

# Convolutional Neural Networks (ConvNet)

1. Recap from last week (chapters 5.1 & 5.2)
2. Using a pretrained ConvNets (chapter 5.3)
  - Feature extraction
  - Fine-tuning a pretrained convnet
3. Visualizing what ConvNets learn (chapter 5.4)
  - Visualizing activations
  - Visualizing filters
  - Visualizing heatmaps of class activation

# ConvNet

- class of deep Artificial Neural Networks (ANN)
- mainly applied for analyzing visual imagery.
- common applications

classification



Cat

object detection



Dog, Dog, Cat

segmentation



Dog, Dog, Cat

video processing, natural language processing, speech recognition

# ConvNet architecture

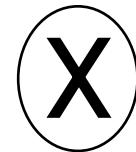
```
model <- keras_model_sequential() %>%
  layer_conv_2d(filters = 32, kernel_size = c(3, 3), activation = "relu",
                input_shape = c(150, 150, 3)) %>%
  layer_max_pooling_2d(pool_size = c(2, 2)) %>%
  layer_conv_2d(filters = 64, kernel_size = c(3, 3), activation = "relu") %>%
  layer_max_pooling_2d(pool_size = c(2, 2)) %>%
  layer_conv_2d(filters = 128, kernel_size = c(3, 3), activation = "relu") %>%
  layer_max_pooling_2d(pool_size = c(2, 2)) %>%
  layer_conv_2d(filters = 128, kernel_size = c(3, 3), activation = "relu") %>%
  layer_max_pooling_2d(pool_size = c(2, 2)) %>%
  layer_flatten() %>%
  layer_dropout(rate = 0.5) %>%
  layer_dense(units = 512, activation = "relu") %>%
  layer_dense(units = 1, activation = "sigmoid")

model %>% compile(
  loss = "binary_crossentropy",
  optimizer = optimizer_rmsprop(lr = 1e-4),
  metrics = c("acc")
)
```

# Convolution process

0	0	0	0	0	0	1
0	1	0	1	1	0	0
0	0	1	0	0	1	1
0	0	1	0	0	0	0
0	0	0	0	1	0	0
0	1	1	1	1	1	0
0	0	0	0	0	0	0

Image input



Random learnable  
**weights**

0	0	1
1	0	0
0	1	1

Kernel (3X3)  
Stride (1,1)

dot-product of image pixels  
with a kernel weights

1	2	0	2	4
1	2	2	0	0
1	0	2	2	1
3	2	2	2	2
0	1	1	1	1

Feature maps

# Hyperparameters

- The size of the feature map can be controlled by the following hyper-parameters:

**Stride:** no. of pixels to skip when sliding over the input.

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0
0	0	0	1	0	1	1	0	0	0
0	0	0	1	0	0	1	1	0	0
0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0
0	0	1	1	1	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

Image input

**Padding:** no. of zeros added around the input.

0	0	1
1	0	0
0	1	1

3x3 Kernel

**Kernel size:** sets the size of the filter

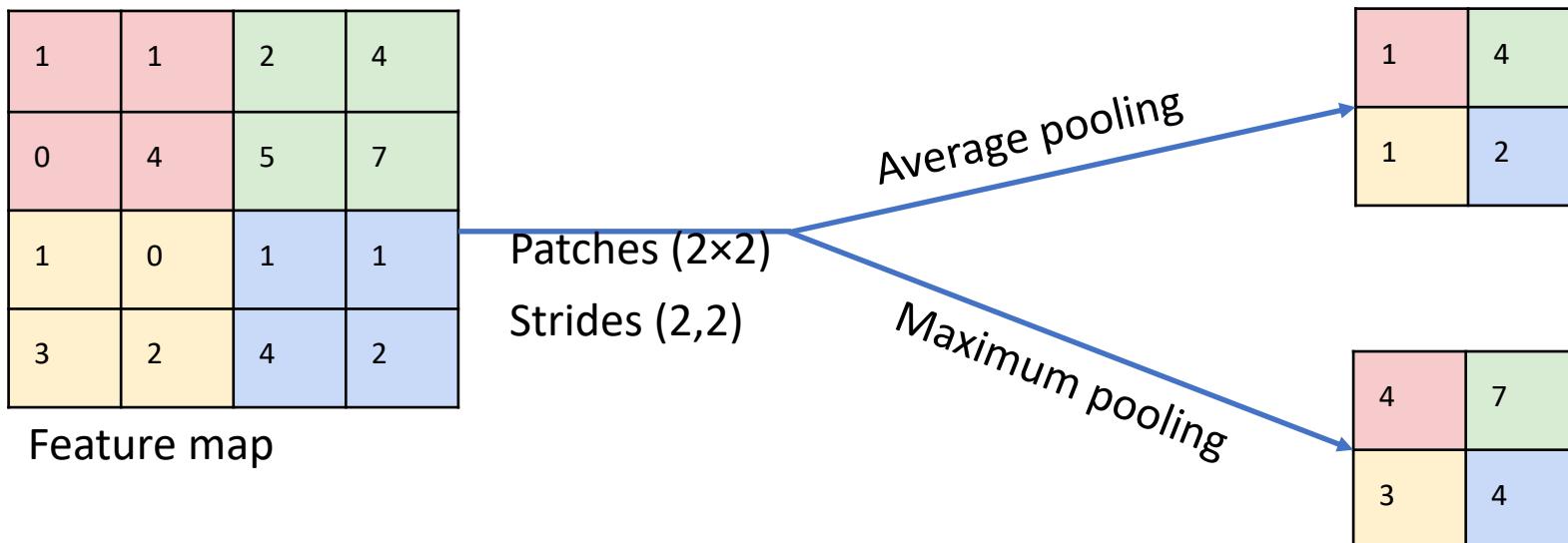
**No. of kerners:** sets the depth of the output.

