

Solution: Bayesian experimental design

Chose acquisition design $\mathbf{W}[\mathbf{w}]$ that allows for **maximal** information gain

$$\mathbf{y} = \mathbf{W}(\mathbf{x})$$

where \mathbf{W} is a binary sampling mask derived from density \mathbf{w}

Collect data by maximizing the Kullback-Leibler divergence:

$$\max_{\mathbf{W}} D_{KL}(p(\mathbf{x} | \mathbf{y}) || p(\mathbf{x})) .$$

Maximize Expected information gain (EIG) averages over all possible designs

$$\max_{\mathbf{W}} \{ EIG(\mathbf{W}) = \mathbb{E}_{p(\mathbf{y}|\mathbf{W})} [D_{KL}(p(\mathbf{x} | \mathbf{y}) || p(\mathbf{x}))] \} .$$

Relation

conditional neural density & EIG

Maximizing the expected *posterior density* is *equivalent* to maximizing the expected *information gain*

$$\begin{aligned}\max_{\mathbf{W}} \text{EIG}(\mathbf{W}) &= \mathbb{E}_{p(\mathbf{y}|\mathbf{W})} \left[D_{KL}(p_{\theta}(\mathbf{x}|\mathbf{y}) || p(\mathbf{x})) \right] = \mathbb{E}_{p(\mathbf{y}|\mathbf{W})} \left[\mathbb{E}_{p(\mathbf{x}|\mathbf{y})} \left[\log p_{\theta}(\mathbf{x}|\mathbf{y}) - \log p(\mathbf{x}) \right] \right] \\ &= \mathbb{E}_{p(\mathbf{y}|\mathbf{W})} \left[\mathbb{E}_{p(\mathbf{x}|\mathbf{y})} \left[\log p_{\theta}(\mathbf{x}|\mathbf{y}) \right] \right] \text{ law of total expectation} \\ &= \mathbb{E}_{p(\mathbf{x},\mathbf{y}|\mathbf{W})} \left[\log p_{\theta}(\mathbf{x}|\mathbf{y}) \right] \text{ same as neural posterior objective!}\end{aligned}$$

Thus optimizing under the posterior density objective will increase the EIG!