Statistical learning of latent variable models for complex data analysis

Faicel Chamroukhi

Fédération Normandie-Mathématiques

Normandie - Mathématiques

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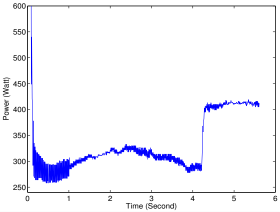
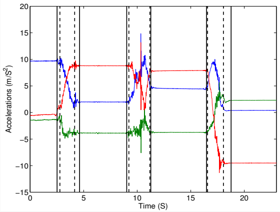
Temporal data

Temporal data with regime changes



Railway data



Human activity data

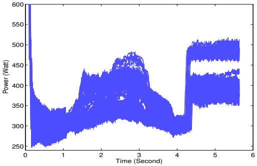
- Data with regime changes over time
- Abrupt and/or smooth regime changes
- Multidimensional temporal data

Objectives

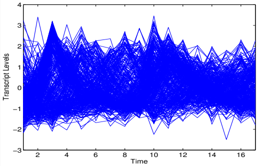
Temporal data modeling and segmentation

Functional data

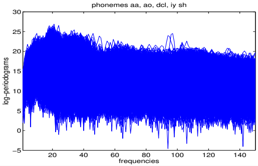
Many curves to analyze



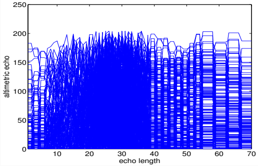
Railway switch curves



Yeast cell cycle curves



Phonemes curves

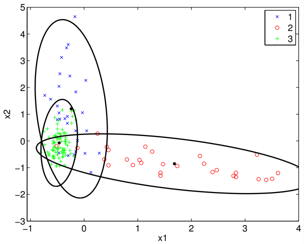


Satellite waveforms

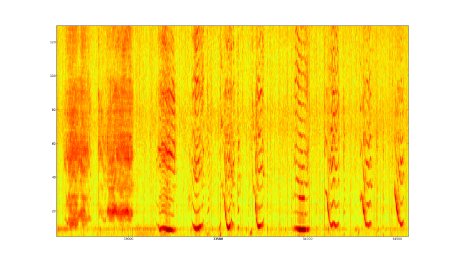
Objectives

- Curve clustering/classification (functional data analysis framework)
- Deal with the problem of regime changes $\hookrightarrow$ Curve segmentation

Multivariate data



Diabetes Benchmark



Spectrum of bioacoustic data

Objectives

- Clustering/Segmentation
- Dimensionality reduction

Data with atypical features

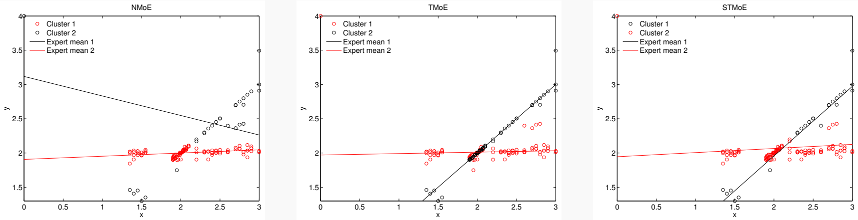


Figure: Fitting MoLE to the tone data set with ten outliers $(0, 4)$.

- Data with possible atypical observations
- Data with possibly asymmetric and heavy-tailed distributions

Objectives

- Derive robust models to fit at best the data
- Deal with other possible features like skewness, heavy tails

Thmes de recherche et contributions

Scientific context

- The area of statistical learning and analysis of complex data.
- **Data :** Complex data $\hookrightarrow$ *heterogeneous, temporal/dynamical, functional, incomplete, high-dimensional,...*
- **Objective:** Transform the data into knowledge :
  $\hookrightarrow$ Reconstruct hidden structure/information, groups/hierarchy of groupes, summarizing prototypes, underlying dynamical processes, etc

Modeling framework

- Latent variable models : $f(x|\boldsymbol{\theta}) = \int_z f(x, z|\boldsymbol{\theta})\mathrm{d}z$

  Generative formulation :

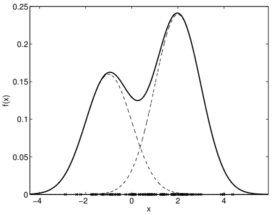
$$\begin{aligned} z &\sim q(z|\boldsymbol{\theta}) \\ x|z &\sim f(x|z, \boldsymbol{\theta}) \end{aligned}$$

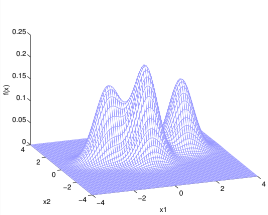
$\hookrightarrow$ Mixture models : $f(x|\boldsymbol{\theta}) = \sum_{k=1}^{K} \mathbb{P}(z = k) f(x|z = k, \boldsymbol{\theta}_k)$ and extensions

Mixture modeling framework

Mixture modeling framework

- Mixture density: $f(x|\boldsymbol{\theta}) = \sum_{k=1}^{K} \pi_k f_k(x|\boldsymbol{\theta}_k)$





- Generative model

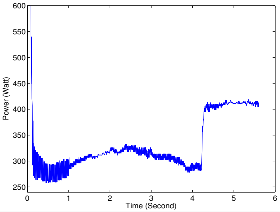
$$
\begin{aligned}
z &\sim \mathcal{M}(1; \pi_1, \ldots, \pi_K) \\
x|z &\sim f(x|\boldsymbol{\theta}_z)
\end{aligned}
$$

$\hookrightarrow$ Algorithms for inferring $\boldsymbol{\theta}$ from the data

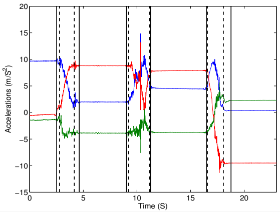
Outline

Temporal data

Temporal data with regime changes



Railway data



Human activity data

- Data with regime changes over time
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- Multidimensional temporal data

Objectives

Temporal data modeling and segmentation

Outline

1. Mixture models for temporal data segmentation
   - Regression with hidden logistic process
   - Multiple hidden process regression
   - Non-normal mixtures of experts
2. Mixture models for functional data analysis
3. Bayesian (non-)parametric mixtures for spatial and multivariate data

Mixture models for temporal data segmentation

$\boldsymbol{y} = (y_1, \ldots, y_n)$ a time series of n univariate observations $y_i \in \mathbb{R}$ observed at the time points $\mathbf{t} = (t_1, \ldots, t_n)$

Times series segmentation context

- Time series segmentation is a popular problem with a broad literature
- Common problem for different communities, including statistics, detection, signal processing, machine learning, finance

- The observed time series is generated by an underlying process
  $\hookrightarrow$ segmentation $\equiv$ recovering the parameters the process' states.
- Conventional solutions are subject to limitations in the control of the transitions between these states

- $\hookrightarrow$ Propose generative latent data modeling for segmentation and approximation
- $\hookrightarrow$ segmentation $\equiv$ inferring the model parameters and the underling process

Regression with hidden logistic process

Let $\boldsymbol{y} = (y_1, \ldots, y_n)$ be a time series of n univariate observations $y_i \in \mathbb{R}$ observed at the time points $\mathbf{t} = (t_1, \ldots, t_n)$ governed by K regimes.

The Regression model with Hidden Logistic Process (RHLP) [1]

$$\begin{aligned} y_i &= \boldsymbol{\beta}_{z_i}^T \boldsymbol{x}_i + \sigma_{z_i} \epsilon_i \quad ; \quad \epsilon_i \sim \mathcal{N}(0,1), \quad (i = 1, \ldots, n) \\ Z_i &\sim \mathcal{M}(1, \pi_1(t_i; \mathbf{w}), \ldots, \pi_K(t_i; \mathbf{w})) \end{aligned}$$

Polynomial segments $\boldsymbol{\beta}_{z_i}^T \boldsymbol{x}_i$ with $\boldsymbol{x}_i = (1, t_i, \ldots, t_i^p)^T$ with logistic probabilities

$$\pi_k(t_i; \mathbf{w}) = \mathbb{P}(Z_i = k | t_i; \mathbf{w}) = \frac{\exp{(w_{k1} t_i + w_{k0})}}{\sum_{\ell=1}^K \exp{(w_{\ell 1} t_i + w_{\ell 0})}}$$

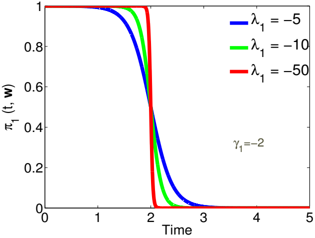
$$f(y_i | t_i; \boldsymbol{\theta}) = \sum_{k=1}^K \pi_k(t_i; \mathbf{w}) \mathcal{N}\left(y_i; \boldsymbol{\beta}_k^T \boldsymbol{x}_i, \sigma_k^2\right)$$

- Both the mixing proportions and the component parameters are time-varying

Illustration

- Modeling with the logistic distribution allows activating simultaneously and preferentially several regimes during time

$$\pi_k(t_i;\mathbf{w}) = \frac{\exp\left(\lambda_k(t_i+\gamma_k)\right)}{\sum_{\ell=1}^{K}\exp\left(\lambda_\ell(t_i+\gamma_\ell)\right)}$$

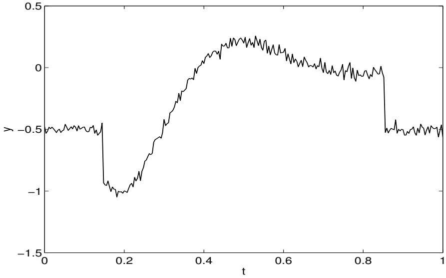


⇒ The parameter w_{k1} controls the quality of transitions between regimes

⇒ The parameter w_{k0} is related to the transition time point

- Ensure time series segmentation into contiguous segments

Illustration of the principle of the method



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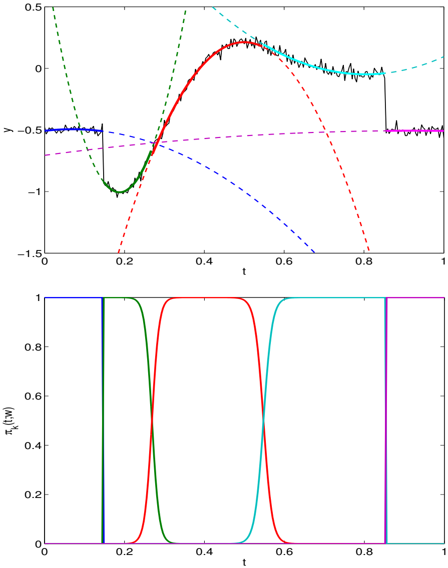


