# Foundations of Artificial Intelligence

## 14. Deep Learning

Learning from Raw Data

Joschka Boedecker and Wolfram Burgard and
Frank Hutter and Bernhard Nebel and Michael Tangermann


Albert-Ludwigs-Universität Freiburg

July 10, 2019

# Motivation: Deep Learning in the News

The New York Times

**Science**

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## Scientists See Promise in Deep-Learning

A voice recognition program translated a speech given by Richard F. Rashid Chinese.

By JOHN MARKOFF
Published: November 23, 2012

Using an artificial intelligence technique inspired by theories al the brain recognizes patterns, technology companies are reportin gains in fields as diverse as computer vision, speech recognitior



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NOVEMBER 25, 2012

## IS "DEEP LEARNING" A REVOLUTION IN ARTIFICIAL INTELLIGENCE?

BY GARY MARCUS



Can a new technique known as deep learning revolutionize artificial intelligence, as yesterday's front-page article at the New York *Times* suggests? There is good reason to be excited about deep learning, a sophisticated "machine learning" algorithm that far exceeds many of its predecessors in its abilities to recognize syllables and images. But there's also good reason to be skeptical. While the *Times* reports that "advances in an artificial intelligence technology that can recognize patterns offer

MIT Technology Review

## 10 BREAKTHROUGH TECHNOLOGIES 2013

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### Deep Learning

**With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart.**

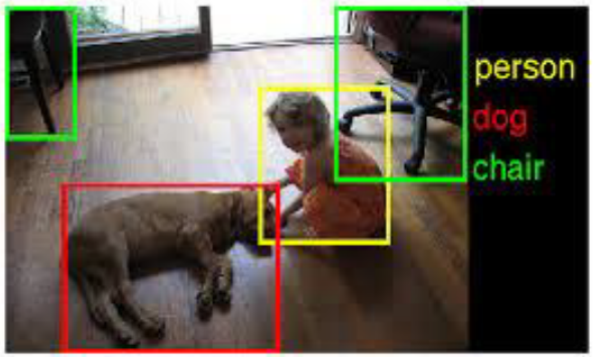
# Lecture Overview

# Lecture Overview

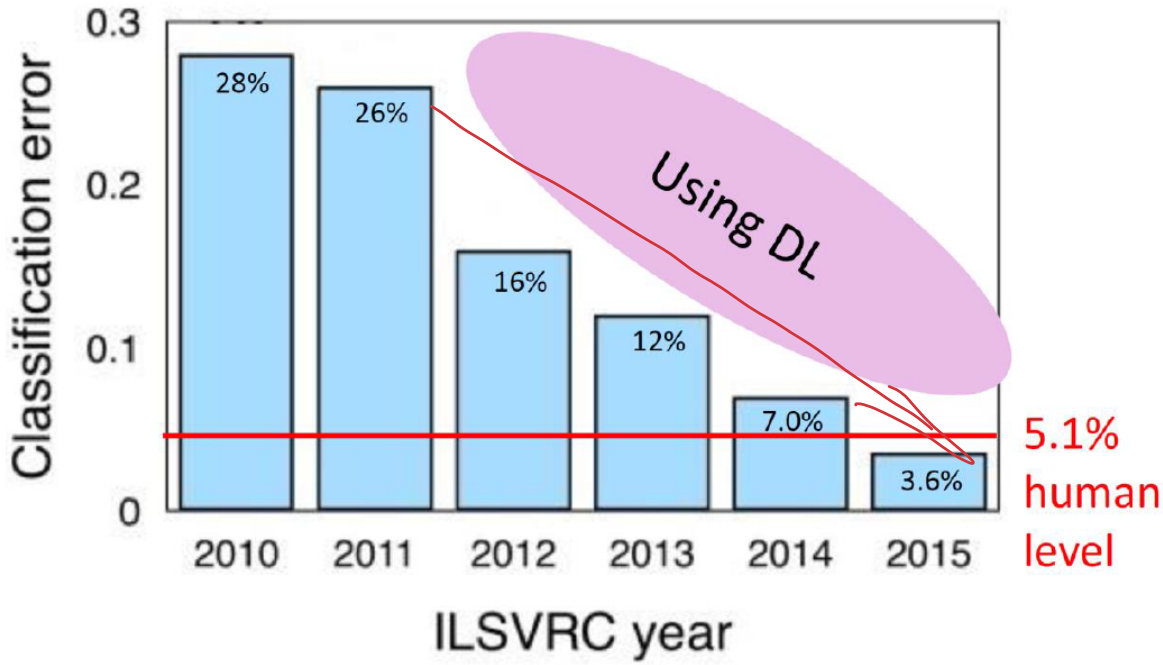
# Motivation: Why is Deep Learning so Popular?

- Excellent empirical results, e.g., in computer vision

Object recognition




Self-driving cars



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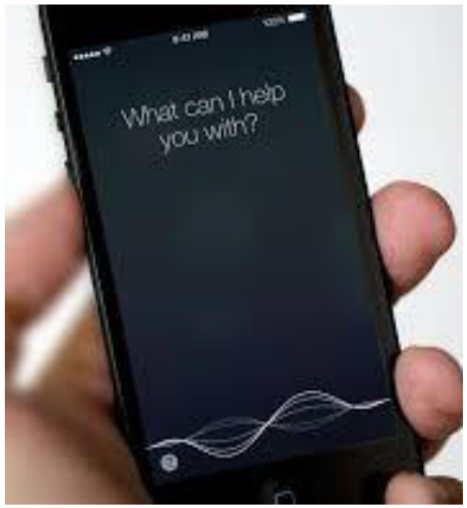



skype™ Auto-Translator

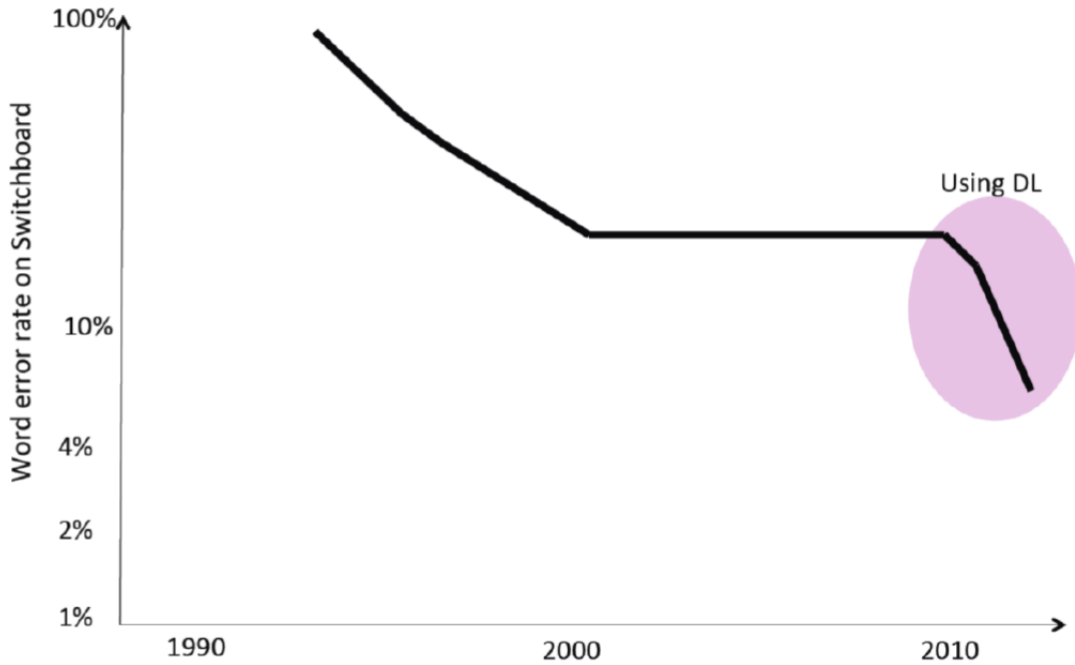
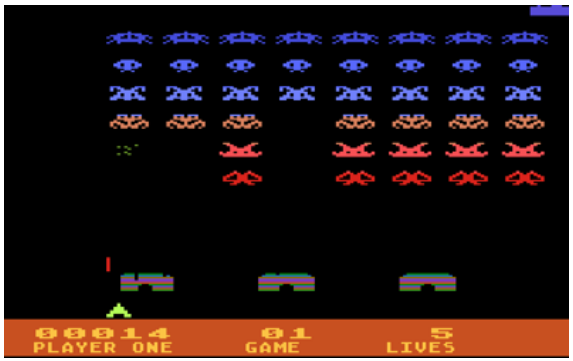



Image credit: Yoshua Bengio (data from Microsoft speech group)

# Motivation: Why is Deep Learning so Popular?

- Excellent empirical results, e.g., in reasoning in games

  - Superhuman performance in playing Atari games
    [Mnih et al, Nature 2015]




  - Beating the world's best Go player
    [Silver et al, Nature 2016]

# An Exciting Approach to AI: Learning as an Alternative to Traditional Programming

- We don't understand how the human brain solves certain problems
  - Face recognition
  - Speech recognition
  - Playing Atari games
  - Picking the next move in the game of Go
- We can nevertheless learn these tasks from data/experience

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- If the task changes, we simply re-train
- We can construct computer systems that are too complex for us to understand anymore ourselves...
  - E.g., deep neural networks have millions of weights.
  - E.g., AlphaGo, the system that beat world champion Lee Sedol
    - David Silver, lead author of AlphaGo cannot say why a move is good
    - Paraphrased: "You would have to ask a Go expert."

