



**UNIVERSITÄT BONI** 

### **RESEARCH AREA**

# A toolbox for Neural samplers in Lattice field theories

TRA Matter, HISKP, Bethe Center, LAMARR

Talk based on: <u>https://pos.sissa.it/453/286/pdf</u>



## Kim A. Nicoli

## Normalizing Flows for LFT



#### Input:

- Action\* S[U]
- Samples (HMC)

\*Here U should denote generalized field configurations e.g., scalar fields, gauge fields.

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## ML black(-box) magic:

- Train generative models
  - Normalizing Flows
  - Autoregressive Models
  - Diffusion Models
- Learn normalized densities

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## Generative Models



### Output:

- Normalized density  $q_{\theta}(U)$
- Approximation of target p(U)
- Embarrassingly parallel sampling

Not possible with standard HMC







## Why Normalizing Flows for LFT?

- Lattice configurations are sampled i.i.d., thus **reducing autocorrelation**.
- Sampling is **embarrassingly parallel**, e.g., faster and more efficient.
- Direct estimation of thermodynamic observables (partition function, free energy, etc.).
- **Inductive biases**, e.g., symmetries, are easy to incorporate.
- The trained models can be used for *interpolation* (extrapolation) in parameter space.
- **Transfer** weights of flows trained on smaller systems to train on larger ones.



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## Plenary talk by Gurtei Kanwar (LATTICE 23)



## What is NeuLat?

• 1+1D  $\phi^4$ -theory

- 1+1D U(1) gauge theory
- No such effort was made **yet** to combine existing tools into one software.
- NeuLat is meant to be a **<u>community-wide</u>** effort.
- The **core team** of NeuLat:
  - Expertise in ML **software development**.
  - Expertise in **LFT**.
  - (2022)), and trivializing maps with flows (Bacchio S. et al. (2023)).

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## NeuLat is an ML-based software package for benchmarking and test models for LFT e.g.,

• Various contributions to the field: asymptotically unbiased estimators (Nicoli K.A. et al.), thermodynamic observables (Nicoli K.A. et al.), mode-dropping estimators (Nicoli K.A. et al.), path gradients (Vait L. et al.







## What are the benefits?

- Faster development of **new ideas**.
- Easier to **reproduce** newly published results (in the flow-based sampling community).
- Easier for people to enter the community and experiment with state-of-the-art techniques.
- Save the effort of re-implementing standard methods (e.g., architecture, estimators, etc.).
- Allow for immediate <u>extension to other fields</u> in physics (e.g., condensed matter physics).
- Similar examples for ML frameworks in other scientific communities:
  - SchNetPack Deep Neural Networks for Atomistic Systems -
  - <u>BGFlow Boltzmann Generators (BG) and other sampling methods</u>

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## Why NeuLat?

Many tools have been independently proposed.

### No reference implementation exists.

- Often needs to reimplement existing code.
- Different ML libraries.
- Different code styles and structures.
- Big (unnecessary) overhead (often seen also in the ML community).
- Excellent repositories are already available (though limited in scope).
  - <u>fthmc: Field Transformation HMC</u>
  - l2hmc-qcd I2hmc-acc
  - nflows
  - <u>GomalizingFlow</u>



Julia package from A. Tomiya and collaborators!

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Credits: <u>xkcd.com/927</u>

Shout-out to Sam Foreman et al., for the great work!



## NeuLat

### Goal: incorporate as many contributions from 5 years of research progress into a single software framework.



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## $N \in U L A T$



## Software Overview

- PyTorch backend
- MCMC-based sampling
- Flow-based sampling (e.g., <u>nflows</u>)
- Observable estimation (e.g., <u>py-uwerr</u>)

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## Basic Workflow

**Step 0**: Define the action of the physical system to simulate.

**Step 1**: Build a Markov chain and a custom normalizing flow model.

**Step 2**: Specify loss and optimizer and train the flow model.

**Step 3**: Estimate observables using samples from HMC and trained flow.

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```
1 n_samples, train_steps, batch = 1000, 1000, 500
2 action = Phi4Action(kappa=0.3, lamb=0.022)
4 hmc_chain = HMCMarkovChain(action, lat_shape=[16, 16], burn_in=100)
5 \text{ model} = Flow(
      lat_shape=[16, 16],
      base_dist=NormalDistribution(),
      coupling=NiceCoupling(),
      n_couplings=6
```

```
optim = torch.optim.Adam(model.parameters(), lr=learning_rate)
13 loss_fn = ReverseKLLoss()
14 for _ in range(train_steps):
      configs, log_probs = model.sample_and_log_prob(batch)
      loss = loss_fn(action(configs), log_probs)
      optim.zero_grad(); loss.backward(); optim.step()
```

```
obs = (Magnetization(), AbsMagnetization(), action)
```

```
21 flow_obs = IidEst(obs).evaluate(model.sample(n_samples))
22 hmc_obs = CorrelatedEst(obs).evaluate(hmc_chain.sample(n_samples))
```





## Key Features

• **Density Estimation**: Learn approximations of targeted Boltzmann distributions  $q_{\theta} \approx p$ .

#### • <u>Sampling:</u>

- MCMC implementations (HMC, Cluster algorithms, etc.).
- Neural Importance Sampling (see <u>Albergo et al. (2019</u>), <u>Kanwar et al. (2020</u>), <u>Nicoli et al. (2021</u>) + refs. therein).
- Neural HMC (see same papers referenced above).

#### • Estimation:

- Asymptotically unbiased estimators for physical observables (see <u>Nicoli et al. (2020</u>).
- Direct estimation of thermodynamic observables with flows and HMC (see Nicoli et al. (2021)).
- Sampling in the presence of mode-collapse (see <u>Nicoli et al. (2023)</u>).
- **Customizable**: Easy to incorporate a new action/theory or customize new, equivariant flow-layers.

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... and more!



## Conclusion

- We presented <u>NeuLat</u>, a software for flow-based simulation of LFT.
- The software is meant to be accessible, **modular**, and easy to **extend** and **maintain**.
- The first **release** of the software is planned for the **upcoming months**.

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• This eliminates the **overhead** of re-implementing existing code between different formats.

• NeuLat is aimed to be a community-wide effort. Get in touch if you would like to contribute.



