

# **Electrons in a Quantum Dot**

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# Main task: Learn the probability distribution from a Hamiltonian

Goal:  $p(x) = e^{-\beta H(x)} / Z$       Normalization factor  $Z$  is unknown

K-L divergence

$$\mathbf{KL}(p_\theta || p) \equiv \int dx p_\theta(x) [\ln p_\theta(x) - \ln p(x)] \geq 0 \quad \text{equal to zero iff } p_\theta(x) = p(x)$$

$$\min_{\theta} \left\{ \int dx p_\theta(x) \left[ \frac{1}{\beta} \ln p_\theta(x) + H(x) \right] \right\} \geq -\frac{1}{\beta} \ln Z = F$$

$$\Leftrightarrow \min_{\theta} \left\{ \mathbb{E}_{x \sim p_\theta(x)} [H(\mathbf{x}) + k_B T \ln p_\theta(\mathbf{x})] \right\}$$

How to parametrize the distribution  $p_\theta$  ?

One possible way is to generate the  $p_\theta(x)$  from a simple distribution  $N(z)$ .

$$z \xrightarrow{g} x$$

$$p_\theta(x) = N(z) \left| \frac{\partial z}{\partial x} \right|$$

$$\ln p_\theta(x) = \ln N(z) - \ln \left| \frac{\partial x}{\partial z} \right|$$

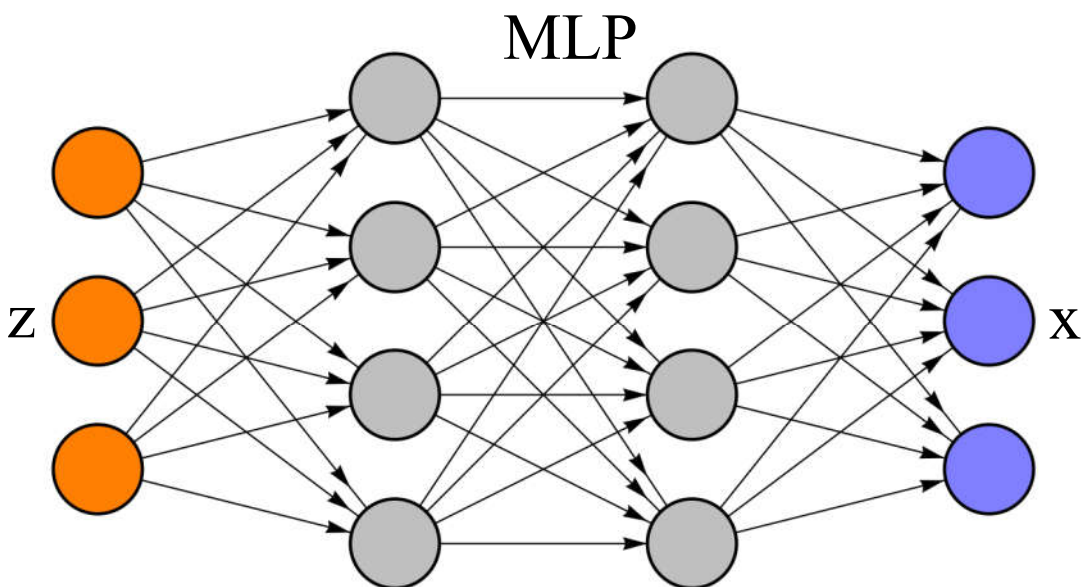
$$\nabla \mathcal{L} = \mathbb{E}_{z \sim \mathcal{N}(z)} [\nabla f(g(z))]$$

