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Machine learning – Block 4

- Practicalities
- Introduction
- Convolution
- Convolutional Neural Networks
 - The Convolution Layer
 - The Pooling Layer
 - Regularization
 - Examples
- Transfer learning
- Practical Methodology

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Autumn 2023



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This week's lecture

- Practicalities
 - Introduction
 - Convolution
 - Convolutional Neural Networks
 - The Convolution Layer
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 - Regularization
 - Examples
 - Transfer learning
 - Practical Methodology
-
- Previous assignments
 - The Mini-Project and Master Thesis Projects
 - Convolutional Neural Networks
 - Transfer Learning



Assignment 3: Evaluation

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- A little bit to easy VG part.
- How to think when building networks? Art and Science.
Random search and try to get as low training error as possible.
- Keras lecture? Describe parameters?



On this weeks assignment

- Practicalities
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- It takes long time to run the models this week. Start early!





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Mini-project

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Mini-project

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- Submission Tuesday (tomorrow) at 23.59!
- Supervised problem of choice on **real data**.



Mini-project

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- 2-3 students.



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Mini-project

- Submission Tuesday (tomorrow) at 23.59!
- Supervised problem of choice on **real data**.
- 2-3 students.
- *Hint!* Submit page 1 of the project as project proposal.
- 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 projects

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- Still discussions... hopefully out today.





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Section 2

Introduction



Convolutional Neural Networks

- Acknowledgements: Anders Eklund, Linköping University.

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Convolutional Neural Networks

- **Acknowledgements:** Anders Eklund, Linköping University.
- **Convolutional** Neural Networks are behind great progress in the 2010s.
- Revolutionized **Computer Vision**.

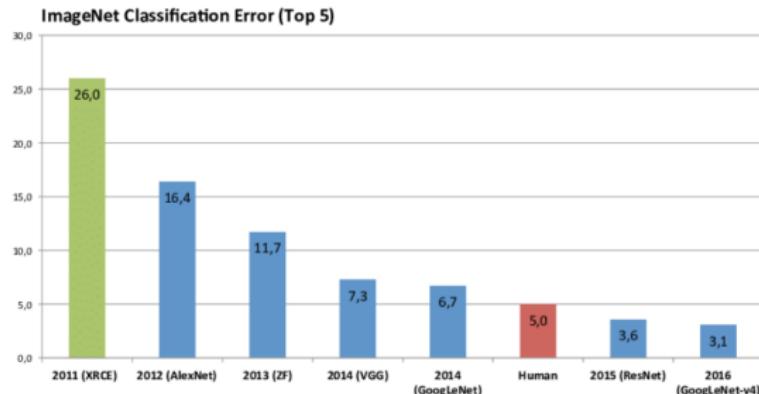


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Convolutional Neural Networks

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- Revolutionized Computer Vision.
- Also called: ConvNets, Convolutional nets, Convolutional networks

Figure: ImageNet performance (Roessler, 2019)



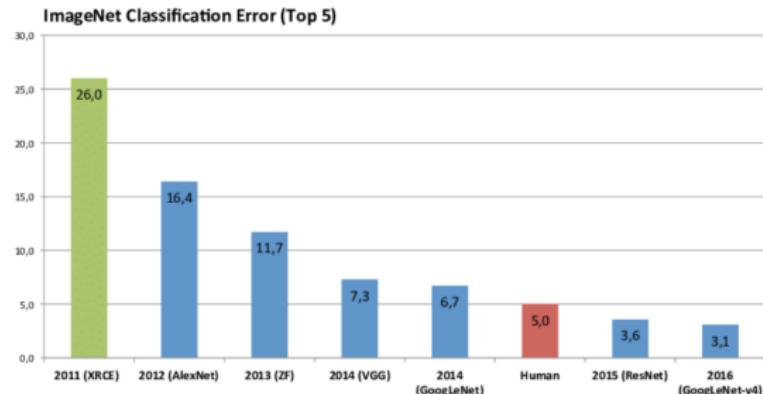


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- Special architecture that works well for data with a **grid structure**
 1. 1D-grids: Time series



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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)



Convolutional Neural Networks

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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)



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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



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- Problems
 - Image Classification
 - Image Segmentation



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● Problems

- Image Classification
- Image Segmentation
- Object Detection



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- Problems
 - Image Classification
 - Image Segmentation
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 - Object Localization



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



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



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Computer Vision

- **Problems**
 - Image Classification
 - Image Segmentation
 - Object Detection
 - Object Localization
- **Focus:** 2D and 3D data
- **Very Large Datasets:**
 - ImageNet: 14M Images, 20k classes, 1M bounding boxes
- Many different pre-trained models (e.g. VGG16)



