



Massachusetts  
Institute of  
Technology



# Flow-based MCMC for $SU(N)$ Lattice Gauge Theory

Gurtej Kanwar

Based on ...

... flow-based sampling for lattice QFT:

[Albergo, GK, Shanahan [PRD100 \(2019\) 034515](#)]

[Albergo, Boyda, Hackett, GK, Cranmer, Racanière, Rezende, Shanahan [2101.08176](#)]

... flows for compact vars & lattice gauge theories:

[GK, Albergo, Boyda, Cranmer, Hackett, Racanière, Rezende, Shanahan [PRL125 \(2020\) 121601](#)]

[Rezende, Papamakarios, Racanière, Albergo, GK, Shanahan, Cranmer [ICML \(2020\) 2002.02428](#)]

[Boyda, GK, Racanière, Rezende, Albergo, Cranmer, Hackett, Shanahan [PRD103 \(2021\) 074504](#)]

**MITP Workshop: Machine Learning Techniques in Lattice QCD (May 24-28, 2021)**

# Motivations

**Critical slowing down** and **topological freezing** obstruct MCMC sampling near the continuum limit. See [K. Clark, Mon].

- **Problem:** Local/diffusive Markov chain updates
- Generative ML models can directly sample, may be used to propose global updates

ML models provide flexible “variational ansatz” distribution  $q(U)$ .

**After optimizing the model “ansatz”:**

$$q(U) = e^{-S_{\text{eff}}(U)} \approx p(U) = e^{-S(U) - \log Z}$$

$\updownarrow$

$$S_{\text{eff}}(U) \approx S(U) + \log Z$$

Efficiently sampled

Desired target

# Generative modeling for LQFT

[L. Funcke, Tue]

## Estimating thermodynamic observables:

- Flow-based models precisely estimate  $\log Z$
- Asymptotic exactness  $N \rightarrow \infty$

[S. Foreman, Thur]

## Improved HMC updates:

- Flows/INNs describing modified HMC updates to  $(\pi, U)$
- Topological freezing can be avoided
- Detailed balance for exactness

[D. Rezende, Mon] & this talk

## Flow-based MCMC:

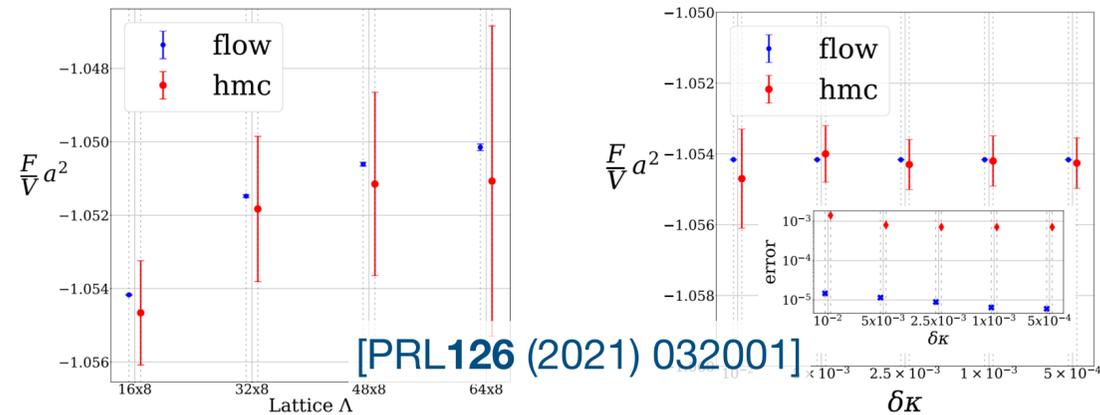
- Flows directly propose new configs
- Metropolis step (satisfying balance) for exactness

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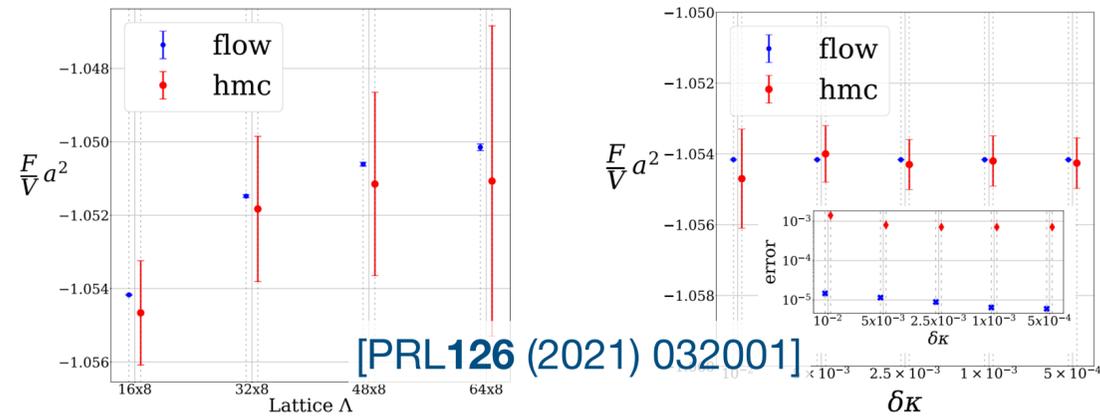
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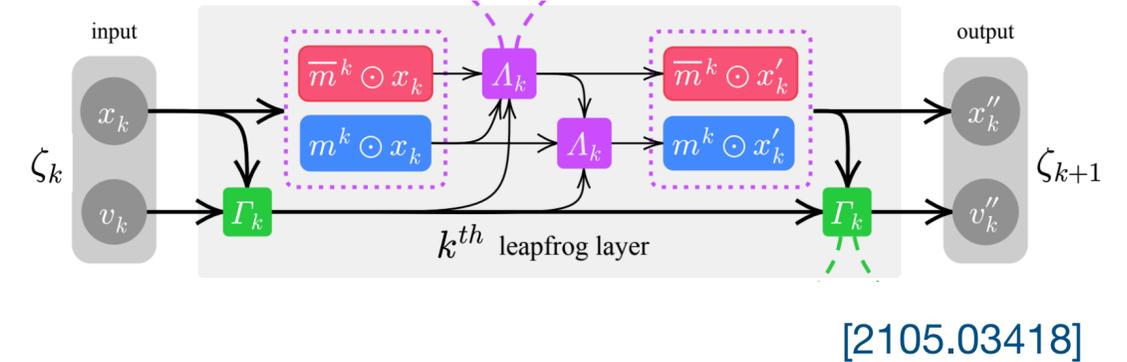
[L. Funcke, Tue]

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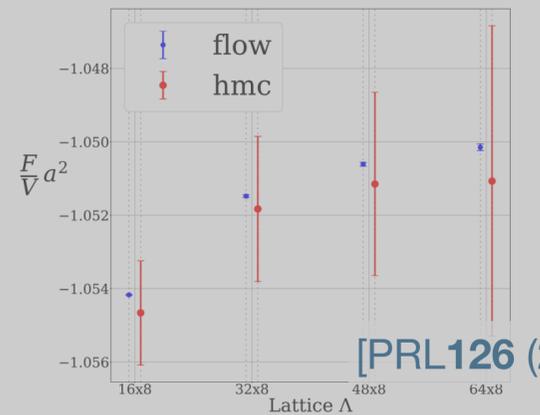
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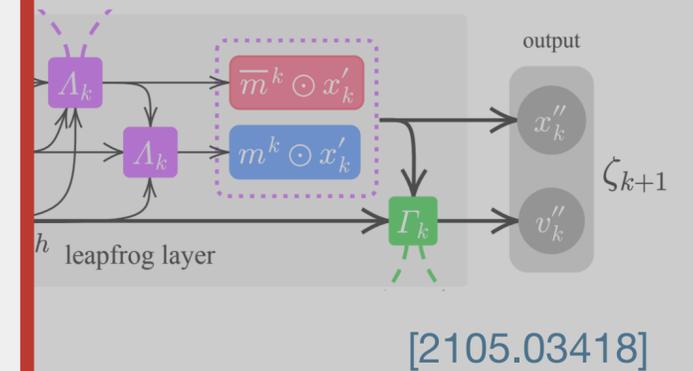
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## Estimating thermodynamic observables



## Improved HMC updates:

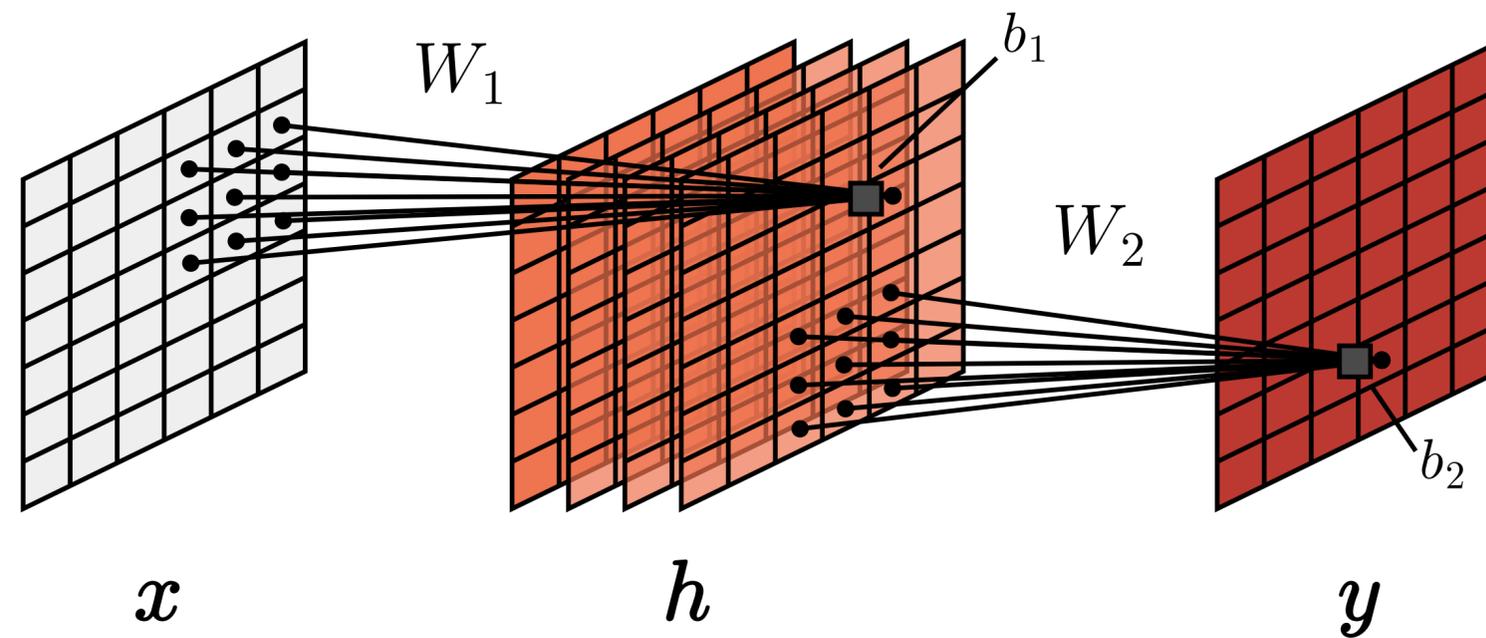


## Common theme:

Black-box ML components wrapped inside exact schemes

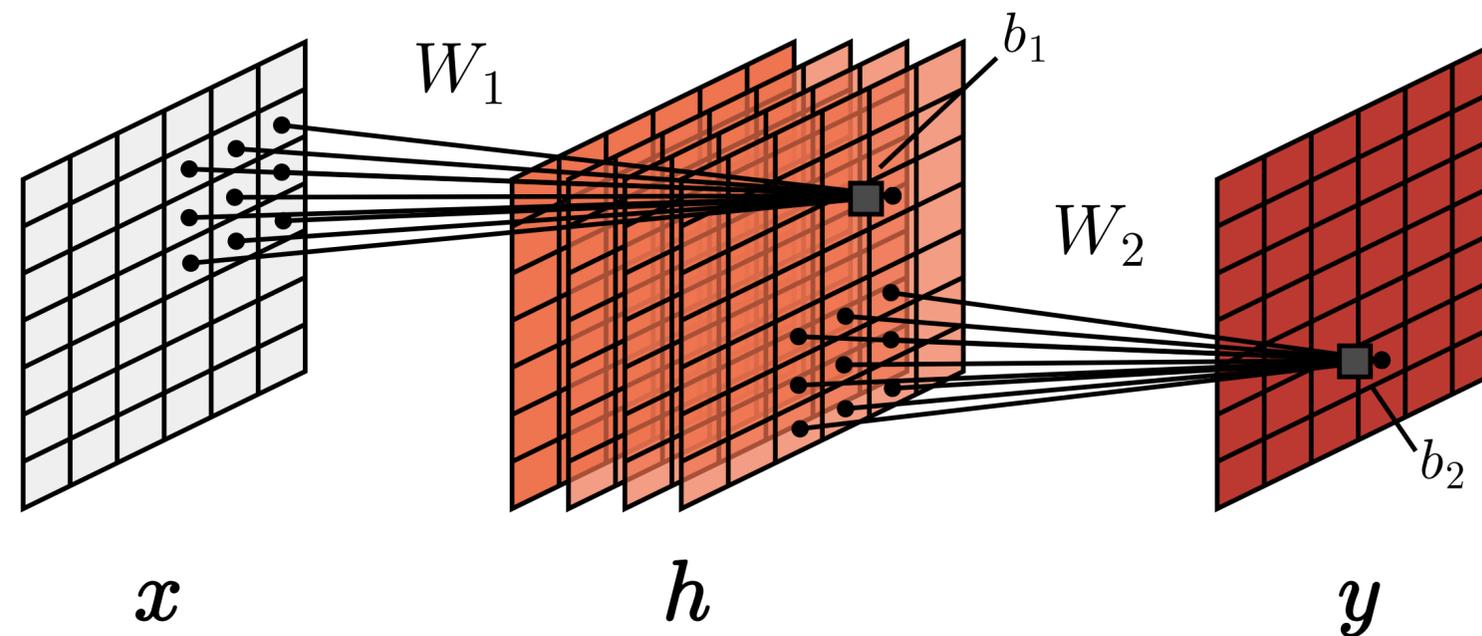
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# Flow-based sampling



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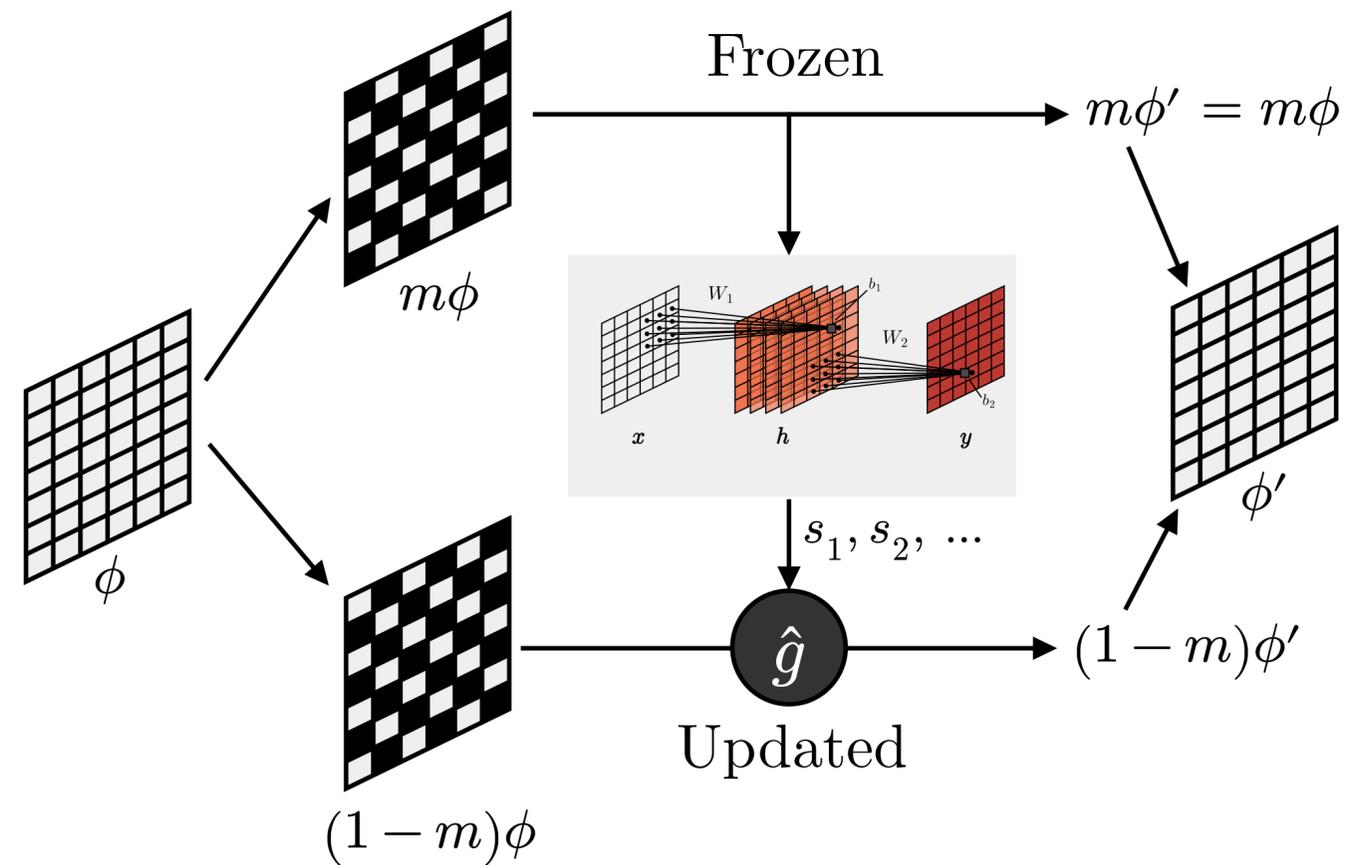
**(Convolutional) neural networks:** Black-box (local) function approximators