$$\text{where } f(x) = \frac{1}{\beta} \ln p_\theta(x) + H(x)$$

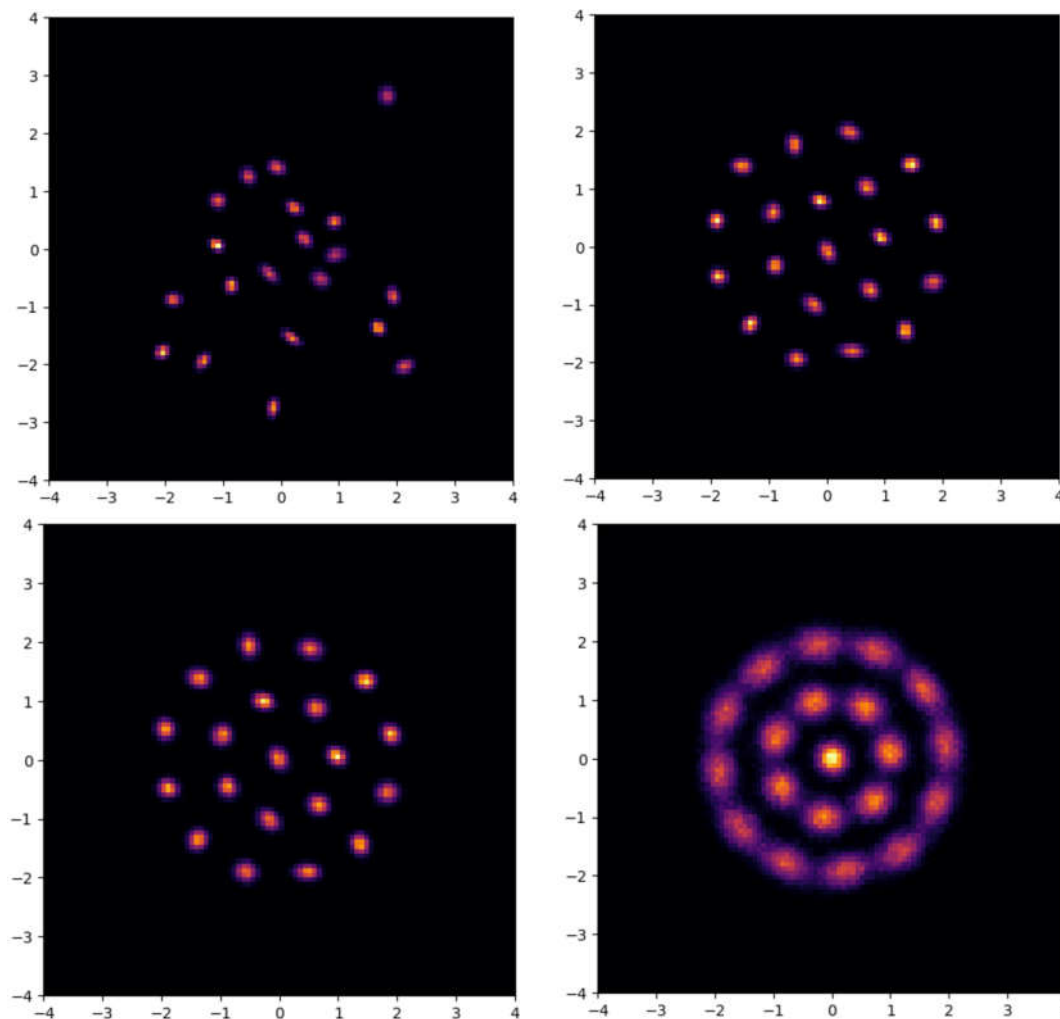
# Network

$$z \rightarrow z_1 = \sigma(W_1 z + b_1) \rightarrow \dots \rightarrow x = W_n z_{n-1} + b_{n-1}$$

