

Simulation-Based Inference

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Algorithm 1: Training Procedure.

Input: Forward model f , prior over physical parameters $P(\mathbf{z})$.

Output: Approximate posterior $Q_\phi(\mathbf{z}|\mathbf{x})$. Also a likelihood $P_{\mathbf{w}}(\mathbf{x}|\mathbf{z})$.

1 repeat

2 Simulate $\{(\mathbf{z}_i, \mathbf{x}_i)\}_{i=1}^N$ pairs, using $\mathbf{x}_i \leftarrow f(\mathbf{z}_i)$, $\mathbf{z}_i \sim P(\mathbf{z})$.

3 Train $Q_\phi(\mathbf{z}|\mathbf{x})$ via ML:

$$\arg \max_{\phi} \sum_{i=1}^N \log Q_\phi(\mathbf{z}_i|\mathbf{x}_i)$$

4 Train a neural likelihood (or likelihood-ratio?)

$$\arg \max_{\mathbf{w}} \sum_{i=1}^N \log P_{\mathbf{w}}(\mathbf{x}_i|\mathbf{z}_i)$$

5 Minimise a divergence (e.g. D_{KL}):

$$\arg \min_{\phi} D_{\text{KL}}[Q_\phi(\mathbf{z}|\mathbf{x}_{\text{true}}) \| P(\mathbf{z}|\mathbf{x}_{\text{true}})]$$

where $P(\mathbf{z}|\mathbf{x}_{\text{true}}) \propto P_{\mathbf{w}}(\mathbf{x}_{\text{true}}|\mathbf{z})P(\mathbf{z})$.

6 until *Until reconstructions match the data*

The ELBO has the following form:

$$\mathcal{L}(\phi) = \mathbb{E}_{Q_\phi(\mathbf{z}|\mathbf{x}_{\text{true}})} [\log P(\mathbf{z}, \mathbf{x}_{\text{true}}) - \log Q_\phi(\mathbf{z}|\mathbf{x}_{\text{true}})] \quad (1)$$

$$= \mathbb{E}_{Q_\phi(\mathbf{z}|\mathbf{x}_{\text{true}})} \left[\log P_{\mathbf{w}}(\mathbf{x}_{\text{true}}|\mathbf{z}) - \log \frac{Q_\phi(\mathbf{z}|\mathbf{x}_{\text{true}})}{P(\mathbf{z})} \right] \quad (2)$$

We optimise an MC approximation of this objective, using K terms

$$\mathcal{L}(\phi) \approx \sum_{i=1}^K \log P_{\mathbf{w}}(\mathbf{x}_{\text{true}:j}|\mathbf{z}_i) - \log Q_\phi(\mathbf{z}_i|\mathbf{x}_{\text{true}:j}) + \log P(\mathbf{z}_i),$$

where $\mathbf{z}_i \sim Q_\phi(\mathbf{z}_i|\mathbf{x}_{\text{true}:j})$.