Deep Learning Basics

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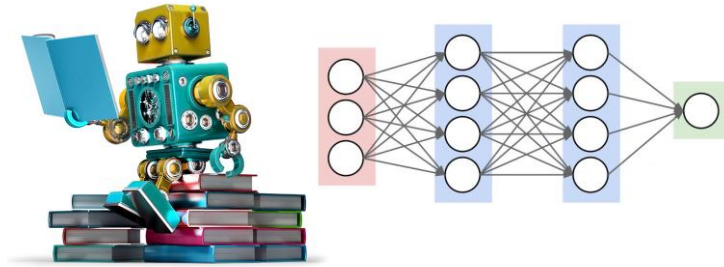
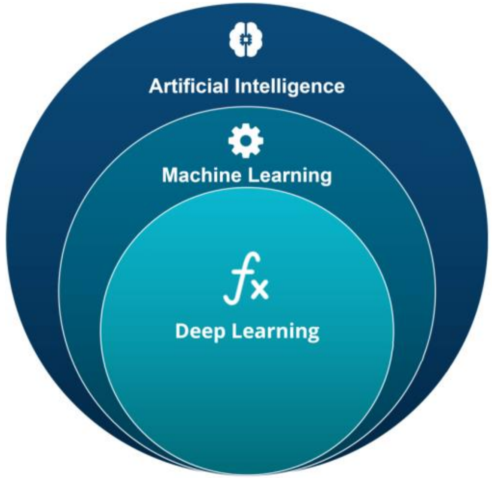
AI4NETS

Deep Learning Basics



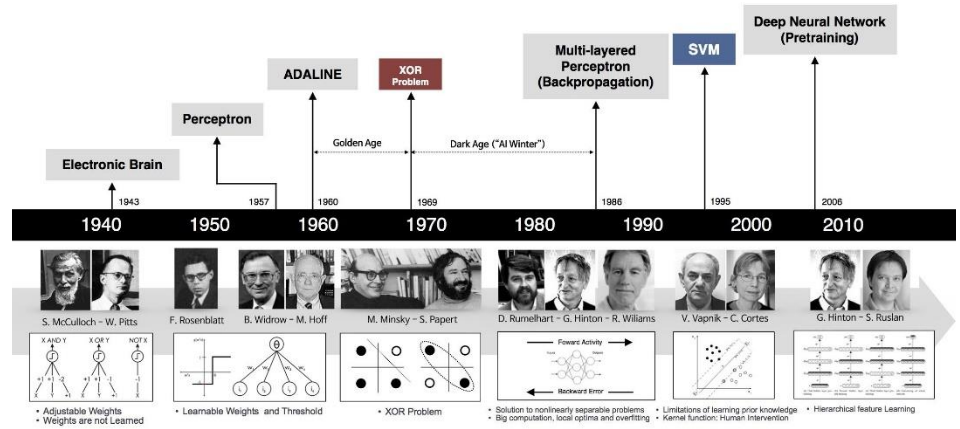
- Deep Learning 101
- Definitions and main Components
- Training Deep Neural Networks
- Convolutional Neural Networks (CNNs)



Deep Learning (http://www.deeplearningbook.org), by I. Goodfellow, Y. Bengio, A. Courville

Deep Learning – a bit of History

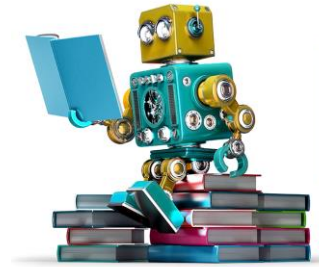
- 1943: Neural networks
- 1957: Perceptron
- 1974-86: Backpropagation, RBM, RNN
- 1989-98: CNN, MNIST, LSTM, Bidirectional RNN

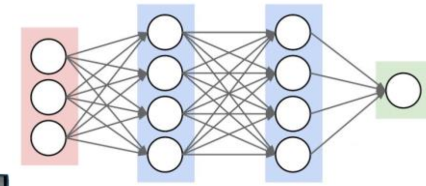


- 2006: "Deep Learning"
- 2009: ImageNet
- 2012: AlexNet, Dropout
- 2014: GANs
- 2014: DeepFace

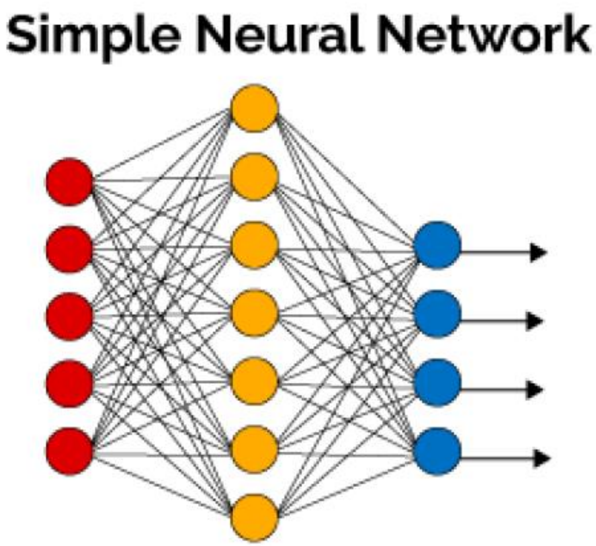
- 2016: AlphaGo
- 2017: AlphaZero, CapsNets
- 2018: BERT Transformers
- 2020: GPT-3
- 2022: GATO

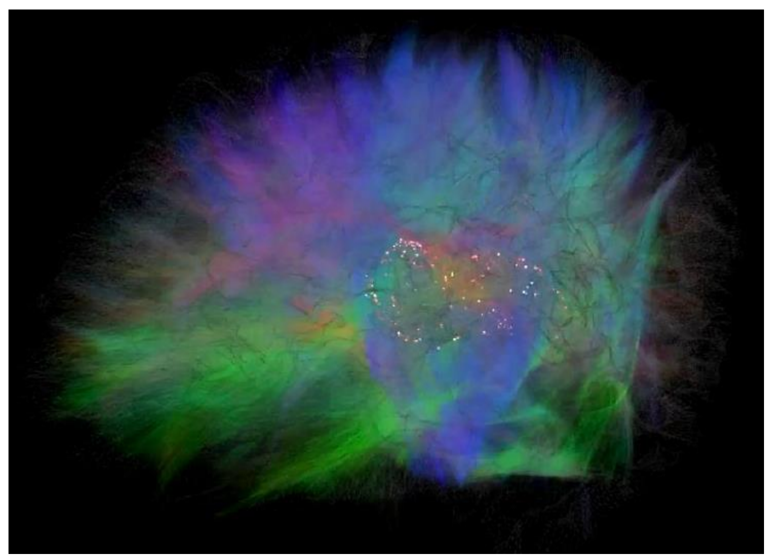
Deep Learning 101





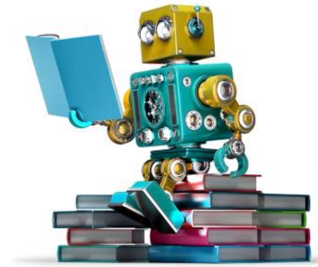
- What is Deep Learning (DL)?
- **Recall:** a feedforward network with a single layer is sufficient to represent (approximate) **any function**...
- ...but **the layer may be infeasibly large** and may fail to learn and generalize correctly...

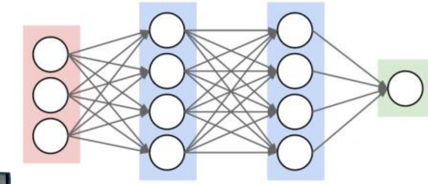




- Visualization of the human brain:
- **3% of the human brain neurons**
- **0.0001% of neural synapses**

Deep Learning 101

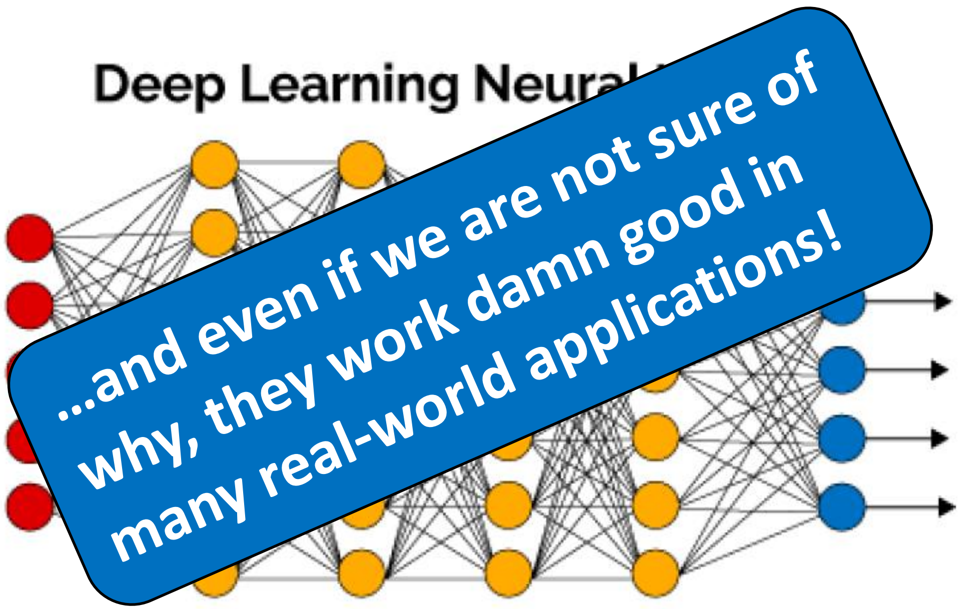




- What is Deep Learning (DL)?

