

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ



علوم شناختی

جلسه ۲۲ (ب)

یادگیری بازنمایی و یادگیری عمیق

Representation Learning and Deep Learning

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PART 3: APPLICATIONS



Chapter 12: Machine Learning: From Expert Systems to Deep Learning



Chapter 12.2: Representation learning and deep learning



Limitations of ID3

- ID3 can work only after the database is already highly organized, i.e., after a process of feature engineering.
- It cannot work with raw data such as pictures.
- E.g. CAPTCHA as an effective tool to detect bots from humans.

Different ways of representing: An example

- Multiplying 43 by 17 in decimal notation.
- Multiplying XXXXIII by XVII in Roman notation.
- Multiplying 101011 by 10001 in binary notation.

Feature engineering

- **The task:**
coding the examples in the database in terms of features that will make it easier to solve the relevant problem.

- **Representation learning/
Feature learning/
Deep learning:**
Programs and algorithms that would be able to do feature engineering.

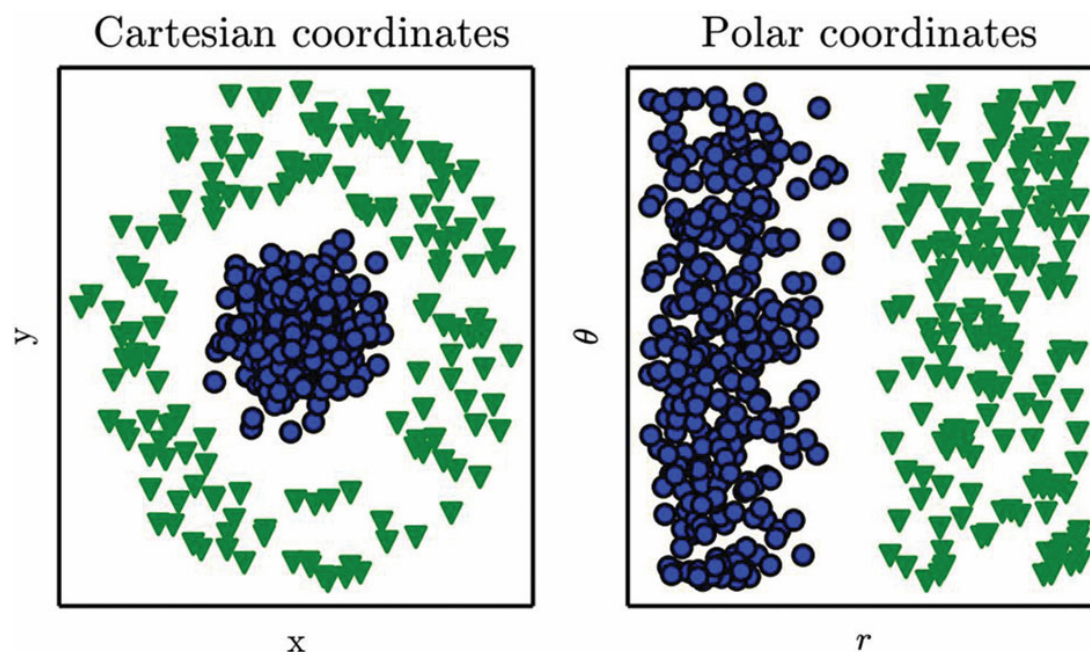
Deep learning

“Representation learning is 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 methods are representation-learning methods with multiple levels of representation, obtained by composing simple but non-linear modules that each transform the representation at one level (starting with the raw input) into a representation at a higher, slightly more abstract level.”

(LeCun, Bengio, and Hinton 2015)

Deep learning



Different ways of distinguishing two groups in a database of examples. The lefthand representation uses Cartesian coordinates, while the right-hand representation uses polar coordinates. The right-hand representation makes it much easier, for example, to write the equation for a line separating the two groups.

Deep learning and the visual cortex

- Deep learning systems are typically constructed from multiple layers of artificial neural networks, which is different from traditional machine learning.
- Appeal to mammalian visual cortex as a model.
- The visual system takes a complex pattern of unstructured stimuli in the visual field and interpret them into representations that can then serve as input to more complex cognitive functions, such as object recognition.

Natural representation learning system

- Information in the visual cortex is processed hierarchically.
- The first station is the *lateral geniculate nucleus* (LGN), which receives input directly from the retina.
- LGN projects to area V1 (the primary visual cortex), where information processing proper begins.