$K = 5$ polynomial components of degree $p = 2$

EM-RHLP

- **E-Step**: compute the posterior component memberships:

$$\tau_{ik}^{(q)} = \mathbb{P}(Z_i = k | y_i, t_i; \boldsymbol{\theta}^{(q)}) = \frac{\pi_k(t_i; \mathbf{w}^{(q)})\mathcal{N}(y_i; \boldsymbol{\beta}_k^{T(q)}\boldsymbol{x}_i, \sigma_k^{2(q)})}{\sum_{\ell=1}^{K} \pi_\ell(t_i; \mathbf{w}^{(q)})\mathcal{N}(y_i; \boldsymbol{\beta}_\ell^{T(q)}\boldsymbol{x}_i, \sigma_\ell^{2(q)})} \cdot$$

- **M-Step**: compute the parameter update $\boldsymbol{\theta}^{(q+1)} = \arg\max_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}, \boldsymbol{\theta}^{(q)})$

$$\mathbf{w}^{(q+1)} = \arg\max_{\mathbf{w}} \sum_{i=1}^{n}\sum_{k=1}^{K} \tau_{ik}^{(q)} \log \pi_k(t_i; \mathbf{w})$$ weighted logistic regression

$$\boldsymbol{\beta}_k^{(q+1)} = \Big[\sum_{i=1}^{n} \tau_{ik}^{(q)} \boldsymbol{x}_i \boldsymbol{x}_i^T\Big]^{-1} \sum_{i=1}^{n} \tau_{ik}^{(q)} y_i \boldsymbol{x}_i$$ weighted polynomial regression

$$\sigma_k^{2(q+1)} = \frac{1}{\sum_{i=1}^{n} \tau_{ik}^{(q)}} \sum_{i=1}^{n} \tau_{ik}^{(q)} (y_i - \boldsymbol{\beta}_k^{T(q+1)} \boldsymbol{x}_i)^2$$

EM-RHLP

Parameter estimation via a the EM algorithm: EM-RHLP

- Parameter estimation via a the EM algorithm (EM-RHLP)

  M-Step: includes a weighted logistic regression problem $\hookrightarrow$ IRLS (and weighted polynomial regressions)

- EM-RHLP algorithm complexity: $\mathcal{O}(I_{\text{EM}} I_{\text{IRLS}} K^3 p^3 n)$ (more advantageous than dynamic programming).

Time series approximation and segmentation

1. Approximation: a curve prototype $\hat{y}_i = \mathbb{E}[y_i|t_i;\hat{\boldsymbol{\theta}}] = \sum_{k=1}^{K} \pi_k(t_i;\hat{\mathbf{w}})\hat{\boldsymbol{\beta}}_k^T \boldsymbol{x}_i$

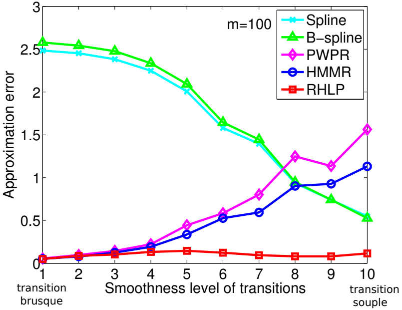
   $\hookrightarrow$ The RHLP can be used as nonlinear regression model $y_i = f(t_i;\boldsymbol{\theta}) + \epsilon_i$ by covering functions of the form $f(t_i;\boldsymbol{\theta}) = \sum_{k=1}^{K} \pi_k(t_i;\mathbf{w})\boldsymbol{\beta}_k^T \boldsymbol{x}_i$ [3]

2. Curve segmentation: $\hat{z}_i = \arg\max_k \mathbb{E}[z_i|t_i;\hat{\mathbf{w}}] = \arg\max_k \pi_k(t_i;\hat{\mathbf{w}})$

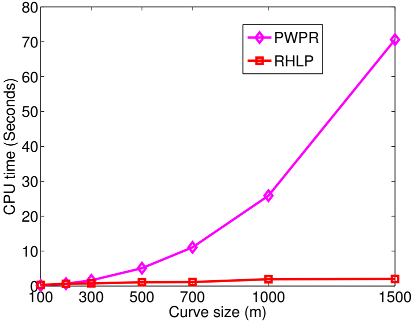
   Model selection: Application of BIC, ICL ($\nu_{\boldsymbol{\theta}} = K(p+4) - 2.$)

Evaluation in modeling and segmentation

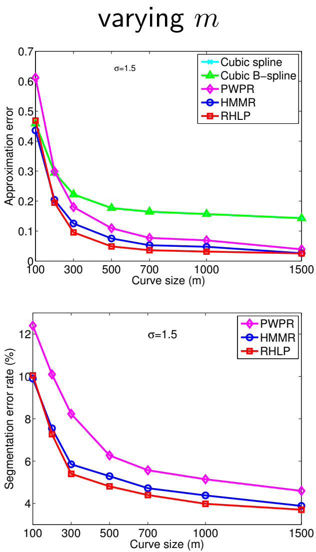
Approximation error as a function of the speed of transitions



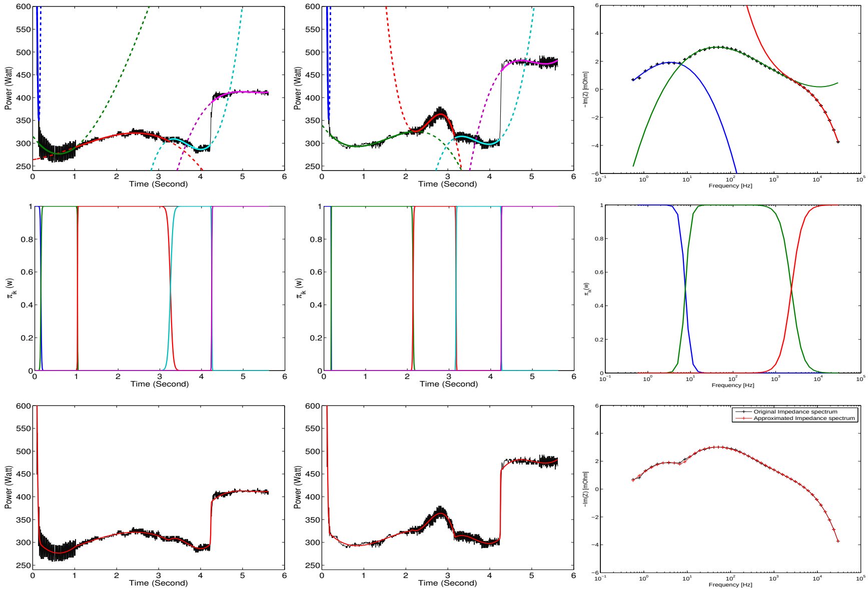
Computing time



Evaluation in approximation and segmentation



Application to real data



Joint segmentation of multivariate time series

Multiple hidden process regression

- Data: $(\boldsymbol{y}_1, \ldots, \boldsymbol{y}_n)$ a time series of n multidimensional observations $\boldsymbol{y}_i = (y_i^{(1)}, \ldots, y_i^{(d)})^T \in \mathbb{R}^d$ observed at instants $\mathbf{t} = (t_1, \ldots, t_n)$.
- Model

$$
\begin{aligned}
y_i^{(1)} &= \boldsymbol{\beta}_{z_i}^{(1)T} \boldsymbol{x}_i + \sigma_{z_i}^{(1)} \epsilon_i \\
\vdots \quad & \quad \vdots \\
y_i^{(d)} &= \boldsymbol{\beta}_{z_i}^{(d)T} \boldsymbol{x}_i + \sigma_{z_i}^{(d)} \epsilon_i
\end{aligned}
$$

  Vectorial form: $\boldsymbol{y}_i = \mathbf{B}_{z_i}^T \boldsymbol{x}_i + \mathbf{e}_i \quad ; \quad \mathbf{e}_i \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_{z_i}), \quad (i = 1, \ldots, n)$

- The latent process $\mathbf{z} = (z_1, \ldots, z)$ simultaneously governs the univariate time series components

↪ Multiple regression with hidden logistic process: Multiple RHLP [6]

↪ Multiple Hidden Markov model regression (MHMMR) [7]

Multiple hidden Markov model regression

- MHMMR: Estimation by the EM algorithm (as for HMMs)

  ↪ Solve multiple regression problems

Application to human activity time series

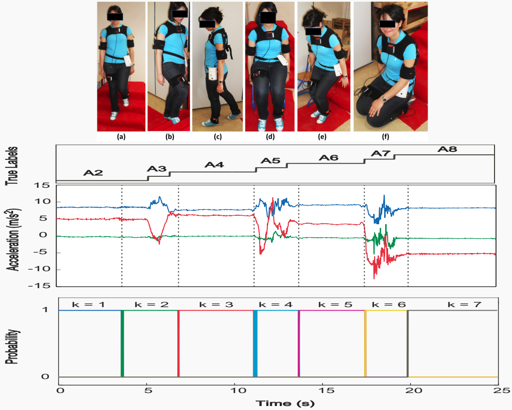


Figure: MHMMR Segmentation of acceleration data issued from three body-worn sensors (Data from the LISSI Lab/University of Paris 12)

Multiple regression with hidden logistic process

- MRHLP: Estimation by the EM algorithm (as for the RHLP)

  ↪ Solve multiple regression problems

Application to human activity time series

Problem: Activity recognition from multivariate acceleration time series

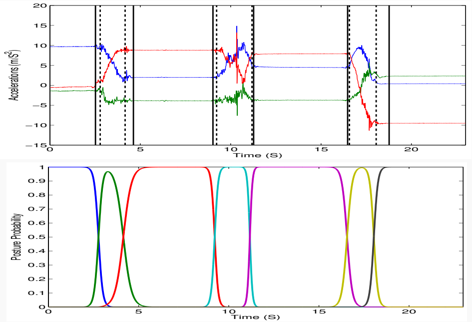


Figure: MRHLP segmentation of acceleration data issued from three body-worn sensors (Data from the LISSI Lab/University of Paris 12)

Data with atypical features

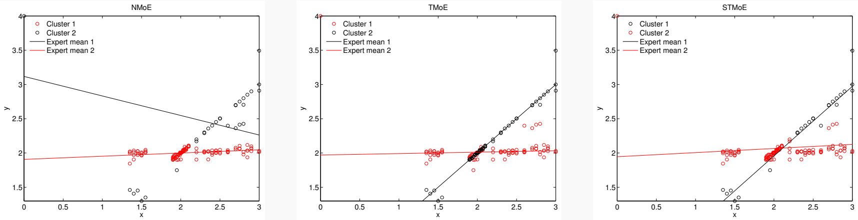


Figure: Fitting MoLE to the tone data set with ten outliers $(0, 4)$.

