

Lecture 15: Deep Learning

Machine Learning, Summer Term 2019

July 11, 2019

Michael Tangermann Frank Hutter Marius Lindauer

University of Freiburg



Motivation: Deep Learning in the News

The New York Times

Science

WORLD U.S. N.Y. / REGION BUSINESS TECHNOLOGY SCIENCE HEALTH SPORTS OPINION ENVIRONMENT SPACE & COSMOS



Scientists See Promise in Deep-Learning



A voice recognition program translated a speech given by Richard F. Rashid. [Read more](#)

By JOHN MARKOFF
Published: November 23, 2012

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

THE NEW YORKER

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SEARCH

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

Introduction Past Years The 10 Technologies

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

- 1 Motivation: Why is Deep Learning so Popular?
- 2 Representation Learning and Deep Learning
- 3 Multilayer Perceptrons
- 4 Optimization of Neural Networks in a Nutshell
- 5 Overview of Some Advanced Topics
 - Convolutional neural networks
 - Recurrent neural networks
 - Deep reinforcement learning
- 6 Limitations
- 7 Wrapup

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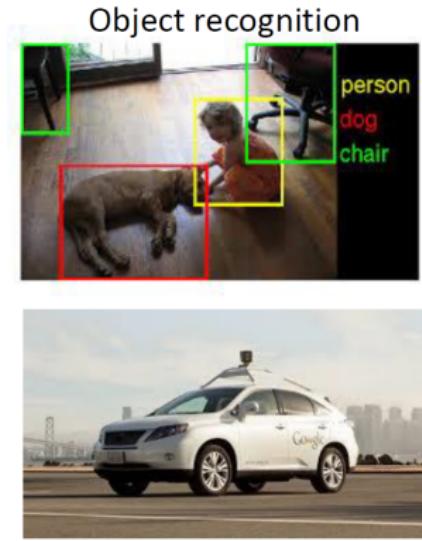
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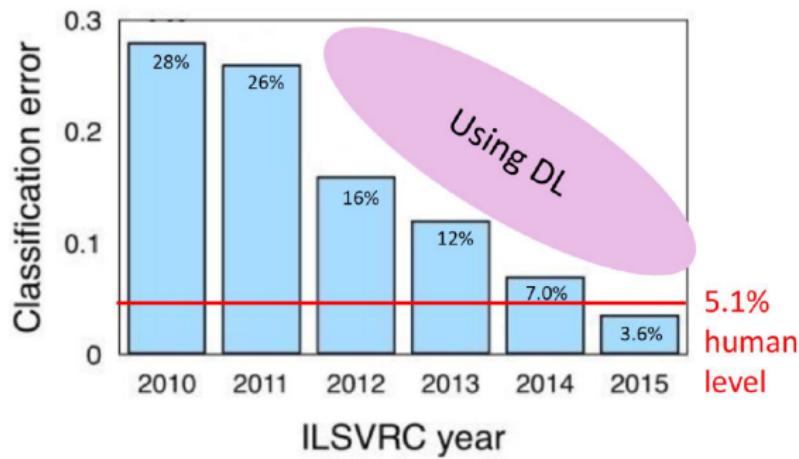
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Motivation: Why is Deep Learning so Popular?

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



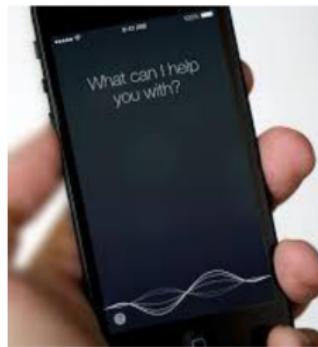
Object recognition
Self-driving cars



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Speech recognition



Auto-Translator

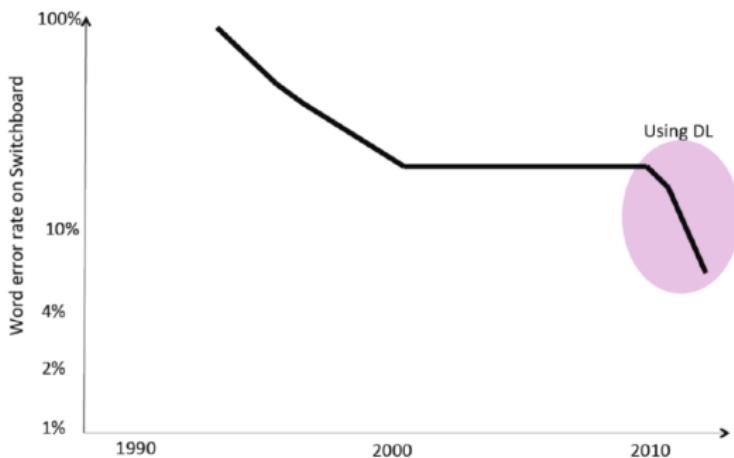
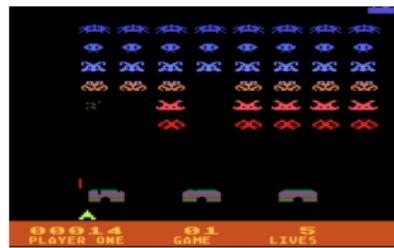


Image credit: Yoshua Bengio (data from Microsoft speech group)

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."

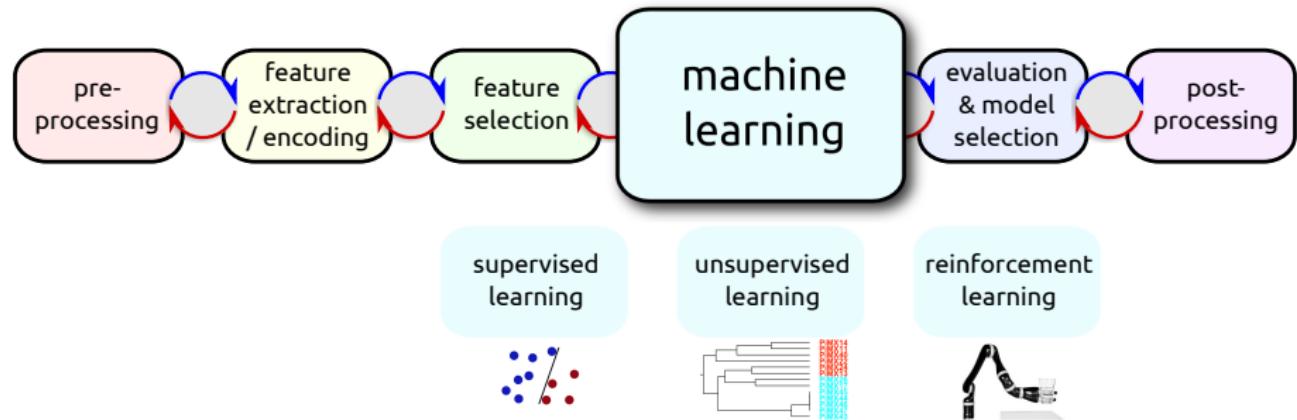
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- Learning from data / experience may be more human-like
 - Babies develop an intuitive understanding of physics in their first 2 years
 - Formal reasoning and logic comes **much** later in development

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

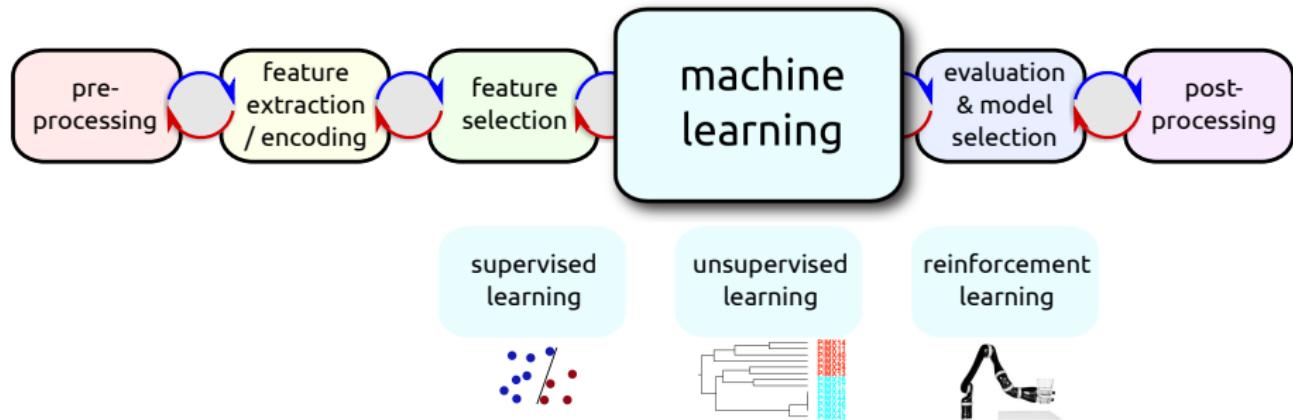
- Learning from data / experience may be more human-like
 - Babies develop an intuitive understanding of physics in their first 2 years
 - Formal reasoning and logic comes **much** later in development
- Learning enables **fast reaction times**
 - It might take a long time to train a neural network
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