- **In simple terms:** using a neural network with **several layers** of nodes between input and output.

- **Deep Neural Networks (DNNs):**

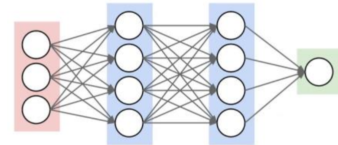


- exceptionally **effective at learning patterns.**

- **hierarchical structure**…

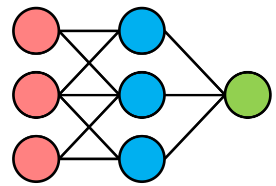
- …can learn the hierarchies of **knowledge** that seem to be **useful in solving real-world problems**…

Deep Learning 101

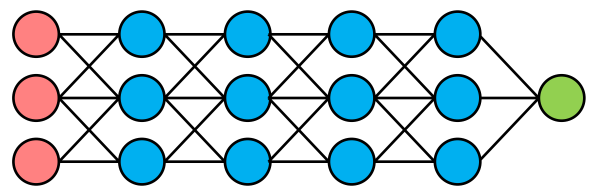


- hmmm…OK, but: multilayer neural networks have been around for 25 years. **What's actually new?**

- We have always had **good algorithms** to **learn** the **weights** in **networks with 1 hidden layer…**

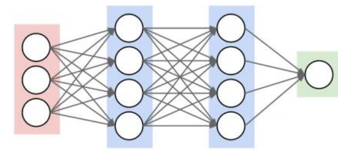


- …but **these algorithms** are **not good** at learning the weights for **networks with more hidden layers**

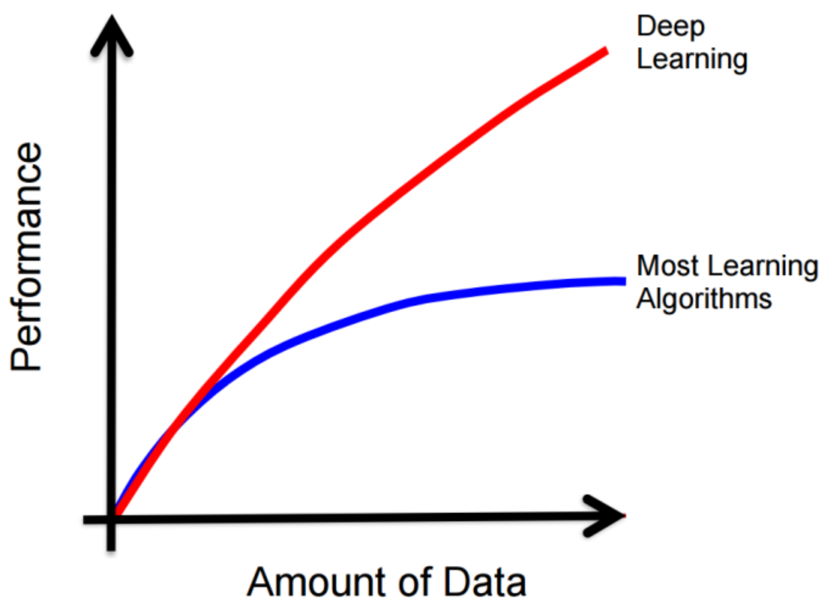


- **What's new is**: algorithms to **train many-layer networks**

Deep Learning 101



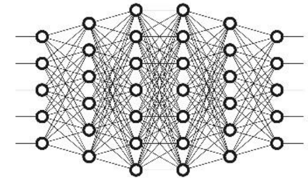
- Why Deep Learning: **Scalable** Machine Learning
- The **more** the training **data**, the **better** the **performance**
- **Why now: data, hardware**, community, tools, investment



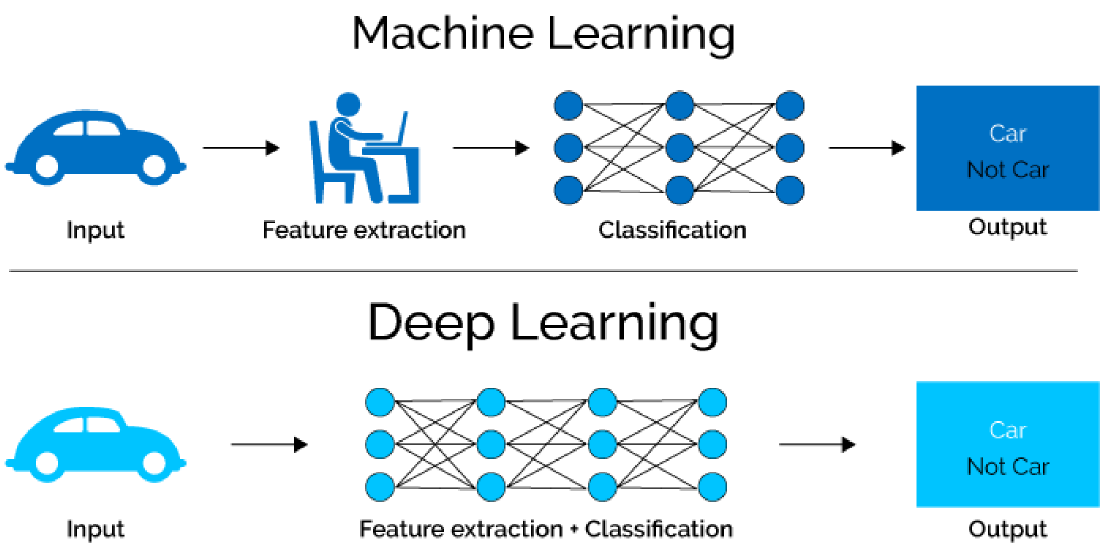
Exciting progress:

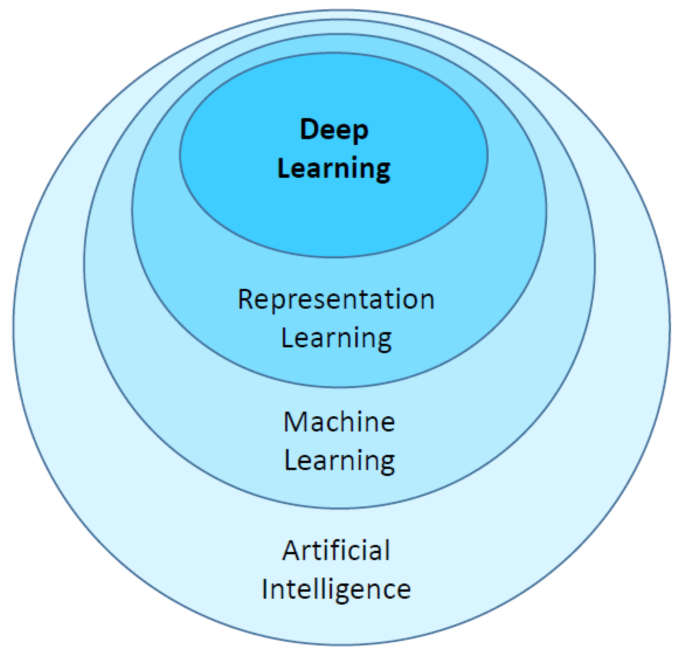
- Face recognition
- Image classification
- Speech recognition
- Text-to-speech generation
- Handwriting transcription
- Machine translation
- Medical diagnosis
- Cars: drivable area, lane keeping
- Digital assistants
- Ads, search, social recommendations
- Gaming

Deep Learning 101

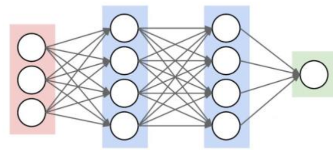


- One of the keys behind DL is the automatic **learning of data representations**
- DL algorithms attempt to learn (multiple levels of) representation by using a **hierarchy of multiple layers**

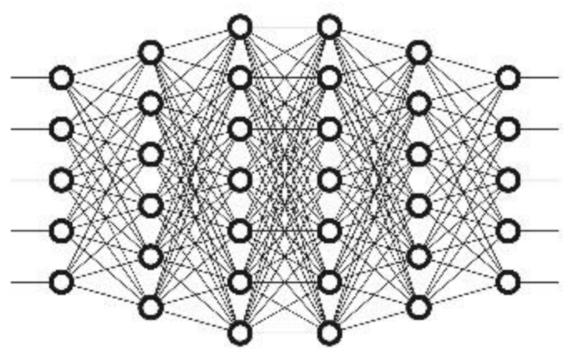




Deep Learning – Why is it Useful?



