Machine Learning Tools for the Visualisation of BigData

We all love images!

Statutory warning: Has been produced in the same facility which produces maths and may contains traces of maths.

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Learning Machines and Data!

Linear and nonlinear methods to compress

Introduction

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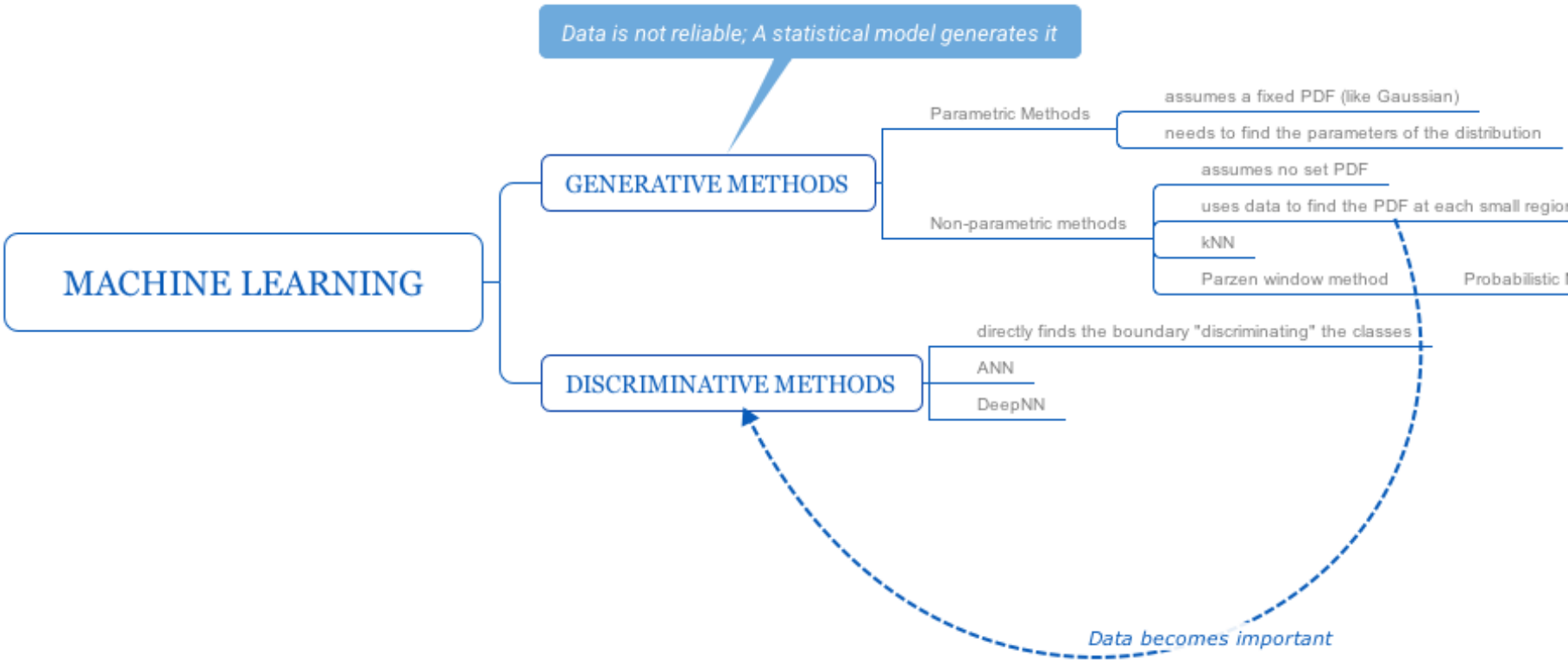
- Machines are reliable and can have way more dimensions than "we can understand"
- We need to see things to understand (whether to extract new information or to classify known classes)
- We shall discuss some basic ways to make big-data small (!) enough to visualise them
- We shall present an open source tool we have developed which anyone can use to view large datasets

Taxonomy of Machine Learning



Squeezing the information out!-I

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- few underlying "factor" determine the large dimension data
- Factor analysis (as old as statistics!)

Discrete Karhunen-Loeve expansion

- Let $\mathbf{x}$ be n dimensional random vector (of data from sensors); represented in terms of n independent vectors:
  $\mathbf{x} = y_1\phi_1 + y_2\phi_2 + ... = \sum_i y_i\phi_i$ (like coordinate systems)
- Lets calculate only m $(m < n)$ y_is, and use constants for the rest
- $\hat{\mathbf{X}}(m) = \sum_{i=1}^{m} \mathbf{y}_i\phi_i + \sum_{i=m+1}^{n} b_i\phi_i$

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- Error: $\Delta\mathbf{X}(m) = \sum_{i=m+1}^{n}(\mathbf{y}_i - b_i)\phi_i$ (prove this)
- Minimize the mean-squared error, i.e. $E(||\Delta\mathbf{X}(m)||^2)$ (WHY?)