Deep Learning in the ML Design Cycle



- Much reduced need for preprocessing
- No more need for manual feature engineering (extraction & selection)
 - useful features are learned automatically

Deep Learning in the ML Design Cycle



- Much reduced need for preprocessing
- No more need for manual feature engineering (extraction & selection)
 - useful features are learned automatically
- End-to-end training:
 - replacing most of the ML pipeline by a single approach
 - directly optimizing a single loss function

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From fixed basis functions to learned representations

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vs

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- **Representation Learning:** parametrize basis functions and adapt to the data to discover useful representations automatically

Representation learning

“a set of methods that allows a machine to be fed with raw data and to automatically discover the representations needed for detection or classification”

Some definitions

Representation learning

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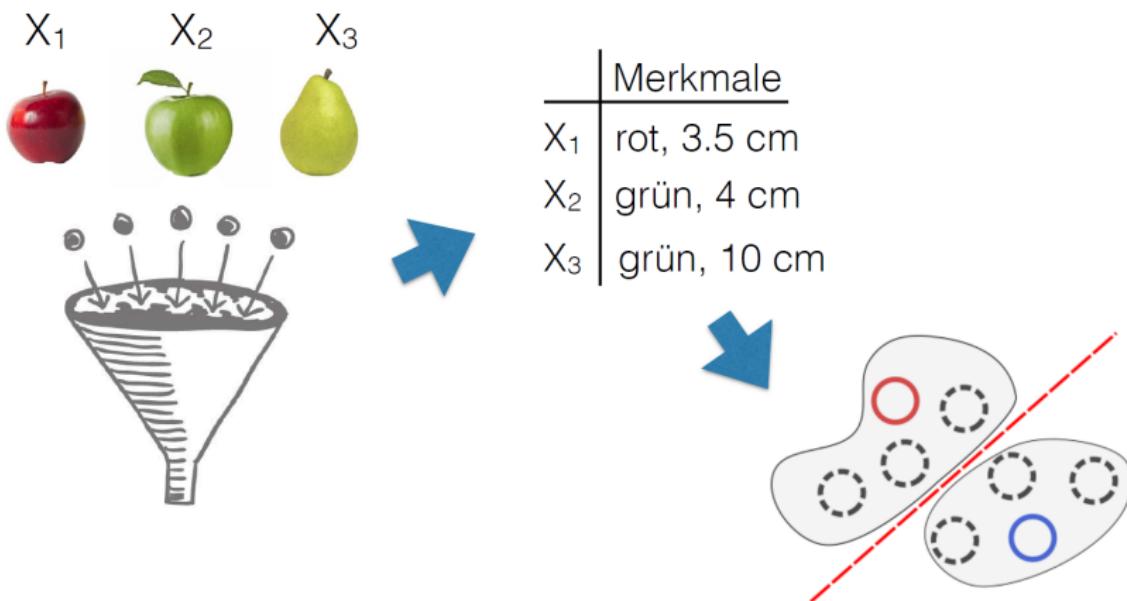
Deep learning

“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)

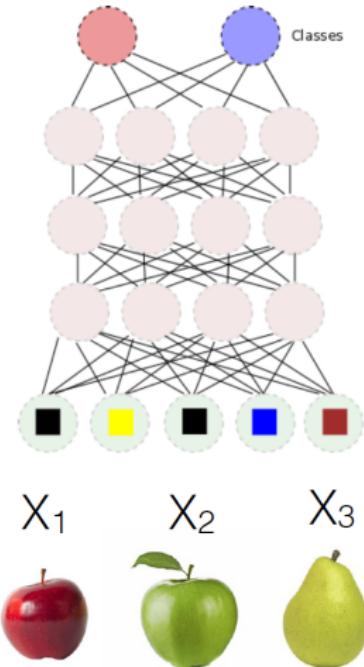
Standard Machine Learning Pipeline

- 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**

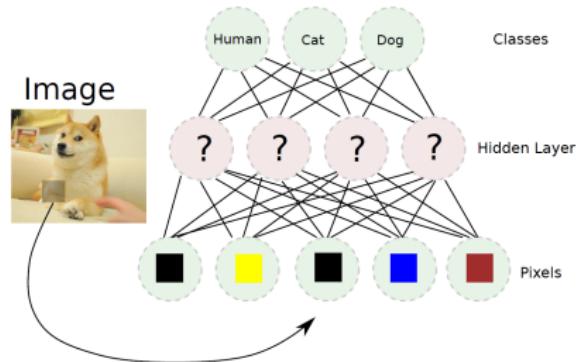


Representation Learning Pipeline

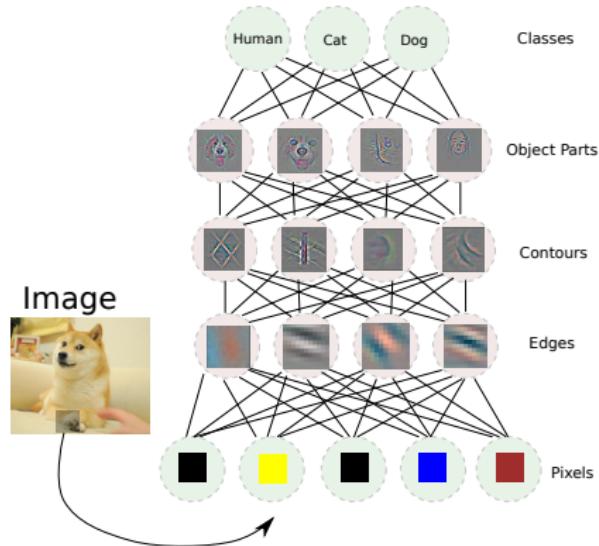
- Jointly learn features and classifier, directly from raw data
- This is also referred to as **end-to-end learning**



Shallow vs. Deep Learning

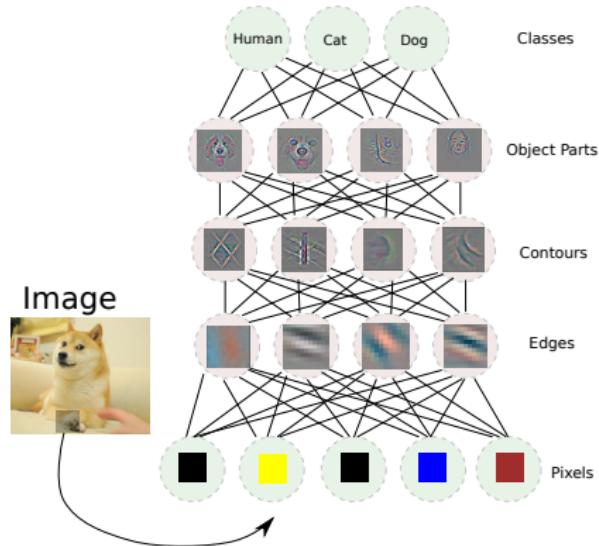


Shallow vs. Deep Learning



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

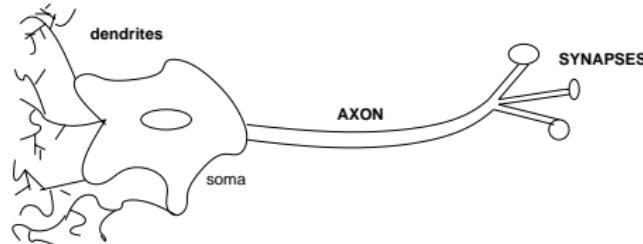
Shallow vs. Deep Learning



- **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 dendrites of other cells via synapses
- Learning: adaptation of the synapse's efficiency, its synaptic 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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- Alternative theoretically motivated methods outperformed NNs
 - Exaggerated 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

