

# Bayesian Non-Parametrics for Personalized Medicine

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Stochastic modeling and graphical models for the analysis and prediction of phenotype interactions

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# Who I am

## Academical Background

- Telecommunication Engineer, Technical University of Madrid (4 years)
- MSc. in Information Technology, University of Stuttgart (2.5 years)

## Professional Experience

- Research Internship at Sony EuTEC, Stuttgart (9 months)
- Research Internship at Sony Corporation, Tokyo (1 year)

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# Previous Research Projects

- 2009 – Bachelor Th *“Statistical Bounds for DOA estimation in Antenna Arrays”*
- 2010 – Sony EuTec: *“Personalization and Recommendation Systems”*
- 2011 – MSc. Th: *“Emotion Recognition from Speech signals and Perception of Music”*
- 2012 – Sony Corporation: *“Adaptive Learning Technologies for Education”*
- 2013 – *“Scalar Quantization for Lossy Source Coding of Continuous Sources”*

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# Research Overview

*Aim: Model complex relationships between genetics, epigenetics and environment to infer latent information.*

1. Modeling
2. Inference

**A1 Biomarker discovery**

**A2 Data Integration**

**A3 Causal Mechanism of Disease**

**A4 Gene-Environment Interactions**

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# 1. Modeling

Goal: comparative density estimation of group data

Some motivating applications

- Pediatrics: children weight and height evolution with age.
- Social Sciences: gender impact on salary income.
- Pharmaceuticals: monitoring drug responses according to patient's characteristics.

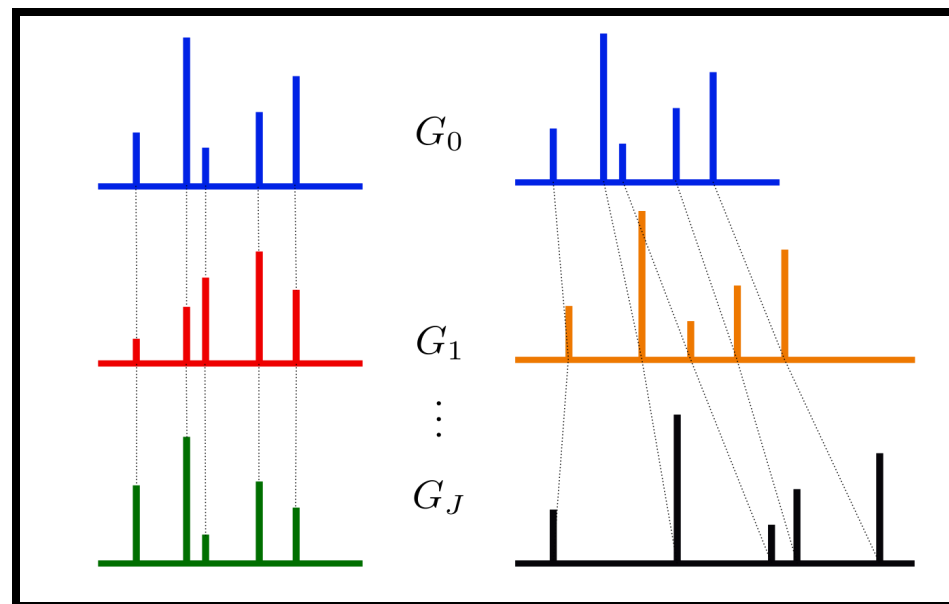
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# Dependent Dirichlet Process

- The DDP places a prior over a collection  $G_1 \dots G_J$  of random distributions
- Based on Dirichlet Process, where  $G \sim \text{DP}(H, \alpha)$ 
  - $\alpha$ : concentration parameter
  - $H$ : base measure
- $G_j = \sum_{k=1}^{\infty} \pi_{jk} \delta_{\phi_{jk}}$

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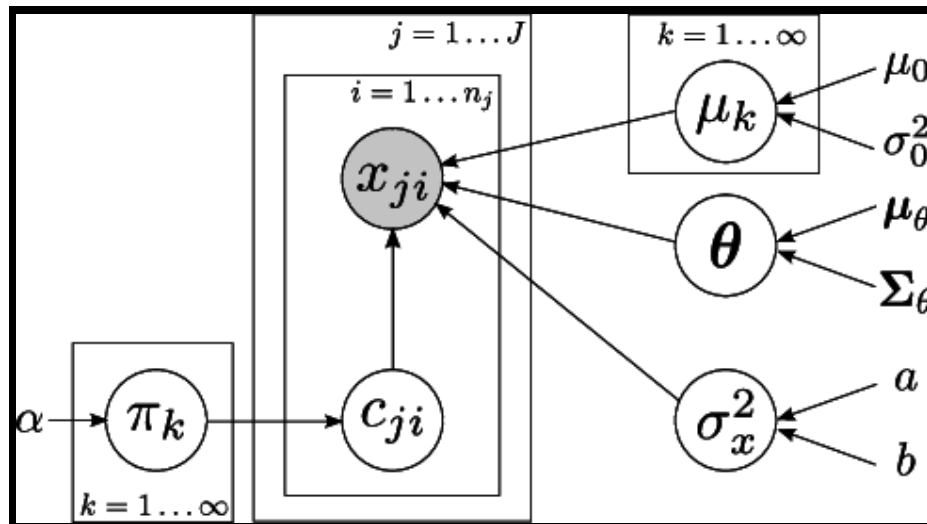
# Hierarchical DP vs Single-p DDP