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  - Babies develop an intuitive understanding of physics in their first 2 years
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  - Formal reasoning and logic comes much later in development
- Learning enables fast reaction times
  - It might take a long time to train a neural network
  - But predicting with the network is very fast
  - Contrast this to running a planning algorithm every time you want to act

# Lecture Overview

# Some definitions

## Representation learning

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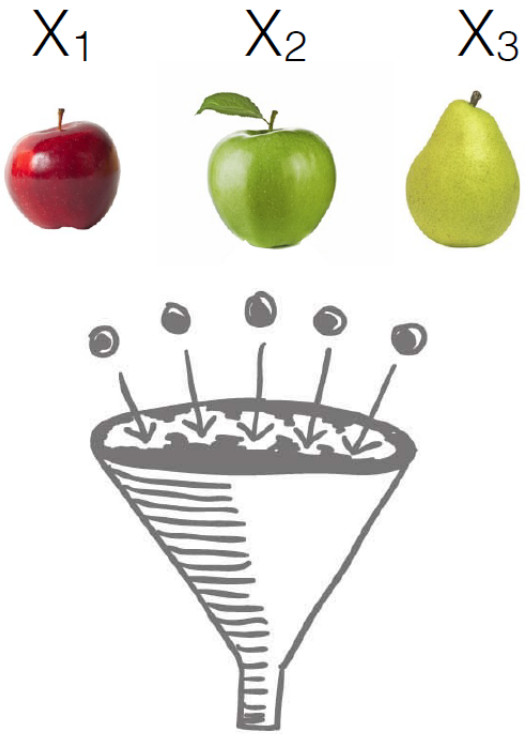
## Deep learning

"representation learning methods with multiple levels of representation, obtained by composing simple but nonlinear modules that each transform the representation at one level into a [...] higher, slightly more abstract (one)"

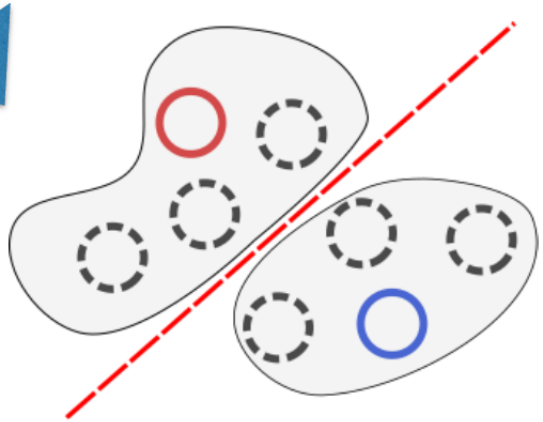
(LeCun et al., 2015)

# Standard Machine Learning Pipeline

- Standard machine learning algorithms are based on high-level attributes or features of the data
- E.g., the binary attributes we used for decisions trees
- This requires (often substantial) feature engineering

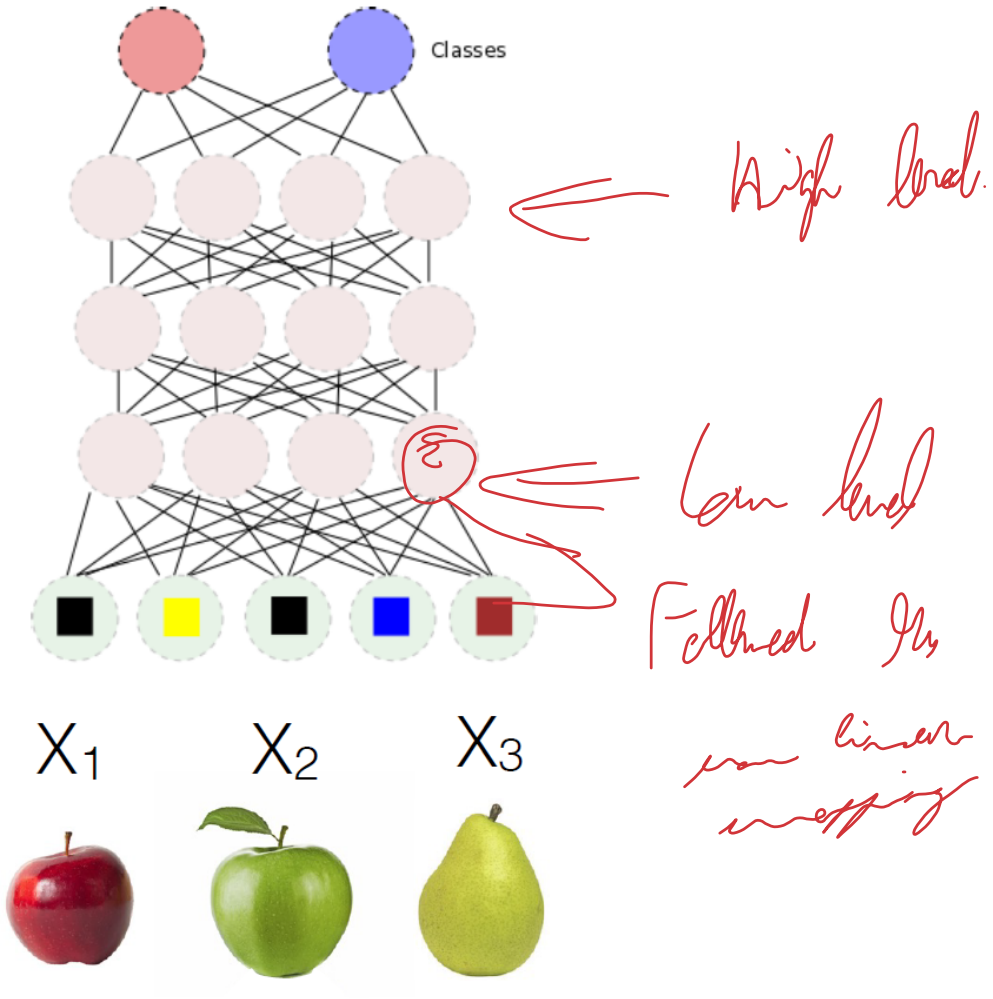



| | Merkmale |
|---|---|
| $X_1$ | rot, 3.5 cm |
| $X_2$ | grün, 4 cm |
| $X_3$ | grün, 10 cm |

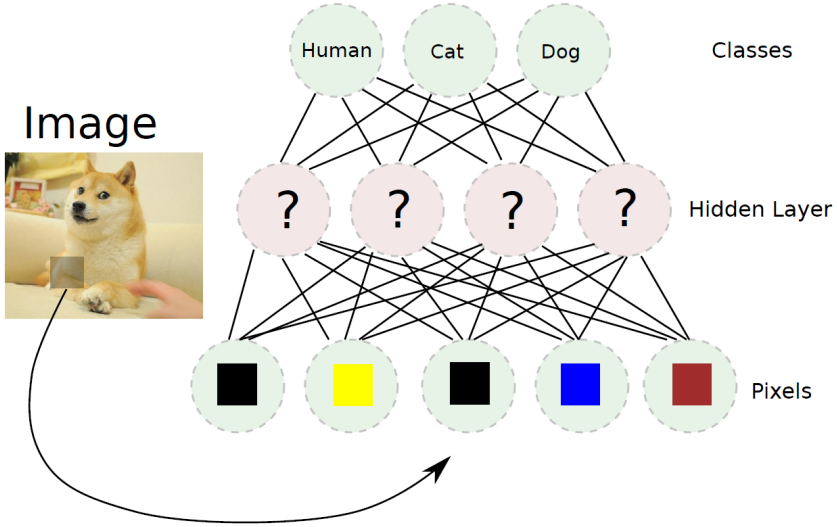


# Representation Learning Pipeline

- Jointly learn features and classifier, directly from raw data
- This is also referrred to as end-to-end learning



