



DE LA RECHERCHE À L'INDUSTRIE

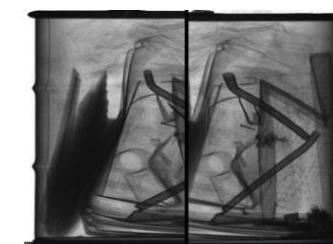
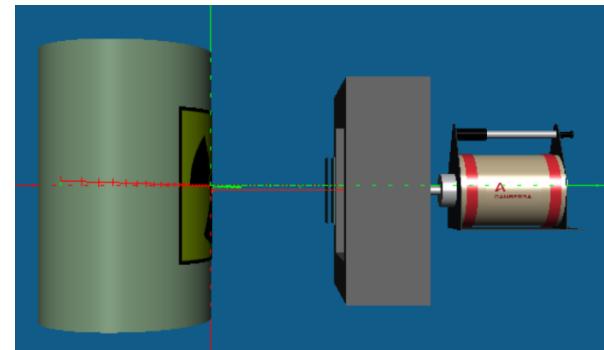
Bayesian Approach for Multigamma Radionuclide Quantification Applied on Weakly Attenuating Nuclear Waste Drums

Workshop MASCOT-NUM, 21-22 November 2022

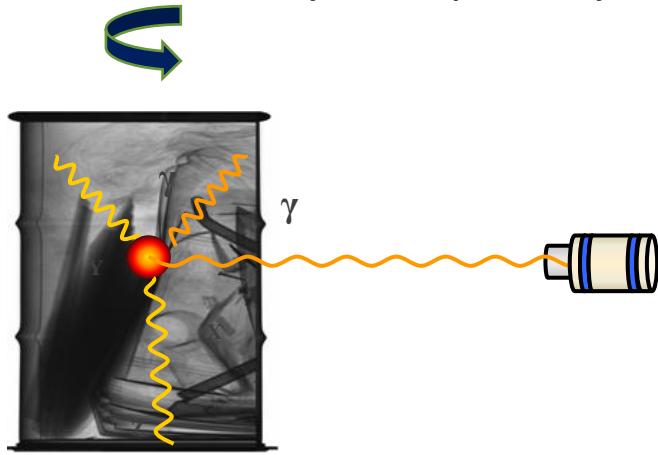
Aloïs CLEMENT

I'm sorry, but I'm a nuclear physicist.

- *In situ* nuclear measurement of radioactive items
- Gamma spectrometry : HPGe 30% (Canberra)
- Software : Génie 2000, ISOCS
- Waste drums : 100 et 200 L
- Actinides : U, Pu, Am, Np



- Aims : identify and quantify actinides



$$A = \frac{S(E)}{\epsilon(E, env) t I_\gamma(E)}$$

$$m = \frac{A}{A_m}$$

Multi-gamma radionuclide :

$$\mathbf{E} = (E_1, \dots, E_N)$$

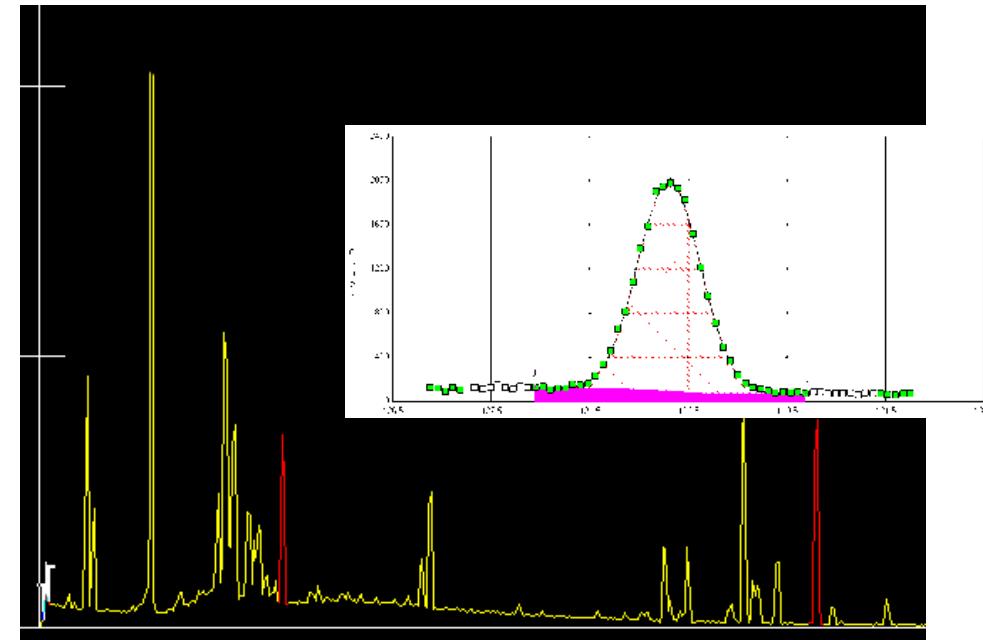
$$A = \frac{\mathbf{S}(\mathbf{E})}{\epsilon(\mathbf{E}, env) t \mathbf{I}_\gamma(\mathbf{E})}$$