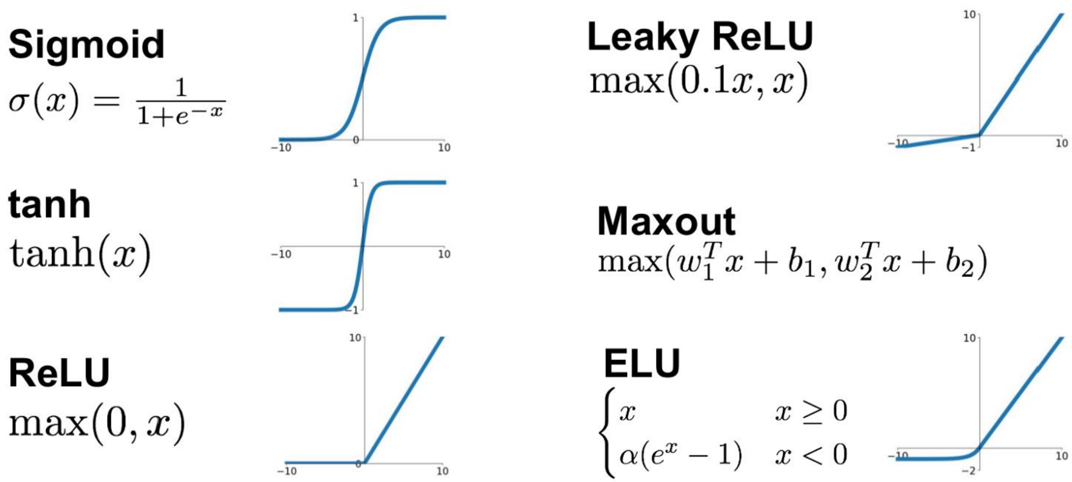
- **Manually designed features** are often **over-specified**, **incomplete** and **take a long time** to design and validate.
- **Learned Features** are **easy to adapt**, **fast to learn**.
- **Deep learning** provides a very flexible, (almost?) universal, learnable framework to **represent world, visual and linguistic information**.
- Can learn both **unsupervised** and **supervised.**
- Effective **end-to-end** joint system **learning**.
- **Use massive amounts of training data.**

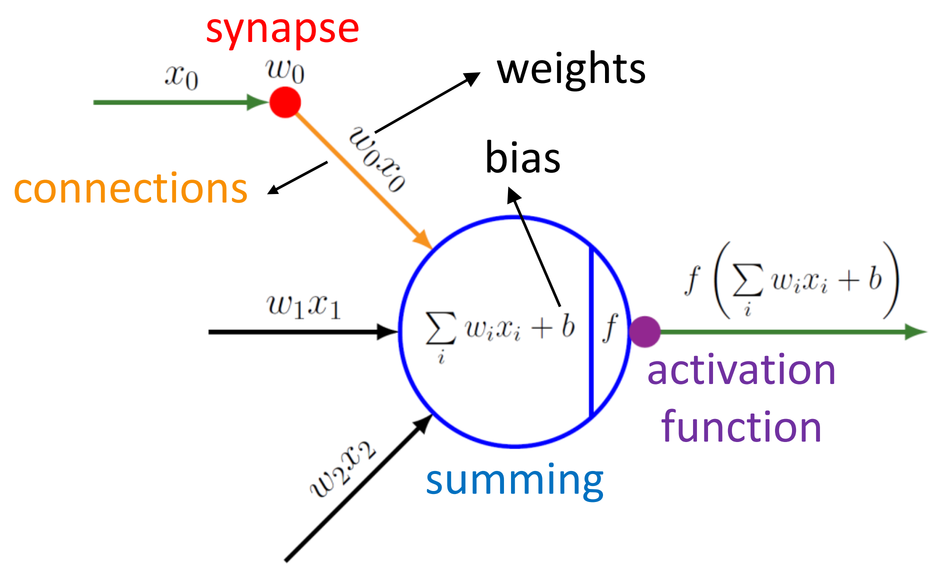


Neural Networks – Neuron Model

- Artificial neurons are the computational building blocks for **Artificial Neural Networks** (ANNs)

- *Inspired* by natural brain neurons…



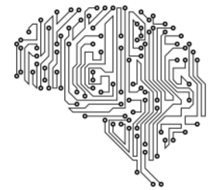


- …but **natural neurons** and the **human brain** have probably **nothing to do with ANNs**!

ANNs (DNNs) vs the Human Brain

Human Brain

- Humans can **learn from very few examples** (embedded past knowledge)
- 100 billion neurons, 1.000 trillion synapses (**DNNs x 10 M**)
- Human brain has **no layers**, brain **works asynchronously**
- **No clue how it learns,** certainly **NOT** through **backpropagation**
- **Life-long learning** (non-stop learning), unsupervised and through exploration
- **Energy-efficient** (very little power)

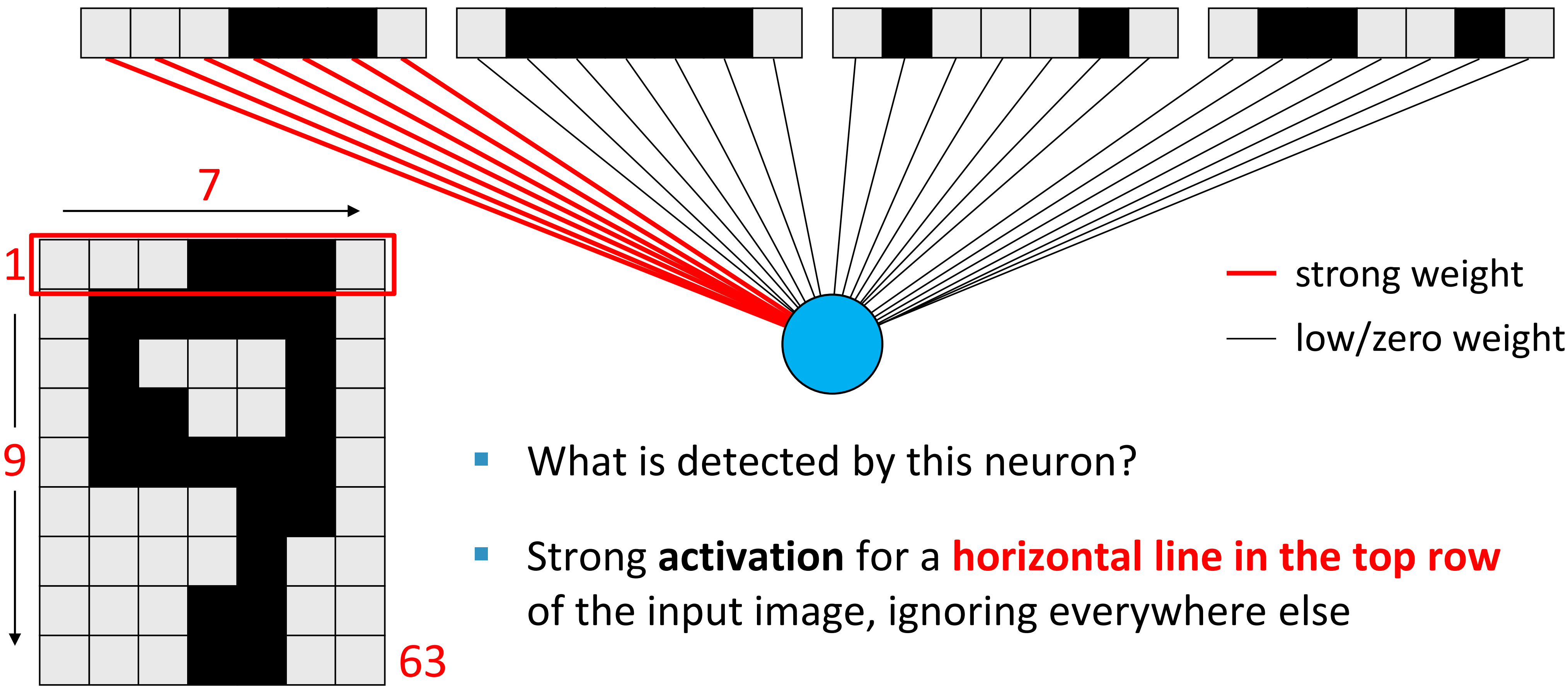


DNNs

- DNNs need **thousands/millions of examples**, even to **learn basic** mappings
- **ResNet 152**: **60 million connections** (weights)
- DNNs are **synchronous**
- Learning by gradient-descent (**backpropagation**)
- Mostly on **supervised learning**
- **Get ready to pay the energy bill!**

Deep Learning – Intuitive Example

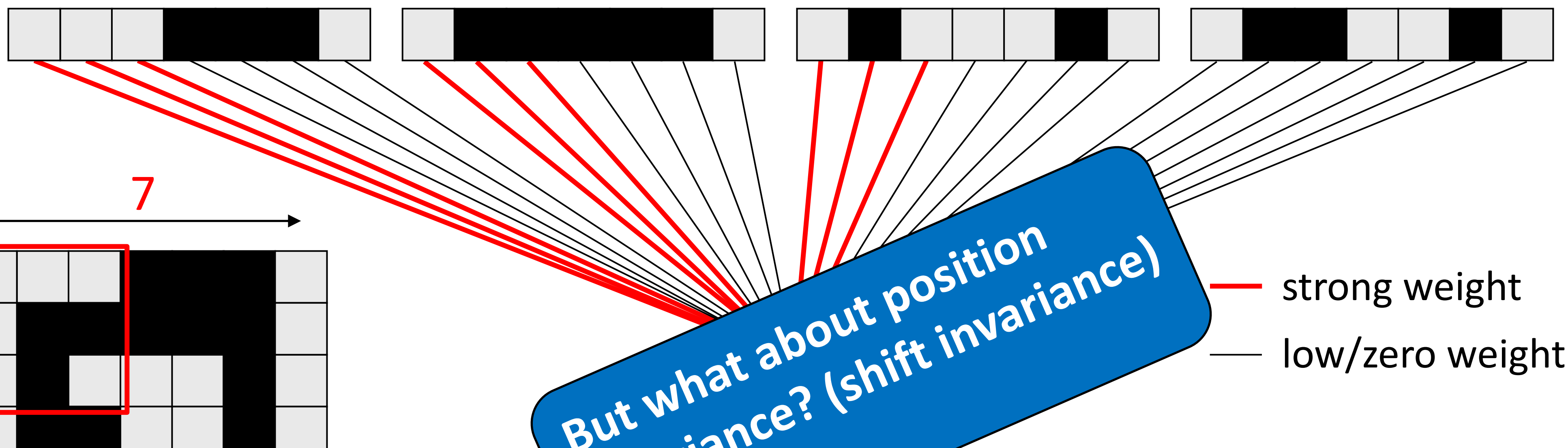
- Automatic **learning** of **data representations** **– how?**
- **Input raw data**, connection **weights learn** to detect specific **feature maps**

