Convolutional Neural Networks and Data Augmentation

June course: Deep Learning in Computer Vision

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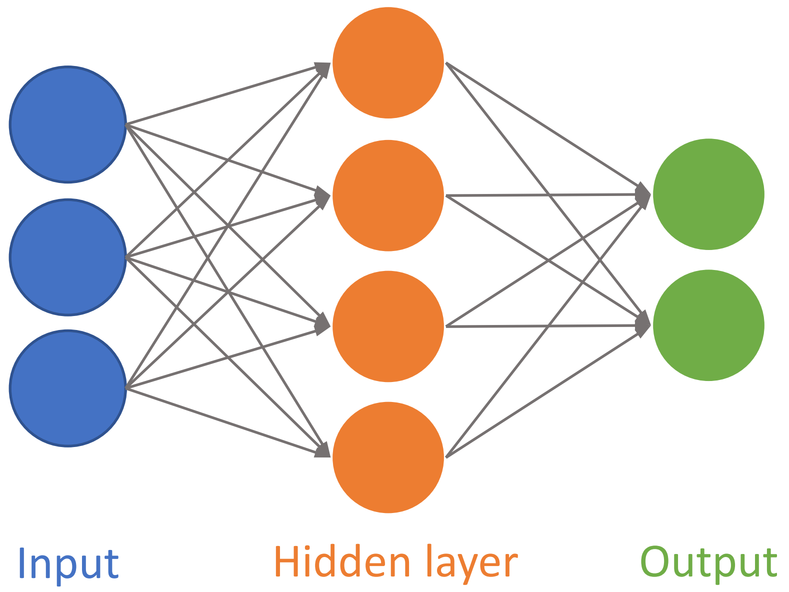
Outline – What you're going to see

- Convolutions recap
- CNN
  - Convolutions
  - Max pooling
  - Stride/padding
  - Backprop
- Combatting overfitting:
  - Dropout
  - Data augmentation

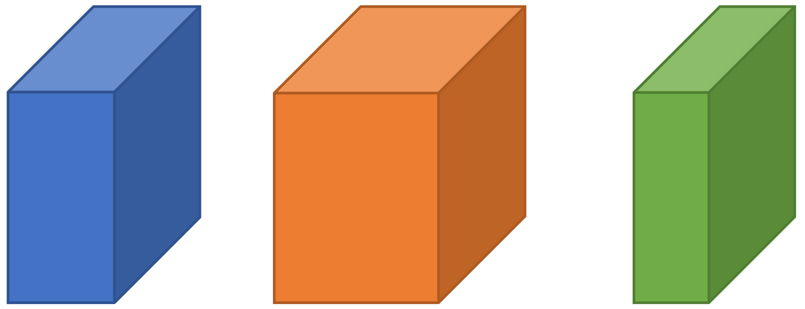
What is a CNN?

- Convolutional Neural Network
  - Uses convolutions
- Local connectivity
- Weight sharing

Before:
(Fully connected)



After:
(Convolutional)



Convolutions

- Convolutions and cross correlation are related operations, but convolution involves rotating the filter 180 degrees.
  - We will refer to cross correlation as "convolution" in this course, as is common in deep learning

9	1	2	2	7
10	3	10	5	1
2	6	10	10	9
10	10	5	8	10
7	10	9	10	7

*

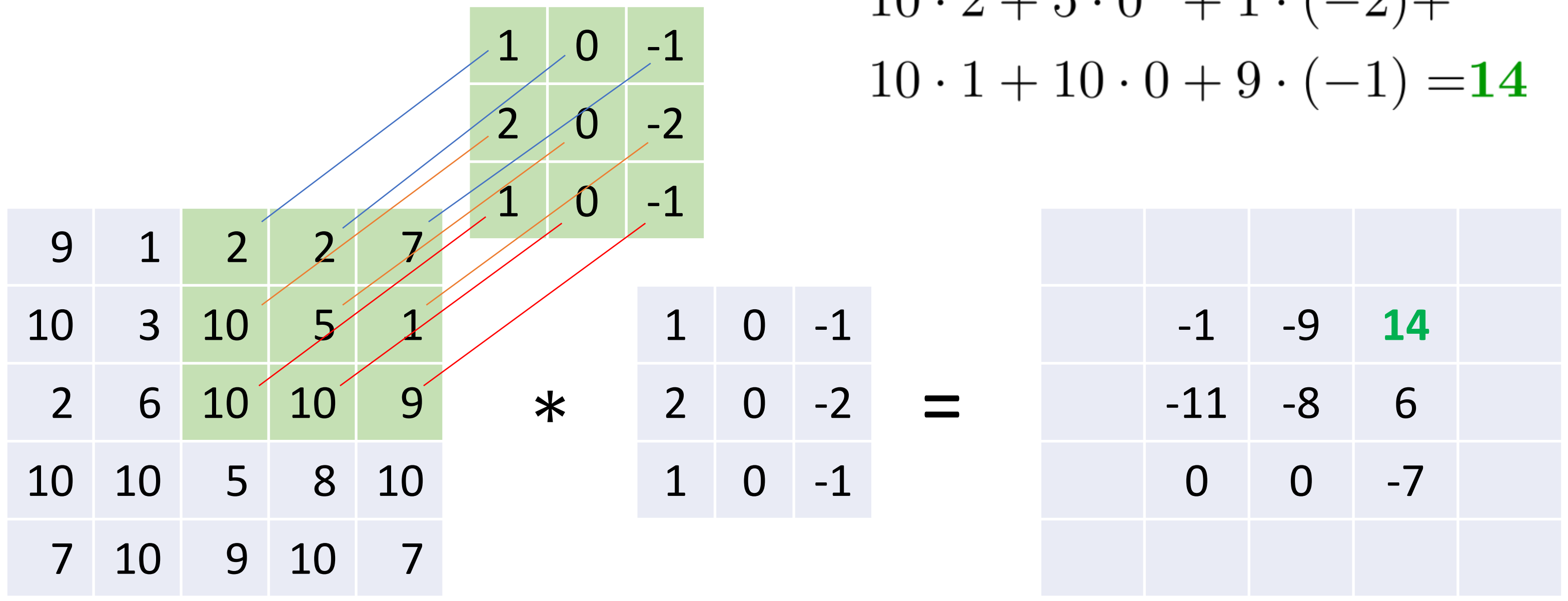
1	0	-1
2	0	-2
1	0	-1

=

	-1	-9	?	
	-11	-8	6	
	0	0	-7	

Convolutions

$$2 \cdot 1 + 2 \cdot 0 \;\; + 7 \cdot (-1) +$$
$$10 \cdot 2 + 5 \cdot 0 \;\; + 1 \cdot (-2) +$$
$$10 \cdot 1 + 10 \cdot 0 + 9 \cdot (-1) = \mathbf{14}$$



9	1	2	2	7
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*

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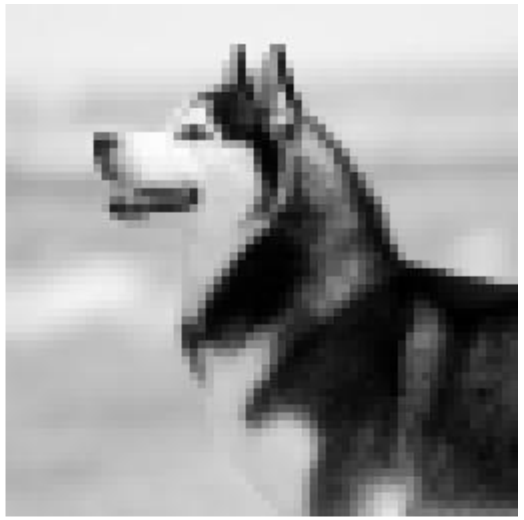
1	0	-1

=

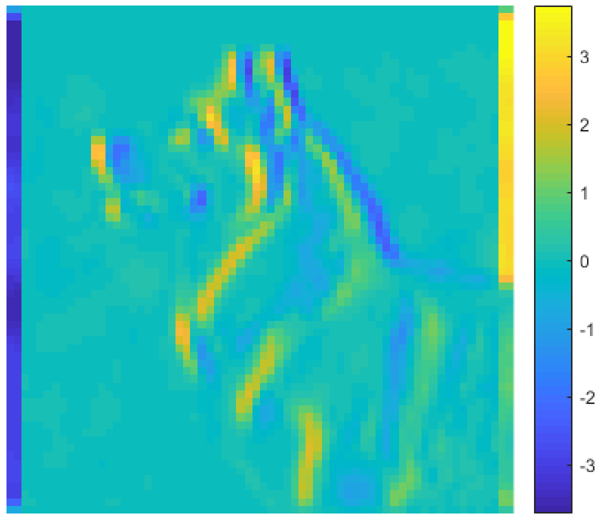
	-1	-9	**14**	
	-11	-8	6	
	0	0	-7	

Convolutions

- This filter detects vertical edges



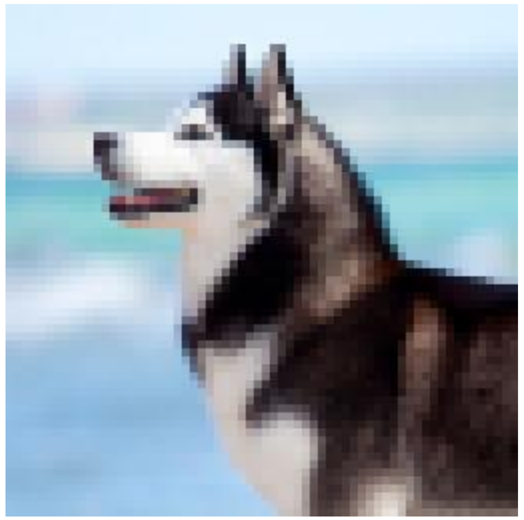
$$* \begin{array}{|c|c|c|}\hline 1 & 0 & -1 \\ \hline 2 & 0 & -2 \\ \hline 1 & 0 & -1 \\ \hline \end{array} =$$



Convolutions

- What do we do when images have multiple channels?

e.g. color images



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1	0	-1
2	0	-2
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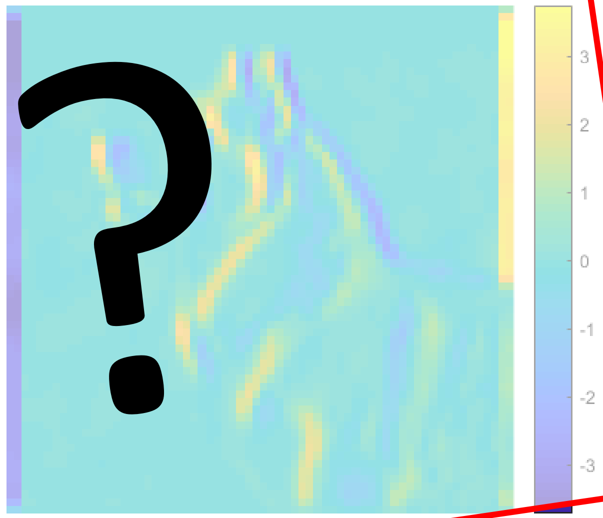
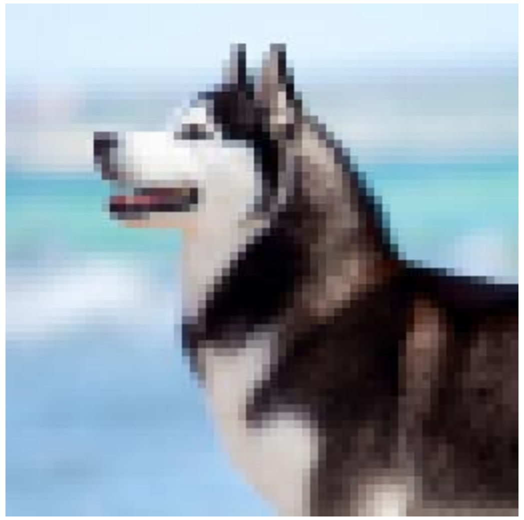


Convolutions

- What do we do when images have multiple channels?
  - One filter per channel



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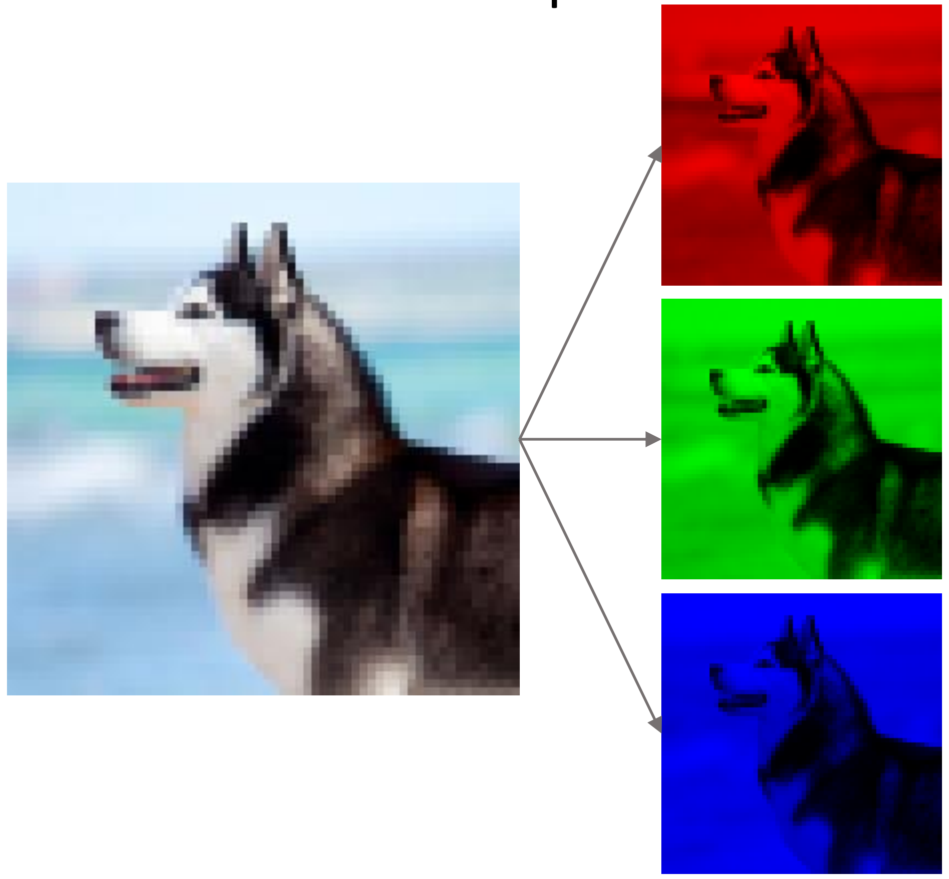

