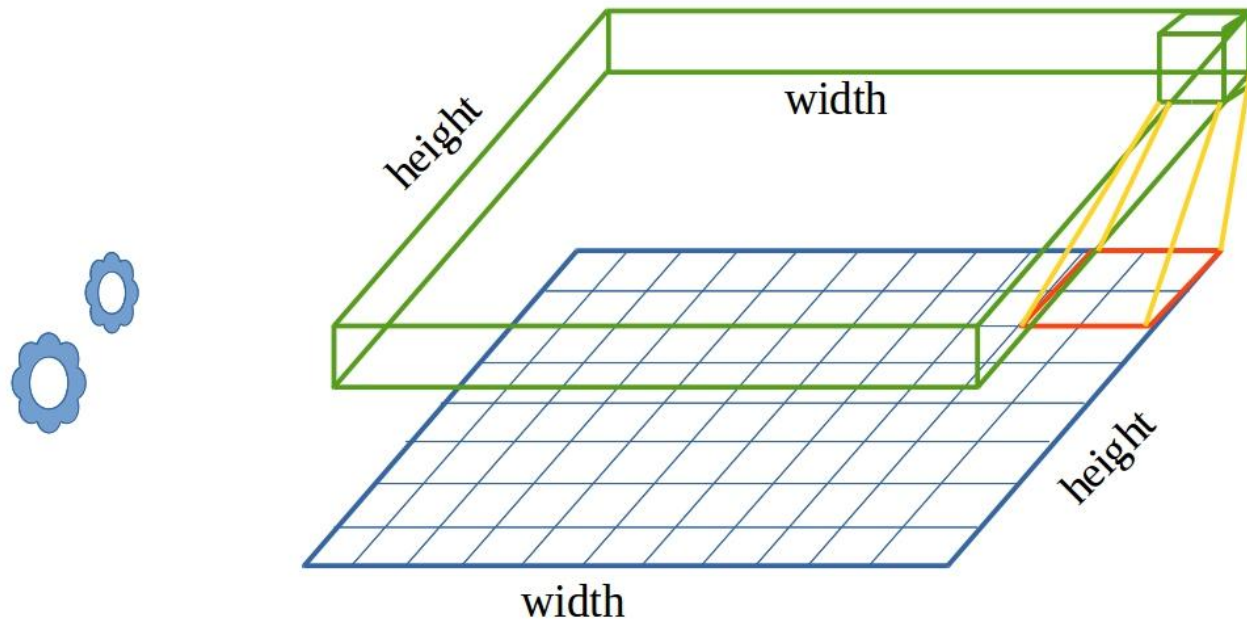


# Convolutions

$$z2 = w1 * x2 + w2 * x3 + w3 * x4 + w4 * x5$$



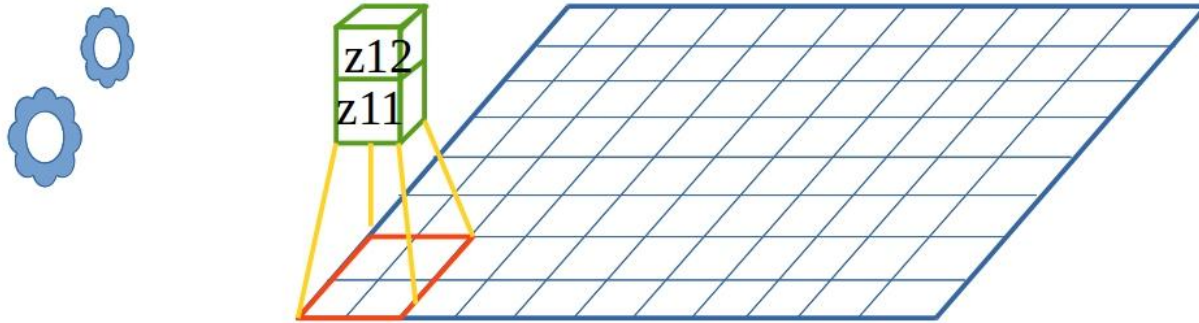
# Convolutions



# Convolutions

$$z_{11} = w_{11} * x_1 + w_{12} * x_2 + w_{13} * x_3 + w_{14} * x_4$$

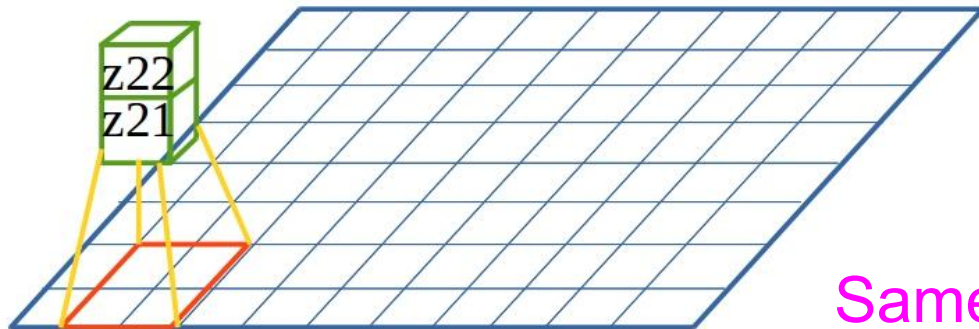