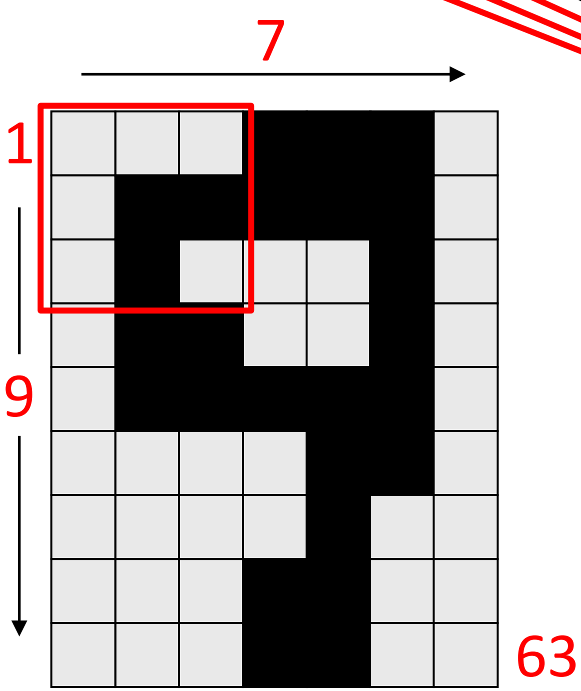


- What is detected by this neuron?
- Strong **activation** for a **horizontal line in the top row** of the input image, ignoring everywhere else

Deep Learning – Intuitive Example

- Automatic **learning** of **data representations – how?**
- **Input raw data**, connection **weights learn** to detect specific **feature maps**





- Wha… this neuron?
- Strong …ctivation for a **dark area in the top left corner** of the input image, ignoring everywhere else

Deep Learning – Training

- **Training a NN** means **setting**/tuning **all the free-parameters** (weights and bias)

- This is achieved by solving an optimization problem, minimizing a certain **loss function**, which quantifies the **gap between prediction and ground truth**:

- **Regression**
  - Mean Squared Error (MSE)

Prediction

$$MSE = \frac{1}{N}\sum(t_i - s_i)^2$$

Ground Truth

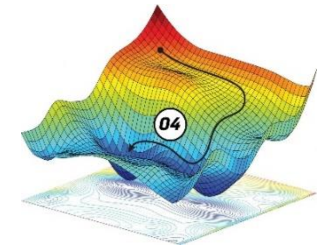
- **Classification**
  - Cross Entropy Loss (CE)

Classes　　Prediction (p)

$$CE = -\sum_{i}^{C} t_i log(s_i)$$

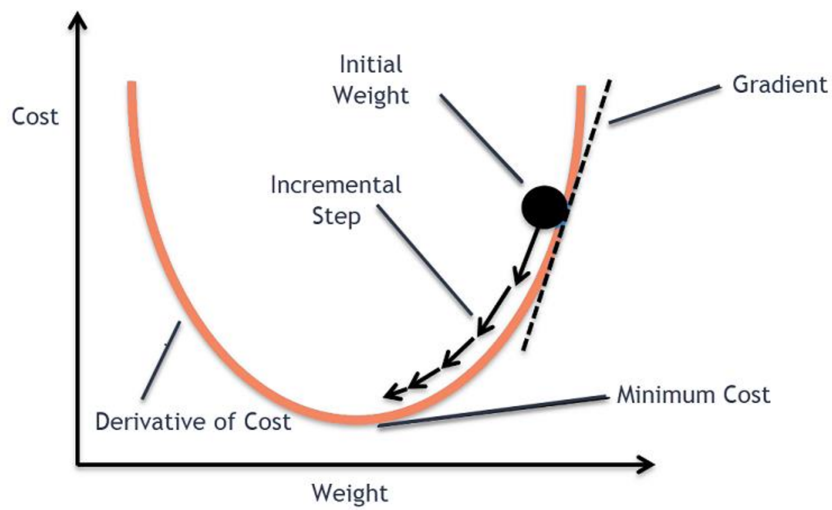
binary {0,1} correct class

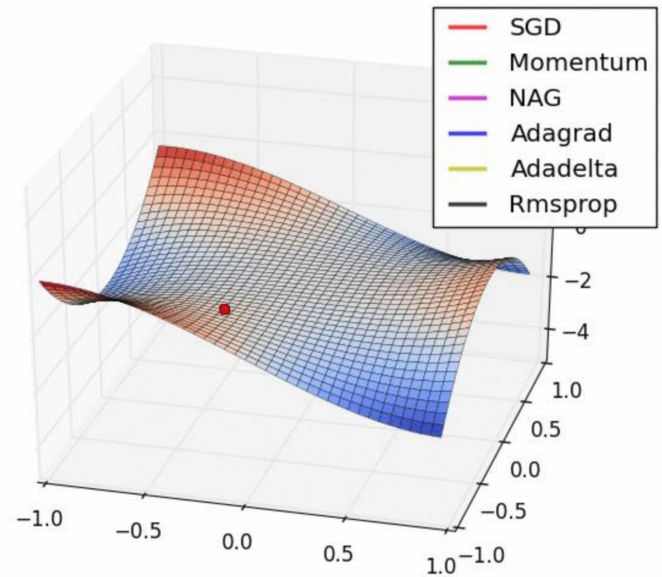
Optimization by Gradient Descent



- How to iteratively minimize the loss function?
  - e.g.: **Stochastic Gradient Descent (SGD),** Adaptive Moment Estimation (Adam), RMSprop, etc.

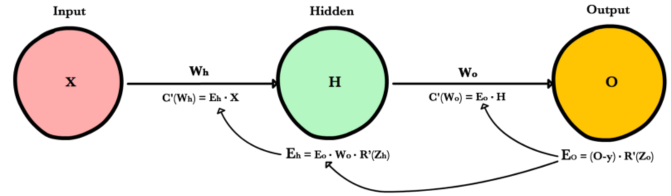
- Update the weights and bias by moving in the negative direction of the **loss function derivate**





- **Gradient** is computed for the loss function **w.r.t. weights/bias** ($\boldsymbol{\theta}$)
- e.g., for MSE → $J_n(\boldsymbol{\theta}) = \|\boldsymbol{\theta}^T \boldsymbol{x}_n - \boldsymbol{y}_n\|^2$ → $\nabla_\theta J_n(\boldsymbol{\theta}) = \boldsymbol{\theta}^T\left(\boldsymbol{\theta}\ \boldsymbol{x}_n - \boldsymbol{y}_n\right) = \boldsymbol{\theta}^T\boldsymbol{\theta}\boldsymbol{x}_n - \boldsymbol{\theta}^T\boldsymbol{y}_n$

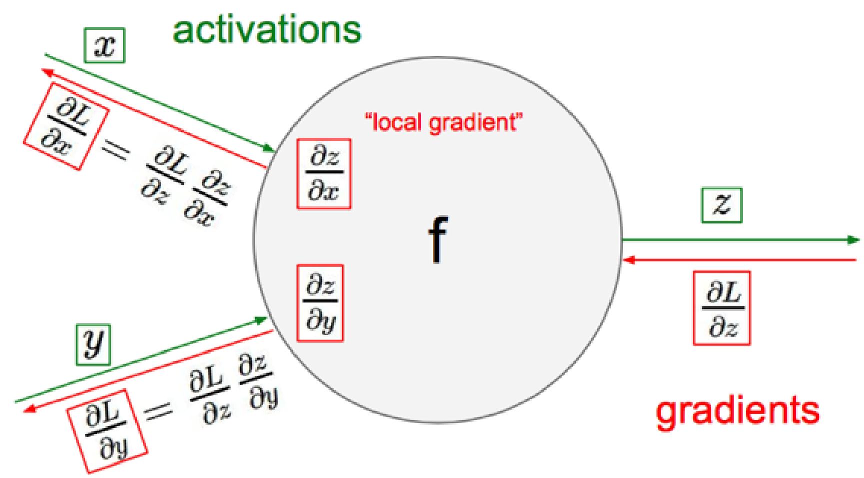
Backpropagation



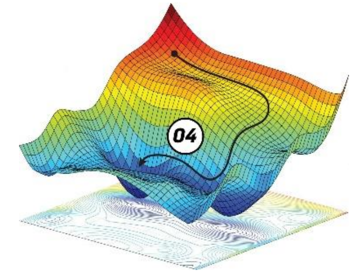
- Update each element of θ → $\theta_j^{new} = \theta_j^{old} - \alpha \frac{d}{d\theta_j^{old}} J(\theta)$
- Matrix notation for all parameters → $\theta^{new} = \theta^{old} - \alpha \nabla_\theta J(\theta)$

  learning rate

- Computing the **analytical expression** for the gradient is **straightforward**
- …but **numerically evaluating** the gradient is **computationally expensive**
- Solution: **backpropagation**
- Use the **chain rule** to sequentially compute the gradient through each node, re-using previous computations



Batch Gradient Descent



- **How often** and based on **which data** do we **update weights?**
  - **Epoch:** represents one iteration over the entire training data (**size *m***)
  - **Batch:** if data is too big, we split it in **batches**
  - **Iteration:** an epoch is composed of **data-size/batch-size** iterations

(1) **Batch gradient descent:** take **all the training data** to take one gradient decent step. This is very slow if you have large data set.

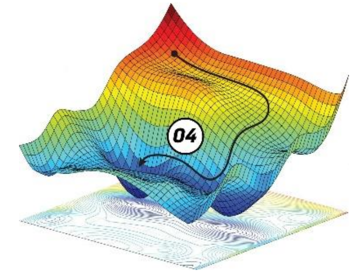
(2) **Online-training /stochastic gradient descent:** each training example (or few of them) is a batch in itself. Weights are updated for each training example.

