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- The Mini-Project
- Convolutional Neural Networks
  - Computer Vision Problems
  - Convolutions
  - Convolutions in Neural Networks
  - Data Augmentation - Regularization for CNNs
  - Examples
- Transfer learning

# Machine learning, big data and artificial intelligence – Block 5

Måns Magnusson  
Department of Statistics, Uppsala University

December 2020



# This week's lecture

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- The Mini-Project
- Convolutional Neural Networks
  - Computer Vision Problems
  - Convolutions
  - Convolutions in Neural Networks
  - Data Augmentation - Regularization for CNNs
  - Examples
- Transfer learning

- The Mini-Project and Master Thesis Projects
- Convolutional Neural Networks
- Transfer Learning



# Mini-project

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- Time to start think about the project.

- The Mini-Project
- Convolutional Neural Networks
  - Computer Vision Problems
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# Mini-project

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- The Mini-Project
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  - Convolutions in Neural Networks
  - Data Augmentation - Regularization for CNNs
  - Examples
- Transfer learning

- Time to start think about the project.
- Supervised problem of choice on **real data**.



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## Mini-project

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- 2-3 students.



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## Mini-project

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- Time to start think about the project.
- Supervised problem of choice on **real data**.
- 2-3 students.
- Supply a **project proposal** of data and problem at the end of *16th of December 23.59*.
- *Hint!* Submit page 1-1.5 of the project as project proposal.
- Deadline is after all lectures on supervised learning



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- Deadline is after all lectures on supervised learning
- Feel free to combine it with your master thesis project.
- Check with me if you have questions.
- The project should result in a 4 page report (PDF) using the **ICML LaTeX template**.



# Master thesis proposals

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- Stochastic EM, probabilistic programming and Topic Models.





# Master thesis proposals

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- Stochastic EM, probabilistic programming and Topic Models.
- BERT for article segmentation/reconstruction.



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- CNN for newspaper segmentation.



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- Stochastic EM, probabilistic programming and Topic Models.
- BERT for article segmentation/reconstruction.
- CNN for newspaper segmentation.
- BERT for legal predictions.
- Send me a note if you are interested (of any) before Thursday 23.59!

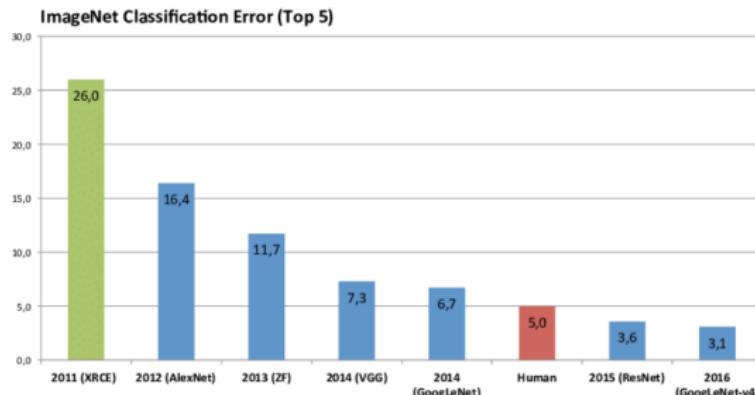


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# Convolutional Neural Networks

- Convolutional Neural Networks are behind great progress in the 2010s.
- It has revolutionized Computer Vision.
- Also called: ConvNets, Convolutional nets, Convolutional networks

Figure: ImageNet performance (Roessler, 2019)



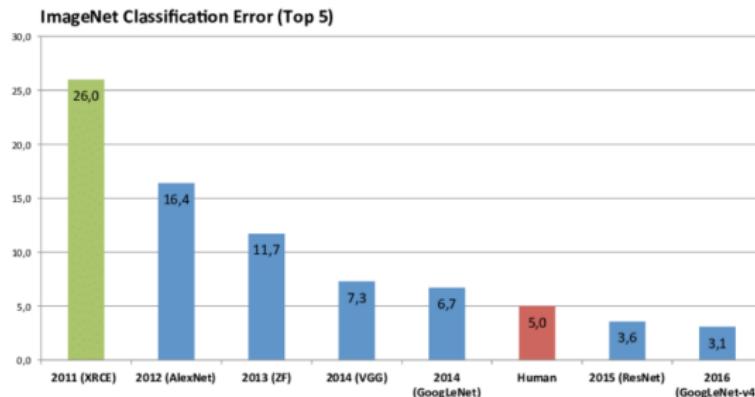


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- Special architecture that works well for data with a **grid structure**
  1. 1D-grids: Time series
  2. 2D-grids: Gray-scale Images (pixels)
  3. 3D-grids: Color Images (pixels and channels)
  4. 4D-grids: Color Video (pixels, channels, frames)