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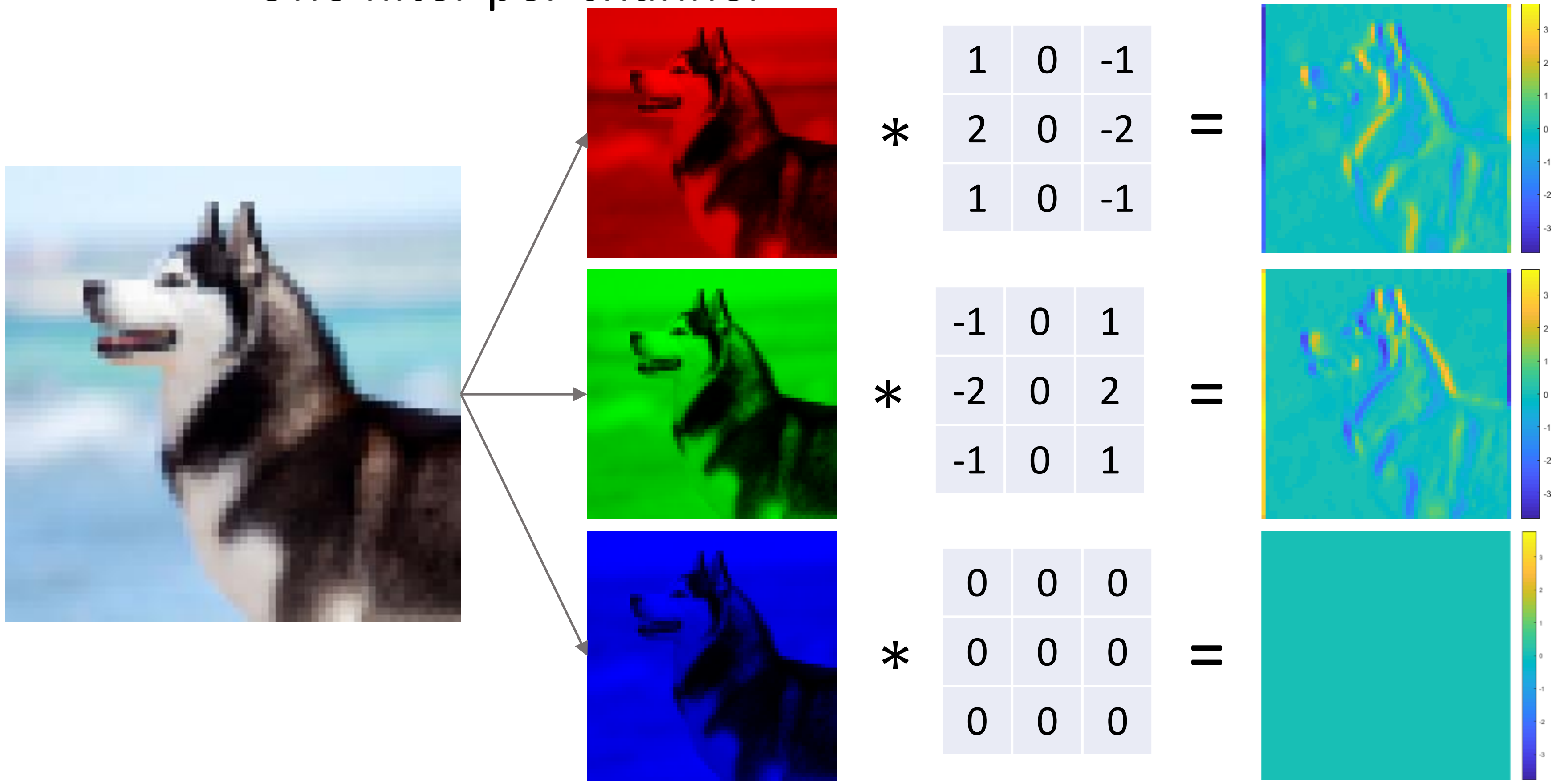

$$* \begin{array}{|c|c|c|}\hline 1 & 0 & -1 \\ \hline 2 & 0 & -2 \\ \hline 1 & 0 & -1 \\ \hline\end{array} =$$

$$* \begin{array}{|c|c|c|}\hline -1 & 0 & 1 \\ \hline -2 & 0 & 2 \\ \hline -1 & 0 & 1 \\ \hline\end{array} =$$

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Convolutions

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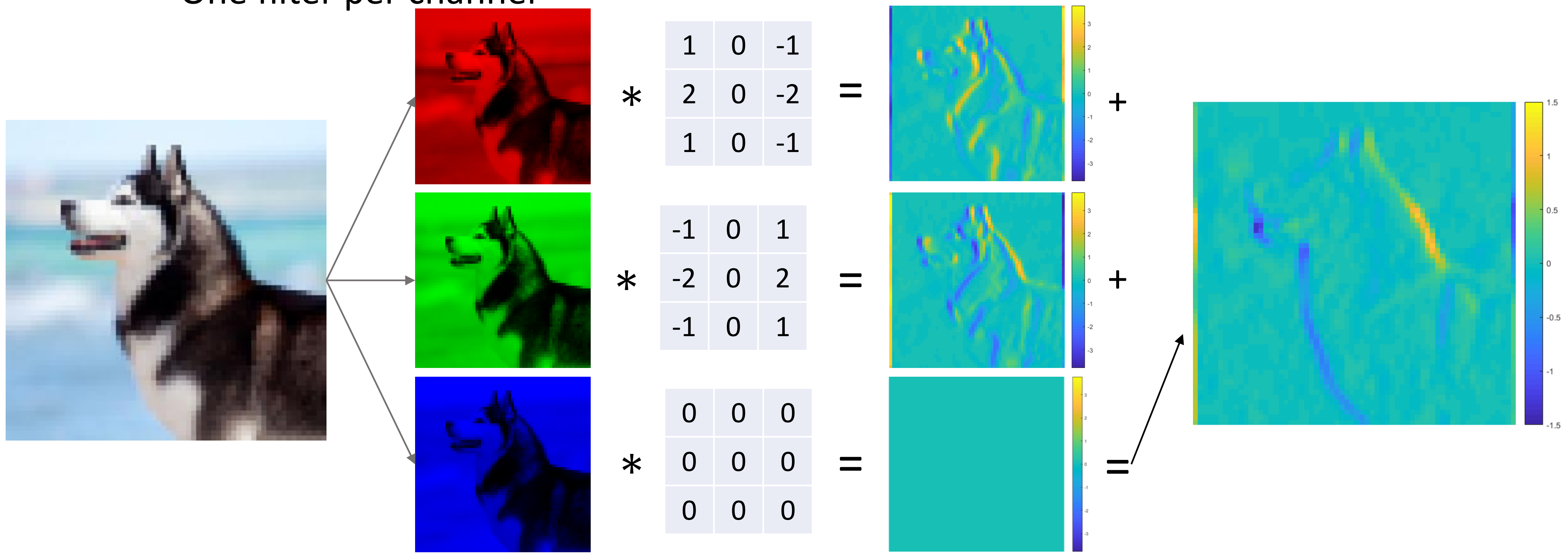


$$R * \begin{bmatrix}1 & 0 & -1\\2 & 0 & -2\\1 & 0 & -1\end{bmatrix} = \quad +$$

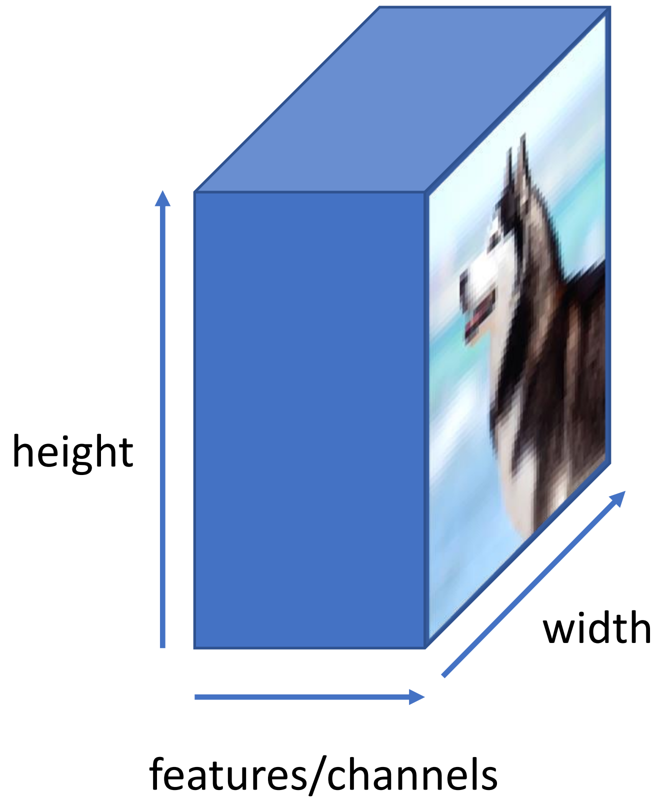
$$G * \begin{bmatrix}-1 & 0 & 1\\-2 & 0 & 2\\-1 & 0 & 1\end{bmatrix} = \quad +$$

$$B * \begin{bmatrix}0 & 0 & 0\\0 & 0 & 0\\0 & 0 & 0\end{bmatrix} = \quad =$$

What is a CNN?

- Exploit 2d layout of images
- Images are volumes

- Color image → three channels
  - Represented in computer as $3 \times 64 \times 64$

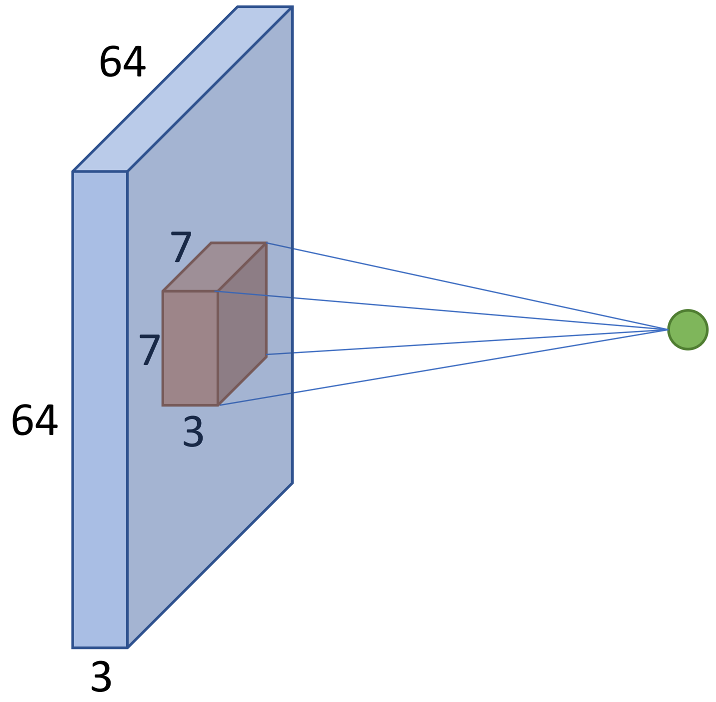


What is a CNN?

- Let’s look at a single neuron
- Input is 3 channels, 64×64
- 7×7 convolution

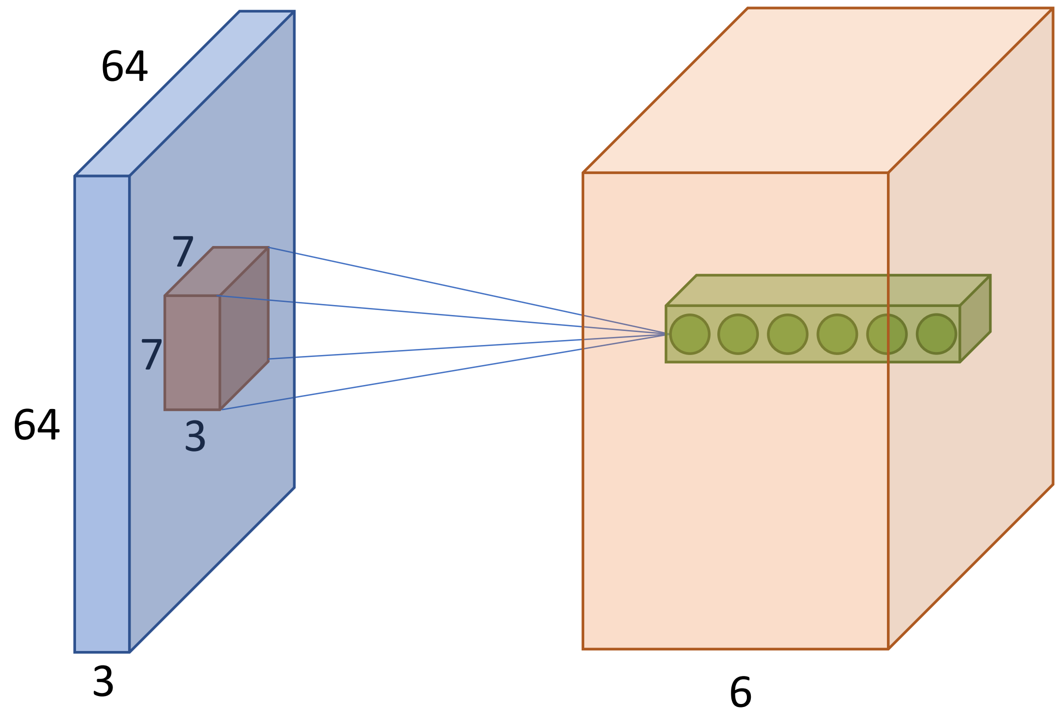
- Each neuron looks at a $3 \times 7 \times 7$ volume in the input layer
  - Requires as many weights + one bias

- Spatially: locally connected
- Depthwise: Fully connected



What is a CNN?