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Example: Object Detection

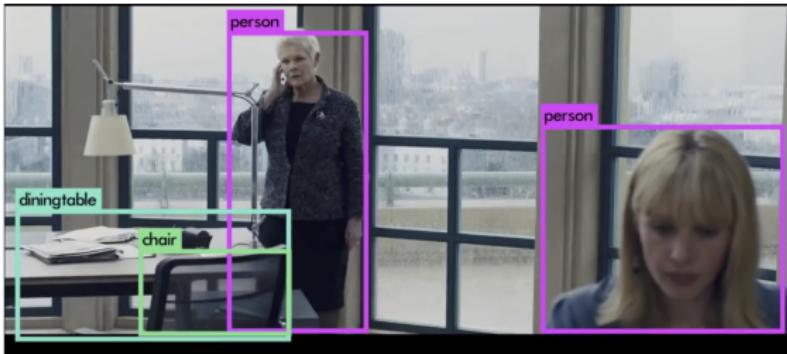
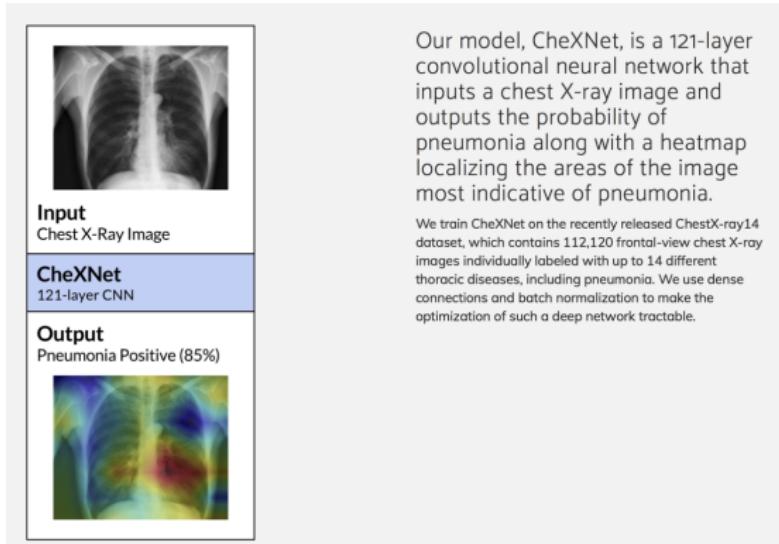


Figure: Object detection (see
<https://www.youtube.com/watch?v=VOC3huqHrss>)



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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 coordinate
 2. a value (light intensity)



What is an Image?

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- 2-dimensional object
- Each pixel has:
 1. a coordinate
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- **Grayscale:** single channel
- **Color:** three channel (RGB)



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What is an Image?

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



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MNIST example

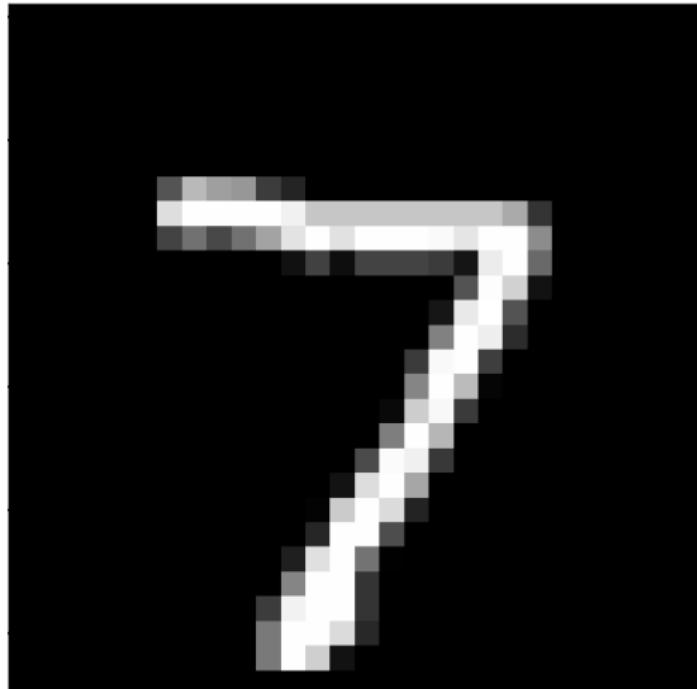


Figure: Example from the MNIST dataset (28 by 28 pixels)



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How to train models for images?

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

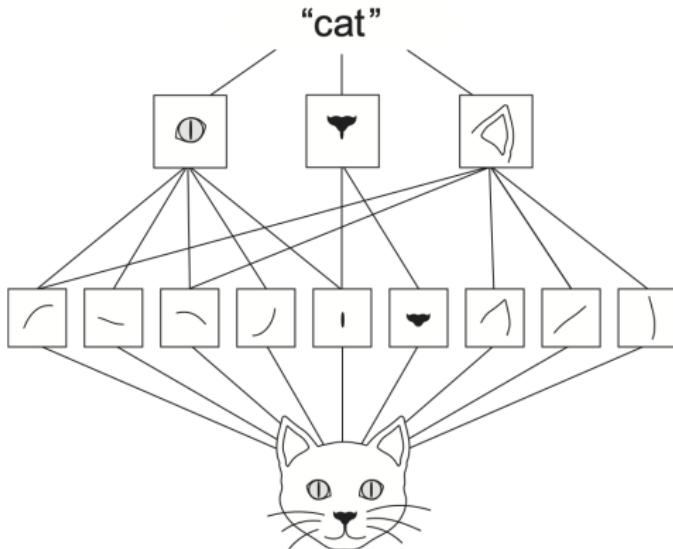


Figure: The representations of a cat (Chollet and Allair, 2018, Fig 5.2)



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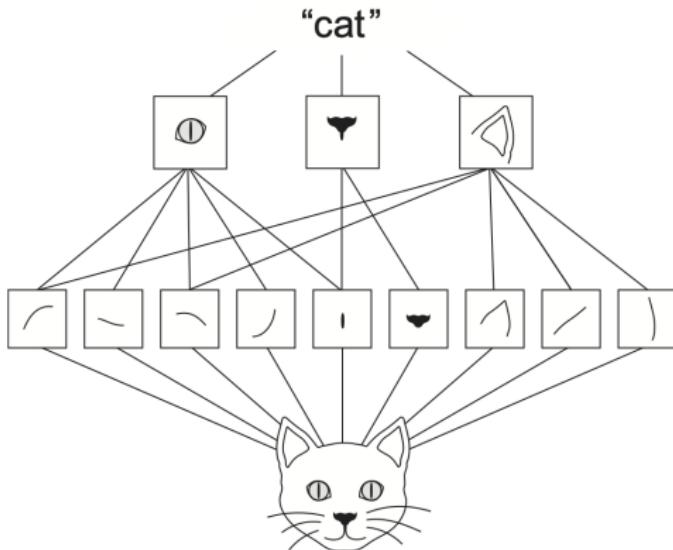