Let suppose :

$$\mathbf{Y}^{obs} = \frac{\mathbf{S}(\mathbf{E})}{t \mathbf{I}_\gamma(\mathbf{E}) A_m}$$

$$\mathbf{Y}^{obs} = m \epsilon(\mathbf{E}, env)$$

Inverse problem to solve



$$\mathbf{Y}^{\text{obs}} = m\epsilon(\mathbf{E}, \text{env}) + \boldsymbol{\xi}^{\text{obs}} \quad \boldsymbol{\xi}^{\text{obs}} \sim N(\mathbf{0}, \Sigma^{\text{obs}})$$

Likelihood function **Priors**
 Bayes theorem : $\pi(m, \text{env} | \mathbf{Y}^{\text{obs}}) = \frac{\pi(\mathbf{Y}^{\text{obs}} | m, \text{env}) \pi(m | \text{env}) \pi(\text{env})}{\int \pi(\mathbf{Y}^{\text{obs}} | m, \text{env}) \pi(m | \text{env}) \pi(\text{env})}$
Posterior

$$\pi(m, \text{env} | \mathbf{Y}^{\text{obs}}) \propto \pi(\mathbf{Y}^{\text{obs}} | m, \text{env}) \pi(m | \text{env}) \pi(\text{env})$$



What about the « env » environment variable ?

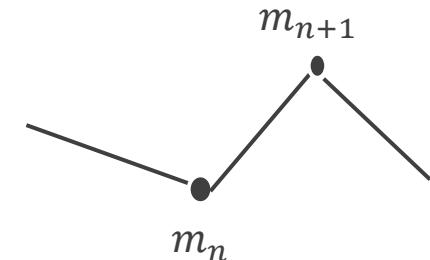
$$\pi(m, \mathbf{X} | \mathbf{Y}^{\text{obs}}) \propto \pi(\mathbf{Y}^{\text{obs}} | m, \mathbf{X}) \pi(m | \mathbf{X}) \pi(\mathbf{X})$$

Observation likelihood

Priors

- Independent Y_i^{obs} : $\pi(\mathbf{Y}^{\text{obs}} | m, \mathbf{X}) = \prod_{i=1}^N \pi(Y_i^{\text{obs}} | m, \mathbf{X}) = \prod_{i=1}^N \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(Y_i^{\text{obs}} - m\epsilon(\mathbf{X}))^2}{2\sigma_i^2}}$
- Independent (m, X_i) : $\pi(m | \mathbf{X}) \pi(\mathbf{X}) = \pi(m) \pi(\mathbf{X}) = \pi(m) \prod_{i=1}^D \pi(X_i)$

MCMC : Metropolis-Hastings algorithm

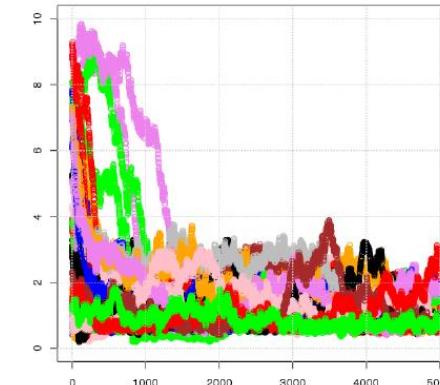


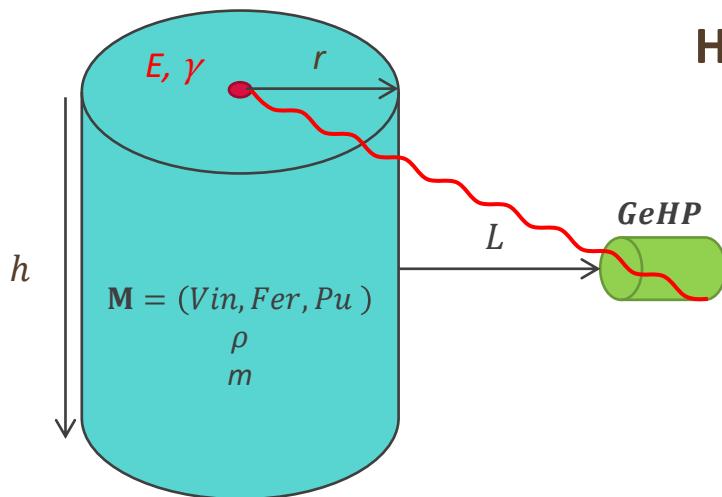
$$m_{n+1} \leftarrow m_n + A \cdot \delta, \quad \delta \sim N(0, k_m)$$

$$\rho = \min\left(\frac{\pi(m_{n+1}, \mathbf{X}_{n+1} | \mathbf{Y}^{\text{obs}})}{\pi(m_n, \mathbf{X}_n | \mathbf{Y}^{\text{obs}})}, 1\right)$$