$$n = 20, \beta = 10$$

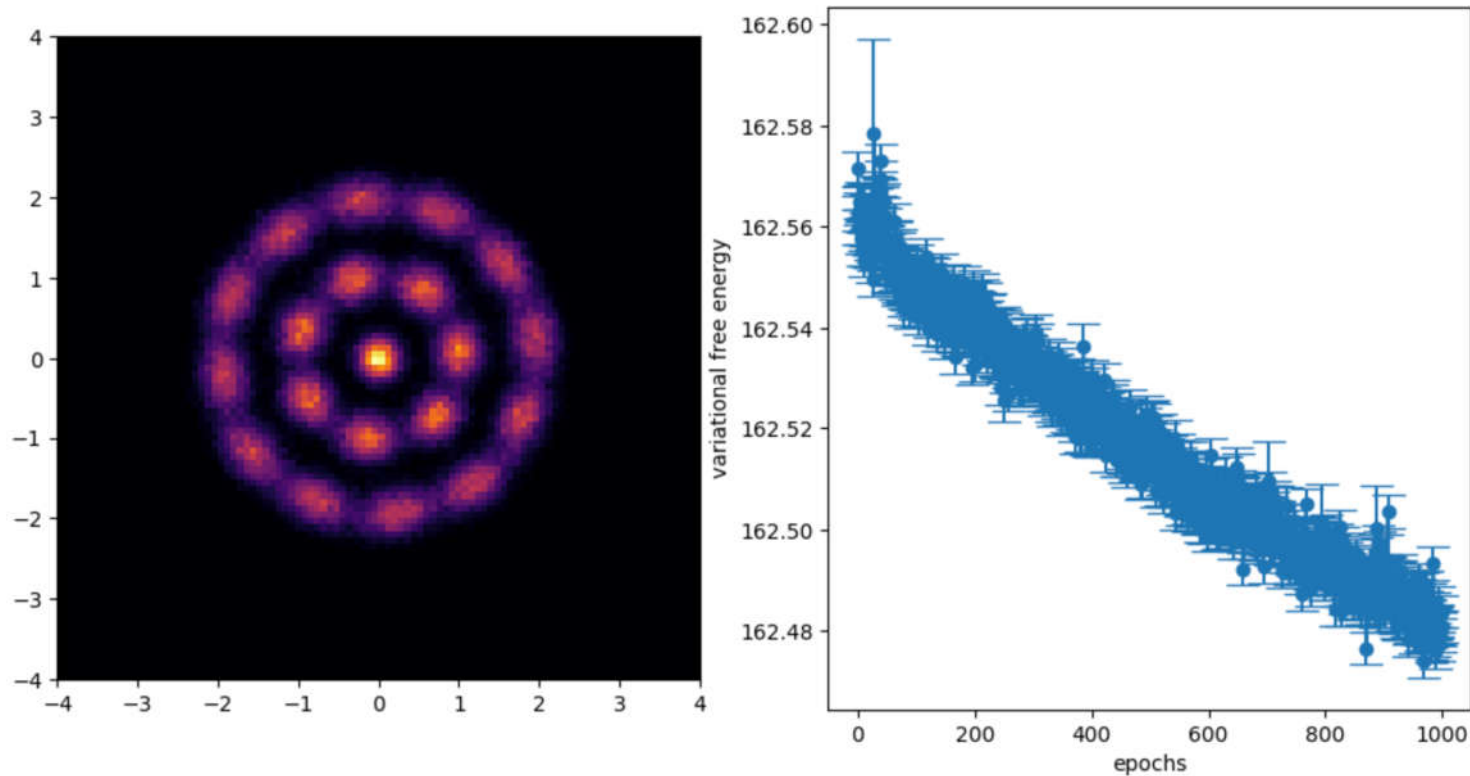


$n \cdot \text{dim} + \text{hidden layers} + n \cdot \text{dim}$



# Final result

$$n = 20, \beta = 10$$

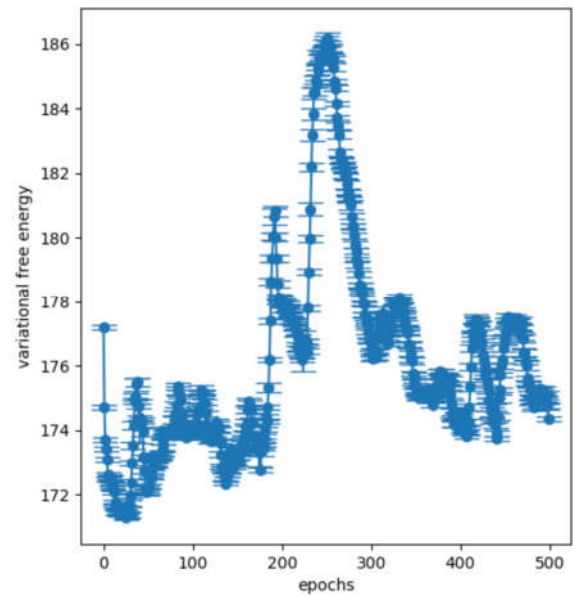
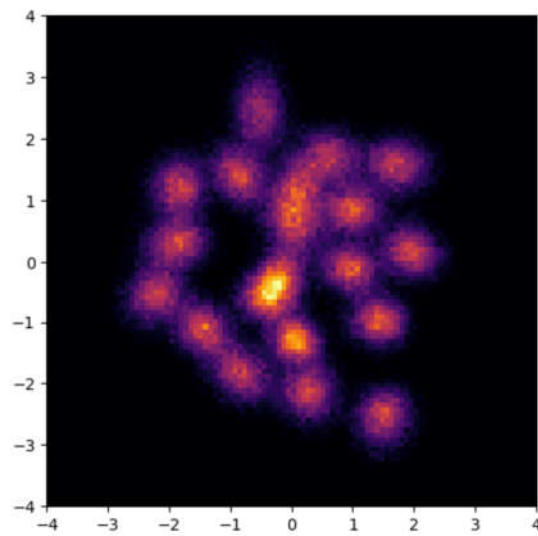
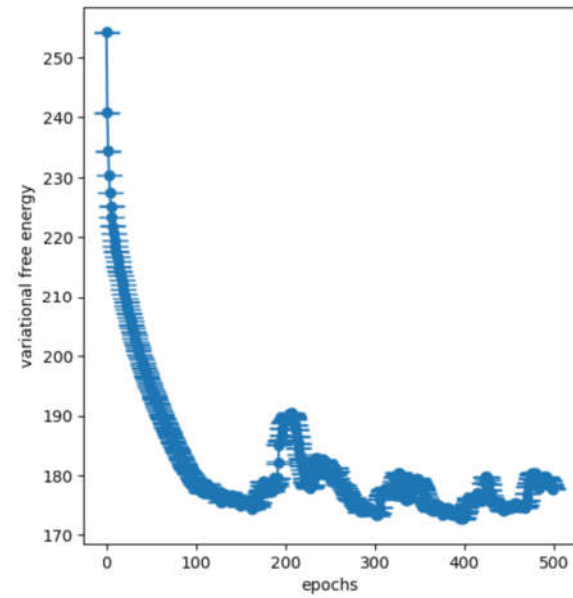
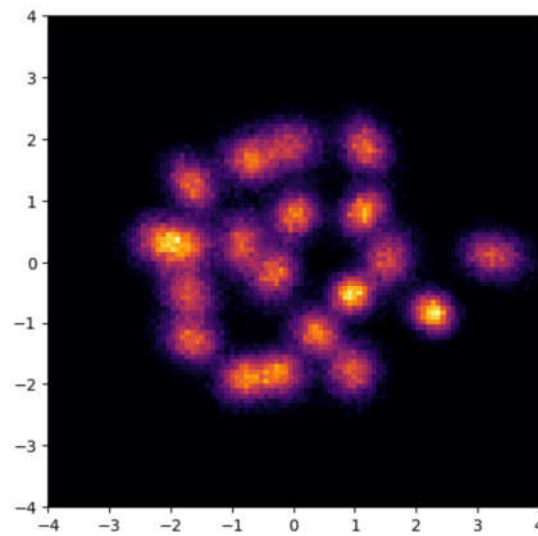