# Flow-based sampling

**(Convolutional) neural networks:** Black-box (local) function approximators

**Coupling layers:** Invertible transformations, tractable Jacobian

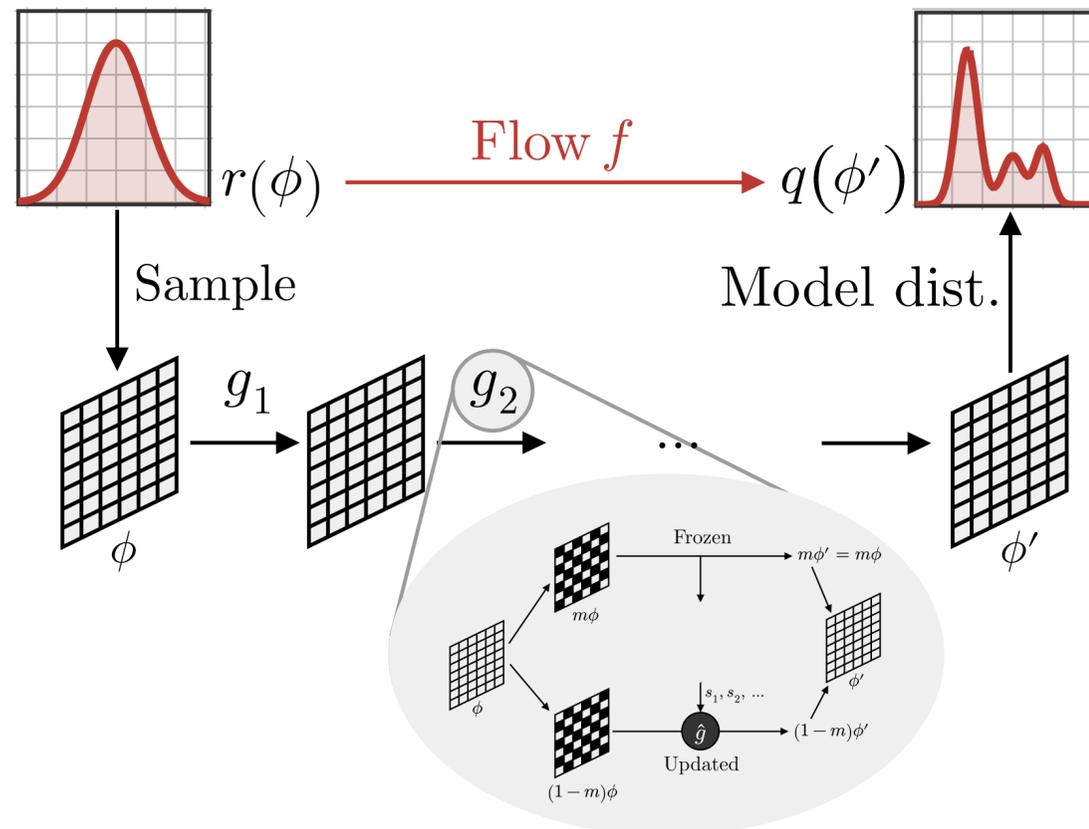


# Flow-based sampling

**(Convolutional) neural networks:** Black-box (local) function approximators

**Coupling layers:** Invertible transformations, tractable Jacobian

**Flow-based model:** Transform prior density to **computable** and **sample-able** output model density



$$q(\phi') = r(\phi) \left| \det \frac{\partial [f(\phi)]_i}{\partial \phi_j} \right|^{-1}$$

# Flow-based sampling

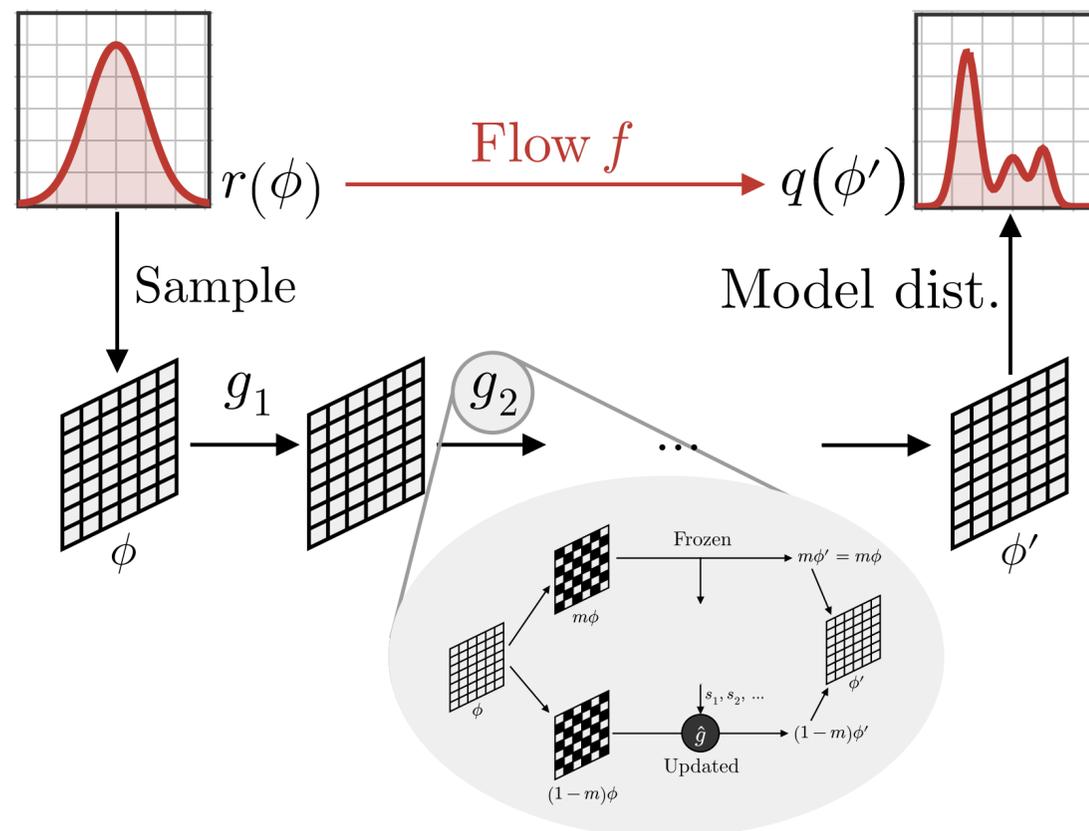
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## Training:

- Measure KL divergence
- Apply gradient-based opt



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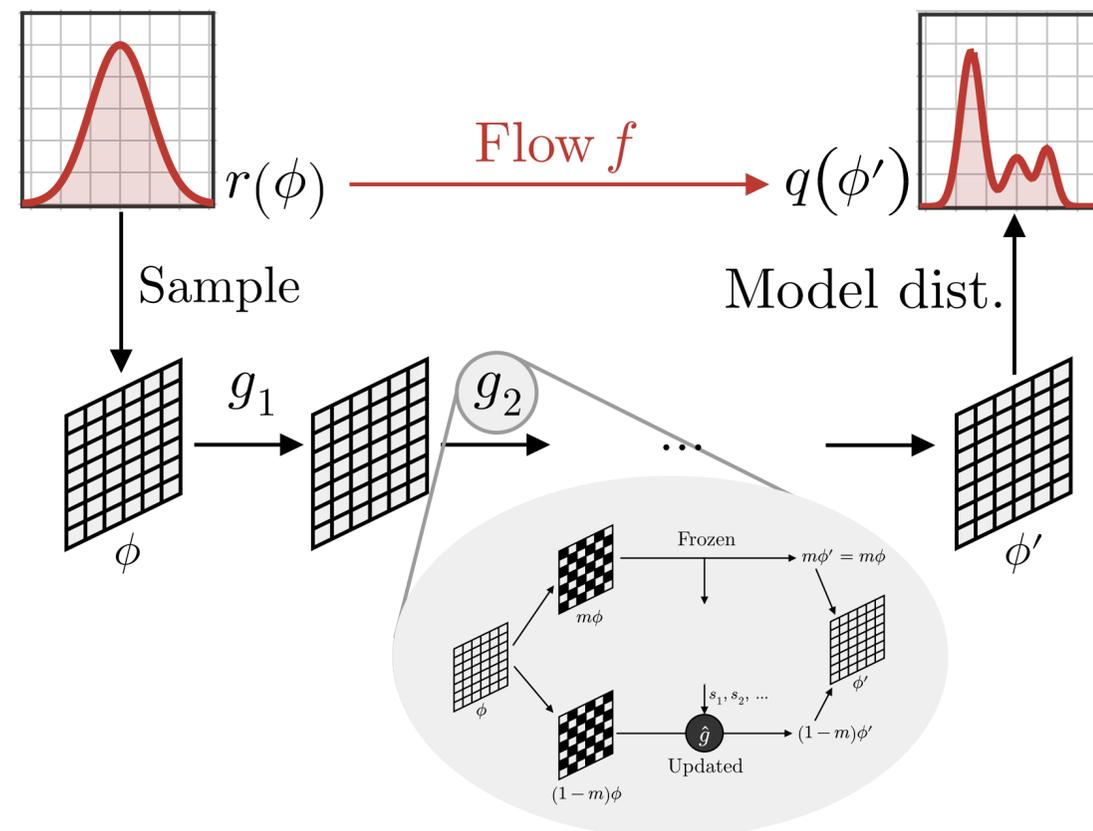
**Flow-based model:** Transform prior density to **computable** and **sample-able** output model density

## Training:

- Measure KL divergence
- Apply gradient-based opt

## Exactness:

- Use  $q(\phi')$  and  $p(\phi')$  to correct approximation



$$q(\phi') = r(\phi) \left| \det \frac{\partial [f(\phi)]_i}{\partial \phi_j} \right|^{-1}$$

# Symmetries in flows

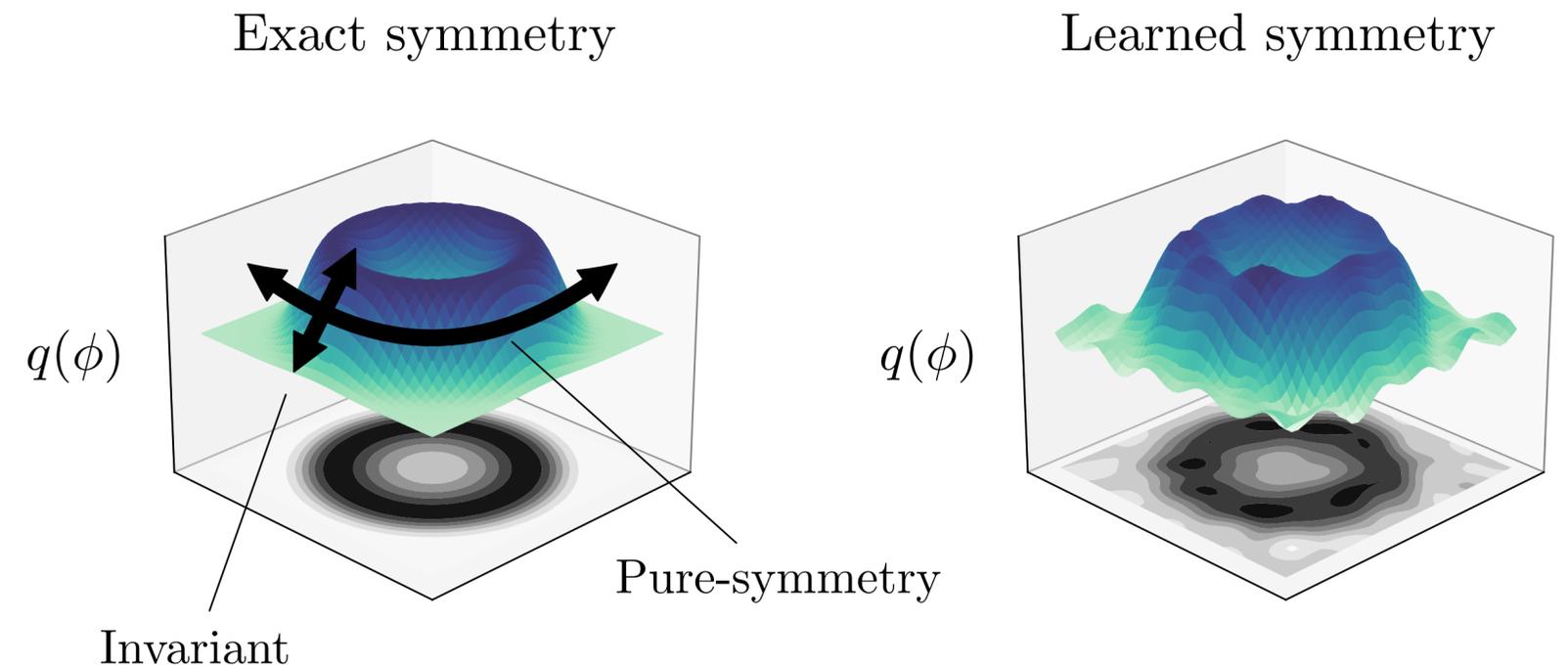
**Invariant** prior + **equivariant** flow = symmetric model

[Cohen, Welling 1602.07576]

$$r(t \cdot U) = r(U) \quad f(t \cdot U) = t \cdot f(U)$$

Symmetries...

- Reduce data complexity of training
- Reduce model parameter count
- See [D. Luo, Wed] and [A. Tomiya, Fri]



# Towards lattice QCD

This talk: **SU(N) gauge symmetry** of Lattice QCD [ $\pm$  small detour into U(1)]

- See [D. Rezende, Mon] and upcoming paper with

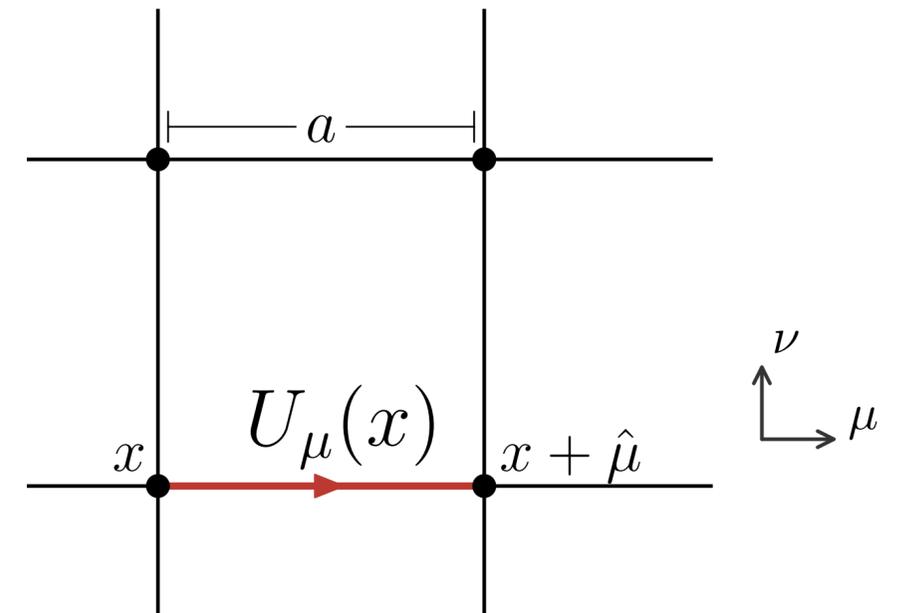
M. S. Albergo, S. Racanière, D. J. Rezende, J. M. Urban, D. Boyda, K. Cranmer, D. C. Hackett, P. E. Shanahan

for more on fermions

**Wilson gauge action** - prototypical, gauge-invariant lattice action

$$S(U) = -\frac{\beta}{N} \sum_x \sum_{\mu < \nu} \text{ReTr} P_{\mu\nu}(x) \quad \leftarrow \text{For U(1): } N = 1 \text{ and no Tr}$$

$$P_{\mu\nu}(x) = U_\mu(x) U_\nu(x + \hat{\mu}) U_\mu^\dagger(x + \hat{\nu}) U_\nu^\dagger(x)$$