- Multiple neurons:
- 6 channels (features) output
- Each layer in the output has its own weights
- $6 \times 3 \times 7 \times 7$ weights for this layer



Mathematical definitions

- Forward pass:

$$z_{i,j}^{\ell,f} = \sum_{c=1}^{C} \sum_{m=-M}^{M} \sum_{m=-N}^{N} w_{m,n}^{\ell,f,c} \cdot a_{i+m,j+n}^{\ell-1,c}$$

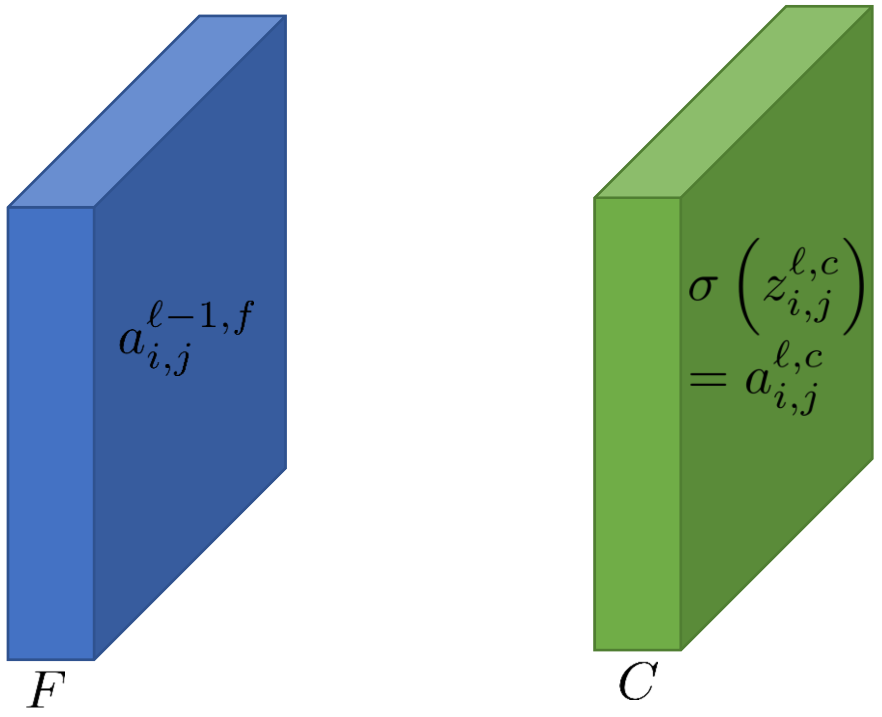
$$a_{i,j}^{\ell,f} = \sigma\left(z_{i,j}^{\ell,f}\right)$$

$$\delta_{i,j}^{\ell,f} = \frac{\partial \mathcal{L}}{\partial z_{i,j}^{\ell,f}}$$

- Backward pass:

$$\delta_{i,j}^{\ell,c} = \frac{\partial L}{\partial z_{i,j}^{\ell,f}} = \sigma'\left(z_{i,j}^{l,c}\right) \sum_{f=1}^{F} \sum_{m=-M}^{M} \sum_{m=-N}^{N} w_{m,n}^{\ell+1,f,c} \cdot \delta_{i-m,j-n}^{\ell+1,c}$$

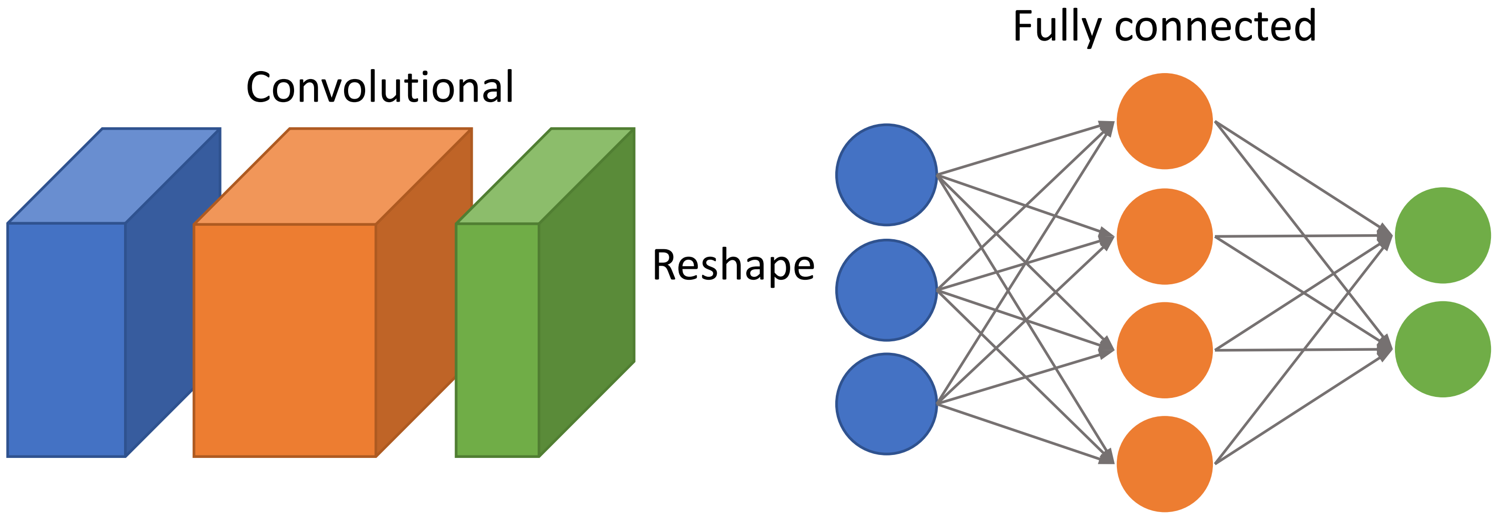
$$\frac{\partial \mathcal{L}}{\partial w_{m,n}^{\ell,f,c}} = \sum_{i} \sum_{j} \delta_{i,j}^{l,f} \cdot a_{i+m,j+n}^{l-1,c}$$



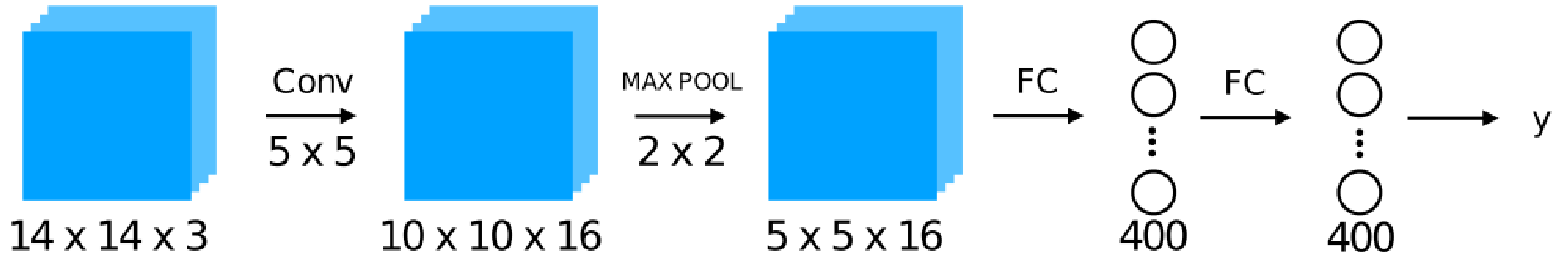
Wow such image!

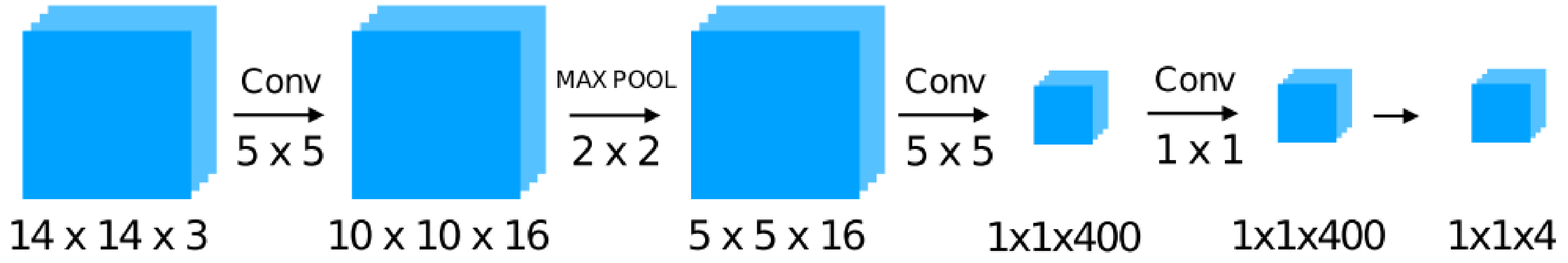
What is a CNN?

- Local connectivity
- Weight sharing
- Usually followed by a fully connected network to output a classification



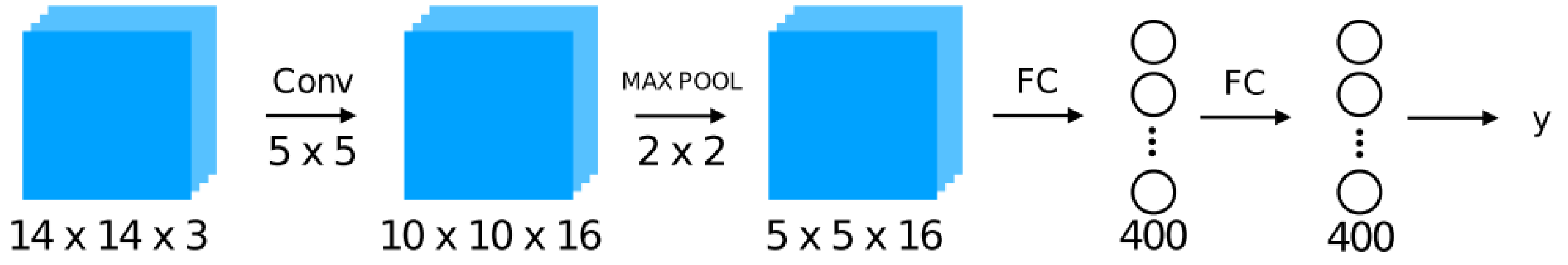
Fully connected layers as convolutional layers

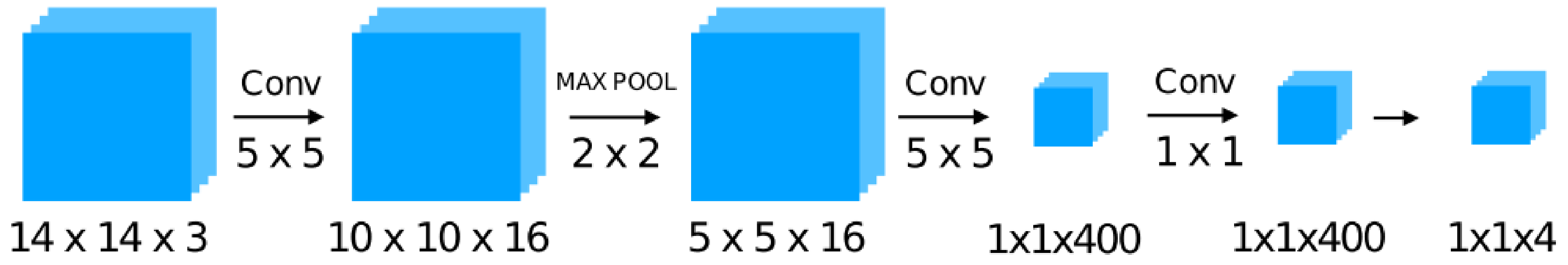




- These two networks are equivalent. Why?

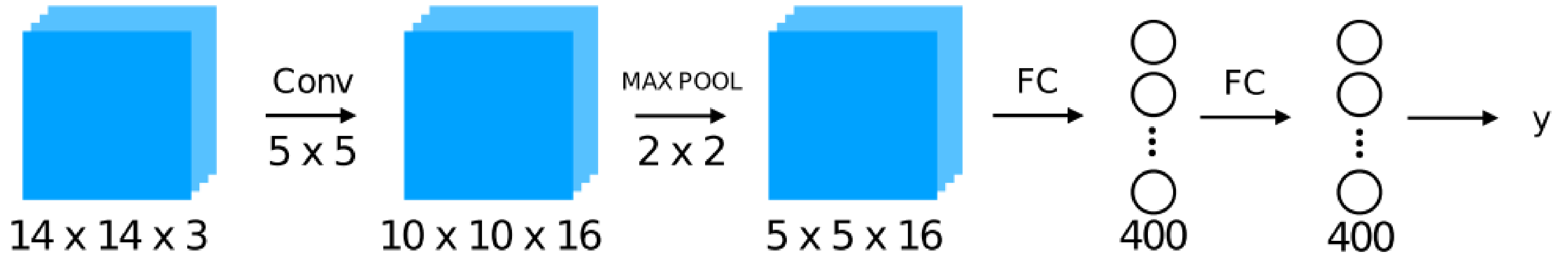
Fully connected layers as convolutional layers

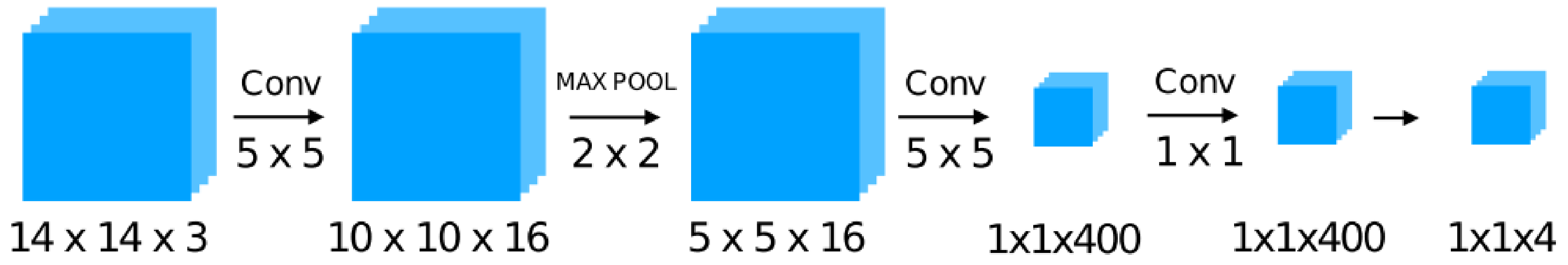




- These two networks are equivalent. Why?
  - Convolving with an image-size kernel ⇔ FCN on pixels and channels