- Data with possible atypical observations
- Data with possibly asymmetric and heavy-tailed distributions

Objectives

- Derive robust models to fit at best the data
- Deal with other possible features like skewness, heavy tails

Mixture of Experts (MoE) modeling framework

- Observed pairs of data $(\boldsymbol{x}, y)$ where $y \in \mathbb{R}$ is the response for some covariate $\boldsymbol{x} \in \mathbb{R}^p$ governed by a hidden categorical random variable Z
- Mixture of experts (MoE) (Jacobs et al., 1991; Jordan and Jacobs, 1994) :

$$f(y|\boldsymbol{x};\boldsymbol{\Psi}) = \sum_{k=1}^{K} \underbrace{\pi_k(\boldsymbol{r};\boldsymbol{\alpha})}_{\text{Gating network}} \underbrace{f_k(y|\boldsymbol{x};\boldsymbol{\Psi}_k)}_{\text{Experts}}$$

- Gating function of some predictors $\boldsymbol{r} \in \mathbb{R}^q$: $\pi_k(\boldsymbol{r};\boldsymbol{\alpha}) = \frac{\exp(\boldsymbol{\alpha}_k^T \boldsymbol{r})}{\sum_{\ell=1}^{K} \exp(\boldsymbol{\alpha}_\ell^T \boldsymbol{r})}$
- MoE for regression usually use normal experts $f_k(y|\boldsymbol{x};\boldsymbol{\Psi}_k)$

Objectives

- Overcome (well-known) limitations of modeling with the normal distribution.

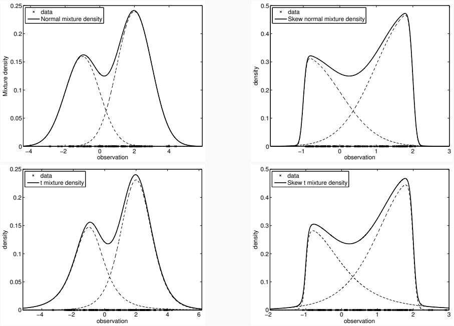
$\hookrightarrow$ Not adapted for a set of data containing a group or groups of observations with asymmetric behavior, heavy tails or atypical observations

Non-normal mixtures of experts

Non-normal mixtures of experts (NNMoE)

1. the t MoE (TMoE) (Robustness, heavy tails) [11]
2. the skew-normal MoE (SNMoE) (skewness) [14]
3. the skew-t MoE (STMoE) (skewness, robustness, heavy tails) [15]

Non-normal mixtures



$\pi_k = [0.4, 0.6]$, $\mu_k = [-1, 2]$; $\sigma_k = [1, 1]$; $\nu_k = [3, 7]$; $\lambda_k = [14, -12]$;

The skew t mixture of experts (STMoE) model

- A K-component mixture of skew t experts (STMoE) is defined by:

$$f(y|\boldsymbol{r}, \boldsymbol{x}; \boldsymbol{\Psi}) = \sum_{k=1}^{K} \pi_k(\boldsymbol{r}; \boldsymbol{\alpha}) \, \mathrm{ST}(y; \mu(\boldsymbol{x}; \boldsymbol{\beta}_k), \sigma_k^2, \lambda_k, \nu_k)$$

- kth expert: has a skew t distribution (Azzalini and Capitanio, 2003):

$$f\big(y|\boldsymbol{x}; \mu(\boldsymbol{x}; \boldsymbol{\beta}_k), \sigma^2, \lambda, \nu\big) = \frac{2}{\sigma} \, t_\nu(d_y(\boldsymbol{x})) \, T_{\nu+1}\left(\lambda \, d_y(\boldsymbol{x}) \sqrt{\frac{\nu + 1}{\nu + d_y^2(\boldsymbol{x})}}\right)$$

Model characteristics

$\hookrightarrow$ For $\{\nu_k\} \to \infty$, the STMoE reduces to the SNMoE

$\hookrightarrow$ For $\{\lambda_k\} \to 0$, the STMoE reduces to the TMoE.

$\hookrightarrow$ For $\{\nu_k\} \to \infty$ and $\{\lambda_k\} \to 0$, it approaches the NMoE.

$\hookrightarrow$ The STMoE is flexible as it generalizes the previously described models to accommodate situations with asymmetry, heavy tails, and outliers.

Parameter estimation via the ECM algorithm

1. E-Step: requires the following conditional expectations:

$$\begin{aligned}
\tau_{ik}^{(m)} &= \mathbb{E}_{\boldsymbol{\Psi}^{(m)}}\left[Z_{ik}|y_i, \boldsymbol{x}_i, \boldsymbol{r}_i\right], \\
w_{ik}^{(m)} &= \mathbb{E}_{\boldsymbol{\Psi}^{(m)}}\left[W_i|y_i, Z_{ik}=1, \boldsymbol{x}_i, \boldsymbol{r}_i\right], \\
e_{1,ik}^{(m)} &= \mathbb{E}_{\boldsymbol{\Psi}^{(m)}}\left[W_i U_i|y_i, Z_{ik}=1, \boldsymbol{x}_i, \boldsymbol{r}_i\right], \\
e_{2,ik}^{(m)} &= \mathbb{E}_{\boldsymbol{\Psi}^{(m)}}\left[W_i U_i^2|y_i, Z_{ik}=1, \boldsymbol{x}_i, \boldsymbol{r}_i\right], \\
e_{3,ik}^{(m)} &= \mathbb{E}_{\boldsymbol{\Psi}^{(m)}}\left[\log(W_i)|y_i, Z_{ik}=1, \boldsymbol{x}_i, \boldsymbol{r}_i\right].
\end{aligned}$$

$\hookrightarrow$ Calculated analytically except $e_{3,ik}^{(m)}$ $\hookrightarrow$ I adopted a one-step-late (OSL) approach as in Lee and McLachlan (2014)

$\hookrightarrow$ Note that Lee and McLachlan (2015) presented an exact series-based truncation approach for the multivariate skew t mixture models

2. CM-Steps: Include weighted logistic regressions and linear regressions

$\hookrightarrow$ Predicted response: $\hat{y} = \mathbb{E}_{\hat{\boldsymbol{\Psi}}}(Y|\boldsymbol{r}, \boldsymbol{x})$ with $\mathbb{E}_{\hat{\boldsymbol{\Psi}}}(Y|\boldsymbol{r}, \boldsymbol{x}) = \sum_{k=1}^{K} \pi_k(\boldsymbol{r}; \hat{\boldsymbol{\alpha}}_n)\mathbb{E}_{\hat{\boldsymbol{\Psi}}}(Y|Z=k, \boldsymbol{x})$

$\hookrightarrow$ Predicted class: $\hat{z} = \arg\max_{k=1}^{K} \mathbb{E}[Z|\boldsymbol{r}, \boldsymbol{x}; \hat{\boldsymbol{\Psi}}]$

$\hookrightarrow$ Model selection: Select (K, p) using BIC or ICL

Tone perception data set

- Recently studied by Bai et al. (2012) and Song et al. (2014) by using, respectively, robust t regression mixture and Laplace regression mixture
- Data consist of $n = 150$ pairs of “tuned” variables, considered here as predictors (x), and their corresponding “strech ratio” variables considered as responses (y).

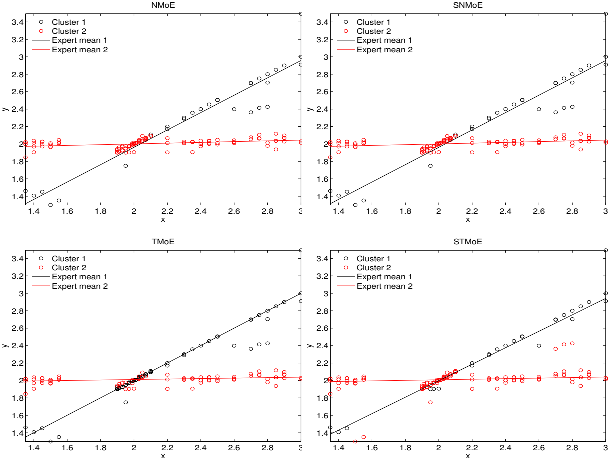


Figure: Fitting the MoE models to the tone data set

Robustness of the NNMoE

Experimental protocol as in Nguyen and McLachlan (2016)

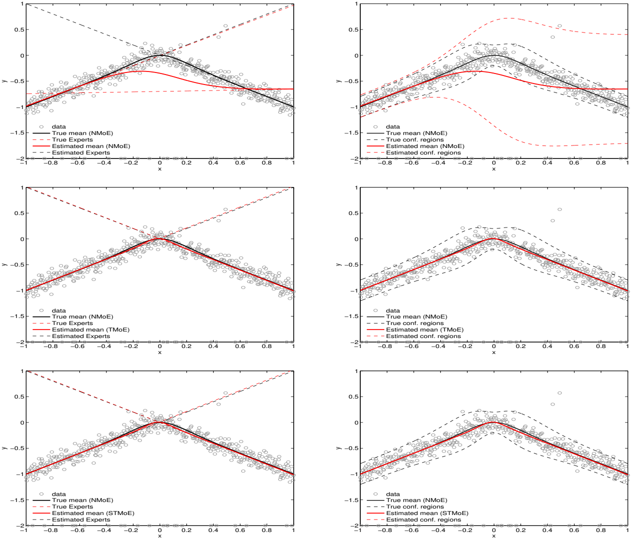


Figure: Fitted MoE to $n = 500$ observations generated according to the NMoE with 5% of outliers $(x; y = -2)$: NMoE fit (top), TMoE fit (middle), STMoE fit (bottom).