# Shallow vs. Deep Learning



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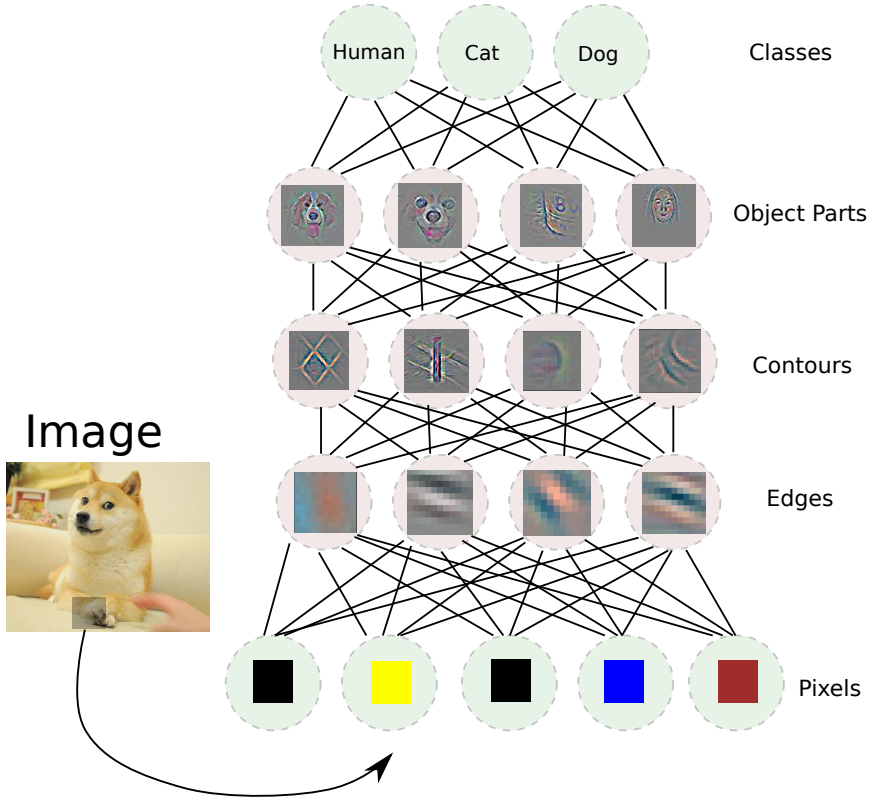
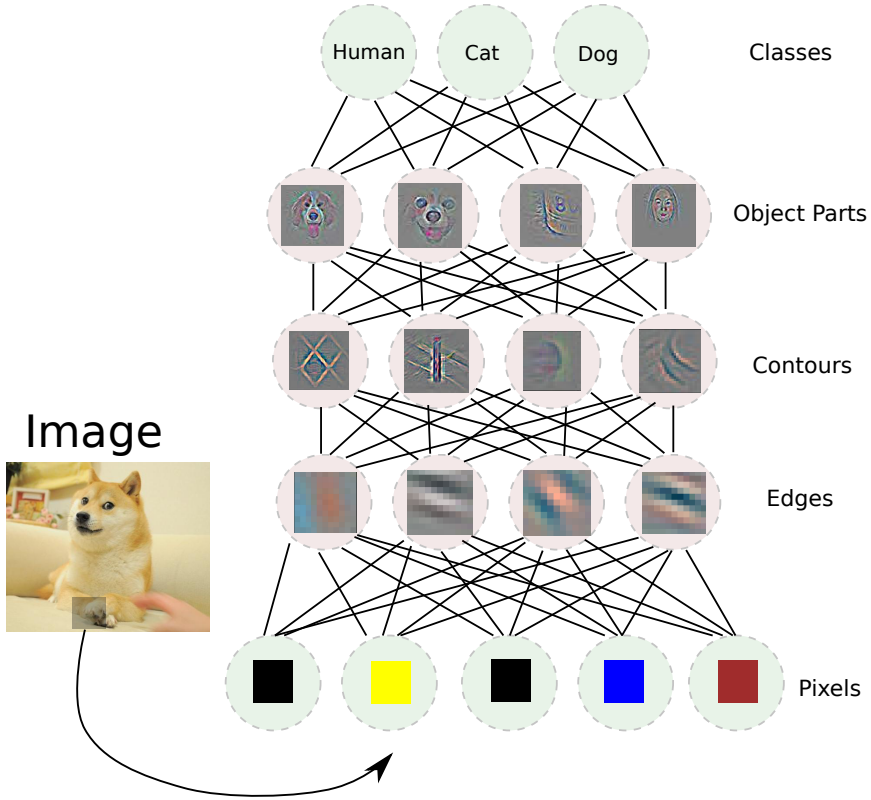



- Deep Learning: learning a hierarchy of representations that build on each other, from simple to complex

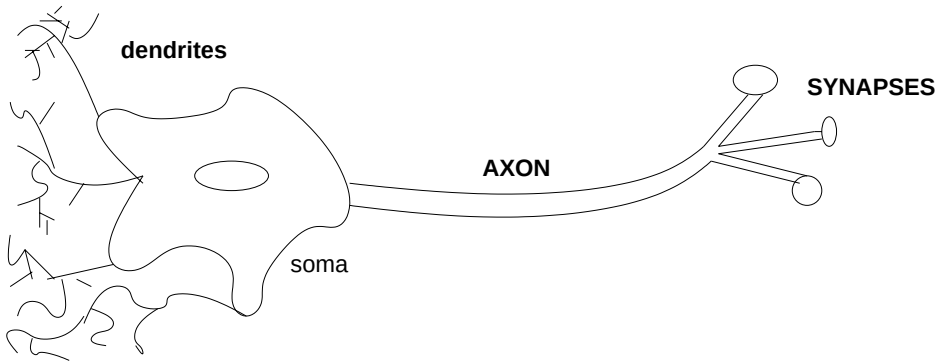
# Shallow vs. Deep Learning




- Deep Learning: learning a hierarchy of representations that build on each other, from simple to complex
- Quintessential deep learning model: Multilayer Perceptrons

# Biological Inspiration of Artificial Neural Networks

- Dendrites input information to the cell
- Neuron fires (has action potential) if a certain threshold for the voltage is exceeded
- Output of information by axon
- The axon is connected to dentrites of other cells via synapses
- Learning: adaptation of the synapse's efficiency, its synaptical weight



# A Very Brief History of Neural Networks

- Neural networks have a long history
  - 1942: artificial neurons (McCulloch/Pitts)
  - 1958/1969: perceptron (Rosenblatt; Minsky/Papert)
  - 1986: multilayer perceptrons and backpropagation (Rumelhart)
  - 1989: convolutional neural networks (LeCun)

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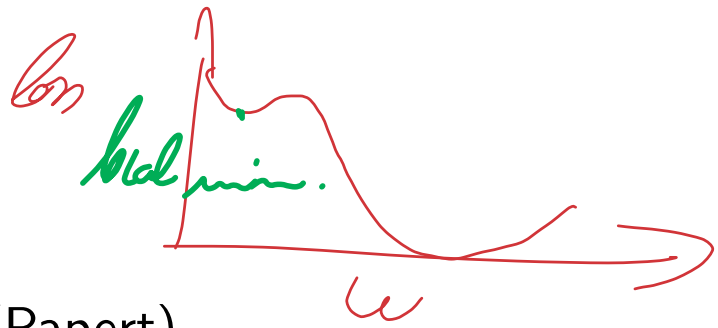

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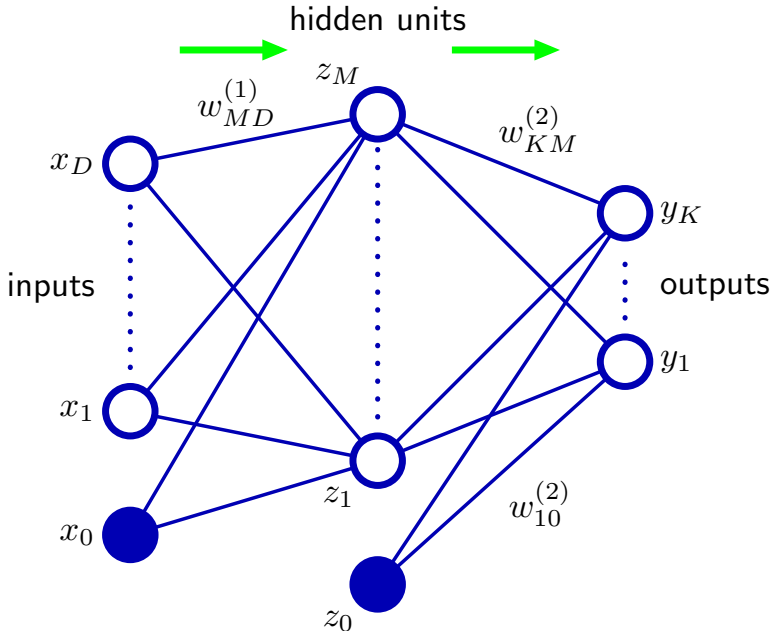
- Alternative theoretically motivated methods outperformed NNs
  - Exaggeraged expectations: "It works like the brain" (No, it does not!)
- Why the sudden success of neural networks in the last 5 years?
  - Data: Availability of massive amounts of labelled data
  - Compute power: Ability to train very large neural networks on GPUs
  - Methodological advances: many since first renewed popularization

# Lecture Overview



The advance doesn't depend only on the computer power, but also on the methodological improvements

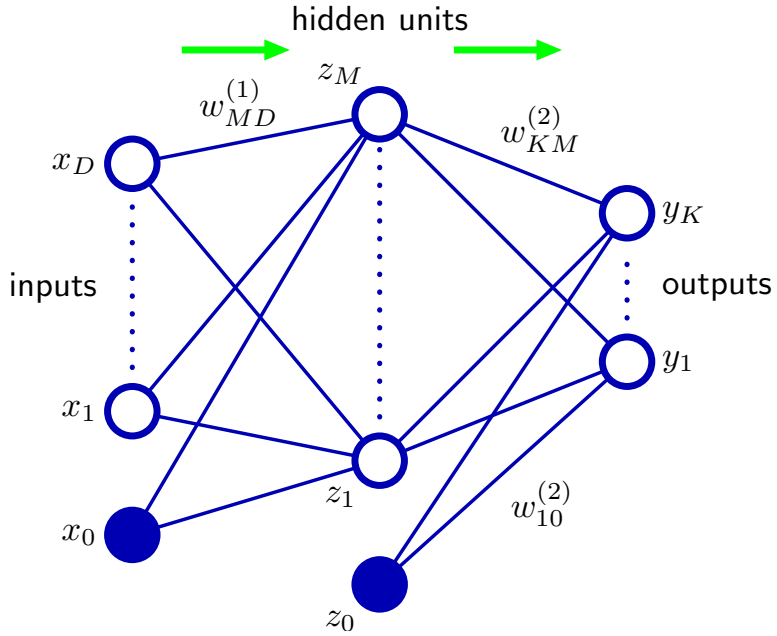
# Multilayer Perceptrons




[figure from Bishop, Ch. 5]

- Network is organized in layers
  - Outputs of $k$-th layer serve as inputs of $k+1$th layer
- Each layer $k$ only does quite simple computations:
  - Linear function of previous layer's outputs $z_{k-1}$: $a_k = W_k z_{k-1} + b_k$
  - Nonlinear transformation $z_k = h_k(a_k)$ through activation function $h_k$

# Multilayer Perceptrons

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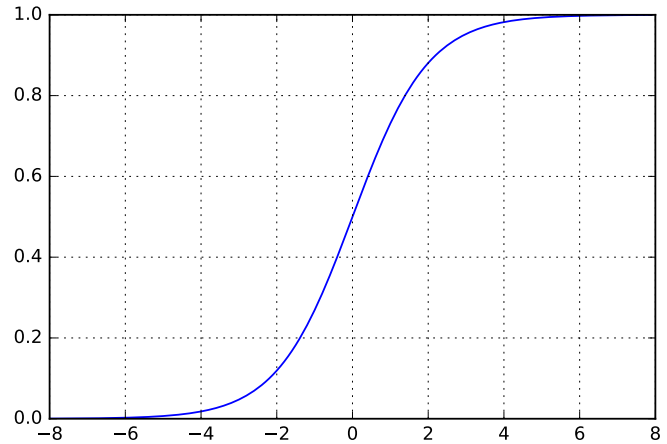
- Parameters/weights $w$ of the network: all $W_k, b_k$, flattened into a single vector

