

Simulate, optimise, cluster: the algorithmic organisations of pluri-dimensional space from 1953 onwards

Adrian Mackenzie
Sociology,
Lancaster

Prediction: exact means simulated: Monte Carlo

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Equation of State Calculations by Fast Computing Machines

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A general method, suitable for fast computing machines, for investigating such properties as equations of state for substances consisting of interacting individual molecules is described. The method consists of a modified Monte Carlo integration over configuration space. Results for the system have been obtained on the Los Alamos MANIAC and are presented here to the free volume equation of state and to a four-term virial coefficient expansion.

We set up the calculation on a system composed of $N=224$ particles ($i=0, 1 \cdots 223$) placed inside a square of unit side and unit area. The particles were arranged initially in a trigonal lattice of fourteen particles per row by sixteen particles per column, alternate rows being displaced relative to each other as shown in Fig. 2.

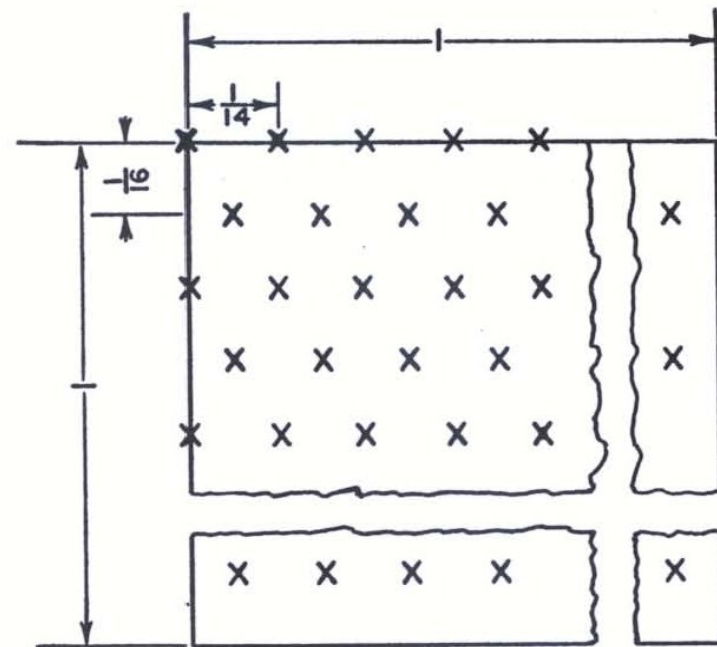


FIG. 2. Initial trigonal lattice.

Simulated means open

Bayesian modeling to unmask and predict influenza A/H1N1pdm dynamics in London

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suggests an unusual dominant peak in the summer. We embed an age-structured model into a Bayesian synthesis of multiple evidence sources to reveal substantial changes in contact patterns and health-seeking behavior throughout the epidemic, uncovering two similar infection waves, despite large differences in the reported levels of disease. We show how this approach, which allows for real-time learning about model parameters as the epidemic progresses, is also able to provide a sequence of nested projections that are capable of accurately reflecting the epidemic evolution.