Tone perception data set (noisy case)

- Consider the same scenario used in Bai et al. (2012) and Song et al. (2014) (the last and more difficult scenario) by adding 10 identical pairs $(0, 4)$

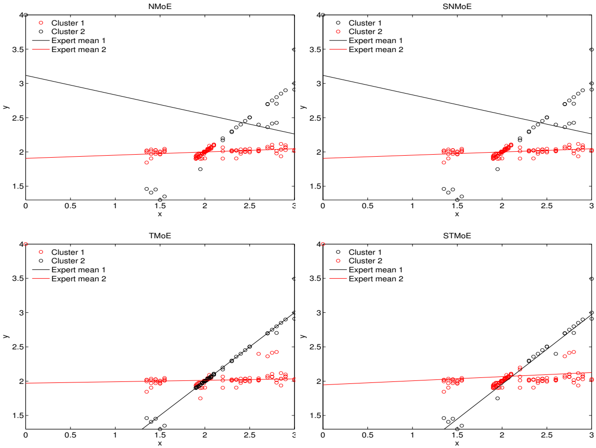
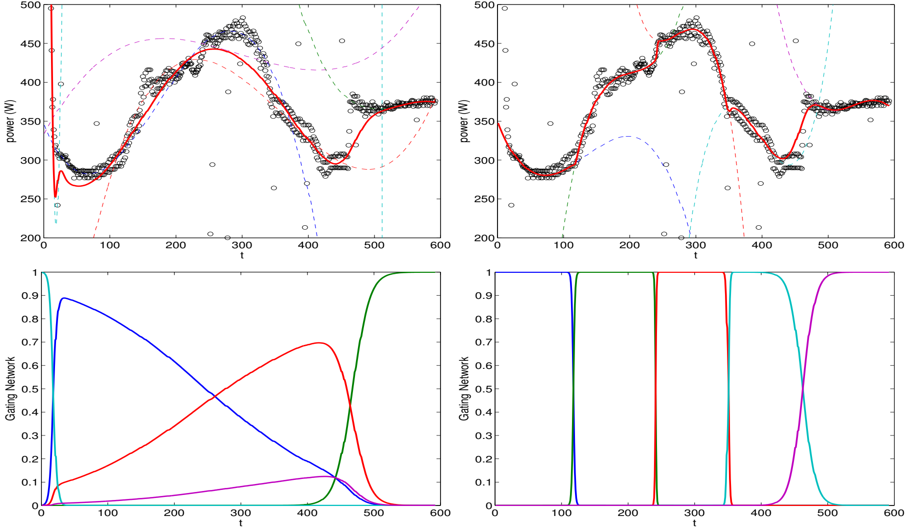


Figure: Fitting MoLE to the tone data set with ten added outliers $(0, 4)$.

$\hookrightarrow$ In this noisy case the t mixture of regressions fails (is affected severely by the outliers) as showed in Song et al. (2014)

Temporal railway data segmentation

- $n = 562$ temporal data
- 30 added artificial outliers



Outline

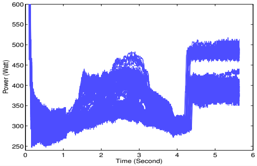
1. Mixture models for temporal data segmentation

2. Mixture models for functional data analysis
   - Mixture of piecewise regressions
   - Mixture of hidden Markov model regressions
   - Mixture of hidden logistic process regressions
   - Functional discriminant analysis
   - Regularized regression mixtures for functional data

3. Bayesian (non-)parametric mixtures for spatial and multivariate data

Functional data analysis context

Many curves to analyze



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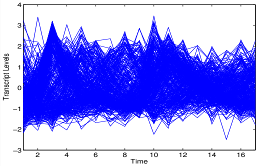
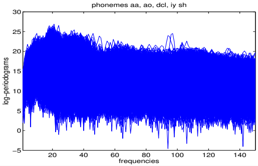
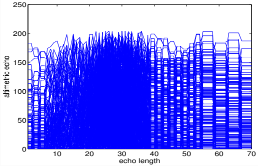


Yeast cell cycle curves



Phonemes curves



Satellite waveforms

Objectives

- Curve clustering/classification (functional data analysis framework)
- Deal with the problem of regime changes $\hookrightarrow$ Curve segmentation

Functional data analysis context

Data

- The individuals are entire functions (e.g., curves, surfaces)
- A set of n univariate curves $((\boldsymbol{x}_1, \boldsymbol{y}_1), \ldots, (\boldsymbol{x}_n, \boldsymbol{y}_n)$
- $(\boldsymbol{x}_i, \boldsymbol{y}_i)$ consists of m_i observations $\boldsymbol{y}_i = (y_{i1}, \ldots, y_{im_i})$ observed at the independent covariates, (e.g., time t in time series), $(x_{i1}, \ldots, x_{im_i})$

Objectives: exploratory or decisional

1. Unsupervised classification (clustering, segmentation) of functional data, particularly curves with regime changes: [4] [9], [C11] [16]
2. Discriminant analysis of functional data: [2], [5]

Functional data clustering/classification tools

- A broad literature (Kmeans-type, Model-based, etc)

$\Rightarrow$ Mixture-model based cluster and discriminant analyzes

Mixture modeling framework for functional data

- The functional mixture model:

$$f(\boldsymbol{y}|\boldsymbol{x};\boldsymbol{\Psi}) = \sum_{k=1}^{K} \alpha_k f_k(\boldsymbol{y}|\boldsymbol{x};\boldsymbol{\Psi}_k)$$

- $f_k(y|\boldsymbol{x})$ are tailored to functional data: can be polynomial (B-)spline regression, regression using wavelet bases etc, or Gaussian process regression, functional PCA

  $\hookrightarrow$ more tailored to approximate smooth functions

  $\hookrightarrow$ do not account for segmentation

Here $f_k(y|\boldsymbol{x})$ itself exhibits a clustering property via hidden variables (regimes):

1. Riecewise regression model (PWR)
2. Regression model with a hidden Markov process (HMMR)
3. Regression model with hidden logistic process (RHLP)

Piecewise regression mixture model (PWRM) [9]

- A probabilistic version of the K-means-like approach of (Hébrail et al., 2010)

$$f(\boldsymbol{y}_i|\boldsymbol{x}_i;\boldsymbol{\Psi}) = \sum_{k=1}^{K}\alpha_k \underbrace{\prod_{r=1}^{R_k}\prod_{j\in I_{kr}}\mathcal{N}(y_{ij};\boldsymbol{\beta}_{kr}^T\boldsymbol{x}_{ij},\sigma_{kr}^2)}_{\text{PWR}}$$

$I_{kr} = (\xi_{kr}, \xi_{k,r+1}]$ are the element indexes of segment r for component k

- $\hookrightarrow$ Simultaneously accounts for curve clustering and segmentation

Parameter estimation

1. Maximum likelihood estimation: EM-PWRM
2. Maximum classification likelihood estimation: CEM-PWRM

$\hookrightarrow$ a generalization of the K-means-like algorithm of Hébrail et al. (2010):

M-step: includes wighted piecewise regressions $\hookrightarrow$ dynamic programming

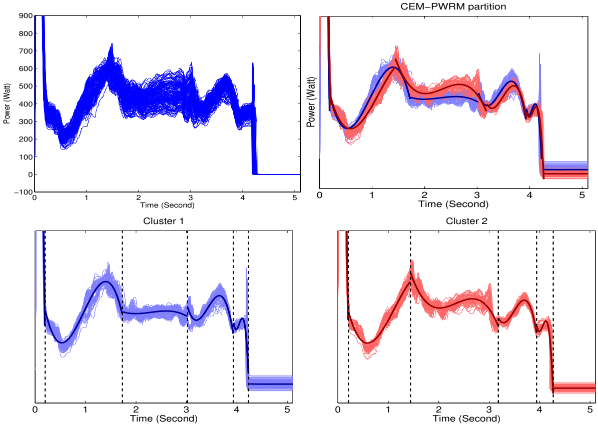
Complexity in $\mathcal{O}(I_{\text{EM}}KRnm^2p^3)$: Significant computational load for large m

Curve clustering: $\hat{z}_i = \arg\max_k \tau_{ik}(\hat{\boldsymbol{\Psi}})$ with $\tau_{ik}(\hat{\boldsymbol{\Psi}}) = \mathbb{P}(Z_i|\boldsymbol{x}_i,\boldsymbol{y}_i;\hat{\boldsymbol{\Psi}})$

Application to switch operation curves

Data set: $n = 146$ real curves of $m = 511$ observations.

Each curve is composed of $R = 6$ electromechanical phases (regimes)

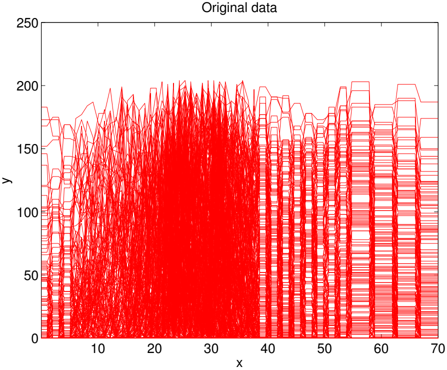


EM-GMM	EM-PRM	EM-PSRM	K-means-like	CEM-PWRM
721.46	738.31	734.33	704.64	703.18

Table: Estimated intra-cluster inertia for the switch curves.

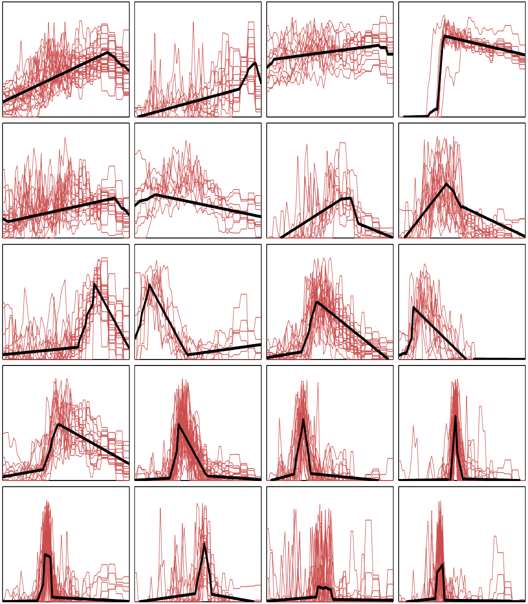
Application to Topex/Poseidon satellite data

The Topex/Poseidon radar satellite data[1] contains $n = 472$ waveforms of the measured echoes, sampled at $m = 70$ (number of echoes)
We considered the same number of clusters (twenty) and a piecewise linear approximation of four segments per cluster as in Hébrail et al. (2010).