(3) **Mini-batch gradient descent:** split the available data in batches of fixed size. Each gradient descent step takes batch-size of data samples to take one gradient decent step. Faster than batch gradient decent.

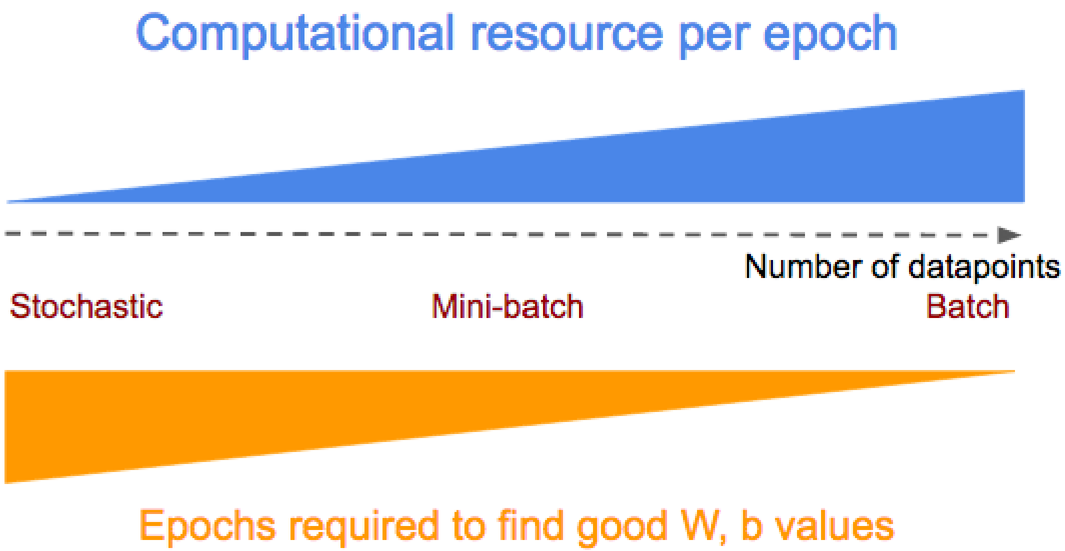
batch size: (2) ... (3) ... (1)

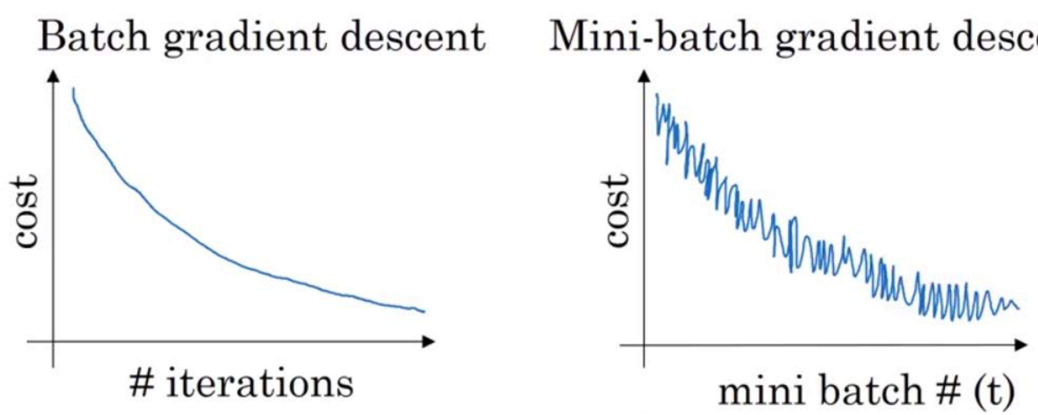
1 ⟷ *m*

Batch Gradient Descent – Tradeoffs

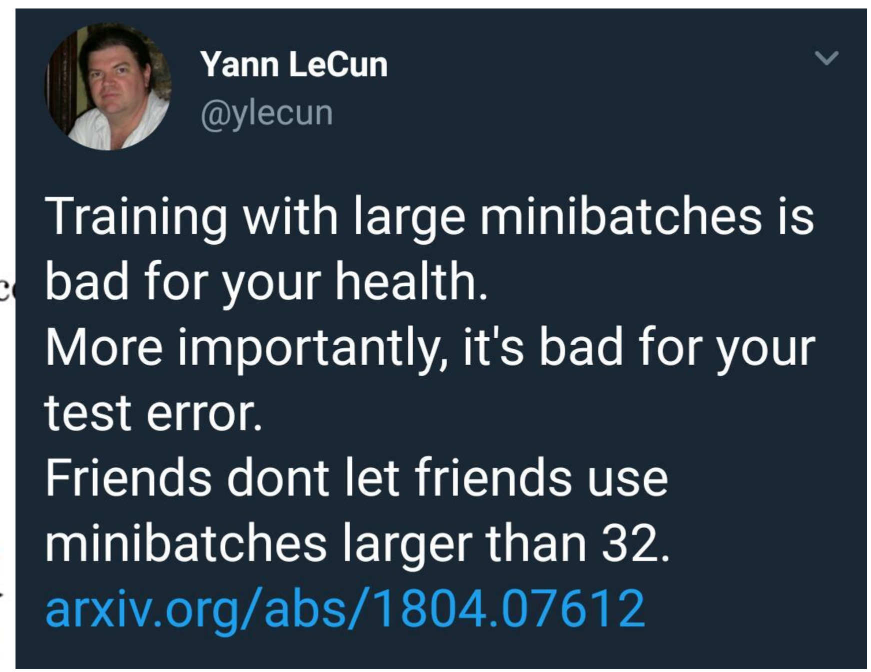


- What's better, **smaller** or **larger** **batch size**?



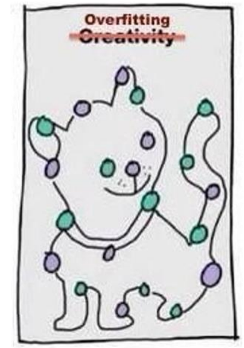


- Larger batch size = needs more computational resources
- Smaller batch size = (empirically) better generalization


Yann LeCun
@ylecun

Training with large minibatches is bad for your health.
More importantly, it's bad for your test error.
Friends dont let friends use minibatches larger than 32.
arxiv.org/abs/1804.07612

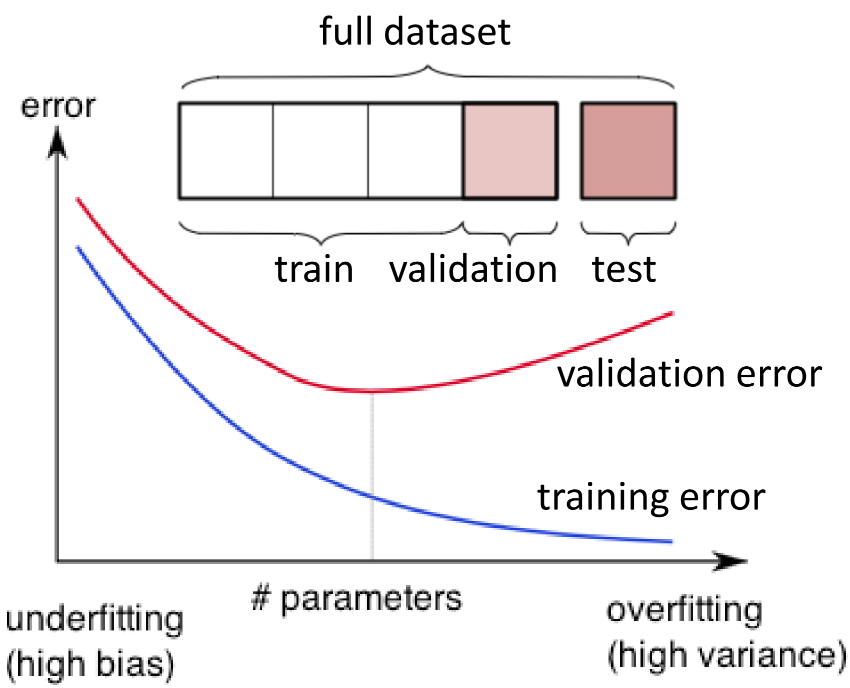
Regularization – fighting overfitting



Most important part of learning: generalize to unseen data

(1) Early stopping: stop the training when the algorithm stops learning the underlying model

(2) Dropout: randomly drop units (along with their connections) during training. **At each iteration**, each unit is retained with fixed **probability *p*** (usually $p >$ 0.5), independent of other units



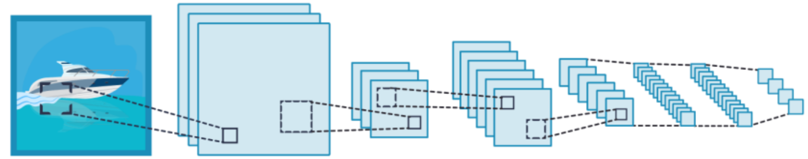
(3) Weight penalty/decay (e.g., L2): prevent big weights. Results in smoother models. e.g., ($w/2$; $w/2$) is better than (w; 0)

(4) L1 weight decay: allows for a few weights to remain large

Data Normalization

- Data normalization helps to **speed up the learning process**, by keeping activations from going too high/too low.
- **Input normalization:** normalize network inputs, e.g.: normalize to [0,1], or according to mean & var., etc.
- **Batch normalization (BN):** normalize hidden layer inputs to mini-batch mean & var. During training, the distribution of each layer's inputs changes as the parameters of the previous layers change. BN reduces impact of earlier layers on later layers.
- Many other alternatives:
  - Layer normalization (LN) – conceived for RNNs
  - Instance normalization (IN) – conceived for Style Transfer
  - Group normalization (GN) – conceived for CNNs

