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# GlobalSensitivity.jl: Performant and Parallel Global Sensitivity Analysis with Julia

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## Summary

Global Sensitivity Analysis (GSA) methods are used to quantify the uncertainty in the output of a model with respect to the parameters. These methods allow practitioners to measure both parameters' individual contributions and the contribution of their interactions to the output uncertainty. GlobalSensitivity.jl is a Julia (Bezanson et al., 2017) package containing implementations of some of the most popular GSA methods. Currently it supports Delta Moment-Independent (Borgonovo, 2007; Plischke et al., 2013), DGSM (Sobol' & Kucherenko, 2009), EASI (Plischke, 2010, 2012), eFAST (A. Saltelli et al., 1999; Andrea Saltelli & Bolado, 1998), Morris (Campolongo et al., 2007; Morris, 1991), Fractional Factorial (Andrea Saltelli et al., 2008), RBD-FAST (Tarantola et al., 2006), Sobol (Andrea Saltelli, 2002; Andrea Saltelli et al., 2008; Sobol', 2001) and regression-based sensitivity (Ridolfi & Mooij, 2016) methods.

## Statement of need

Global Sensitivity Analysis has become an essential part of modeling workflows for practitioners in various fields such as Quantitative Systems Pharmacology and Environmental Modeling (Jakeman et al., 2006; Andrea Saltelli et al., 2020; Sher et al., 2022; Zhang et al., 2015). It can be used primarily in two stages, either before parameter estimation to simplify the fitting problem by fixing unimportant parameters or for analysis of the input parameters' influence on the output. There are already some popular packages in R and Python, such as sensitivity and SALib (Herman & Usher, 2017) for global sensitivity analysis. GlobalSensitivity.jl provides Julia implementations of some of the popular GSA methods mentioned in the previous section. Thus it benefits from the performance advantage of Julia, provides a convenient unified API for different GSA methods by leveraging multiple dispatch, and has a parallelized implementation for some of the methods. This package allows users to conveniently perform GSA on arbitrary functions and get the sensitivity analysis results and provides out-of-the-box support for differential equations based models defined using the SciML interface (Rackauckas et al., 2020; Rackauckas & Nie, 2017).

### Examples

The following tutorials in documentation 1 and 2 cover workflows of using GlobalSensitivity.jl on the Lotka-Volterra differential equation, popularly known as the predator-prey model. We present a showcase on how to use multiple GSA methods, analyze their results, and leverage Julia's parallelism capabilities to perform global sensitivity analysis at scale. The plots have been created using the Makie.jl package (Danisch & Krumbiegel, 2021), while many of the plots in the documentation use the Plots.jl package (Christ et al., 2022).

The ability to introduce parallelism with GlobalSensitivity.jl by using the batch keyword argument is shown in the below code snippet. In the batch interface, each column `p[:, i]` is a set of parameters, and we output a column for each set of parameters. Here we present the use of [Ensemble Interface] through `EnsembleGPUArray` to perform automatic multithreaded-parallelization of the ODE solves.

```
using GlobalSensitivity, QuasiMonteCarlo, OrdinaryDiffEq

function f(du, u, p, t)
  du[1] =  p[1] * u[1] - p[2] * u[1] * u[2] #prey
  du[2] = -p[3] * u[2] + p[4] * u[1] * u[2] #predator
end

u0 = [1.0; 1.0]
tspan = (0.0, 10.0)
p = [1.5, 1.0, 3.0, 1.0]
prob = ODEProblem(f, u0, tspan, p)
t = collect(range(0, stop = 10, length = 200))

f1 = function (p)
  prob_func(prob, i, repeat) = remake(prob; p = p[:, i])
  ensemble_prob = EnsembleProblem(prob, prob_func = prob_func)
  sol = solve(
      ensemble_prob,Tsit5(),
      EnsembleThreads();
      saveat = t,trajectories = size(p, 2))
  # Now sol[i] is the solution for the ith set of parameters
  out = zeros(2, size(p, 2))
  for i in 1:size(p, 2)
    out[1, i] = mean(sol[i][1, :])
    out[2, i] = maximum(sol[i][2, :])
  end
  out
end

samples = 10000
lb = [1.0, 1.0, 1.0, 1.0]
ub = [5.0, 5.0, 5.0, 5.0]
sampler = SobolSample()
A,B = QuasiMonteCarlo.generate_design_matrices(samples, lb, ub, sampler)

sobol_result = gsa(f1, Sobol(), A, B, batch=true)
```

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