[1]Satellite data are available at
http://www.lsp.ups-tlse.fr/staph/npfda/npfda-datasets.html.

CEM-PWRM clustering of the satellite data



Mixture of hidden logistic process regressions [4]

- The mixture of regressions with hidden logistic processes (MixRHLP):

$$f(\boldsymbol{y}_i|\boldsymbol{x}_i;\boldsymbol{\Psi}) = \sum_{k=1}^{K}\alpha_k \underbrace{\prod_{j=1}^{m_i}\sum_{r=1}^{R_k}\pi_{kr}(x_j;\mathbf{w}_k)\mathcal{N}\left(y_{ij};\boldsymbol{\beta}_{kr}^T\boldsymbol{x}_j,\sigma_{kr}^2\right)}_{\text{RHLP}}$$

$$\pi_{kr}(x_j;\mathbf{w}_k) = \mathbb{P}(H_{ij}=r|Z_i=k,x_j;\mathbf{w}_k) = \frac{\exp\left(w_{kr0}+w_{kr1}x_j\right)}{\sum_{r'=1}^{R_k}\exp\left(w_{kr'0}+w_{kr'1}x_j\right)},$$

- Two types of component memberships:

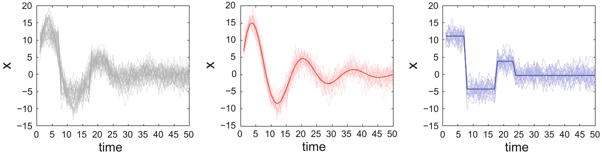
  ↪ cluster memberships (global) $Z_{ik}=1$ iff $Z_i=k$

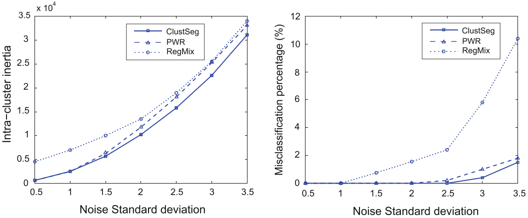
  ↪ regime memberships for a given cluster (local): $H_{ijr}=1$ iff $H_{ij}=r$

  MixRHLP deals better with the quality of regime changes

- Parameter estimation via the EM algorithm: EM-MixRHLP
- EM-MixRHLP has complexity in $\mathcal{O}(I_{\text{EM}}I_{\text{IRLS}}KR^3nmp^3)$ (K-means type for piecewise regression is in $\mathcal{O}(I_{\text{KM}}KRnm^2p^3)$ ↪ EM-MixRHLP is computationally attractive for large values of m and moderate values of R.

EM-MixRHLP clustering of simulated data





Functional discriminant analysis

Supervised classification context

- Data: a training set of labeled functions $((\boldsymbol{x}_1, y_1, c_1), \ldots, (\boldsymbol{x}_n, y_n, c_n))$ where $c_i \in \{1, \ldots, G\}$ is the class label of the ith curve
- Problem: predict the class label c_i for a new unlabeled function $(\boldsymbol{x}_i, \boldsymbol{y}_i)$

Tool: Discriminant analysis

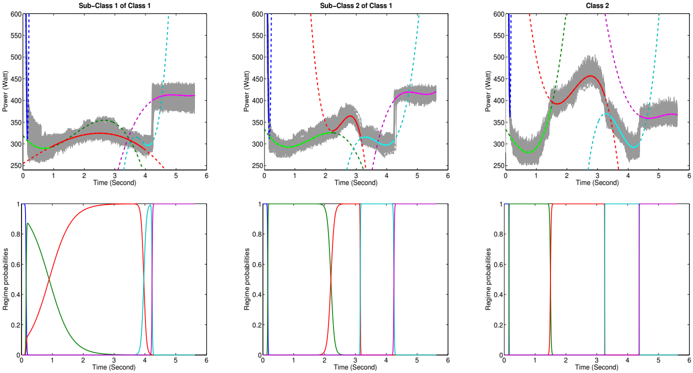
Use the Bayes' allocation rule

$$\hat{c}_i = \arg \max_{1 \leq g \leq G} \frac{\mathbb{P}(C_i = g) f(\boldsymbol{y}_i | \boldsymbol{x}_i; \boldsymbol{\Psi}_g)}{\sum_{g'=1}^{G} \mathbb{P}(C_i = g') f(\boldsymbol{y}_i | \boldsymbol{x}_i; \boldsymbol{\Psi}_{g'})},$$

based on a generative model $f(\boldsymbol{y}_i | \boldsymbol{x}_i; \boldsymbol{\Psi}_g)$ for each group g

- Homogeneous classes: Functional Linear Discriminant Analysis [8]
- Dispersed classes: Functional Mixture Discriminant Analysis [5]

Applications to switch curves



Approach	Classification error rate (%)	Intra-class inertia
FLDA-PR	11.5	10.7350×10^9
FLDA-SR	9.53	9.4503×10^9
FLDA-RHLP	8.62	8.7633×10^9
FMDA-PRM	9.02	7.9450×10^9
FMDA-SRM	8.50	5.8312×10^9
FMDA-MixRHLP	**6.25**	$\mathbf{3.2012 \times 10^9}$

Regularized regression mixtures

The finite Gaussian regression mixture model

$$f(\boldsymbol{y}_i|\boldsymbol{x}_i;\boldsymbol{\theta}) = \sum_{k=1}^{K} \pi_k \, \mathcal{N}(\boldsymbol{y}_i; \mathbf{X}_i\boldsymbol{\beta}_k, \sigma_k^2 \mathbf{I}_{m_i})$$

- The parameter $\boldsymbol{\theta}$ is usually estimated by ML: $\log L(\boldsymbol{\theta}) = \sum_{i=1}^{n} \log f(\boldsymbol{y}_i|\boldsymbol{x}_i;\boldsymbol{\theta})$
- the EM algorithm is the usual tool

↪ requires careful initialization (Biernacki et al., 2003)

↪ requires the number of components K to be supplied by the user (or BIC, ICL etc)

Idea of the proposed approach [8]

↪ A fully unsupervised fitting of regression mixtures
↪ EM-like algorithm which is robust with regard initialization and infers the number of components from the data

Regularized regression mixtures [8]

- Penalized log-likelihood criterion:

$$\mathcal{J}(\lambda, \mathbf{\Psi}) = \log L(\mathbf{\Psi}) - \lambda H(\mathbf{z}), \quad \lambda \geq 0$$
$$= \sum_{i=1}^{n} \log \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{y}_i; \mathbf{X}_i \boldsymbol{\beta}_k, \sigma_k^2 \mathbf{I}_m) + \lambda n \sum_{k=1}^{K} \pi_k \log \pi_k$$

- $H(\mathbf{Z}) = -\mathbb{E}[\log \mathbb{P}(\mathbf{Z})]$: - entropy accounting for model complexity
- $\lambda \geq 0$ is a smoothing parameter

EM-like algorithm for unsupervised learning [8]

initialization : $K^{(0)} = n$; $\pi_k^{(0)} = \frac{1}{K^{(0)}}$, $(\boldsymbol{\beta}_k^{(0)}, \sigma_k^{2(0)})$: polynomial regression

1. **E-step**: Posterior component memberships $\tau_{ik}^{(q)} = \mathbb{P}(Z_i = k | \boldsymbol{x}_i, \boldsymbol{y}_i; \widehat{\boldsymbol{\Psi}})$
2. **M-step**: $\pi_k^{(q+1)} = \frac{1}{n} \sum_{i=1}^{n} \tau_{ik}^{(q)} + \lambda \pi_k^{(q)} \left(\log \pi_k^{(q)} - \sum_{h=1}^{K} \pi_h^{(q)} \log \pi_h^{(q)}\right)$

$$\boldsymbol{\beta}_k^{(q+1)} = \left[\sum_{i=1}^{n} \tau_{ik}^{(q)} \mathbf{X}_i^T \mathbf{X}_i\right]^{-1} \sum_{i=1}^{n} \tau_{ik}^{(q)} \mathbf{X}_i^T \mathbf{y}_i \quad \sigma_k^{2(q+1)} = \frac{\sum_{i=1}^{n} \tau_{ik}^{(q)} \|\mathbf{y}_i - \mathbf{X}_i \boldsymbol{\beta}_k\|^2}{m \sum_{i=1}^{n} \tau_{ik}^{(q)}}$$

The penalization coefficient λ is set in an adaptive way

$\hookrightarrow$ However, does not guarantee the ascent property of the objective function

Phonemes data

Phonemes data set used in Ferraty and Vieu (2003)[2]

1000 log-periodograms (200 per cluster)

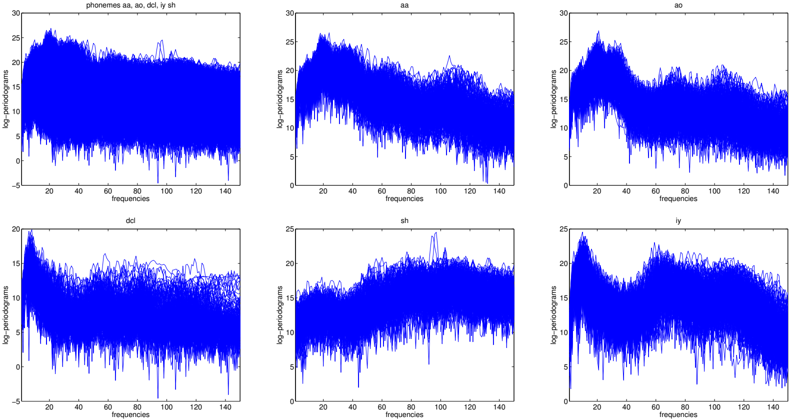


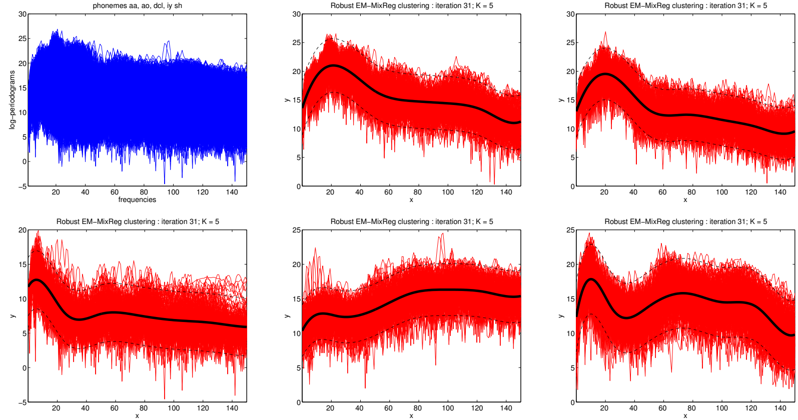
Figure: Original phoneme data and curves of the five classes: "ao", "aa", "yi", "dcl", "sh".