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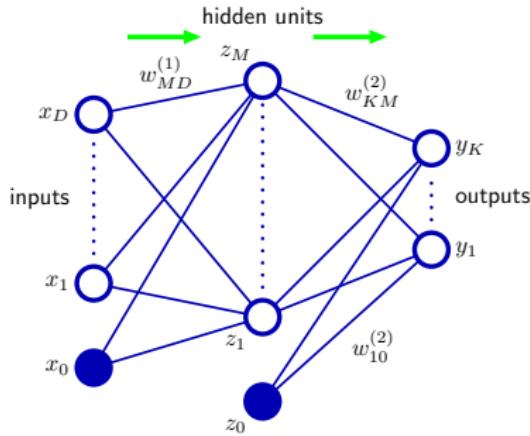
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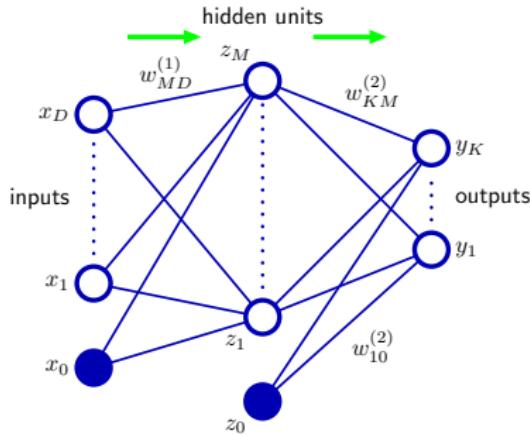
Multilayer Perceptrons



[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 \mathbf{z}_{k-1} : $\mathbf{a}_k = \mathbf{W}_k \mathbf{z}_{k-1} + \mathbf{b}_k$
 - Nonlinear transformation $\mathbf{z}_k = h_k(\mathbf{a}_k)$ through **activation function** h_k

Multilayer Perceptrons



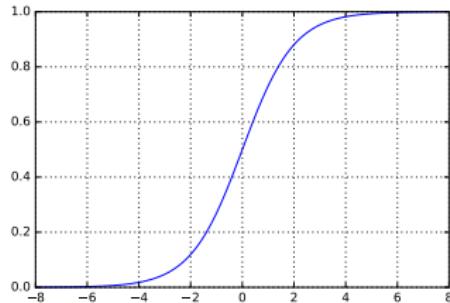
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- **Parameters/weights w** of the network: all $\mathbf{W}_k, \mathbf{b}_k$, flattened into a single vector

Activation Functions - Examples

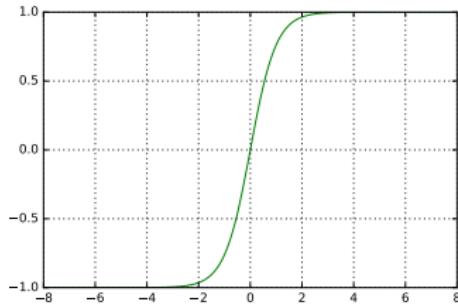
Logistic sigmoid activation function:

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



Logistic hyperbolic tangent activation function:

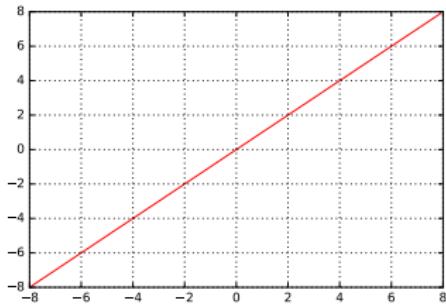
$$\begin{aligned} h_{tanh}(a) &= \tanh(a) \\ &= \frac{\exp(a) - \exp(-a)}{\exp(a) + \exp(-a)} \end{aligned}$$



Activation Functions - Examples (cont.)

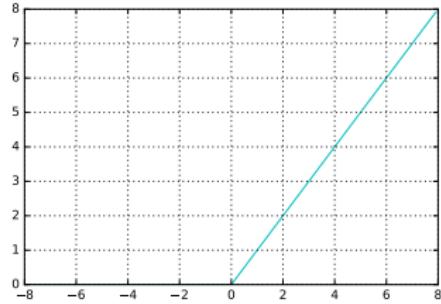
Linear activation function:

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



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

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

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

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

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- For classification:

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

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

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

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

Optimizing a loss / error function

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

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

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

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Optimization theory

- A **global minimum** \mathbf{u}^* is a point such that:

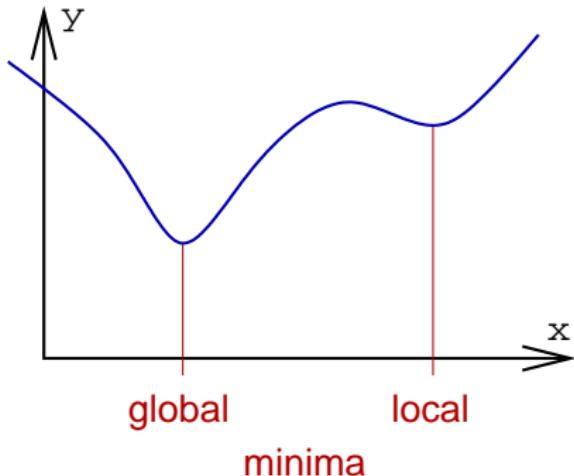
$$f(\mathbf{u}^*) \leq f(\mathbf{u})$$

for all \mathbf{u} .

- A **local minimum** \mathbf{u}^+ is a point such that exist $r > 0$ with

$$f(\mathbf{u}^+) \leq f(\mathbf{u})$$

for all points \mathbf{u} with
 $\|\mathbf{u} - \mathbf{u}^+\| < r$



Optimization theory (cont.)

- Analytical way to find a minimum:

For a local minimum \mathbf{u}^+ , the gradient of f becomes zero:

$$\frac{\partial f}{\partial u_i}(\mathbf{u}^+) = 0 \quad \text{for all } i$$

Hence, calculating all partial derivatives and looking for zeros is a good idea

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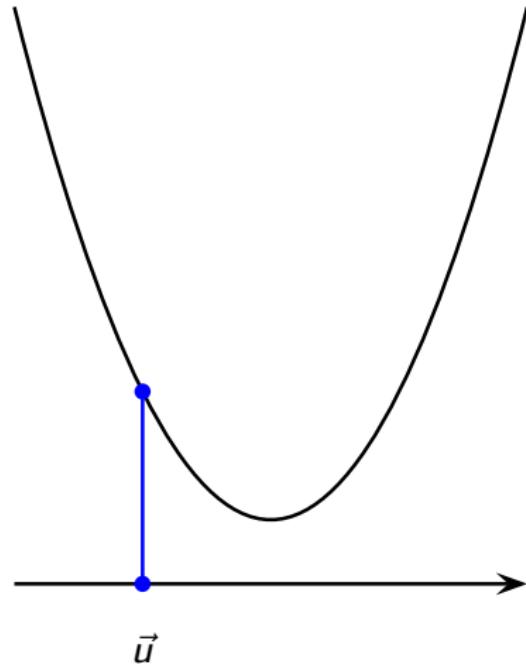
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Hence, calculating all partial derivatives and looking for zeros is a good idea

- But: for neural networks, we can't write down a solution for the minimization problem in closed form
 - even though $\frac{\partial f}{\partial u_i} = 0$ holds at (local) solution points
 - need to resort to iterative methods

Optimization theory (cont.)

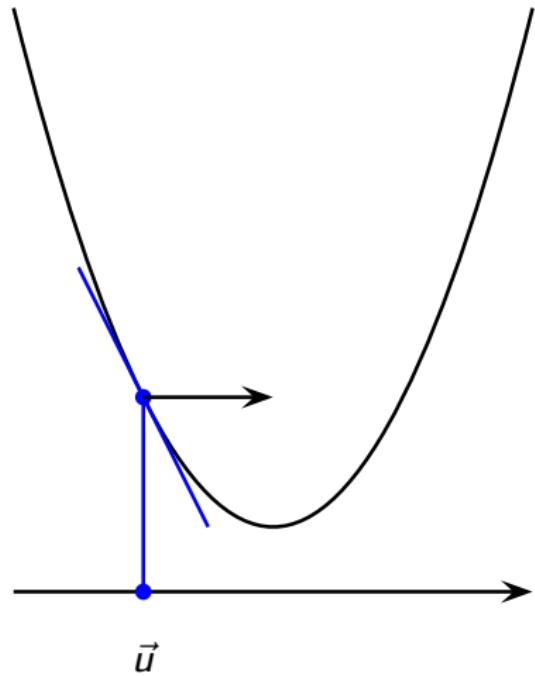
- Numerical way to find a minimum, searching:
assume we start at point \mathbf{u} .
Which is the best direction to search for a point \mathbf{v} with
 $f(\mathbf{v}) < f(\mathbf{u})$?