- High number of $\epsilon(\mathbf{X})$ estimations ($\approx 10^5$) by the simulation code MCNP6.2
- Time-consuming

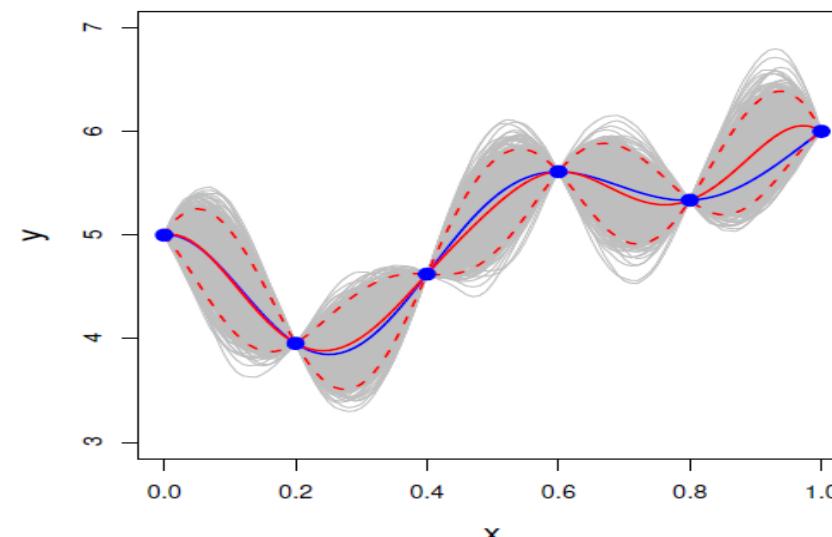
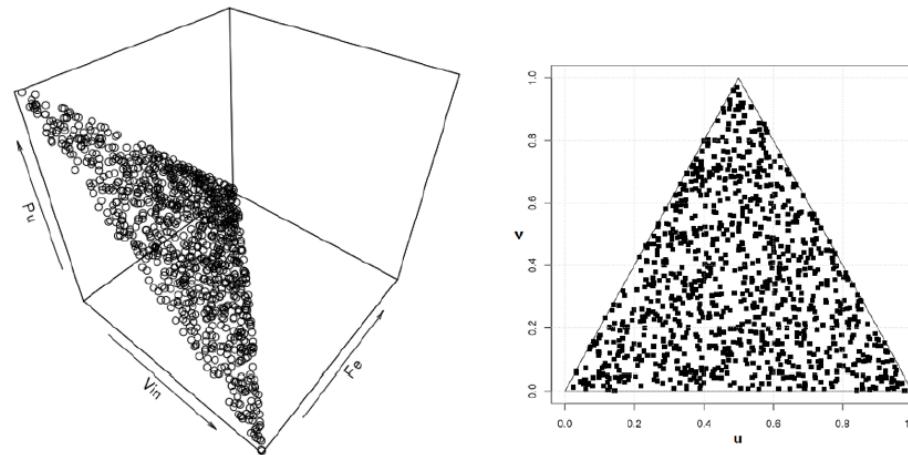
Surrogate model f of the measurement efficiency
 $\epsilon = f(\mathbf{X})$



