

Global Optimization through Normalizing Flow

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Suppose that we are trying to solve the global optimization problem of the form

$$\begin{aligned} \mathbf{x}^* &= \operatorname{argmin}_{\mathbf{x}} V(\mathbf{x}) \\ \text{s.t. } \mathbf{x} &\in \mathbb{R}^n \end{aligned}$$

which is equivalent to sampling the distribution

$$\rho(\mathbf{x}) = \frac{e^{-\beta V(\mathbf{x})}}{Z},$$

where Z is the normalization factor, which is usually intractable.

Following the spirit of normalizing flow, we assume the complicated distribution can be derived from the Gaussian distribution by a bijection f , namely,

$$\rho^*(\mathbf{x}) = \mathcal{N} \circ f(\mathbf{x}) \left| \det \frac{\partial f}{\partial \mathbf{x}} \right|,$$

where $\mathcal{N}(z)$ is the standard n -dimensional normal distribution

$$\mathcal{N}(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}.$$

Also notice that the distribution $\rho^*(\mathbf{x})$ is already normalized.

$$\int \rho^*(\mathbf{x}) d\mathbf{x} = \int \mathcal{N} \circ f(\mathbf{x}) \left| \det \frac{\partial f}{\partial \mathbf{x}} \right| d\mathbf{x} = \int \mathcal{N}(z) dz$$

The loss function chosen to train the flow can be the KL divergence.

$$\begin{aligned} \mathcal{L} &= \text{KL}(\rho^* \parallel \rho) = \int d\mathbf{x} \rho^*(\mathbf{x}) [\log \rho^*(\mathbf{x}) - \log \rho(\mathbf{x})] \\ &= \int d\mathbf{x} \rho^*(\mathbf{x}) \left[\beta V(\mathbf{x}) + \log Z - \frac{1}{2} f(\mathbf{x})^2 + \log \left| \det \frac{\partial f}{\partial \mathbf{z}} \right| - \frac{1}{2} \log 2\pi \right] \\ &= \mathbb{E}_{\tilde{\mathbf{x}} \sim \rho^*(\mathbf{x})} \left[\beta V(\mathbf{x}) - \frac{1}{2} f(\mathbf{x})^2 + \log \left| \det \frac{\partial f}{\partial \mathbf{z}} \right| \right] + \text{const.} \end{aligned}$$

and the sample $\tilde{\mathbf{x}}$ is easy to get.

$$\tilde{z} \sim \mathcal{N}(z), \tilde{\mathbf{x}} = f^{-1}(\tilde{z})$$