## STRIDERNETwith base Equivariant Graph Neural Network

To evaluate STRIDERNETapproach using an equivariant graph neural network, we implement Neural Equivariant Interatomic Potentials (NequIP) GNN following the architecture of (Batzner et al., 2022) with the final layer replaced to predict displacement vector for each node instead of energy. The basic configuration of hyperparameters is tabulated in Table 1.

| Hyper-parameters              |   |
|-------------------------------|---|
| PARAMETER                     | VALUE   |
| Input node features           | One hot node type, Node potential energy, Mean neighborhood energy, Sum neighborhood energy |
| Input edge features           | Edge distance vector  |
| Hidden Irreps                 | 128x0e + 64x1e +4x2e  |
| Spherical harmonic Irreps     | 1x3e + 1x0e   |
| Radial MLP non-linearity      | Swish   |
| Radial MLP hidden layers      | 32  |
| Radial MLP layers             | 1   |
| Nequip convolution layers     | 2   |
| No. of Bessel basis functions | 8   |
| Trajectory length $(T)$       | 10  |
| Gradient accumulation steps   | 2   |
| Graphs training batch size    | 2   |
| Gradient clipping             | 0.5   |

Table 1. Hyper-parameters of Equivariant STRIDERNET

In figure 1 and 2 we show the performance of the model on the training and the validation data during the course of training. In both figures, we observe that the model is unable to reduce the energy of the system. Despite the best efforts, we observe that the model is not converging.

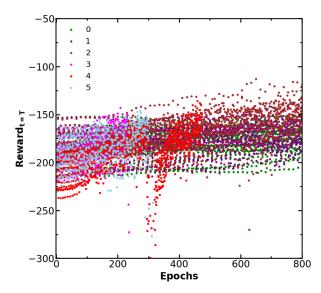


Figure 1. Reward curves of STRIDERNET with equivariant GNN on binary LJ system with 100 atoms. The labels [0-3] corresponds to same basic configuration as Table 1 with different learning rates of  $5 \times 10^{-3}$ ,  $1 \times 10^{-2}$ ,  $2 \times 10^{-2}$  and  $5 \times 10^{-2}$  respectively. The labels [4&5] corresponds to learning rate of  $5 \times 10^{-2}$  and increased batch size of 3 and 4 respectively.

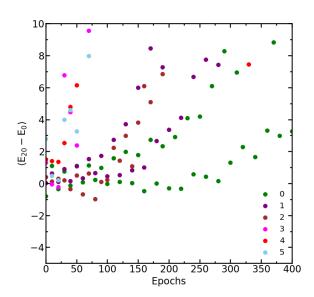


Figure 2. Validation curves of STRIDERNET with equivariant GNN on binary LJ system with 100 atoms. The labels [0-3] corresponds to same basic configuration as Table 1 with different learning rates of  $5 \times 10^{-3}$ ,  $1 \times 10^{-2}$ ,  $2 \times 10^{-2}$  and  $5 \times 10^{-2}$  respectively. The labels [4&5] corresponds to learning rate of  $5 \times 10^{-2}$  and increased batch size of 3 and 4 respectively.

## References

Batzner, S., Musaelian, A., Sun, L., Geiger, M., Mailoa, J. P., Kornbluth, M., Molinari, N., Smidt, T. E., and Kozinsky, B. E (3)-equivariant graph neural networks for data-efficient and accurate interatomic potentials. *Nature communications*, 13 (1):2453, 2022.