

ML2 : The landscape of machine learning

Pierre CHAINAIS



► Books :

- **T. Hastie, R. Tibshirani et J. Friedman (2009)**
The Elements of Statistical Learning
Springer Series in Statistics, disponible en ligne.
- **C. M. Bishop (2009)**
Pattern Recognition and Machine Learning, *Springer*.
- **K.P. Murphy (2012)**
Machine Learning : a probabilistic perspective
The MIT Press.

► Slides, TP... online on Moodle .

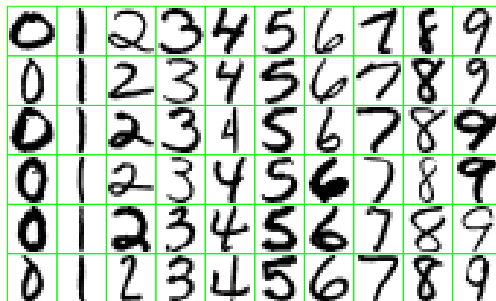
► Evaluation : TP + short exams + final test

- ➊ Linear models for regression
- ➋ Classification and theory of decision
- ➌ Linear models for supervised classification
- ➍ Dimension reduction
- ➎ Unsupervised classification, clustering
- ➏ Evaluation of performances
- ➐ Decision trees
- ➑ Boosting : AdaBoost (clever learning)
- ➒ Support vector machines (kernel approaches)
- ➓ Neural networks (deep learning)

Examples

Character recognition

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- ▶ to identify the numbers on images (0,..., 9) from a 16x16 gray level image (0 to 255).
- ▶ **Supervised classification**

SPAM

WINNING NOTIFICATION! We are pleased to inform you of the result of the Lottery Winners International Program held on the 4th november 2013.

You have been approved for a lump sum pay out of 175,000 euros.

CONGRATULATIONS!!!

NON SPAM

Dear Pascal,

Could you please send me the report #1234 on the project advancement?

Thanks in advance.

Regards, Clara

- ▶ Basis of reference mails, identified as SPAM or NOT
- ▶ Purpose : predict whether a new mail is SPAM or NOT
- ▶ Avoid to delete important messages ! (false alarm)
- ▶ **Supervised classification**



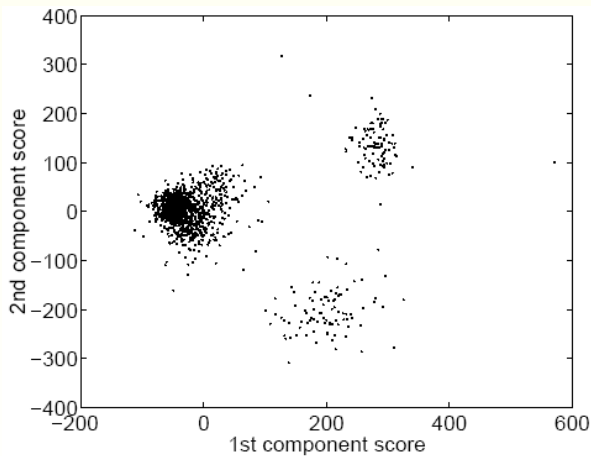
64 sequences (individuals) of 6830 genetical responses to a reference

- ▶ Which are the groups of similar samples? (similarities and links between individuals)
- ▶ Which are the genes with similar expressions? (similarities and links between genes)
- ▶ Are there genes which are more characteristic than others? (extraction of characteristics)
- ▶ **Clustering**

Examples

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Clouds of points : identification of groups (clusters)

