Synthetic likelihood is hardly efficient

Surrogate is fitted at each parameter value separately

- BOLFI - Bayesian optimization for likelihood-free inference:
  - Model the discrepancy as a function of the parameter $\Delta(\theta) = d(x(\theta), x^o)$ conditioned on simulated data $\{(\theta_i, \Delta(\theta_i)))\}_{i=1}^t$using a Gaussian process

$$\Delta(\theta) \mid \{(\theta_i, \Delta(\theta_i))\}_{i=1}^t \sim \text{GP}(\mu_{1:t}(\theta), v_{1:t}(\theta) + \sigma_n^2)$$

Synthetic likelihood is hardly efficient

Surrogate is fitted at each parameter value separately

- BOLFI - Bayesian optimization for likelihood-free inference:
    - Likelihood can be approximated from the surrogate (pointwise) by

$$p(x^o \mid \theta) \approx \Phi\left(\frac{\epsilon - \mu_{1:t}(\theta)}{\sqrt{v_{1:t}(\theta) + \sigma_n^2}}\right)$$

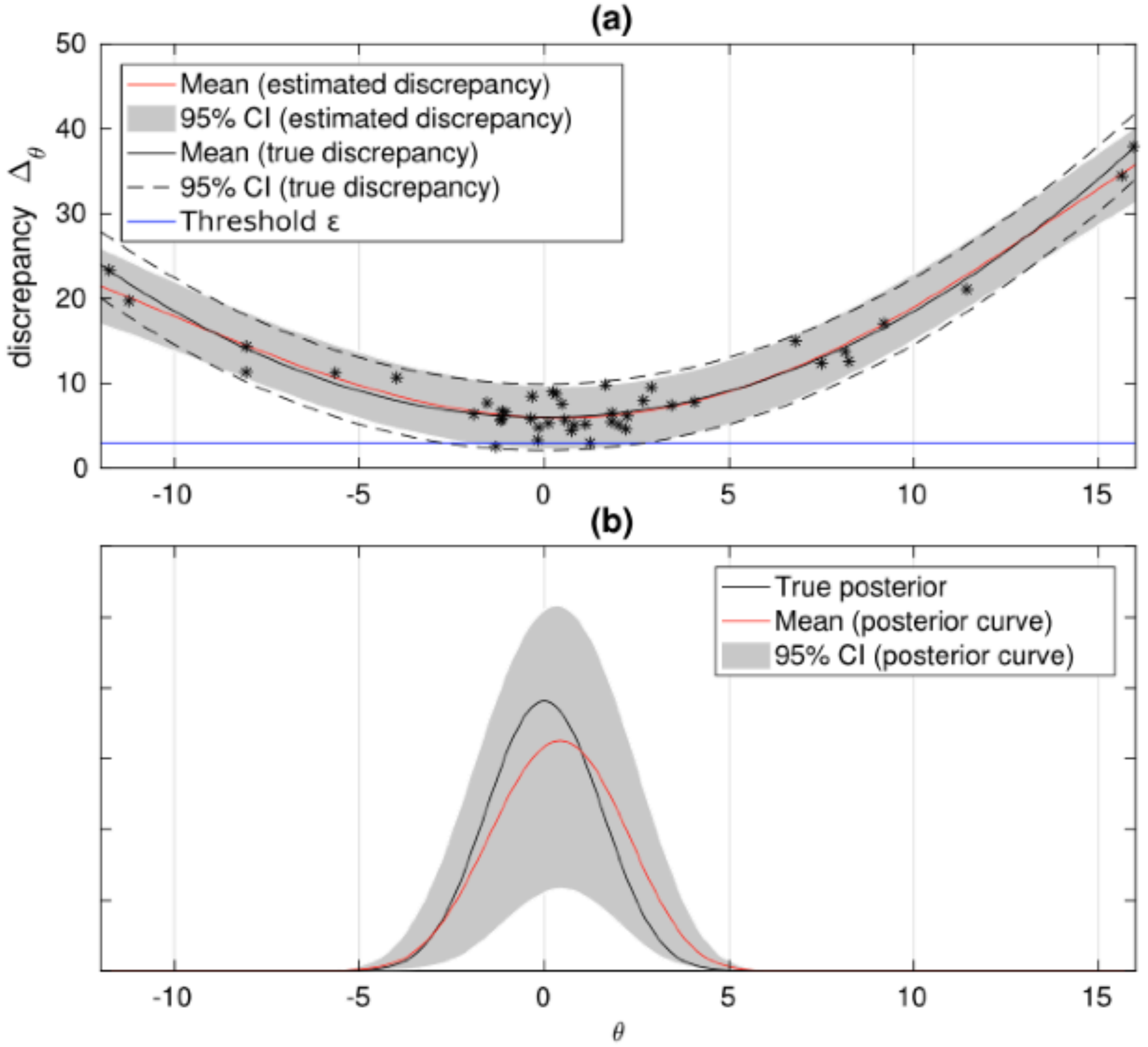

Figure from M. Järvenpää, “Efficient Acquisition Rules for Model-Based Approximate Bayesian Computation”, 2019