# Towards lattice QCD

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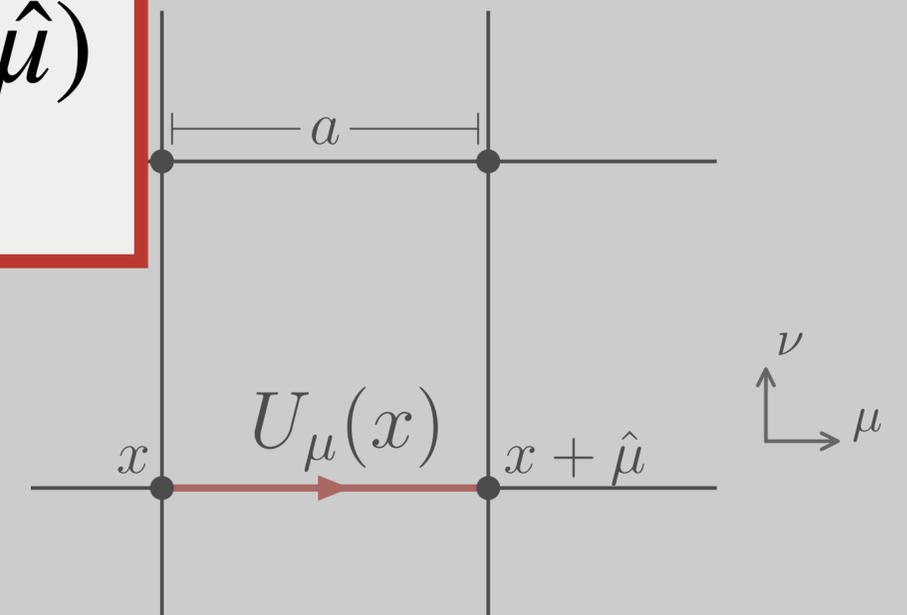
**Wilson gauge action**

Invariant under  
gauge transforms:

$$U_\mu(x) \rightarrow \Omega(x) U_\mu(x) \Omega^\dagger(x + \hat{\mu})$$

$$S(U) = -\frac{\beta}{N} \sum_{x, \mu < \nu}$$

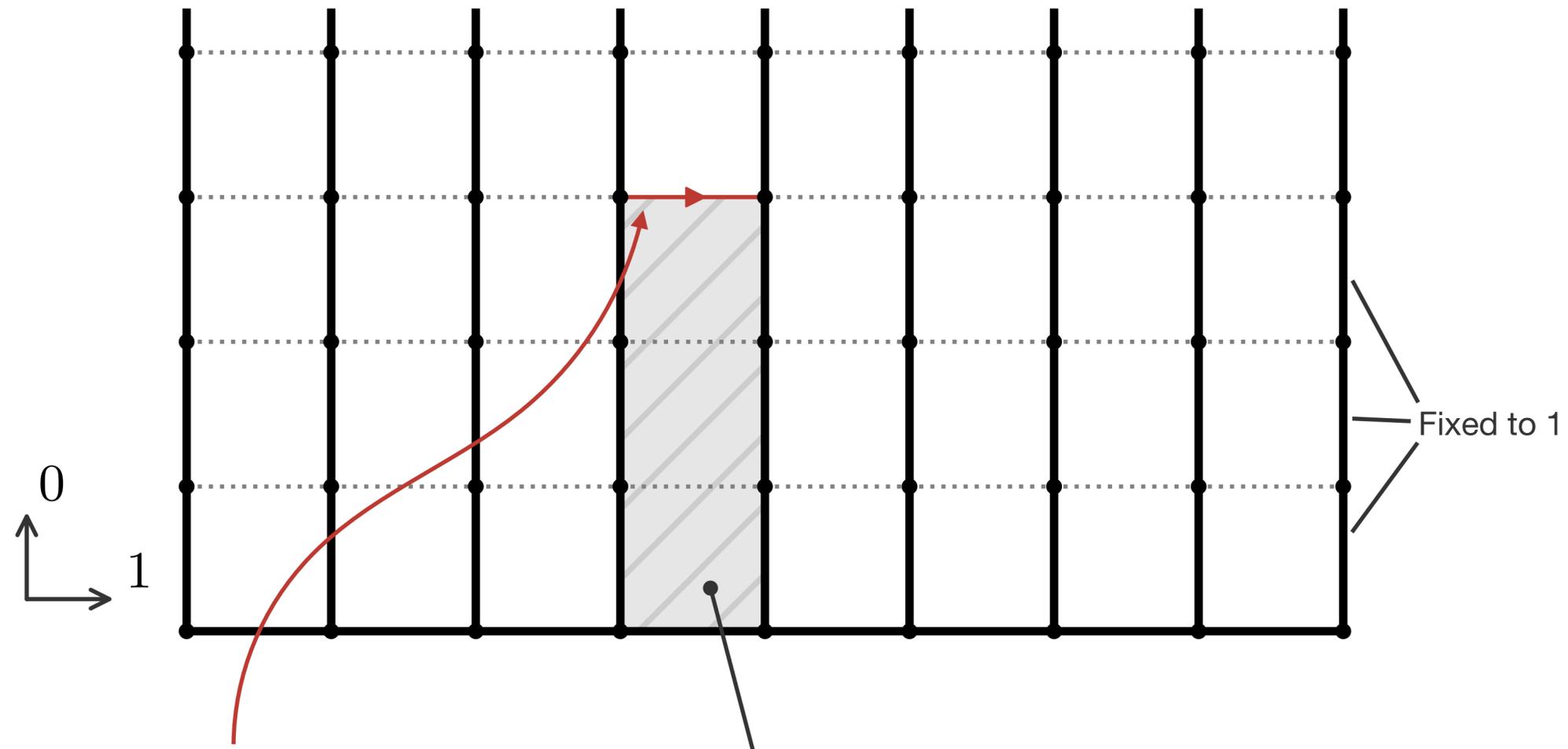
$$P_{\mu\nu}(x) = U_\mu(x) U_\nu(x + \hat{\mu}) U_\mu^\dagger(x + \hat{\nu}) U_\nu^\dagger(x)$$



# Gauge fixing?

Where gauge DoFs are explicitly factored out, e.g. maximal tree

**Explicit** gauge fixing is at odds with **translational symmetry** + **locality**



**Link** physically encodes **Wilson loop** around shaded region

# Gauge fixing?

Where gauge DoFs are fixed by solving  
a constraint, e.g. Landau gauge

**Implicit** gauge fixing difficult to act on via **flow-based models**

$$\left. \begin{array}{l} \text{Landau gauge: } U_{\mu}^{\text{fix}}(x) = \operatorname{argmin}_{U^{\Omega}} \sum_x \sum_{\mu=1}^{N_d} \operatorname{ReTr}[U_{\mu}^{\Omega}(x)] \\ \text{Coulomb gauge: } U_{\mu}^{\text{fix}}(x) = \operatorname{argmin}_{U^{\Omega}} \sum_x \sum_{\mu=1}^{N_d-1} \operatorname{ReTr}[U_{\mu}^{\Omega}(x)] \end{array} \right\} \begin{array}{l} \text{Unclear how to invertibly} \\ \text{transform } U_{\mu}^{\text{fix}}(x). \end{array}$$

# Gauge symmetries in **un-fixed** flows

Choose to act on the un-fixed link representation  $U_\mu(x)$ .

Carefully construct architecture to enforce...

## Gauge-invariant prior:

Not very difficult!  
Uniform distribution works.

With respect to  
Haar measure

$$r(U) = 1$$

## Gauge-equivariant flow:

Coupling layers acting on  
(untraced) Wilson loops.

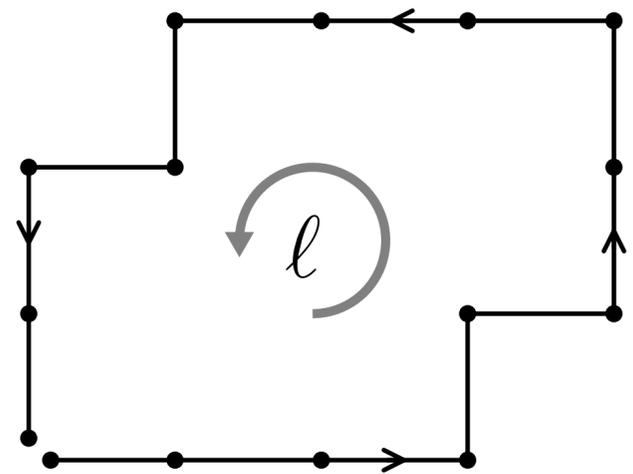
Loop transformation easier  
to satisfy.

# Gauge symmetries in **un-fixed** flows

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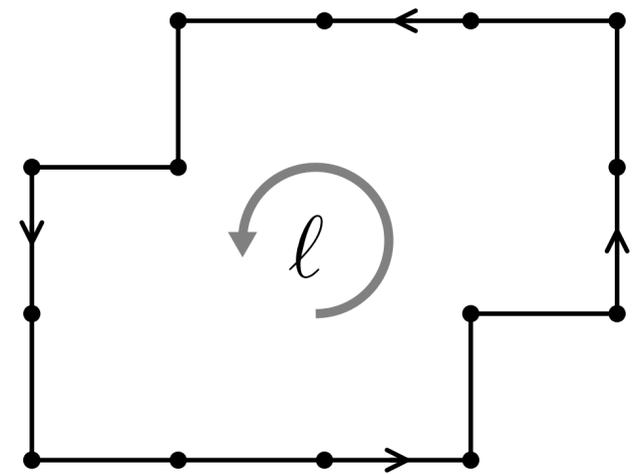
Carefully cons

Open loop



$$W_\ell(x) \rightarrow \Omega(x)W_\ell(x)\Omega^\dagger(x)$$

Closed loop



$$\text{tr } W_\ell(x) \rightarrow \text{tr } W_\ell(x)$$

Gauge

Not  
Uniform

ariant flow:

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# Gauge-equivariant coupling layer

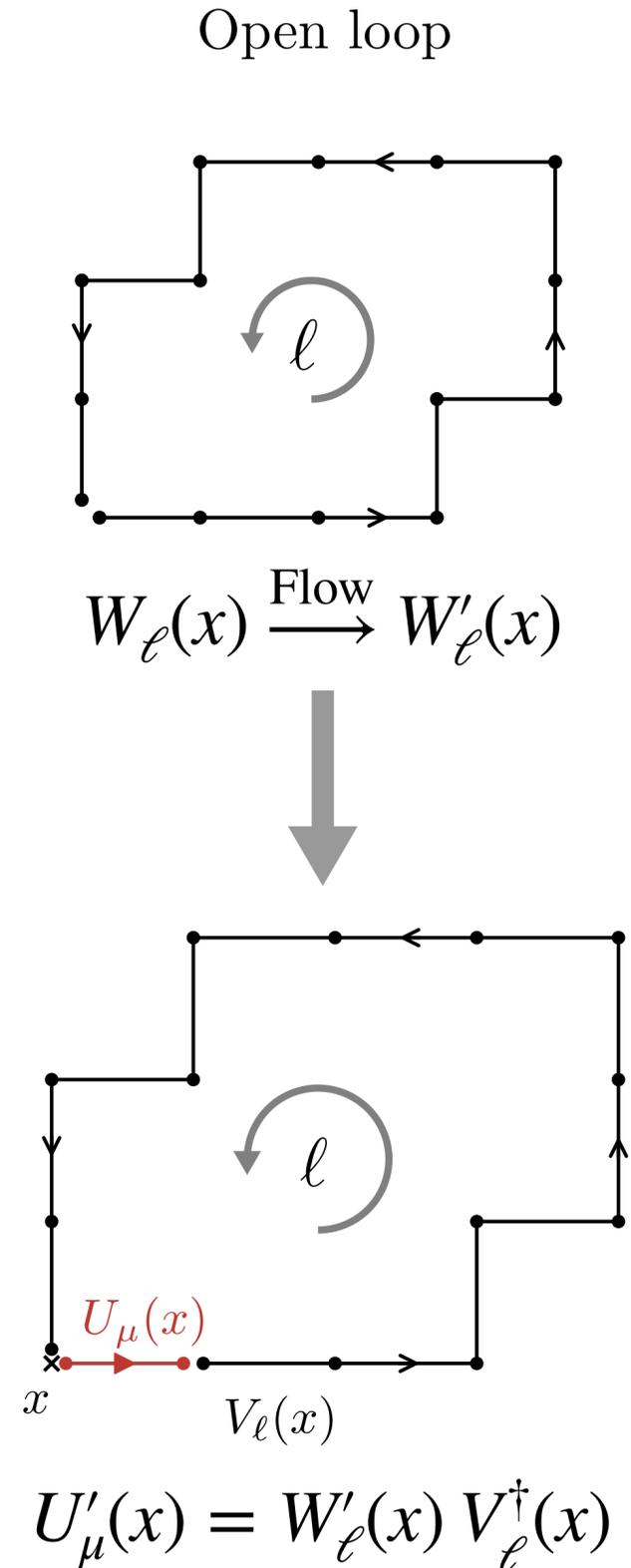
Compute a **field of Wilson loops**  $W_\ell(x)$ .

**Inner coupling layer** [function of  $W_\ell(x)$ ]

- “**Actively**” update a subset of loops.\*
- Condition on “**frozen**” closed loops.  
Gauge invariant!

**Outer coupling layer** [function of  $U_\mu(x)$ ]

- Solve for link update to satisfy actively updated loops.
- Other loops in  $W_\ell(x)$  may “**passively**” update.



[GK, Albergo, Boyda, Cranmer, Hackett, Racanière, Rezende, Shanahan [PRL125 \(2020\) 121601](#)]

[Boyda, GK, Racanière, Rezende, Albergo, Cranmer, Hackett, Shanahan [PRD103 \(2021\) 074504](#)]

# Gauge-equivariant coupling layer

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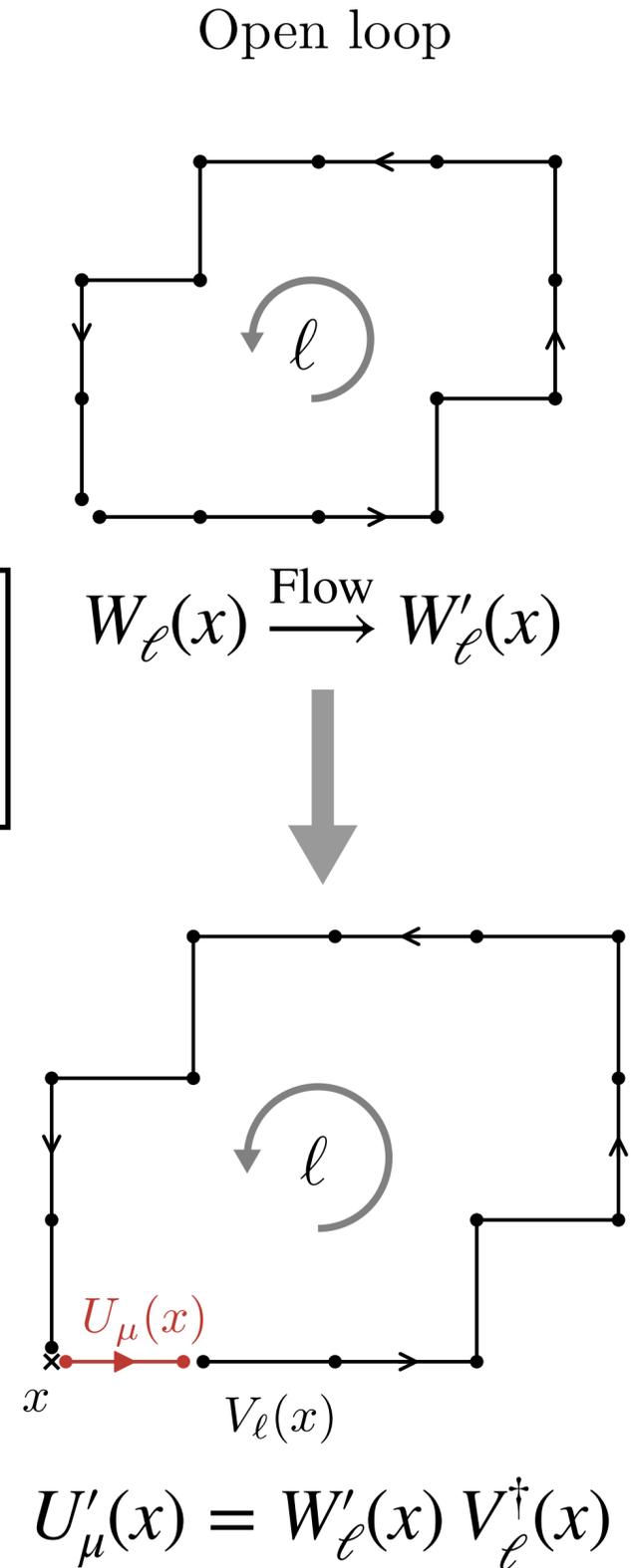
**Inner coupling layer** [function of  $W_\ell(x)$ ]

- “**Actively**” update a subset of loops.\*
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Gauge invariant!