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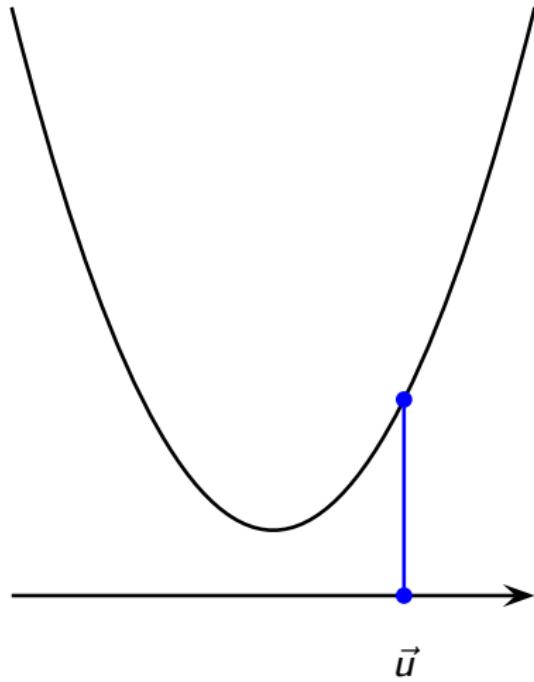


slope is negative (descending), go right!

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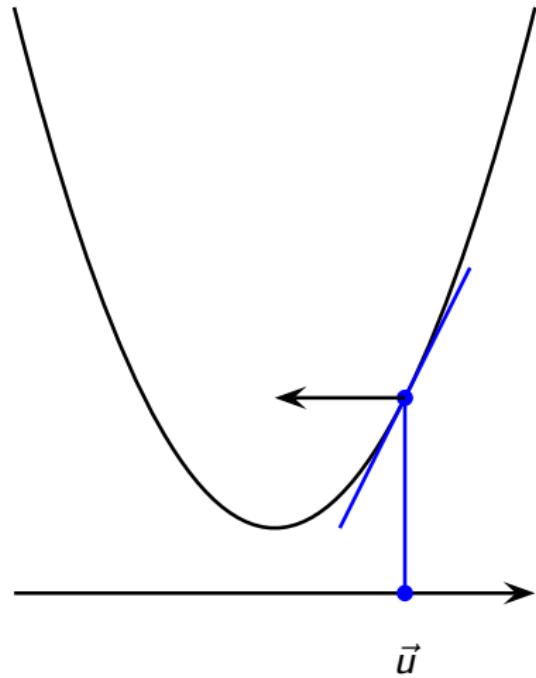
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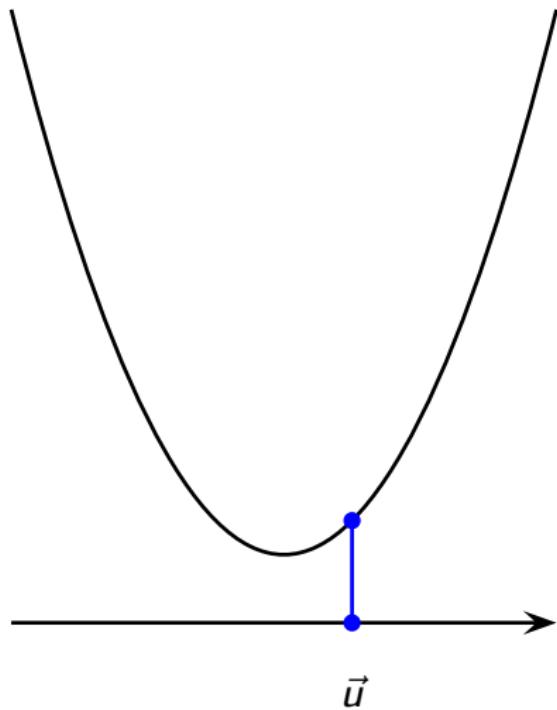
slope is positive (ascending), go left!

Optimization theory (cont.)

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Which is the best stepwidth?

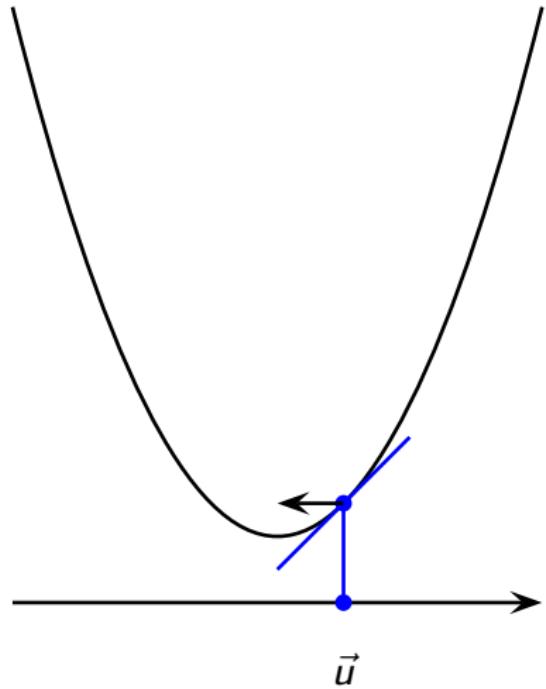


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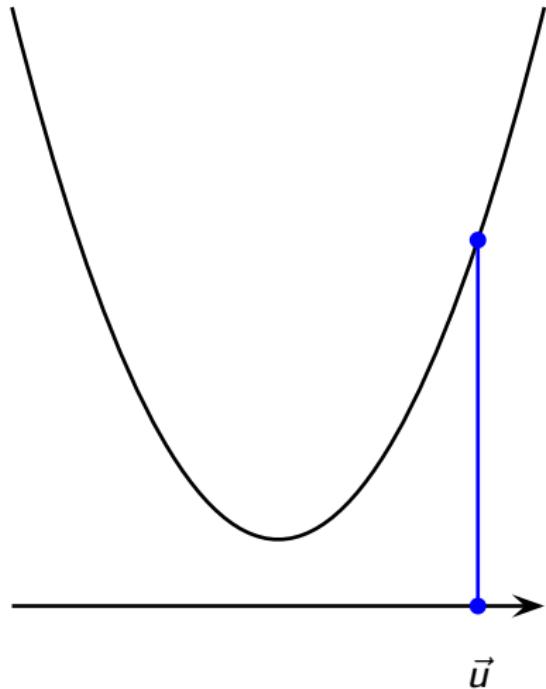
slope is small, small step!

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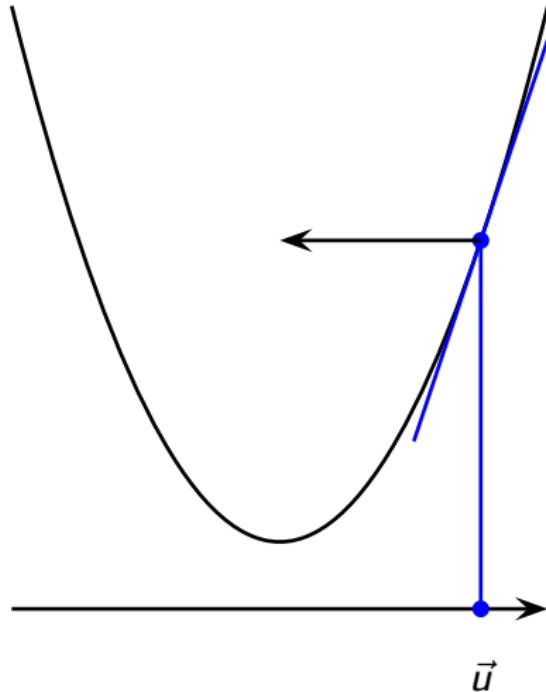


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slope is large, large step!

Optimization theory (cont.)

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Which is the best stepwidth?

