Calibration of computer models

Extension to Stochastic Simulator

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Outline

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Stochasticity in Computer Experiments

Basic model for a stochastic simulator:

$$f(\mathbf{x}) = m(\mathbf{x}) + v,\ v \sim N(0, \sigma_v^2(x)), \qquad (1)$$

where

- $m(\mathbf{x})$ is the expected value: $\mathbb{E}_f[f(\mathbf{x})]$,
- v independent variability representing randomness of the simulator,
- variance σ_v^2 may depend on $\mathbf{x}$, be constant.

Remarks

- If $\sigma_v^2 = 0$ deterministic simulator,
- What does stochasticity acknowledge for? numerical approximation (Monte Carlo), aleatory experiment.

Extension of KOH

$$y_i^e = y^e(\mathbf{x}_i^e) = f(\mathbf{x}_i^e, \boldsymbol{\theta}) + \delta(\mathbf{x}_i^e) + \epsilon_i, \tag{2}$$

where

- $\mathbf{y}^e = \{y_1^e, \ldots, y_{n_e}^e\}$ are real-world field observations at controllable (or measurable) inputs $(\mathbf{x}_i)_{1 \leq \ldots \leq n_e}$,
- f is a stochastic simulator,
- ϵ is measurement error for the observations,
- δ is the discrepancy may be assumed to be stochastic.

Remarks: If reality is stochastic, δ has to be stochastic and may be heteroskedastic as the simulator.
y_S is the simulator with additional unknown, non-measurable, inputs u_C, $y_F(x)$ (with variance σ_ϵ^2), and $\delta_{\mathrm{MD}}(x)$ is an important term that accounts for the simulator not being a perfect representation of reality. y_F "observes" reality with error ϵ; reality = $y_S + \delta_{\mathrm{MD}}$.

[Sung et al., 2019] use a hetGP for the discrepancy (but with a deterministic simulator), estimating parameters via maximum likelihood and following [Tuo et al., 2015] to avoid confounding.

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Stochastic Kriging

[Ankenman et al., 2010]
Observation model:

$$y_i = f(\mathbf{x}_i) = m(\mathbf{x}_i) + v_i, \quad \text{with} \quad v_i \overset{ind}{\sim} \mathcal{N}(0, r(\mathbf{x}_i)) .$$

In homoskedastic cases $r(\mathbf{x}_i) = \tau^2$ which is called the nugget.

From a design with replications:

- 'full-N" dataset, n of unique x_i-values in X_N with $n << N$, a_i replicates at unique locations,
- compute

$$\bar{y}_i = \frac{1}{a_i} \sum_{j=1}^{a_i} y_i^{(j)} \quad \text{and} \quad \hat{\sigma}_i^2 = \frac{1}{a_i - 1} \sum_{j=1}^{a_i} (y_i^{(j)} - \bar{y}_i)^2.$$

predictions with BLUP for M when GP is assumed on M:

$$\mu_n^{\mathrm{SK}}(\mathbf{x}) = k_n^\top(\mathbf{x})(C_n + S_n)^{-1}\,\bar{Y}_n$$
$$\sigma_n^{\mathrm{SK}}(\mathbf{x})^2 = c_{S,\psi}(\mathbf{x},\mathbf{x}) -^2 k_n^\top(\mathbf{x})(C_n + S_n)^{-1} k_n(\mathbf{x}),$$

$k_n(\mathbf{x}) = (c_{S,\psi}(\mathbf{x}, \bar{\mathbf{x}}_1), \ldots, c_{S,\psi}(\mathbf{x}, \bar{\mathbf{x}}_n))^\top$ $S_n = [\hat{\sigma}^2_{1:n}]A_n^{-1} = \mathrm{Diag}(\hat{\sigma}_1^2/a_1, \ldots, \hat{\sigma}_n^2/a_n)$, and $C_n = \{c_{S,\psi}(\bar{\mathbf{x}}_i, \bar{\mathbf{x}}_j)\}_{1 \le i,j \le n}$.

Modeling the variance

- In [Ankenman et al., 2010], no specific model for the variance,
- [Goldberg et al., 1997] assumes $\log(r(\mathbf{x})) \sim GP$ for modeling heteroskedasticity, and they estimate the combined parameters of the two GPs with an MCMC scheme.

[Binois et al., 2018] make use of Stochastic Kriging with GP model for $\log(r(\mathbf{x}))$.

