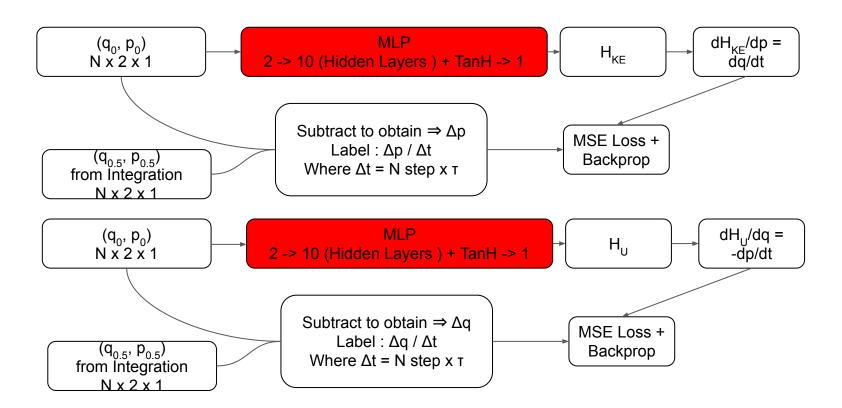
# MD ML 7

2 Models

### Proposed Hamiltonian Architecture



### **Training Setting**

Optimizer : Adam

Learning Rate (LR): 1e-3

Scheduler : None

Seed : 937162211 ( 9-digit Prime Number )

Epochs: 100

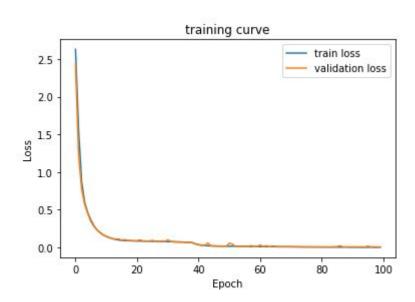
Batch Size : 32 / Shuffle

Large Time Step : 0.01 (1 Step) = 0.01

Ground Truth : 0.01

Final Statistic :  $\Delta q = 0.00034 (5 d.p)$ 

 $\Delta p = 0.00099 (5 d.p)$ 



#### Remarks:

- 1. Tried using scheduler of reduce on plateau, patience = 10, factor = 0.99, loss stuck at ~1.2
- 2. Temperature used: 1 10, interval 1
- 3. Tried 50 epochs, loss seems to be fluctuating
- 4. Seed to consider:
  - a. Random.seed
  - b. Numpy.seed
  - . Torch.seed
  - d. Torch.cuda.seed

### Distribution Sampling

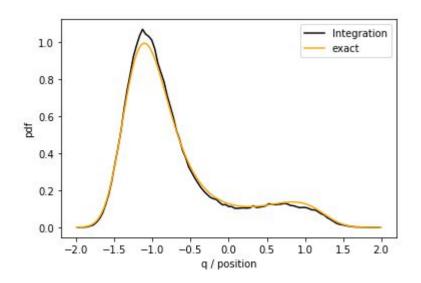
To update the distribution, we use the following splitting:

$$P(t = t + \Delta t) = [L_{\chi} (L_{p(\Delta t/n)} L_{q(\Delta t/n)} L_{p(\Delta t/n)})^{n} L_{\chi}]P(t = t)$$

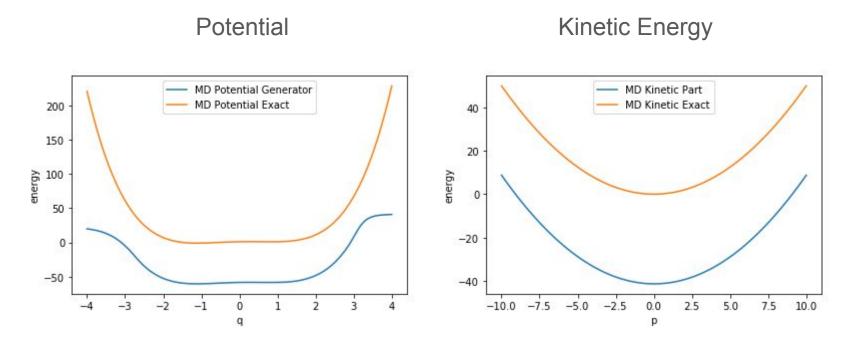
Where  $\Delta t/n = 0.01$  for the ground truth reference to calculate the **mean absolute error** 

- 1.  $(L_{p(\Delta t/n)} L_{q(\Delta t/n)} L_{p(\Delta t/n)})^n$  can be replaced by the model separately where n = 1
- 2. The constant random term is kept constant for Model and exact integration and the distribution is sampled after each update

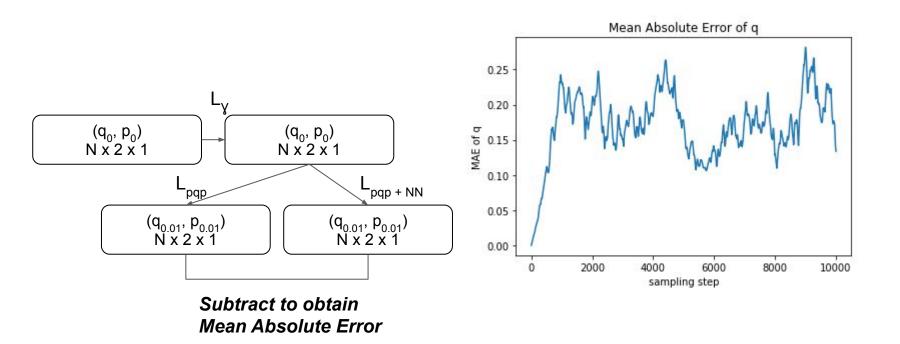
## Distribution Performance ( 10<sup>4</sup> Sampling )



