Foundations of Artificial Intelligence

14. Deep Learning
Learning from Raw Data

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Scientists See Promise in Deep-Learning

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...
Lecture Overview

1 Motivation: Why is Deep Learning so Popular?
2 Representation Learning and Deep Learning
3 Multilayer Perceptrons
4 Overview of Some Advanced Topics
5 Limitations
6 Wrapup
Lecture Overview

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Motivation: Why is Deep Learning so Popular?

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

Object recognition

Self-driving cars

![Diagram showing classification error over years with percentages decreasing from 28% to 3.6% starting in 2010 and ending in 2015. The year 2015 is highlighted with 5.1% human level classification error.]
Motivation: Why is Deep Learning so Popular?

- Excellent empirical results, e.g., in speech recognition

Speech recognition

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

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

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- 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.”
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
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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
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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**
“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”

**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

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<th>X₂</th>
<th>X₃</th>
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Representation Learning Pipeline

- Jointly learn features and classifier, directly from raw data
- This is also referred to as end-to-end learning
Deep Learning: learning a hierarchy of representations that build on each other, from simple to complex
- **Deep Learning**: learning a hierarchy of representations that build on each other, from simple to complex
- Quintessential deep learning model: **Multilayer Perceptrons**
• **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 **synaptical weight**
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)
A Very Brief History of Neural Networks

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  - 1942: artificial neurons (McCulloch/Pitts)
  - 1958/1969: perceptron (Rosenblatt; Minsky/Papert)
  - 1986: multilayer perceptrons and backpropagation (Rumelhart)
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- Alternative theoretically motivated methods outperformed NNs
  - Exaggerated expectations: “It works like the brain” (No, it does not!)
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- 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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Multilayer Perceptrons

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 $h_k$
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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:

\[ h_{\text{logistic}}(a) = \frac{1}{1 + \exp(-a)} \]

Logistic hyperbolic tangent activation function:

\[ h_{\text{tanh}}(a) = \tanh(a) = \frac{\exp(a) - \exp(-a)}{\exp(a) + \exp(-a)} \]
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
    \[ \hat{y}(x, w) = h_{\text{linear}}(a) = a \]
  - Loss function: e.g., squared error:
    \[ L(w) = \frac{1}{2} \sum_{n=1}^{N} \{ \hat{y}(x_n, w) - y_n \}^2 \]
Output layer and loss functions

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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):
    \[ L(w) = - \sum_{n=1}^{N} \{ y_n \ln \hat{y}_n + (1 - y_n) \ln(1 - \hat{y}_n) \} \]
Given training data $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ and topology of an MLP

Task: adapt weights $w$ to minimize the loss:

$$\minimize_w L(w; \mathcal{D})$$
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:

$$\min_w L(w; \mathcal{D})$$

- We optimize this function by gradient-based optimization
  - We can compute gradients of $L(w; \mathcal{D})$
    - Efficiently, using a technique called backpropagation
Given training data $D = \langle (x_i, y_i) \rangle_{i=1}^{N}$ and topology of an MLP

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$$\min_w L(w; D)$$

We optimize this function by gradient-based optimization

- We can compute gradients of $L(w; D)$
  - Efficiently, using a technique called backpropagation
- Stochastic gradient descent (SGD)
  - We can use small batches of the data, i.e., $L(w; D_{batch})$
  - This yields approximate gradients quickly
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Motivation: Why is Deep Learning so Popular?

Representation Learning and Deep Learning

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Overview of Some Advanced Topics

Limitations

Wrapup
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

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

[slide credit: Andrej Karpathy]
Convolution Layer

A 32x32x3 image

A 5x5x3 filter $w$

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

$$w^T x + b$$

[slide credit: Andrej Karpathy]
Convolutions illustrated (cont.)

32x32x3 image
5x5x3 filter

convolve (slide) over all spatial locations

activation map

[slide credit: Andrej Karpathy]
Convolutions – several filters

32x32x3 image
5x5x3 filter

convolve (slide) over all spatial locations

activation maps

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

[From recent Yann LeCun slides]

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

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Feedforward vs Recurrent Neural Networks

1. Recurrent Neural Networks
   1.1 First Impressions

There are two main differences between feedforward and recurrent neural networks in terms of their dynamics and operational principles. Recurrent neural networks (RNNs) are designed to maintain information about past inputs, allowing them to capture temporal patterns. This is achieved by introducing feedback connections that loop back to earlier layers, enabling the network to process sequential data over time.

In contrast, feedforward networks process data in a single direction, from input to output, without any feedback connections. This makes them ideal for tasks where the order of inputs is not crucial, but for tasks that involve sequences, such as speech recognition or natural language processing, RNNs are more suitable.

[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

temporal
classification

many to one
Sequence to sequence mapping (cont.)

Many to many

Video frame labeling

Automatic translation

(University of Freiburg)
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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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- **Value-based deep RL**
  - Basically value iteration, but using a deep neural network (= function approximator) to generalize across many states and actions
  - Approximate optimal state-value function $U(s)$
    or state-action value function $Q(s, a)$
Deep Reinforcement Learning

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**Model-based deep RL**
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- Approximate \( T \) with a deep neural network (learned from data)
- Plan using this approximate transition model
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→ Use deep neural networks to represent policy / value function / model
Motivation: Why is Deep Learning so Popular?

Representation Learning and Deep Learning

Multilayer Perceptrons

Overview of Some Advanced Topics

Limitations

Wrapup
Deep Learning Focuses on Perception

- Excellent results for perception tasks from raw data
  - Computer vision (from raw pixels)
  - Speech recognition (from raw audio)
  - Text recognition (from raw characters)
  - ...
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  - No top-down reasoning
  - No logic, planning, etc.
  - Although there are some modern works on memory mechanisms, attention, etc.
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- 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

Even for very strong networks we can find adversarial examples

- By following the gradient of the cost function w.r.t the input

\[ x + \epsilon \text{sign}(\nabla_x J(\theta, x, y)) = x + \epsilon \text{sign}(\nabla_x J(\theta, x, y)) \]

\[ x + 0.007 \times \text{sign}(\nabla_x J(\theta, x, y)) \]

\[ y = \text{“panda”} \quad \text{w/ 57.7% confidence} \]

\[ \text{“nematode”} \quad \text{w/ 8.2% confidence} \]

\[ \text{“gibbon”} \quad \text{w/ 99.3% confidence} \]
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Excellent empirical results in many domains
- very scalable to big data
- but beware: not a silver bullet
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Analogy to the ways humans process information
  - mostly tangential
Summary: Why is Deep Learning so Popular?

- Excellent empirical results in many domains
  - very scalable to big data
  - but beware: not a silver bullet

- Analogy to the ways humans process information
  - mostly tangential

- Allows end-to-end learning
  - no more need for many complicated subsystems
  - e.g., dramatically simplified Google’s translation pipeline
Excellent empirical results in many domains
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Analogy to the ways humans process information
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Allows end-to-end learning
- no more need for many complicated subsystems
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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
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