

# Approximate Bayesian Computation for Parameter Inference

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# Approximate Bayesian Computation (ABC)

# Beating the curse of dimensionality for parameter inference

We want to avoid needing to train new networks for every parameter value  $\theta$  (expensive!) then computing the likelihood of the experimental data. Instead we compute the likelihood of simulated data under set of target variational distributions trained on experimental data. This assumes simulations and experimental data are "exchangeable" when computing the posterior

**Variational step:** we learn  $N_t$  target distributions by training a deep network on the experimental data. In this way we have  $N_t$  variational target distributions

**ABC step:** We sample parameters from our prior  $\theta \sim \pi(\theta)$ , and produce  $N$  Monte Carlo trajectories  $\mathbf{x}(t)$ . We compute the likelihood of the simulated trajectory with a tolerance  $\epsilon$  (with a tolerance schedule). This replaces the distance metric in ABC with a variational likelihood