\* This “**kernel**” must satisfy:  
 $h(W_\ell^\Omega(x)) = h^\Omega(W_\ell(x))$

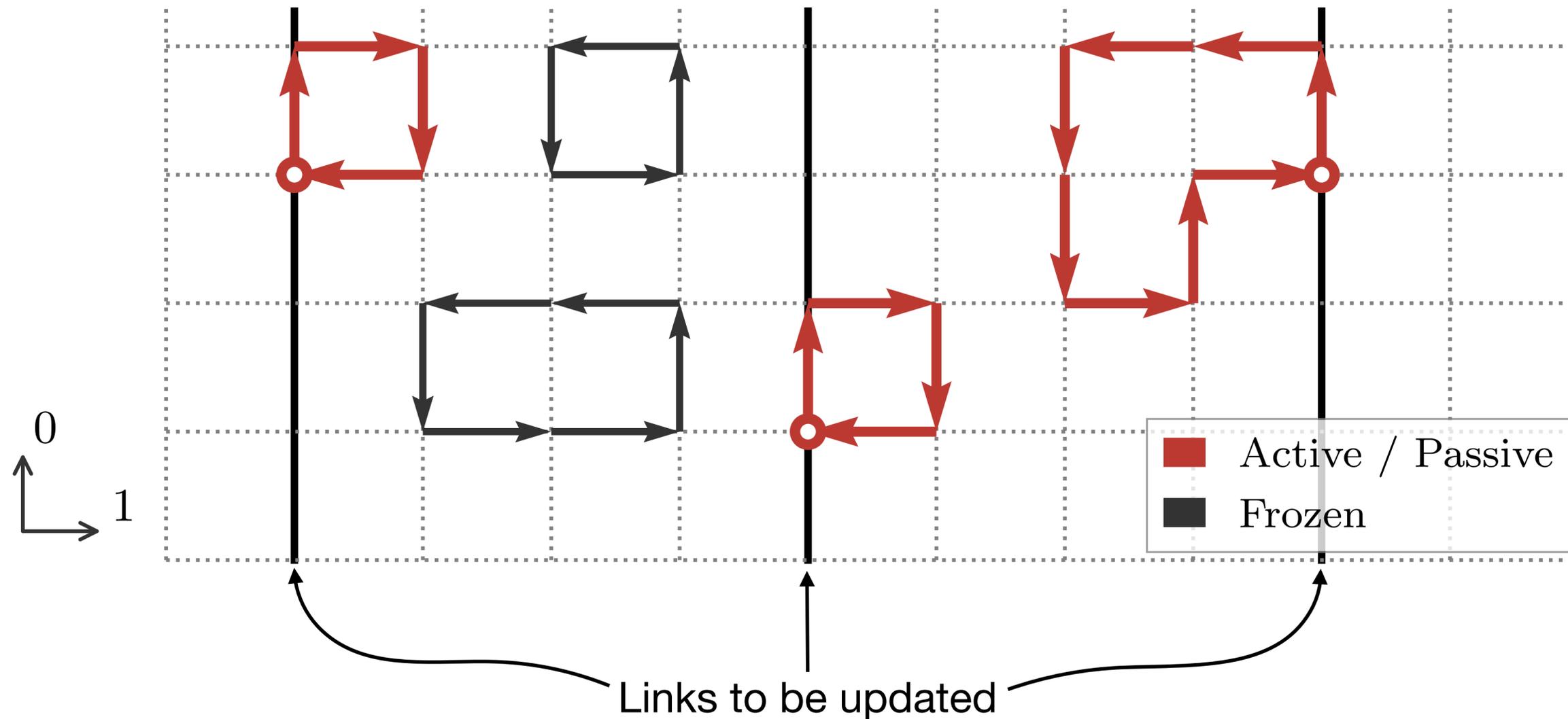
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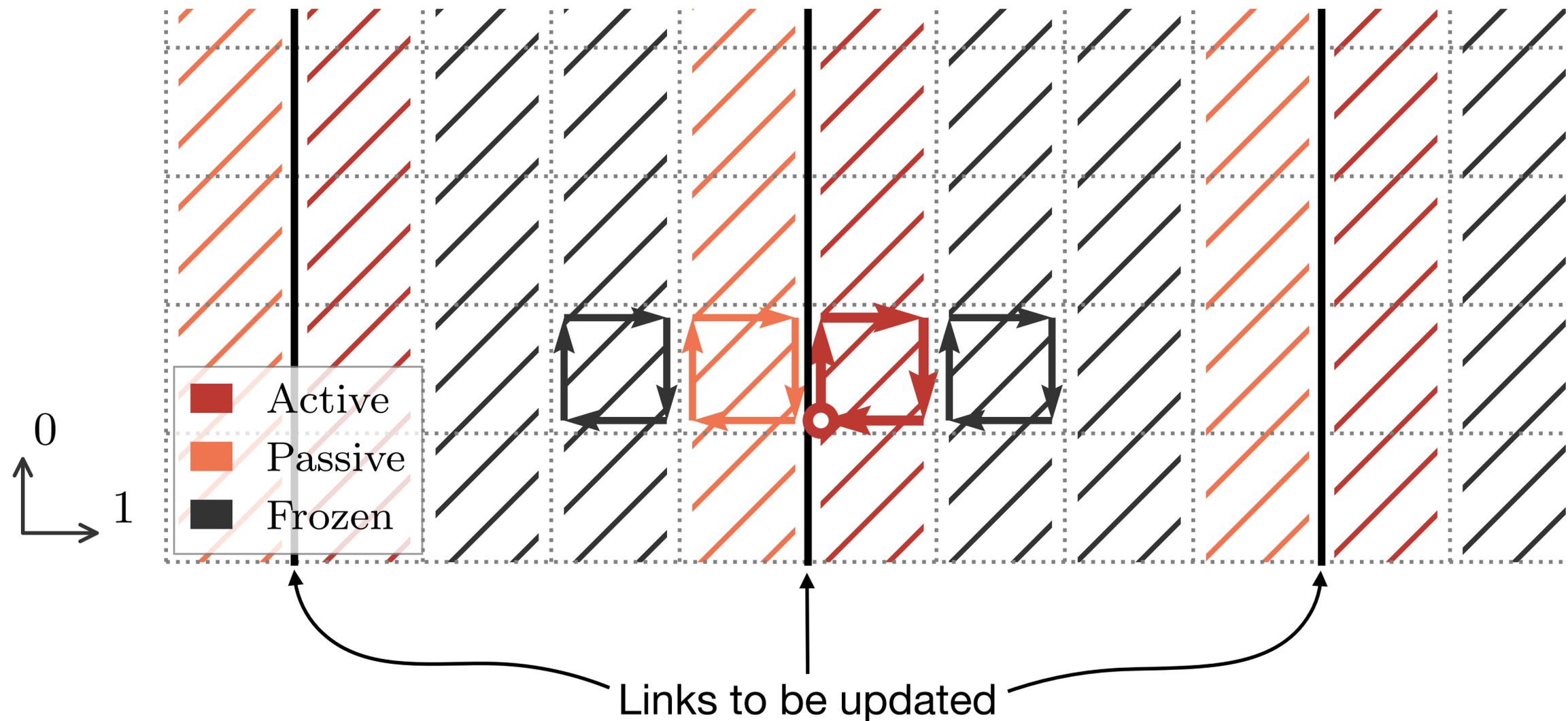
# Active, passive, and frozen loops

Examples of active/passive/frozen loops



# Active, passive, and frozen loops

Passive-Active-Frozen-Frozen (PAFF) pattern



# U(1) kernels

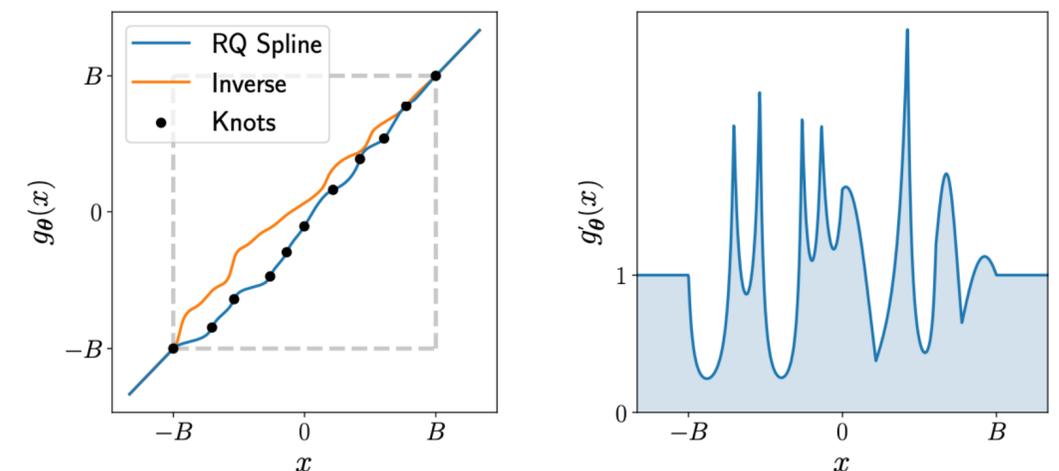
Conjugation equivariance trivially satisfied:  $h(\Omega W \Omega^\dagger) = h(W) = \Omega h(W) \Omega^\dagger$ .

Invertible maps on U(1) variables:

- **Periodic / compact domain** must be addressed.
- For details, see:

[Rezende, Papamakarios, Racanière, Albergo, GK, Shanahan, Cranmer;  
ICML (2020) 2002.02428]

[Durkan, Bekasov, Murray, Papamakarios 1906.04032]



## Non-compact projection:

- Map  $\theta \rightarrow x \in \mathbb{R}$ , e.g.  $\arctan(\theta/2)$
- Transform  $x \rightarrow x'$  as usual
- Map  $x' \rightarrow \theta' \in [-\pi, \pi]$

## Circular invertible splines:

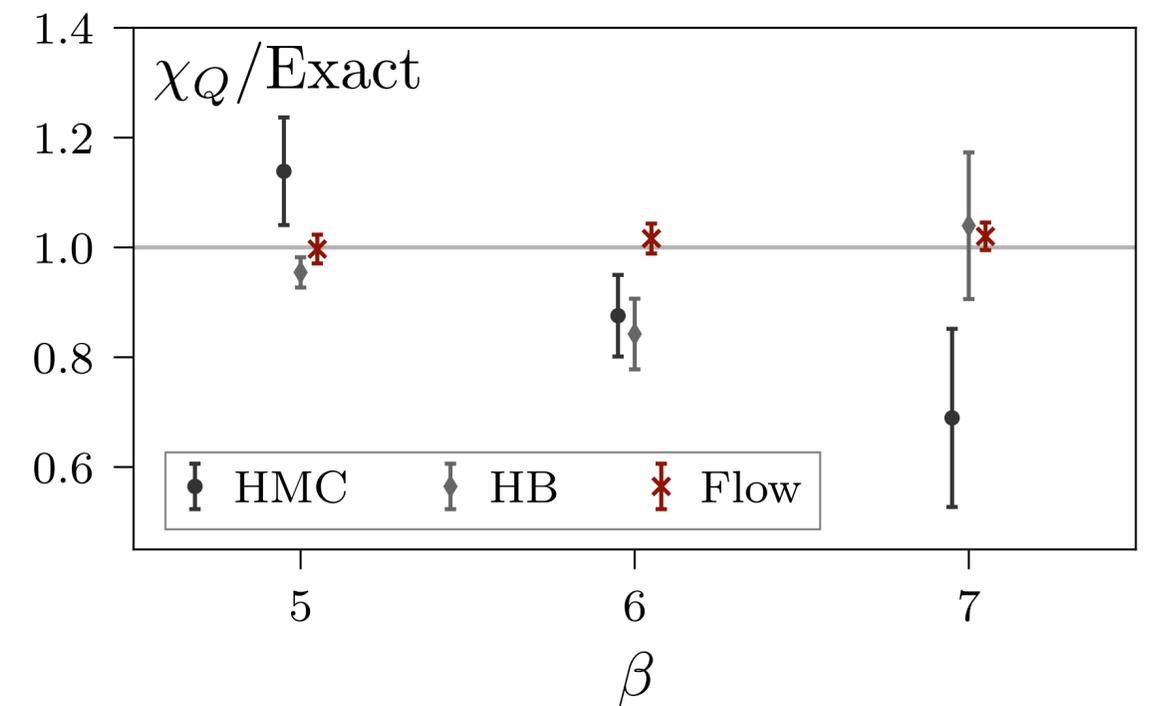
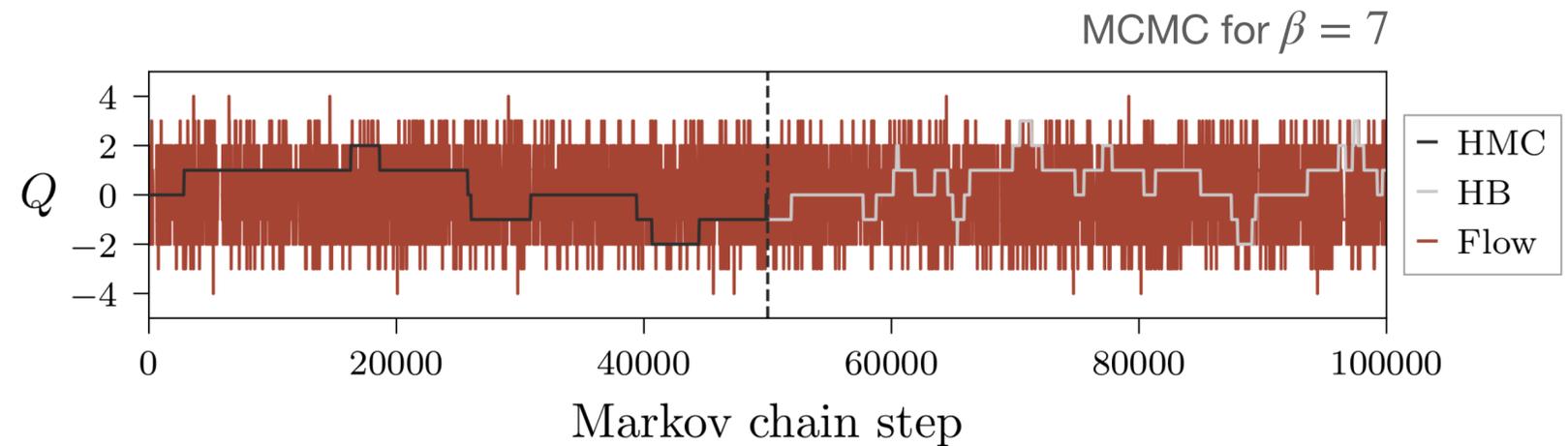
- Spline “knots” trainable fns
- Identify endpoints  $\pi$  and  $-\pi$
- Number of knots  $\leftrightarrow$  expressivity

# Learning U(1) gauge theory

There is exact lattice topology in 2D.

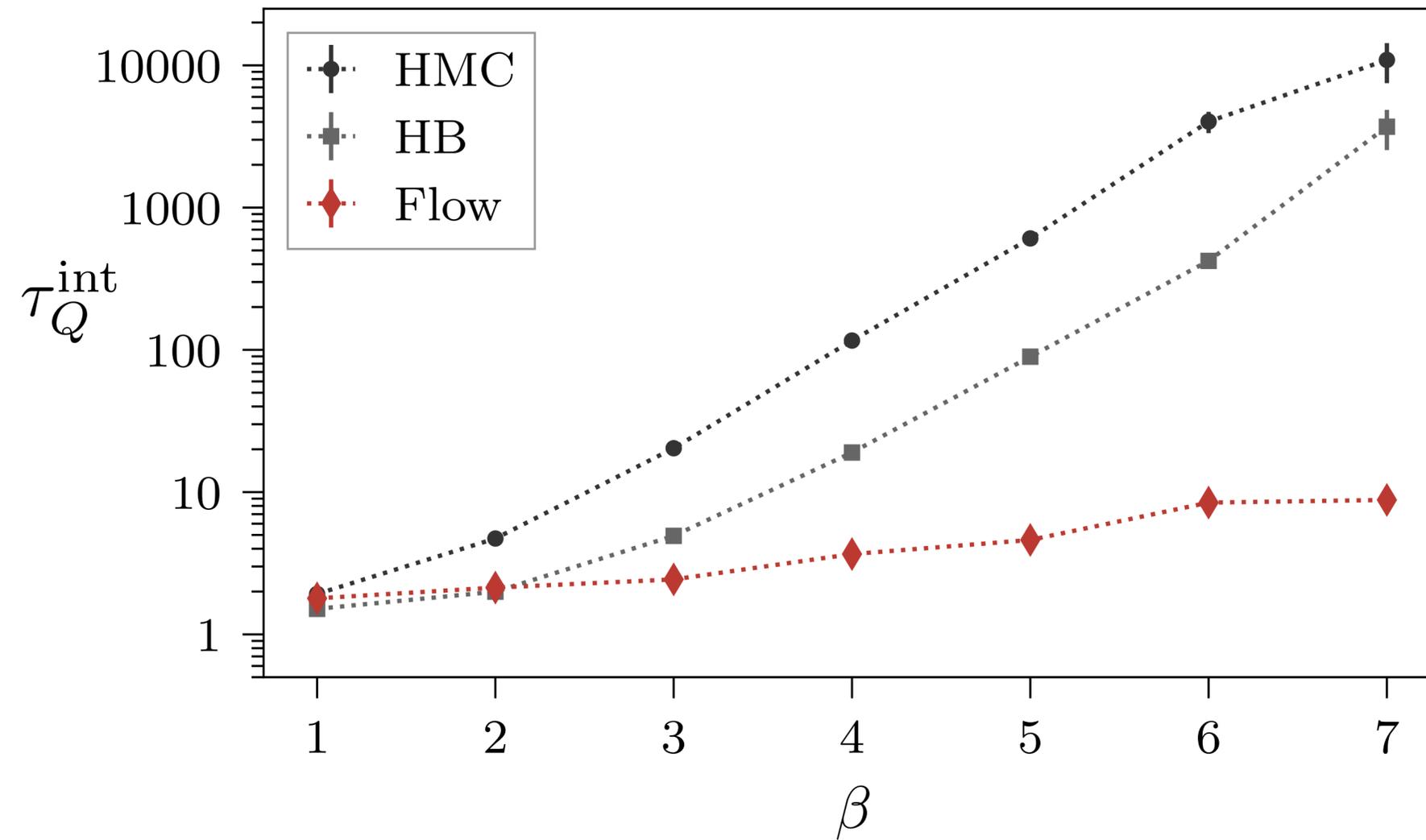
$$Q = \frac{1}{2\pi} \sum_x \arg(P_{01}(x))$$

- Compared **flow**, **analytical**, **HMC**, and **heat bath** on  $16 \times 16$  lattices for  $\beta = \{1, \dots, 7\}$
- Topo freezing in HMC and heat bath
- Gauge-equiv flow-based model at each  $\beta$
- Flow-based MCMC observables agree



Topological susceptibility  $\chi_Q = \langle Q^2/V \rangle$

# Topological freezing mitigated



# SU(N) kernels: **strategy**

SU(N) matrix-conj. equivariance is **non-trivial**.

$$h(\Omega W \Omega^\dagger) = \Omega h(W) \Omega^\dagger$$

## Useful observations:

- Conjugation only rotates eigenvectors.
- Spectrum is invariant.
- Wilson loop spectrum encodes gauge-invariant physics → **This is what we want to transform.**

**Strategy:** Invertibly transform only the spectrum of  $W$  via a “spectral map”.

Or, “spectral flow”.