# Activation Functions - Examples

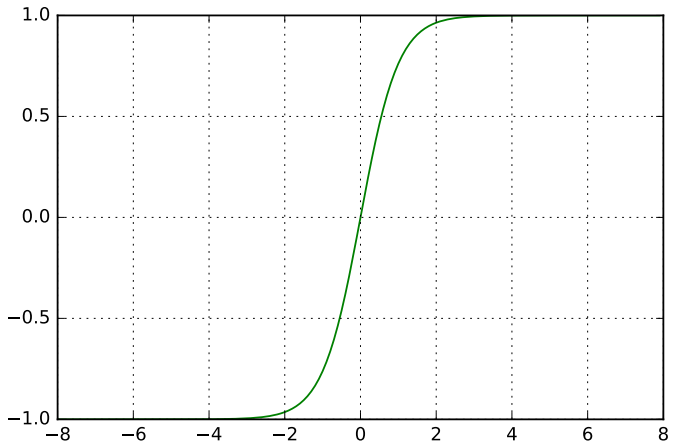
Logistic sigmoid activation function:

$$h_{logistic}(a) = \frac{1}{1 + \exp(-a)}$$




Logistic hyperbolic tangent activation function:

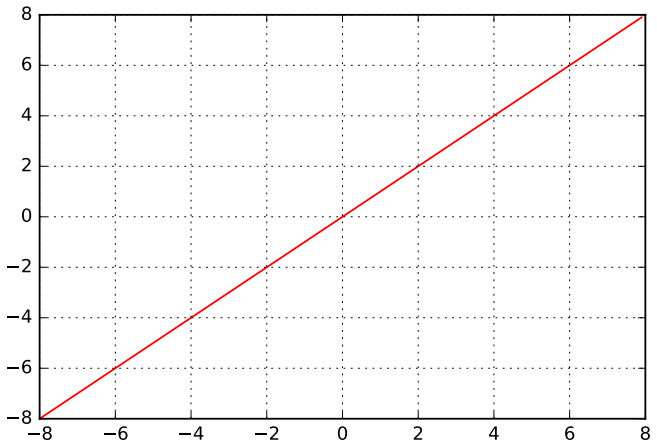
$$h_{tanh}(a) = \tanh(a) = \frac{\exp(a) - \exp(-a)}{\exp(a) + \exp(-a)}\}$$



# Activation Functions - Examples (cont.)

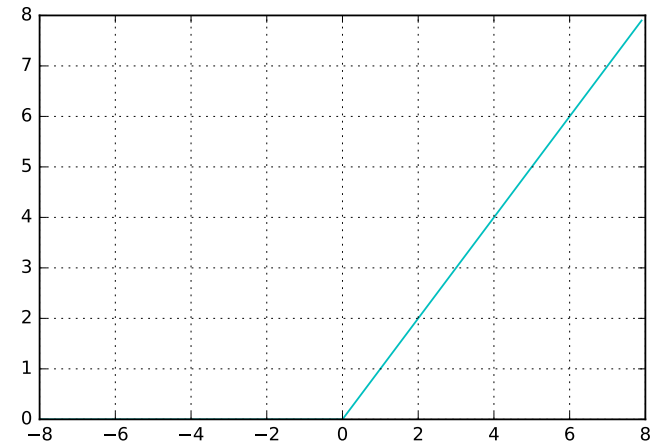
Linear activation function:

$$h_{linear}(a) = a$$




Rectified Linear (ReLU) activation function:

$$h_{relu}(a) = \max(0, a)$$



# Output layer and loss functions

- For regression:
  - Single output neuron with linear activation function

$$\hat{y}(x, w) = h_{linear}(a) = a$$

  - Loss function: e.g., squared error:

$$L(w) = \frac{1}{2} \sum_{n=1}^{N} \{\hat{y}(x_n, w) - y_n\}^2$$

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- For classification:
  - Single output unit with, e.g., logistic activation function:

$$\hat{y}(x, w) = h_{logistic}(a) = \frac{1}{1 + \exp(-a)}$$

  - Loss function: negative log likelihood of the data under the predictive distribution this specifies; (aka cross entropy):

$$L(w) = -\sum_{n=1}^{N} \{y_n \ln \hat{y}_n + (1 - y_n) \ln(1 - \hat{y}_n)\}$$

# Optimizing a loss / error function

- Given training data $\mathcal{D} = \langle (x_i, y_i) \rangle_{i=1}^{N}$ and topology of an MLP
- Task: adapt weights $w$ to minimize the loss:

$$\underset{w}{minimize}\ L(w; \mathcal{D})$$

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- We optimize this function by gradient-based optimization
  - We can compute gradients of $L(w; \mathcal{D})$
    - Efficiently, using a technique called backpropagation

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  - We can compute gradients of $L(w; \mathcal{D})$
    - Efficiently, using a technique called backpropagation
  - Stochastic gradient descent (SGD)
    - We can use small batches of the data, i.e., $L(w; \mathcal{D}_{batch})$
    - This yields approximate gradients quickly

# Lecture Overview

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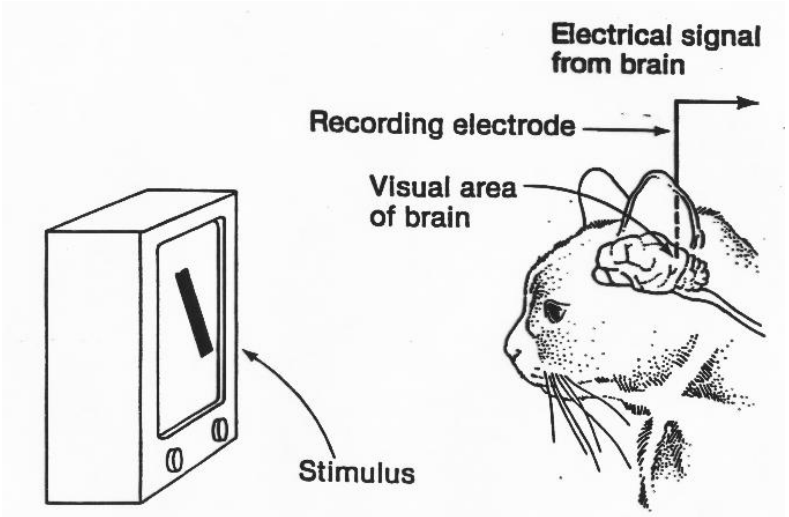
# Historical context and inspiration from Neuroscience

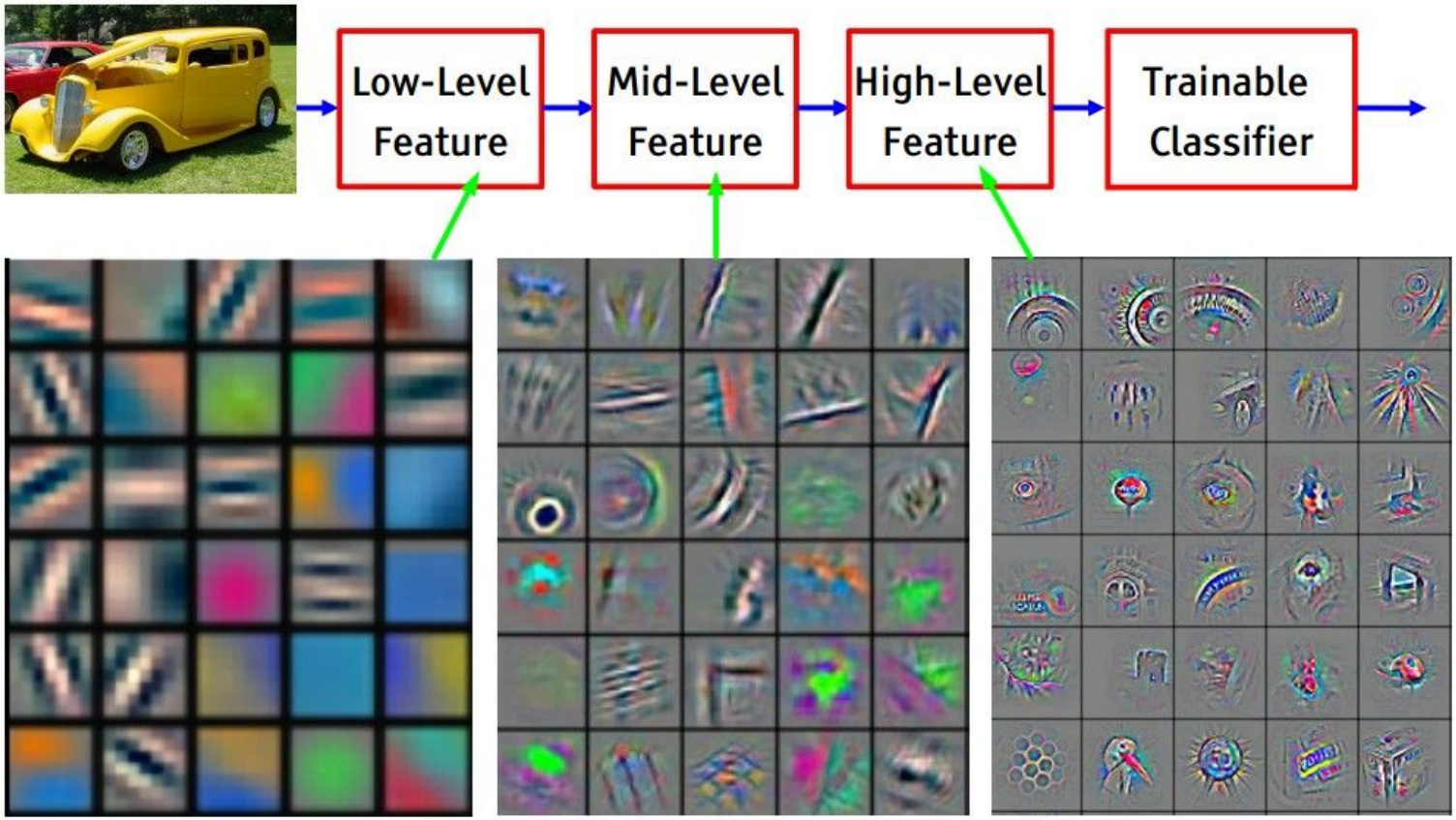
Hubel & Wiesel (Nobel prize 1981) found in several studies in the 1950s and 1960s:

- Visual cortex has feature detectors (e.g., cells with preference for edges with specific orientation)
  - edge location did not matter
- Simple cells as local feature detectors
- Complex cells pool responses of simple cells
- There is a feature hierarchy



# Learned feature hierarchy

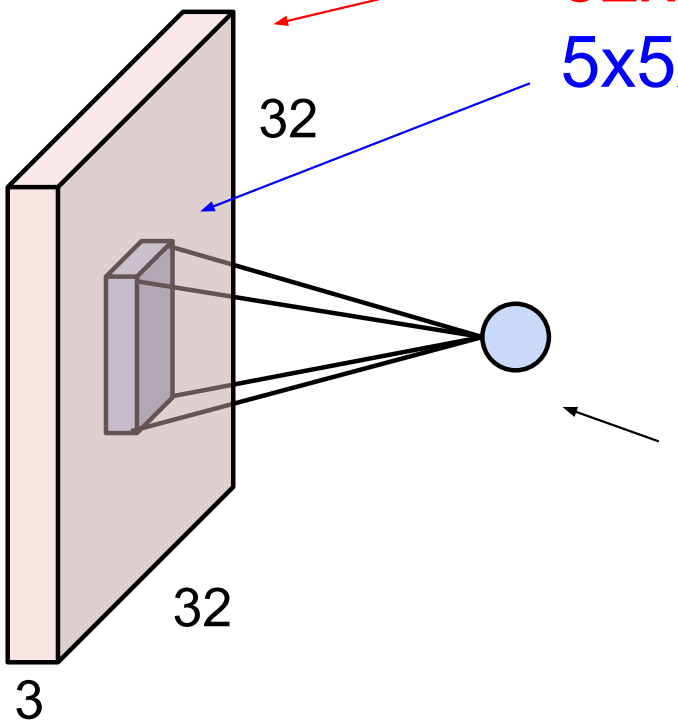
*[From recent Yann LeCun slides]*




Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

[slide credit: Andrej Karpathy]

# Convolutions illustrated

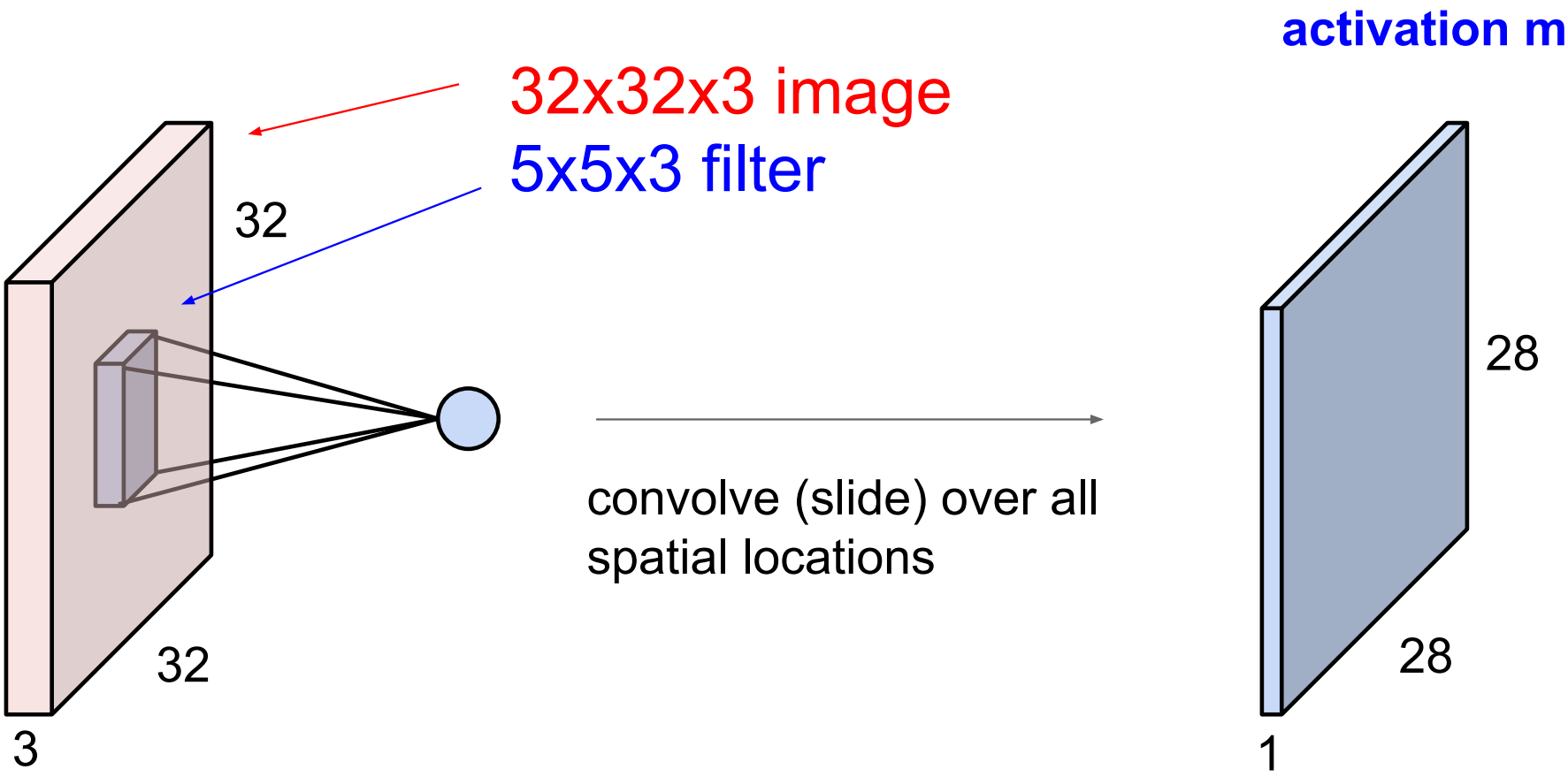



**1 number:**
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

[slide credit: Andrej Karpathy]

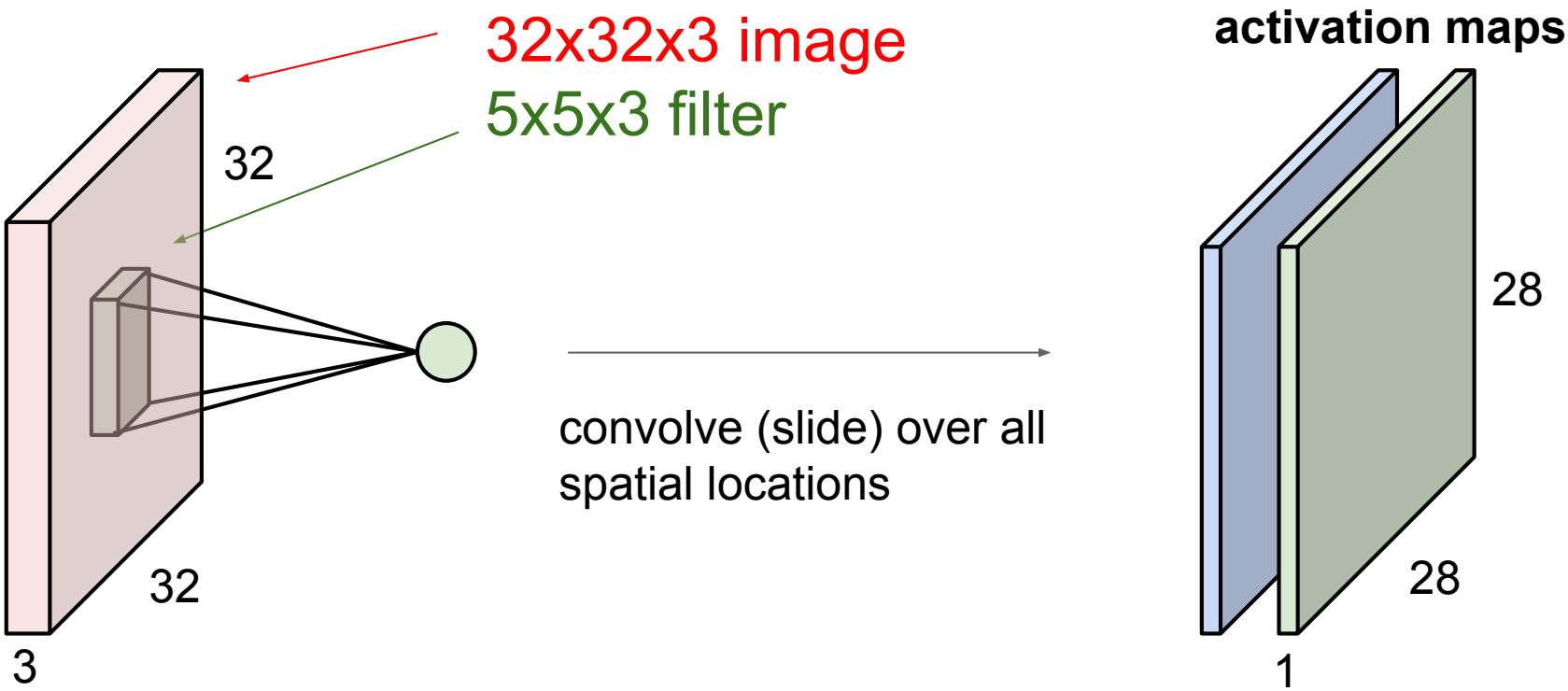
# Convolutions illustrated (cont.)




