

Update on 1st paper

- Most typos/format changes have been done based on the comments from the PRL reviewers.
 - Proper way to cite from D-WAVE?
 - Plots for single particle?
 - Rewrite the theory part with clearer setup and definitions.

evidence lower bound (ELBO) to the true log-likelihood:

$$\log p_{\theta}(\mathbf{x}) \geq \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})}[\log p_{\theta}(\mathbf{x}|\mathbf{z})] - \text{KL}[q_{\phi}(\mathbf{z}|\mathbf{x})||p_{\theta}(\mathbf{z})] \quad (1)$$

$\text{KL}[Q||P]$ is the Kullback-Liebler divergence between two probability distributions, Q and P while \mathbb{E}_p denotes an expectation value over the distribution p . The variables \mathbf{x} and \mathbf{z} represent data (in this case a vector of calorimeter cell energies) and latent variable respectively. The approximating posterior, $q_{\phi}(\mathbf{z}|\mathbf{x})$ and the generative, $p_{\theta}(\mathbf{x}|\mathbf{z})$ distributions are often parameterized using neural networks. In the original VAE framework [6, 19], $q_{\phi}(\mathbf{z}|\mathbf{x})$ and $p_{\theta}(\mathbf{z})$ are assumed to be factorized Gaussian distributions, $\mathcal{N}(\boldsymbol{\mu}_{\phi}(\mathbf{x}), \boldsymbol{\Sigma}_{\phi}^2(\mathbf{x}))$ and $\mathcal{N}(\mathbf{0}, \mathbf{I})$ respectively.

CaloDVAE [7, 8] is a hierarchical discrete VAE which extends the VAE framework by introducing discrete latent variables $\mathbf{z}_i \in \{0, 1\}$ in the latent space. Both the encoder, $q_{\phi}(\mathbf{z}|\mathbf{x}, \mathbf{e})$, and decoder, $p_{\theta}(\mathbf{x}|\mathbf{z}, \mathbf{e})$, are conditioned on energy [18, 20] and are modelled by fully connected neural networks. The approximate posterior of the VAE has a hierarchical structure $q_{\phi}(\mathbf{z}|\mathbf{x}, \mathbf{e}) = \prod_i q_{\phi_i}(\mathbf{z}_i|\mathbf{z}_{j<i}, \mathbf{x}, \mathbf{e})$ with N latent groups and the latent distribution of the VAE is modelled by an RBM where $\mathbf{z} = [\mathbf{z}_1, \dots, \mathbf{z}_N]$ are partitioned into 2 equal subsets to make the 2 sides of the RBM [18]. The RBM is modeled by probability distribution $p_{RBM} = e^{\mathbf{a}_l^T \mathbf{z}_l + \mathbf{a}_r^T \mathbf{z}_r + \mathbf{z}_l^T \mathbf{W} \mathbf{z}_r} / Z$ where Z is the partition function and $(\mathbf{a}_l, \mathbf{a}_r, \mathbf{W})$ are the RBM parameters which are trained along with the VAE parameters (θ, ϕ) .