$$z_{12} = w_{21} * x_1 + w_{22} * x_2 + w_{23} * x_3 + w_{24} * x_4$$



# Convolutions

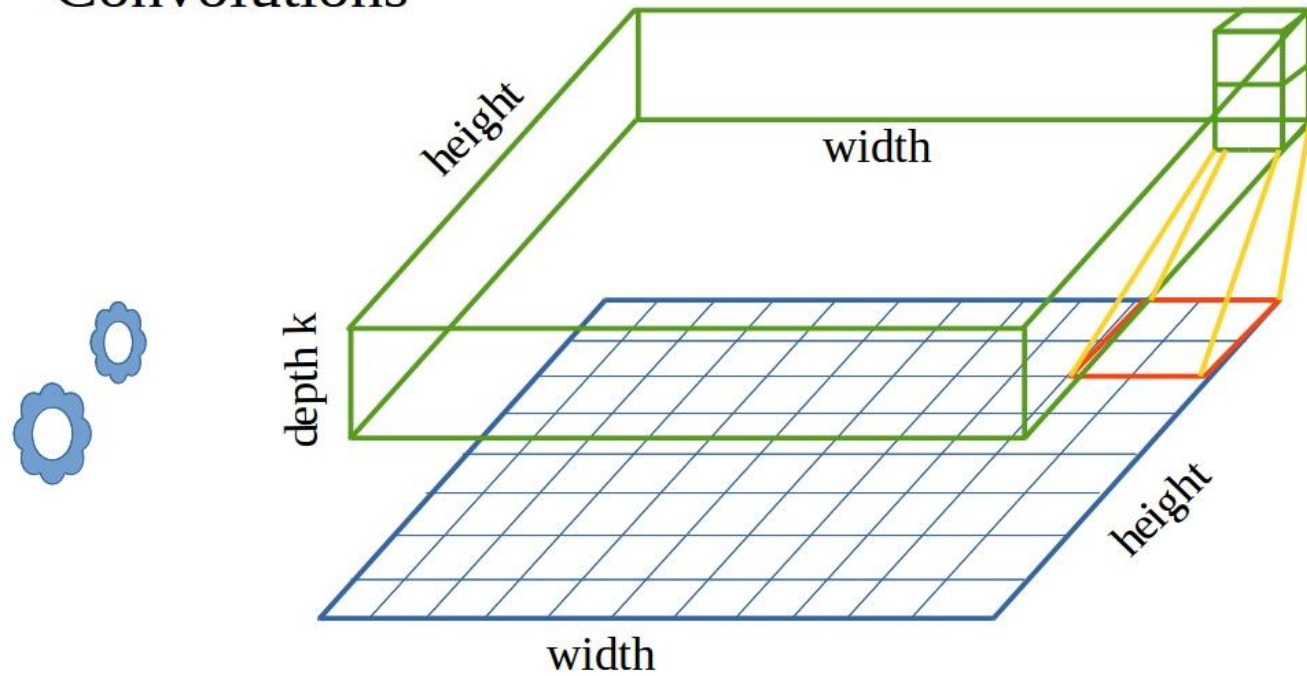
$$z_{21} = w_{11} * x_2 + w_{12} * x_3 + w_{13} * x_4 + w_{14} * x_5$$

$$z_{22} = w_{21} * x_2 + w_{22} * x_3 + w_{23} * x_4 + w_{24} * x_5$$



Same weights!