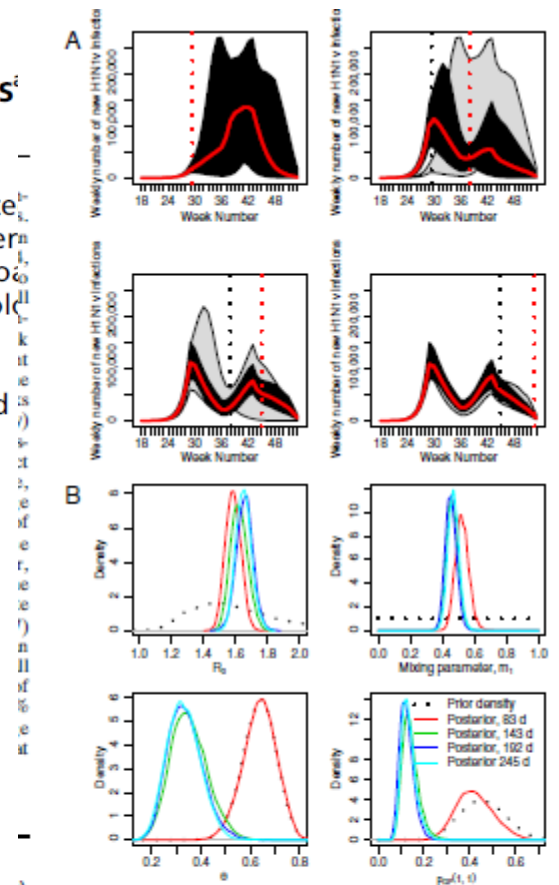


Fig. 4. (A) Sequential epidemic reconstructions/projections based on 83, 143, 192, and 245 d of surveillance data. The gray shaded area shows the 95% CrI for the epidemic construction from the temporally previous analysis, with the darker shaded area showing the “current” analysis. The solid red line indicates the posterior median number of infections, the dotted red vertical line shows the time at which the surveillance data ends, and the dotted gray vertical line shows the time at which the previous batch of surveillance data ended. (B) Sequentially obtained posterior density estimates, plotted alongside corresponding prior distributions for the parameters R_0 , m_1 , θ , and $p_{01}(1,1)$.

Markov chain Monte Carlo changed our emphasis from “closed form” solutions to algorithms, expanded our impact to solving “real” applied problems and to improving numerical algorithms using statistical ideas, and led us into a world where “exact” now means “simulated”

Christian Robert and George Casella, 2008,18.

Optimise in order to classify: 1957

From the Perceptron to kiddydar

Psychological Review
Vol. 65, No. 6, 1958

THE PERCEPTRON: A PROBABILISTIC MODEL FOR INFORMATION STORAGE AND ORGANIZATION IN THE BRAIN¹

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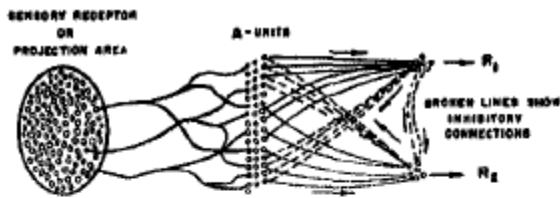


FIG. 2A. Schematic representation of connections in a simple perceptron.

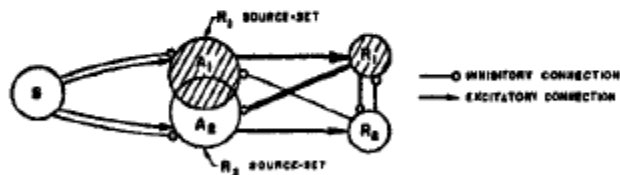


FIG. 2B. Venn diagram of the same perceptron (shading shows active sets for R_1 response).