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# Application to Marathon dB

Study of Age/gender impact on marathon performance

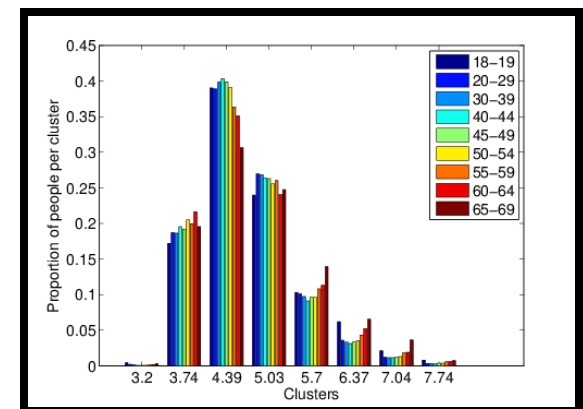
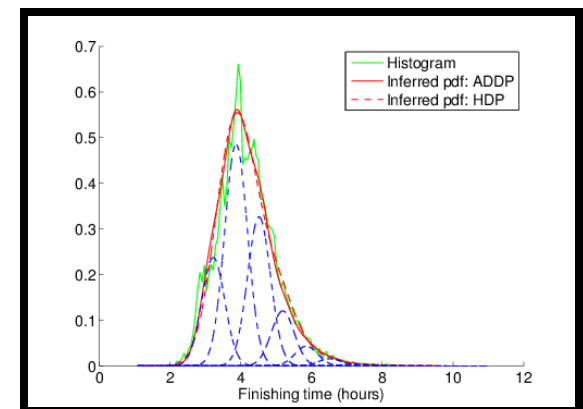
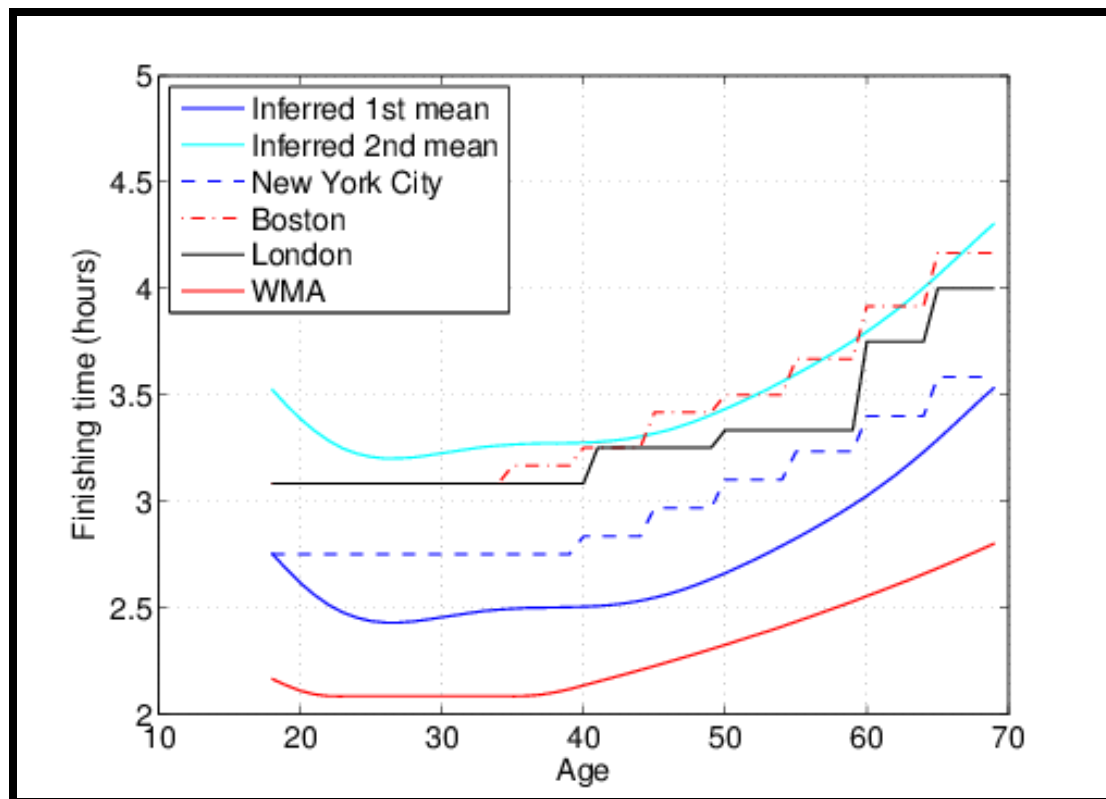