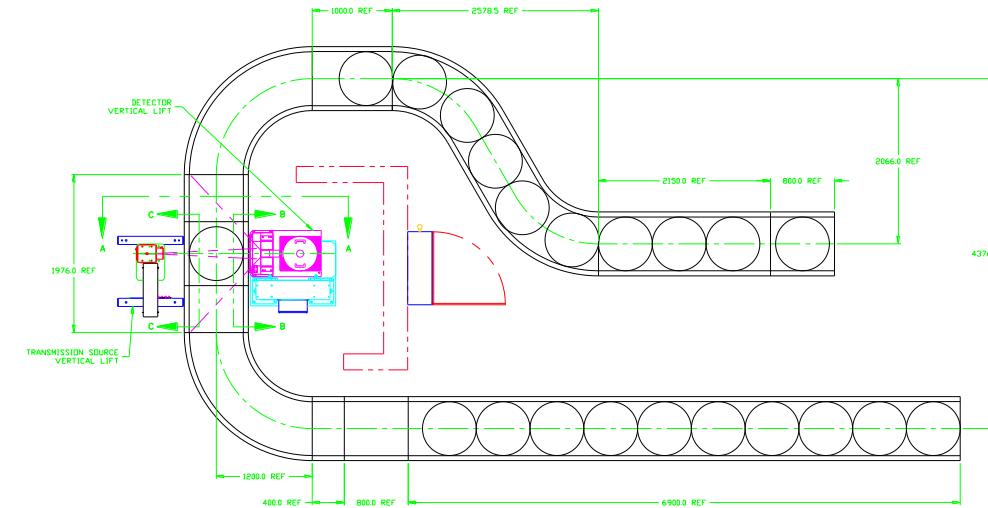
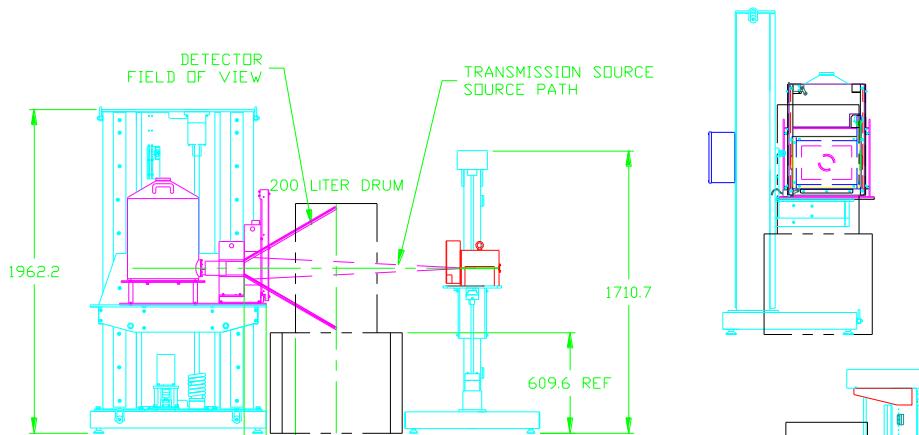


How could I estimate « env » and $\epsilon(E, env)$?

- Input: $\mathbf{X} = \{ E, r, h, \mathbf{M}, L, \rho \}$ et m ($\text{Card}(\mathbf{X}) = 8$)
- DoE: Latin Hypercube Sampling ($n = 500$)
- Surrogate model: Kriging :
 - Universal Kriging (UK) : $f(X) = \mu(X) + Z(X)$
 - Deterministic : $\mu(X) = \sum_{j=1}^p \beta_j f_j(X)$
 - Stochastic : $Z(X)$: Matérn 5/2
- $\epsilon(E, env) \approx f(\mathbf{X}) = f(E, r, h, \rho, L, \mathbf{M})$



MADAGASCAR : Automatic Nuclear Waste Drum Measurement Device



MADAGASCAR : Validity range

- Bulk density < 0.4
- Detection limit : 1 MBq
- Maximal activity: 200 GBq
- 100L and 200L drums
- Measurement distance : \approx 60 cm
- Global uncertainties: \pm 42%

Validation steps :

0. Convergence analysis
1. Linearity :
Assay on plutonium standards
2. Reproducibility
Repetitions on 10 items (drums)
3. Comparison
Comparison of results between MADAGASCAR and the Bayesian approach

