

# Sorry arima, I'm going Bayesian

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# Sommaire

## Application numérique : Une alternative à l'algorithme E-M pour le mélange de gaussiennes

Échantillon  $\mathbf{x} = (\mathbf{x}_1, \dots, \mathbf{x}_N)$  suivant une loi  $f(\mathbf{x}_i, \theta)$  avec des variables latentes  $\mathbf{z} = (\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_n)$

Maximisation de  $L(\theta; \mathbf{X}) = p(\mathbf{x}|\theta) = \int p(\mathbf{x}, \mathbf{z}|\theta) d\mathbf{Z}$

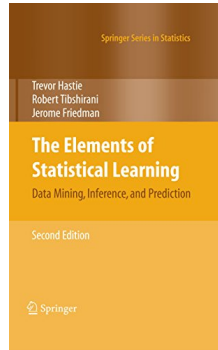
$$E \left[ L(\mathbf{x}; \theta) | \theta^{(c)} \right] = E \left[ L((\mathbf{x}, \mathbf{z}); \theta) | \theta^{(c)} \right] - E \left[ \sum_{i=1}^n \log f(\mathbf{z}_i | \mathbf{x}_i, \theta) | \theta^{(c)} \right]$$

$$L(\mathbf{x}; \theta) = Q(\theta; \theta^{(c)}) - H(\theta; \theta^{(c)})$$

$$\theta^{(c+1)} = \arg \max_{\theta} \left( Q(\theta, \theta^{(c)}) \right) \quad \text{fait tendre la suite } L(\mathbf{x}; \theta^{(c+1)})$$

vers un max local

$$p(\mathcal{C}_1 | \mathbf{x}) = \frac{p(\mathcal{C}_1) p(\mathbf{x} | \mathcal{C}_1)}{p(\mathcal{C}_1) p(\mathbf{x} | \mathcal{C}_1) + p(\mathcal{C}_2) p(\mathbf{x} | \mathcal{C}_2)}$$



## Application : mélange de gaussiennes

- Les données  $\mathbf{x}$  viennent de gaussiennes  $\{C_1, \dots, C_M\}$
- $\mathbf{z}_i \in \{1, \dots, m\}$  si un individu  $i$  vient de  $C_1, \dots, C_M$

$$\mathbf{x}_i | (\mathbf{z}_i = j) \sim \mathcal{N}(\mu_j, \sigma_j^2) \quad \mathbb{P}(\mathbf{z}_i = j) = \pi_j$$

- E-M : maximisation de

$$\ell_{\theta}(\mathbf{x}) = \sum_{n=1}^N \log \left( \sum_{j=1}^M \pi_j \mathcal{N}_{\mu_j, \sigma_j^2}(\mathbf{x}_n) \right)$$

$$\theta = (\pi, \mu, \sigma^2)$$

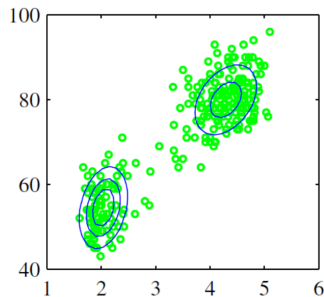


Figure – Mélange de deux gaussiennes [F. Sur, Introduction à l'apprentissage automatique]

## Application : Échantillonneur de Gibbs pour le mélange de 2 gaussiennes

Pour 2 gaussiennes : 
$$\begin{cases} \mathbf{x}_i | (\mathbf{z}_i = 1) \sim \mathcal{N}(\mu_1, \sigma_1^2) & \mathbb{P}(\mathbf{z}_i = 1) = \pi_1 \\ \mathbf{x}_i | (\mathbf{z}_i = 2) \sim \mathcal{N}(\mu_2, \sigma_2^2) & \mathbb{P}(\mathbf{z}_i = 2) = \pi_2 = 1 - \pi_1 \end{cases}$$

■ On veut obtenir  $\Theta = (\mathbf{z}, \mu) = (\mathbf{z}_1, \dots, \mathbf{z}_1, \mu)$  ( $\pi, \sigma$  fixés à  $\hat{\pi}, \hat{\sigma}$ )

■  $\mathbf{z} | \mu$  : utiliser 
$$\mathbb{P}(\mathbf{z}_i = j | \mu, \mathbf{x}) = \frac{\hat{\pi}_j p_{\mathcal{N}}(\mathbf{x}_i, \mu_j, \hat{\sigma}_j)}{\hat{\pi}_1 p_{\mathcal{N}}(\mathbf{x}_i, \mu_1, \hat{\sigma}_1) + \hat{\pi}_2 p_{\mathcal{N}}(\mathbf{x}_i, \mu_2, \hat{\sigma}_2)} \quad j \in \{1, 2\}$$

■  $\mu | \mathbf{z}$  :

(à priori)

$$\begin{aligned} \mathbf{x}_i | \mu, \mathbf{z}_i = j &\sim \mathcal{N}(\mu_j, 1/\hat{\tau}_j) \\ \mu_j &\sim \mathcal{N}(\mu_0, 1/\tau_0) \end{aligned}$$

$$(\tau_j = 1/\sigma_j^2, \bar{x} = \frac{1}{N} \sum_{i=\mathbf{0}}^N x_i)$$

(à postérieur)

$$\begin{aligned} p(\mu_j | \mathbf{z}_i, \mathbf{x}) &\propto p(\mathbf{x} | \mu, \mathbf{z}_i = j) p(\mu_j) \\ &\sim \mathcal{N}(\mu'_0, 1/\tau'_0) \end{aligned}$$