[2]Data from `http://www.math.univ-toulouse.fr/staph/npfda/`

EM-like clustering results for Phonemes

Phonemes data set used in Ferraty and Vieu (2003)[3]

1000 log-periodograms (200 per cluster)



	EM-PRM	EM-SRM	EM-bSRM
Estimated K	5	5	5
Misc. error rate	14.29 %	14.09 %	14.2 %

[3] Data from http://www.math.univ-toulouse.fr/staph/npfda/

Yeast cell cycle data

- Time course Gene expression data as in Yeung et al. (2001) [4]
- 384 genes expression levels over 17 time points.

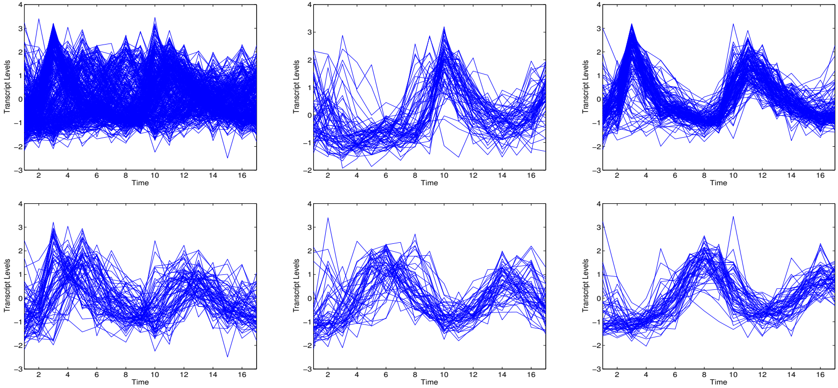


Figure: The five "actual" clusters of the used yeast cell cycle data according to Yeung et al. (2001).

[4] http://faculty.washington.edu/kayee/model/

EM-like clustering results for yeast cell cycle data

- Time course Gene expression data as in Yeung et al. (2001)
- 384 genes expression levels over 17 time points.

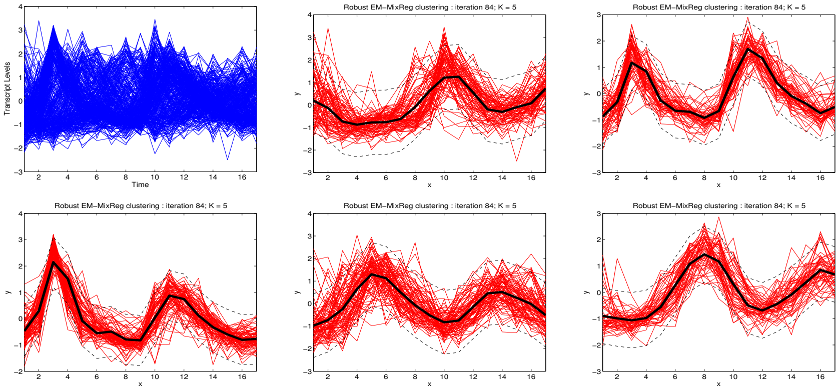


Figure: EM-like clustering results with the bSRM model.

Rand index: 0.7914 which indicates that the partition is quite well defined.

Outline

Bayesian spatial spline regression with mixed-effects

- Data: $((\boldsymbol{x}_1, \boldsymbol{y}_1), \ldots, (\boldsymbol{x}_n, \boldsymbol{y}_n))$ a sample of n surfaces $\boldsymbol{y}_i = (y_{i1}, \ldots, y_{im_i})^T$ and their spatial coordinates $\boldsymbol{x}_i = ((x_{i11}, x_{i12}), \ldots, (x_{im_i1}, x_{im_i2}))^T$.
- Propose regression and regression mixtures, with three additional features:

1. Include random effects
2. Models for spatial functional data
3. A full Bayesian inference

Bayesian spatial spline regression with mixed-effects [Esann 2016, 13]

$$\boldsymbol{y}_i = \mathbf{S}_i(\boldsymbol{\beta} + \mathbf{b}_i) + \mathbf{e}_i, \quad \mathbf{e}_i \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I}_{m_i}), \ (i = 1, \ldots, n)$$

- $\boldsymbol{\beta}$: fixed-effects regression coefficients
- $\mathbf{b}_i$: random subject-specific regression coefficients $\mathbf{b}_i \perp \mathbf{e}_i \sim \mathcal{N}(\mathbf{0}, \xi^2 \mathbf{I}_{m_i})$
- $\mathbf{S}_i$ is a spatial design matrix.

- $\mathbf{S}_i$ constructed from the Nodal basis functions (NBF) (Malfait and Ramsay, 2003) used in (Ramsay et al., 2011; Sangalli et al., 2013; Nguyen et al., 2014)
- NBFs extend the univariate B-spline bases to bivariate surfaces.

$$\mathbf{S}_i = \begin{pmatrix} s(\boldsymbol{x}_1;\mathbf{c}_1) & s(\boldsymbol{x}_1;\mathbf{c}_2) & \cdots & s(\boldsymbol{x}_1;\mathbf{c}_d) \\ s(\boldsymbol{x}_2;\mathbf{c}_1) & s(\boldsymbol{x}_2;\mathbf{c}_2) & \cdots & s(\boldsymbol{x}_2;\mathbf{c}_d) \\ \vdots & \vdots & \ddots & \vdots \\ s(\boldsymbol{x}_{m_i};\mathbf{c}_1) & s(\boldsymbol{x}_{m_i};\mathbf{c}_2) & \cdots & s(\boldsymbol{x}_{m_i};\mathbf{c}_d) \end{pmatrix}$$

d: number of basis functions d

$\boldsymbol{x}_{ij} = (x_{ij1}, x_{ij2})$ the two spatial coordinates of y_{ij}

$\mathbf{c} = (c_1, c_2)$ is a node center parameter, with v/h shape parameters δ_1 and δ_1

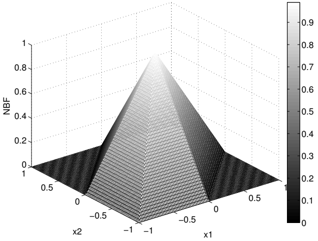


Figure: Nodal basis function $s(\boldsymbol{x}, \mathbf{c}, \delta_1, \delta_2)$, where $\mathbf{c} = (0, 0)$ and $\delta_1 = \delta_2 = 1$.

Bayesian mixture of spatial spline regressions

Data: A sample of n surfaces $(\boldsymbol{y}_1, \ldots, \boldsymbol{y}_n)$ and their spatial covariates $(\mathbf{S}_1, \ldots, \mathbf{S}_n)$ issued from K sub-populations

- Bayesian mixture of spatial spline regression models with mixed-effects (BMSSR):

$$f(\boldsymbol{y}_i|\mathbf{S}_i;\boldsymbol{\Psi}) = \sum_{k=1}^{K} \pi_k \, \mathcal{N}\left(\boldsymbol{y}_i; \mathbf{S}_i(\boldsymbol{\beta}_k + \mathbf{b}_{ik}), \sigma_k^2 \mathbf{I}_{m_i}\right)$$

$\hookrightarrow$ Useful for density estimation and model-based clustering of heterogeneous surfaces

Hierarchical prior from for the BMSSR

$$\begin{array}{lcl}
\boldsymbol{\pi} & \sim & \mathcal{D}(\alpha_1, \ldots, \alpha_K) \\
\boldsymbol{\beta}_k & \sim & \mathcal{N}(\boldsymbol{\mu}_{\mathbf{0}}, \Sigma_0) \\
\mathbf{b}_{ik}|\xi_k^2 & \sim & \mathcal{N}(\mathbf{0}_d, \xi_k^2 \mathbf{I}_d) \\
\xi_k^2 & \sim & \mathcal{IG}(a_0, b_0) \\
\sigma_k^2 & \sim & \mathcal{IG}(g_0, h_0).
\end{array}$$

Bayesian inference of the BMSSR

- For the BMSSR, the parameter $\boldsymbol{\Psi}$ is augmented by the unknown components labels $\mathbf{z} = (z_1, \ldots, z_n)$

Bayesian inference of the BMSSR using Gibbs sampling

- Sample from the analytic full conditional distributions:

$$Z_i|... \sim \mathcal{M}(1; \tau_{i1}, \ldots, \tau_{iK}) \text{ with } \tau_{ik}(1 \leq k \leq K) = \mathbb{P}(Z_i = k|\boldsymbol{y}_i, \mathbf{S}_i; \boldsymbol{\Psi})$$
$$\boldsymbol{\pi}|... \sim \mathcal{D}\left(\alpha_1 + n_1, \ldots, \alpha_K + n_K\right)$$
$$\boldsymbol{\beta}_k|... \sim \mathcal{N}(\boldsymbol{\nu}_0, \mathbf{V}_0)$$
$$\mathbf{b}_{ik}|... \sim \mathcal{N}(\boldsymbol{\nu}_1, \mathbf{V}_1)$$
$$\sigma_k^2|... \sim \mathcal{IG}(g_1, h_1)$$
$$\xi_k^2|... \sim \mathcal{IG}\left(a_1, b_1\right)$$

- relabel the obtained posterior parameter samples if label switching by the K-means-like algorithm of (Celeux, 1999; Celeux et al., 2000).