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- Problems
  - Image Classification



# Computer Vision

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  - Image Classification
  - Image Segmentation



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  - Image Classification
  - Image Segmentation
  - Object Detection



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- Problems
  - Image Classification
  - Image Segmentation
  - Object Detection
  - Object Localization
- Focus: 2D and 3D data



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- Problems
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  - Object Detection
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- Focus: 2D and 3D data
- Very Large Datasets:
  - ImageNet: 14M Images, 20k classes, 1M bounding boxes



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    - Object Localization
  - Focus: 2D and 3D data
  - Very Large Datasets:
    - ImageNet: 14M Images, 20k classes, 1M bounding boxes
  - Many different trained models and transfer learning



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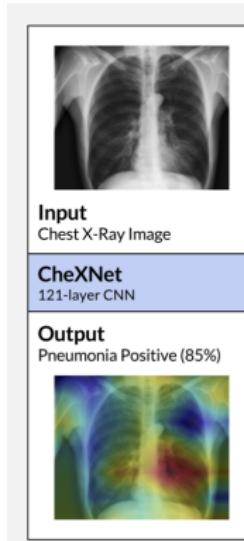


Figure: Object detection (see  
<https://www.youtube.com/watch?v=VOC3huqHrss>)



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## Example: Pneumonia detection



Our model, CheXNet, is a 121-layer convolutional neural network that inputs a chest X-ray image and outputs the probability of pneumonia along with a heatmap localizing the areas of the image most indicative of pneumonia.

We train CheXNet on the recently released ChestX-ray14 dataset, which contains 112,120 frontal-view chest X-ray images individually labeled with up to 14 different thoracic diseases, including pneumonia. We use dense connections and batch normalization to make the optimization of such a deep network tractable.

**Figure:** Rajpurkar et al. (2017). Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225.



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## Example: Fracture detection



Figure 1. 2 images from the dataset. The area within the red box is the section presented to the network in order to classify the image. The left image is of a wrist fracture while the right image is without any apparent fracture.

**Figure:** Olczak et al, (2017) Artificial intelligence for analyzing orthopedic trauma radiographs, Acta Orthopaedica, 88:6, 581-586



# What is an Image?

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- 2-dimensional object
- Each pixel has:
  1. a value (light intensity)
  2. a coordinate



# What is an Image?

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  1. a value (light intensity)
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- **Grayscale:** single channel
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# What is an Image?

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- Each pixel has:
  1. a value (light intensity)
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- **Grayscale:** single channel
- **Color:** three channel (RGB)
- Spatial and hierarchical correlation structures



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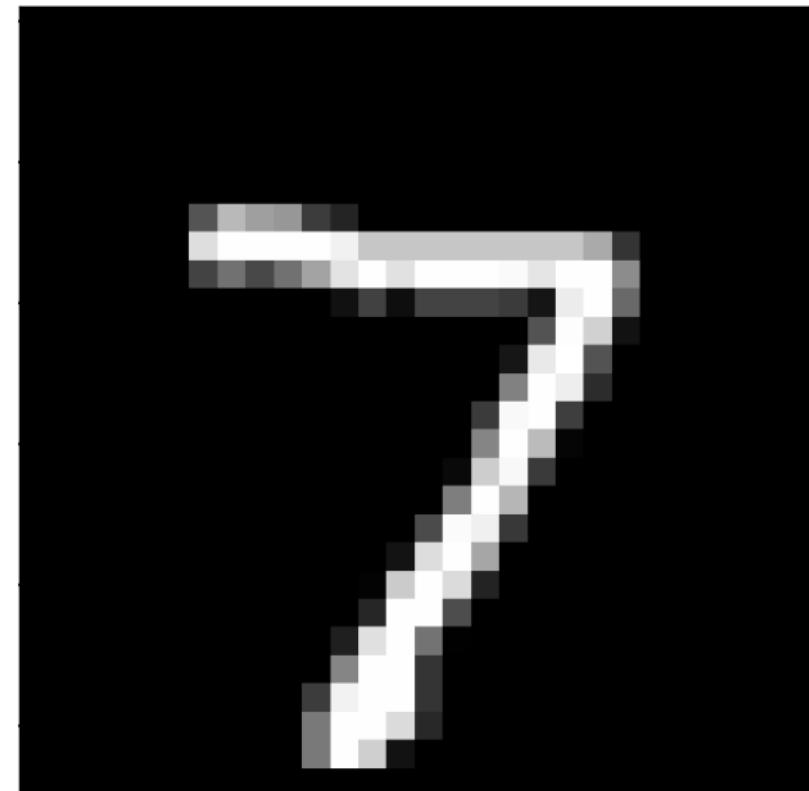