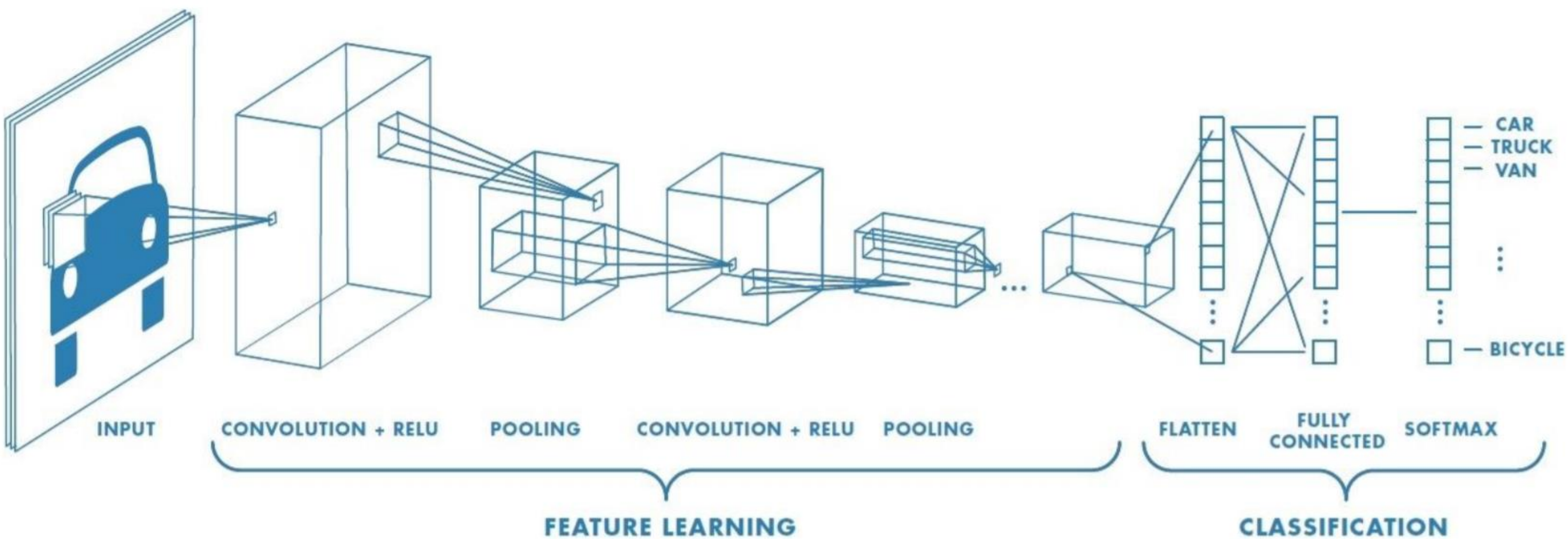
Convolutional Networks (CNN)



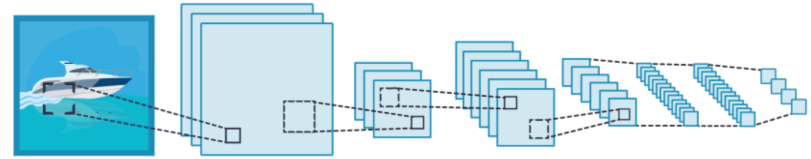
- **Convolutional Neural Networks**: build spatial features, reducing the number of parameters needed for image processing

- **CNNs** are specially conceived for **image processing tasks**, their success is the **primary reason why deep learning is so popular**

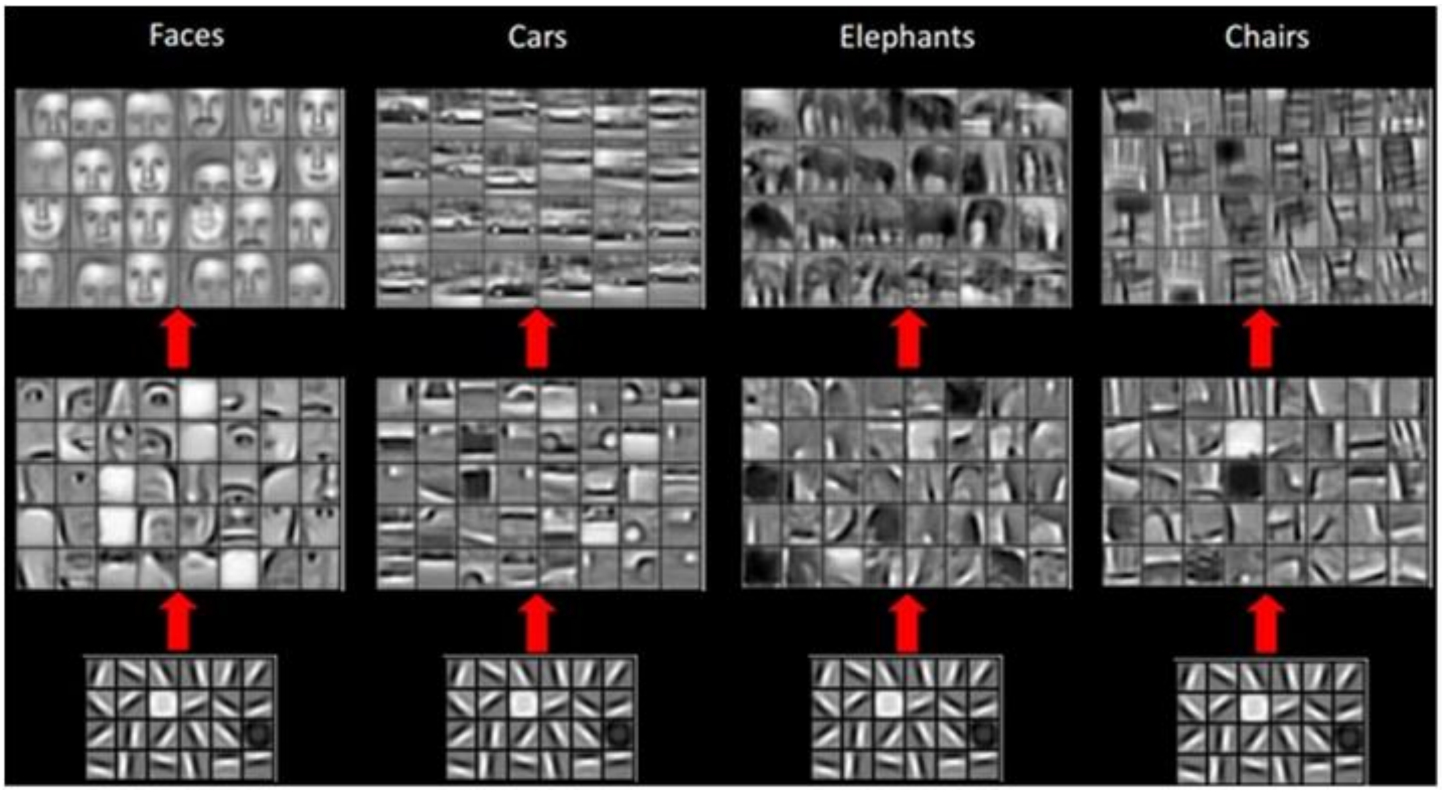
- Convolutional neural networks are composed by **a set of layers with specific functionality**



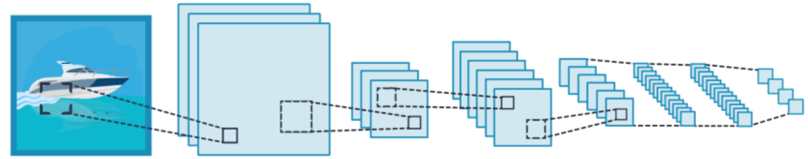
Convolutional Networks (CNN)



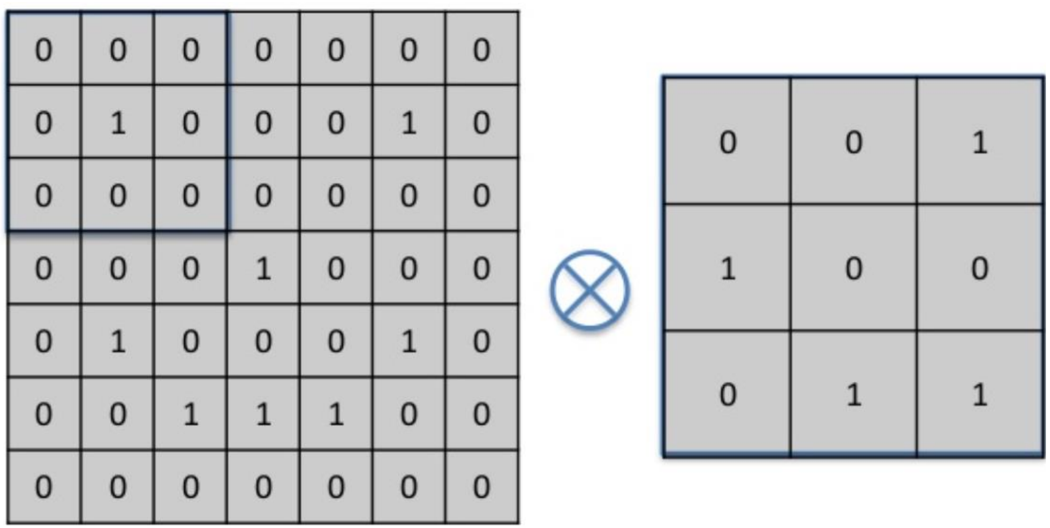
- CNNs detect features in images and learn how to recognize objects with them
- **Layers near the start** detect **simple features** like edges
- **Deeper layers** can detect more **complex features** like eyes, noses, or an entire face