Illustration on simulated surfaces' approximation

A sample of 100 simulated noisy surfaces from $\mu(\mathbf{x}) = \frac{\sin(\sqrt{1+x_1^2+x_2^2})}{\sqrt{1+x_1^2+x_2^2}}$

The simulated data include mixed effects.

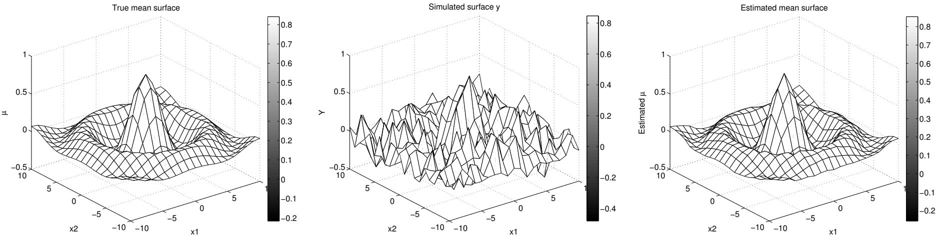


Figure: True mean surface (left), an example of noisy surface (middle), A BSSR fit $\hat{\mu}(\boldsymbol{x}) = \mathbf{S}_i\hat{\boldsymbol{\beta}}$ from 100 surfaces using 15×15 NBFs (right).

Empirical sum of squared error: $SSE = \sum_{j=1}^{m}(\mu_j(\boldsymbol{x}) - \hat{\mu}_j(\boldsymbol{x}))^2$ ($m = 441$ here): 0.0865 (a very reasonable fit)

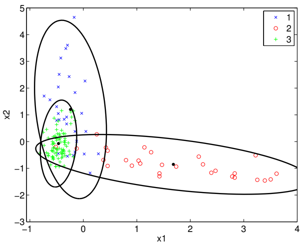
Handwritten digit clustering using the BMSSR

- BMSSR applied on a subset of the ZIPcode data set (issued from MNIST)
- Each individual $\boldsymbol{y}_i$ contains $m_i = 256$ observations
  A subset of 1000 digits randomly chosen from the test set

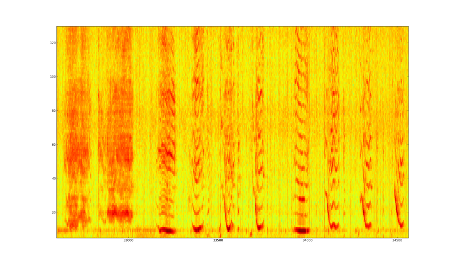
Figure: Cluster mean images obtained by the BMSSR model with 12 mixture components.

The best solution is selected in terms of the Adjusted Rand Index (ARI) values, which promotes a partition with $K = 12$ clusters (ARI: 0.5238).

Multivariate data



Diabetes Benchmark



Spectrum of bioacoustic data

Objectives

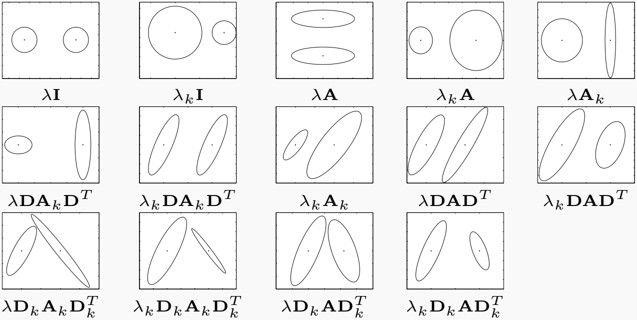
- Clustering
- Dimensionality reduction

Model-Based clustering of multidimensional data

- Data: $(\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n)$ A sample of n i.i.d observations in $\mathbb{R}^d$ from K sub-populations, with K possibly unknown
- Objective: clustering and dimensionality reduction

Parsimonious mixtures

- Finite Gaussian mixtures: $f(\boldsymbol{x}_i; \boldsymbol{\theta}) = \sum_{k=1}^{K} \pi_k \, \mathcal{N}(\boldsymbol{x}_i; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$
- Eigenvalue decomposition of the covariance matrix[a] $\boldsymbol{\Sigma}_k = \lambda_k \mathbf{D}_k \mathbf{A}_k \mathbf{D}_k^T$



[a] Celeux and Govaert (1995); Banfield and Raftery (1993)

Dirichlet Process Parsimonious Mixtures

- Bayesian parametric inference: (Bensmail, 1995; Bensmail and Celeux, 1996; Bensmail et al., 1997; Bensmail and Meulman, 2003)

- $\hookrightarrow$ Mixture models for multivariate data in a fully Bayesian framework
- $\hookrightarrow$ Dirichlet Process and Parsimonious Mixtures [C5,6,8], [11]

Dirichlet Processes (DP)

DP(α, G_0) (Ferguson, 1973) is a distribution over distributions:

$$\tilde{\boldsymbol{\theta}}_i | G \sim G \; ; \quad G|\alpha, G_0 \sim \text{DP}(\alpha, G_0) \; , i = 1, 2, \ldots$$

Pólya urn representation (Blackwell and MacQueen, 1973)

$$\tilde{\boldsymbol{\theta}}_i | \tilde{\boldsymbol{\theta}}_1, \ldots \tilde{\boldsymbol{\theta}}_{i-1} \quad \sim \quad \frac{\alpha}{\alpha + i - 1} G_0 + \sum_{k=1}^{K_{i-1}} \frac{n_k}{\alpha + i - 1} \delta_{\boldsymbol{\theta}_k}$$

DP places its probability mass on an infinite mixture of Dirac deltas

$$G = \sum_{k=1}^{\infty} \pi_k \delta_{\boldsymbol{\theta}_k} \quad \boldsymbol{\theta}_k | G_0 \sim G_0, \; k = 1, 2, \ldots, \text{ with} \sum_{k=1}^{\infty} \pi_k = 1$$

$\hookrightarrow$ The generated parameters $\tilde{\boldsymbol{\theta}}_i$ for a DP process exhibit a clustering property

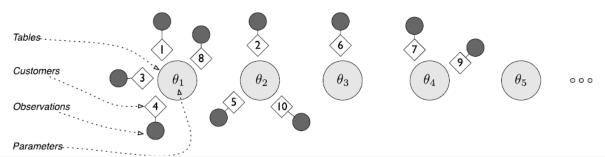
DPM: Generative model

$$
\begin{aligned}
G|\alpha, G_0 &\sim \text{DP}(\alpha, G_0) \\
\tilde{\boldsymbol{\theta}}_i|G &\sim G \\
\boldsymbol{x}_i|\tilde{\boldsymbol{\theta}}_i &\sim f(.|\tilde{\boldsymbol{\theta}}_i)
\end{aligned}
$$

Chinese Restaurant Process mixtures (Pitman, 2002; Samuel and Blei, 2012)

- Latent variables $(z_1, \ldots, z_n)$
- Predictive distribution:

$$p(z_i = k|z_1, ..., z_{i-1}; \alpha) = \frac{\alpha}{\alpha + i - 1}\delta(z_i, K_{i-1} + 1) + \sum_{k=1}^{K_{i-1}} \frac{n_k}{\alpha + i - 1}\delta(z_i, k)\,.$$



- Generative model:

$$
\begin{aligned}
z_i|\alpha &\sim \text{CRP}(\mathbf{z}_{\backslash i}; \alpha) \\
\boldsymbol{\theta}_{z_i}|G_0 &\sim G_0 \\
\mathbf{x}_i|\boldsymbol{\theta}_{z_i} &\sim f(.|\boldsymbol{\theta}_{z_i})
\end{aligned}
$$

Implemented parsimonious models

Decomposition	Model-Type	Prior	Applied to
$\lambda \mathbf{I}$	Spherical	$\mathcal{IG}$	λ
$\lambda_k \mathbf{I}$	Spherical	$\mathcal{IG}$	λ_k
$\lambda \mathbf{A}$	Diagonal	$\mathcal{IG}$	each diagonal element of $\lambda \mathbf{A}$
$\lambda_k \mathbf{A}$	Diagonal	$\mathcal{IG}$	each diagonal element of $\lambda_k \mathbf{A}$
$\lambda \mathbf{DAD}^T$	General	$\mathcal{IW}$	$\mathbf{\Sigma} = \lambda \mathbf{DAD}^T$
$\lambda_k \mathbf{DAD}^T$	General	$\mathcal{IG}$ and $\mathcal{IW}$	λ_k and $\mathbf{\Sigma} = \mathbf{DAD}^T$
$\lambda \mathbf{DA}_k \mathbf{D}^T$*	General	$\mathcal{IG}$	each diagonal element of $\lambda \mathbf{A}_k$
$\lambda_k \mathbf{DA}_k \mathbf{D}^T$*	General	$\mathcal{IG}$	each diagonal element of $\lambda_k \mathbf{A}_k$
$\lambda \mathbf{D}_k \mathbf{AD}_k^T$	General	$\mathcal{IG}$	each diagonal element of $\lambda \mathbf{A}$
$\lambda_k \mathbf{D}_k \mathbf{AD}_k^T$	General	$\mathcal{IG}$	each diagonal element of $\lambda_k \mathbf{A}$
$\lambda \mathbf{D}_k \mathbf{A}_k \mathbf{D}_k^T$*	General	$\mathcal{IG}$ and $\mathcal{IW}$	λ and $\mathbf{\Sigma}_k = \mathbf{D}_k \mathbf{A}_k \mathbf{D}_k^T$
$\lambda_k \mathbf{D}_k \mathbf{A}_k \mathbf{D}_k^T$	General	$\mathcal{IW}$	$\mathbf{\Sigma}_k = \lambda_k \mathbf{D}_k \mathbf{A}_k \mathbf{D}_k^T$

Bayesian inference using Gibbs sampling

- Posterior distribution for the component labels:
  $p(z_i = k|\mathbf{z}_{-i}, \mathbf{X}, \mathbf{\Theta}, \alpha) \propto p(\mathbf{x}_i|z_i; \mathbf{\Theta}) p(z_i|\mathbf{z}_{-i}; \alpha)$ with $p(z_i|\mathbf{z}_{-i}; \alpha)$ the CRP prior
- Posterior distribution for the component parameters:
  $p(\boldsymbol{\theta}_k|\mathbf{z}, \mathbf{X}, \mathbf{\Theta}_{-k}, \alpha; H) \propto \prod_{i|z_i=k} p(\mathbf{x}_i|z_i = k; \boldsymbol{\theta}_k) p(\boldsymbol{\theta}_k; H)$ with $p(\boldsymbol{\theta}_k; H)$: Prior distribution over $\boldsymbol{\theta}_k$