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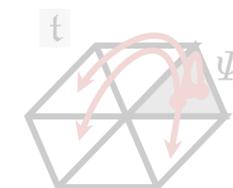
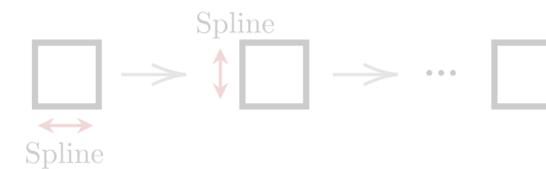
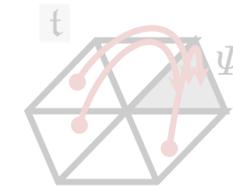
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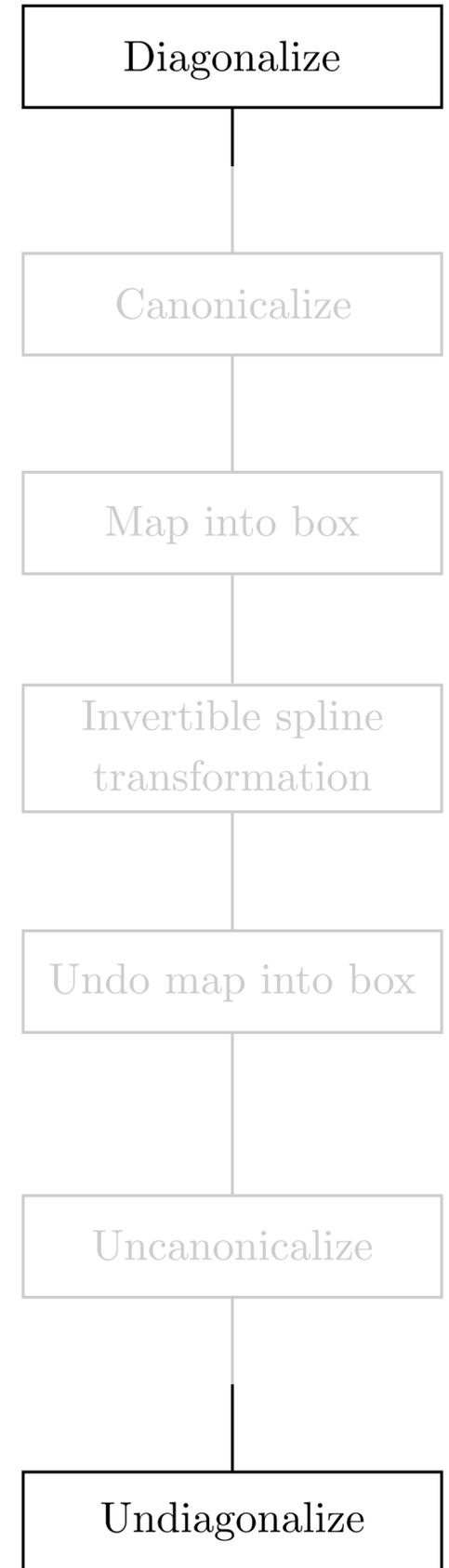
**Strategy:** Invertibly transform only the spectrum of  $W$  via a “spectral map”.

Or, “spectral flow”.

$$W = P \begin{pmatrix} e^{i\phi_1} & & \\ & \ddots & \\ & & e^{i\phi_N} \end{pmatrix} P^\dagger$$

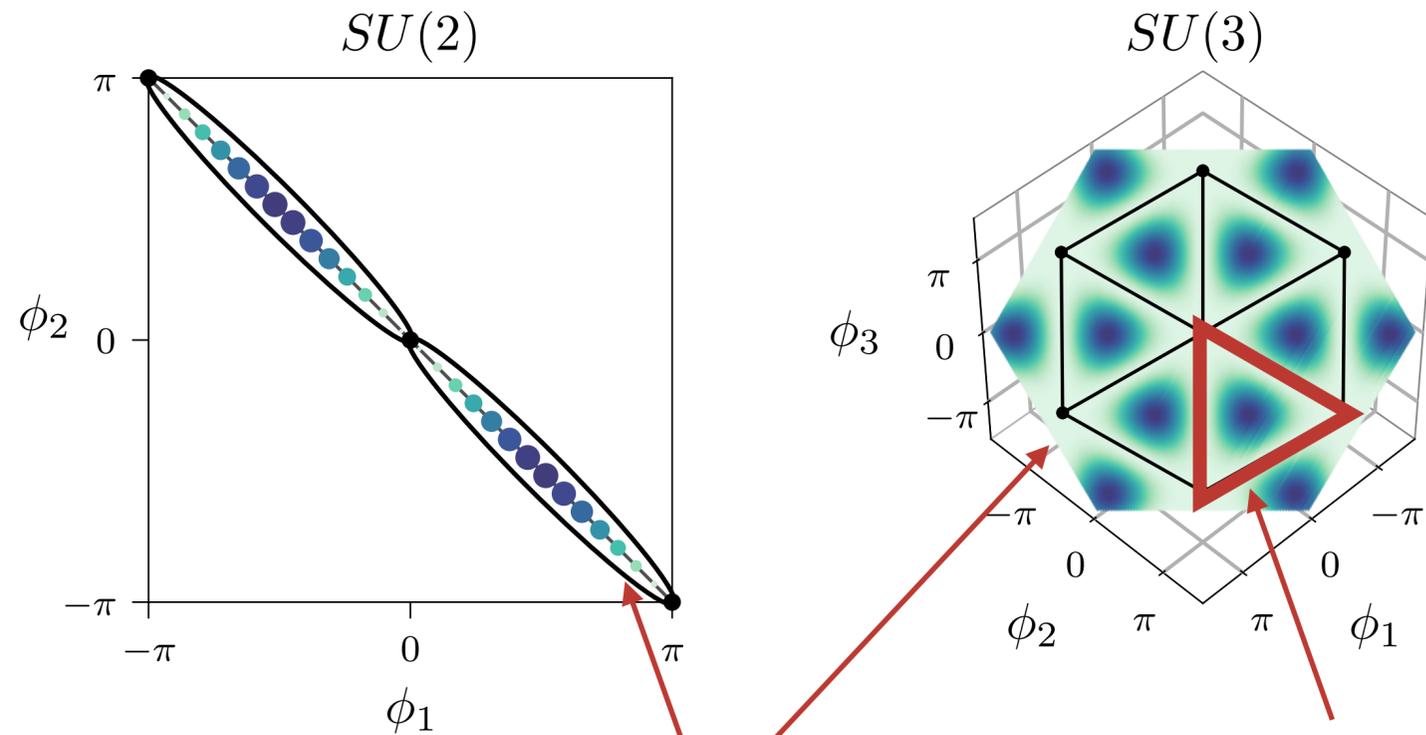


$$W' = P \begin{pmatrix} e^{i\phi'_1} & & \\ & \ddots & \\ & & e^{i\phi'_N} \end{pmatrix} P^\dagger$$



# SU(N) kernels: Permutation equivariance

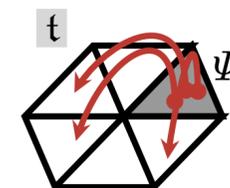
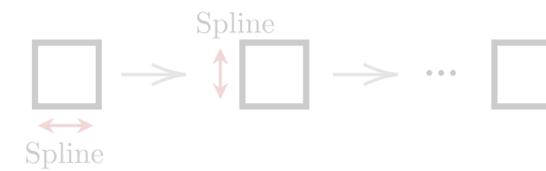
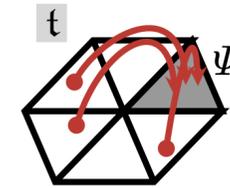
See also [J. Thaler, Wed]  
for perm-inv NNs



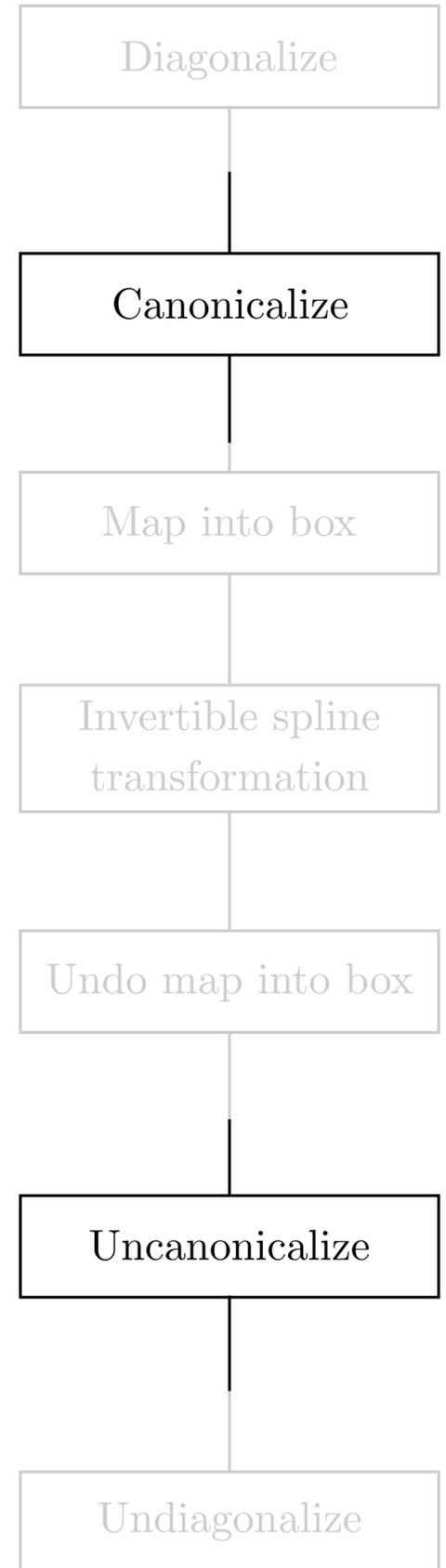
Sub-manifold of  
 $\det = 1$  eigenvalues

“Cell”, related by  
perms of eigenvalues  
to other cells.

$$W = P \begin{pmatrix} e^{i\phi_1} & & \\ & \ddots & \\ & & e^{i\phi_N} \end{pmatrix} P^\dagger$$

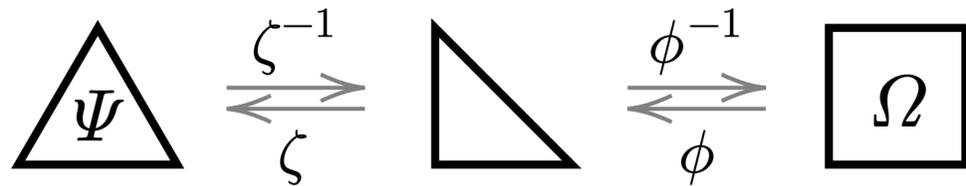


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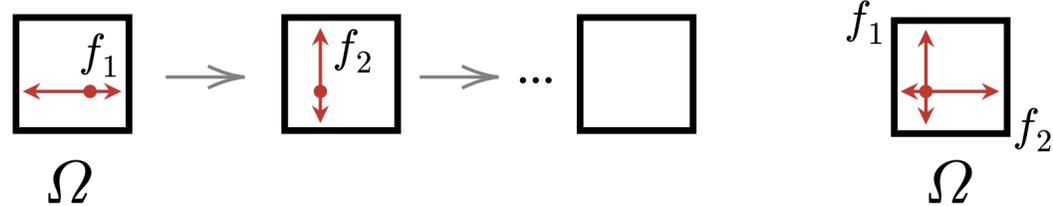
# SU(N) kernels: Transform the canonical cell

Change variables to rectilinear box  $\Omega$

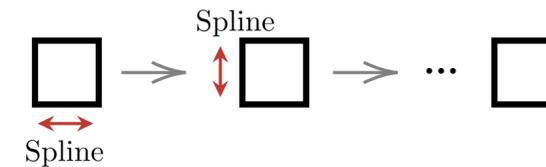
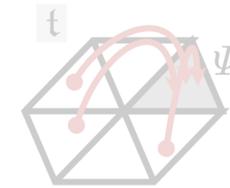


Transform by acting on coords of box  $\Omega$ , either...

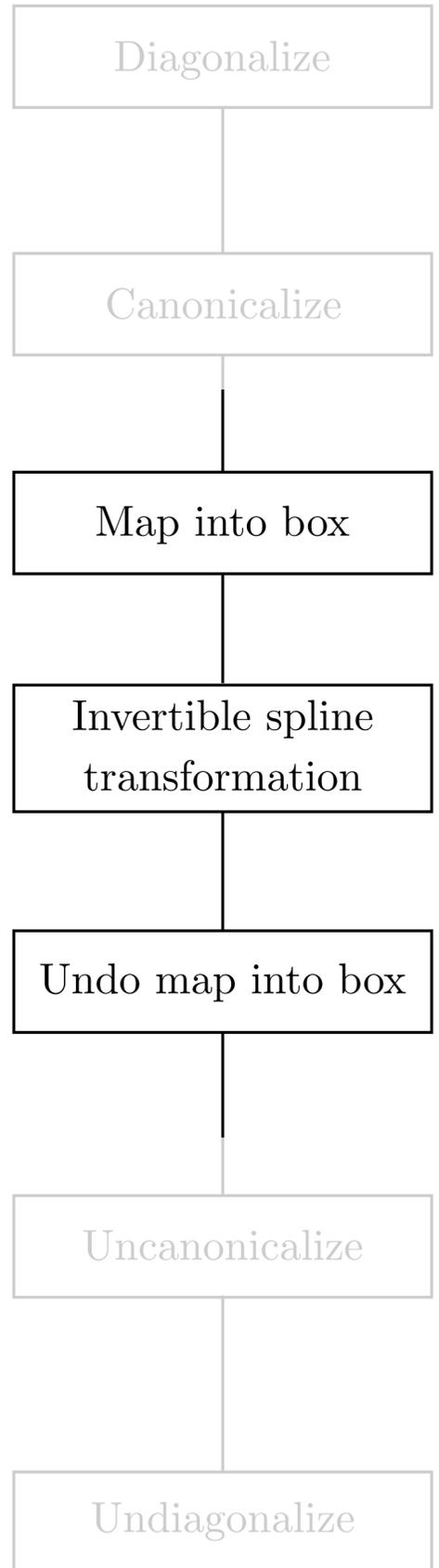
Autoregressive ... or ... Independent



$$W = P \begin{pmatrix} e^{i\phi_1} & & \\ & \ddots & \\ & & e^{i\phi_N} \end{pmatrix} P^\dagger$$



$$W' = P \begin{pmatrix} e^{i\phi'_1} & & \\ & \ddots & \\ & & e^{i\phi'_N} \end{pmatrix} P^\dagger$$

