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Accelerating Simulation-Based Inference with Differentiable Simulators.

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Recent advances in simulation-based inference algorithms using neural density estimators have demonstrated an ability to achieve high-fidelity posteriors. However, these methods require a large number of simulations, and their applications are extremely time-consuming.

To tackle this problem, we are investigating SBI methodologies that can make use of not only samples from a simulator (which is the case when using a black-box simulator), but also the derivative of a given sample. While state-of-the-art neural density estimators such as normalizing flows are powerful tools to approximate density, their architecture does not always allow to include the simulation gradients.

In this work we present a dedicated approach to density estimation that allows us to incorporate the gradients of a simulator, and thus reduces the number of simulations needed to achieve a given posterior estimation quality. We also compare the simulation cost of existing SBI methods to our method.

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