Modeling computation kernels with Stan

Hoël Jalmin
Tutored by Arnaud Legrand and Tom Cornebize

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With the current need for high performance computing, and the hardware complexity:

- How to predict the duration of computations?
- How to quantify incertainty?

For this talk:

1. Brief presentation of the context
2. Introduction to Bayesian sampling through Stan
3. Examples of application

Modern context

- HPC systems use thousands of nodes, cache, hyperthreading, etc $\rightarrow$ makes it difficult to predict performance
- Some functions (like DGEMM in the BLAS library) are used everywhere, and called thousands of times in a program.

Previous work

- Simulating high performance programs to optimize them at a lesser cost
- Elaborated complex models within a few percent of reality but needed to evaluate and confirm them

Model Let's say $y \sim \mathcal{N}(\alpha * x + \beta, \sigma)$

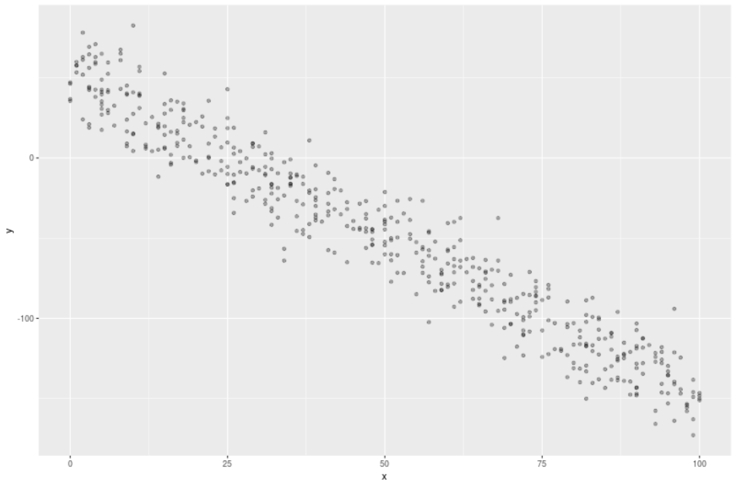
- α, β, σ: Model parameters
- y: Dependent data (posterior)
- x: Independent data

We observe some data and need to find model parameters

The vocabulary

- Posterior: The distribution of the parameters
- Likelihood: A function of the parameters, the model
- Prior: Existing knowledge of the system, guesses on the parameters values (σ>0 per example)

A Bayesian Sampler, Stan

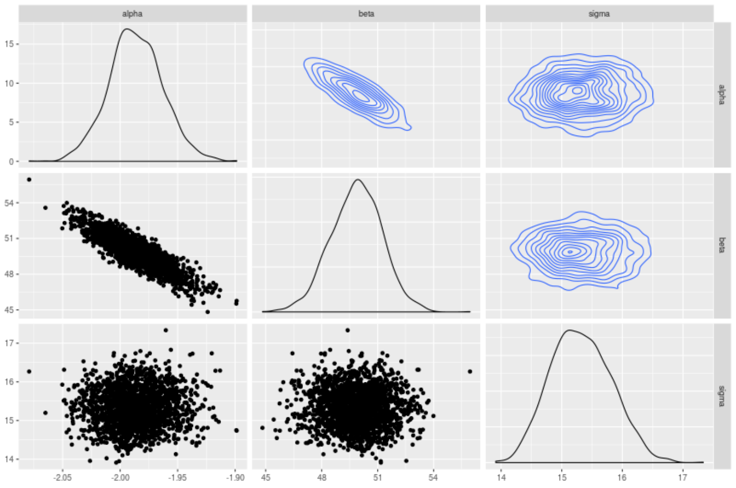


Using this data, we'll try to find the parameters that were used to generate it.

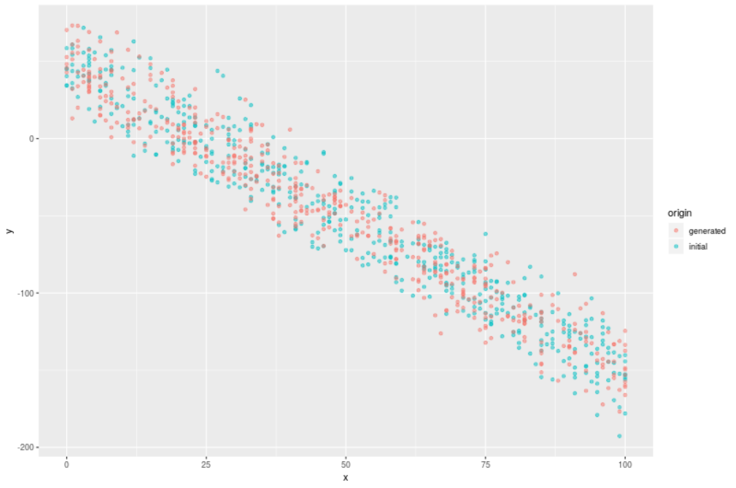
The Stan model

```
library(rstan)

modelString = "data { // the observations
    int<lower=1> N; // number of points
    vector[N] x;
    vector[N] y;
}
parameters { // what we want to find
    real beta;
    real alpha;
    real<lower=0> sigma; // indication: sigma cannot be negative
}
model {
    // We define our priors
    beta   ~ normal(0, 10);
    alpha ~ normal(0, 10);
    sigma       ~ normal(0, 10);

    // Then, our likelihood function
    y ~ normal(alpha*x + beta, sigma);
}
"
sm = stan_model(model_code = modelString)
```