- general principle:

$$v_i \leftarrow u_i - \epsilon \frac{\partial f}{\partial u_i}$$

$\epsilon > 0$ is called learning rate

Gradient descent

- Gradient descent approach:

Require: mathematical function f , learning rate $\epsilon > 0$

Ensure: returned vector is close to a local minimum of f

- 1: choose an initial point \mathbf{u}
- 2: **while** $\|grad f(\mathbf{u})\|$ not close to 0 **do**
- 3: $\mathbf{u} \leftarrow \mathbf{u} - \epsilon \cdot grad f(\mathbf{u})$
- 4: **end while**
- 5: **return** \mathbf{u}

Calculating partial derivatives

- Our typical loss functions are defined across data points:

$$L(\mathbf{w}) = \sum_{n=1}^N L_n(\mathbf{w}) = L(f(\mathbf{x}_n; \mathbf{w}), y_n)$$

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- The method of **backpropagation** makes consistent use of the **chain rule** of calculus to compute the partial derivatives $\frac{\partial L_n}{\partial w_j}$ w.r.t. each network weight w_j , **re-using previously computed results**
 - Backpropagation is not covered here, but, e.g., in ML lecture

Do we need gradients based on the entire data set?

- Using the entire set is referred to as **batch gradient descent**

Do we need gradients based on the entire data set?

- Using the entire set is referred to as **batch gradient descent**
- Gradients get more accurate when based on more data points
 - But using more data has diminishing returns w.r.t reduction in error
 - Usually **faster progress** by **updating more often** based on cheaper, less accurate estimates of the gradient

Do we need gradients based on the entire data set?

- Using the entire set is referred to as **batch gradient descent**
- Gradients get more accurate when based on more data points
 - But using more data has diminishing returns w.r.t reduction in error
 - Usually **faster progress** by **updating more often** based on cheaper, less accurate estimates of the gradient
- Common approach in practice: compute gradients over **mini-batches**
 - Mini-batch: small subset of the training data
 - Today, this is commonly called **stochastic gradient descent (SGD)**

Stochastic gradient descent

- Stochastic gradient descent (SGD)

Require: mathematical function f , learning rate $\epsilon > 0$

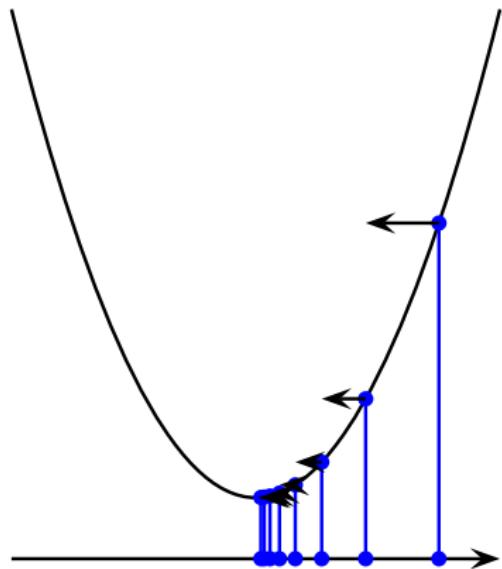
Ensure: returned vector is close to a local minimum of f

- 1: choose an initial point \mathbf{w}
- 2: **while** stopping criterion not met **do**
- 3: Sample a minibatch of m examples $\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(m)}$ with corresponding targets $\mathbf{y}^{(i)}$ from the training set
- 4: Compute gradient $\mathbf{g} \leftarrow \frac{1}{m} \nabla_{\mathbf{w}} \sum_{i=1}^m L(f(\mathbf{x}^{(i)}; \mathbf{w}), \mathbf{y}^{(i)})$
- 5: Update parameter: $\mathbf{w} \leftarrow \mathbf{w} - \epsilon \cdot \mathbf{g}$
- 6: **end while**
- 7: **return** \mathbf{w}

- Note: $\nabla_{\mathbf{w}} L := [\frac{\partial L}{\partial w_1}, \dots, \frac{\partial L}{\partial w_K}]$ for K weights

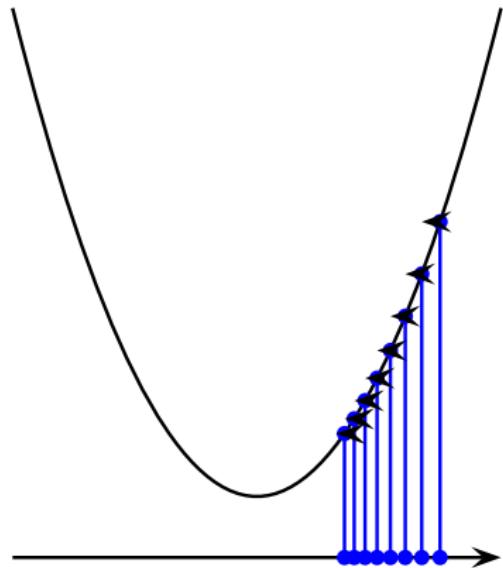
Problems with suboptimal choices for learning rate

- choice of ϵ
 - case small ϵ : convergence



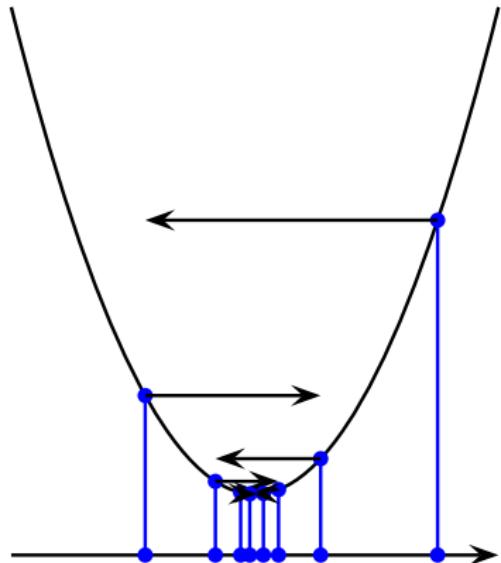
Problems with suboptimal choices for learning rate

- choice of ϵ
 - 2. case very small ϵ : convergence, but it may take very long



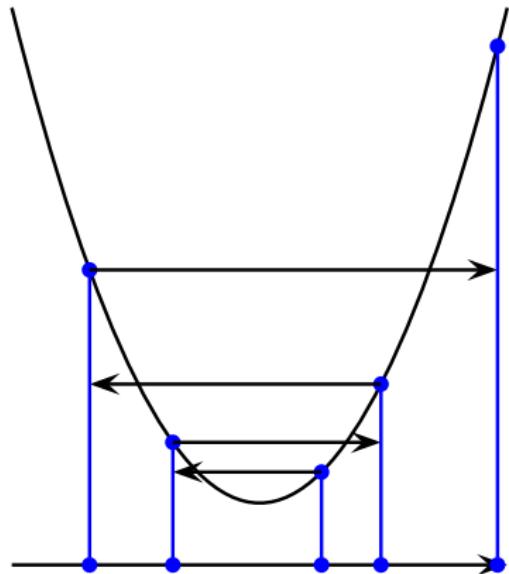
Problems with suboptimal choices for learning rate

- choice of ϵ
 - 3. case medium size ϵ : convergence



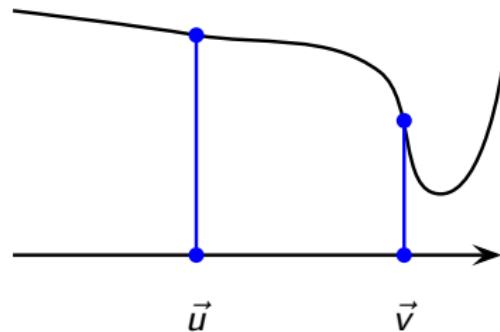
Problems with suboptimal choices for learning rate

- choice of ϵ
 - 4. case large ϵ : divergence



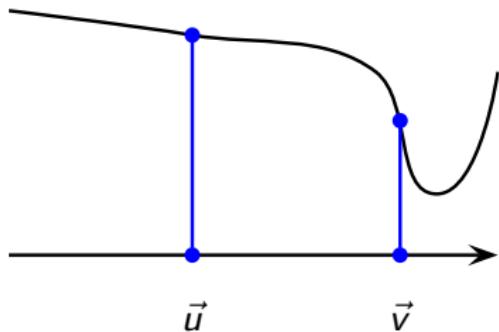
Other reasons for problems with gradient descent

- flat spots and steep valleys:
need larger ϵ in \mathbf{u} to jump over
the uninteresting flat area but
need smaller ϵ in \mathbf{v} to meet the
minimum