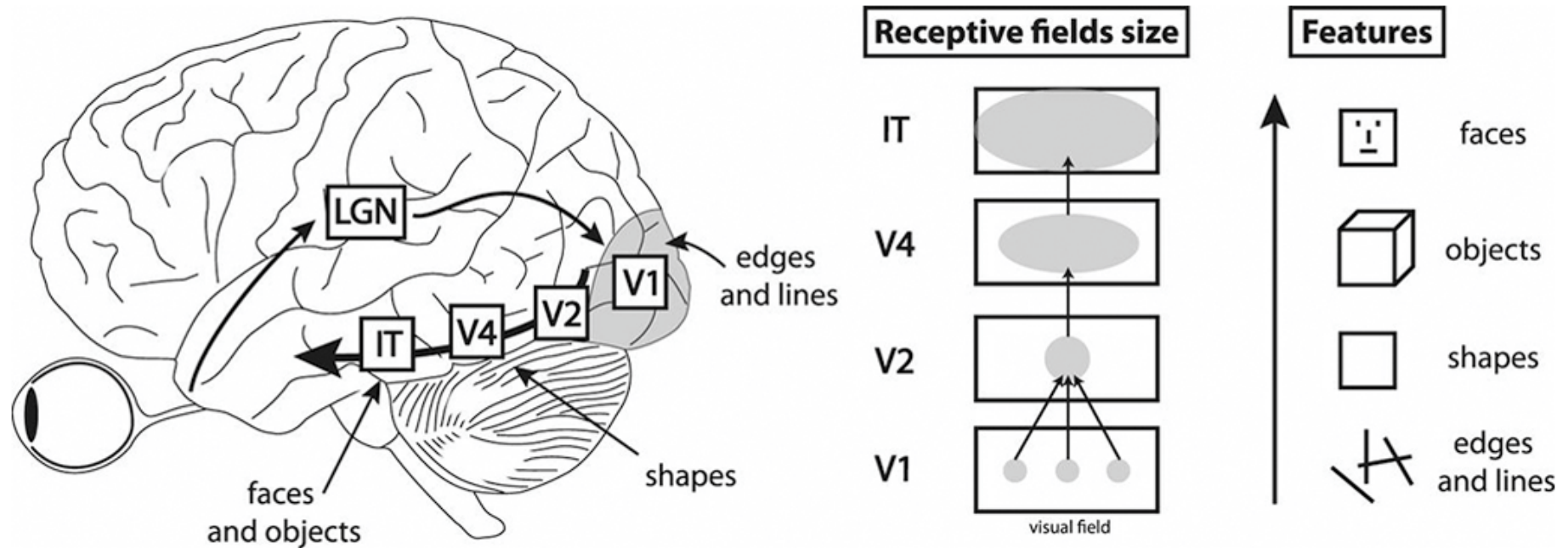
Parsing the raw data

- V1 takes the retinotopic map coming from LGN and filters it in a way that accentuates edges and the contours.
- Area V1 projects to area V2 (the secondary visual cortex), where neurons are tuned to the same features as neurons in V1, as well as to more complex features, such as shape and depth.

Parsing the raw data (cont.)

- Through the ventral pathway, neurons go from V2 to V4 and construct further representations that incorporate more information about figure/ground segmentation, as well as about colors.
- Representations then go to the inferior temporal cortex (ITC). The fusiform face area (FFA) is specialized for face recognition. The fusiform body area (FBA) is specialized for identifying the human body and body parts.

Hierarchical visual processing



An illustration of hierarchical visual processing. Stimuli are processed in a series of visual areas, which process features of increasing complexity. (Figure 1 from Manassi, Sayim, and Herzog 2013)

Deep learning systems

An artificial representation learning system has the task of taking complex and unstructured raw data and transforming it into representations that can serve as inputs to systems carrying out more complex tasks, such as classification.

The selectivity/invariance problem

- The object recognition systems need to be sensitive to, e.g., the relatively small differences between a Samoyed and a white wolf.
- But it also needs to be sensitive to invariance through large differences (e.g. when a Samoyed sitting down is more similar to a white wolf sitting down than it is to a Samoyed lying down)

Solving the problem

- Deep learning networks, such as ConvNets solve the problem because they are composed of stacked hierarchies of simple networks
- Each of the simple networks focuses on a single feature, abstracting away from other features and surrounding detail

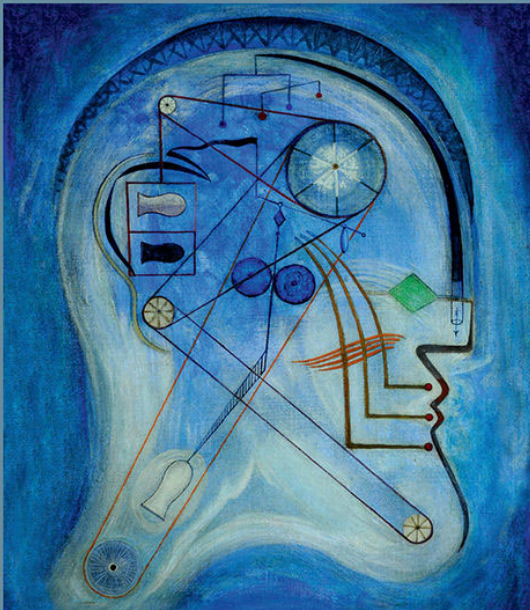


José Luis Bermúdez

Cognitive Science

An Introduction to the Science of the Mind

Third Edition



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Chapter 12 (Section 12.2)

CHAPTER TWELVE

Machine Learning: From Expert Systems to Deep Learning

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Overview

This chapter is dedicated to machine learning, one of the hottest topics in contemporary AI and the key to the success of multi-billion-dollar corporations such as Google, Facebook, and Amazon.

We begin in Section 12.1 by introducing the idea of expert systems, computer programs that are designed to replicate (and improve on) the performance of human experts in specialized domains, such as identifying diseases in humans and plants, or processing credit card applications. These programs can often be represented as decision trees. There are different ways of constructing expert systems, however. One way is to start with human experts and write a program that codifies their collective knowledge. Alternatively, machine learning algorithms can be used to construct a decision tree by analyzing large databases of examples and deriving rules that can then be used to classify new examples. We illustrate this through ID3, which is an example of a traditional machine learning algorithm.

Traditional algorithms such as ID3 are still highly dependent upon how their databases are labeled and constructed. They typically require lengthy and complex processes of *feature*