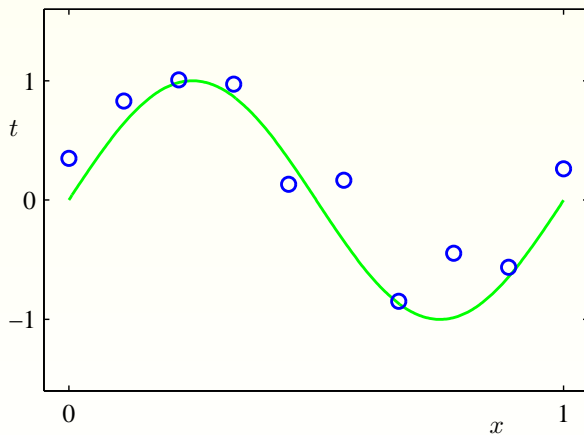


clustering : unsupervised classification

Examples

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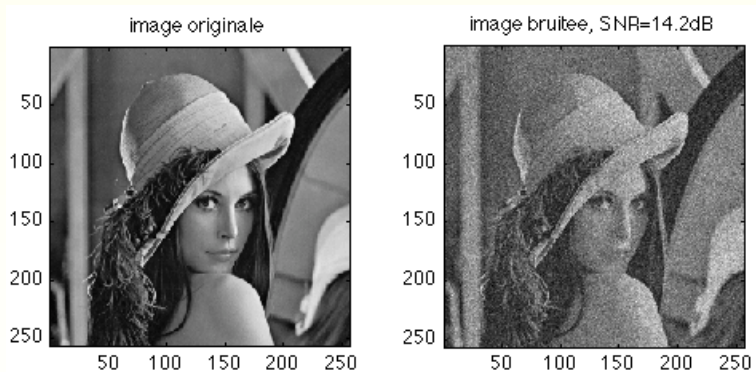
Approximation of functions, modelling, denoising, inpainting...



Regression

Examples

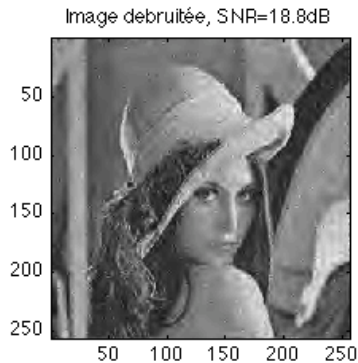
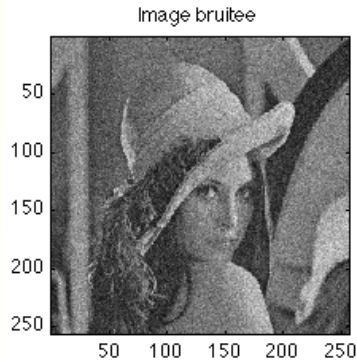
Approximation of functions, modelling, denoising, inpainting...



Regression

Examples

Approximation of functions, modelling, denoising, inpainting...



Regression

Examples

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Approximation of functions, modelling, denoising, inpainting...



Regression

Examples

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Approximation of functions, modelling, denoising, inpainting...



Regression

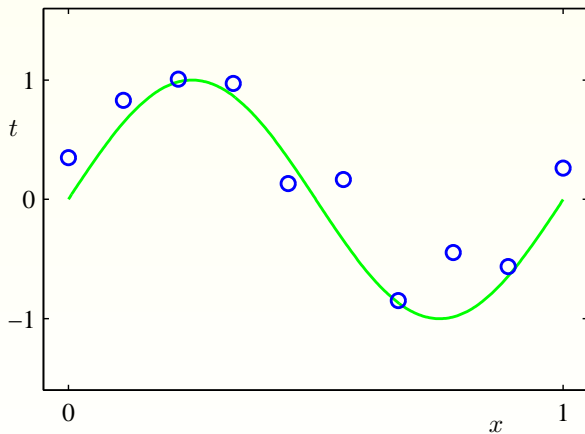
ML2 : The landscape of machine learning

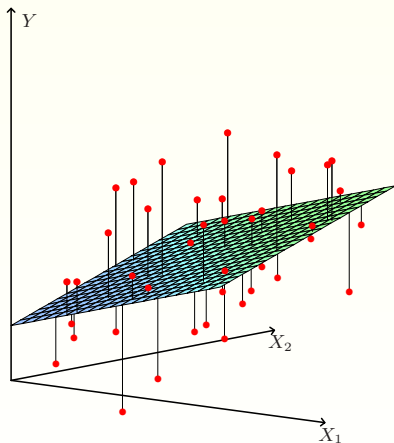
1. Linear models for regression

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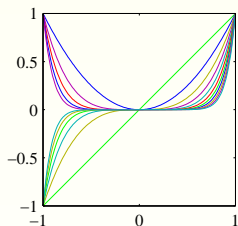
- 1 Linear models for regression
 - Position of the problem
 - Examples of bases of functions
 - Least square estimation
 - Linear regression
 - General case : bases of functions
 - Multiple outputs
 - Geometrical interpretation
 - Regularized least squares
 - Bayesian approach
 - Cost functions for regression
 - The bias-variance compromise