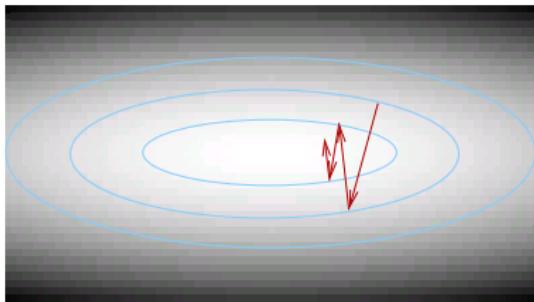


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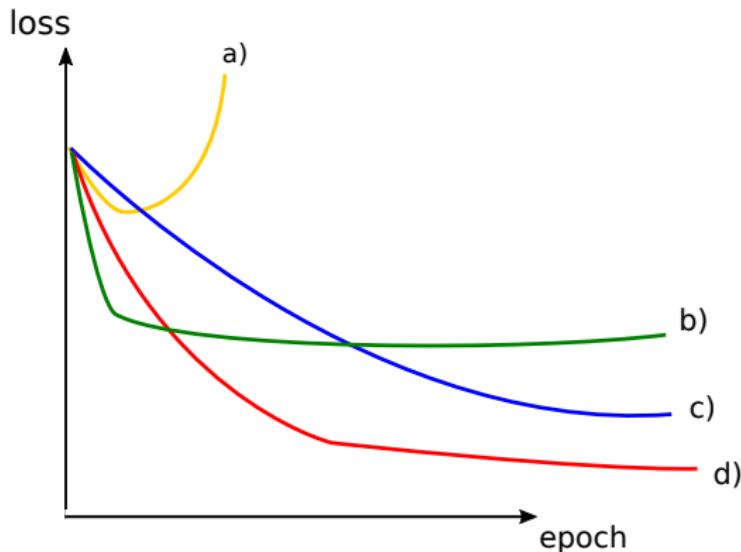


- zig-zagging:
in higher dimensions: ϵ is not
appropriate for all dimensions



Learning rate quiz

Which curve denotes low, high, very high, and good learning rate?



Gradient descent – Conclusion

- Pure gradient descent is a nice framework
- In practice, stochastic gradient descent is used
- Finding the right learning rate ϵ is tedious

Gradient descent – Conclusion

- Pure gradient descent is a nice framework
- In practice, stochastic gradient descent is used
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Heuristics to overcome problems of gradient descent:

- Gradient descent with **momentum**
- Individual learning rates for each dimension
- Adaptive learning rates
- Decoupling steplength from partial derivates

Lecture Overview

1 Motivation: Why is Deep Learning so Popular?

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5 Overview of Some Advanced Topics

- Convolutional neural networks
- Recurrent neural networks
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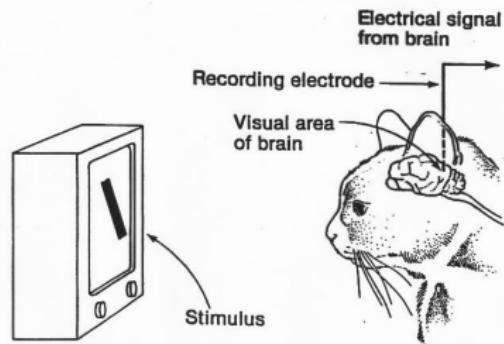
6 Limitations

7 Wrapup

Historical context and inspiration from Neuroscience

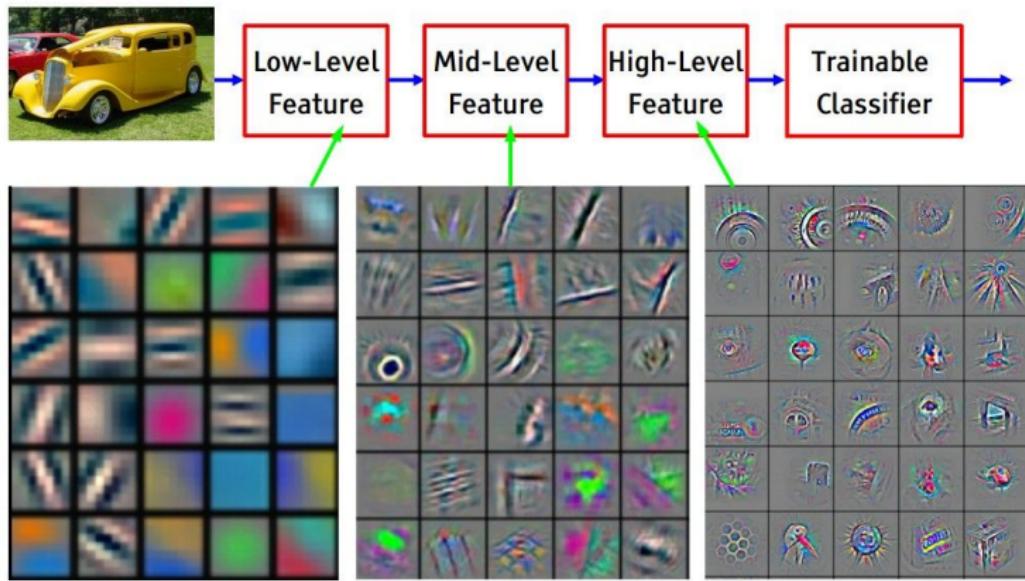
Hubel & Wiesel (Nobel prize 1981) found in several studies in the 1950s and 1960s:

- 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

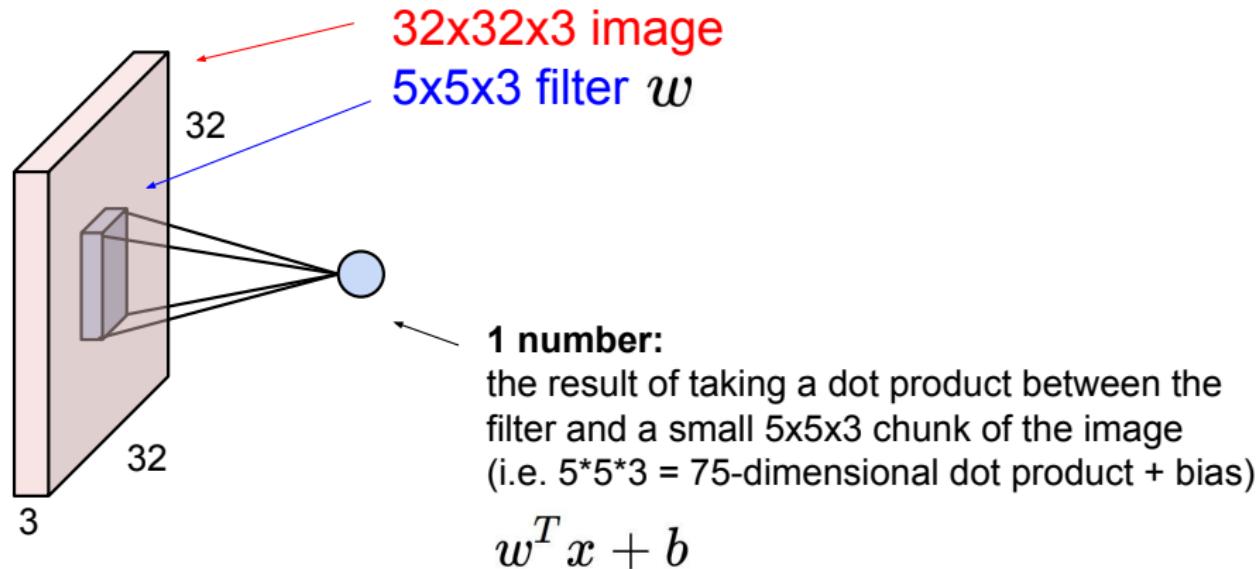
[From recent Yann LeCun slides]