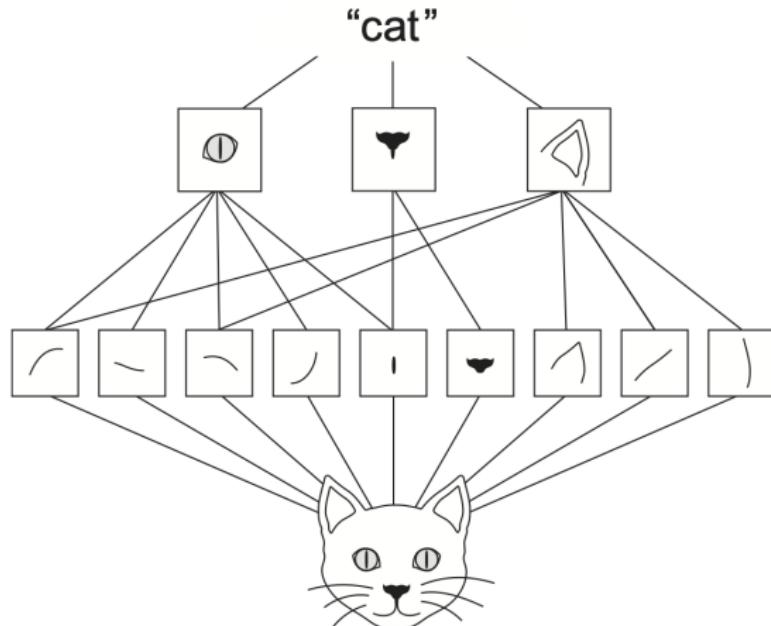
Figure: Example from the MNIST dataset (28 by 28 pixels)



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# How to train models for images?

- We want to learn **representations** of parts of images



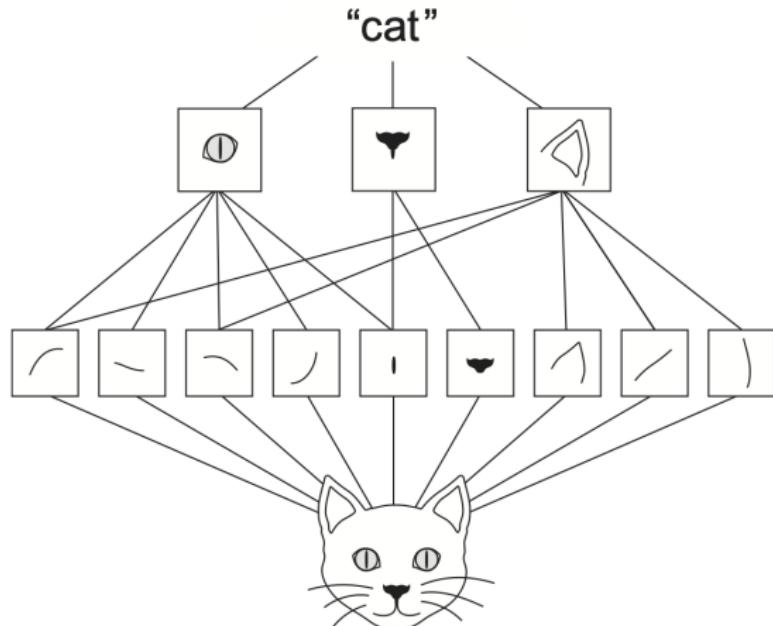
**Figure:** The representations of a cat (Chollet and Allair, 2018, Fig 5.2)



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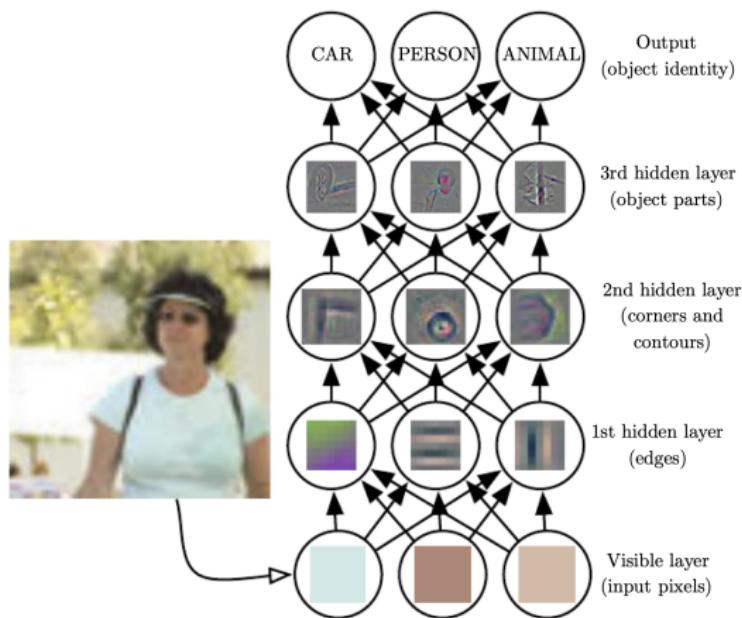
**Figure:** The representations of a cat (Chollet and Allair, 2018, Fig 5.2)

