Machine learning RG actions with a lattice gauge covariant convolutional neural network (L-CNN)



arXiv:2311.17816 [hep-lat], arXiv:2401.06481 [hep-lat]

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Consider an asymptotically free quantum field theory on the lattice, e.g., $SU(N_c)$ lattice gauge theory:

$$Z(\beta) = \int \mathcal{D}U \exp\{-\beta A[U]\} \text{ with}$$

and expectation values for observables:

$$\langle \mathcal{O}_{\xi}(\beta) \rangle = \frac{1}{Z} \int \mathcal{D}U \exp\{-\beta A[U]\}$$

with a characteristic length scale ξ in units of the lattice spacing a:

$$\frac{\xi}{a} \Rightarrow \text{dimen}$$

gauge coupling

$$\beta = \frac{2N_c}{g^2}$$

 $\mathcal{O}_{\xi}[U]$

sionless



lattice spacing *a* from dimensionless $g: \Rightarrow$ dimensional transmutation





critical slowing down ? (topological freezing)

Part I: The FP action

Introduce (coordinate space) renormalization group transformation (RGT):



 \Rightarrow provides solution for avoiding critical slowing down and lattice artefacts



Introduce (coordinate space) renormalization group transformation (RGT):

$$\exp\left\{-\beta' A'[V]\right\} = \int \mathcal{D}U \exp\left\{-\beta' U \exp\left(-\beta' U \exp\left\{-\beta' U \exp\left\{-\beta' U \exp\left\{-\beta' U \exp\left\{-\beta' U \exp\left\{-\beta' U \exp\left\{-\beta' U \exp\left(-\beta' U \exp\left($$

where T[U, V] is a blocking kernel regauge links $V \equiv U'$:

$$T[U, V] = -\frac{\kappa}{N_c} \sum_{x_B, \mu} \left\{ \operatorname{ReTr} \left(V_{\mu}(x_B) \cdot Q_{\mu}^{\dagger}(x_B) \right) - \mathcal{N}_{\mu}^{\beta} \right\}$$

 $(\mathcal{N}^{\beta}_{\mu})$ is a normalization factor guaranteeing $Z(\beta') = Z(\beta)$, i.e., unchanged long-distance physics)

$\cdot \beta \left(A[U] + T[U, V] \right) \right\}$

where T[U, V] is a blocking kernel relating the fine gauge links U to the coarse







Introduce (real space) renormalization group transformation (RGT):

$$\exp\left\{-\beta' A'[V]\right\} = \int \mathcal{D}U \exp\left\{-\right.$$

The effective action $\beta' A'[V]$ is described by infinitely many couplings $\{c'_{\alpha}\}$:



 $\cdot\beta(A[U] + T[U, V])\Big\}$













The effective action $\beta A[V]$ is described by infinitely many couplings $\{c_{\alpha}\}$:

 $\exp\left\{-\beta'A'[V]\right\} = \left[\mathscr{D}U\exp\left\{-\beta(A[U] + T[U, V])\right\}\right]$

Two practical problems:

- how to parametrize RT, i.e., which set $\{c_{\alpha}\}$?
- how to determine $\{c_{\alpha}^{\mathsf{RT}}\}$ or $\{c_{\alpha}^{\mathsf{FP}}\}$?







P. Hasenfratz, F. Niedermayer [Nucl. Phys. B414 (1994) 785, hep-lat/9308004] for $\beta \to \infty$ (on critical surface) the RGT becomes a classical saddle point problem:

 $\{U\}$

The effective action $\beta A[V]$ is described by infinitely many couplings $\{c_{\alpha}\}$:

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Two practical problems:

- how to parametrize RT, i.e., which set $\{c_{\alpha}\}$?
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 $A^{\mathsf{FP}}[V] = \min \left\{ A^{\mathsf{FP}}[U] + T[U, V] \right\}$





The classical FP action A^{FP} defines an action for all β :



critical surface $\xi/a = \infty$ RT **FP** action



The FP action values for rough configurations defined through an inception procedure:



The FP action values for rough configurations defined through an inception procedure:

The classical FP equation can be iterated:

 There are no lattice artefacts on classical configurations:

$$\frac{\delta A^{\mathsf{FP}}[V]}{\delta V} = 0 \quad \Rightarrow \quad \frac{\delta A^{\mathsf{FP}}[U]}{\delta U} = 0$$

