

# Comparison of Regression-Adjusted ABC and Neural Methods for Simulation-Based Inference

## Background

In many modern scientific problems, the likelihood is intractable or prohibitively expensive to evaluate, making classical Bayesian updating impractical. Simulation-Based Inference (SBI) replaces likelihood evaluation with simulations to approximate the posterior. While classical Approximate Bayesian Computation (ABC) can be inefficient due to heavy rejection, recent neural methods—especially Neural Posterior Estimation (NPE)—leverage all simulations and have shown strong performance across benchmark tasks [1].

## Objectives and Methodology

A key omission in [1] is a systematic comparison against **ABC with regression adjustment** (RA-ABC). RA-ABC fits a regression from parameters to discrepancies/summaries to “correct” accepted ABC draws, improving bias and variance relative to vanilla ABC; it also admits flexible non-linear regressors (e.g., neural nets) [2,3]. Further, **recalibration** can post-process RA-ABC outputs to improve coverage and correct residual miscalibration [4].

**Objectives:** (i) Implement RA-ABC (linear and non-linear) and NPE; (ii) compare them on the AISTATS SBI benchmark tasks under matched simulation budgets; (iii) evaluate accuracy, efficiency, and calibration, including the effect of recalibration.

**Methods:** Use the public benchmark tasks and budgets in [1]; implement rejection/SMC ABC with local-linear and neural regression adjustments [2,3]; train NPE with normalising flows following [1]; assess accuracy via C2ST/MMD and posterior-predictive checks; assess calibration via credible-interval coverage, before/after recalibration [4].

## Timeline

Weeks 1–2: Review SBI literature; reproduce benchmark setup [1].

Weeks 3–4: Implement RA-ABC (linear & non-linear) + recalibration [2–4]; implement NPE [1].

Weeks 5–6: Run experiments across all benchmark tasks; analyse accuracy, efficiency, and calibration; compile results.

## References

- [1] Lueckmann, J. M., Boelts, J., Greenberg, D., Goncalves, P., & Macke, J. (2021, March). Benchmarking simulation-based inference. In *International conference on artificial intelligence and statistics* (pp. 343-351). PMLR.
- [2] Li, W., & Fearnhead, P. (2018). Convergence of regression-adjusted approximate Bayesian computation. *Biometrika*, 105(2), 301-318.
- [3] Blum, M. G., & François, O. (2010). Non-linear regression models for Approximate Bayesian Computation. *Statistics and computing*, 20(1), 63-73.
- [4] Rodrigues, G. S., Prangle, D., & Sisson, S. A. (2018). Recalibration: A post-processing method for approximate Bayesian computation. *Computational Statistics & Data Analysis*, 126, 53-66.