

# 1 Method

I trained a Restricted Boltzmann Machine (RBM) on the XOR dataset for 3-bit inputs. Of the 8 combinations, 4 patterns output +1 with probability 0.25, while the others have 0 probability. The goal is to train a network that generates 3-bit patterns with  $P_{\text{Boltzmann}}$  replicating  $P_{\text{data}}$ . I explored various  $M$  values, expecting 8 neurons to be sufficient, with 4 neurons yielding good Kullback-Leibler Divergence results. The network employs the Contrastive Divergence (CD-k) algorithm, with 3 visible neurons,  $M$  hidden neuron and parameters  $v_{\text{max}} = 10000$ ,  $p_0 = 20$ , and  $\eta = 0.005$ . I iterate the dynamics of the trained Boltzmann machine 100,000 times, counting occurrences of patterns with  $P_{\text{data}} \neq 0$ , representing model probabilities. I train 20 different Boltzmann machines for each  $M$  and compute divergences between data probabilities and observed probabilities (Eq. 1).

$$D_{KL} = \sum_{\mu=1}^p P_{\text{data}}(x(\mu)) \log \left[ \frac{P_{\text{data}}(x(\mu))}{P_B(s = x(\mu))} \right] \quad (1)$$

# 2 Results

I compute the upper bound for each divergence score (Eq. 2) and plot the scores of the 20 simulations for each  $M$  alongside KL divergence upper bounds (Fig. 1).

$$D_{KL} \leq \begin{cases} \log(2) (N - \lfloor \log_2(M+1) \rfloor - \frac{M+1}{2^{\lfloor \log_2(M+1) \rfloor}}) & \text{if } M < 2^{N-1} - 1 \\ 0 & \text{if } M \geq 2^{N-1} - 1 \end{cases} \quad (2)$$

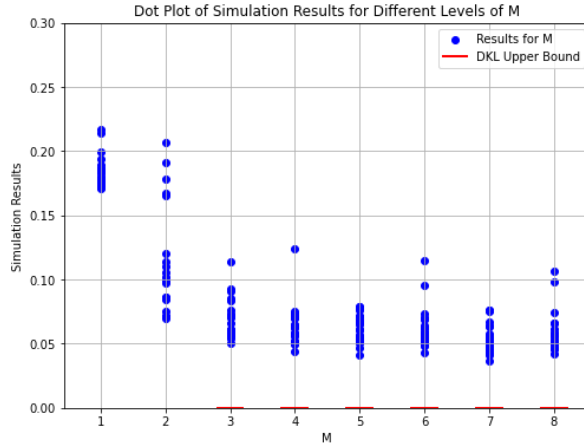


Figure 1: Divergence scores and KL divergence upper bounds for varying  $M$ .

The initial KL bounds of 0.69 and 0.34 are not visible as the plot cuts at 0.30 in order to improve visibility. For  $M = 1, 2$ , simulated divergences are below upper bounds; for  $M > 2$ , they remain above. In the case of  $M = 1, 2$  the divergences are more sensitive to parameter choices as in some instances I observed divergences approach 0.50 and 0.30, indicating a larger margin for error. However, for  $M > 2$ , results are consistently low, suggesting it is easier to fit the problem with more hidden neurons. The mean of the 20 simulations decreases and becomes less dispersed as  $M$  increases, yet I do not achieve perfect zero divergence. Simulated probabilities approach 0.25 but do not always sum to 1, indicating the possibility of generating unseen patterns with low a probability.