or Periods in the Research of the Learning Problem

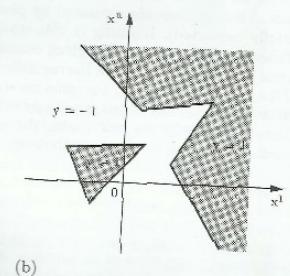
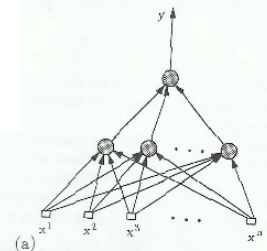
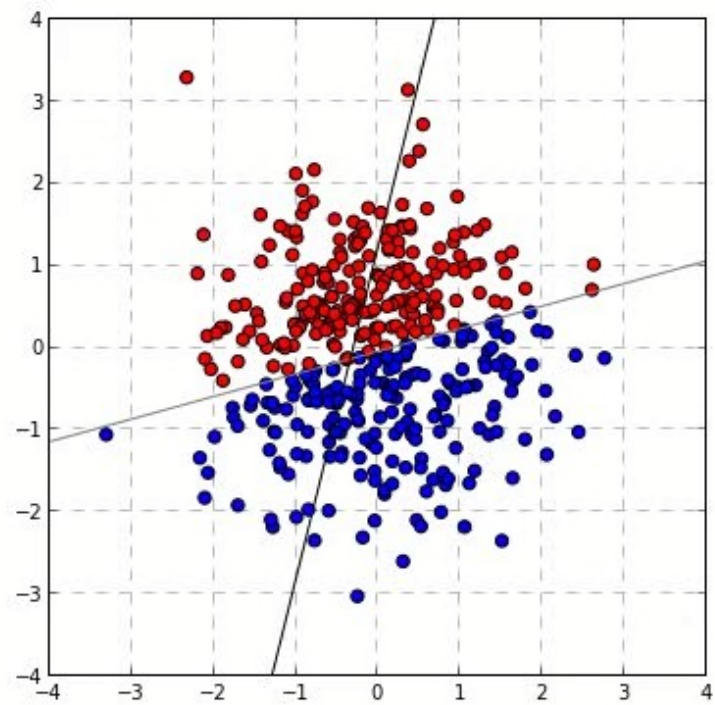
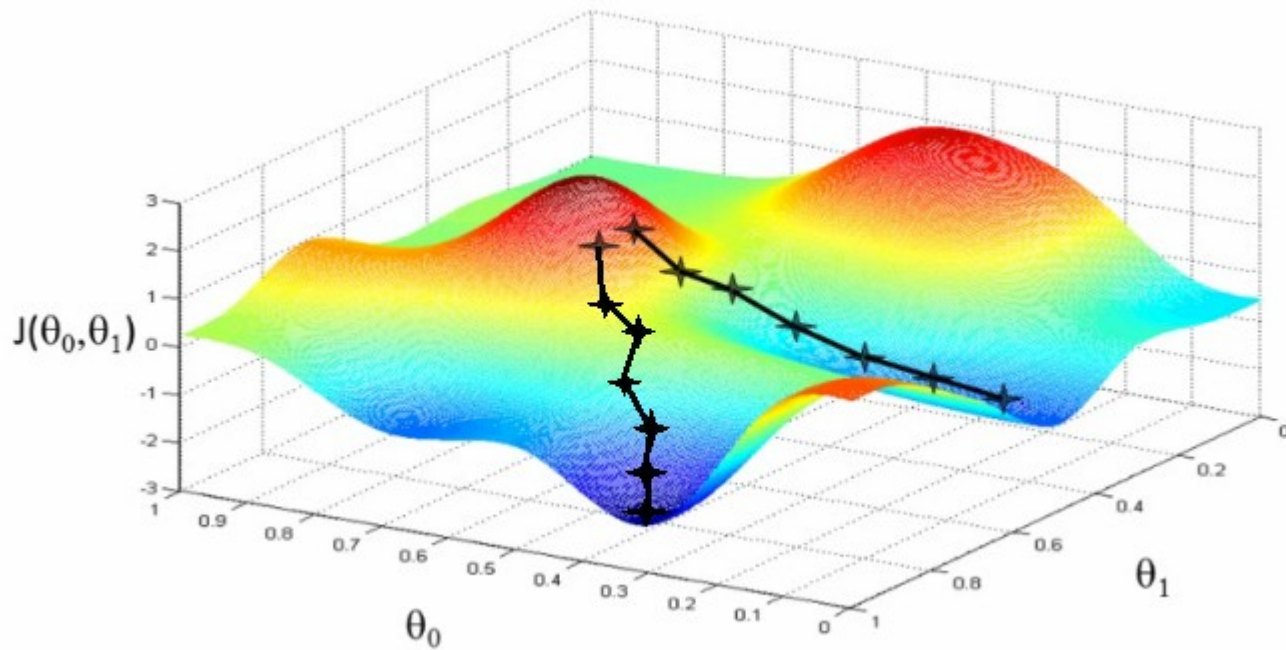


FIGURE 0.2. (a) The perceptron is a composition of several neurons. (b) Geometrically, the perceptron defines two regions in input space where it takes the values -1 and 1 . These regions are separated by a piecewise linear surface.



Optimisation – gradient descent



Kittydar and neural networks

<http://harthur.github.io/kittydar/>

Classify: decision

Machine Learning 1: 81–106, 1986
© 1986 Kluwer Academic Publishers, Boston – Manufactured in The Netherlands

Induction of Decision Trees

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(Received August 1, 1985)

Key words: classification, induction, decision trees, information theory, knowledge acquisition, expert systems

Abstract. The technology for building knowledge-based systems by inductive inference from examples has been demonstrated successfully in several practical applications. This paper summarizes an approach to synthesizing decision trees that has been used in a variety of systems, and it describes one such system, ID3, in detail. Results from recent studies show ways in which the methodology can be modified to deal with information that is noisy and/or incomplete. A reported shortcoming of the basic algorithm is discussed and two means of overcoming it are compared. The paper concludes with illustrations of current research directions.