$A^{\mathsf{FP}}[V] = \min_{\{U\}} \{A^{\mathsf{FP}}[U] + T[U, V]\} = \min_{\{U', U\}} \{A^{\mathsf{FP}}[U'] + T[U', U] + T[U, V]\}$

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 There are no lattice artefacts on classical
 Proof using the chain rule: configurations:

$$\frac{\delta A^{\mathsf{FP}}[V]}{\delta V} = 0 \quad \Rightarrow \quad \frac{\delta A^{\mathsf{FP}}[U]}{\delta U} = 0$$

$$\frac{\delta A^{\rm FP}[V]}{\delta V} = \left[\frac{\delta}{\delta U} (A^{\rm FP}[U] + T[U, V]) \frac{\delta U}{\delta V} + \frac{\delta T[U, V]}{\delta V}\right]_{U}$$

$$\Rightarrow \left. \frac{\delta T[U, v]}{\delta V} \right|_{U_{\min}} = 0 \quad \text{hence } T[U_{\min}, V] = 0$$



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 $+\frac{\delta T[U,V]}{\delta V}$

$$A^{\mathsf{FP}}[V] = A^{\mathsf{FP}}[U_{\mathsf{min}}] \text{ and } \frac{\delta A^{\mathsf{FP}}[U]}{\delta U} \bigg|_{U_{\mathsf{min}}} = 0$$



The classical FP equation can be iterated:

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 Proof using the chain rule: There are no lattice artefacts on classical $\frac{\delta A^{\rm FP}[V]}{\delta V} = \left| \frac{\delta}{\delta U} (A^{\rm FP}[U] + T[U, V]) \frac{\delta U}{\delta V} \right|$ $+\frac{\delta T[U,V]}{\delta V}$ $\Rightarrow A^{rr}[V]$ has scale invariant instanton $\delta A^{\mathsf{FP}}[U]$ $A^{\mathsf{FP}}[V] = A^{\mathsf{FP}}[U_{\mathsf{min}}]$ and solutions δU

 U_{min}



The classical FP equation can be iterated:

• There are no lattice artefacts on classical configurations:

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⁷]has scale invariant instanton solutions



The classical FP equation can be iterated:

• For large β , $A^{FP}[V]$ is very close to $A^{RT}[V]$: There are no lattice artefacts on classical configurations:

$$\frac{\delta A^{\text{FP}}[V]}{\delta V} = 0 \quad \Rightarrow \quad \frac{\delta A^{\text{FP}}[U]}{\delta U} = 0$$

 $\Rightarrow A^{\lceil \lceil}[V]$ has scale invariant instanton solutions

- $A^{\mathsf{FP}}[V] = \min_{\{U\}} \{A^{\mathsf{FP}}[U] + T[U, V]\} = \min_{\{U', U\}} \{A^{\mathsf{FP}}[U'] + T[U', U] + T[U, V]\}$





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 \Rightarrow lattice artefacts expected to be substantially reduced:

$$\mathcal{O}(a^{2n}), \mathcal{O}(g^2 a^{2n}) \quad n = 1, 2, \dots$$

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$$\mathcal{O}(a^{2n}), \mathcal{O}(g^2 a^{2n}) \quad n = 1, 2, \dots$$

 \Rightarrow initiated a large activity, culminating in the discovery of **GW fermions**!

Classically perfect FP actions - locality

Is the FP action local?



 \Rightarrow Consider the couplings $A^{FP} \propto \sum \tilde{\rho}_{\mu\nu}(k) \tilde{A}_{\mu}(k) \tilde{A}_{\nu}(-k)$ k



 couplings fall off exponentially, as desired

Parametrization of the FP actions

Wilson plaquette variable:

$$u_{\mu\nu} = \operatorname{ReTr}\left(1 - U_{\mu\nu}^{pl}\right)$$

from usual links U_{μ}, U_{ν}

- FP action: $A^{FP}[U] = \sum f(u_{\mu\nu}, w_{\mu\nu})$ $\mu < \nu$
- •Asymmetrically smeared links:

$$\begin{aligned} Q_{\mu}^{S} &= \frac{1}{6} \sum_{\lambda \neq \mu} S_{\mu}^{(\lambda)} - U_{\mu} \,, \qquad \qquad Q_{\mu}^{(\nu)} &= \frac{1}{4} \left(\sum_{\lambda \neq \mu, \nu} S_{\mu}^{(\lambda)} + \eta(x_{\mu}) \cdot S_{\mu}^{(\nu)} \right) - \left(1 + \frac{1}{2} \eta(x_{\mu}) \right) U_{\mu} \,, \\ W_{\mu}^{(\nu)} &= U_{\mu} + c_{1}(x_{\mu}) \cdot Q_{\mu}^{(\nu)} + c_{2}(x_{\mu}) \cdot Q_{\mu}^{(\nu)} U_{\mu}^{\dagger} Q_{\mu}^{(\nu)} + \dots \,, \qquad \qquad x_{\mu} = \operatorname{ReTr} \left(Q_{\mu}^{S} \cdot U_{\mu}^{\dagger} \right) \,, \end{aligned}$$

$$\eta(x) = \eta^{(0)} + \eta^{(1)} \cdot x + \eta^{(2)} \cdot x^2 + \dots ,$$

- Parametrization should be as local as possible, but still as expressive as possible.
 - Smeared plaquette

$$w_{\mu\nu} = \operatorname{ReTr}\left(1 - W_{\mu\nu}^{pl}\right)$$

from asymmetrically smeared links

e.g.
$$f(u, w) = \sum_{k,l} p_{kl} u^k w^l$$

$$c_i(x) = c_i^{(0)} + c_i^{(1)} \cdot x + c_i^{(2)} \cdot x^2 + \dots$$

FP action in action

Static quark-antiquark potential, lattice spacings between a = 0.33 fm, \dots , 0.10 fm :



[Niedermayer, Rüfenacht, UW, Nucl.Phys.B 597 (2001) 413, hep-lat/0007007]





Part II: Machine learning the FP action

Machine learning the FP action







 $(\mathcal{U},\mathcal{W}) \to (\mathcal{U},\mathcal{W}')$

 $W'_{x+k\cdot\mu,j} = U_{x,k\cdot\mu}W_{x+k\cdot\mu,j}U^{\dagger}_{x,k\cdot\mu},$

$$(\mathcal{U},\mathcal{W})\times (\mathcal{U}$$





ML architecture: Lattice gauge equivariant Convolutional Neural Network (L-CNN)

[Favoni, Ipp, Müller, Schuh, PRL 128 (2022) 3, 2012.12901]



 $(\mathcal{W}') \to (\mathcal{U}, \mathcal{W}'')$

 $w_{\mathbf{x},i} = \operatorname{Tr} W_{\mathbf{x},i} \in \mathbb{C}$



Machine learning the FP action



ML architecture: Lattice gauge equivariant Convolutional Neural Network (L-CNN)

For given coarse V the FP action value determined by the minimizing confs. U, U', \ldots

 $A^{\mathsf{FP}}[V] = \min_{\{U\}} \{A^{\mathsf{FP}}[U] + T[U, V]\} = \min_{\{U', U\}} \{A^{\mathsf{FP}}[U'] + T[U', U] + T[U, V]\}$

Instead use approximate FP action values $A^{FP}[U]$ in the first iteration

Minimising the RHS is crucial for generating the training data:

- generate ensembles of coarse gauge configurations for a range of field fluctuations
- find minimizing fine configuration



Minimisation evolution of fine configuration U for fixed coarse configuration V



Coarse configuration: SU(3), $V = 8^4$, $\beta^{Wil} = 6.0$



 $3^{\text{WH}} = 6.0 \implies \text{lattice spacing } a \simeq 0.10 \text{ fm}$

Minimisation evolution of fine configuration U for fixed coarse configuration V



Coarse configuration: SU(3), $V = 8^4$, $\beta^{Wil} = 5.4$



 \Rightarrow lattice spacing $a \simeq 0.25$ fm

Minimisation of instanton configuration with ρ/a' on 16⁴ blocked to 8⁴:





Use the exact FP action values for training, plus the derivatives of the FP action:

 $\frac{\delta A^{\mathsf{FP}}[V]}{\delta V^{a}_{x,\mu}} = \frac{\delta T[U,V]}{\delta V^{a}_{x,\mu}} = -\kappa \operatorname{\mathsf{Re}} \operatorname{\mathsf{Tr}}(it^{a} V_{x,\mu} Q^{\dagger}_{x,\mu})$

Gauge invariance of A^{FP} yields conserved local quantity via Noether's theorem:

$$D_{x,\mu}^{FP} = \sum_{a} t^{a} \frac{\delta A^{FP}[V]}{\delta V_{x,\mu}^{a}}$$