- consider latent variances: $\xi_1, \dots, \xi_n$ for the n unique locations,
- GP prior on this matrix $\Xi_n \sim \mathcal{N}_n(0, \nu(C_\xi + g_\xi A_n^{-1}))$ where g_ξ regularizes the behavior of the variance process,
- Estimate parameters by MLE using Woodbury trick which put all the computation in $\mathcal{O}(n^3)$,
- implementation in `hetGP` package.

homoskedastic GP

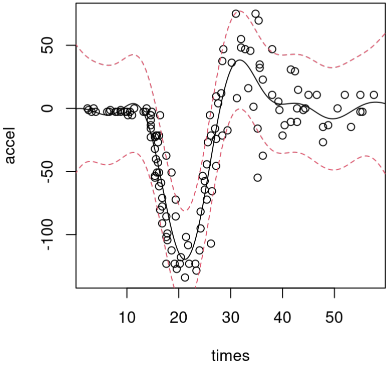

Figure: Homoskedastic GP fit to the motorcycle data via mean (solid-black) and 90% error-bars (dashed-red).

from [Gramacy, 2020]

heteroskedastic GP

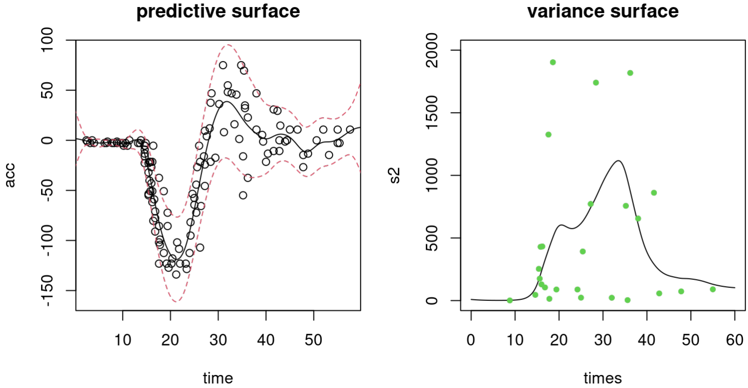

Figure: Heteroskedastic GP fit to the motorcycle data. Left panel shows the predictive distribution via mean (solid-black) and 90% error-bars (dashed-red). Right panel shows the estimated variance surface and moment-based estimates of variance (green dots).

from [Gramacy, 2020]

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Calibration of Stochastic Simulators

$$y_i^e = f(\mathbf{x}_i, \boldsymbol{\theta}^*) + \delta(\mathbf{x}_i) + \epsilon(\mathbf{x}_i)\,. \quad (3)$$

$\delta(\cdot)$ models the difference between the simulator and the physical system:

$$\delta(\mathbf{x}) = \zeta(\mathbf{x}) - f(\mathbf{x}, \theta^*)\,.$$

Here f is Stochastic but its link with reality is questionable. Is reality $\mathbb{E}(f)$ or f? Depending on that, δ should be considered as deterministic or Stochastic and then modeled as a standard GP...

Ocean Example

see https://github.com/Demiperimetre/Ocean

History Matching

[Andrianakis et al., 2015] contains a thorough description of HM whilst applying it to a complex epidemiology model of HIV.

Outline

Basics

Approximate Bayesian Computation produces samples from a posterior distribution $\pi(\boldsymbol{\theta}|\mathbf{y}^e)$ by

- generating samples for $\boldsymbol{\theta}$ from the prior
- and outputs $\mathbf{y}$ from the generating model $\pi(\cdot|\mathbf{y})$ (this implies runs of the simulator),
- samples are kept provided that $\mathbf{y} = \mathbf{y}^e$ or $|h(\mathbf{y}) - h(\mathbf{y}^e)| < tol$,
- accepted $\boldsymbol{\theta}$s produce an approximated posterior sample.

Remark:

- For calibration, *tol* can be interpreted as a bound on the observational error and model discrepancy, leading to a “correct” posterior rather than an approximation [Wilkinson, 2013]. This is then similar to HM with the subjective choice of bounds.
- ABC can be done without the use of a surrogate, but this will require many runs of the simulator itself. Otherwise, very few accepted $\boldsymbol{\theta}$ will be obtained, or an overly high value of *tol* will be required.

Fish example

see https://github.com/jhuang672/fish/blob/master/fish_fits.md

Other papers

[Oakley and Youngman, 2017] removes δ but compensates by inflating the variability in the simulator output.

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