$$F = 162.4838 \pm 0.0032$$

$$\langle E \rangle = 160.8027$$

$$n = 20, \beta = 1.5$$

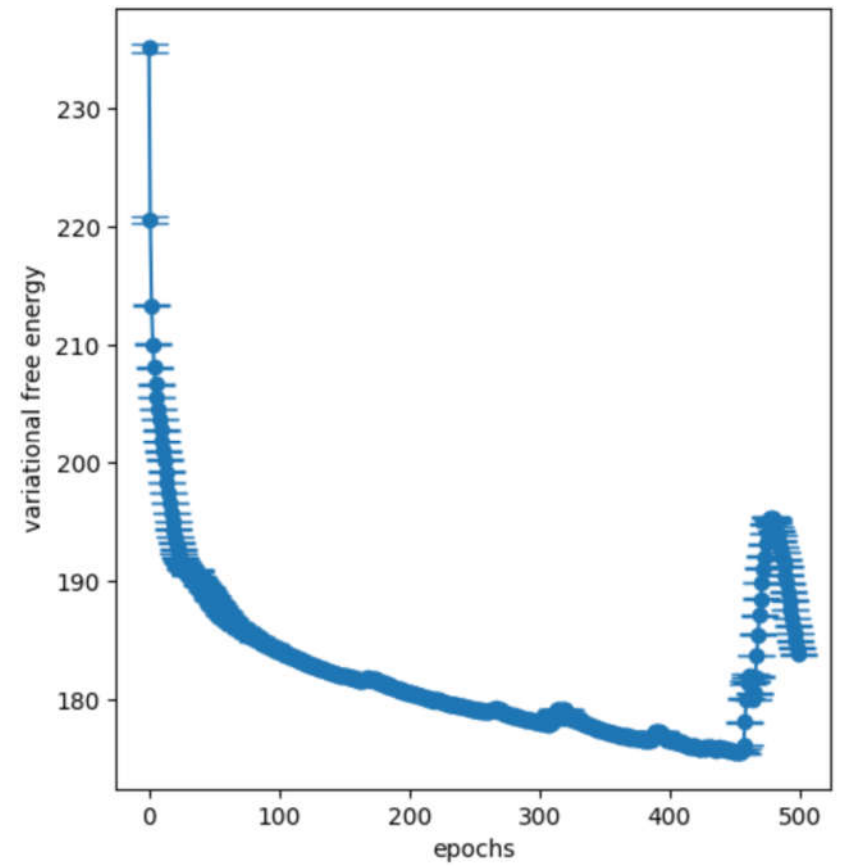
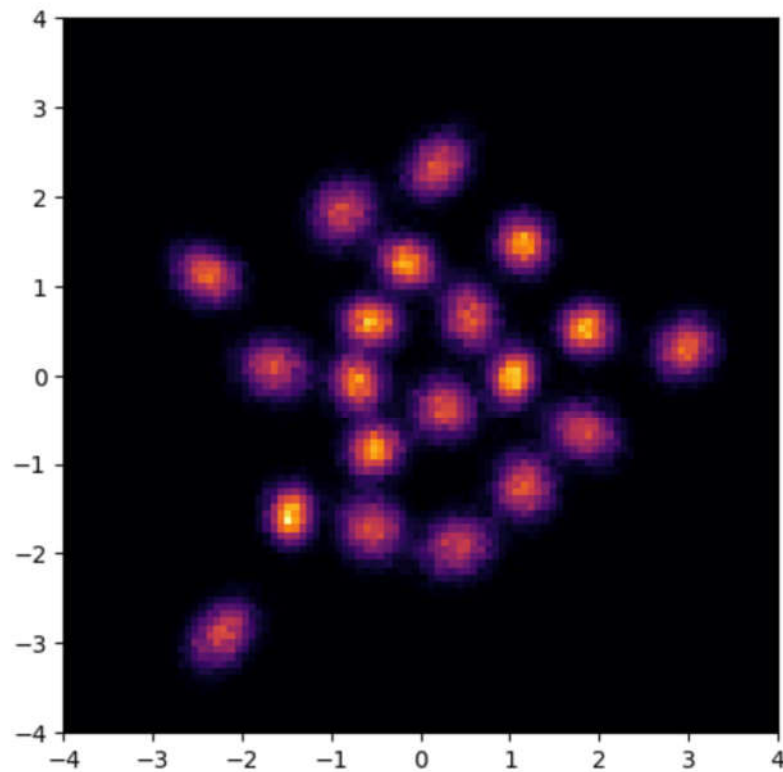
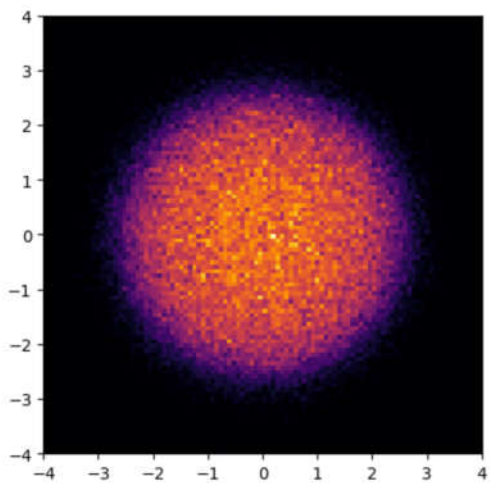
[40, 64, 64, 40]