(= maj des coefs)

$$\begin{aligned} \tau'_{j0} &= \tau_0 + N\hat{\tau}_j \\ \mu'_{j0} &= \frac{N \hat{\tau}_j \bar{x} + \tau_0 \mu_0}{N\hat{\tau}_j + \tau_0} \end{aligned}$$

## Échantillonneur de Gibbs pour une mixture gaussienne

1 Prendre les valeurs initiales  $\Theta_0 = (\mathbf{z}^{(0)}, \mu_1^{(0)}, \mu_2^{(0)}), \mu_0, \tau_0$

2 Pour  $t$  de 1 à ...

■ Pour  $i$  de 1 à  $N$  tirer

$$\mathbf{z}_i^{(t+1)} \in \{1, 2\} \text{ avec } \mathbb{P}(\mathbf{z}_i^{(t+1)} = 1) = \frac{\hat{\pi}_1 p_{\mathcal{N}}(\mathbf{x}_i, \mu_1^{(t)}, \hat{\sigma}_1)}{\hat{\pi}_1 p_{\mathcal{N}}(\mathbf{x}_i, \mu_1^{(t)}, \hat{\sigma}_1) + \hat{\pi}_2 p_{\mathcal{N}}(\mathbf{x}_i, \mu_2^{(t)}, \hat{\sigma}_2)}$$

■ Pour  $j \in \{1, 2\}$

$$\text{Estimer } \tau'_{j0} = \tau_0 + N\hat{\tau}_j \quad \mu'_{j0} = \frac{N\hat{\tau}_j \bar{x} + \tau_0 \mu_0}{N\hat{\tau}_j + \tau_0}$$

$$\text{Tirer } \mu_j^{(t+1)} \sim \mathcal{N}(\mu'_{j0}, 1/\tau'_{j0})$$

```

Z_given_mu <- function(X,Z,mu,pi_1){
  # Z variables latentes

  remove_i <- (c(1:length(X)) !=i) # enleve variable i
  estimate_sigma_1 <- sd(X[(remove_i & Z == 1)]) # classe 1
  estimate_sigma_2 <- sd(X[(remove_i & Z == 2)]) # classe 2

  for (i in 1:length(Z)){

    proba1 <- pi_1 * dnorm(X[i],mu[1],estimate_sigma_1) /
      (pi_1 * dnorm(X[i],mu[1],estimate_sigma_1) +
       (1-pi_1) * dnorm(X[i],mu[2],estimate_sigma_2))

    Z[i] = sample(1:2, size=1,prob=c(proba1, 1-proba1),
      replace=TRUE)
  }
  return(Z)
}

```

```

mu_given_Z = function(X, Z, mu_prior){
  # Z variables latentes
  # mu_prior contient parametres loi a priori de mu

  mu = rep(0,2) ; sigma = rep(0,2)

  for(j in 1:2){

    sample_j_size = sum(Z==j)
    sample_j_mean = mean(X[Z==j])
    sigma[j] = sd(X[Z==j]) ; precision_j = 1 / sigma[j]^2

    precision_post = sample_j_size * precision_j +
      mu_prior$precision

    mean_post = (sample_j_mean * sample_j_size *
      precision_j + mu_prior$mean *
      mu_prior$precision) / precision_post

    mu[j] = rnorm(1,mean_post,sqrt(1/precision_post)) # on
      tire mu selon la loi normale a posteriori
  }
  return(list(mu = mu, sigma = sigma))
}

```

```

echantillonneur_gibbs <- function(X,N_simu){
  # X sont les donnees
  # initialisation
  .
  .
  .

  for (k in 1:N_simu){

    Z <- Z_given_mu(X,Z,mu,pi_1) ; param_post <- mu_given_Z(X, Z, mu_prior)
    mu = param_post$mu

    .
    .
    .
  }
  return(list(Z, mu_1, mu_2))
}

```

## Listing 1 – Implémentation en R

## Blocky block

### Just a Block

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## Blocky block

### Example Block

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## Blocky block

### Alert Block

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## How to use frame-breakings ?

In this template, and only this, I defined a "breakingframe" template frame that should not hold any useful information. The background of this frame is pinkish solid and it is not countable as a separate frame. You can use this as a transitioning page between different topics or for any funny funky stuff to release the tense of the poor audience during your presentation.

```

1      \breakingframe{
2          Put your contents here, such as images, text ..etc. Be as silly as
           possible .. or not!
3      }
```

Look at the next slide, in code, as an example !

## Motivation : Q1

- 1 Stone masonry walls are usually not homogeneous through the thickness
- 2 Leaf-separation effects on the strength capacity
- 3 In-plane and out-of-plane behaviours interaction
- 4 Internal cracking onsets and 3D crack paths (cannot be captured experimentally)

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# The study main phases





# How to arrange stones ?

# Objective function

## Packing objective

$$\text{Minimize } F(\vec{X}_i)_i = || \vec{S}_i - \vec{S}_{i-1} ||$$

$$\text{Fitness}\left(F(\vec{X}_i)\right)_i = F(\vec{X}_i)_i(1 + \xi_1 P_A)^{\xi_2}$$

- $S_i, S_{i-1}$  : locations of  $i$  and  $i - 1$  stones
- $\xi_1$  : penalty multiplier
- $\xi_2$  : penalty exponent
- $P_A$  : penalties summation

Merci de votre  
attention