Looking at the posterior



Looking at the generated data

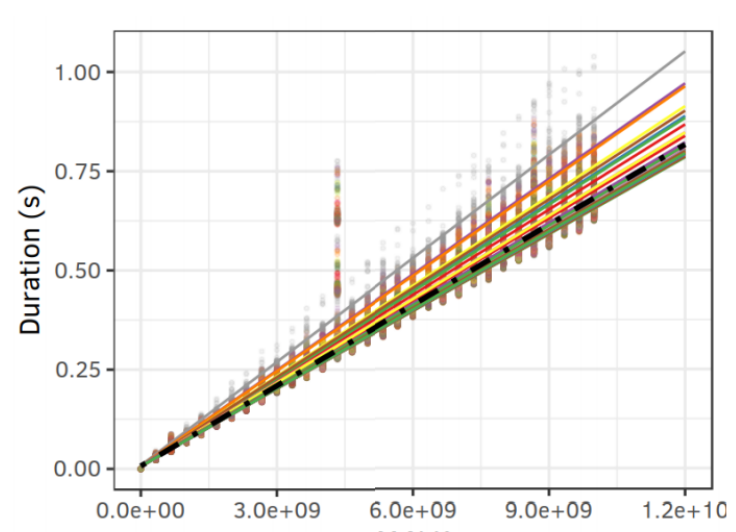


The importance of the priors

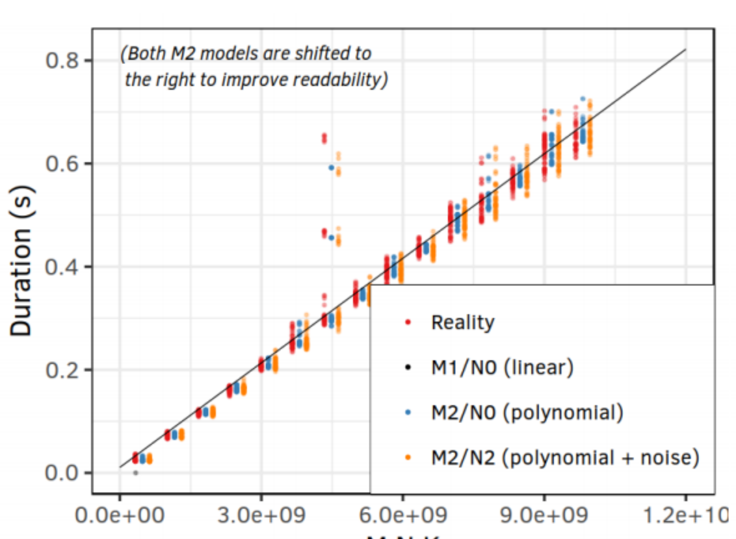
- The priors are necessary to have convergence in the fit
- Non-informative prior vs informative (careful not to have a falsely informative one and introduce bias)
- A little bit of precision is better, but initialisation values can do the trick

The different models for dgemm

- DGEMM's duration depends on the matrix size, on the CPU used to run it, and on residual noise coming from the system.



(Source: Fast and Faithful Performance Prediction of MPI Applications: the HPL Case Study)

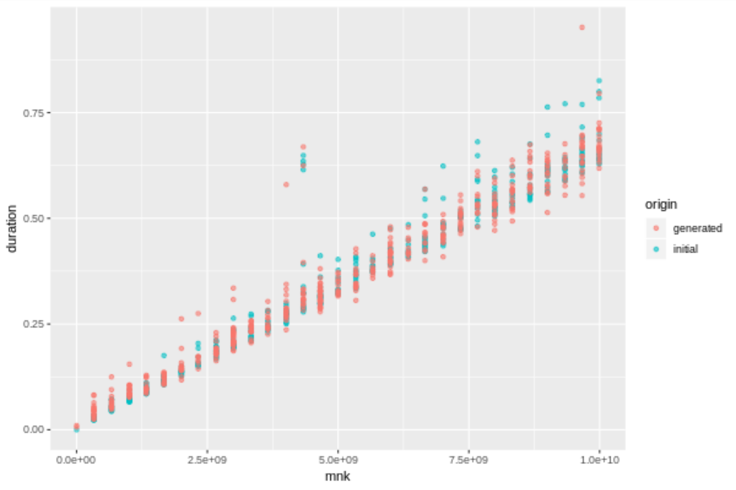


A redo of the last model presented before, using Stan. Like a linear model but with more parameters (in this case 10).