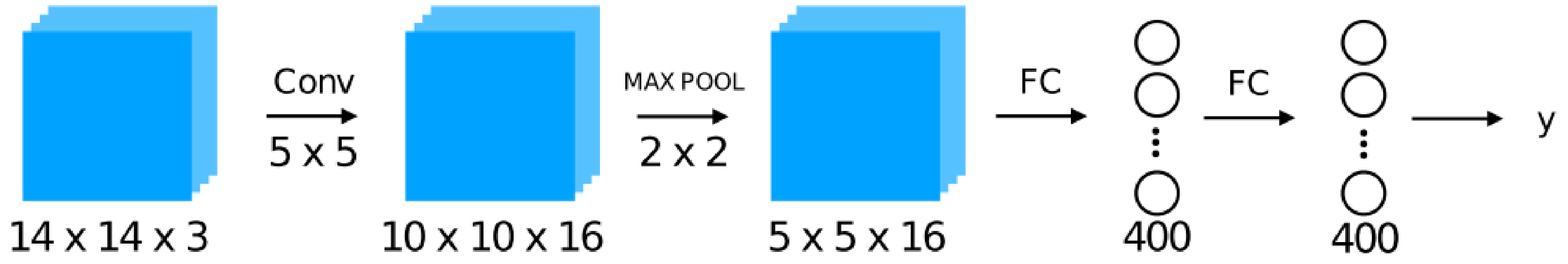
Fully connected layers as convolutional layers

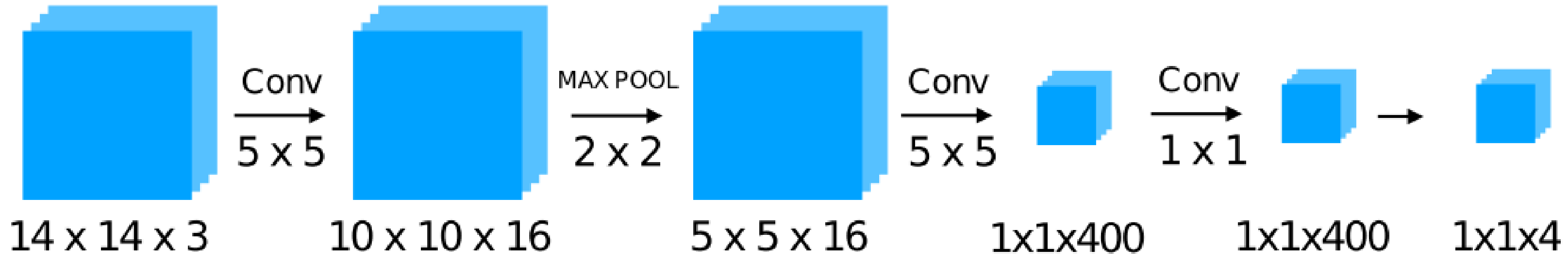




- These two networks are equivalent. Why?
  - Convolving with an image-size kernel ⇔ FCN on pixels and channels
  - Convolving with a 1×1 kernel ⇔ pixel-wise FCN on channels

Fully connected layers as convolutional layers





- What happens if you apply the bottom network to a 100 × 100 × 3 image?
  - Are the two networks still equivalent?
  - What is the size of your output?
  - Which input pixels contribute to the output pixel (25, 30)?

The receptive field

- The receptive field of a CNN output feature is the set of the input features that affect.

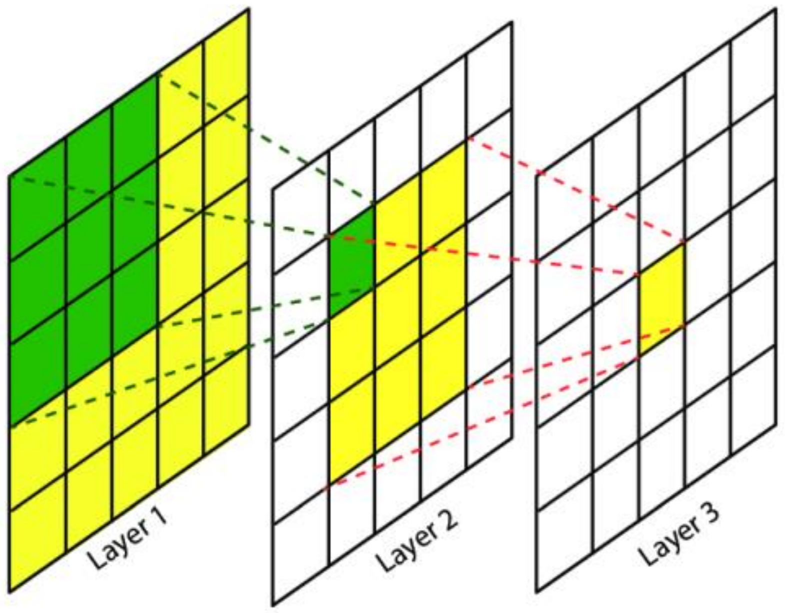


Figure: from Lin et al, Remote Sensing, 2017

Implementation trick

- When computing the loss we often end up computing
- log(Softmax(x)) which is numerically unstable

$$\log(\mathrm{Softmax}(x_i)) = \log\left(\frac{\mathrm{e}^{x_i}}{\sum_j \mathrm{e}^{x_j}}\right) =$$

$$\mathrm{LogSoftmax}(x_i)) = x_i - \log\left(\sum_j \mathrm{e}^{x_j}\right)$$

- Much better!
- nn.CrossEntropyLoss combines LogSoftmax and nn.NLLLoss into one
- Use this instead

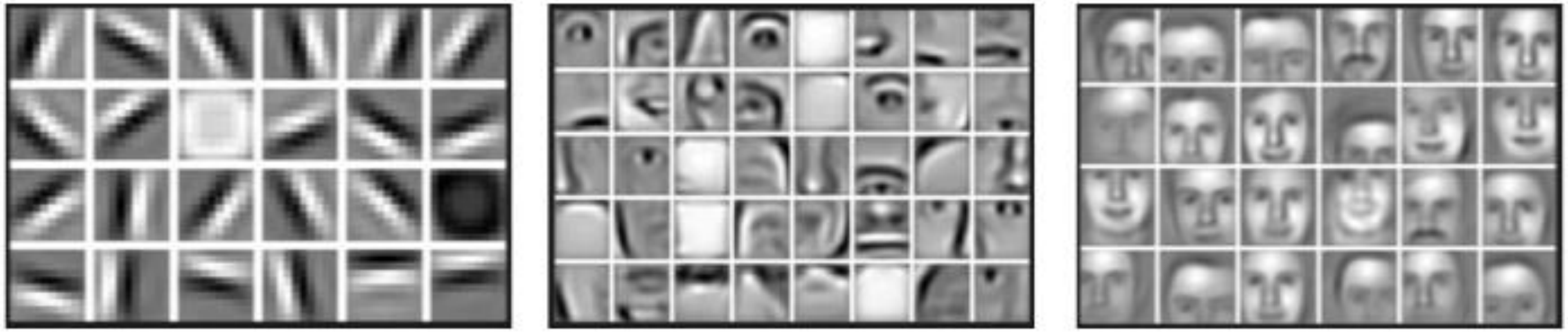
Minibatches revisited

- How do we store a minibatch of images in the computer?
  - 4d tensor with size
    - NCHW (minibatch dimension, channels, height, width)
  - Tensorflow has default (which is slower)
    - NHWC

- Minibatches should be made of data sampled without replacement from your full dataset
  - Once all data has been shown to the network once it is called an epoch
  - After an *epoch y*ou start sampling all your data over again.

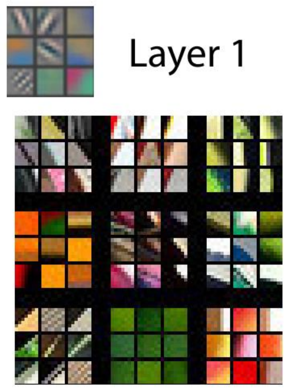
From (2011) Lee et al., Unsupervised Learning of Hierarchical Representations with Convolutional Deep Belief Networks

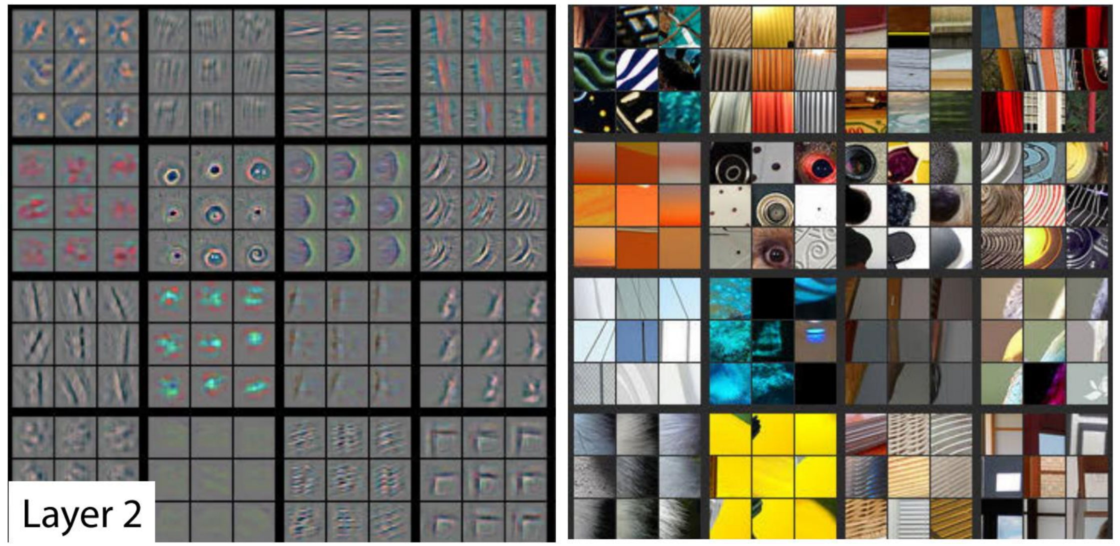
Intuition

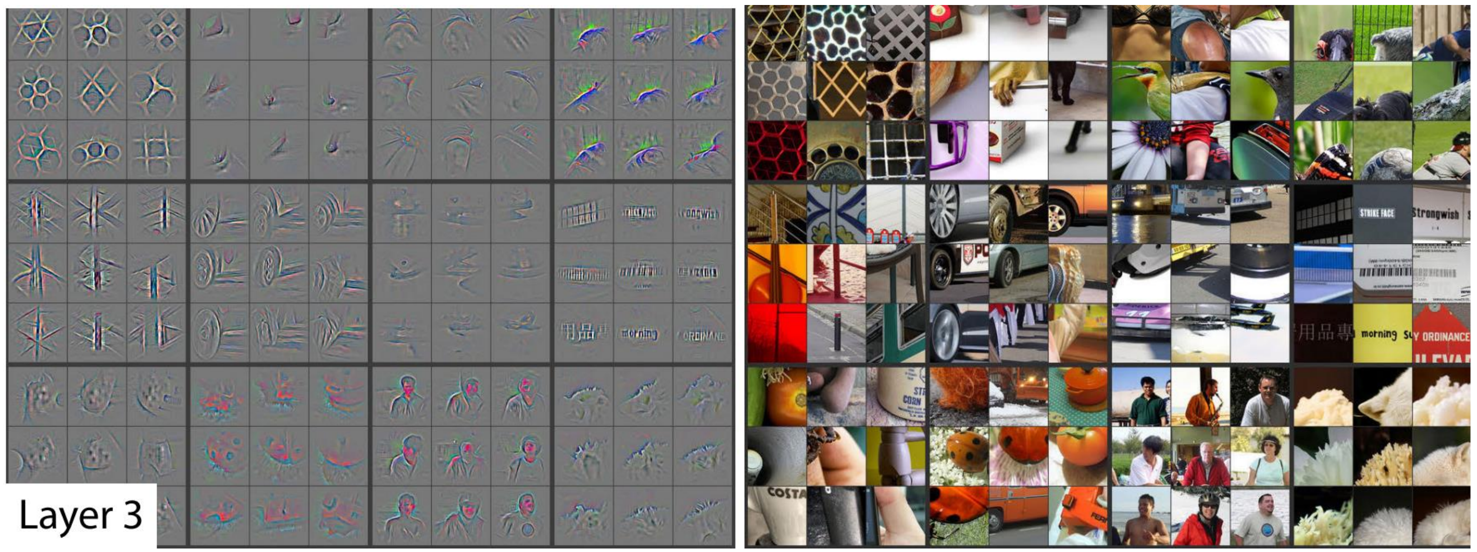

First Layer Representation
Second Layer Representation
Third Layer Representation