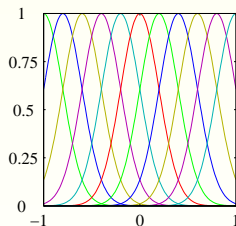


Examples of bases of functions

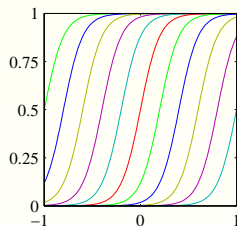
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polynomials



gaussian kernels



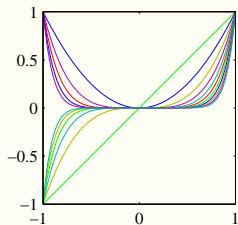
sigmoids

Linear regression

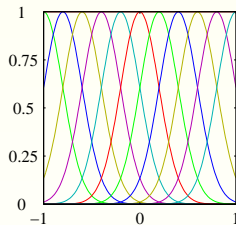
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Example : prediction of the level of prostate specific antigen

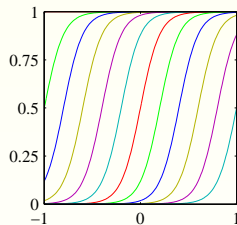
Term	Coefficient	Std. Error	Z Score
Intercept	2.46	0.09	27.60
lcavol	0.68	0.13	5.37
lweight	0.26	0.10	2.75
age	-0.14	0.10	-1.40
lbph	0.21	0.10	2.06
svi	0.31	0.12	2.47
lcp	-0.29	0.15	-1.87
gleason	-0.02	0.15	-0.15
pgg45	0.27	0.15	1.74



polynomials



gaussian kernels



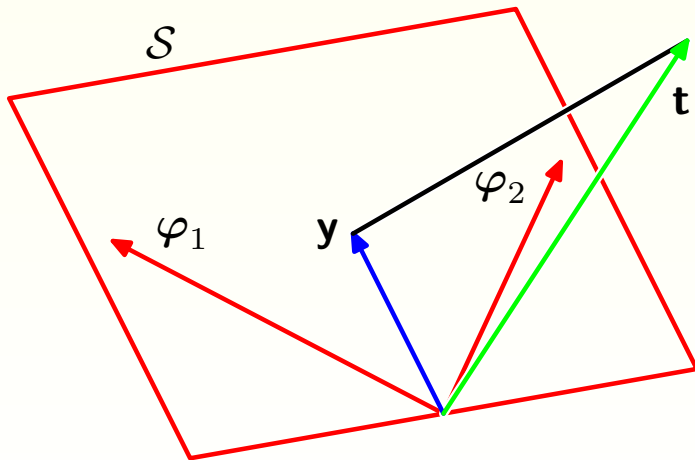
sigmoids

and also local cosines, wavelets...

Linear models for regression

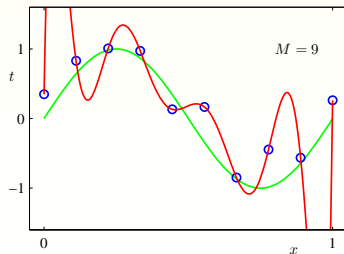
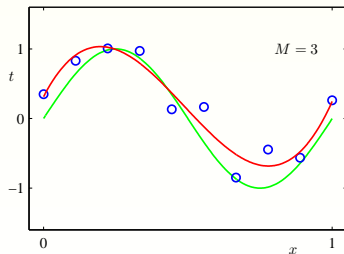
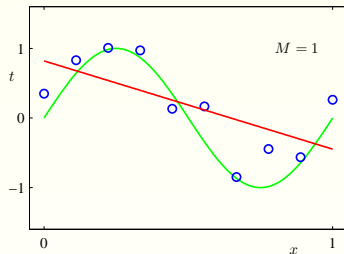
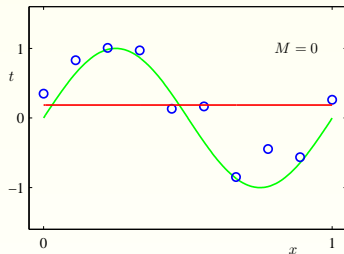
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Geometrical interpretation



Regularized least squares

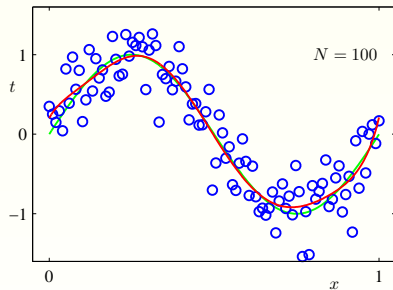
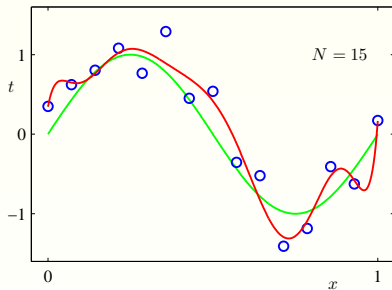
Polynomial approximation : importance of the order