$$n = 20, \beta = 1.5$$

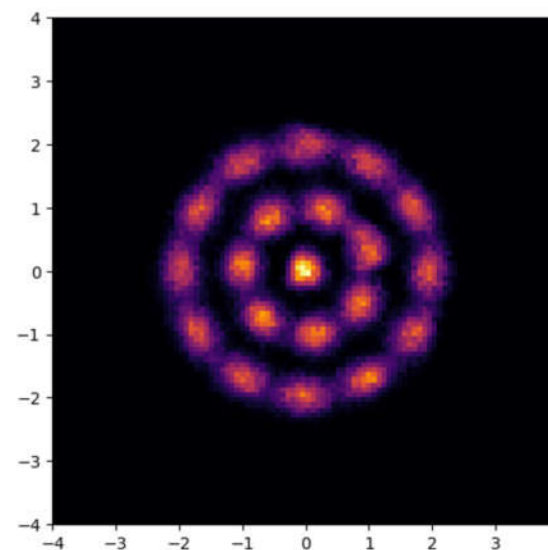
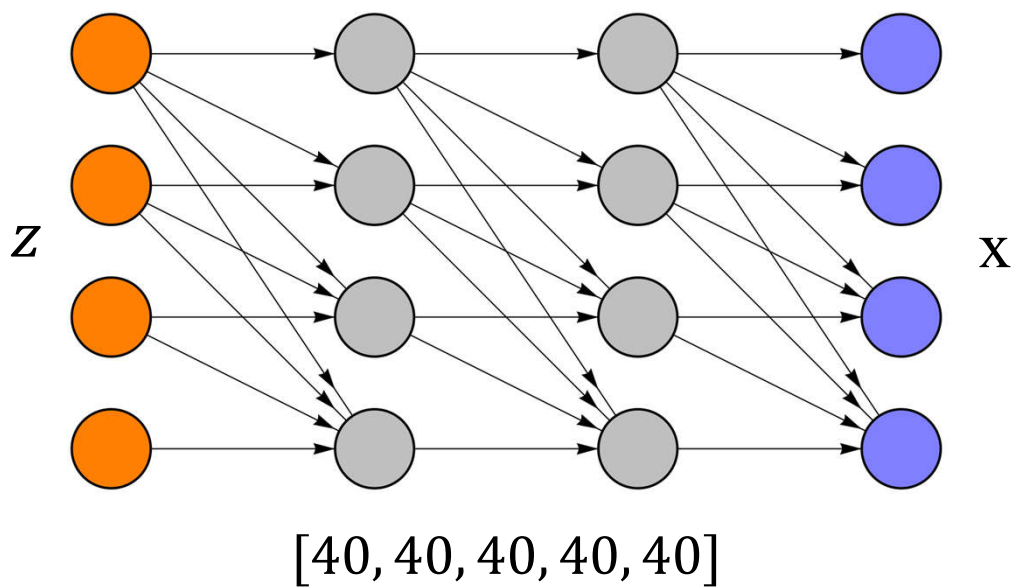
[40, 128, 128, 40]