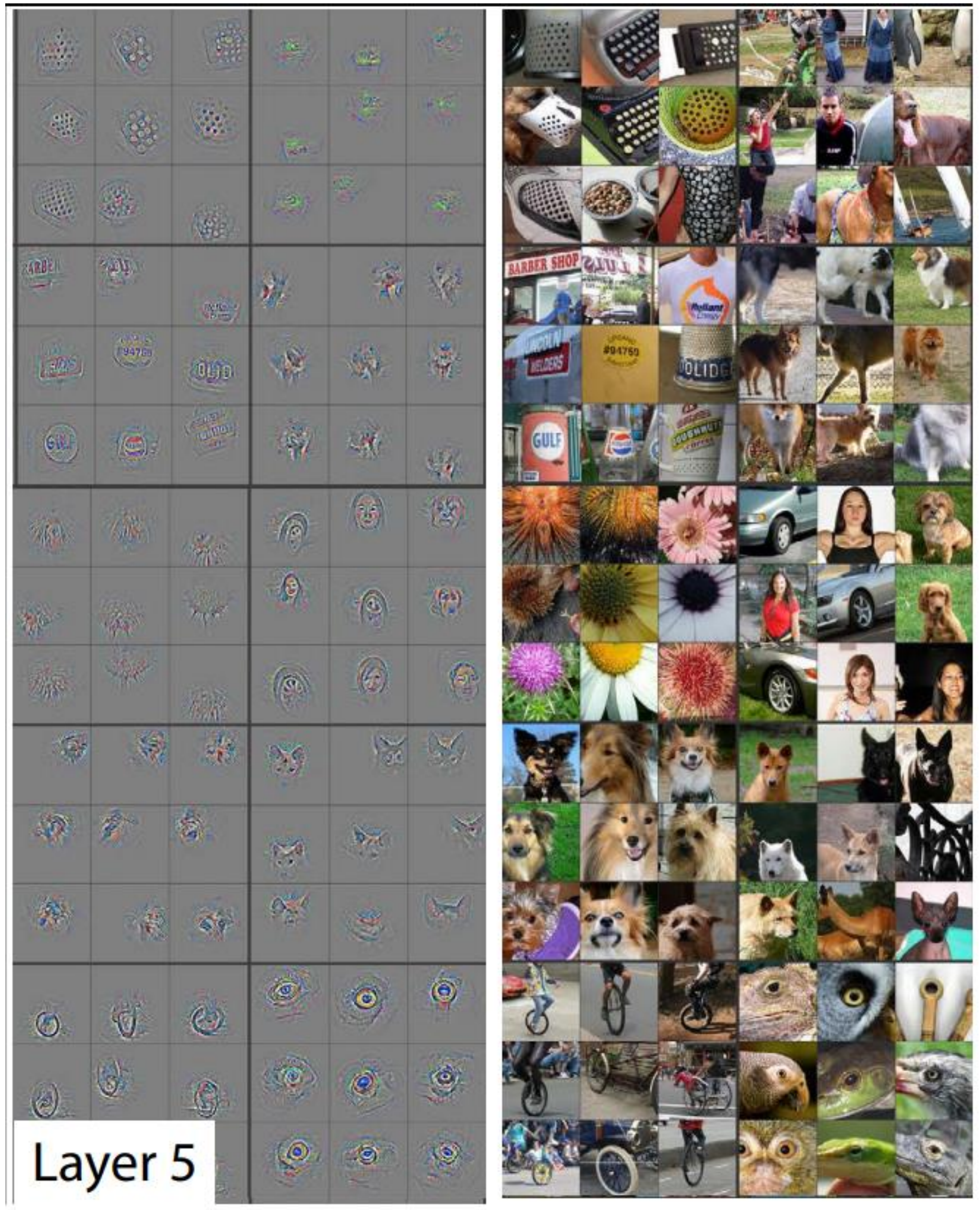
From: (2013) Zeiler and Fergus, Visualizing and Understanding Convolutional Networks
https://arxiv.org/pdf/1311.2901.pdf

Intuition



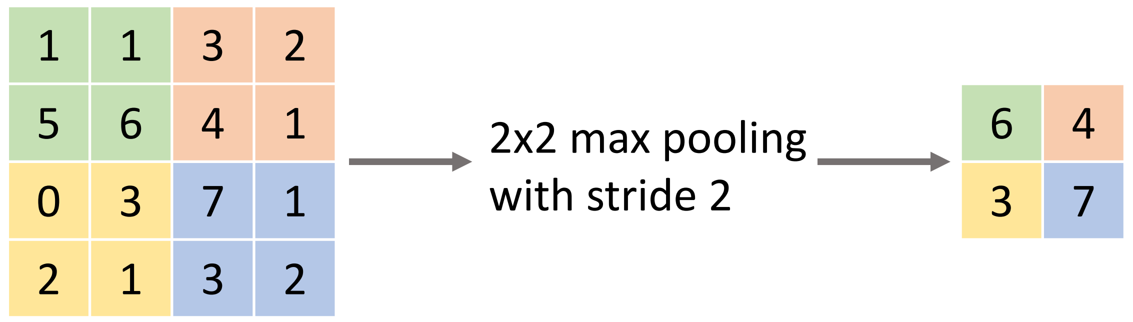






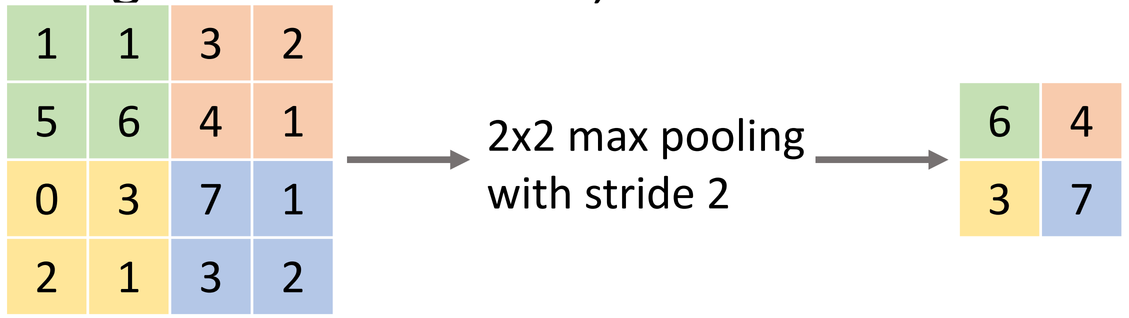
Max Pooling

- Reducing the spatial size of the feature map
- Example:
  - 2x2 max pooling with stride 2
    - For each 2x2 pixels in each channel, retain only the largest number
    - This type of pooling is extremely common in CNNs.



Max Pooling

- Pooling reduces the spatial dimension of the features
  - Not the number of channels
- Number of features is reduced by $2 \cdot 2$
  - Makes computation easier
  - A pooling layer is often followed convolution that doubles the number of features.
  - More higher level features, but lower resolution of them: good for classification



Types of pooling

- Max pooling
  - Max of the values
- Average pooling
  - Mean of the values
- Stochastic pooling
  - A random of the values

- Max pooling is the most common for classification

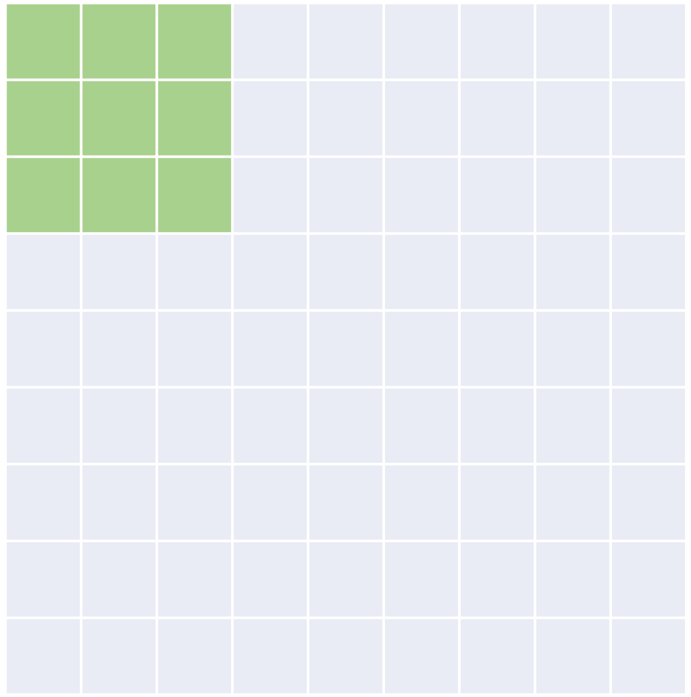
Max pooling – most used

- Max pooling is the most common for networks doing classification
  - For classification is does not matter much where exactly a feature is present
  - Taking the largest value helps make the model invariant to small translations

- Almost all poolings are 2x2 with stride=2.
  - Larger generate worse results.

Strided convolutions

- 3x3 convolution
  Stride = 1



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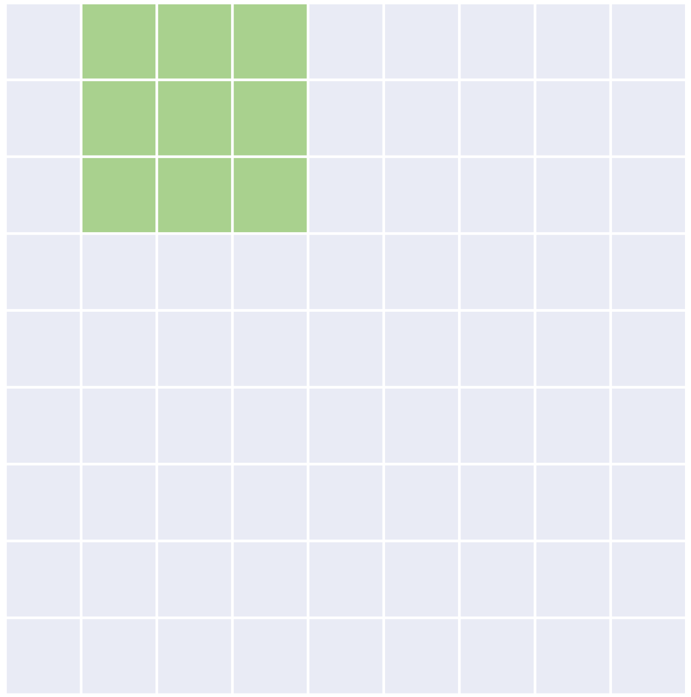

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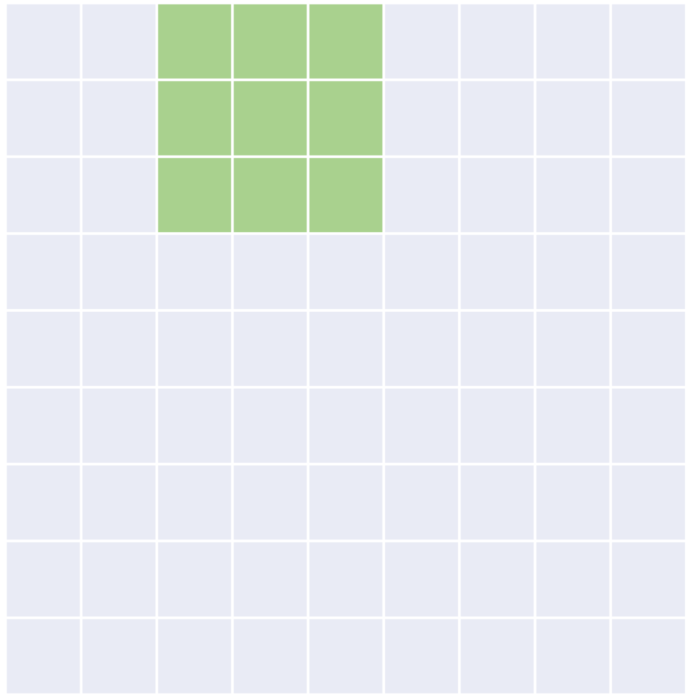

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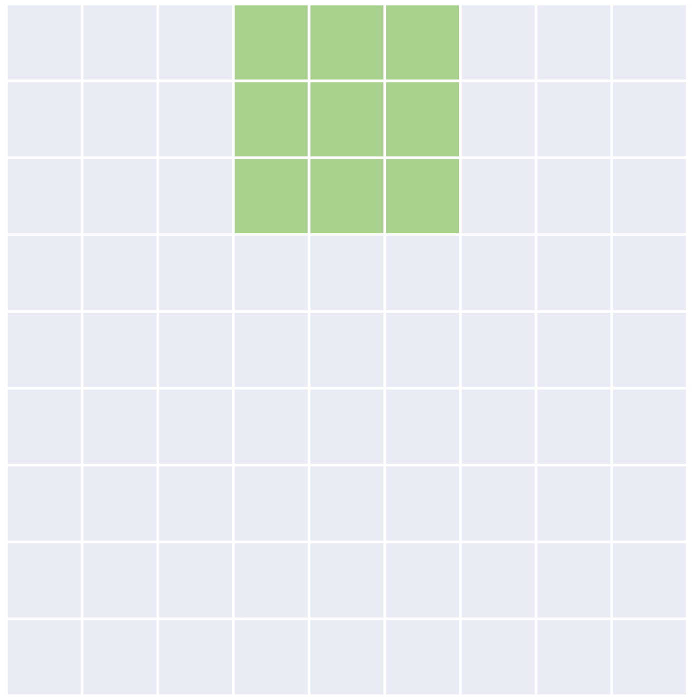

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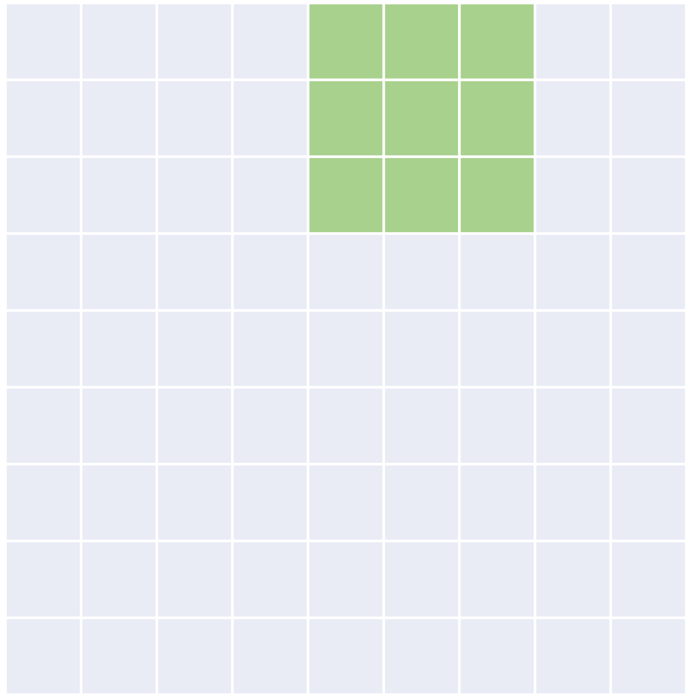