Figure: The representations of a cat (Chollet and Allair, 2018, Fig 5.2)

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



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Learning Representations for Images (again)

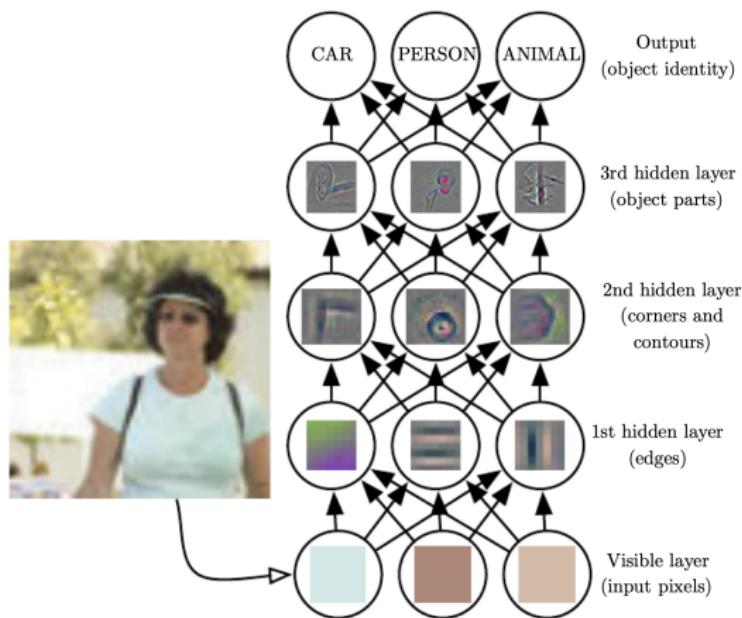


Figure: Learning representations for images (Goodfellow et al, 2017, Fig. 1.2)



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Section 3

Convolution



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Convolution

- Different definitions are common, one example:

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

- Intuition: "Weighting together two functions"
- In a convolutional layer:
 1. $x(t)$: Input
 2. $k(t)$: Kernel, filter, "feature"
 3. $y(t)$: Output, feature map

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Discrete Convolution

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

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



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Discrete Convolution

- 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

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



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Discrete Convolution

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

- 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

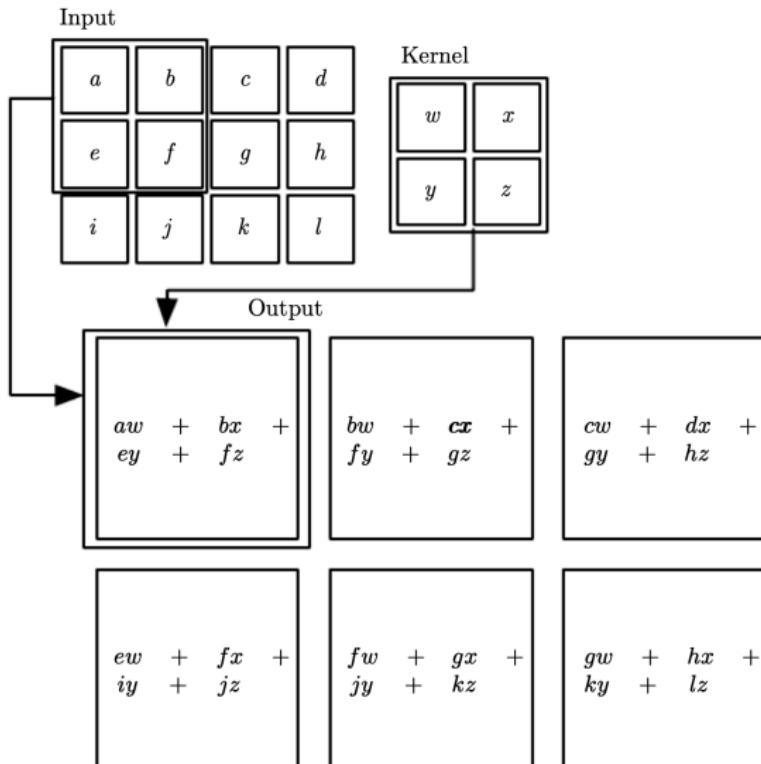


Figure: Convolution for an Image (Goodfellow et al, 2017, Fig. 9.1)



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Convolution of images: Example