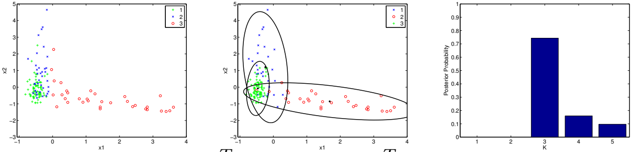
Bayesian model comparison by using Bayes Factors

$BF_{12} = \frac{p(\mathbf{X}|M_1)p(M_1)}{p(\mathbf{X}|M_2)p(M_2)} \approx \frac{p(\mathbf{X}|M_1)}{p(\mathbf{X}|M_2)}$ with the Laplace-Metropolis approximation

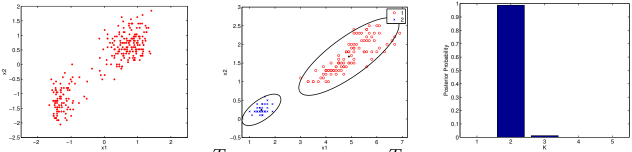
$p(\mathbf{X}|M_m) = \int p(\mathbf{X}|\boldsymbol{\theta}_m, M_m) p(\boldsymbol{\theta}_m|M_m) \mathrm{d}\boldsymbol{\theta}_m \approx (2\pi)^{\frac{\nu_m}{2}} |\hat{\mathbf{H}}|^{\frac{1}{2}} p(\mathbf{X}|\hat{\boldsymbol{\theta}}_m, M_m) p(\hat{\boldsymbol{\theta}}_m|M_m)$

Clustering of benchmarks

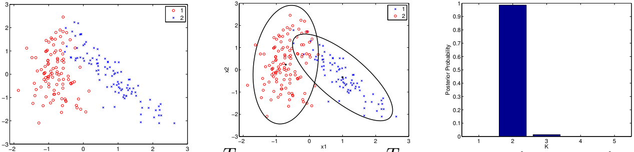
Diabetes data set, Geyser data set, Crabs data set



2 log BF: $\lambda_k \mathbf{D}_k \mathbf{A} \mathbf{D}_k^T \;\; vs \;\; \lambda \mathbf{D}_k \mathbf{A} \mathbf{D}_k^T \; = \; 199.58$ (Decisive)



2 log BF: $\lambda \mathbf{D} \mathbf{A} \mathbf{D}^T \;\; vs \;\; \lambda_k \mathbf{D}_k \mathbf{A} \mathbf{D}_k^T \; = \; 5$ (Substantial)



log 2BF: $\lambda_k \mathbf{D}_k \mathbf{A} \mathbf{D}_k^T \;\; vs \;\; \lambda_k \mathbf{D} \mathbf{A} \mathbf{D}^T \; = \; 36.08$ (Decisive)

Humpback whale song decomposition

- Real fully unsupervised problem
- Data: 8.6 minutes of a Humpback whale song recording (with MFCC)

Figure: Humpback Whale.

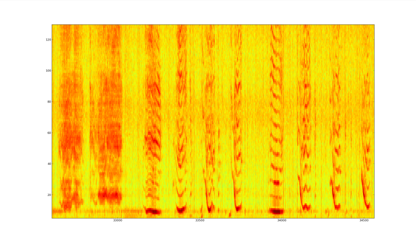
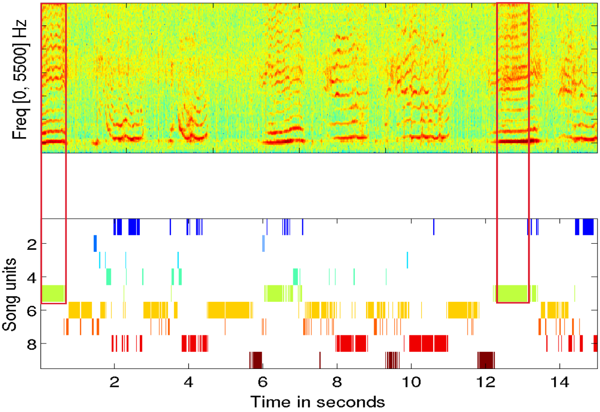


Figure: Spectrum of a signal (20 s).

Objectives

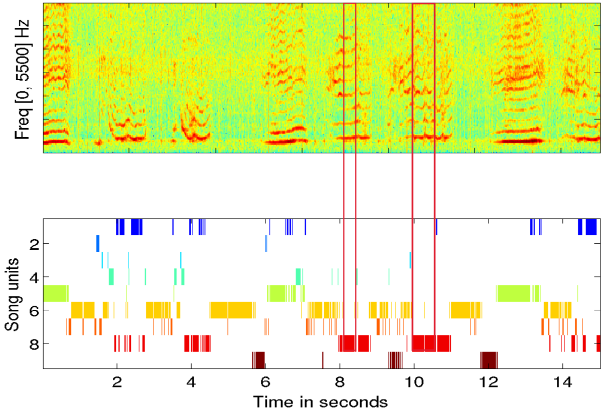
- Discovering “call units”, which can be considered as a whale “alphabet”
- Find a partition of the whale song into clusters (segments), and automatically infer the unknown number of clusters from the data.

Unsupervised decomposition of whale song signals



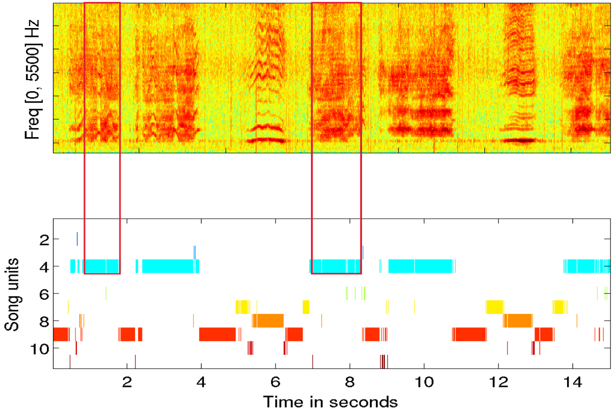
- Sound demo of Unit 5 DPPM $\lambda\mathbf{I}$: (sec. 0) (sec. 12)

Unsupervised decomposition of whale song signals



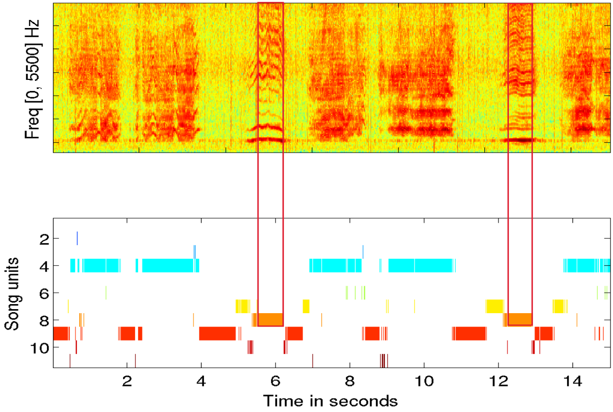
- Sound demo of Unit 8 DPPM $\lambda\mathbf{I}$: (sec. 8) (sec. 10)

Unsupervised decomposition of whale song signals



- Sound demo of Unit 4 DPPM $\lambda_k \mathbf{A}$: (sec. 1) (sec. 7)

Unsupervised decomposition of whale song signals



- Sound demo of Unit 8 DPPM $\lambda_k \mathbf{A}$: (sec. 6) (sec. 12)

Some ongoing research and perspectives

- Model-based co-clustering for high-dimensional functional data

Functional latent block model (FLBM) available soon on arXiv

Data: $\boldsymbol{Y} = (\boldsymbol{y}_{ij})$: n individuals defined on a set $\mathcal{I}$ with d continuous functional variables defined on a set $\mathcal{J}$ where $y_{ij}(t) = \mu(x_{ij}(t); \boldsymbol{\beta}) + \epsilon(t)$, t defined on$\mathcal{T}$.

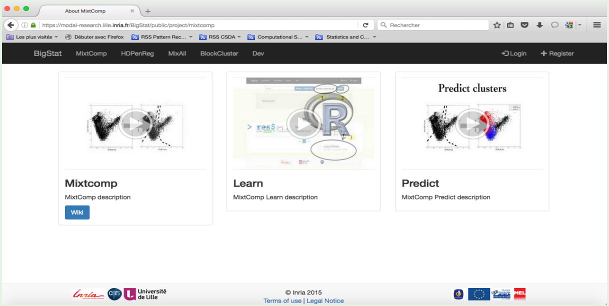
- FLBM model:

$$
\begin{aligned}
f(\boldsymbol{Y}|\boldsymbol{X};\boldsymbol{\Psi}) &= \sum_{(z,w)\in\mathcal{Z}\times\mathcal{W}} \mathbb{P}(\mathbf{Z},\mathbf{W}) f(\boldsymbol{Y}|\boldsymbol{X},\mathbf{Z},\mathbf{W};\boldsymbol{\theta}) \\
&= \sum_{(z,w)\in\mathcal{Z}\times\mathcal{W}} \prod_{i,k} \pi_k^{z_{ik}} \prod_{j,\ell} \rho_\ell^{w_{j\ell}} \prod_{i,j,k,\ell} f(\boldsymbol{y}_{ij}|\boldsymbol{x}_{ij};\boldsymbol{\theta}_{k\ell})^{z_{ik}w_{j\ell}}.
\end{aligned}
$$

- An RHLP is used as a conditional block distribution $f(\boldsymbol{y}_{ij}|\boldsymbol{x}_{ij};\boldsymbol{\theta}_{k\ell})$
- Model inference using Stochastic EM

Some ongoing research and perspectives

Logiciel MixtComp



Mixtures for massive data

- Mixture density estimation for massive data clustering
- Use ensemble methods to distribute the data

  ↪ Bag of Little Boostraps (BLB) (Kleiner et al., 2014)

  ↪ Aggregate local estimators from BLB sub-samples: Hierarchical (mixture) of experts aggregation

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Thank you for your attention!