The model follows this:

$$duration \sim \mathcal{N}(\alpha_1 * mnk + \alpha_2 * mn + \alpha_3 * mk + \alpha_4 * nk + \beta,\\ \gamma_1 * mnk + \gamma_2 * mn + \gamma_3 * mk + \gamma_4 * nk + \delta)$$

The generated data

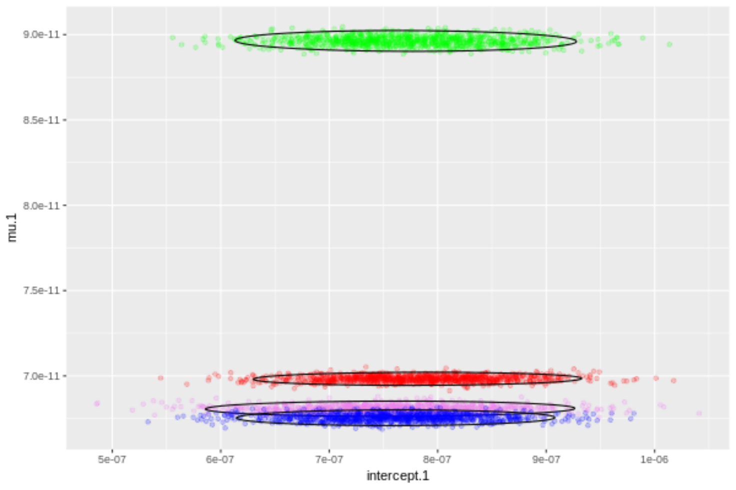


- Much like the previous model, but with different observations for each host
- Added a variable for the number of hosts, and used matrices instead of vectors for all the parameters.

For this model we have:

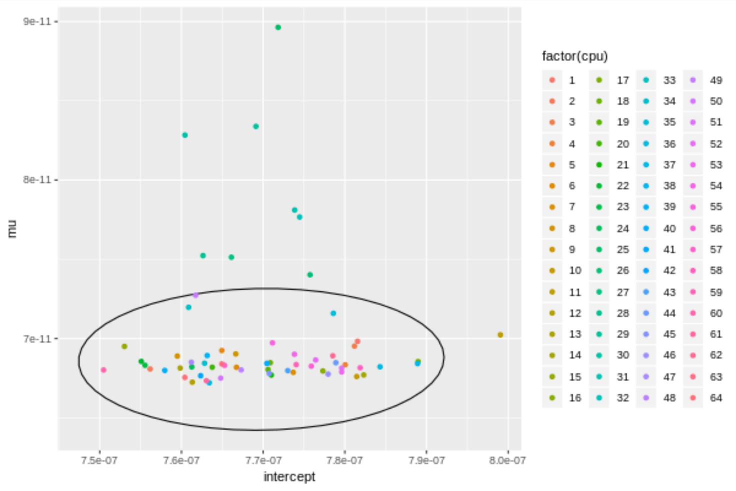
$$duration[i] \sim \mathcal{N}(\alpha_1[i] * mnk + \alpha_2[i] * mn + \alpha_3[i] * mk + \alpha_4[i] * nk + \beta[i], \gamma_1[i] * mnk + \gamma_2[i] * mn + \gamma_3[i] * mk + \gamma_4[i] * nk + \delta[i])$$

The posterior with models depending on the host shows a lot of difference between hosts (here we have 3 ”average” CPU and a slow one):



Posterior visualisation

If we look at the means of the parameters' values for each host, we get a range of values in which most hosts are.



Model 3 : A hierarchical linear model

- Useful to find the value of hyperparameters from which we get the parameters
- From this we could calculate new parameters for new CPUs
- Here μ_α and σ_α are the hyperparameters for α, and the same goes for the other parameters

$\mu_\alpha \sim \mathcal{N}(\alpha$_moy,$\alpha$_sd) with α_moy and α_sd the priors

$\sigma_\alpha \sim \mathcal{N}(0, 1)$

$\alpha[i] \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha)$

$duration[i] \sim \mathcal{N}(\alpha[i] * mnk + \beta[i], \gamma[i] * mnk + \delta[i])$

Conclusion

My contribution

- Created several models to represent the performance of a computation kernel within a few percent of reality
- Model adaptable to changes (addition/removal of CPUs)

Following up work

- Implementing this work in Simgrid research (other computation kernels, network communications, etc)
- Novelty detection and non regression performance tests