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

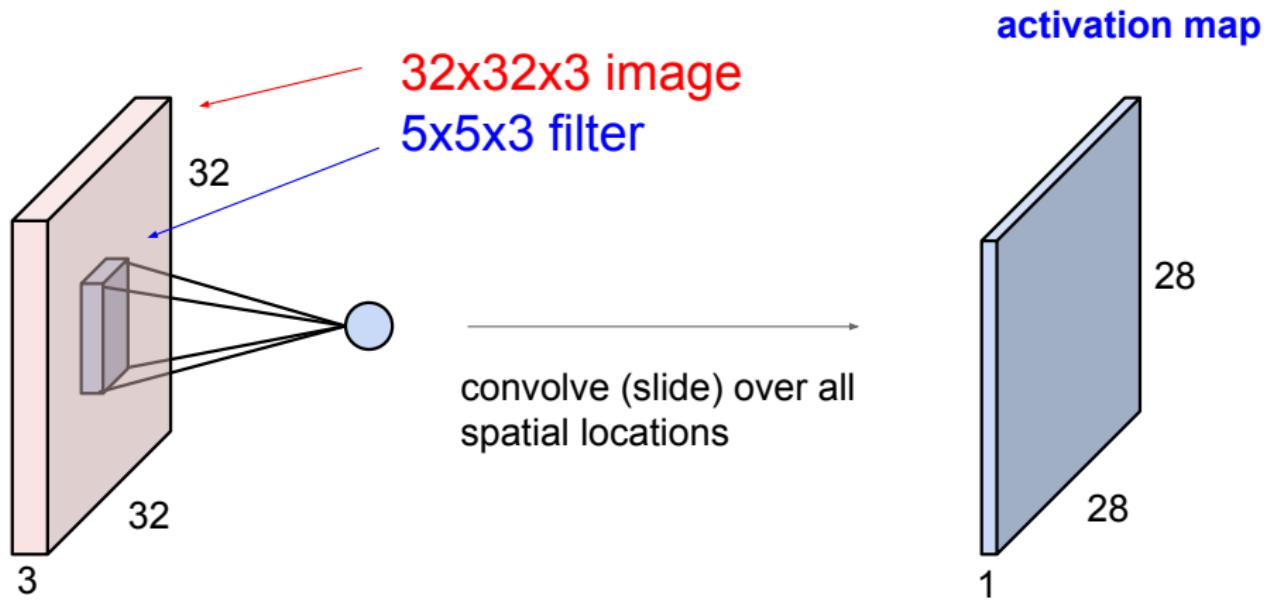
[slide credit: Andrej Karpathy]

Convolutions illustrated



[slide credit: Andrej Karpathy]

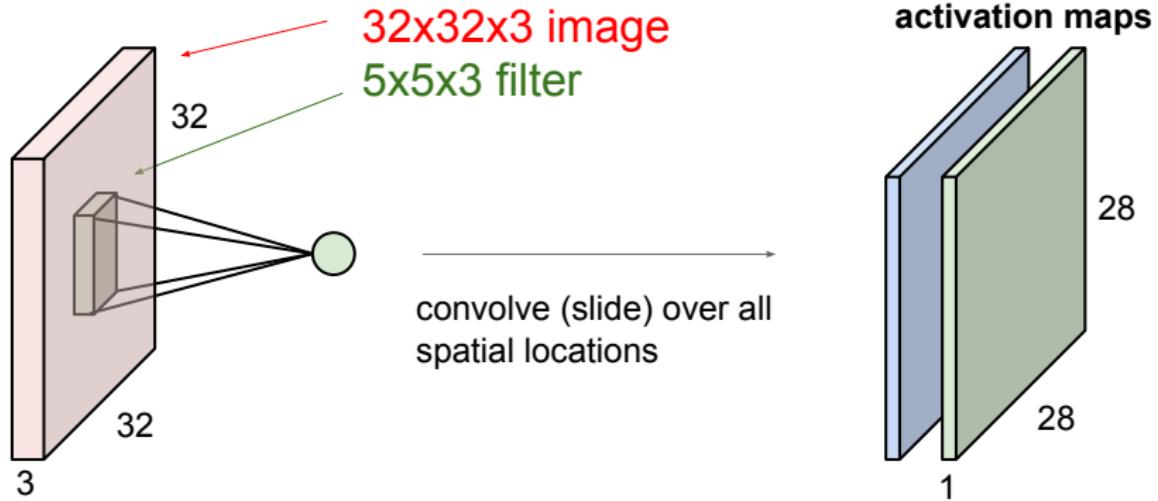
Convolutions illustrated (cont.)



[slide credit: Andrej Karpathy]

Convolutions – several filters

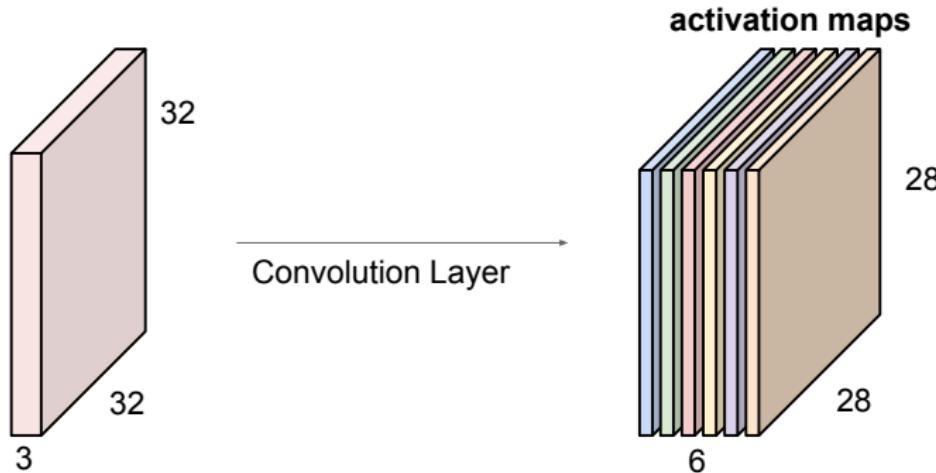
consider a second, green filter



[slide credit: Andrej Karpathy]

Convolutions – several filters

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

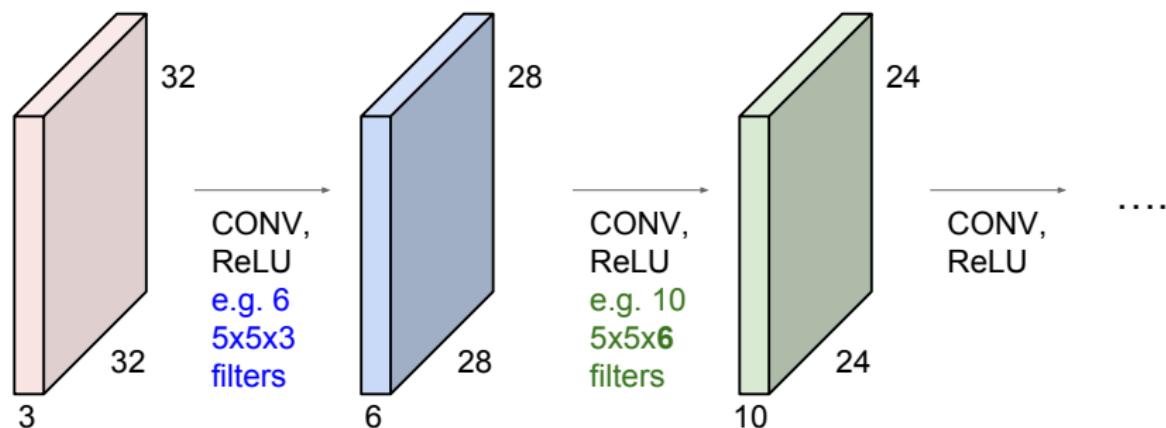


We stack these up to get a “new image” of size 28x28x6!

