Hebbian Learning

Mathew Barrera
William Rummler

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Introduction

- "In the 1940s the neurophysiologist Donald Hebb … verified that once a neuron repeatedly excited another neuron, the threshold of excitation of the latter decreased; that is, the communication between them was facilitated by repeated excitation" (280).

Hebb's Rule

- Basic Form: Equation 6.1 (280)
- Analogy: Figure 6-1 (280)

Effect of the Hebbian Update

- Hebbian: Equation 6.2 (281)
- Linear PE (y = wx): Equation 6.3 (281)
- Unlike LMS or backpropagation, Hebbian learning is intrinsically unstable (281).

Associative Memory

- "The Hebbian PE is a very simple system that creates a similarity measure in its input space according to the information contained in the weights" (283).
- "The Hebbian PE thus implements a type of memory that is called an *associative memory*" (283).

Data Representations in Multidimensional Spaces

- A set of axes that are "attached" to the data cloud is called a *data-dependent* coordinate system (290).
- The realignment of axes to include the direction of largest variance is called the *principal coordinate system* (290).
- Figure 6-6 (290)
- With a simple local learning rule, Hebbian automatically finds the axis of largest variance (292).

Oja's Rule

- "To make Hebbian learning useful we must create a stable version by normalizing the weights" (292).
- Approximated by Equation 6.13 (292)
- Applies a forgetting term for normalization, but causes forgetting of old associations (293).
- Finds a normalized weight vector colinear with the *principal component* of input data (296).

Principal Component Analysis

- *Feature Extraction*: Projecting D-dimensional data onto M-dimensional space, M < D (297).
- Deflation method with non-local Sanger's Rule: Equation 6.17 (299)
- Applications (303-304):
  - Data Compression – Optimal
  - Classification – No Guarantees

Anti-Hebbian Learning

- Anti-Hebbian Rule: Equation 6.19 (304)
- Output space becomes the orthogonal space of the input data (304).
- Performs *decorrelation* from input to output (305).
- Convergence of the weights! (305)

Summary

- Any questions?