Regularized least squares

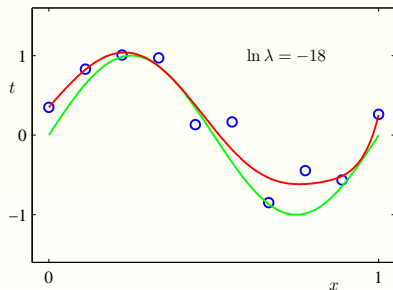
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Polynomial approximation : importance of the order

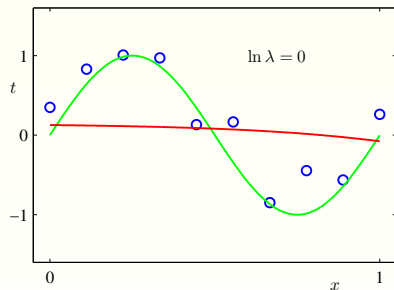


Polynomial approximation + regularization : minimizes higher order coeff.

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average reg.



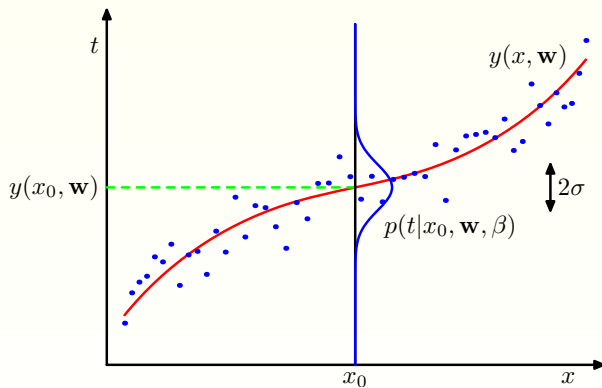
strong reg.

Regularized least squares

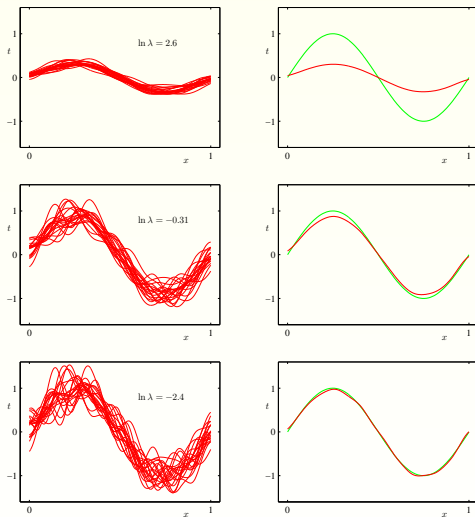
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Example : prediction of the level of prostate specific antigen

Term	LS	Best Subset	Ridge	Lasso	PCR	PLS
Intercept	2.465	2.477	2.452	2.468	2.497	2.452
lcvol	0.680	0.740	0.420	0.533	0.543	0.419
lweight	0.263	0.316	0.238	0.169	0.289	0.344
age	-0.141		-0.046		-0.152	-0.026
lbph	0.210		0.162	0.002	0.214	0.220
svi	0.305		0.227	0.094	0.315	0.243
lcp	-0.288		0.000		-0.051	0.079
gleason	-0.021		0.040		0.232	0.011
pgg45	0.267		0.133		-0.056	0.084
Test Error	0.521	0.492	0.492	0.479	0.449	0.528
Std Error	0.179	0.143	0.165	0.164	0.105	0.152



The bias-variance compromise

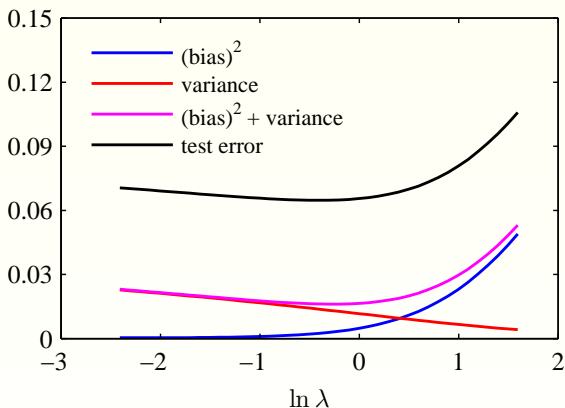


different data averaged estimates
M = 25 Gaussian kernels, N = 25 points,
ridge regression (λ)

The bias-variance compromise

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Determination of an optimum



$M = 25$ Gaussian kernels, $N = 25$ points,
ridge regression (λ)