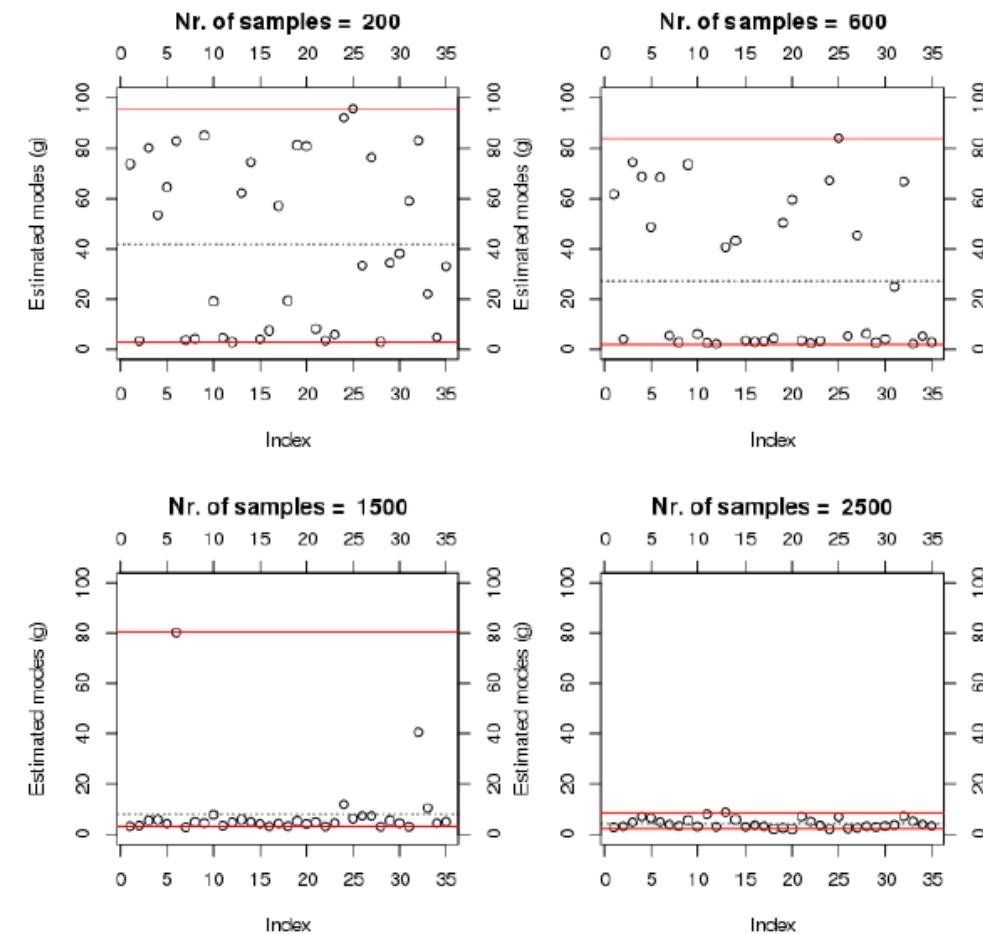
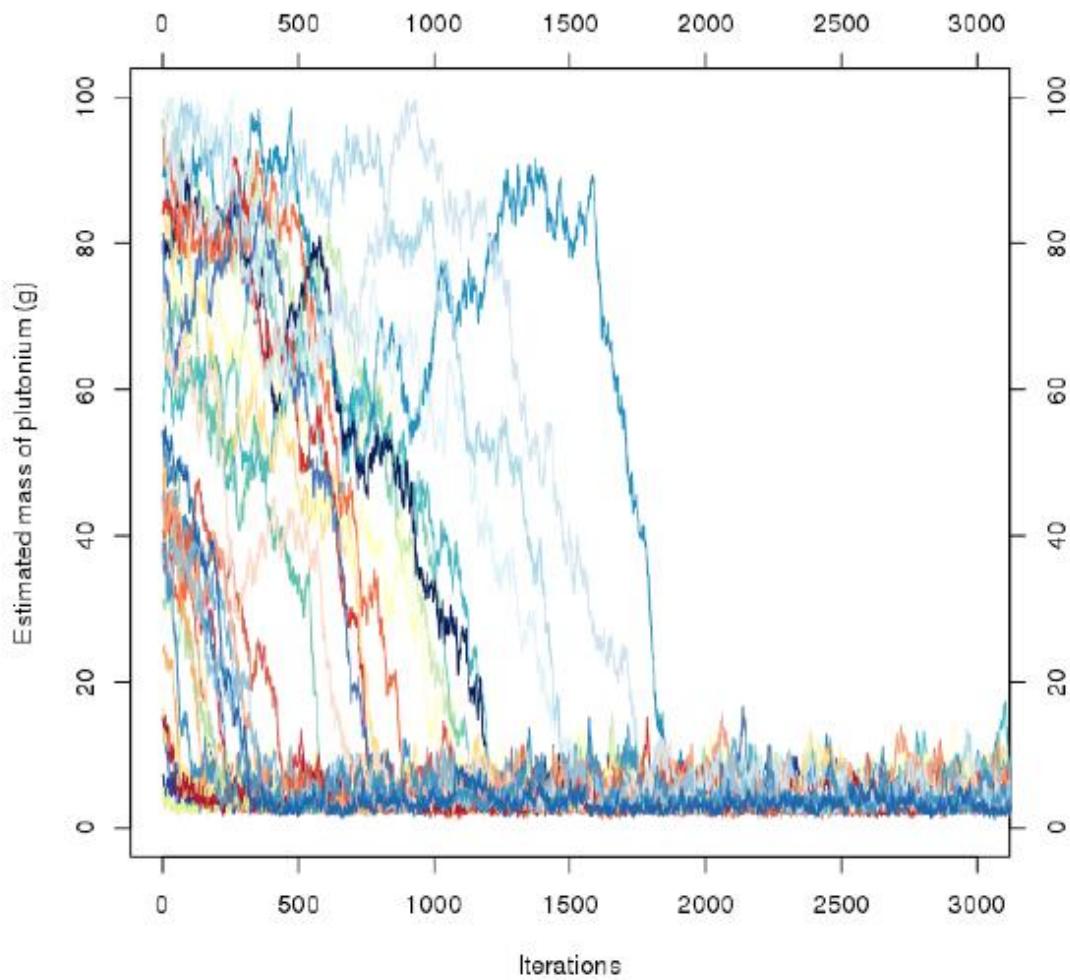
MADAGASCAR : Database

- 242 nuclear drums (100L)
- 6 plutonium standards : 0.4 to 60 grams
- Fixed measurement duration
- Fixed measurement distance : \approx 60 cm
- Global uncertainties: \pm 42%

Hardware :