Convolutional Layer



- **Key idea:** we change weights by ***feature detectors*** or filters, and drastically reduce connections
- **Learning in CNNs** is about calibrating the feature detector values
- In a nutshell: we learn **new filters**, which **discover specific characteristics** of the image
- Convolutional layers work as **feature detectors**, generating the so-called **activation maps**



Input Image Feature Detector

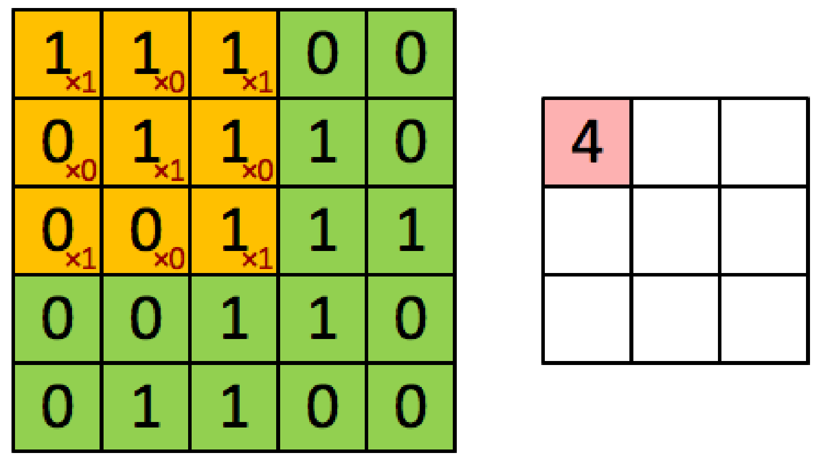
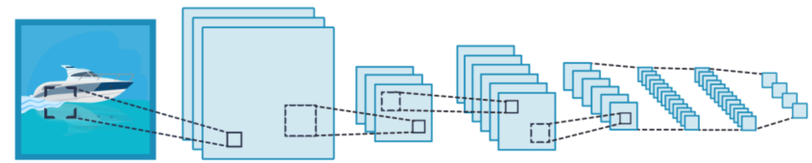
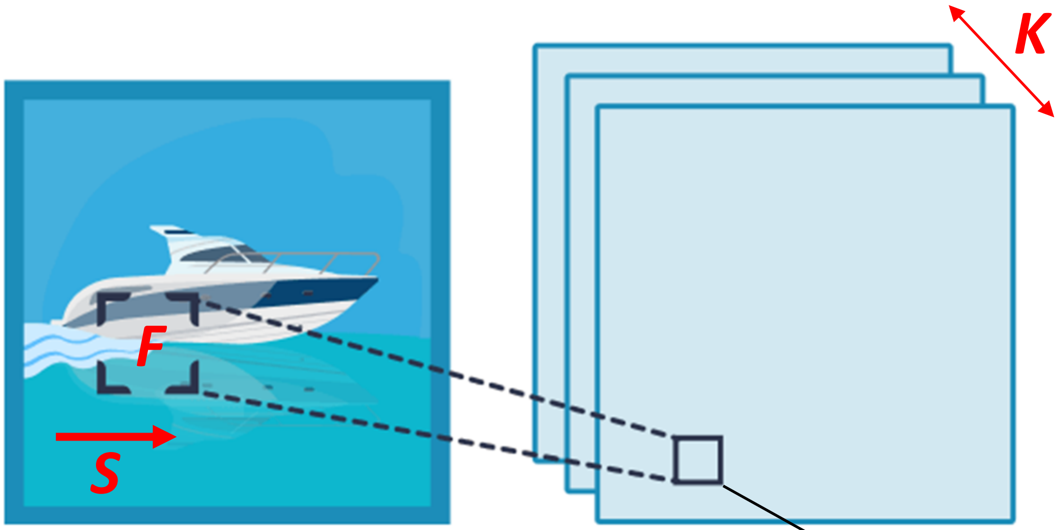


Image Convolved Feature

Convolutional Layer + ReLU





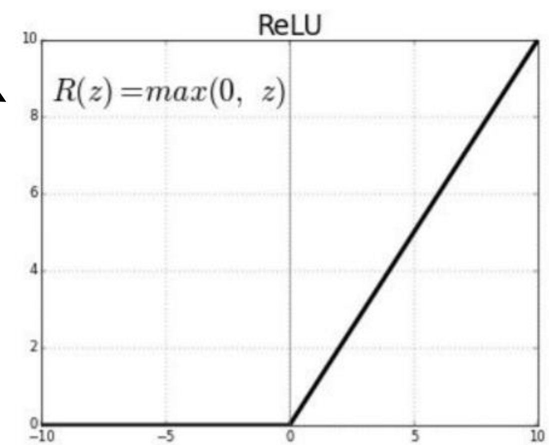
- **Hyper-parameters :**
  - the number of filters ***K***
  - the size of the filters ***F***
  - the stride ***S***

- The convolutional step is combined with an **activation layer**, usually ReLU – Rectifier Linear Unit

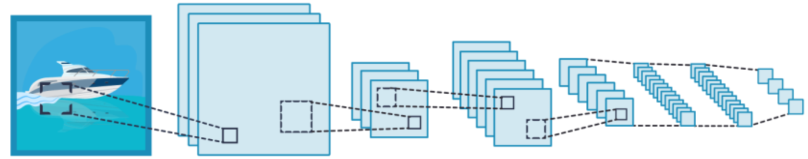
- Used to **increase non-linearity** of the network without affecting receptive fields of convolutional layers

- Prefer ReLU, results in faster training

- **LeakyReLU** addresses the vanishing gradient problem



Pooling Layer



- The main goal of the pooling function is to **progressively reduce the spatial size of the representation** to **reduce the amount of parameters** and computation in the network

- Hence, it **also controls overfitting**

- A **pooling function** replaces the output of the network at a certain location with a **summary statistic of the nearby outputs**

- **Pooling layers** apply **non-linear down-sampling** on activation maps

- Pooling is very aggressive (discard info)