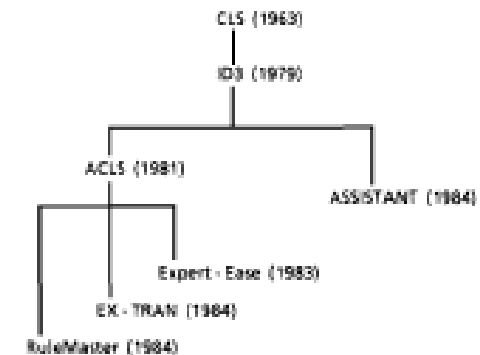
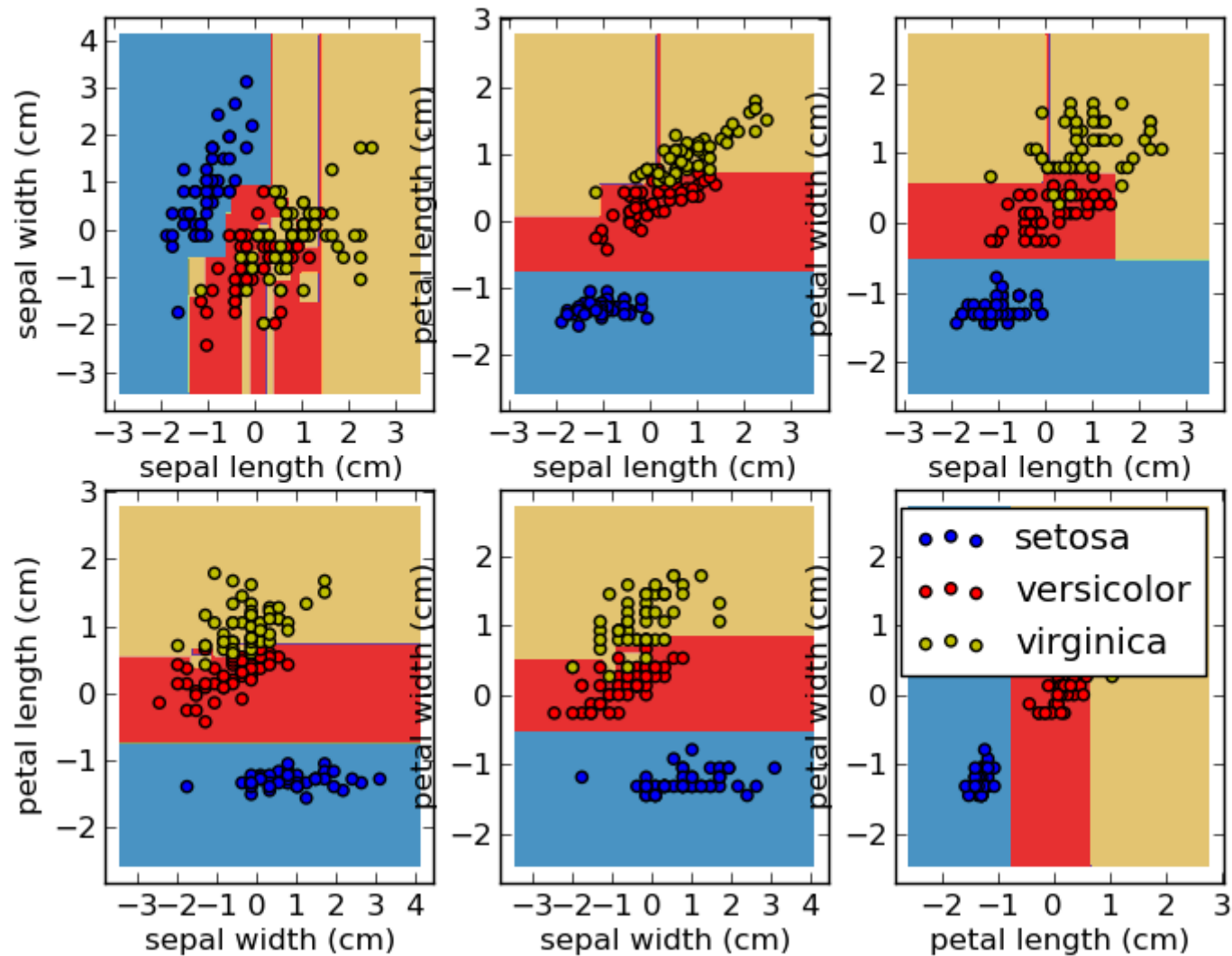


Figure 1. The TDIDT family tree.

The members of this family are sharply characterized by their representation of acquired knowledge as decision trees.

Decision tree

Decision surface of a decision tree using paired features



Random forests and Google Compute Engine

Google I/O Conference 2012