### Hamiltonian Checking (time step: 0.01)



### Mean Absolute Error (time step: 0.01)



### **Training Setting**

Optimizer : Adam

Learning Rate (LR): 1e-3

Scheduler : None

Seed : 937162211 ( 9-digit Prime Number )

Epochs : 100

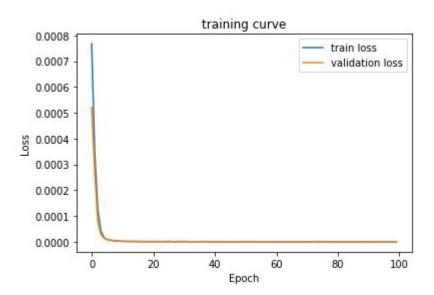
Batch Size : 32 / Shuffle

Large Time Step : 0.01 (50 Step) = 0.5

Ground Truth : 0.01

Final Statistic :  $\Delta q = 0.00018 (5 d.p)$ 

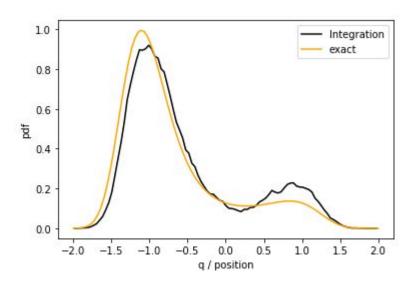
 $\Delta p = 0.00023 (5 d.p)$ 



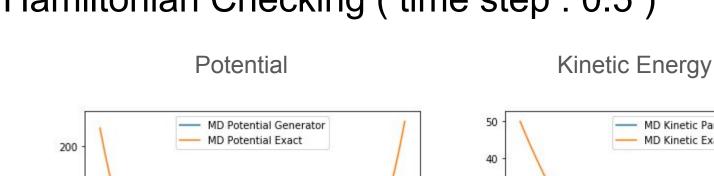
#### Remarks:

- 1. Tried using scheduler of reduce on plateau, patience = 10, factor = 0.99, loss seems to be stuck again
- 2. Temperature used: 1 10, interval 1
- 3. Seed to consider:
  - a. Random.seed
  - b. Numpy.seed
  - c. Torch.seed
  - d. Torch.cuda.seed

# Distribution Performance ( 10<sup>4</sup> Sampling )



### Hamiltonian Checking (time step: 0.5)

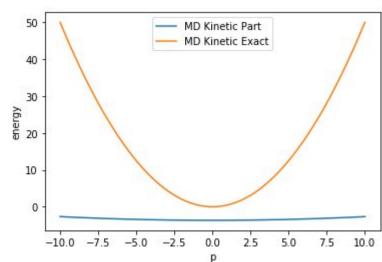


150

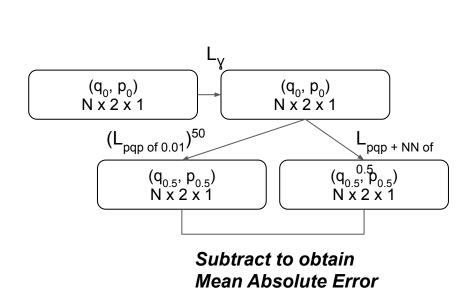
50

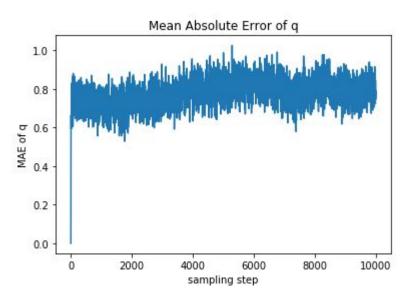
0

energy 100



### Mean Absolute Error (time step: 0.5)





# Analysis

### Literature Review

#### 1) Langevin Process:

- Introduction to the theory of stochastic processes and Brownian motion problems by J. L. Garcia-Palacios (<a href="https://arxiv.org/abs/cond-mat/0701242v1">https://arxiv.org/abs/cond-mat/0701242v1</a>) ⇒ Reference that I used
- 2. Overleaf Document by Liu Wei

#### 2) Hamiltonian Neural Network:

- 1. Hamiltonian Neural Networks by Sam Greydanus, Misko Dzamba, Jason Yosinski (<a href="https://arxiv.org/abs/1906.01563">https://arxiv.org/abs/1906.01563</a>)
- Symplectic Recurrent Neural Networks by Zhengdao Chen, Jianyu Zhang, Martin Arjovsky, Léon Bottou ( https://arxiv.org/abs/1909.13334)

#### 3) Langevin Sampling:

 Robust and efficient configurational molecular sampling via Langevin Dynamics by Benedict Leimkuhler, Charles Matthews (<a href="https://arxiv.org/abs/1304.3269">https://arxiv.org/abs/1304.3269</a>)