- The **trend** now is to **use smaller filter size** and abandon pooling

Max Pooling

29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2x2 →

100	184
12	45

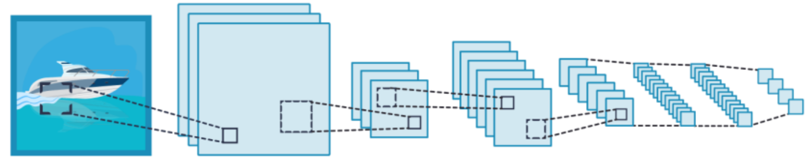
Average Pooling

31	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

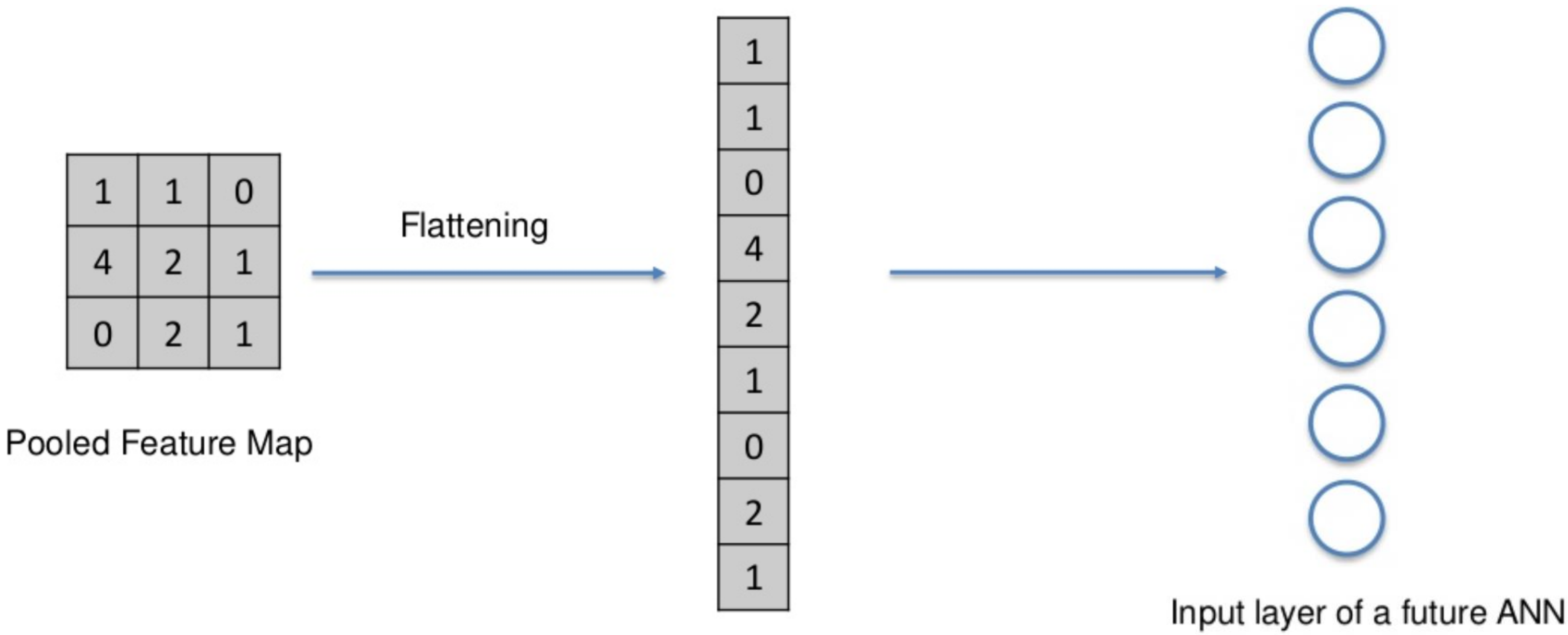
2x2 →

36	80
12	15

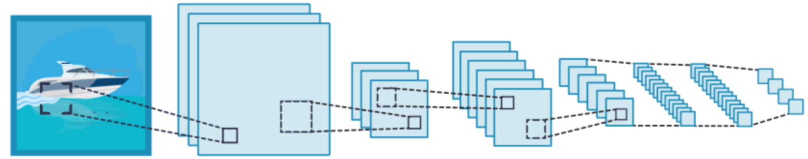
Flattening Layer



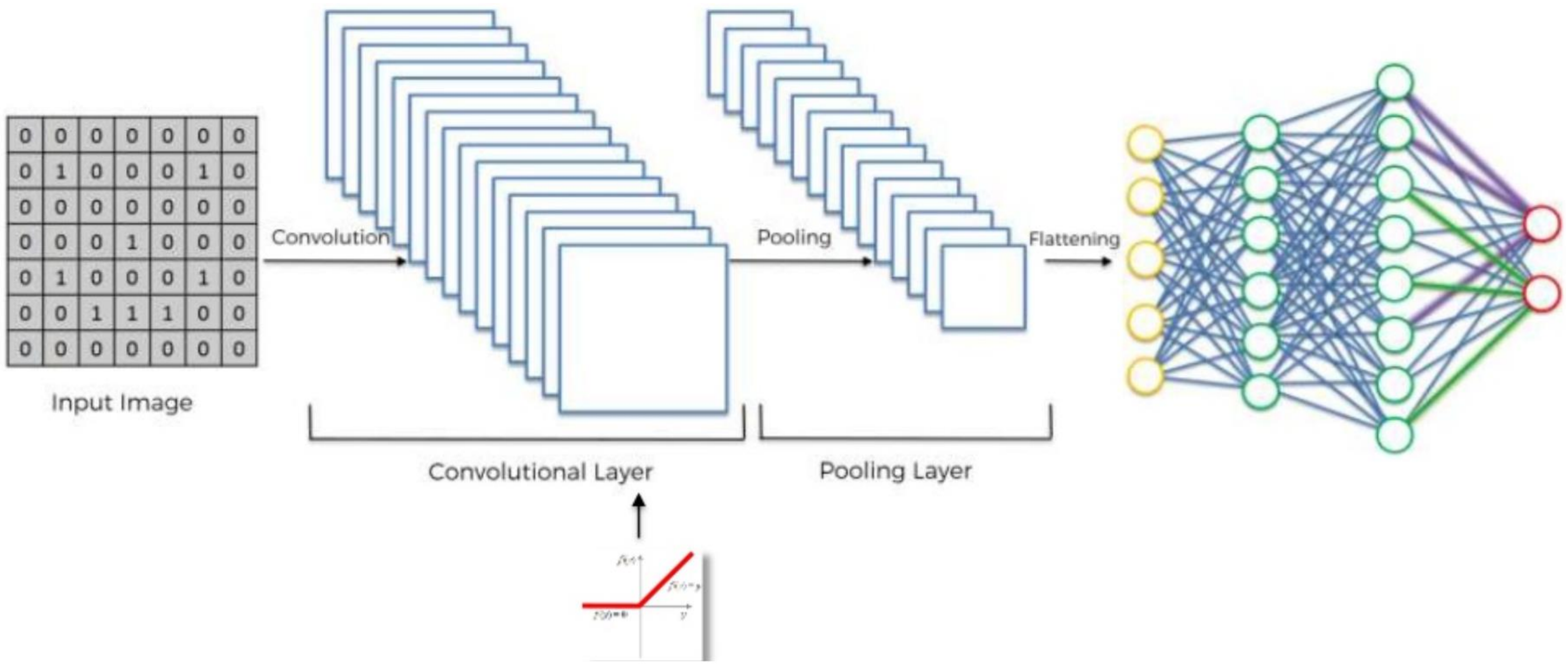
- Flattening is **converting the data into a 1-dimensional array**
- We flatten the **output of the pooling layers** to create a single long feature vector
- And it is connected to the final classification model, which is called a **fully-connected layer**



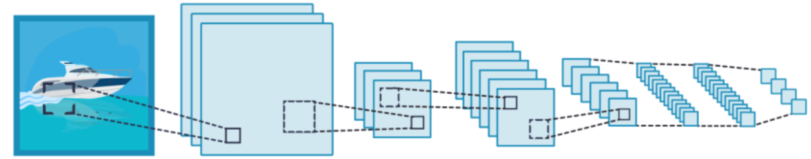
Fully-Connected Layer



- Fully connected layer = **Regular neural network**
- It corresponds to the **final learning phase**, which maps extracted visual features to desired outputs (e.g., classification)
- Common output is a vector, which is then **passed through a *softmax* function** to represent **confidence of classification**



Softmax Layer

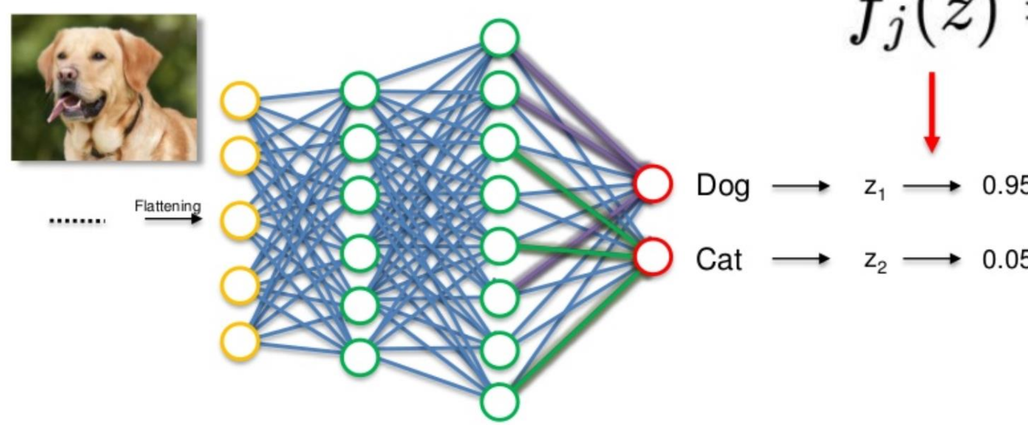


- A special kind of **activation layer**, usually **used at the end of FC layer outputs**
- Can be viewed as a normalizer, producing a **discrete probability distribution** vector
- The Softmax is used as the **activation function in the output layer of the FC Layer**, and ensures that the sum of the outputs is 1.
- The Softmax function takes a **vector of arbitrary real-valued scores** and **squashes it to a vector of values between zero and one that sum to one**

$$P(y = j \mid \mathbf{x}) = \frac{e^{\mathbf{x}^\mathsf{T}\mathbf{w}_j}}{\sum_{k=1}^{K} e^{\mathbf{x}^\mathsf{T}\mathbf{w}_k}}$$

Given sample vector input **x** and weight vectors {$\mathbf{w}_j$}, the predicted probability of y = j

$$f_j(z) = \frac{e^{z_j}}{\sum_k e^{z_k}}$$



The End of CNNs?

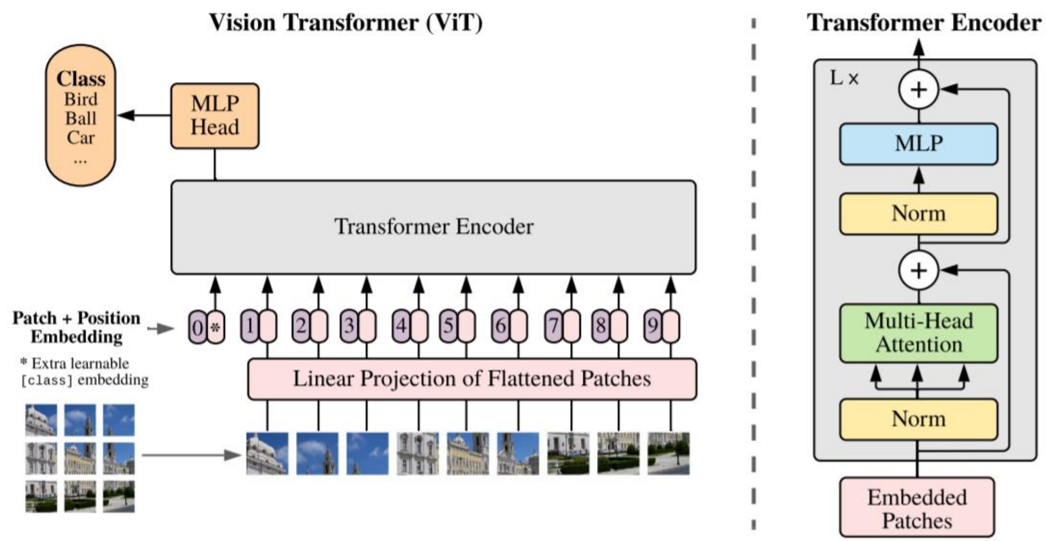
- **ICLR 2021 paper:** ***“An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”***

- *While the **Transformer architecture** has become the de-facto standard for **natural language processing** tasks, its **applications to computer vision remained limited**….**till Vision Transformer (ViT)***

- **Transformers:** a new model to handle sequential data

- Hinton: “Transformers are CapsNets that work”…

- …to be continued…



Thanks

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