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- Optimal choice of ϕ_is, satisfy $\Sigma_X\phi_i = \lambda_i\phi_i$, i.e. eigenvectors of the covariance matrix Σ_X (KL transformation or PCA)

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- LDA maximizes the ratio: $\frac{det[\mathbf{S}_b]}{det[\mathbf{S}_w]}$
- Solution: Eigen vectors of $\mathbf{S}_w^{-1}\mathbf{S}_b$

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- Lets try to preserve the "structure"

Sammon's Mapping

- Structure (in Shannon's sense): geometrical relationships among subsets of the data vectors
- Original data: N data points of L dimension
- Problem: to find best N points in a lower d (2 or 3) dimension, s.t. their interpoint distances approximate the corresponding interpoint distance in the original L-dimensional space

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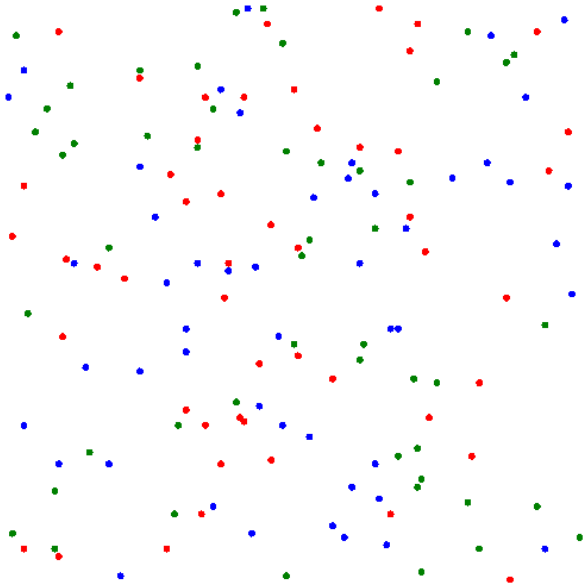
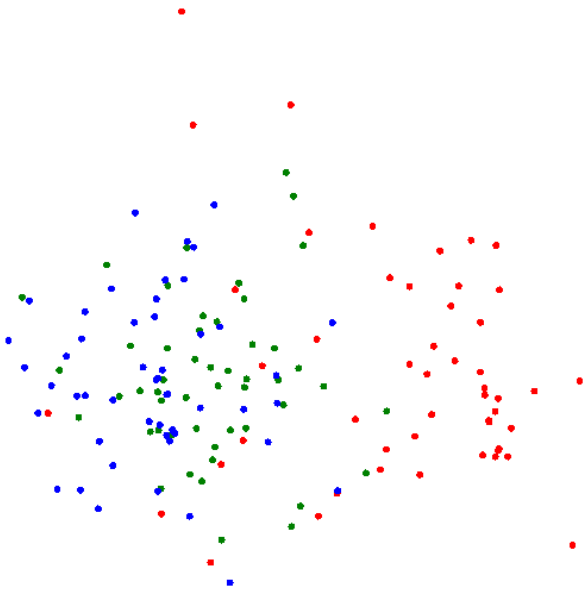
- Good news: Its convex