1	2	0	2	4
1	2	2	0	0
1	0	2	2	1
3	2	2	2	2
0	1	1	1	1

Feature maps

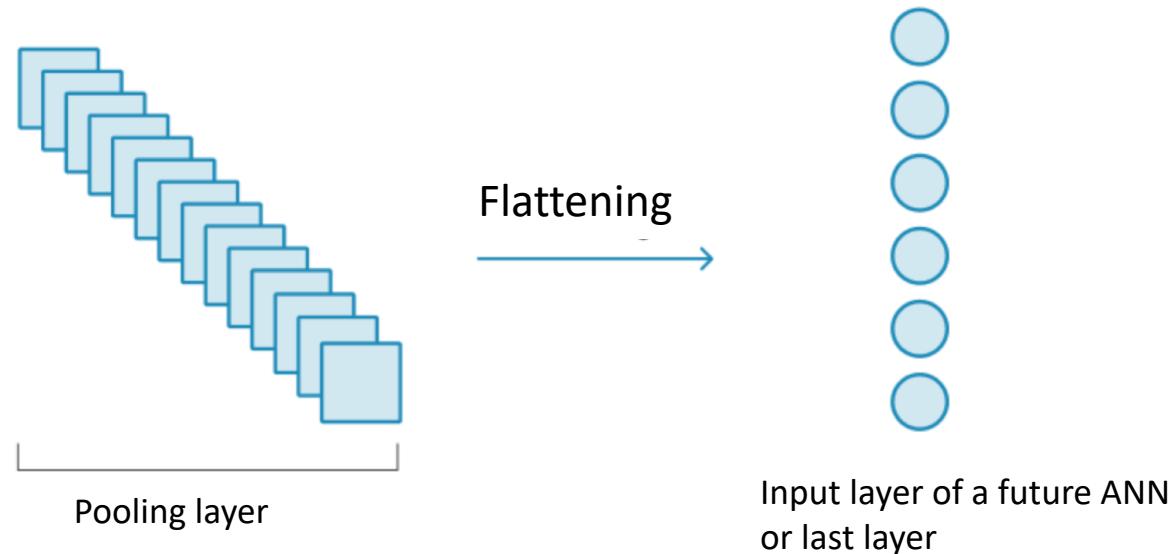
# Pooling process

- Reduces the dimensionality of feature maps but retains important information.
  - Focuses on the main features
  - Reduce computational costs - gets rid of extra data
  - Reduce overfitting - combines neighboring values into a single one
- Types of pooling
  - **Average Pooling:** average value for each patch on the feature map.
  - **Maximum Pooling:** maximum value for each patch of the feature map.