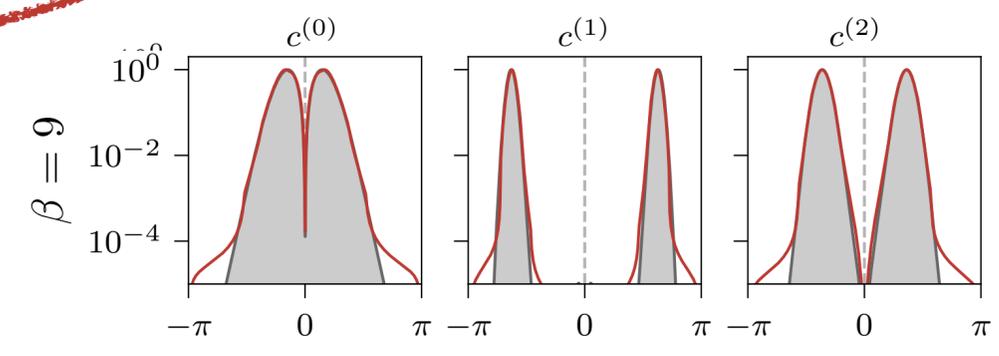
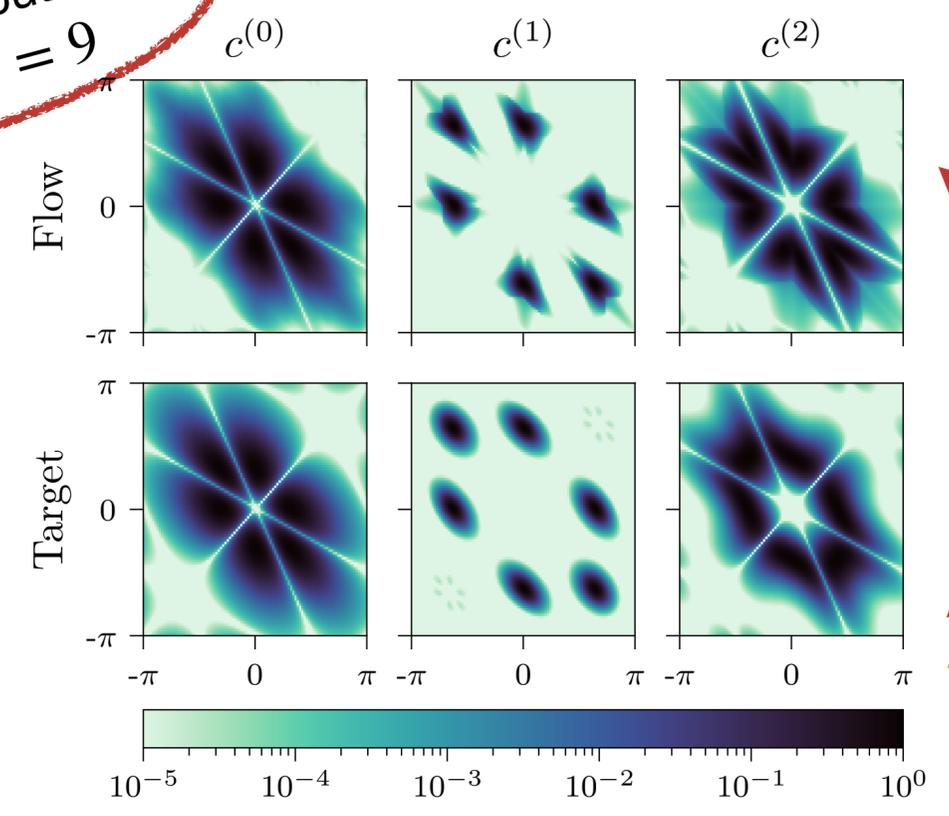
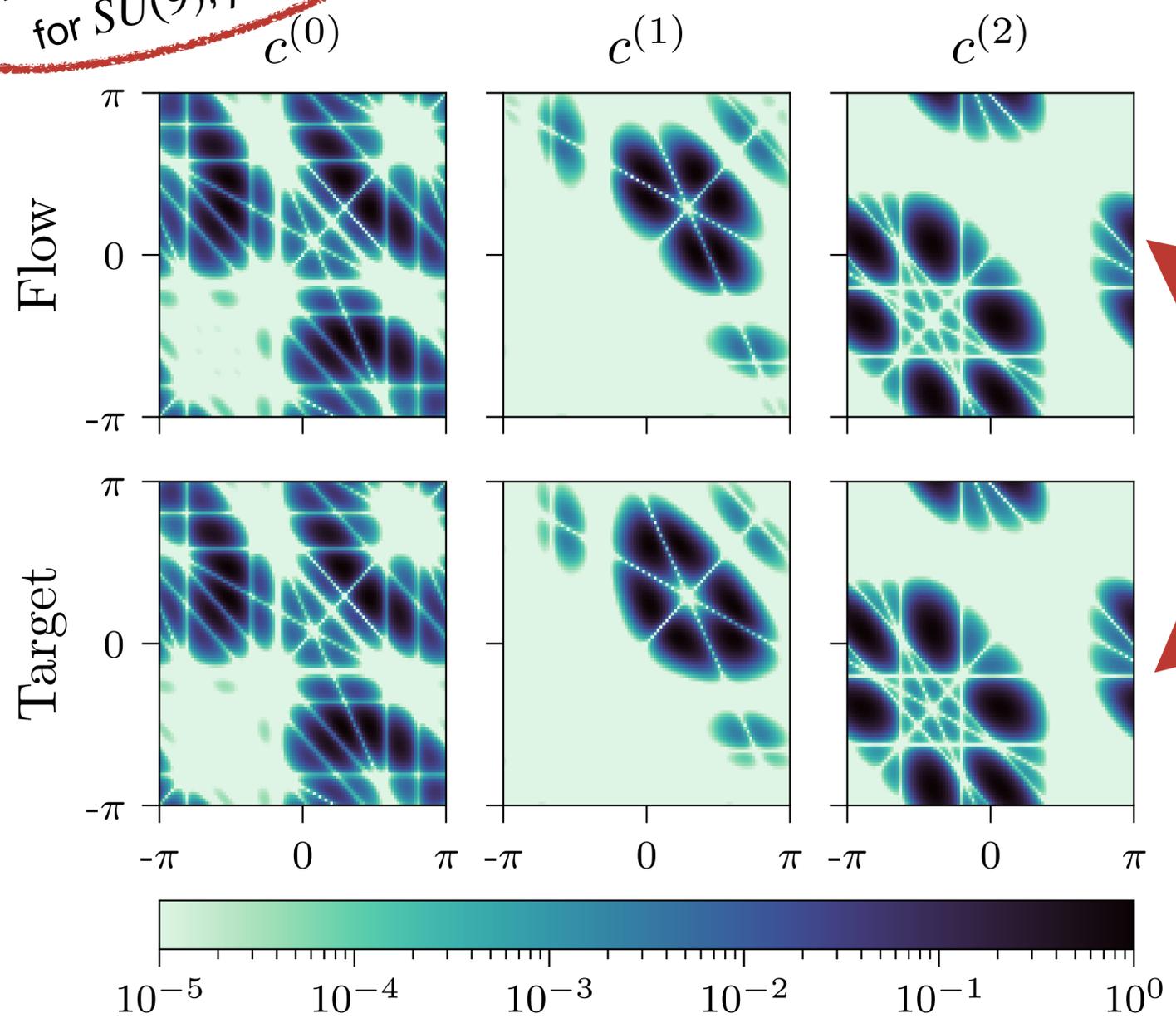


# Testing SU(N) kernels

Plaquette distributions for  $SU(9)$ ,  $\beta = 9$

Plaquette distributions for  $SU(3)$ ,  $\beta = 9$

Plaquette distributions for  $SU(2)$ ,  $\beta = 9$



Density has zeros on vertical, horizontal, and diagonal lines where the slice crosses walls of cells

— Target — Flow

Agree!

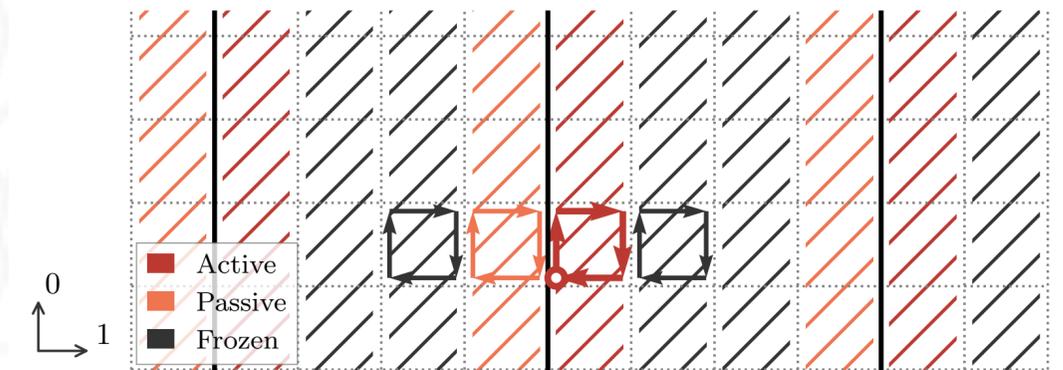
Agree!

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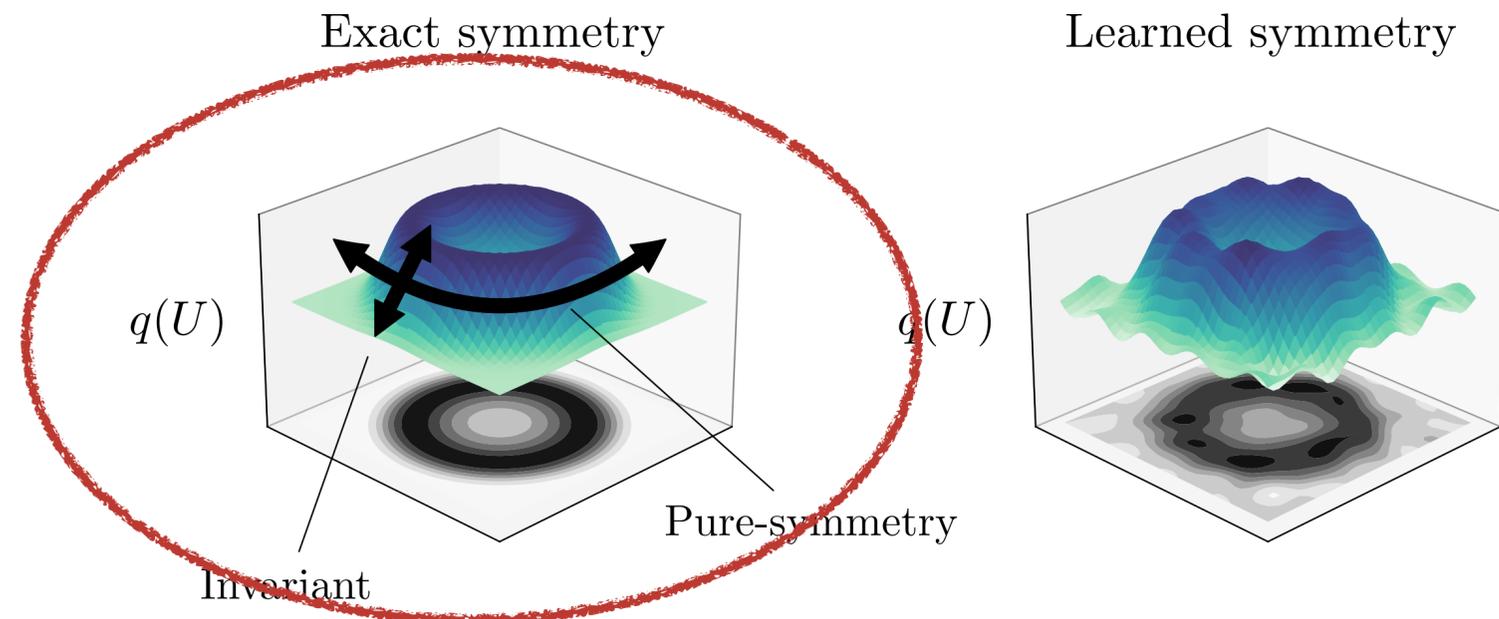
# Learning $SU(2)$ and $SU(3)$ gauge theory

Normalizing flows trained for 2D lattice gauge theory on  $16 \times 16$  lattices.

- Approx matched 't Hooft couplings, giving  $\beta = \{1.8, 2.2, 2.7\}$  for  $SU(2)$  and  $\beta = \{4.0, 5.0, 6.0\}$  for  $SU(3)$
- 48 **PAFF coupling layers**, update all links 6 times
- No equivalent topo freezing, studied **absolute model quality** instead



All flow-based models exactly gauge-equiv by construction



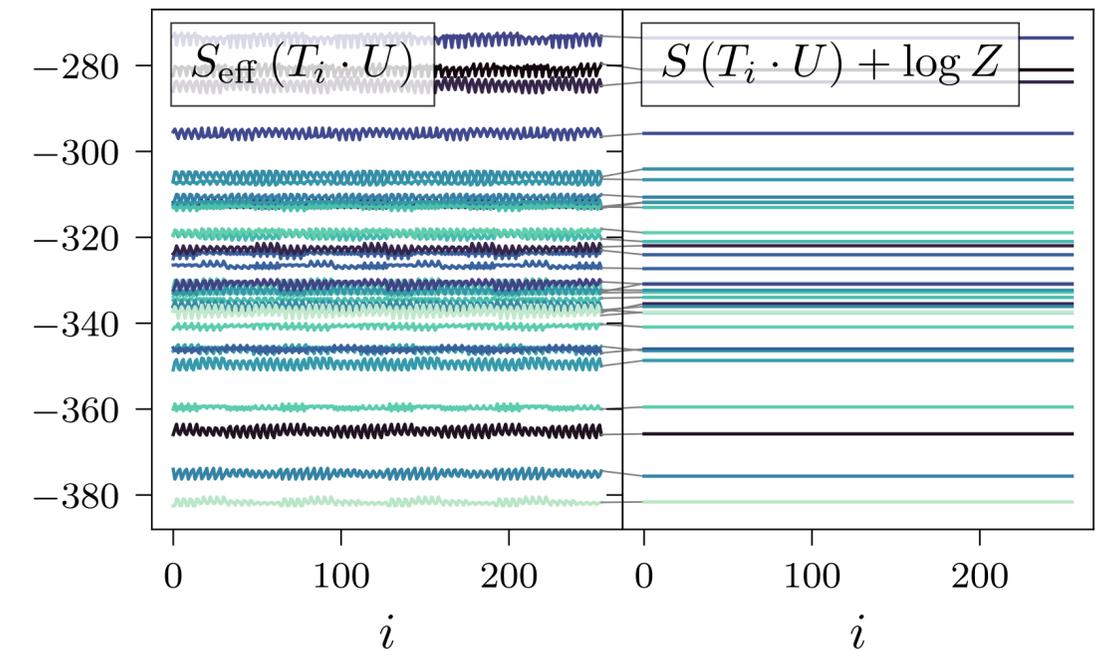
# Results for SU(2) and SU(3) gauge theory

- Flow-based MCMC observables agree with analytical
- **High-quality models:** autocorrelation time in flow-based Markov chain  $\tau_{\text{int}} = 1 - 4$
- Symmetries exactly / approximately reproduced

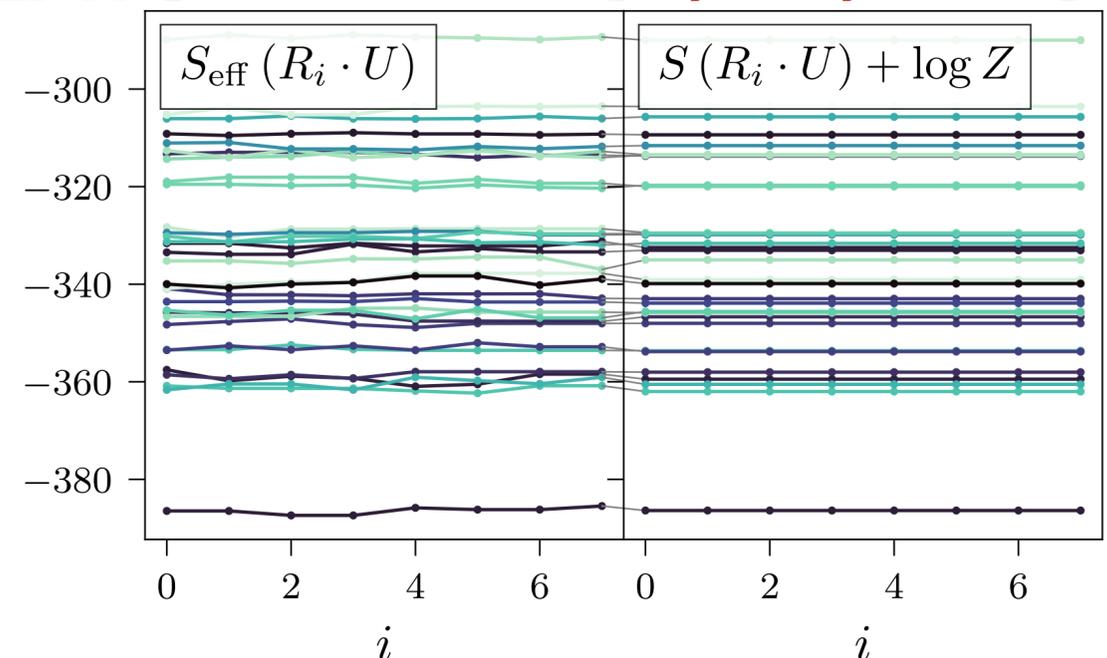
	SU(2)				SU(3)	
$\beta$	1.8	2.2	2.7	4.0	5.0	6.0
ESS(%)	91	80	56	88	75	48

Measure of "effective" # samples from target dist for each sample drawn from model (100% = perfect model)

Exact translational subgroup, residual learned



Rotation and reflection symmetry learned



**Promising early results. No theoretical obstacle to scaling to 4D  $SU(N)$  lattice gauge theory.**

# Summary and Outlook

**Gauge symmetry** encoded in flow models while preserving (most of) translational symmetry

- Gauge equivariant coupling layers
- Kernels for  $U(1)$  and  $SU(N)$

**High-quality models** produced for  $U(1)$ ,  $SU(2)$ , and  $SU(3)$  lattice gauge theory in 1+1D

## Future work:

1. Higher spacetime dims. Choices of untraced loops to transform, gauge-inv loops as input?
2. Training for multimodal distributions  
[Hsieh, Chen, Chen, Albergo, Boyda, Cranmer, Hackett, GK, Saito, Shanahan; **In preparation**]
3. Training hyperparameter tuning, different model arch for inner flows
4. Incorporation of dynamical fermions  
[Albergo, GK, Racanière, Rezende, Urban, Boyda, Cranmer, Hackett, Shanahan; **In preparation**]

# Open Questions

## 1. Universality?

- Limits in which (gauge-equiv) flow-based models capture arbitrary (gauge theory) distributions?
- How to avoid / diagnose silent “expressivity failure”?