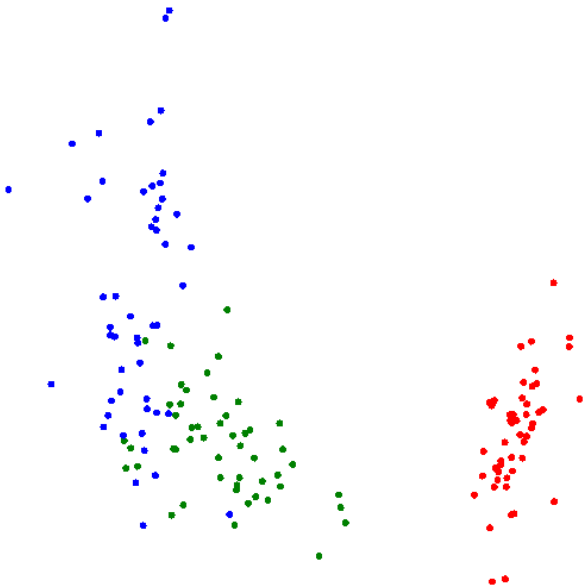
Sammon mapping: 0-iteration



Sammon mapping: 1-iteration



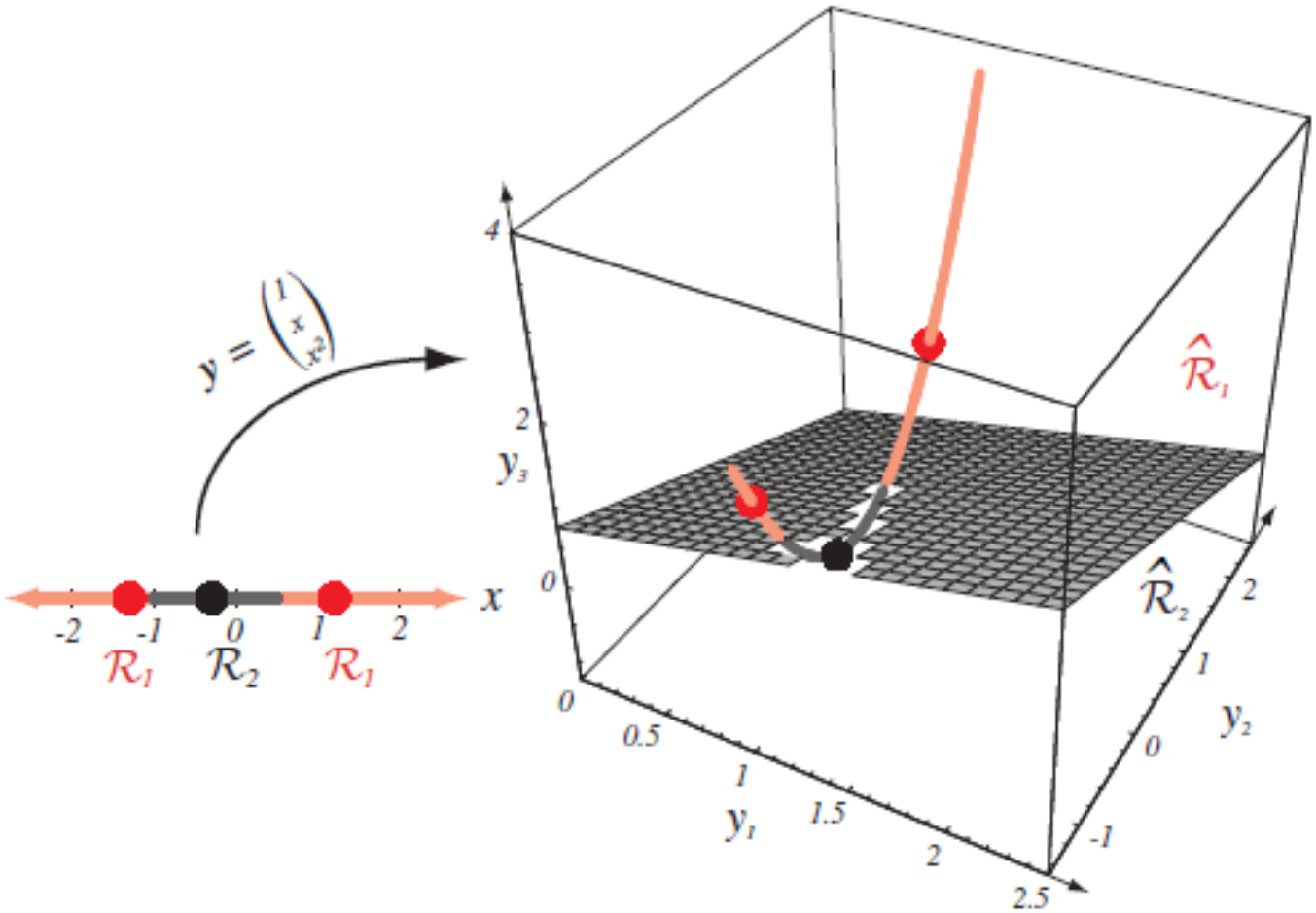
Sammon mapping: 10-iteration



Squeezing the information out!-III

- What if the original data is ill-behaved?
- Boundaries with curves (curves are not pretty here!)

Nonlinear turning into linear in higher dimensional space



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- Lets pass the data through a nonlinear mapping ϕ; then the new $\Sigma_{X,\phi} = \frac{1}{M-1} \sum_{i=1}^{M} \phi(X_i)\phi(X_i)^T = \frac{1}{M-1} \sum_{i=1}^{M} k(X, X)$

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- A range of tools to do so
- We give you a free suite of tools