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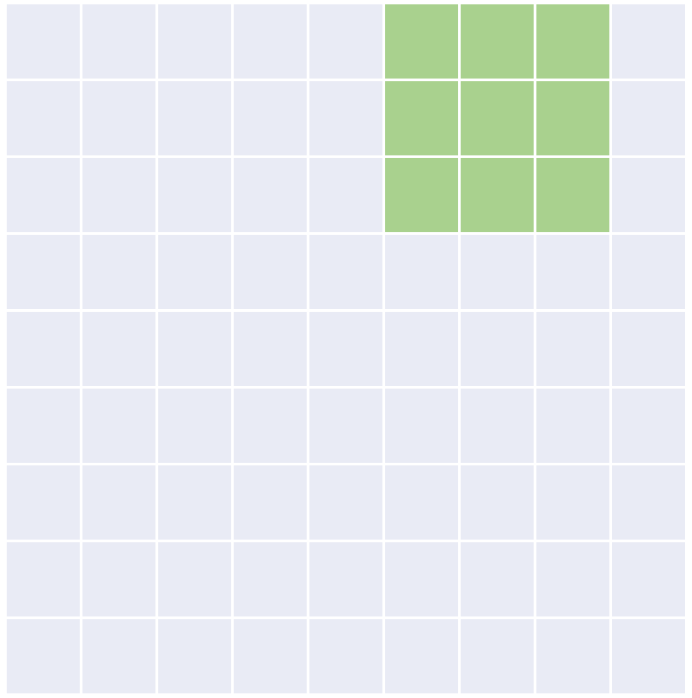

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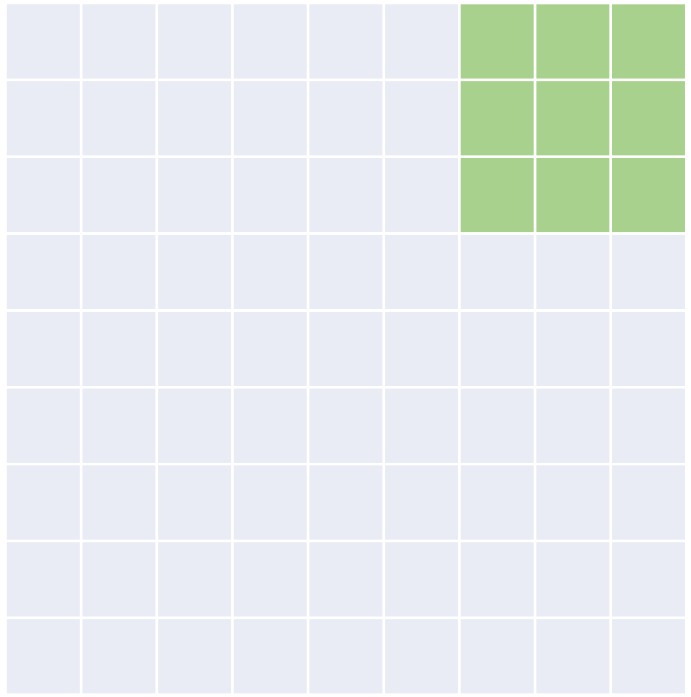

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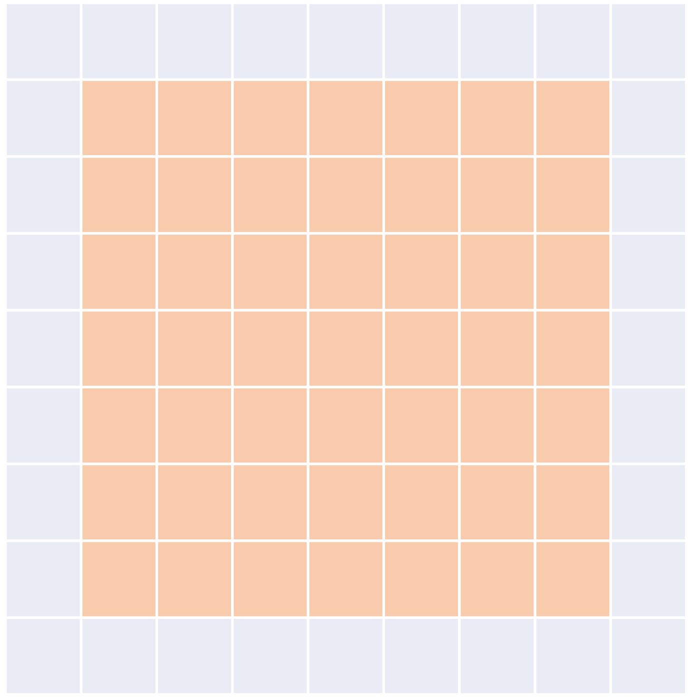
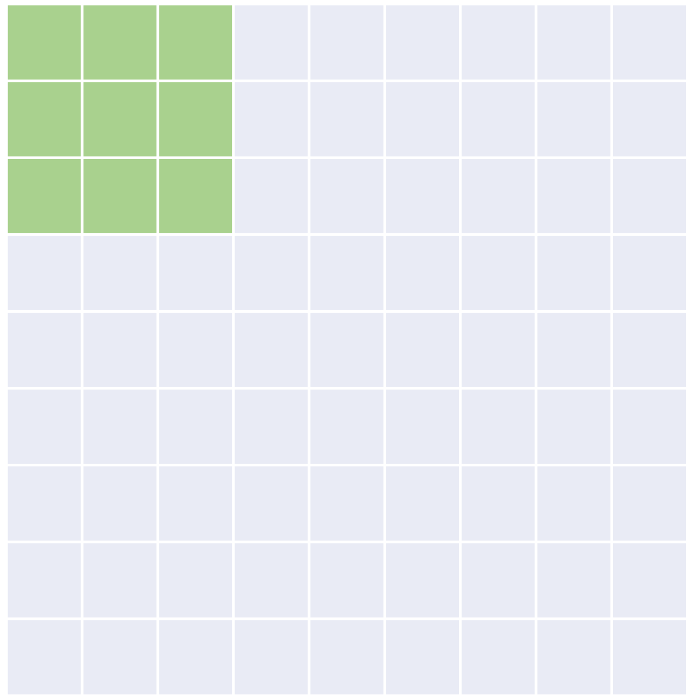


Input size:	9x9
Ouput size:	7x7

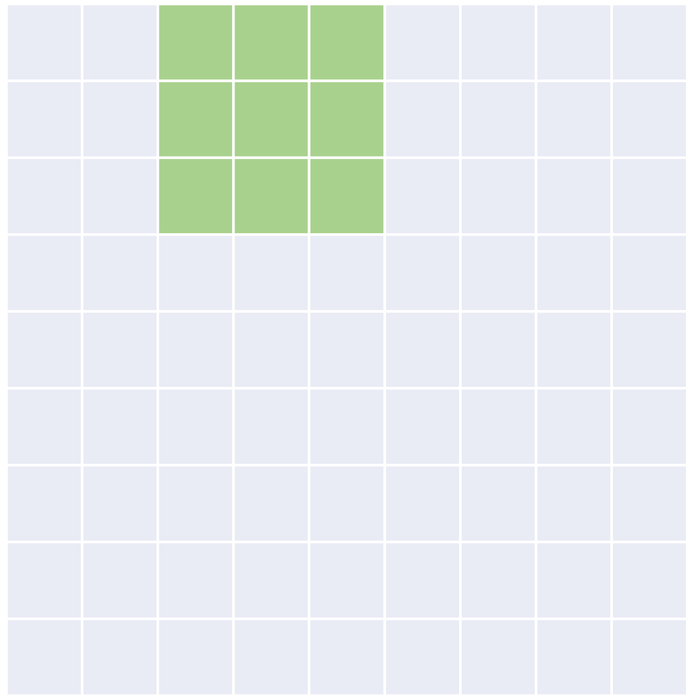
Strided convolutions

- 3x3 convolution
  Stride = 2



Strided convolutions

- 3x3 convolution
  Stride = 2



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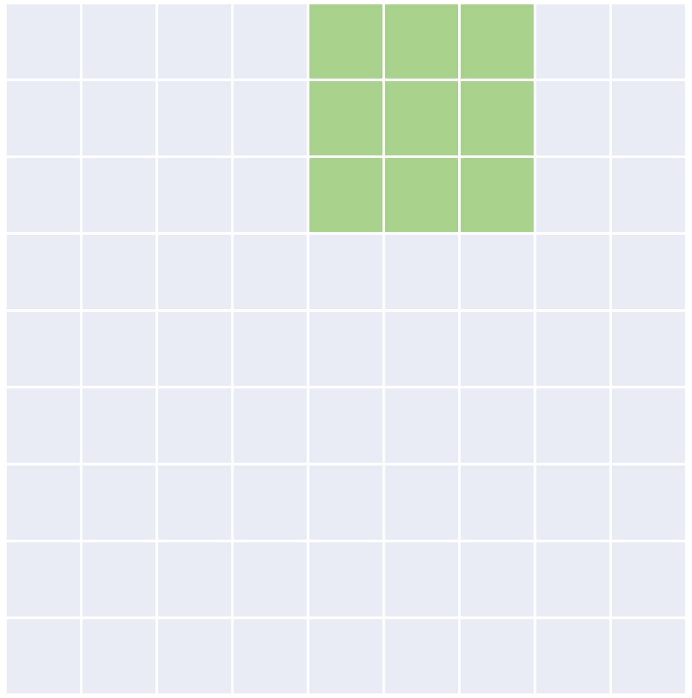

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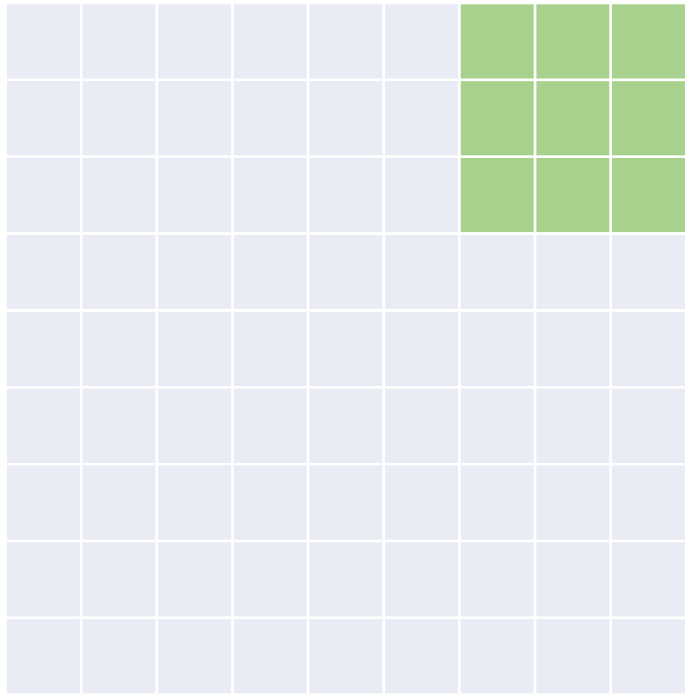

Strided convolutions

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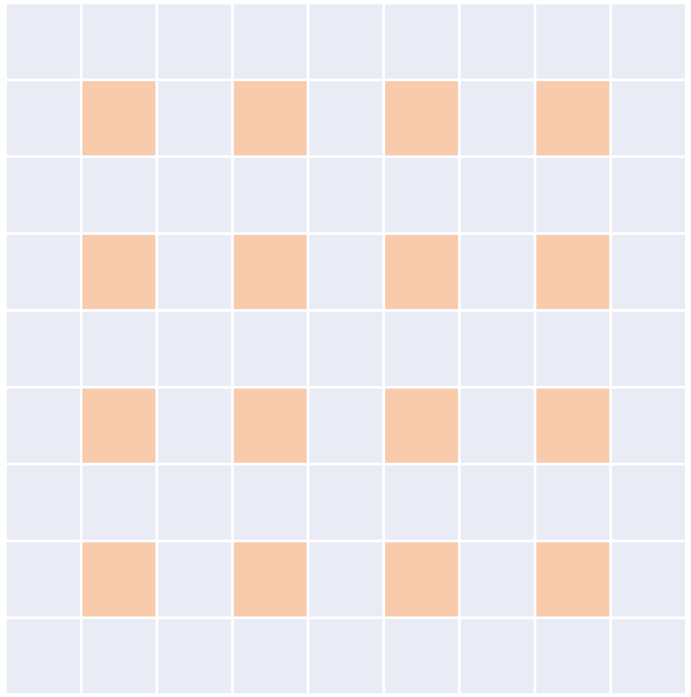


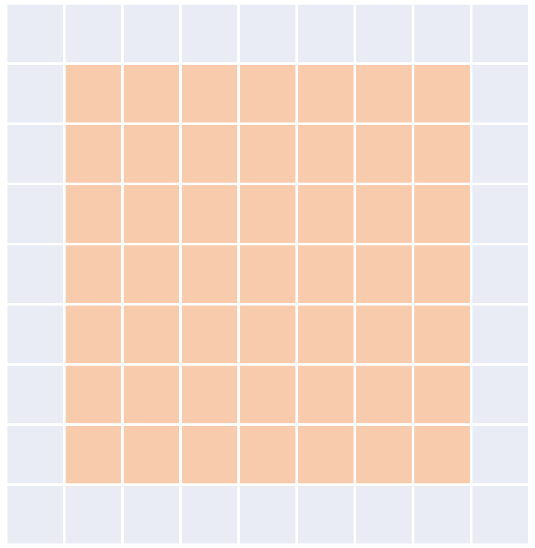
Input size:	9x9
Ouput size:	4x4

Strided convolutions

- Can reduce the size of the image without using pooling
  - Computationally faster than pooling
    - At the risk of being less accurate
  - Perferred in some GANs due to consistent flow of gradients

Padding

- The image size is reduced even for stride=1.
- Artificially increase the size of the image before convolution.
- Padding=1 will increase the size by one at the top, bottom, left and right.
- Usually zeros are used as the padding value in CNNs.