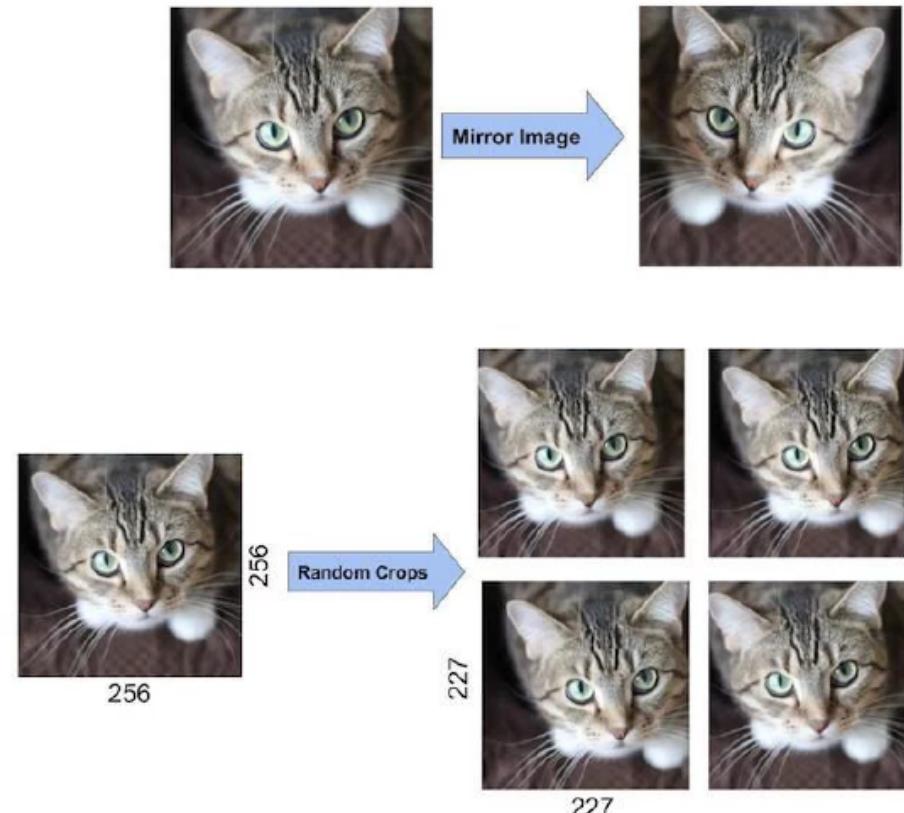
# Dense Layer

- Facilitated by a process called Flattening.
- Flattening transforms the feature maps into **one** vector
- The vector fed into a neural network of  **$n$**  layers.
- Last layer has  **$c$**  neurons, representing the **number of classes** to classify.

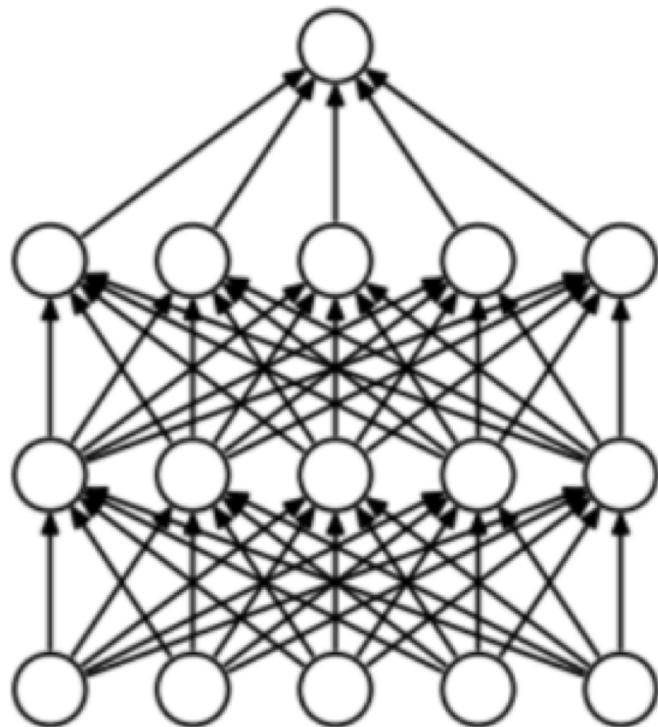


# Data augmentation

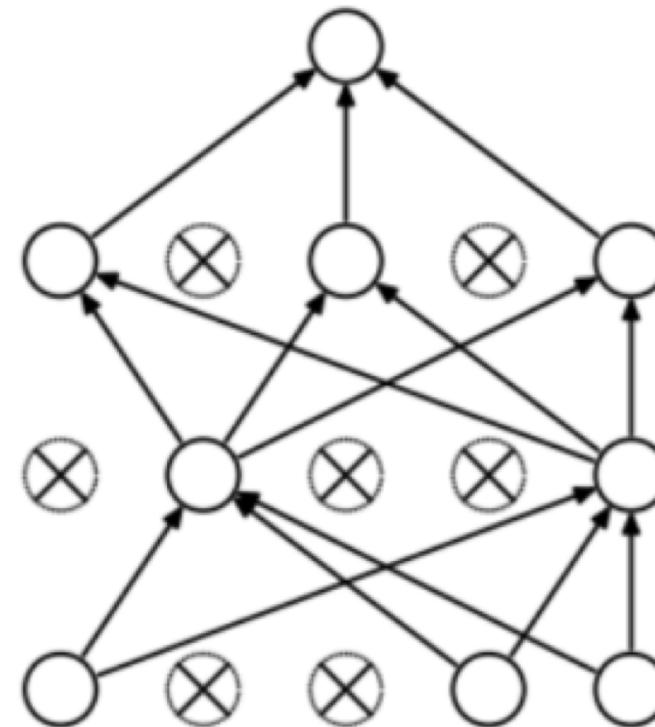
- Data augmentation is used as a way to make models more robust.
- It reduces overfitting by letting models learn harder and more general data representations.
- Most popular:
  - Noise addition
  - Mirroring
  - Rotating
  - Resizing
  - Cropping
  - Occlusion
- Newer methods:
  - Synthetic data



# Drop out



(a) Standard Neural Net



(b) After applying dropout.