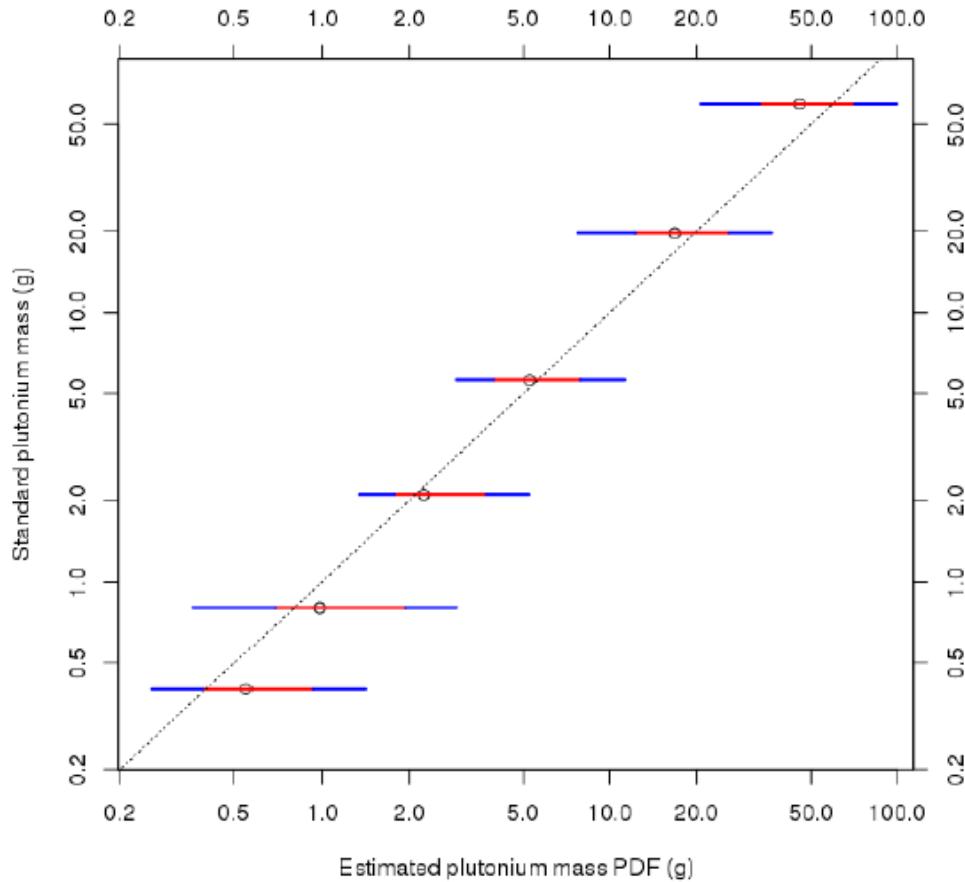
- 72 cores (35 Markov chains)