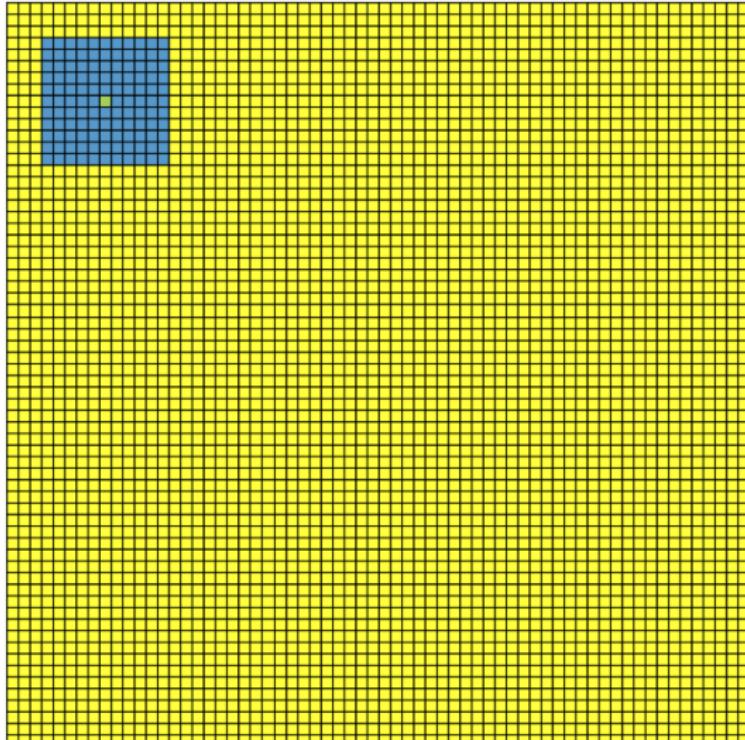


Figure: Convolution example.



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Convolution of images: Examples

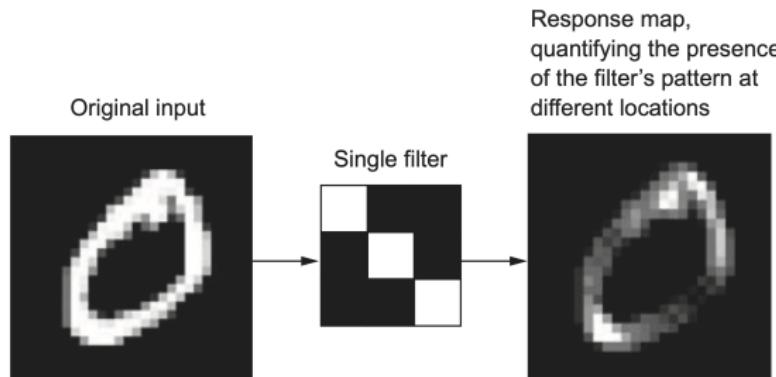


Figure: Convolution for an Image (Chollet and Allaire, 2018, Fig. 5.3)



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



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Convolution of images: Example

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



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Section 4

Convolutional Neural Networks



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Convolutional Neural Networks

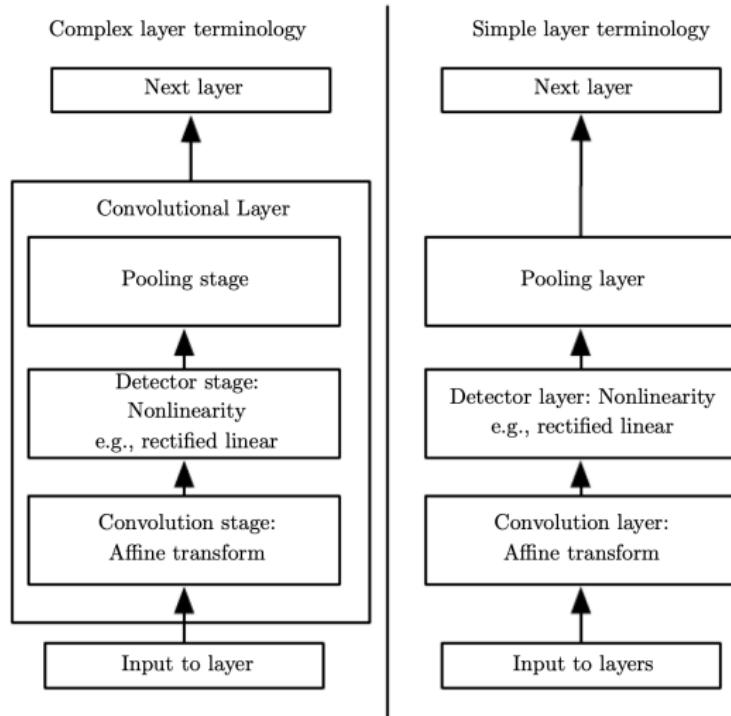


Figure: Convolution layer (Goodfellow et al, 2018, Fig. 9.7)



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- Most convolutional neural networks have:
 1. Many convolutional layers
 2. More kernels higher up in the network
 3. A classification head (usually a feed-forward neural network)



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Convolutional Neural Networks

- Most convolutional neural networks have:
 1. Many convolutional layers
 2. More kernels higher up in the network
 3. A classification head (usually a feed-forward neural network)
- Benefits:
 1. Few(er) parameters (filters)
 2. Captures **local structures**
 3. Efficient computations



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 3. Efficient computations
- How to choose filters?
 1. Before: **manually handcrafted**



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Convolutional Neural Networks

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 2. More kernels higher up in the network
 3. A classification head (usually a feed-forward neural network)
- Benefits:
 1. Few(er) parameters (filters)
 2. Captures **local structures**
 3. Efficient computations
- How to choose filters?
 1. Before: **manually handcrafted**
 2. Now: **learn the filters**



Convolution layer

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- **Input:** Data or Feature Maps



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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)



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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 functions:** Applied element wise on feature maps



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- **Output:** Feature Maps



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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 functions:** Applied element wise on feature maps
- **Output:** Feature Maps
- In Keras:

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



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Padding

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



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Padding

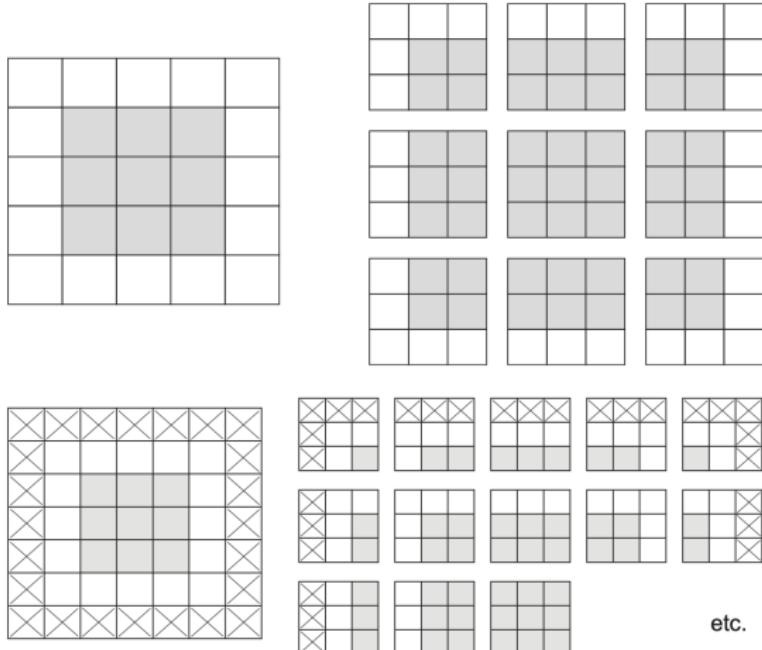


Figure: Padding and valid edge handling (Chollet and Allair (2018), Fig. 5.5, 5.6)



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Stride

- Skip every n th pixel
- Reduces the computations

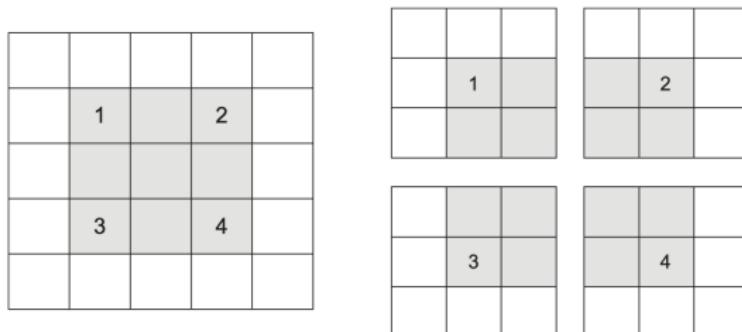


Figure: Strides (Chollet and Allair (2018), Fig. 5.5, 5.6)



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Why Convolution Layers?

- 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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Why Convolution Layers?

- 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 (1000×1000 pixels)
 1. Dense network with 100 nodes: **100M** parameters
 2. CNN network with 100 3×3 filters: **1000** parameters
(900 from filters, 100 bias terms)



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Convolution Neural Nets

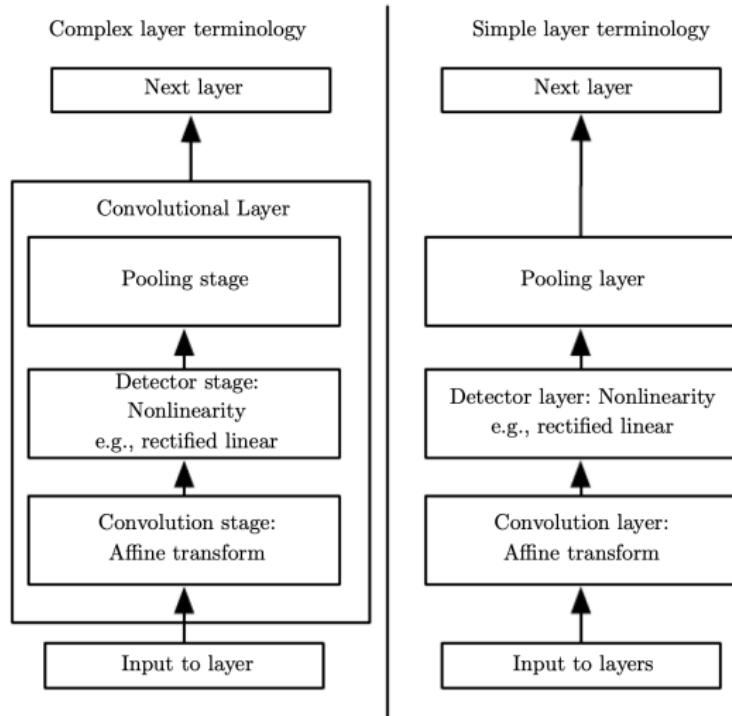


Figure: Convolution layer (Goodfellow et al, 2018, Fig. 9.7)



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Detector stage

- Remember, in feed-forward networks: $\mathbf{h} = \sigma(\mathbf{XW} + b)$
- In CNN:
 1. **W** is the filter



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Detector stage

- Remember, in feed-forward networks: $\mathbf{h} = \sigma(\mathbf{XW} + b)$
- In CNN:
 1. \mathbf{W} is the filter
 2. \mathbf{X} is the input feature map



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Detector stage

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- In CNN:
 1. \mathbf{W} is the filter
 2. \mathbf{X} is the input feature map
 3. \mathbf{XW} is the convolutional feature map



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Detector stage

- Remember, in feed-forward networks: $\mathbf{h} = \sigma(\mathbf{XW} + b)$
- In CNN:
 1. \mathbf{W} is the filter
 2. \mathbf{X} is the input feature map
 3. \mathbf{XW} is the convolutional feature map
 4. b is a bias (one per filter)