- CNN uses **Convolutional Layers** to learn **parameter efficient** representations:



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# Learning Representations for Images (again)



**Figure:** Learning representations for images (Goodfellow et al, 2017, Fig. 1.2)



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# Convolution

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- Different definitions are common, one example:

$$y(t) = \int x(\tau)k(t - \tau)d\tau = (x * k)(t)$$

- "Weighting together two functions"
- In CNNs:

1.  $x(t)$ : Input
2.  $k(t)$ : Kernel, filter, "feature"
3.  $y(t)$ : Output, feature map



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## Discrete Convolution

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- If  $t$  is discrete (as in a grid):

$$y(t) = (x * k)(t) = \sum_{\tau=-\infty}^{\infty} x(\tau)k(t-\tau)$$

- In the case of images we have 2 discrete dimensions

$$Y(i, j) = (X * K) \sum_m \sum_n X(m, n)K(i - m, j - n)$$

- Sometimes the cross-correlation is called convolution:

$$Y(i, j) = (X * K) \sum_m \sum_n X(m, n)K(i + m, j + n)$$

1.  $X(i, j)$ : Input (2D)
2.  $K(i, j)$ : Kernel, filter, "feature" (2D)
3.  $Y(i, j)$ : Output, feature map (2D)



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# Convolution of Images: 2D

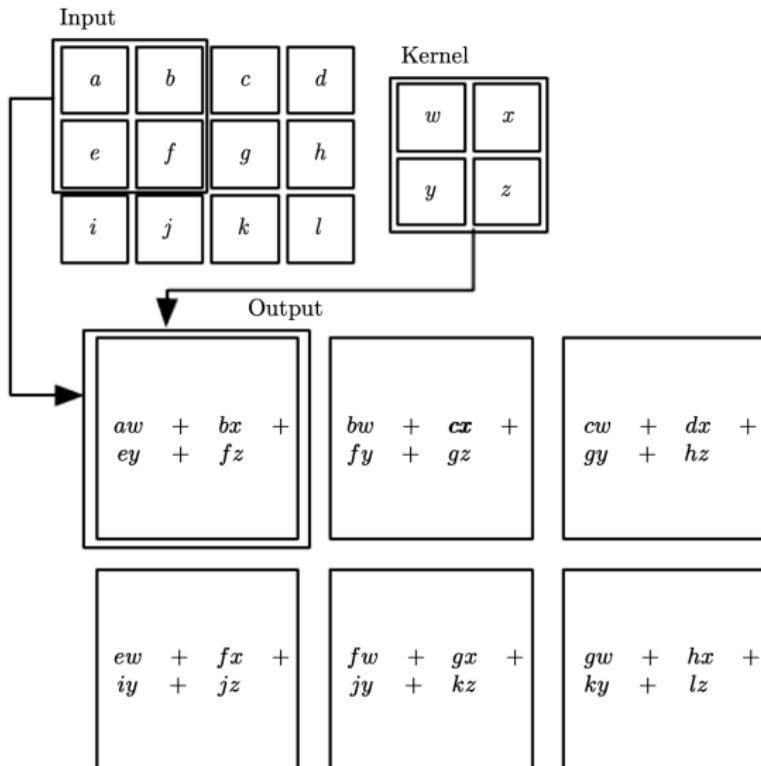


Figure: Convolution for an Image (Goodfellow et al, 2017, Fig. 9.1)



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## Convolution of images: Example