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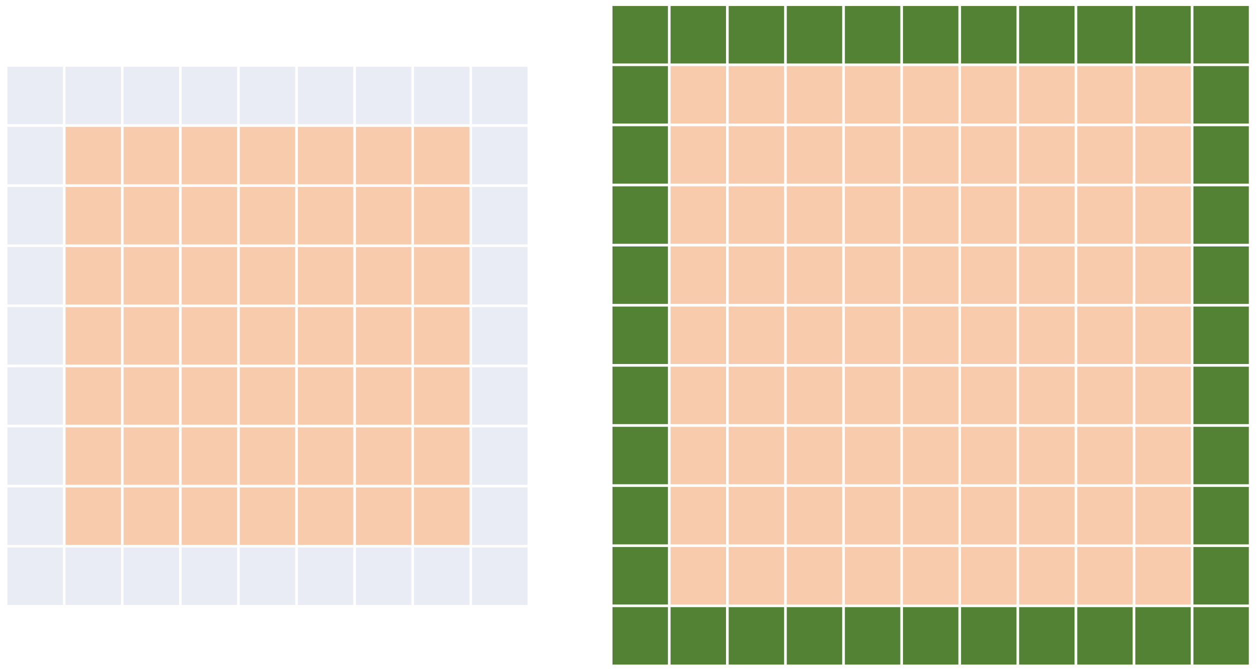


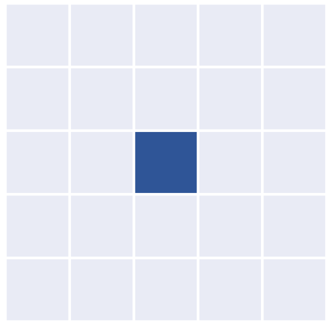
Padding

- Padding with zeros makes sense when the network contains feature maps
  - Positive values indicate the feature is present
  - Zero means this neuron was not activated (the activation was negative and ReLU made it zero)

- If the size needs to be kept constant, you need to pad with:

$$\frac{n-1}{2}$$

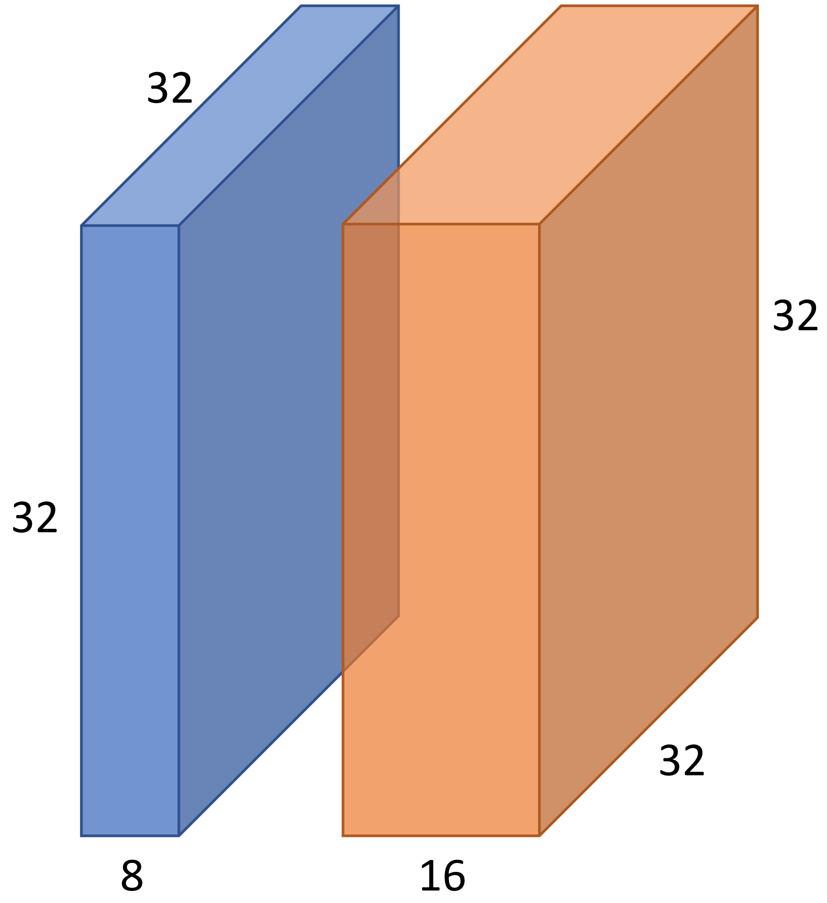
- Visualize the convolution kernel and see how much it has on each side
  - 5x5 → padding=2



Question

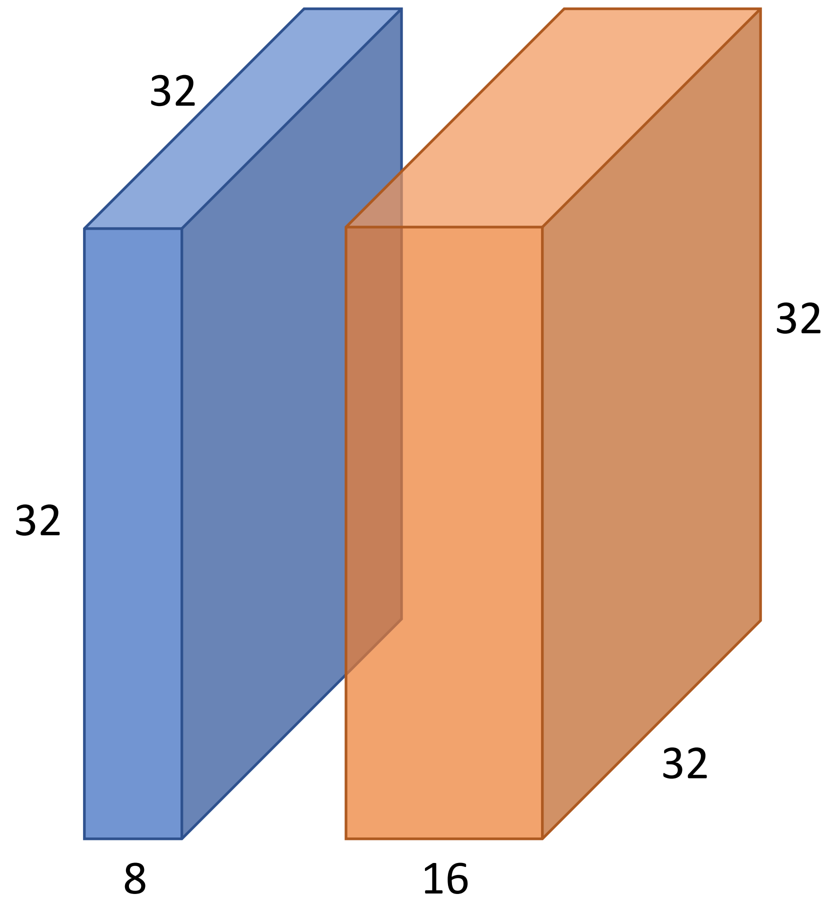
- **DISCUSS WITH YOUR NEIGHBOUR 2 MINUTES**
- Input has 8 channels, and spatial dimensions 32x32
- We perform a 7x7 convolution that produces a new volume with 16 channels and still 32x32 spatially.

- What is the stride?
- What is the padding?
- How many weights (learnable parameters) does the convolution have?



Question

- What is the stride?
  - Stride=1
- What is the padding?
  - Padding=3
- How many weights (learnable parameters) does the convolution have?
  - 16x8x7x7 + 16 bias



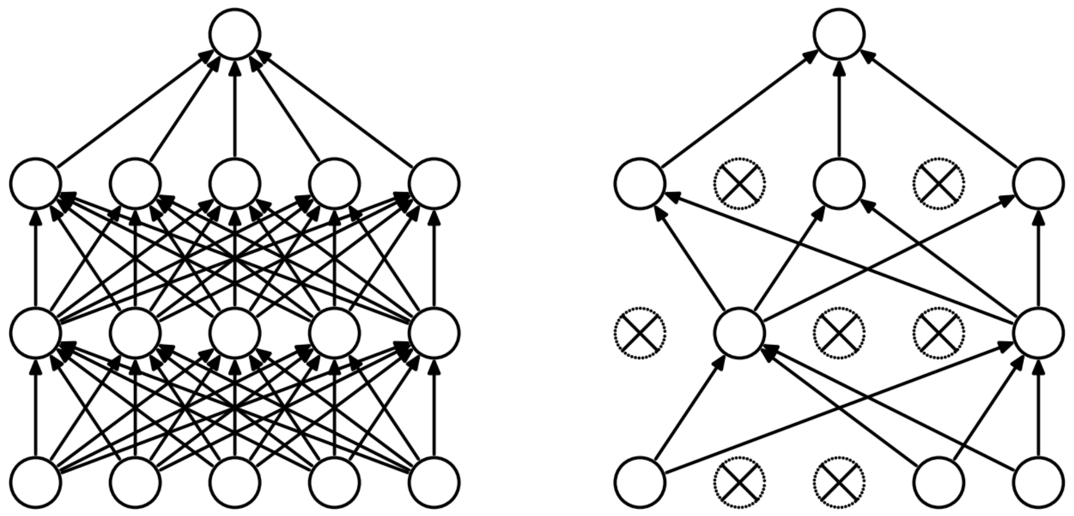
Srivastava et al. Dropout: A Simple Way to Prevent Neural Networks from Overfitting

Dropout

- Background
  - Nerual networks have many weights and can easily **overfit** to your data

Srivastava et al. Dropout: A Simple Way to Prevent Neural Networks from Overfitting

Dropout


(a) Standard Neural Net (b) After applying dropout.

- Background
  - Nerual networks have many weights and can easily **overfit** to your data
- Concept: Model ensembles (averages of many) are always good
  - How can we do this in a single model?
- How it works
  - Each forward pass, we randomly omit each feature with a probability of 0.5
  - This means we are actually sampling from 2^n different architectures
  - Efficient way of performing model averaging with neural networks

Dropout

- Imagine if you each day only had either your right or left arm.
    - You would be forced to become good at using both arms, because you don’t know which arm you will have tomorrow.

- Intuition:
    - Specialized neuron might be good enough to classify correctly
        - Other neurons become lazy
    - Randomly removing neurons forces all neurons to do their best

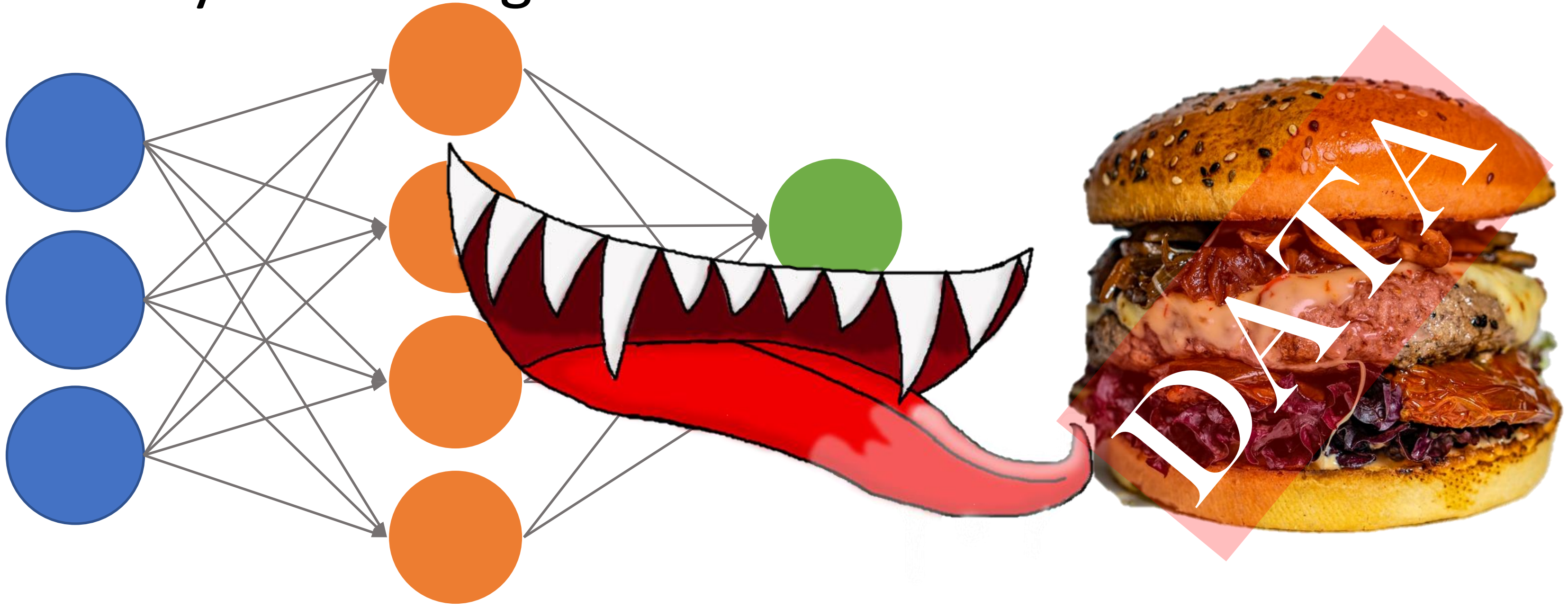
Dropout

- Technical details:
  - The dropped neurons during training means expectation of layer output is smaller than during training
    - This is problematic
  - It is common to scale the activations up by the dropout factor during training
    - For example if we drop p=50% of neurons, during training we multiply the activations by 1/p=2
- This is often handled by the high-level framework you are using
  - As long as you tell the model whether it’s training or testing right now.