Convergence analysis



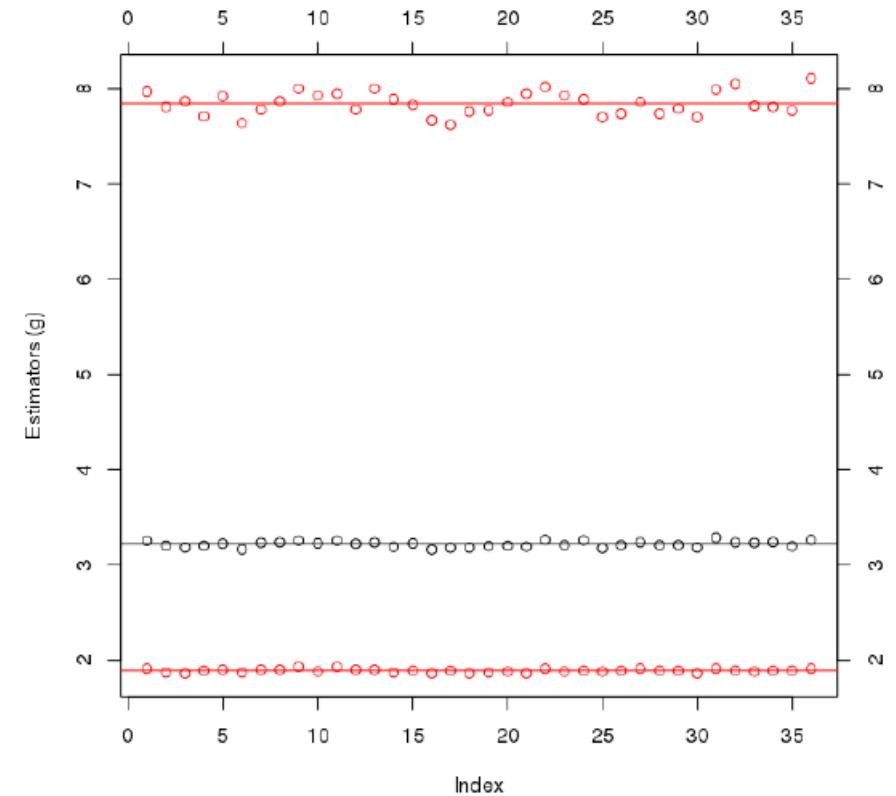
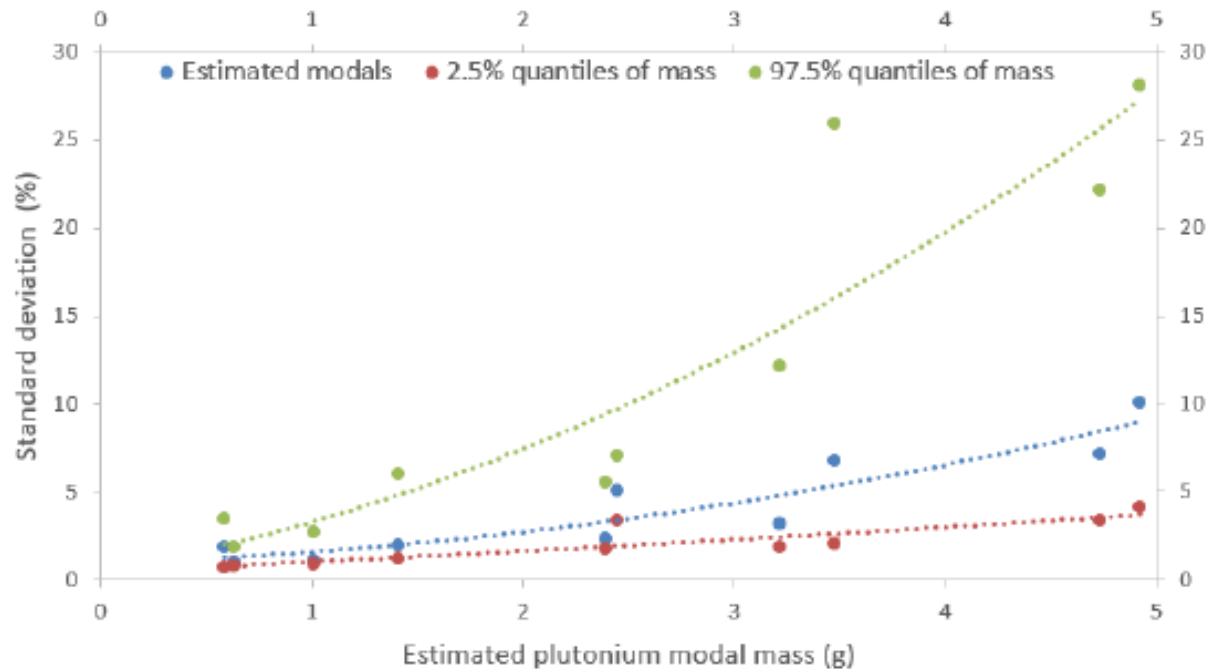
6 plutonium standards: 0.4 to 60 grams

| Item | M_{Pu} (g) | M_{Q1} (g) | M_{Q2} (g) | M_{Mod} (g) | M_{Q3} (g) | M_{Q4} (g) |
|------|--------------|--------------|--------------|---------------|--------------|--------------|
| 1. | 0.400 | 0.26 | 0.39 | 0.55 | 0.93 | 1.42 |
| 2. | 0.800 | 0.36 | 0.69 | 0.98 | 1.95 | 2.94 |
| 3. | 2.104 | 1.35 | 1.79 | 2.26 | 3.72 | 5.22 |
| 4. | 5.619 | 2.93 | 3.94 | 5.27 | 7.91 | 11.3 |
| 5. | 19.731 | 7.71 | 12.2 | 16.9 | 26.0 | 36.4 |
| 6. | 59.541 | 20.8 | 33.3 | 45.6 | 71.0 | 99.8 |