MC

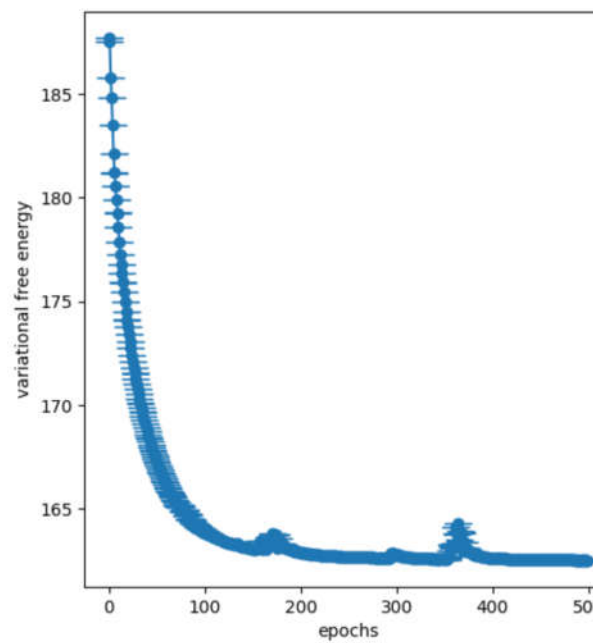


# Network

## Autoregressive MLP



$n = 20, \beta = 10$



Steps: 200+500



# Symmetry

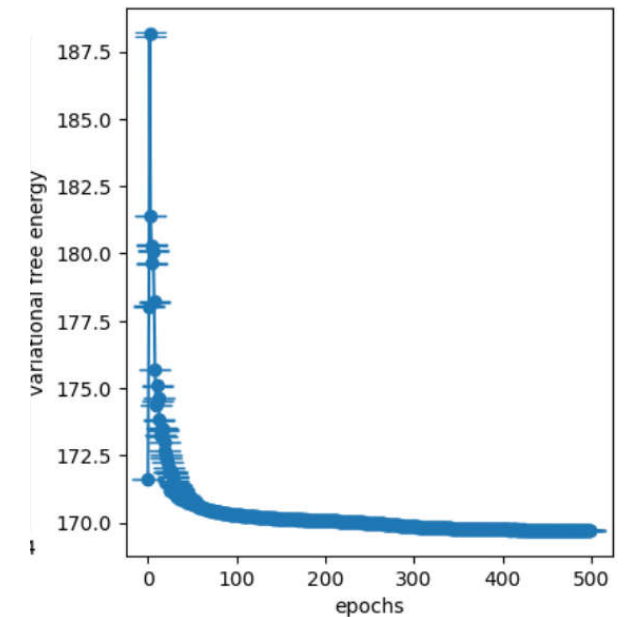
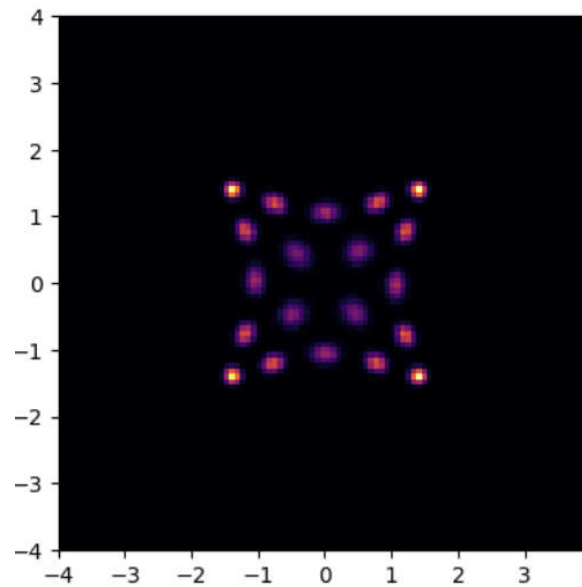
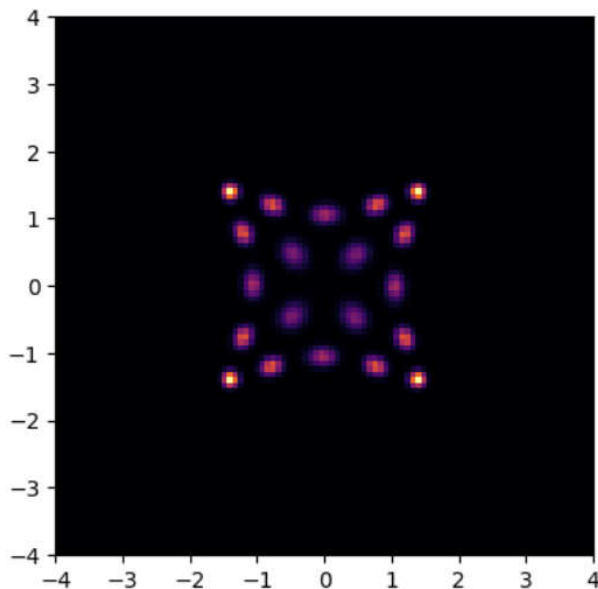
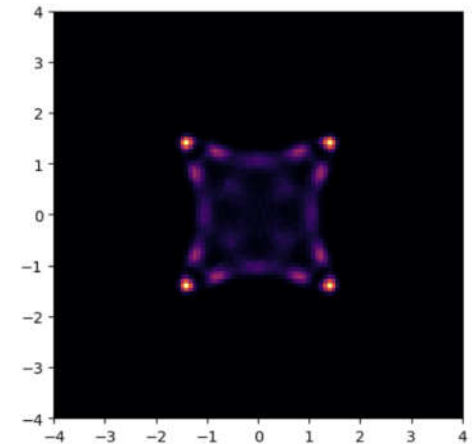
Potential:  $V = x^4 + y^4 - x^2y^2$

