

So following James' suggestion to modify the loss function to use a Gaussian

$$\eta_\lambda(\Lambda; \Lambda_0, \sigma_\Lambda) = \frac{\lambda}{\sqrt{2\pi\sigma_\Lambda^2}} \exp \left[ -\frac{(\Lambda - \Lambda_0)^2}{2\sigma_\Lambda^2} \right], \quad (1)$$

where

$$\Lambda \equiv \Lambda(\xi, \xi') = \delta(\xi, \xi') A(\xi'|\xi), \quad (2)$$

and

$$\delta(\xi, \xi') = \|x - x'\|_2^2 \quad (3)$$

The total loss is then computed by averaging  $\eta_\lambda(\Lambda; \Lambda_0, \sigma_\Lambda)$  over all chains.

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## TODO:

- ☐ Monitor tunneling rate during training.
- ☐ Try increasing the batch size.
- ☐ Try changing the number of leapfrog steps.
- ☐ Try different annealing schedule.
- ☐ Modify the **loss function** as follows:
  1. Let  $\Lambda \equiv \Lambda(\xi, \xi') = \delta(\xi', \xi) A(\xi'|\xi)$ , where  $\delta(\xi', \xi) = \|x - x'\|_2^2$
  2. In terms of  $\Lambda$ , we can write the  $\ell_\lambda(\xi, \xi', A(\xi'|\xi))$  (Eq. 7 from the L2HMC paper) as
 
$$\ell_\lambda(\xi, \xi', A(\xi'|\xi)) = \frac{\lambda^2}{\Lambda(\xi, \xi')} - \frac{\Lambda(\xi, \xi')}{\lambda^2}. \quad (4)$$
  3. We are interested to see how the model behaves if we replace  $\ell_\lambda$  with a quadratic gaussian,  $\eta_\lambda$ :

$$\ell_\lambda(\xi, \xi') \longrightarrow \eta_\lambda(\xi, \xi') \equiv \exp \left[ -\frac{(\Lambda - \Lambda_0)^T (\Lambda - \Lambda_0)}{2\sigma_\Lambda^2} \right] \quad (5)$$

where  $\Lambda_0$  is a parameter related to the “average distance” between the initial and proposed configuration and  $\sigma_\Lambda^2$  controls the width of the Gaussian.

- ☐ Get a reasonable estimate of the **integrated autocorrelation length**.

- ☐ Look at [Neal's](#) proof and see if there's anything in the L2HMC algorithm that might violate reversibility.
- ☐ Try reducing the step size  $\varepsilon$  during inference by some multiplicative factor  $\varepsilon \rightarrow \alpha \cdot \varepsilon$  so that the acceptance probability  $p_x \rightarrow 1$ .
  - In doing so we need to increase the number of run steps by  $1/\alpha$ .
  - See if the bias in the average plaquette scales with  $\varepsilon^2$ .
- ☐ Try and figure out why the Jacobian isn't (*exactly*) the same for the forward and backward updates.
- ☐ Try removing the forward/backward masks during inference (i.e. run strictly forward or run strictly backward)
- ☐ Try eliminating either the first  $x$  update (i.e.  $x \rightarrow x'$ ) or second  $x$  update ( $x' \rightarrow x''$ ) when running inference by setting either  $m^t = [1, 1, \dots, 1]$  and  $\bar{m}^t = [0, 0, \dots, 0]$  or vice versa (i.e. removing the mask when running inference).

## Completed:

- ☒ Implement reversibility checker that ensures that the reversibility condition holds (for both position and momentum)
- ☒ Try with 'float64'. (**Error still present.**)
- ☒ Try as few as 10 hidden nodes and see if the error persists. (**It does.**)
- ☒ Try anti-symmetric Gaussian Mixture Model and see if the trained model is an accurate representation of the target distribution (e.g. by looking at the locations of the means) ([link to post](#)).
- ☒ Loop over `net_weights = [scale_w, translation_w, transformation_w]` from  $[0, 0, 0]$  up to  $[2, 0, 0]$ ,  $[0, 2, 0]$ ,  $[0, 0, 2]$ , and see how the error in the average plaquette changes ([link to post](#)).