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 1. \mathbf{W} is the filter
 2. \mathbf{X} is the input feature map
 3. \mathbf{XW} is the convolutional feature map
 4. b is a bias (one per filter)
 5. σ is the activation function (usually a ReLU)



Pooling layer

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Pooling layer

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



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Pooling layer

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- Most commonly $f = \max$
- Commonly a 2×2 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

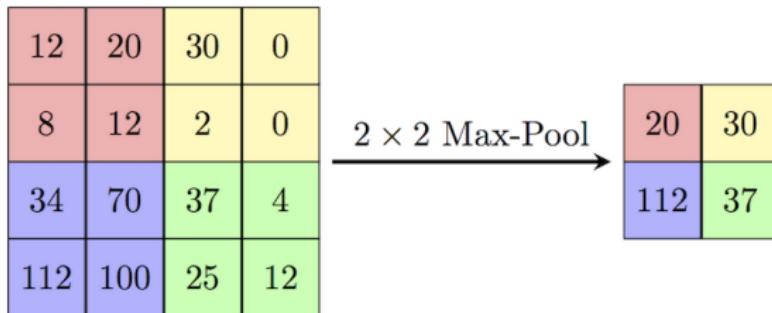


Figure: Strides (Computer Science Wikipedia)



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Using pooling to learn invariances

- pooling over spatial positions: invariant to translation
- pooling over different filters: invariant to transformations

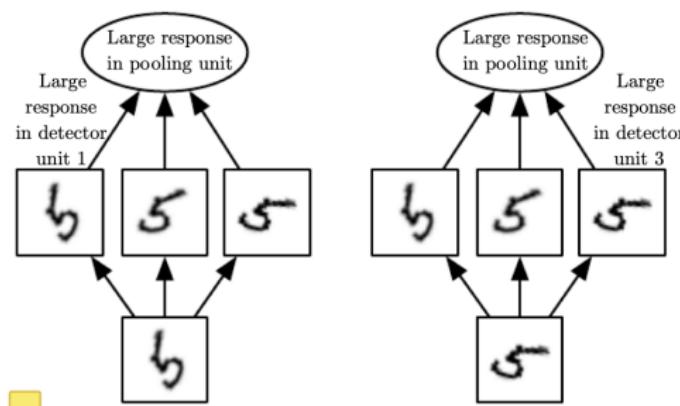


Figure: Learning invariances (Goodfellow et al., 2017, Fig. 9.9)



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Data Augmentation



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



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Data Augmentation



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

- Can be done directly in Keras (data generator)



Popular CNN architectures

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- AlexNet (2012), 5 convolutional layers
 - VGG16 (2014), 16 convolutional layers
 - ResNet (2015), 152 convolutional layers





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VGG16

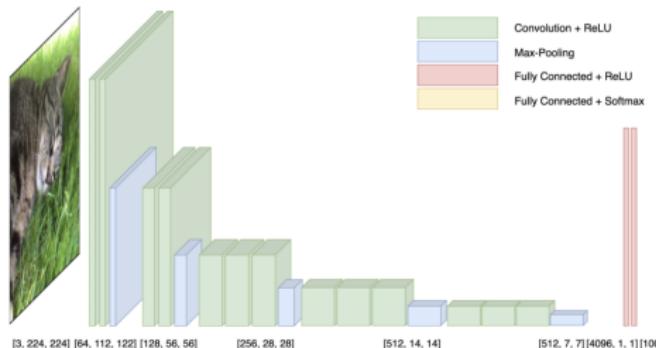


Figure 2.4: Illustration of the data flow through the network VGG16. Data size, of the format $[c, h, w]$, is shown for the input image, output of each max-pooling layer, output after the first two fully connected layers, and the final network output.

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



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Section 5

Transfer learning



Transfer learning

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 - Practical Methodology
- "Transfer knowledge between problems"
 - Learning representations in P_1 will aid generalization in P_2





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Transfer learning

- "Transfer knowledge between problems"
- Learning representations in P_1 will aid generalization in P_2
- A Bayesian perspective: A strong prior



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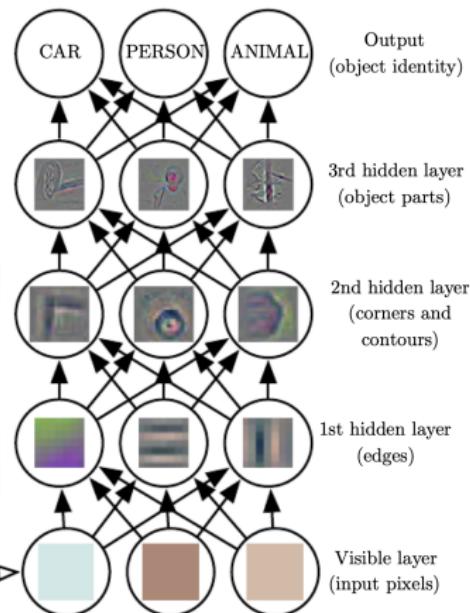


Figure: Learning representations can be crucial (Goodfellow et al, 2017, Fig. 1.2)



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- In practice: Transfer/reuse learned weights or rather some weights



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Transfer learning

- In practice: Transfer/reuse **learned weights** or rather some weights
- Use (large) **pre-trained** models for smaller problems
- A reason for the success of CNN



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Transfer learning

- In practice: Transfer/reuse **learned weights** or rather some weights
- Use (large) **pre-trained** models for smaller problems
- A reason for the success of CNN
- Two types of transfer learning in Neural Networks:
 - Feature extraction (use pre-trained networks for features)
 - Fine Tuning (adapt pre-trained features)