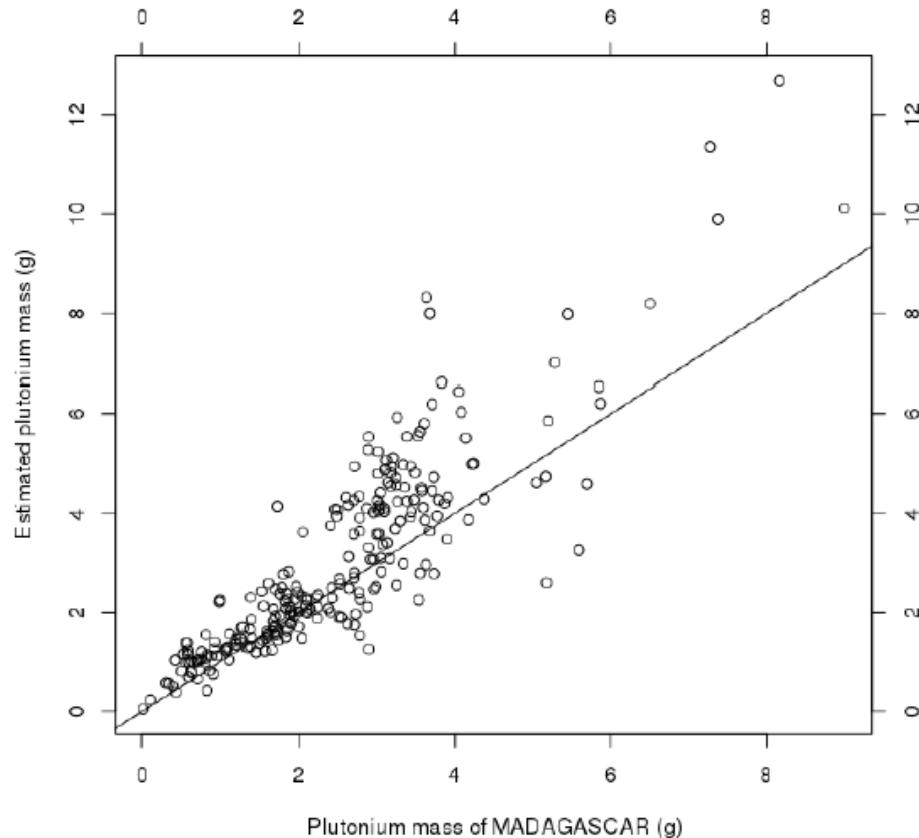


< 30 repetitions on 10 items (drums)

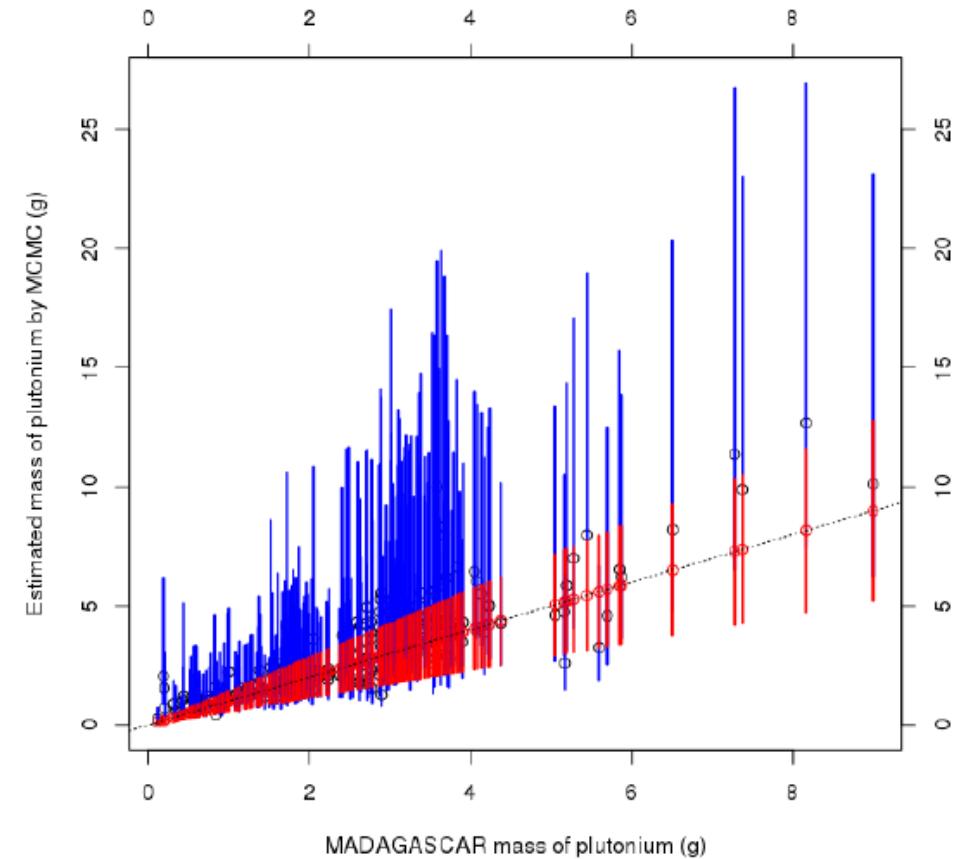
Calculation duration: 15 min



Experimental comparison



91% of estimated masses \in CI95% of
MADAGASCAR



92,3% of estimated mass PDF overlap 50% of
the MADAGASCAR CI95% ($\pm 42\%$)

- Validation : good results on plutonium standards
 - Comparison : good results on simple cases : low bulk density ($< 0,4 \text{ g.cm}^3$)
 - Useful priors for physicists : bulk density, compositions, Gaussian, Uniform, etc.
 - Easy to code (Python) and possibilities to use specific libraries
 - Breaking point with classical approach : scalars vs PDF
 - Available to other RN (Am, FP, activated)
-
- Multigamma RN only
 - Increasing uncertainties



Thanks for your attention