$$p_{\text{sym}}(\mathbf{x}) = \frac{1}{N_g} \sum_g p(g\mathbf{x})$$

$$\mathcal{L} - \mathcal{L}_{\text{sym}} = \int d\mathbf{x} p(\mathbf{x}) \left[ \ln p(\mathbf{x}) - \ln p_{\text{sym}}(\mathbf{x}) \right] \geq 0$$

$C_4$

MC



# Symmetry

$$x = \sigma(Wz + b), p(x) = N(z) \left| \frac{\partial z}{\partial x} \right| \quad \text{With } Gx = \sigma(WGz + b)$$

$$[G, W] = 0, Gb = b$$

$$G = P$$

$$\begin{aligned} W &= I \otimes \lambda_{d \times d} + (11^T) \otimes \gamma_{d \times d} \\ b &= I \otimes C_{d \times 1} \end{aligned}$$

$$G = R$$

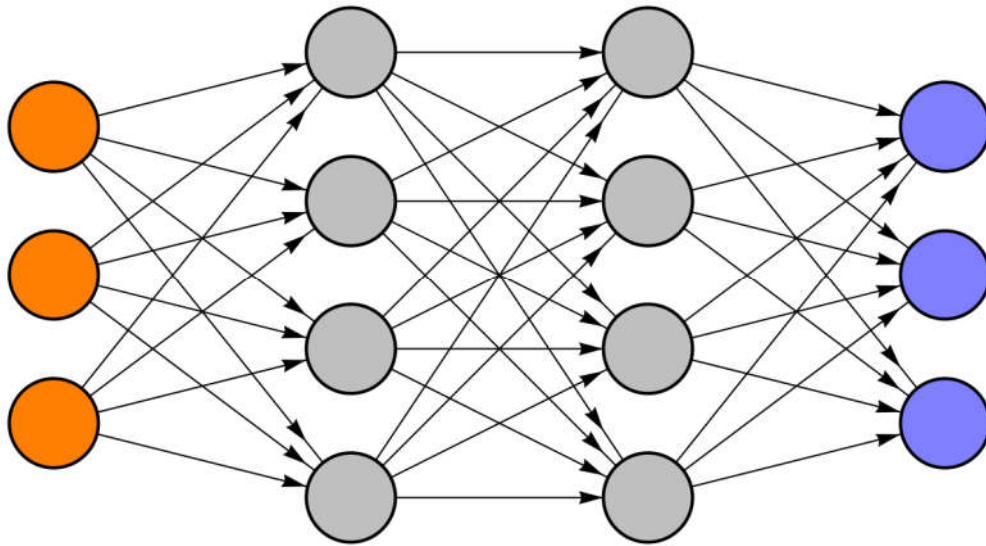
$$\begin{aligned} W &= \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & \cdots w_{nn} \end{pmatrix} \\ w_{ij} &= \begin{pmatrix} a_{ij} & b_{ij} \\ -b_{ij} & a_{ij} \end{pmatrix} \\ b &= 0 \end{aligned}$$