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Feature Extraction

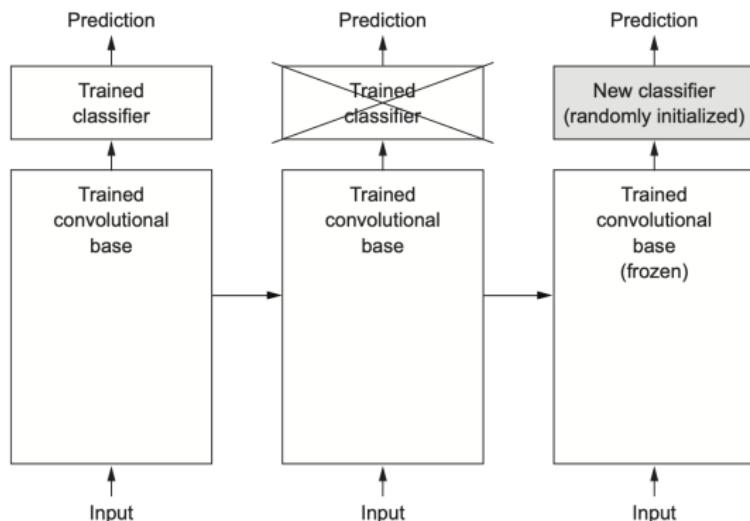


Figure: Using convnets as base for feature extraction (Chollet and Allair, 2018, Fig 5.12)



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Fine-Tuning

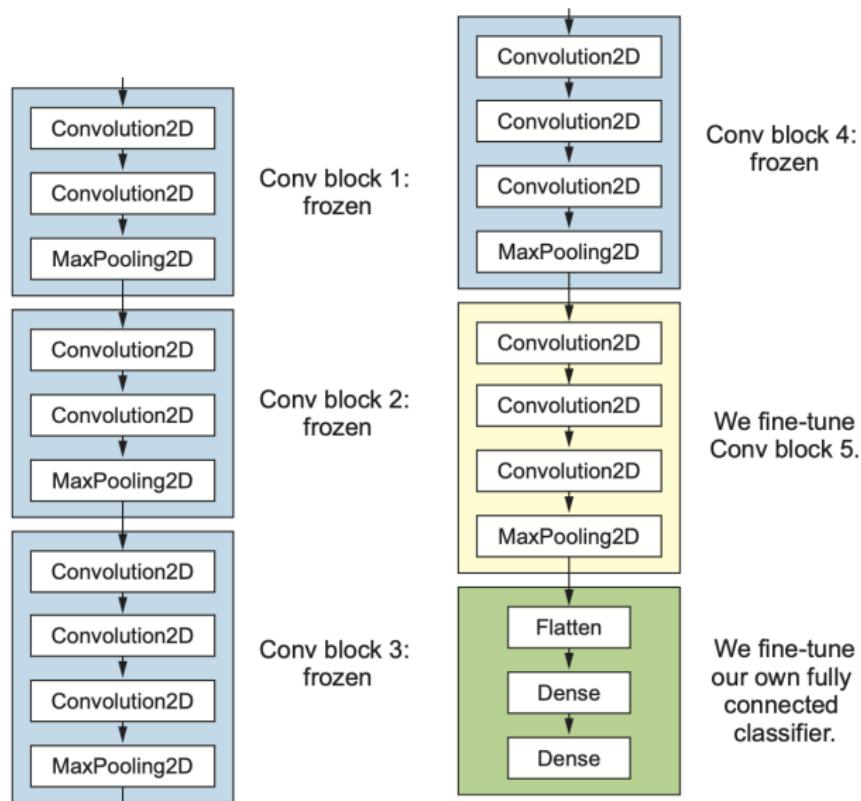


Figure: Finetuning a convolutional base (Chollet and Allair, 2018,
Fig 5.15)



Transfer learning

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- Catastrophic forgetting



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Transfer learning

- Catastrophic forgetting
- Domain adaptation: Same problem but at different input dataset
 - (e.g. language models for legal/medical/political data)



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Transfer learning

- Catastrophic forgetting
- Domain adaptation: Same problem but at different input dataset
(e.g. language models for legal/medical/political data)
- Concept drift: Similar problem



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Transfer learning

- Catastrophic forgetting
- Domain adaptation: Same problem but at different input dataset
 - (e.g. language models for legal/medical/political data)
- Concept drift: Similar problem
- Previously, popular with unsupervised pre-training.





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Section 6

Practical Methodology



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1. Determine your goals



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Practical Methodology

1. Determine your goals
2. Setup your baseline
(establish a working end-to-end pipeline as soon as possible)



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Practical Methodology

1. Determine your goals
2. Setup your baseline
(establish a working end-to-end pipeline as soon as possible)
3. Diagnose your networks performance



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Practical Methodology

1. Determine your goals
 2. Setup your baseline
(establish a working end-to-end pipeline as soon as possible)
 3. Diagnose your networks performance
 4. Make incremental improvements
-
- **General idea:** Increase data and model capacity until goal is reached





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Practical Methodology

1. Determine your goals
 2. Setup your baseline
(establish a working end-to-end pipeline as soon as possible)
 3. Diagnose your networks performance
 4. Make incremental improvements
-
- **General idea:** Increase data and model capacity until goal is reached
 - **End goal:** Good enough performance on test set





1. Determine your goals

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- Why are you building a model?





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1. Determine your goals

- Why are you building a model?
- Set up the metric based on the **overall goal** of the system!
This may need multiple metrics.