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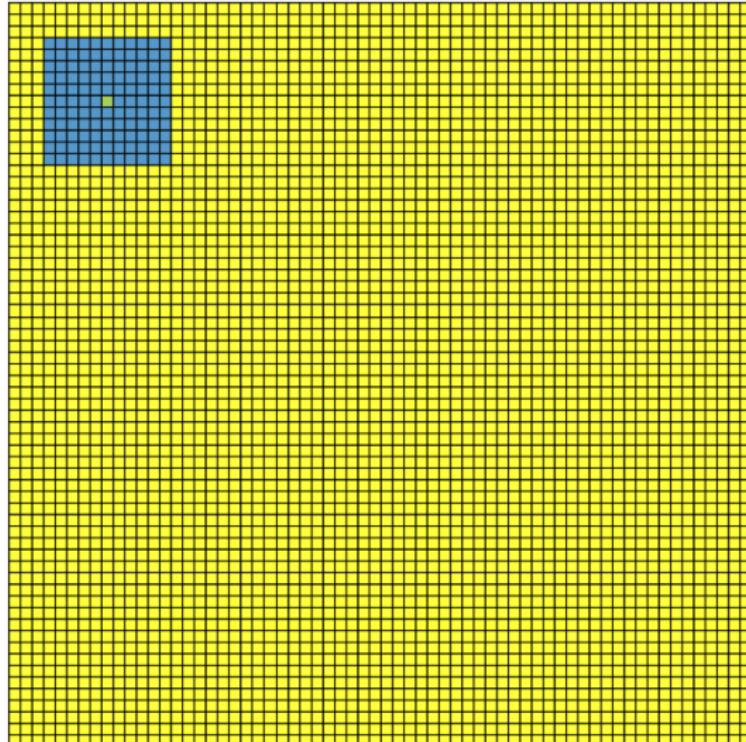
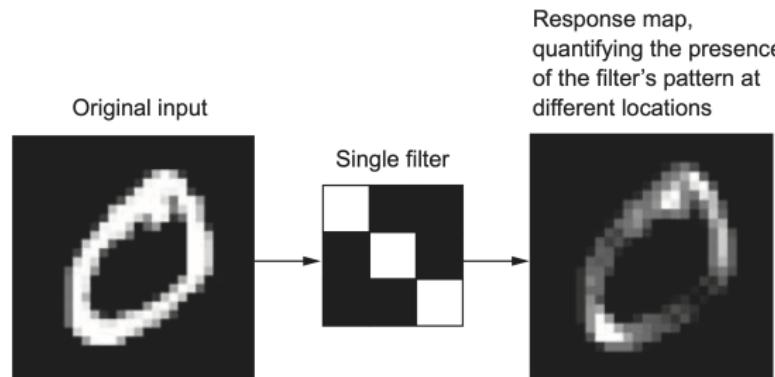


Figure: Convolution example.



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## Convolution of images: Examples



**Figure:** Convolution for an Image (Chollet and Allaire, 2018, Fig. 5.3)



# Convolution of images: Example

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$$X = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 \end{bmatrix}, K = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}$$



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## Convolution of images: Example

---

$$X = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 \end{bmatrix}, K = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}$$

$$Y = \begin{bmatrix} 2 & 1 & 2 & 0 \\ 2 & 1 & 2 & 0 \end{bmatrix},$$



# Convolutions

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- Benefits:
    1. Few parameters (filters)
    2. Captures **local structures**
    3. Efficient computations



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- Benefits:
    1. Few parameters (filters)
    2. Captures **local structures**
    3. Efficient computations
  - How to choose filters?
    1. Before: **manually handcrafted**
    2. Now: **learn the filters using backpropagation → CNN**



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# Convolution layer

---

- **Input:** Data or Feature Maps
- **Parameters:**
  - $N$  filters/kernels of size  $m \times m$
  - $N$  bias terms (one per filter)
- **Activation function:** Applied element wise on feature maps
- **Output:** Feature Maps



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- **Output:** Feature Maps
- In Keras:

```
layer_conv_2d(filters = 32, kernel_size =  
c(3,3), activation = "relu", input_shape =  
c(32,32,3))
```



# Padding

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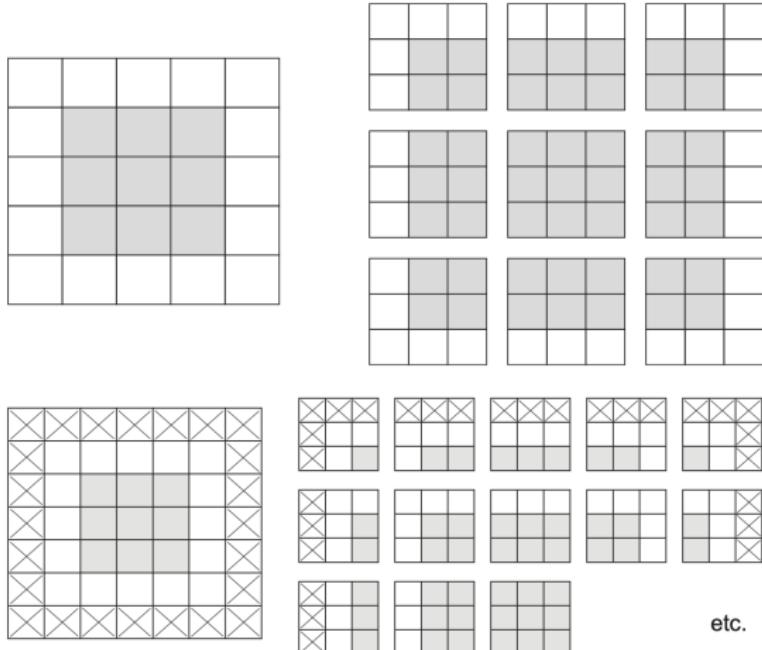
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- Handling edges
- *Padding*: add 0 around the image
- Necessary to **keep size** of feature maps



