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priorsense: Efficient prior and likelihood sensitivity checks for Bayesian models in R

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Software

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Summary

`priorsense` is an R (R Core Team, 2026) package that provides tools for prior and likelihood diagnostics and sensitivity analysis of Bayesian models. It includes functions for performing power-scaling sensitivity analysis. This is a way to check how sensitive the posterior is to perturbations of the prior and likelihood and diagnose the cause of sensitivity. The method does not require refitting the model, so it is computationally efficient. Full details of the method underlying power-scaling sensitivity analysis are described in (Kallioinen et al., 2024).

Statement of need

The prior and likelihood are the underlying components of a Bayesian model. Together with the data, the resulting posterior distribution is derived. Sensitivity checks are an important part of the Bayesian workflow (Gelman et al., 2026) as they can identify:

- whether the posterior is likely to meaningfully change with small changes to the prior
- whether the likelihood is informative or not for some parameters of interest

Before `priorsense` was developed, sensitivity checks were commonly conducted in an ad hoc manner and required expensive recomputations for each modification of the prior or likelihood. `priorsense` fills a clear gap in the Bayesian workflow by providing fast and efficient sensitivity checks that are widely applicable.

State of the field

Bayesian sensitivity analysis has been studied for decades, however much of the previous work was focused on posteriors that could be computed analytically. While probabilistic programming and Markov chain Monte Carlo methods have increased in popularity and use, tools for sensitivity checks that can be used for complex intractable posteriors remain relatively rare. The main other software package that has been developed is `adjustr` (McCartan, 2026), which focuses on flexibility in manual alternative model specification. ArviZ (Martin et al., 2026), a Python suite for Bayesian model diagnostics, also includes diagnostics mirroring those implemented in `priorsense`.

Software design

The `priorsense` package provides tools for efficient sensitivity checks, including numerical and graphical diagnostics. It is directly compatible with `brms` (Bürkner, 2017), Stan (Stan

Development Team, 2026), JAGS (Plummer, 2003) and NIMBLE (de Valpine et al., 2017, 2026), and can be used with posterior draws from other sources.

`priorsense` functions primarily operate on a `priorsense_data` object, which contains all the necessary data to perform the sensitivity checks. Fitted model objects are first coerced to this data object, to ensure consistency regardless of the origin of the posterior draws. The primary user-facing functions for power-scaling sensitivity checks are:

- `powerscale_sensitivity()` for numerical diagnostics
- `powerscale_plot_dens()`, `powerscale_plot_ecdf()` and `powerscale_plot_quantities()` for graphical checks

These can be run directly on outputs from `brms`, Stan, JAGS and NIMBLE fitting procedures, provided that the required log prior and log likelihood evaluations are stored. The easiest way to save these is to include them in the model code. This can be done simply in Stan, JAGS and NIMBLE, and is already included in `brms` model output by default. Vignettes in the package documentation describe how to do this for each supported language.

For efficient computation, power-scaling sensitivity analysis uses Pareto smoothed importance sampling (Vehtari et al., 2024) and importance weighted moment matching (Paananen et al., 2021) from the `iwmm` package (Paananen, 2026). `priorsense` relies on the well-established posterior package (Bürkner et al., 2026) as a backend for manipulating posterior draws and for Pareto smoothed importance sampling. It is therefore compatible with any format of posterior draws that the posterior package supports. Plots are created with `ggplot2` (Wickham, 2016) with additional functions from ggdist (Kay, 2024) and `ggh4x` (van den Brand, 2025). Input checking is done with `checkmate` (Lang, 2017) and tests are implemented with `testthat` (Wickham, 2011).

Research impact statement

The diagnostics provided by `priorsense` seamlessly fit into a modern Bayesian workflow. It has been included in recommended workflows for Bayesian modelling (Gelman et al., 2026) and since its release, `priorsense` has been downloaded from CRAN tens-of-thousands of times and has been used for academic research in fields such as ecology (Vanko et al., 2026), medicine (Mazzinari et al., 2024), psychology (Bezdicek et al., 2024; Gijsen et al., 2024).

AI usage disclosure

No generative AI tools were used by the authors in the development of this software or preparation of this manuscript.

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