[slide credit: Andrej Karpathy]

# Convolutions – several filters

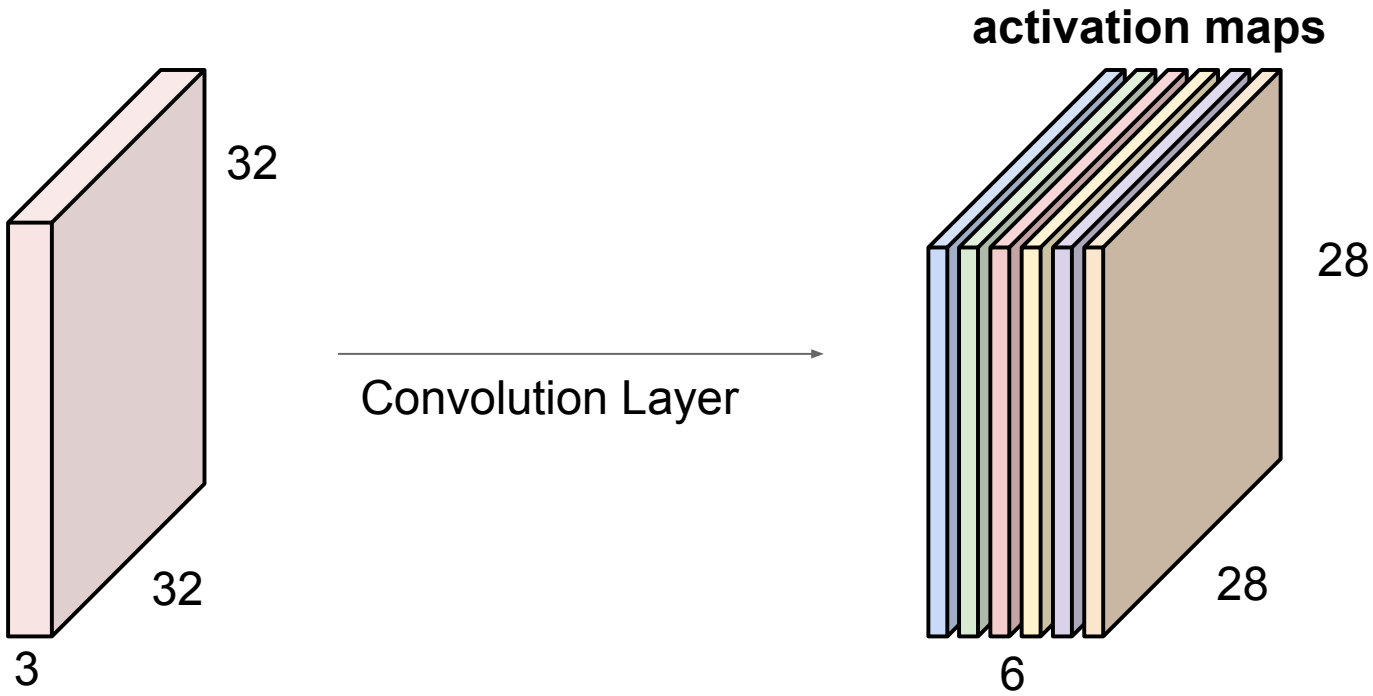
consider a second, green filter




[slide credit: Andrej Karpathy]

# Convolutions – several filters

For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

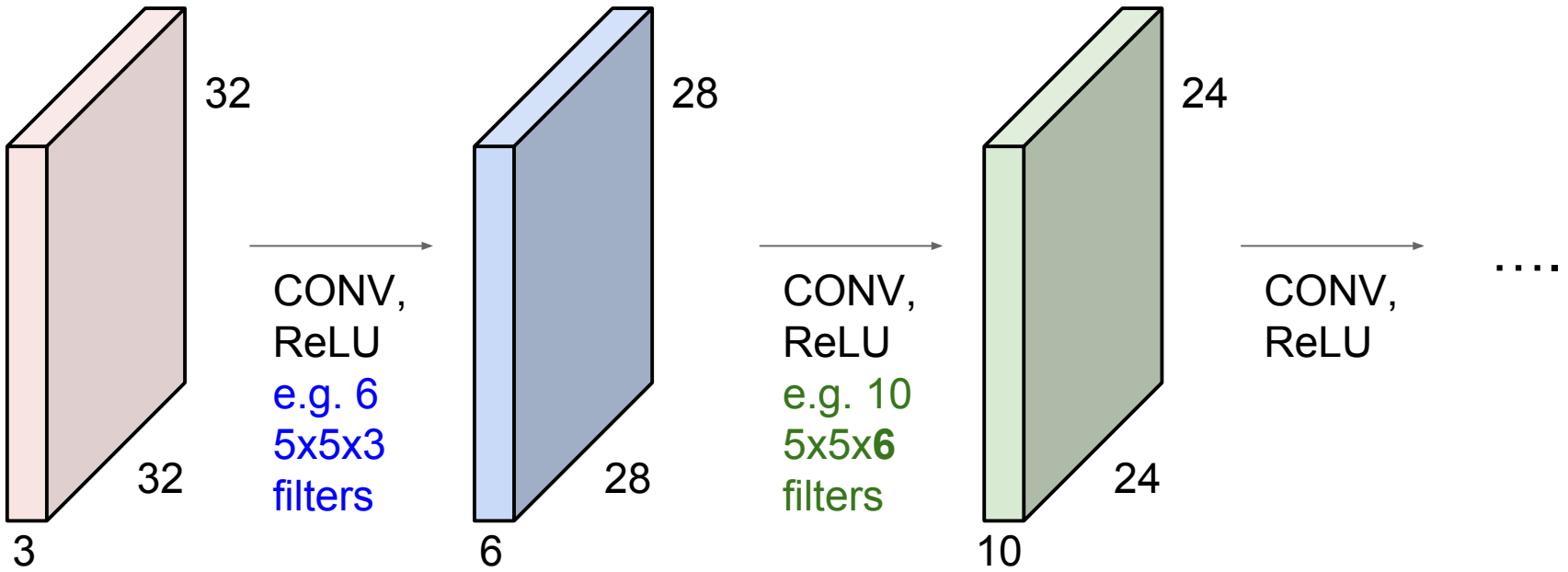



We stack these up to get a "new image" of size 28x28x6!

[slide credit: Andrej Karpathy]

# Stacking several convolutional layers

Convolutional layers stacked in a ConvNet

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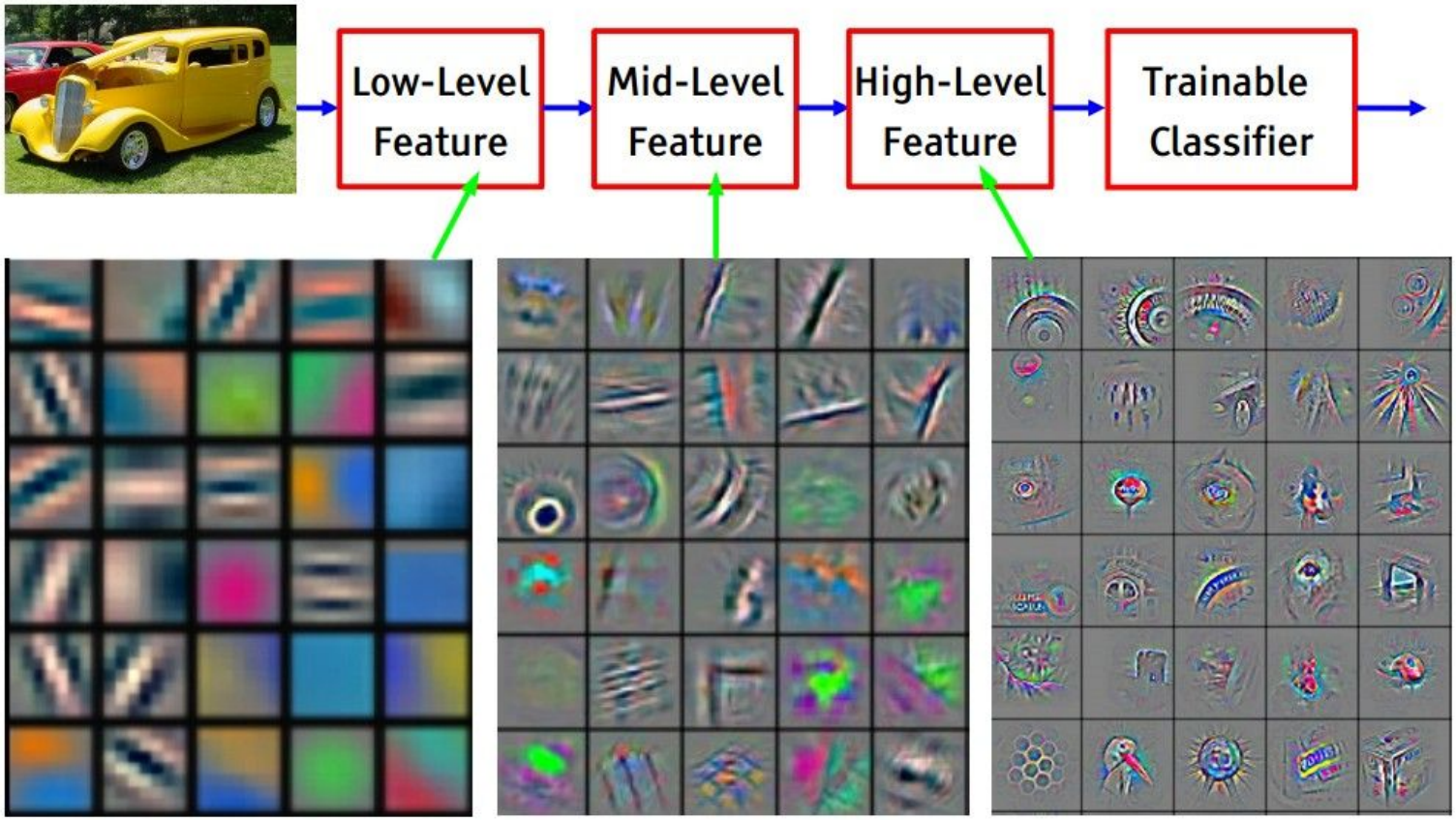