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# Padding



**Figure:** Padding and valid edge handling (Chollet and Allair (2018), Fig. 5.5, 5.6)



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# Stride

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- Skip every  $n$ th pixel
- Reduces the computations

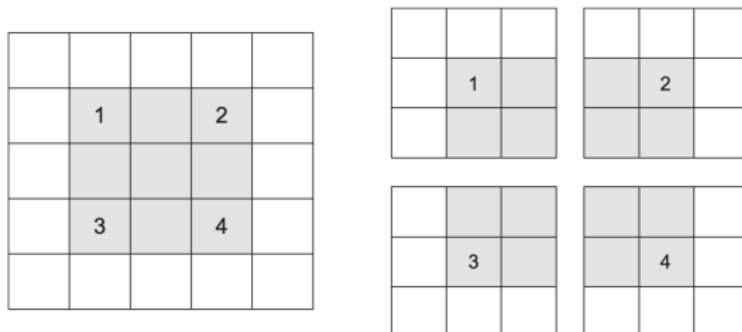


Figure: Strides (Chollet and Allair (2018), Fig. 5.5, 5.6)



# Why Convolution Layers?

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- Captures local spatial structure
  - Reduces the number of parameters (parameter sharing)
    1. The number and size of filters
    2. We use the same filters everywhere



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- Captures local spatial structure
  - Reduces the number of parameters (parameter sharing)
    1. The number and size of filters
    2. We use the same filters everywhere
  - Example: a 1 megapixel image ( $1000 \times 1000$  pixels)
    1. Dense network with 100 nodes: **100M** parameters
    2. CNN network with 100  $3 \times 3$  filters: **1000** parameters  
(900 from filters, 100 bias terms)



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# Convolution Neural Nets

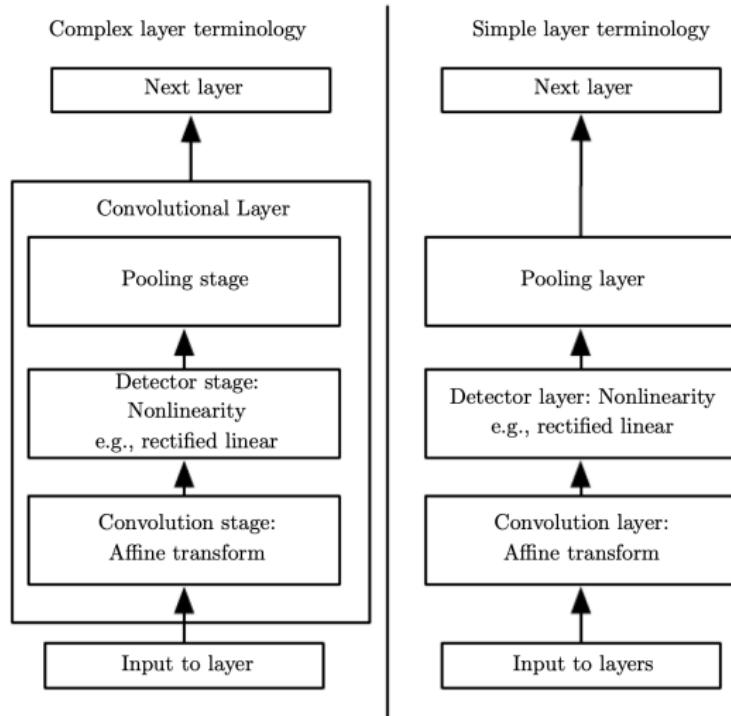


Figure: Convolution layer (Goodfellow et al, 2018, Fig. 9.7)



## Detector stage

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- Remember, in dense networks:  $h = \sigma(XW + b)$
- In CNN:
  1.  $W$  "is the filter"
  2.  $X$  is the input feature map
  3.  $XW$  "is the convolutional feature map"
  4.  $b$  is a bias (one per filter)
  5.  $\sigma$  is the activation function (usually a ReLu)



# Pooling layer

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- 
- A large, faint watermark of the Uppsala University seal is visible at the bottom of the slide, showing stylized letters and the letters 'U' and 'T' prominently.