We will have  $p(Sx) = p(x)$ , while  $N(Sz) = N(z)$

N particles, one layer has  $d + 2d^2$  parameters

# Network

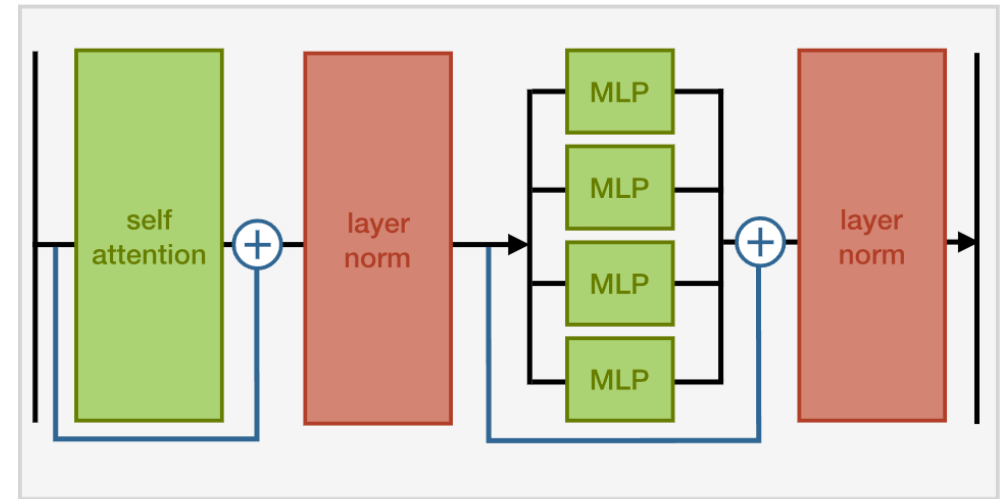
MLP



+

Transformer

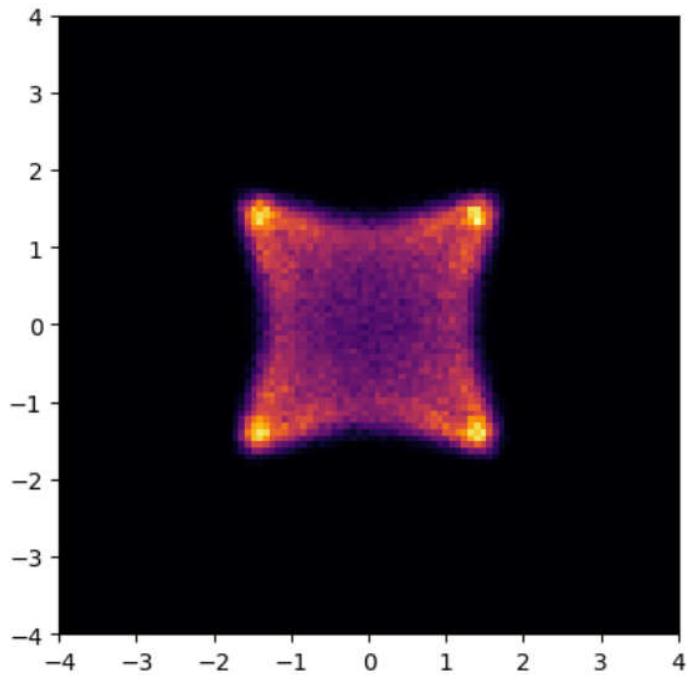
**transformer block**



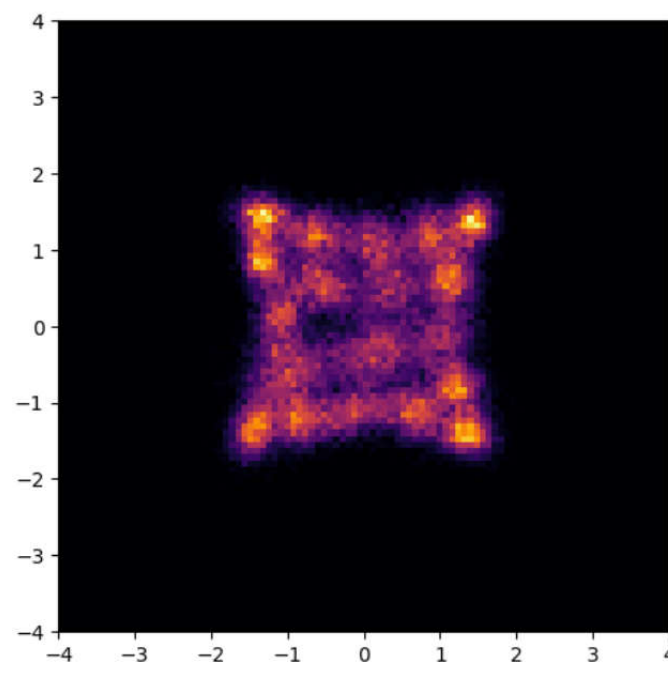
# Better behavior at high temperatures!

$$n = 20, \beta = 1.5$$

MC



MLP + Transformer



MLP only