# Convolutions



# Convolutions

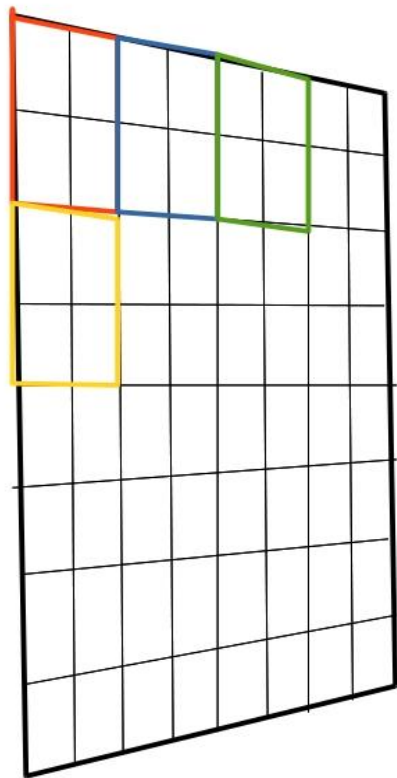
For pictures with 10x10 pixel, you train a 3x3-convolution layer with depth 4. Your slider has size 1x1 and your padding is SAME.



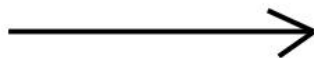
How many weight do you need to train?  
How many nodes has the resulting layer?

# Pooling

Shrinks large layers

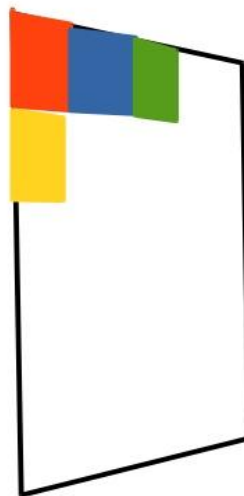


$$y = \max(x_i)$$



Max pooling

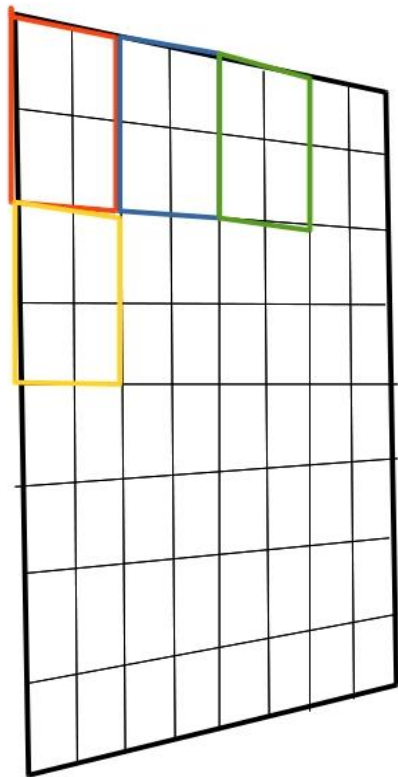
Parameter free!  
Often quite accurate



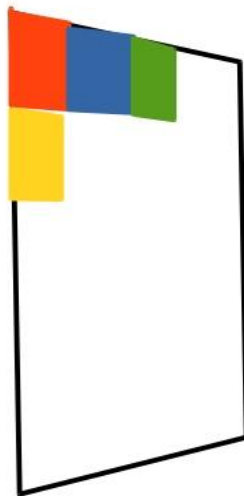
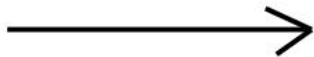


# Pooling

Shrinks large layers



$$y = \text{mean}(x_i)$$



Average pooling

Parameter free!

Often quite accurate

# A typical neural net

Image

Convolution

Max Pooling

Convolution

Max Pooling

Fully connected

Fully connected

Classifier