- Dropout is a well known regularization technique, but BatchNormalization is an often used alternative.

Data augmentation

- Neural networks are very data-hungry
- How to satisfy their hunger?



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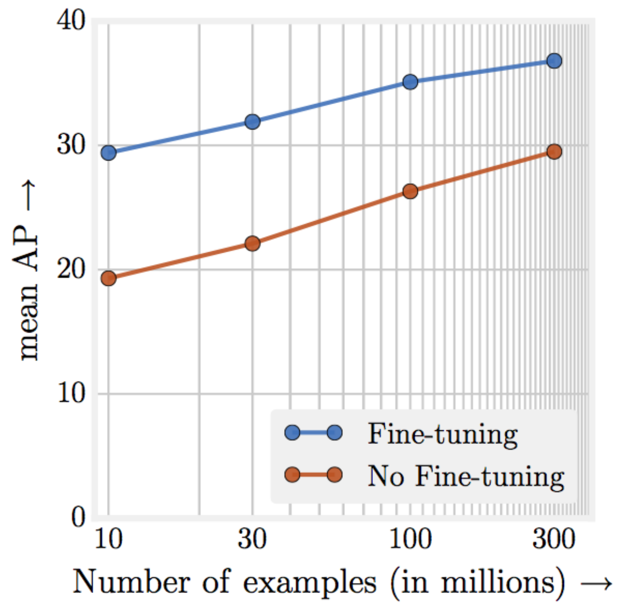

From: https://ai.googleblog.com/2017/07/revisiting-unreasonable-effectiveness.html

Data augmentation

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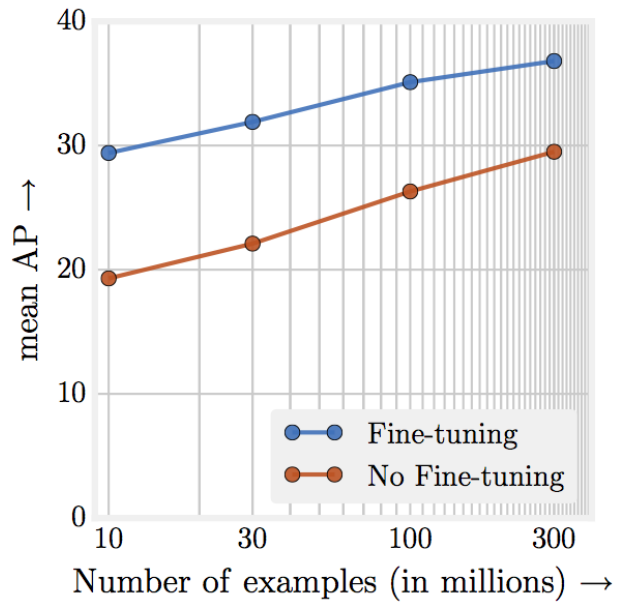
- How to satisfy their hunger?

- "just have enough data"
  - ImageNet has 14 million images
    - not big enough
  - Google has JFT-300M with 300 million images
    - not big enough
    - also not public
- We need to fully utilize the data we do have



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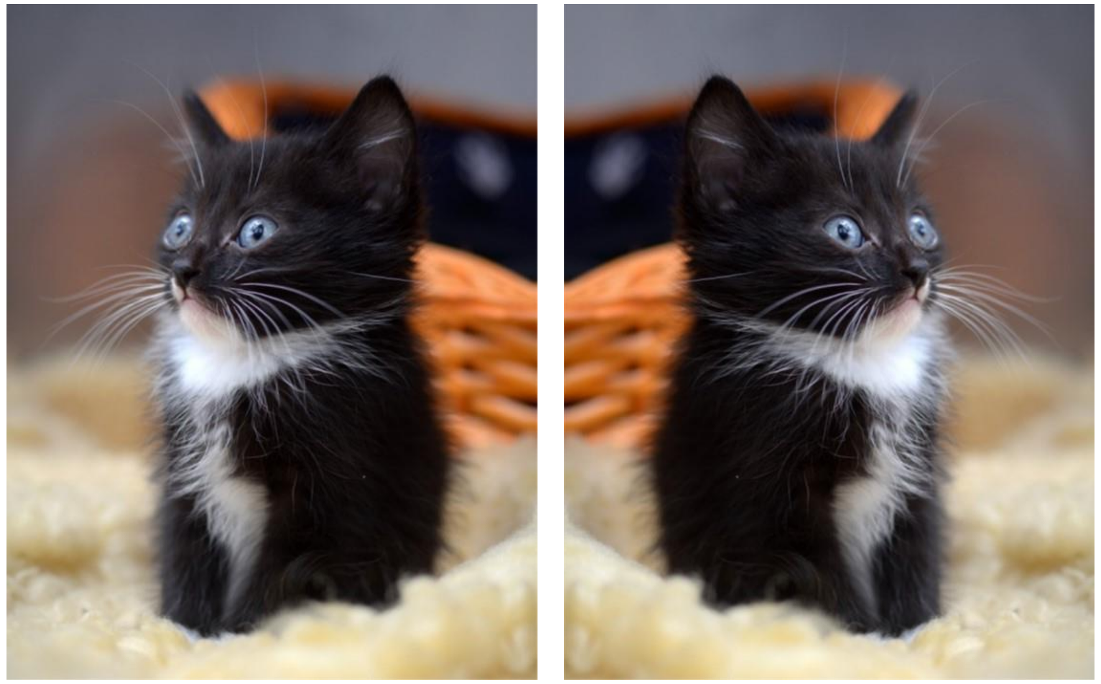

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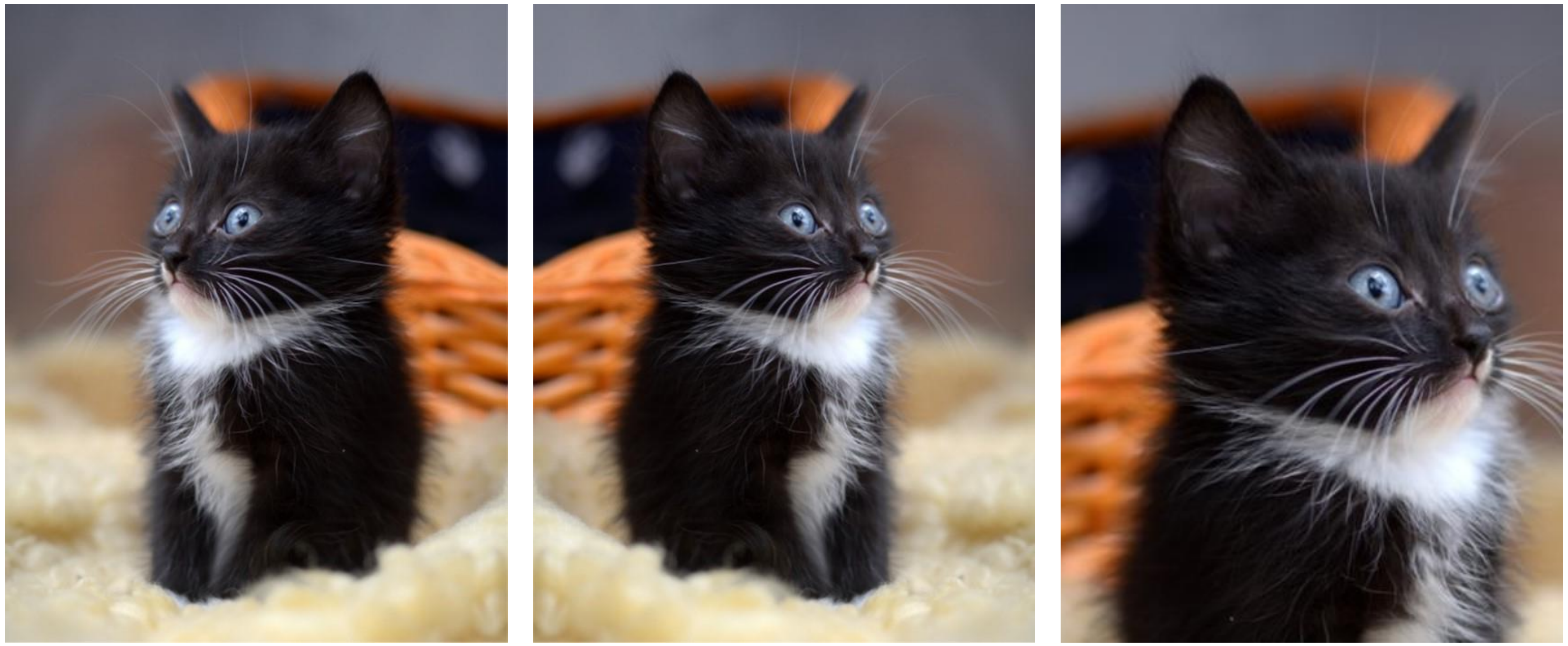

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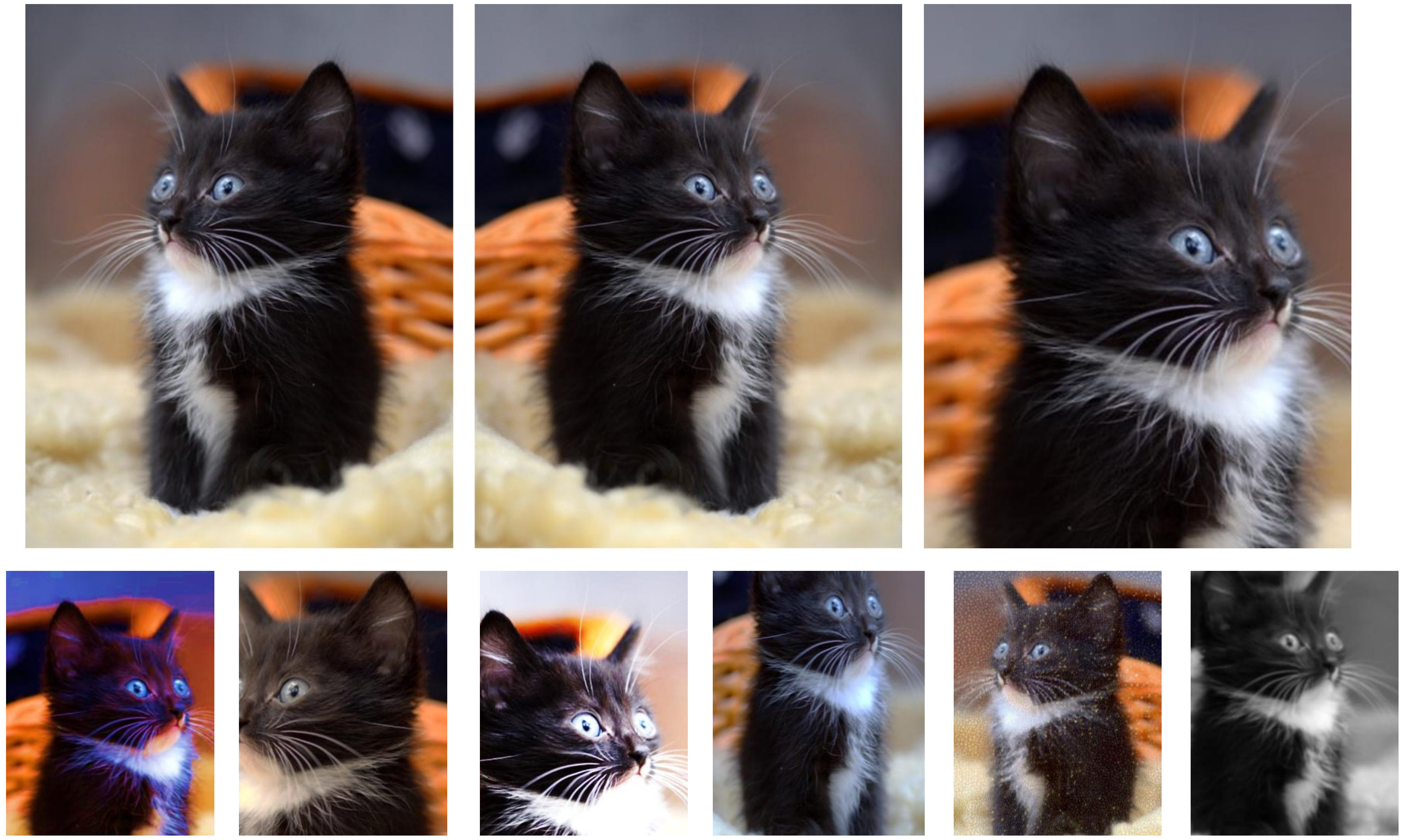

Data augmentation

- Create more data by exploiting things that the label is invariant towards
- Always keep in mind what the images are of
    - Flipping an image of text means that the text is no longer readable

- Types of augmentation:
    - Flips

Data augmentation

- Create more data by exploiting things that the label is invariant towards
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- Types of augmentation:
    - Flips
    - Translation
    - Scale (non-uniform?)
    - Rotation
    - Elastic deformation
    - Lens distortion?
    - Noise
    - Blur
    - Colour changes

What you have learned

- Convolutions recap
- CNN
  - Convolutions
  - Max pooling
  - Stride/padding
  - Backprop
- Combatting overfitting:
  - Dropout
  - Data augmentation

Slides slightly inspired by: Fei-Fei Li & Andrej Karpathy, CS231n:
Convolutional Neural Networks for Visual Recognition, Winter 2015. (Stanford University)

Exercise

- https://colab.research.google.com/drive/1VvWdDFlz7S0PTeQ5QlxqyirIH50_JTDw