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1. Determine your goals

- Why are you building a model?
- Set up the metric based on the **overall goal** of the system!
This may need multiple metrics.
- What is good enough? Remember the **Bayes error**!





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- What performance can you expect?





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This may need multiple metrics.
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- What performance can you expect?
- Some errors are worse than others, e.g. spam filters.
- Handling of uncertain predictions:
- **Coverage:** How large proportions can the system predict?



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This may need multiple metrics.
- What is good enough? Remember the **Bayes error**!
- What performance can you expect?
- Some errors are worse than others, e.g. spam filters.
- Handling of uncertain predictions:
- **Coverage:** How large proportions can the system predict?
- Manual curation can be faster and easier.



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2. Setup your baseline

- Start with...
 - the most simple possible model (logistic regression)



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2. Setup your baseline

- Start with...
 - the most simple possible model (logistic regression)
 - previous approaches/baselines





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2. Setup your baseline

- Start with...
 - the most simple possible model (logistic regression)
 - previous approaches/baselines
 - a simple neural network that is common in the domain/defaults
(CNN for images, Adam as optimizer)

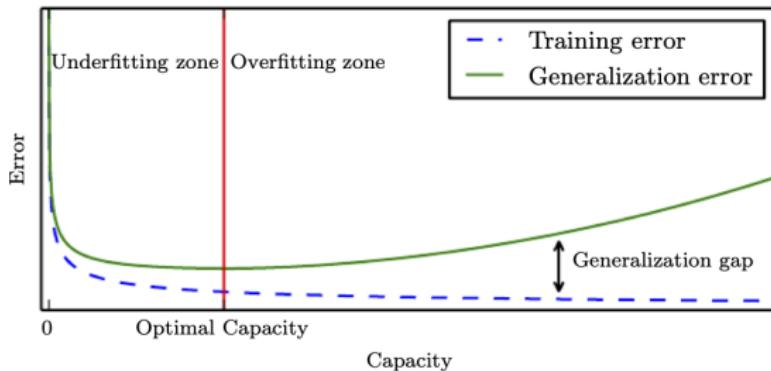




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Remember: Statistical Learning Theory

Figure: Test, training, and model complexity (Goodfellow et al, 2017, Figure 5.3)





3. Diagnose and improve

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3. Diagnose and improve

- High training loss: Training data not fully used
Neural network generally performs best when training error is low
- High test loss: Low data quality, i.e. large Bayes error?





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Neural network generally performs best when training error is low
- High test loss: Low data quality, i.e. large Bayes error?
- Low training error and high test error: Common situation



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 - You can always improve by gather more data, or
 - Regularize to optimal capacity



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Neural network generally performs best when training error is low
- High test loss: Low data quality, i.e. large Bayes error?
- Low training error and high test error: Common situation
 - You can always improve by gather more data, or
 - Regularize to optimal capacity
- How to know the improvements of additional data?



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Learning curve

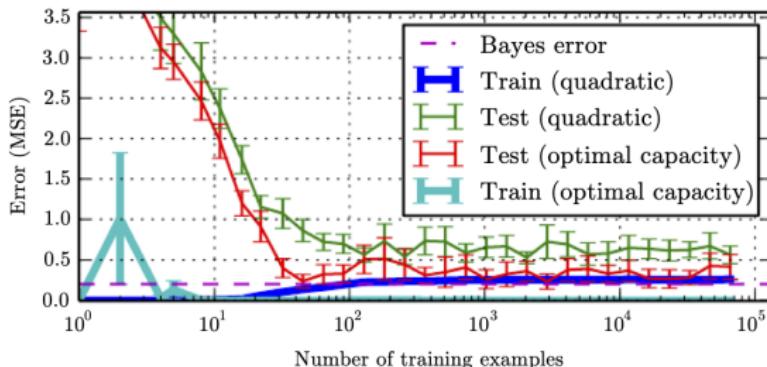


Figure: Learning curve to assess the need for more data (Goodfellow et al., 2017, Fig 5.4)



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3. Diagnosing and improving your model: Regularization

- Best performance: Larger model that is regularized well.
- Warning: Avoid **the algorithm rabbit hole**



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- Hyperparameter Search Goal:
adjust the model capacity to match the complexity of the task.



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adjust the model capacity to match the complexity of the task.
- Marginal hyperparameter has a U-shaped error function
(ideally)



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- Marginal hyperparameter has a U-shaped error function (ideally)
- Neural Networks Steps:
 1. Get good training error. E.g. by tune learning rate and increasing capacity
 2. Tune hyperparameters (regularization):
Requires monitoring both training and test error



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Hyper-parameter optimization

- Neural networks has many hyperparameters
- What is a hyperparameter in a neural network?



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Hyper-parameter optimization

- Neural networks has many hyperparameters
- What is a hyperparameter in a neural network?
- Grid search:
 - Setup a grid of potential values
 - For 1-4 hyperparameter: grid search can work well
 - Usually iterative/repeated grid search is best: start with three values, and work iteratively
 - Grows exponentially with the number of parameters





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 - Setup a grid of potential values
 - For 1-4 hyperparameter: grid search can work well
 - Usually iterative/repeated grid search is best: start with three values, and work iteratively
 - Grows exponentially with the number of parameters
- Random search
 - Specify a marginal distribution for each hyperparameter (additional work)
 - Common: uniform on log scale
 - Can also be done iteratively
 - Can be exponentially more efficient
 - Generally reduce the error faster in setting with many hyper parameters



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 - Visualize the model predictions



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 - Visualize the model predictions
 - Analyze the worst errors: **why?**



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- Visualize the model predictions
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- Monitor activation function statistics. Are some never activated?