## 2. Hierarchical structures?

- Asymptotic freedom, RG information
- Hierarchical models to efficiently capture many scales?

E.g. Hierarchical based on “disentangled” and “decimators”: [Li, Wang **PRL121 (2018) 260601**]

## 3. Continuum scaling?

- How to scale model expressivity as  $a \rightarrow 0$ ?
- Computational cost?
- How to scale model training?

Posted last night: [Del Debbio, Marsh-Rossney, Wilson **2105.12481**]

# Backup Slides



# Exactness: Reweighting

- Also possible to reweight independently drawn samples:

$$\langle \mathcal{O} \rangle = \frac{\int \mathcal{D}U q(U) \left[ \mathcal{O}(U) \frac{p(U)}{q(U)} \right]}{\int \mathcal{D}U q(U) \left[ \frac{p(U)}{q(U)} \right]}$$

- May be preferable when observables  $\mathcal{O}(U)$  are efficiently computed, and sampling is expensive.
- Observables  $\mathcal{O}(U)$  are expensive in lattice QCD. We prefer resampling or MCMC approaches in these settings.

# Translational equivariance

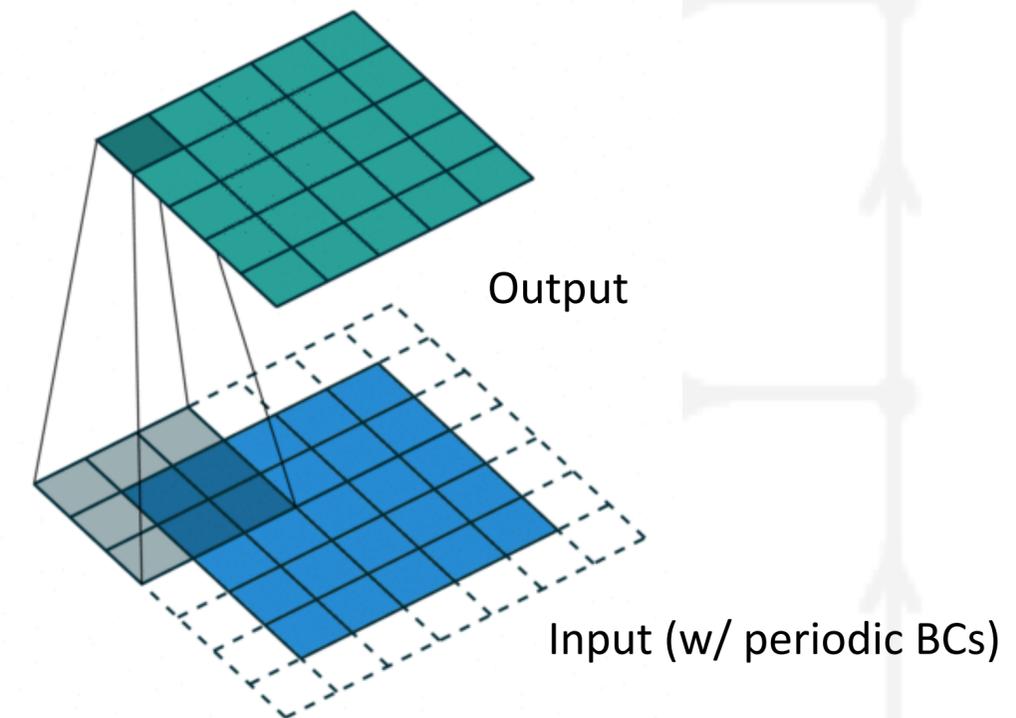
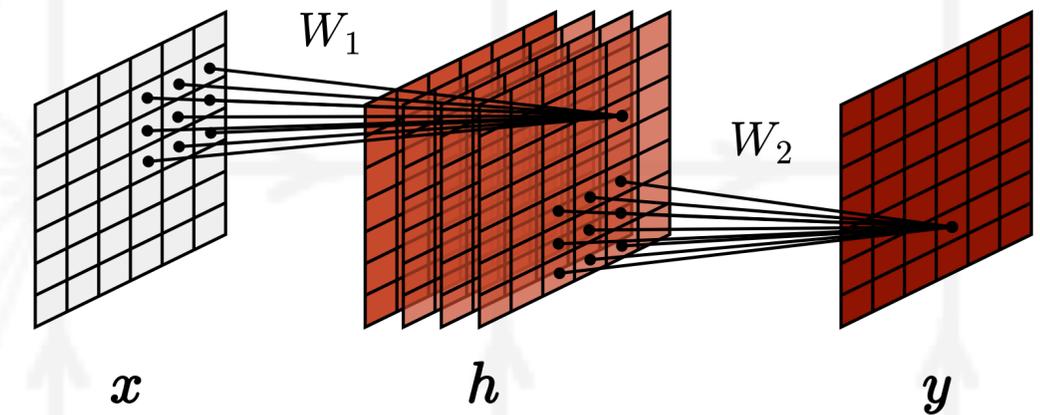
## 1. Make context functions Convolutional Neural Nets:

- Compute output value for each site from linear transform of nearby DOF only
- Reuse same weights, scanning kernel across the lattice

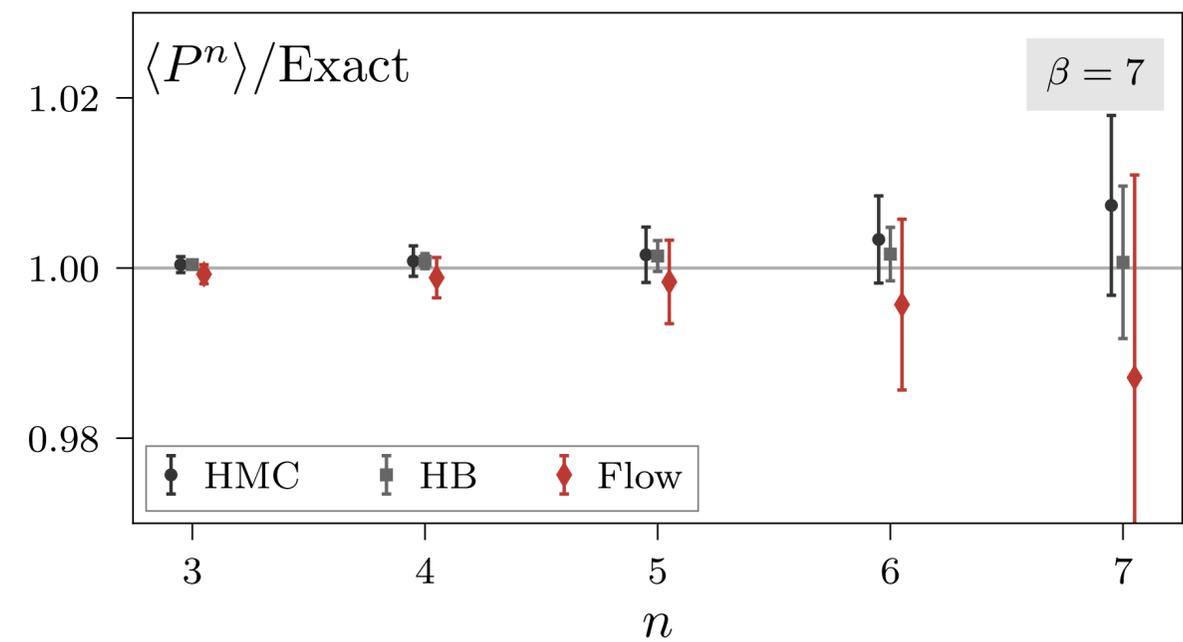
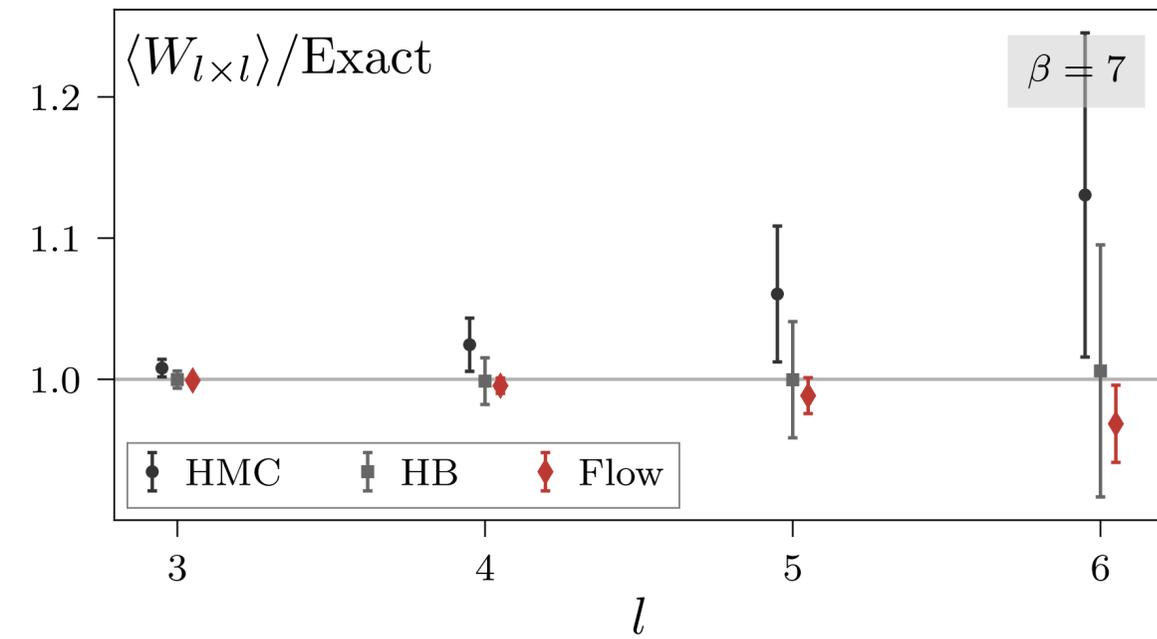
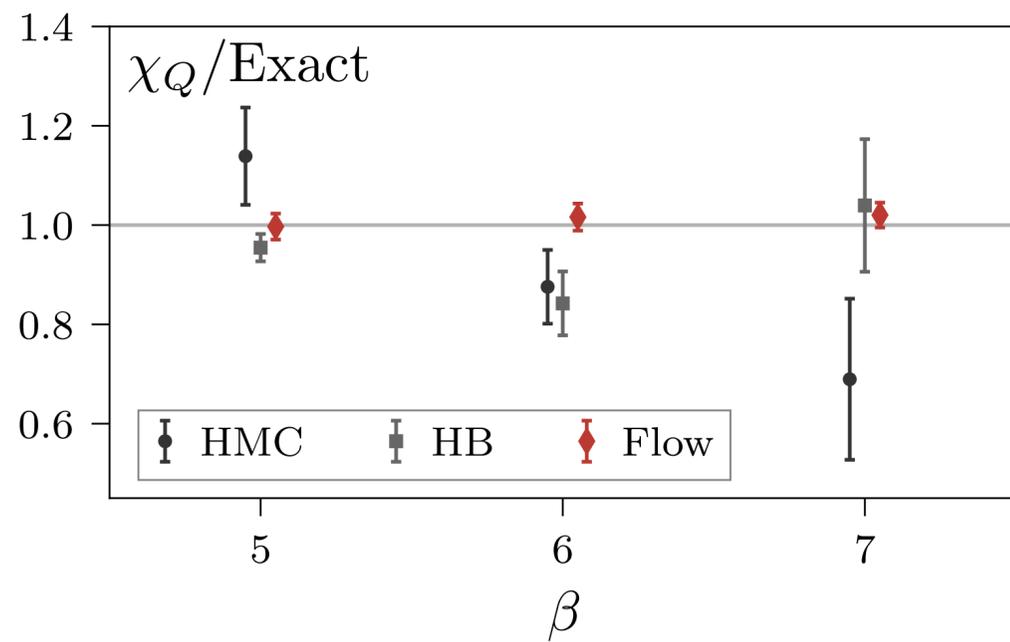
CNNs are equivariant under translations.

## 2. Make masking pattern (mostly) translationally invariant.

- E.g. checkerboard is symmetric modulo  $\mathbb{Z}_2$  even/odd
- Gauge theory: translational equiv modulo  $\mathbb{Z}_4 \times \mathbb{Z}_4$



# U(1) study observables



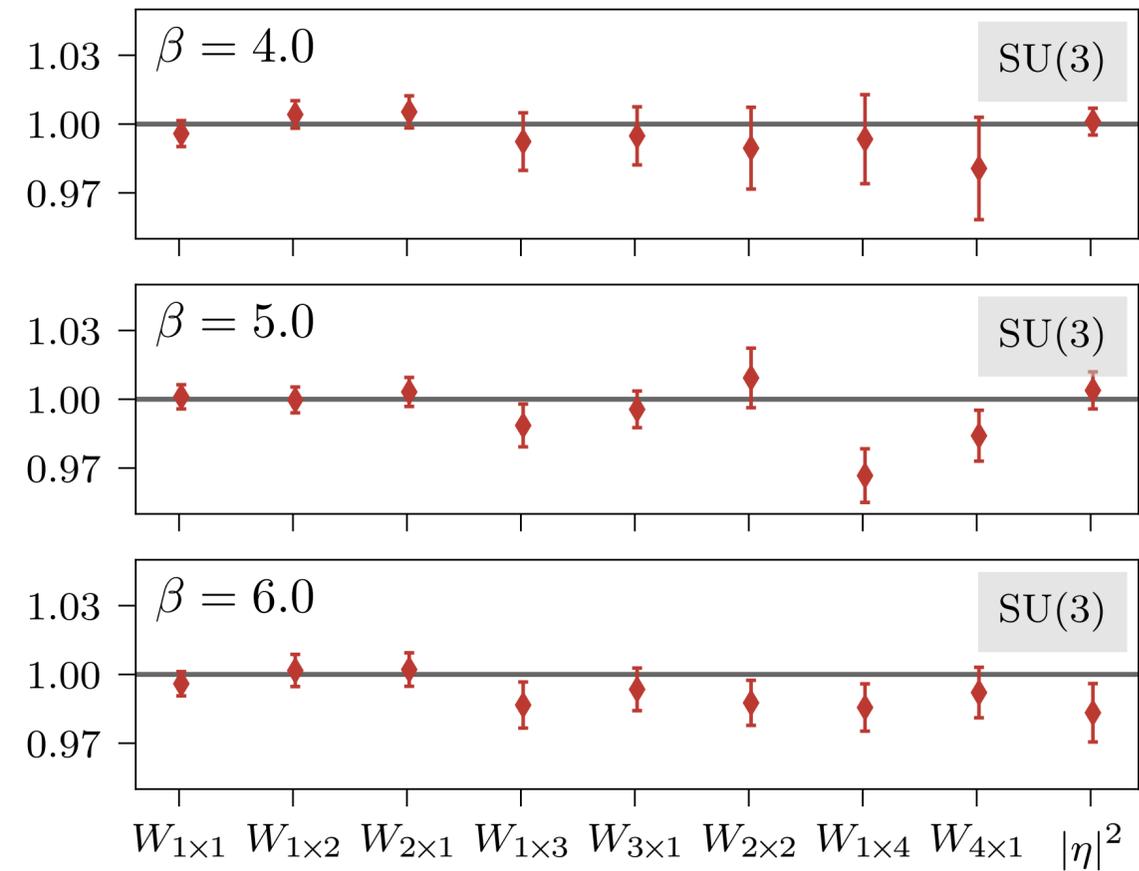
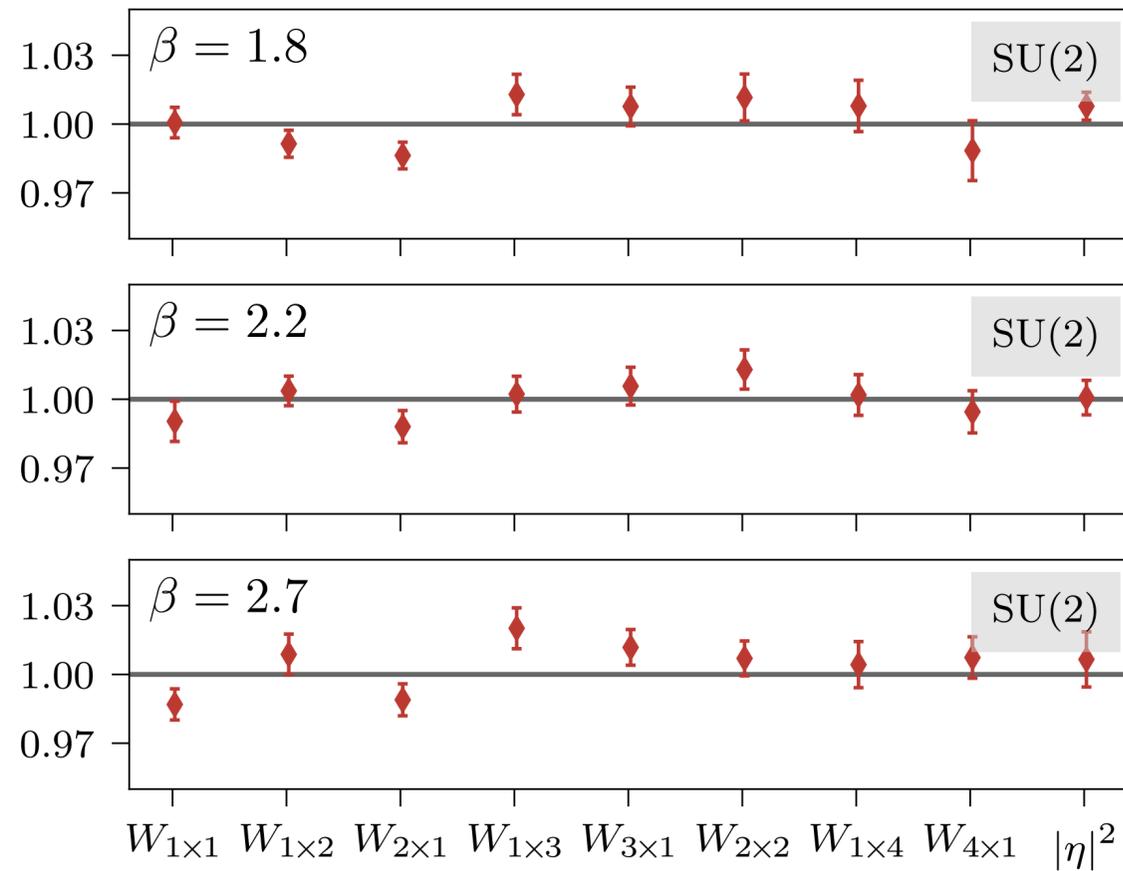
# Map into canonical cell