[slide credit: Andrej Karpathy]

Stacking several convolutional layers

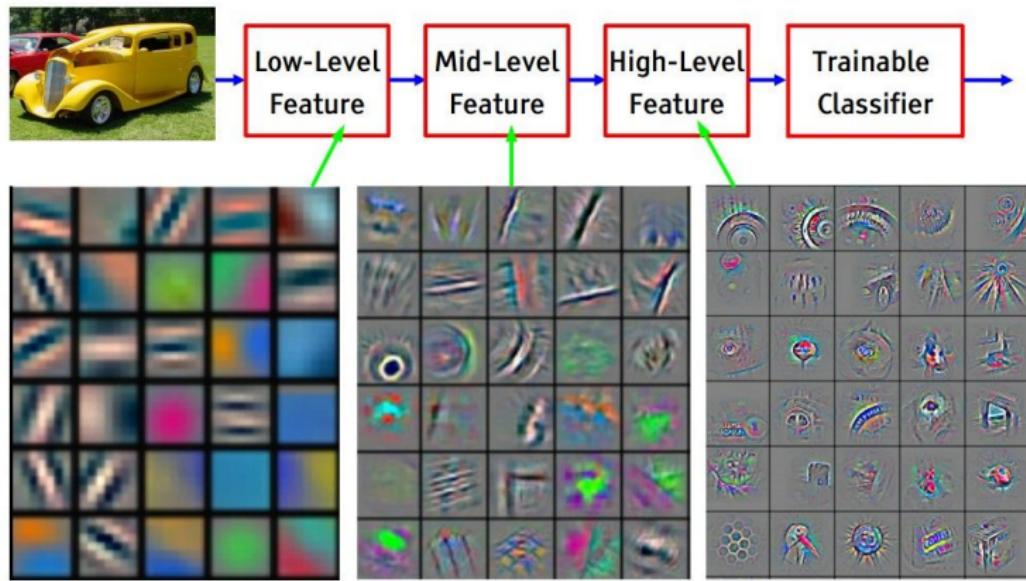
Convolutional layers stacked in a ConvNet



[slide credit: Andrej Karpathy]

Learned feature hierarchy

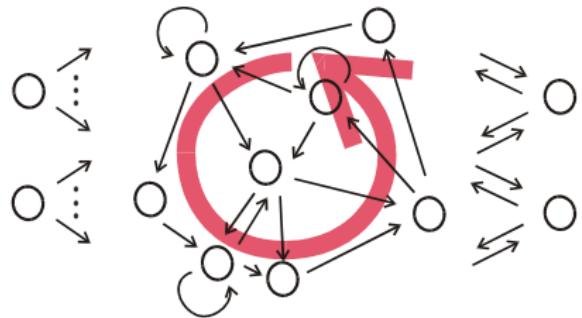
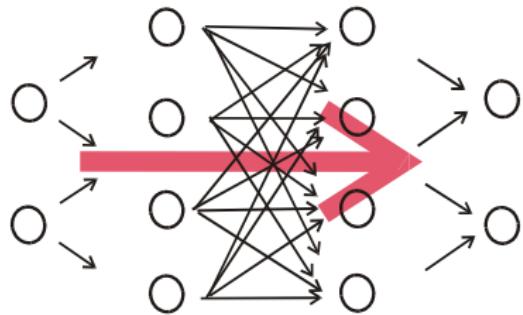
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Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

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Feedforward vs Recurrent Neural Networks



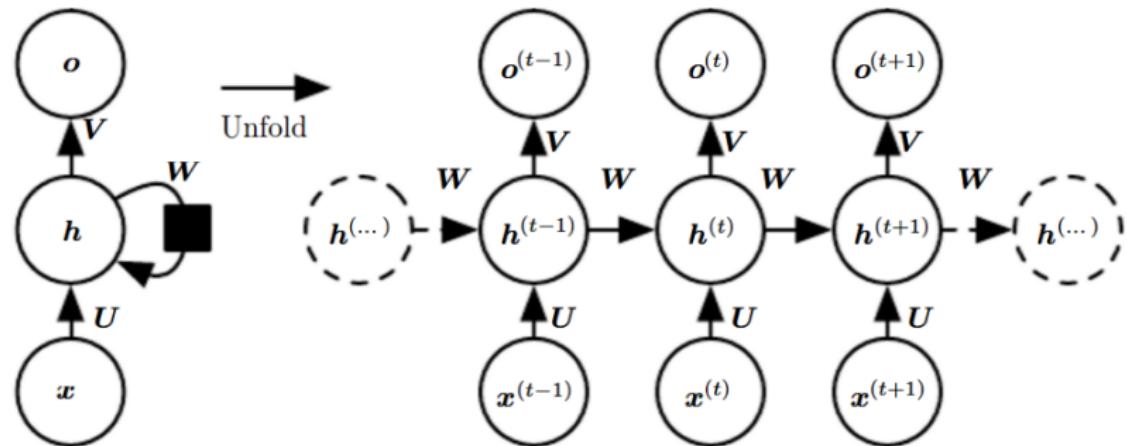
[Source: Jaeger, 2001]

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

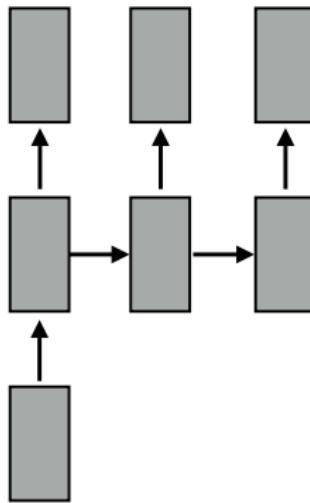
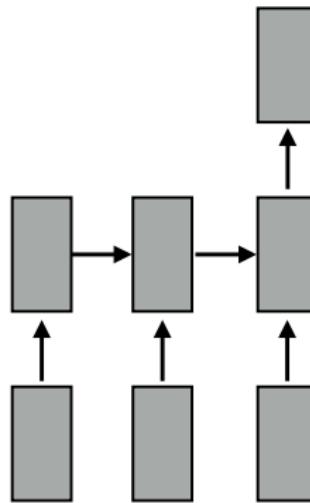


image caption
generation

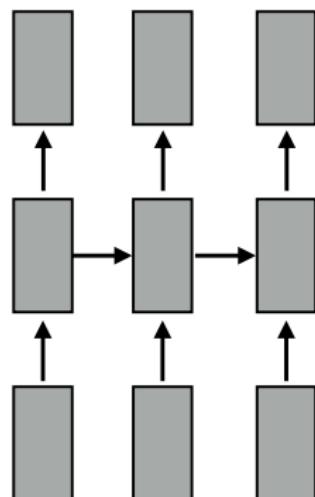
many to one



temporal
classification

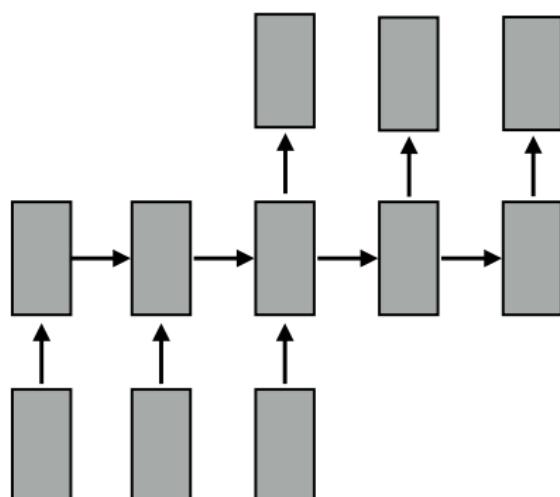
Sequence to sequence mapping (cont.)

many to many



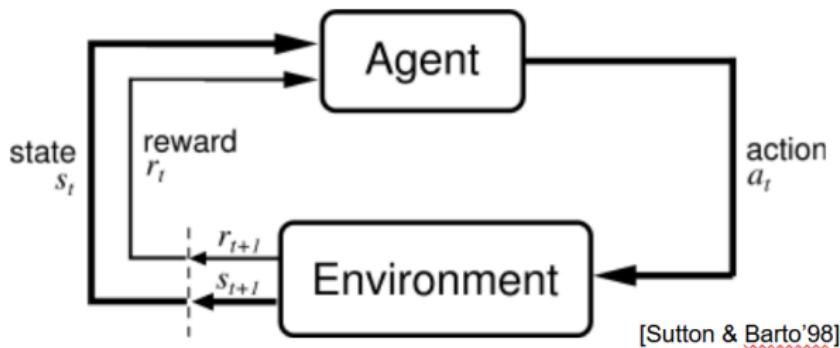
video
frame labeling

many to many



automatic
translation

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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- Basically value iteration, but using a deep neural network (= function approximator) to generalize across many states and actions
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→ Use deep neural networks to represent policy / value function / model

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Deep Learning Focuses on Perception

- Excellent results for perception tasks from raw data
 - Computer vision (from raw pixels)
 - Speech recognition (from raw audio)
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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 ×



=



\mathbf{x}

$y = \text{"panda"}$
w/ 57.7%
confidence

$\text{sign}(\nabla_{\mathbf{x}} J(\boldsymbol{\theta}, \mathbf{x}, y))$

"nematode"
w/ 8.2%
confidence

$\mathbf{x} + \epsilon \text{sign}(\nabla_{\mathbf{x}} J(\boldsymbol{\theta}, \mathbf{x}, y))$

"gibbon"
w/ 99.3%
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
- 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