# Pooling layer

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- Similar to a convolution
- We take a function  $f$  that return one value per pooling kernel
- Most commonly  $f = \max$
- Commonly a  $2 \times 2$  pooling kernel with stride 2
- **Why?** Reduce the size of feature map, but keep the activation



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- 
- Similar to a convolution
  - We take a function  $f$  that return one value per pooling kernel
  - Most commonly  $f = \max$
  - Commonly a  $2 \times 2$  pooling kernel with stride 2
  - **Why?** Reduce the size of feature map, but keep the activation
  - In Keras:  
`layer_max_pooling_2d(pool_size = c(2, 2))()`



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# Max Pooling

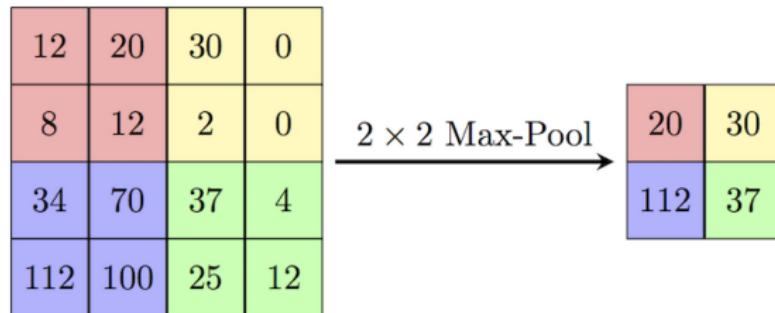


Figure: Strides (Computer Science Wiki: "Max-pooling / Pooling")



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# Data Augmentation

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Figure: Data Augmentation (Chollet and Allair, 2018, Fig 5.10)



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# Data Augmentation

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Figure: Data Augmentation (Chollet and Allair, 2018, Fig 5.10)



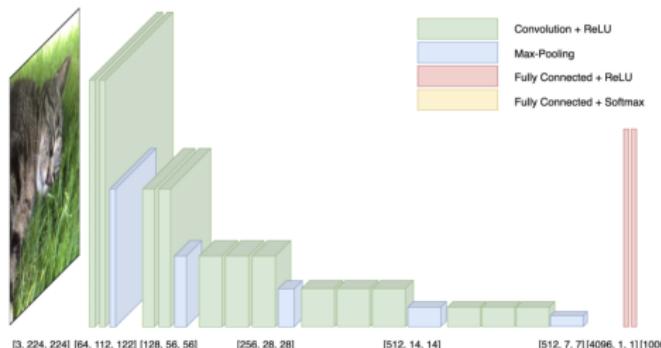
# Popular CNN architectures

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- AlexNet (2012), 5 convolutional layers
  - VGGNet (2014), 16 convolutional layers
  - ResNet (2015), 152 convolutional layers



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**Figure 2.4:** Illustration of the data flow through the network VGG16. Data size, of the format  $[c, h, w]$ , is shown for the input image, output of each max-pooling layer, output after the first two fully connected layers, and the final network output.

Jesper Westell, Multi-Task Learning using Road Surface Condition Classification and Road Scene Semantic Segmentation, LIU-IMT-TFK-A-19/570-SE



# Transfer learning

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- "Transfer knowledge between problems"
- In practice: Transfer/reuse learned weights





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- "Transfer knowledge between problems"
  - In practice: Transfer/reuse learned weights
  - Commonly: Use (large) pre-trained models for smaller problems
  - One of the main reasons for the success of (convolutional) neural networks



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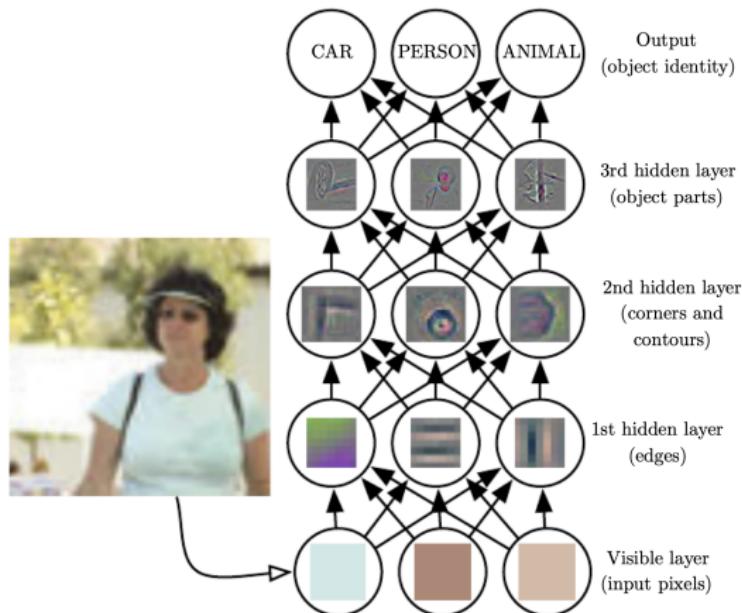
# Transfer learning