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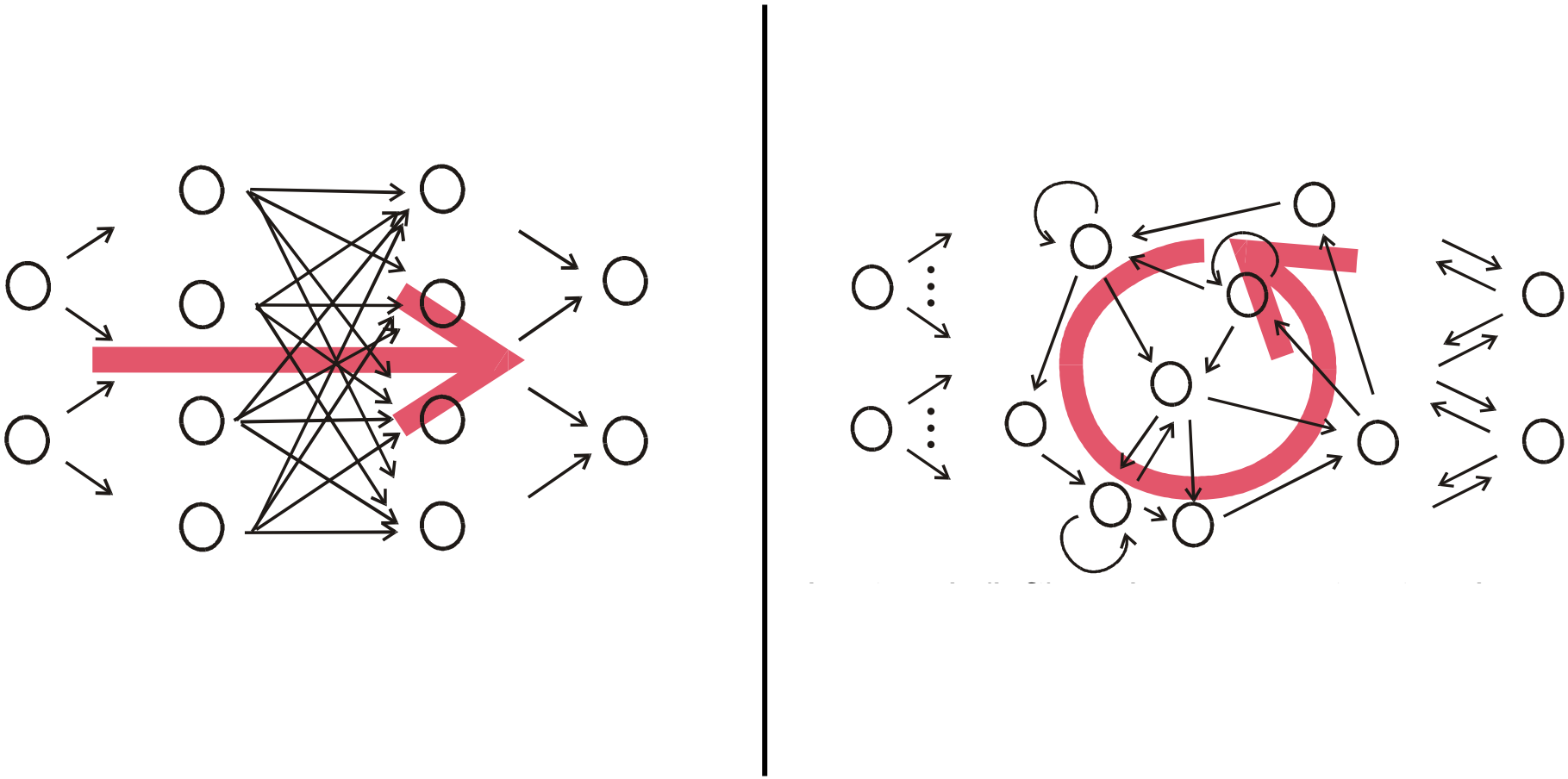
# Lecture Overview

# Feedforward vs Recurrent Neural Networks



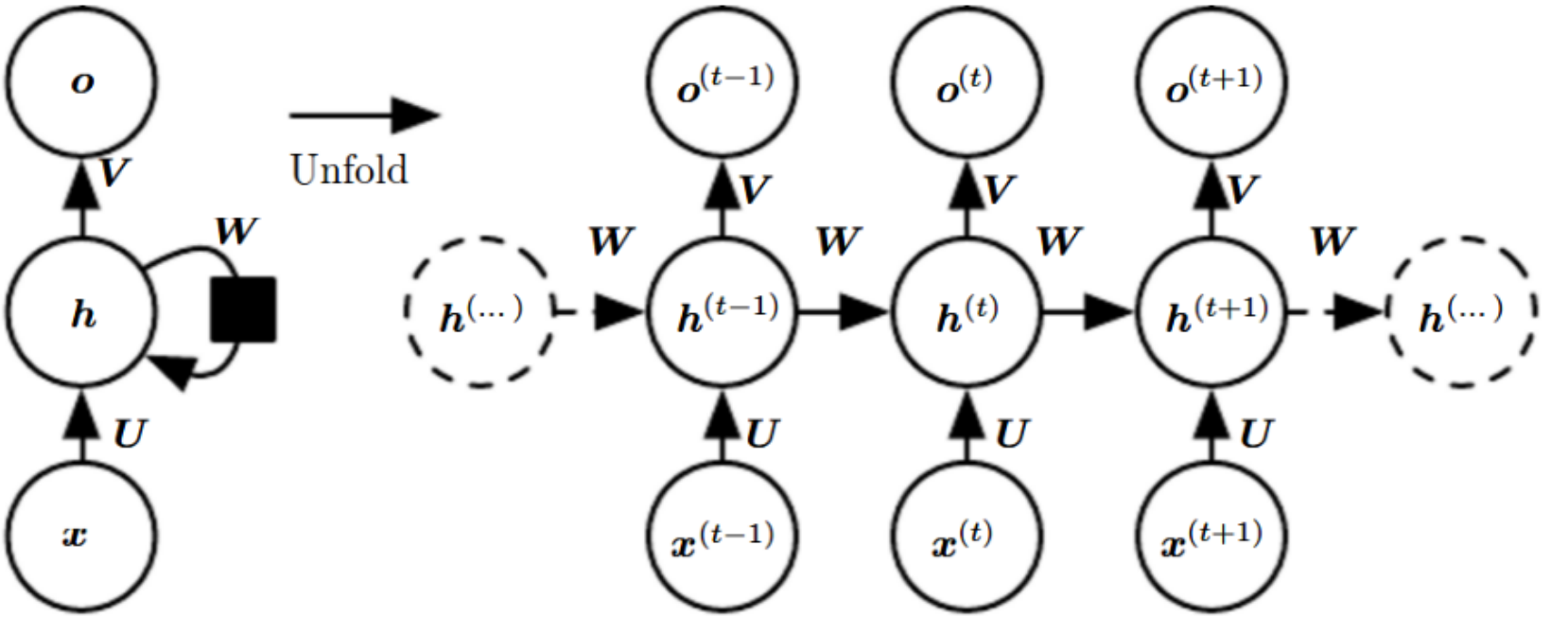
[Source: Jaeger, 2001]

# Recurrent Neural Networks (RNNs)

- Neural Networks that allow for cycles in the connectivity graph
- Cycles let information persist in the network for some time (state), and provide a time-context or (fading) memory
- Very powerful for processing sequences
- Implement dynamical systems rather than function mappings, and can approximate any dynamical system with arbitrary precision
- They are Turing-complete [Siegelmann and Sontag, 1991]

# Abstract schematic

With fully connected hidden layer:




[Goodfellow et al'2016]