- $J$  populations of runners
- $G_j = \sum_{k=1}^{\infty} \pi_k \delta_{\phi_{jk}}$
- $x_{ji} | c_{ji} = k, \mu_k, \theta_j, \sigma_x^2 \sim \mathcal{N}(x_{ji} | \mu_k + \theta_j, \sigma_x^2)$
- $\theta \sim \mathcal{N}(0, \Sigma_\theta)$
- $(\Sigma_\theta)_{ij} = \sigma_\theta^2 \cdot \exp\left(-\frac{(i-j)^2}{2\nu^2}\right) + \kappa\delta(i-j)$

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## Results: Bayesian Non-Parametrics for Marathon Analysis

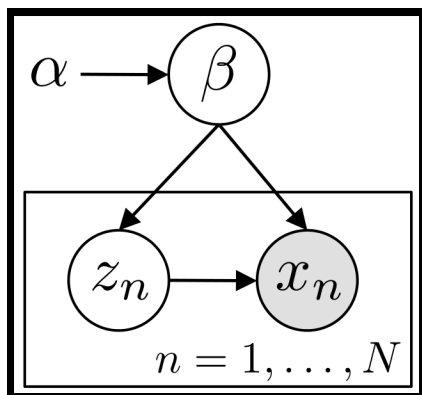


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## 2. Inference

Scala pBNP toolbox for parallel MCMC Inference in BNP models

$$p(\beta, \mathbf{x}, \mathbf{z}|\alpha) = p(\beta|\alpha) \prod_{n=1}^N p(x_n, z_n|\beta)$$

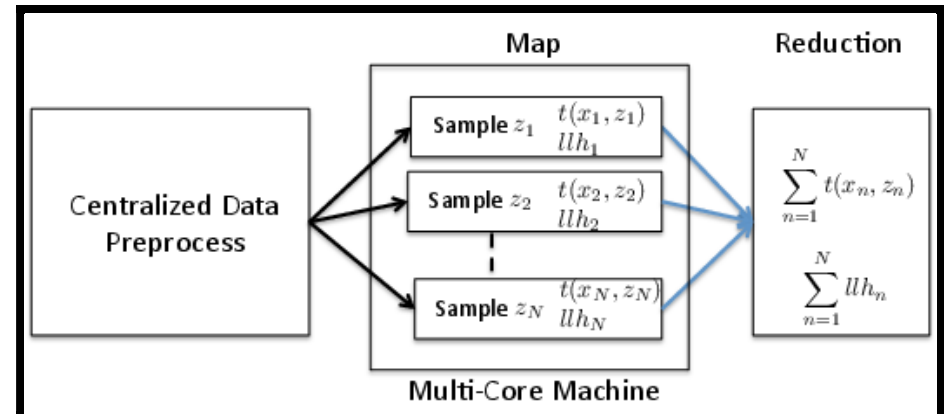


1. Sample  $\beta$  from  $p(\beta|\mathbf{z}, \mathbf{x}, \alpha)$
2. Sample  $z_n$  from  $p(z_n|x_n, \beta)$  for  $n = 1, \dots, N$

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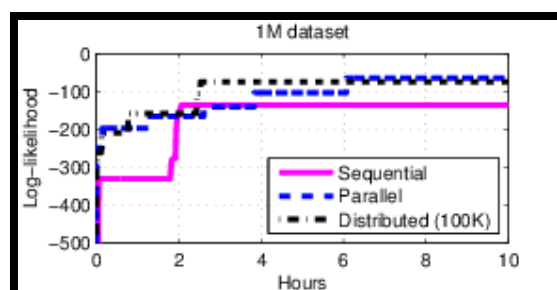
# Scala pBNP toolbox

1. Functional programming
2. Parallel/distributed
3. DP/IBP models
4. Easy extension to any lik model
5. Flexible Framework

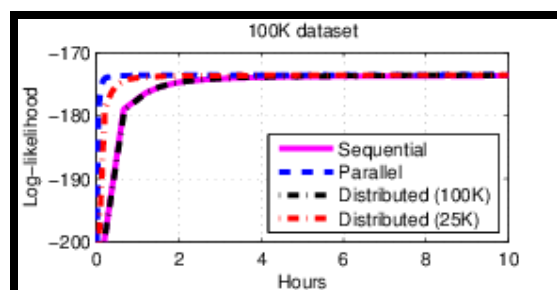


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## Results: Scala pBNP toolbox



Algorithm \ $N$	100K	1M	5M	50M
Sequential	0.1349	1.3963	-	-
Parallel	0.0123	0.1397	0.8736	-
Distributed (100K)	0.1795	0.1512	0.2143	1.3429



Algorithm \ $N$	100K	1M
Sequential	9.9169	-
Parallel	0.6791	26.4195
Distributed (100K)	10.7375	32.8588
Distributed (25K)	3.1215	9.6388

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MARIE CURIE ACTIONS



Initial Training Network "Machine Learning for Personalized Medicine"

# Impact of Marie Curie-ITN

1. Quality Training
2. Multidisciplinary work
3. Link to Society

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