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- "Transfer knowledge between problems"
- In practice: Transfer/reuse learned weights
- Commonly: Use (large) pre-trained models for smaller problems
- One of the main reasons for the success of (convolutional) neural networks
- Two types of transfer learning:
  - Feature extraction
  - Fine Tuning



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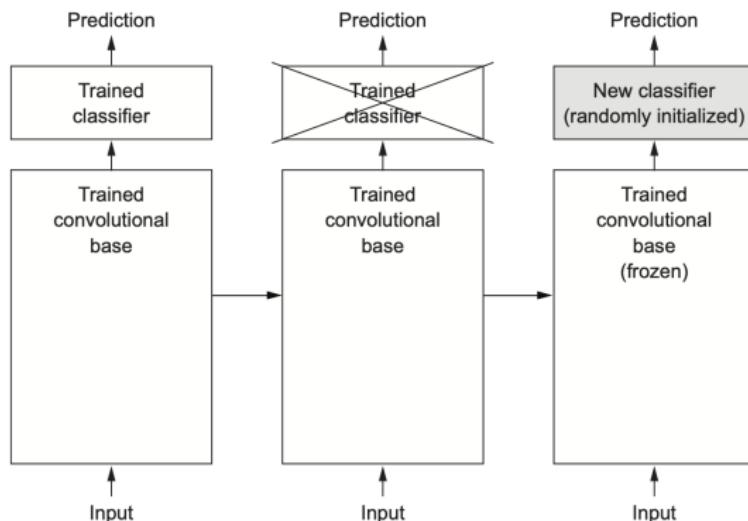


**Figure:** Learning representations can be crucial (Goodfellow et al, 2017, Fig. 1.2)



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# Feature Extraction



**Figure:** Using convnets as base for feature extraction (Chollet and Allair, 2018, Fig 5.12)



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# Fine-Tuning

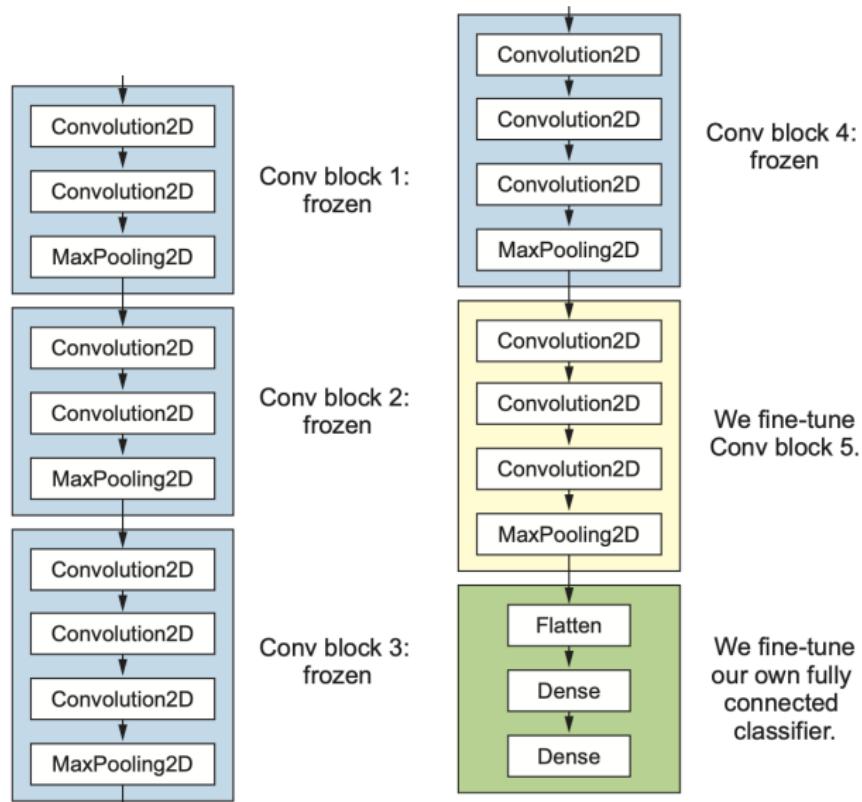


Figure: Finetuning a convolutional base (Chollet and Allair, 2018,  
Fig 5.15)