# Sequence to sequence mapping

one to many

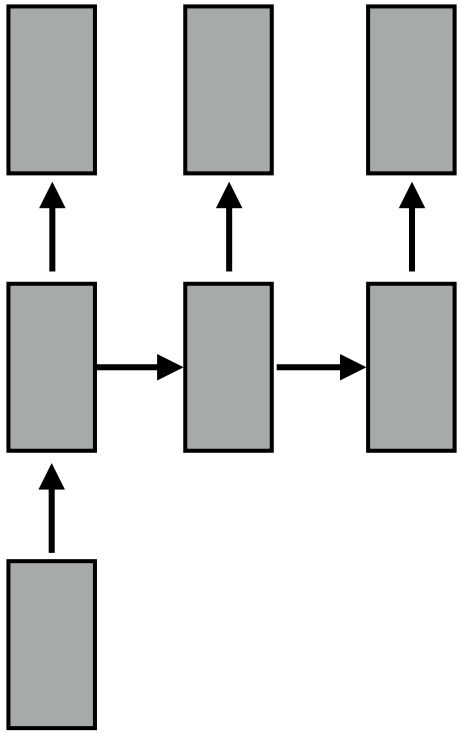
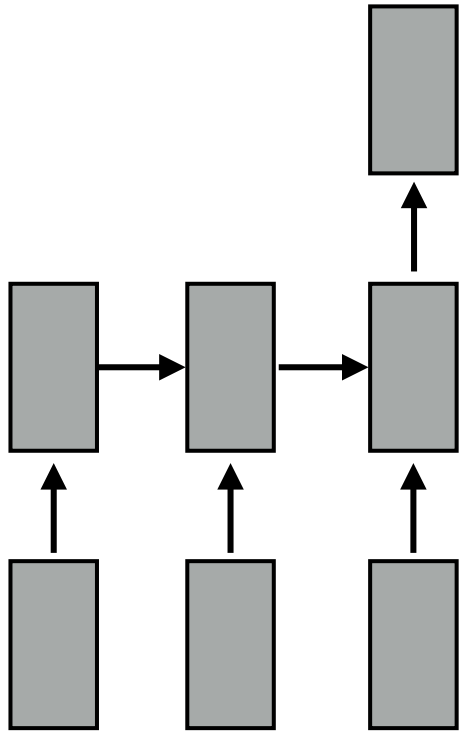


image caption generation

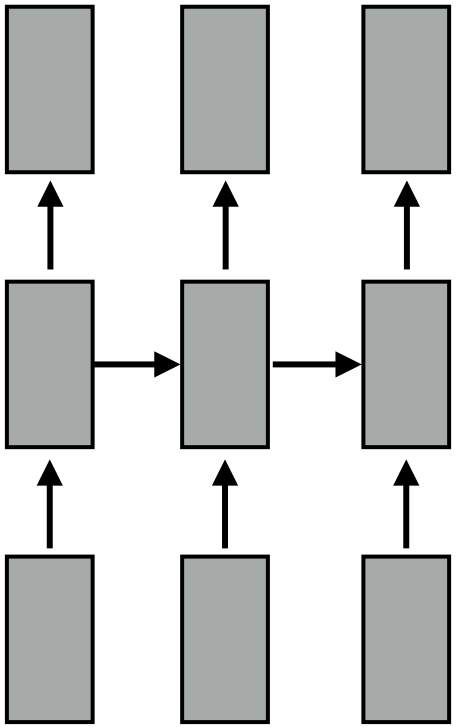
many to one



temporal classification

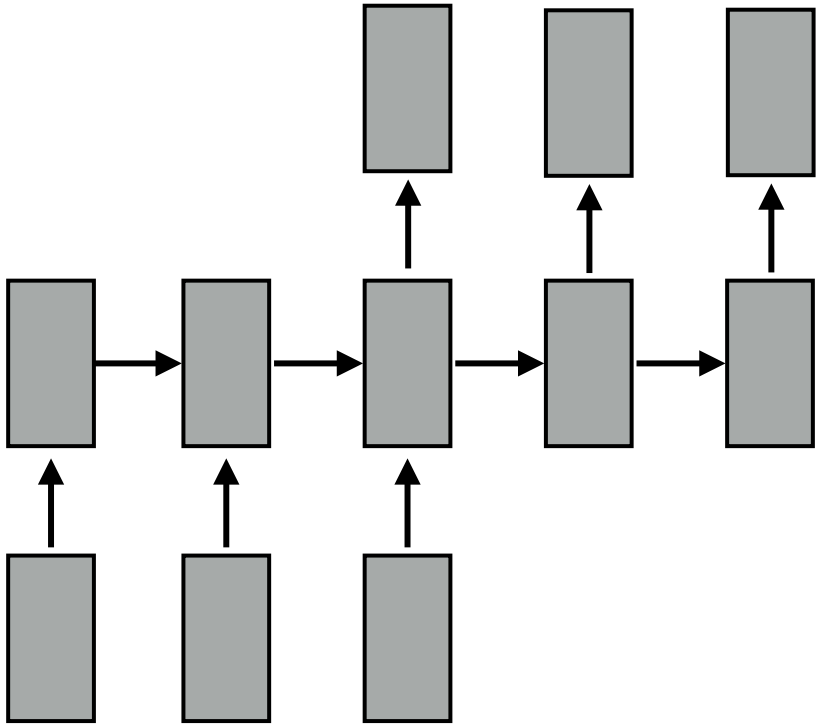
# Sequence to sequence mapping (cont.)

many to many



video
frame labeling

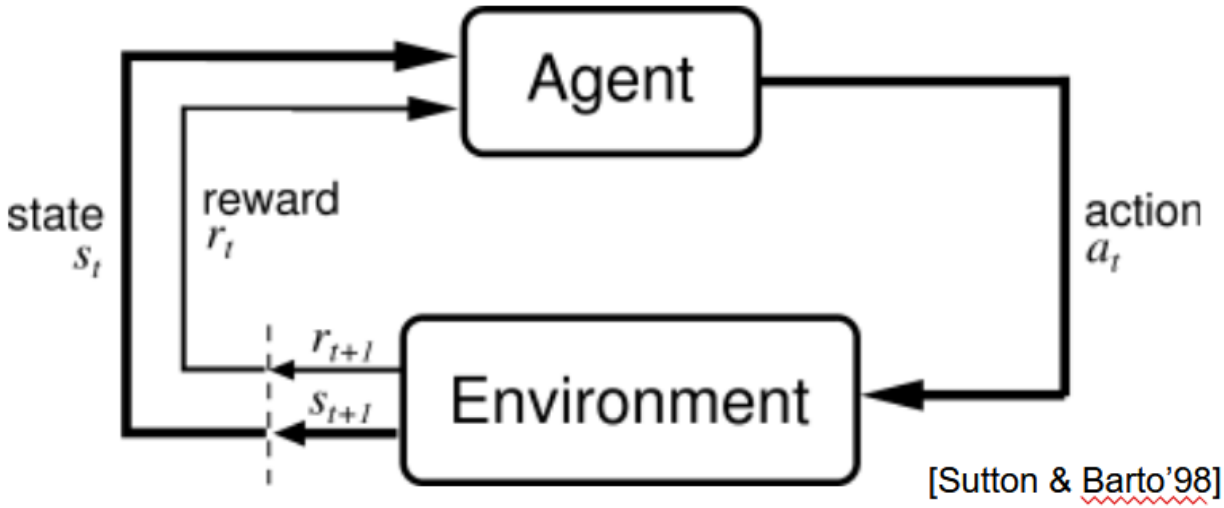
many to many



automatic
translation

# Lecture Overview

# Reinforcement Learning




- Finding optimal policies for MDPs
- Reminder: states $s \in S$, actions $a \in A$, transition model $T$, rewards $r$
- Policy: complete mapping $\pi : S \rightarrow A$ that specifies for each state $s$ which action $\pi(s)$ to take

# Deep Reinforcement Learning

- Policy-based deep RL
  - Represent policy $\pi : S \rightarrow A$ as a deep neural network with weights $w$
  - Evaluate $w$ by "rolling out" the policy defined by $w$
  - Optimize weights to obtain higher rewards (using approx. gradients)
  - Examples: AlphaGo & modern Atari agents

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$\to$ Use deep neural networks to represent policy / value function / model

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  - Computer vision (from raw pixels)
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  - No top-down reasoning
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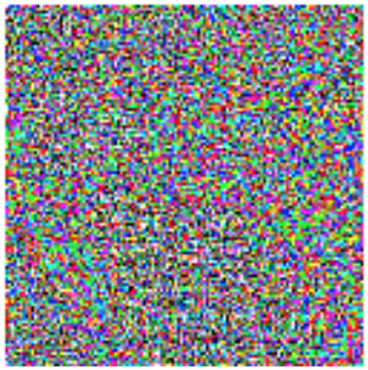
  - Although there are some modern works on memory mechanisms, attention, etc.
- Deep networks can be combined with more traditional methods
  - E.g., AlphaGo: combination with Monte Carlo Tree Search (MCTS)
  - Some work on combining logic with deep learning

# Adversarial examples: we're very far from human-level performance

$+ .007 \times$



$=$

| $\boldsymbol{x}$ | $\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$ | $\boldsymbol{x} + \epsilon \text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$ |
|---|---|---|
| $y =$"panda" | "nematode" | "gibbon" |
| w/ 57.7% | w/ 8.2% | w/ 99.3% |
| confidence | confidence | confidence |

- Even for very strong networks we can find adversarial examples
  - By following the gradient of the cost function w.r.t the input

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- Allows end-to-end learning
  - no more need for many complicated subsystems
  - e.g., dramatically simplified Google's translation pipeline
- Very versatile/flexible
  - easy to combine building blocks
  - allows supervised, unsupervised, and reinforcement learning

# Lots of Work on Deep Learning in Freiburg

- Computer Vision (Thomas Brox)
  - Images, video
- Robotics (Wolfram Burgard)
  - Navigation, grasping, object recognition
- Neurorobotics (Joschka Boedecker)
  - Robotic control
- Machine Learning (Frank Hutter)
  - Foundations: optimization, neural architecture search, learning to learn
- Neuroscience (Tonio Ball, Michael Tangermann, and others )
  - EEG data and other applications from BrainLinks-BrainTools

$\rightarrow$ Details when the individual groups present their research

# Summary by learning goals

Having heard this lecture, you can now . . .

- Explain the terms representation learning and deep learning
- Explain why deep learning is so popular
- Describe the main principles behind MLPs
- Discuss some limitations of deep learning
- On a high level, describe
  - Convolutional Neural Networks
  - Recurrent Neural Networks
  - Deep Reinforcement Learning