Want to permute eigenvalues into canonical order

- Sorting doesn't work directly: discontinuities when  $\theta_k$  jumps across the  $\pm\pi$  boundary
- Simply trying all  $N!$  permutations is slow for large  $N$
- Need to ensure permutation taking points in the same cell to canonical is the same

Short algorithm based on sorting works; Algorithm 1 of [‡]

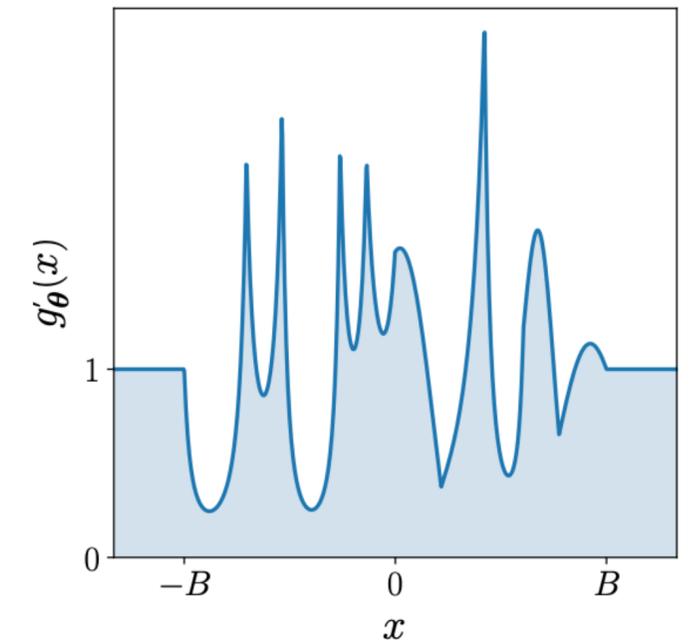
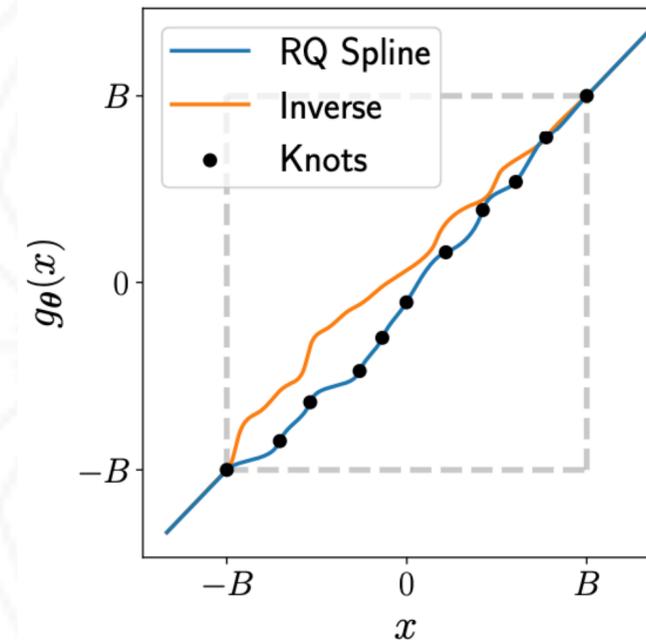
# SU(N) study observables



# Details of $SU(2)$ models

- Inner flow on open box  $\Omega$  is a spline flow with **4 knots**

- $B$  and  $-B$  boundaries align to 0 and 1 edges of the open box



- CNNs to compute the knot locations

- 32 hidden channels
- 2 hidden layers

[Durkan, Bekasov, Murray, Papamakarios 1906.04032]

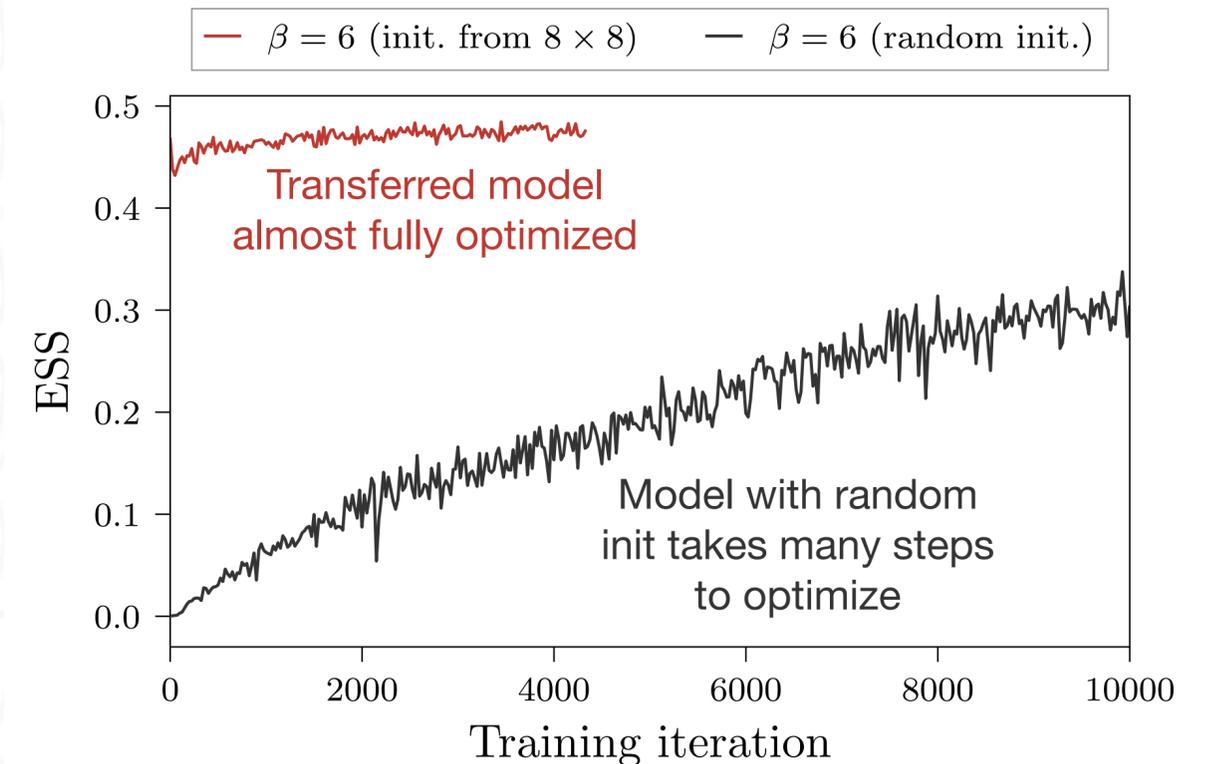
# Gauge theory model training

- Adam optimizer ~ stochastic grad. descent with momentum
  - Batches of size 3072 per gradient descent step
  - Monitored value of **effective sample size (ESS)**

$$\text{ESS} = \frac{\left(\frac{1}{n} \sum_i w(U_i)\right)^2}{\frac{1}{n} \sum_i w(U_i)^2}, \quad U_i \sim q(U)$$

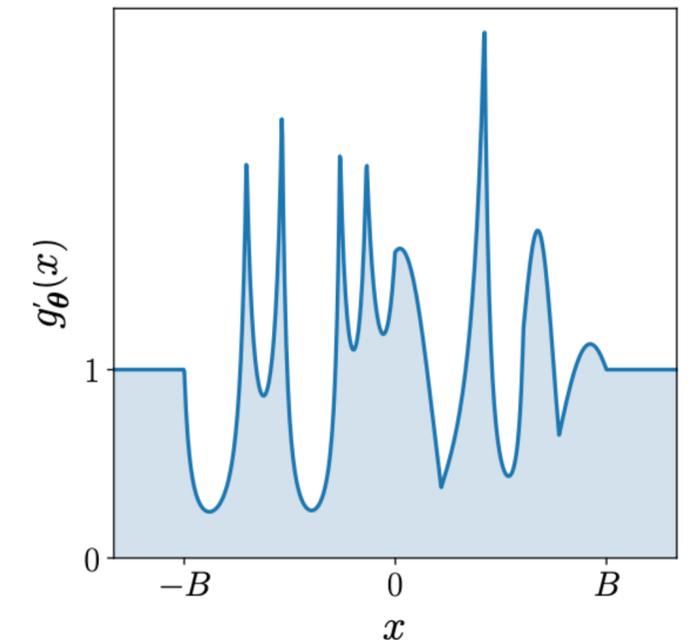
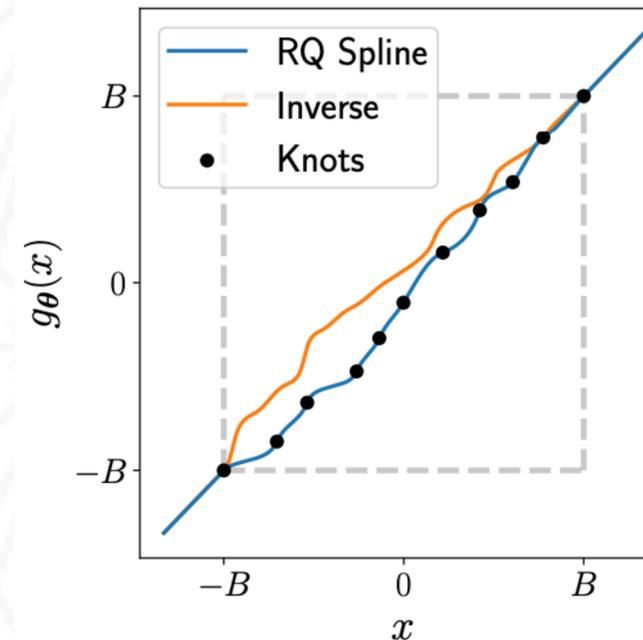
$$w(U) = p(U)/q(U) \quad \text{“reweighting factors”}$$

- **Transfer learning:** model trained first on  $8 \times 8$  then used to initialize model for training on  $16 \times 16$



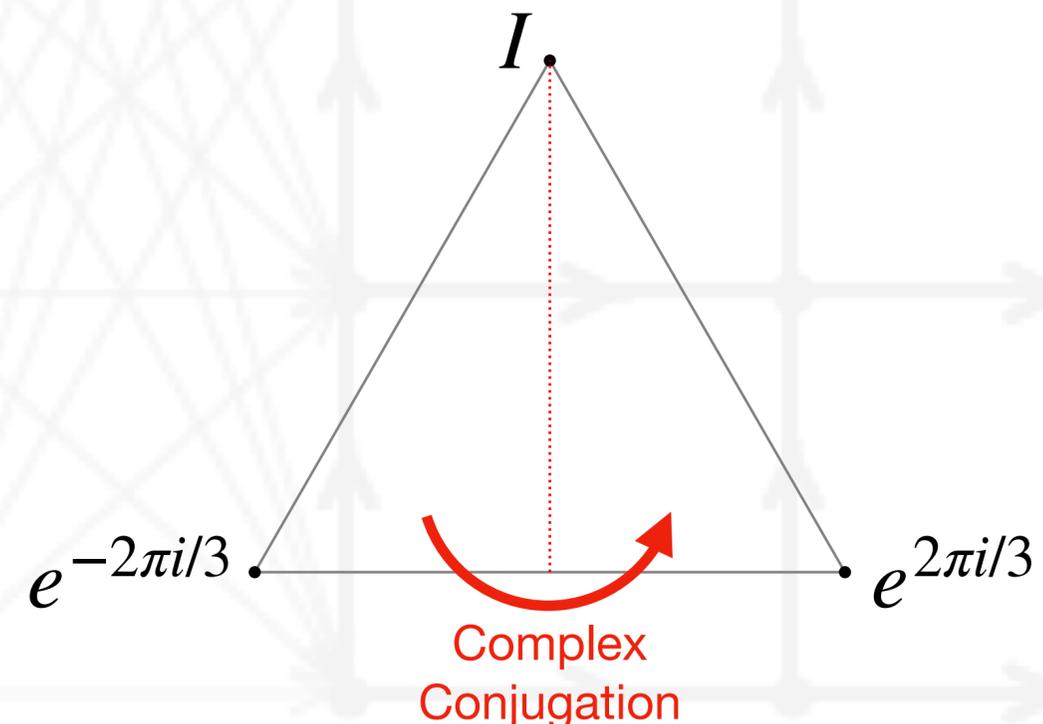
# Details of $SU(3)$ models

- Inner flow on open box  $\Omega$  is a spline flow with **16 knots**
  - $B$  and  $-B$  boundaries align to 0 and 1 edges of the open box



[Durkan, Bekasov, Murray, Papamakarios 1906.04032]

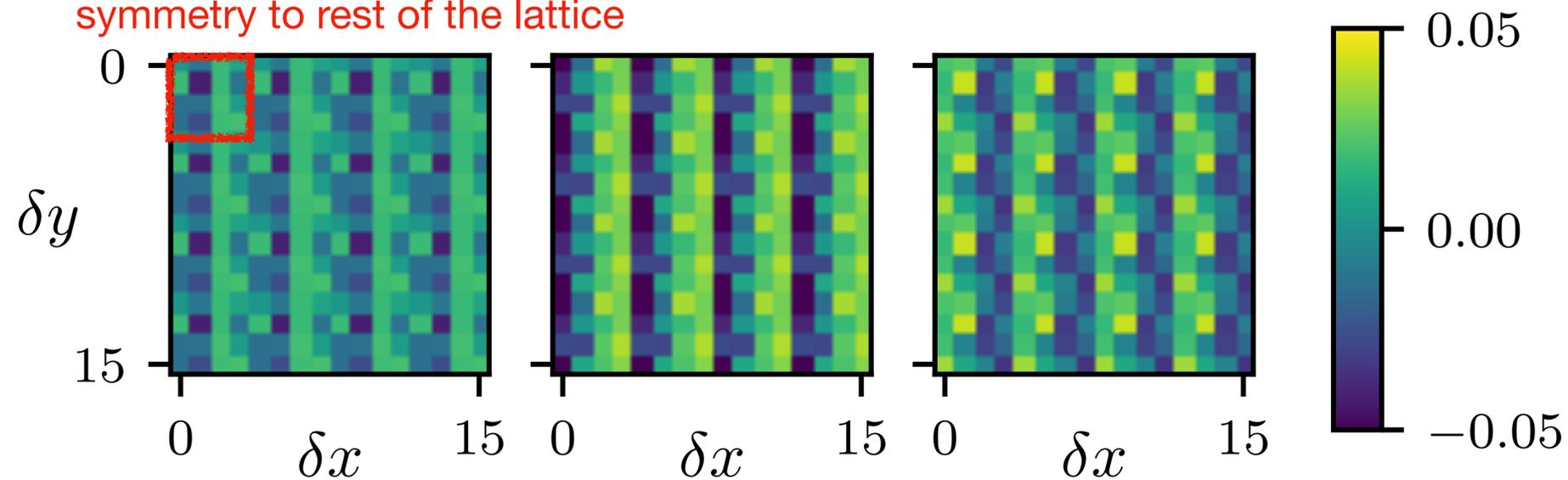
- CNNs to compute the knot locations
  - 32 hidden channels
  - 2 hidden layers
- Exact conjugation equivariance also imposed



# Translational symmetry breaking pattern

- Masking patten = repeating tile of size  $1 \times 4$
- Rotate / translate the pattern between layers
- $\mathbb{Z}_4 \times \mathbb{Z}_4$  symmetry breaking

Log density in 4x4 region extends by unbroken part of translational symmetry to rest of the lattice



# Center symmetry

Using **only contractible loops** in coupling layers enforces center symmetry.

## Fundamental fermions:

- Center symmetry explicitly broken
- Must include non-contractible loops (e.g. Polyakov) in the set of frozen and/or transformed loops