- FP action values
- FP action derivatives



 \Rightarrow yields 4 x 8 x Volume (link) (color) (position) data per configuration

$$\implies \sum_{\mu} \mathscr{D}^B_{\mu} D^{FP}_{x,\mu} [V] = 0$$

 \Rightarrow consistency check satisfied up to the accuracy in minimization

data set for supervised ML

Machine learning the FP action: Architecture

FP action parameterised by

$$A^{\text{L-CNN}}[V] = \sum_{x} A_{x}^{\text{pre}}[V] \sum_{n=0}^{\infty} b^{(n)} \left(N_{x}[V] - N_{x}[1] \right)^{n}$$

with
$$A_{x}^{\text{pre}}[V] = \frac{1}{N_{c}} \sum_{C} \sum_{m=1}^{M} c^{(m)} [\text{ReTr}(a - U_{x,C})]^{m} \text{ for example Wil, tlSym, ...}$$

Note: $N_{x}[V \to 1] - N_{x}[1] \simeq C$

$$A^{\text{L-CNN}}[V] = \sum_{x} A_{x}^{\text{pre}}[V] \sum_{n=0}^{\infty} b^{(n)} \left(N_{x}[V] - N_{x}[1] \right)^{n}$$

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Note: $N_{x}[V \to 1] - N_{x}[1] \simeq C$

In practice we use:

 $A^{\text{L-CNN}}[V] = \sum A_x^{\text{pre}}[V] \exp\left(N_x[V] - N_x[1]\right)$ $\boldsymbol{\chi}$



Machine learning the FP action: Loss functions

ML loss function from two weighted contributions:

$$\begin{split} L_{1} &= \frac{1}{L^{4}N_{cfg}} \sum_{i=1}^{N_{cfg}} \left| A^{\text{FP}}[V_{i}] - A^{\text{L-CNN}}[V_{i}] \right| \\ L_{2} &= \frac{1}{32L^{4}N_{cfg}} \sum_{i=1}^{N_{cfg}} \sum_{x,\mu} \text{Tr} \left[\left(D_{x,\mu}^{\text{FP}}[V_{i}] - D_{x,\mu}^{\text{L-CNN}}[V_{i}] \right)^{2} \right] \end{split}$$

$$L = w_1 L_1 + w_2 L_2$$

Technical point: derivatives in L-CNN are given through back propagation (since they are derivatives of part of loss function w.r.t. input)



Machine learning the FP action: L-CNN

Architecture search:



 \Rightarrow 3 L-Bilin layers, kernel sizes {2,2,1}, output channels {12,24,24} with 443k parameters

Machine learning the FP action: Results

Superiority of L-CNN over old parameterizations of FP action:



Machine learning the FP action: Results

Restricted training ranges:



Transfer learning:

	relative error (test data)		
finetuned model	4^4	6^4	8^4
4^4	0.178~%	0.201~%	0.181~%
6^4	0.185~%	0.196~%	0.177~%
8^4	0.191~%	0.202~%	0.176 %
	derivative error (test data)		
finetuned model	4^4	6^4	8^4
4^4	$\mathbf{7.63 imes 10^{-2}}$	8.19×10^{-2}	8.22×10^{-2}
6^4	$\boldsymbol{7.39\times10^{-2}}$	7.93×10^{-2}	7.96×10^{-2}
8^4	$7.36 imes \mathbf{10^{-2}}$	7.91×10^{-2}	7.93×10^{-2}

Machine learning the FP action: Results

Restricted training ranges:



⇒ new L-CNN parametrization is indeed very flexible and accurate

Finetuning on instantons:



Machine learning the FP action: Locality

Locality of L-CNN trained FP action:



 $\hat{\rho}_{\mu\nu}(r) = \frac{1}{\sqrt{N_c^2 - 1}} \sqrt{\sum_{a,b} D_{\mu\nu}^{ab}(x,y) D_{\mu\nu}^{ab}(x,y)}$

where $D^{ab}_{\mu\nu}(x,y) = \frac{\delta^2 A}{\delta V^a_{x\,\mu} \delta V^b_{y\,\mu}}$

- couplings fall off exponentially, as desired
- even on coarse configurations

Machine learning the FP action: Symmetries

Test of lattice symmetries:

translations:

 $U \rightarrow U' = U_{(rot)}$ rotations:

 $U \rightarrow U' = U_{(refl)}$ reflections:

a priori not present, but learned!





FP action with L-CNN:

So far, two questions were addressed:

- can the FP action be parametrised sufficiently well?
- is the FP action sufficiently local for truncations to work?

- Could provide a solution to critical slowing down and topological freezing... how good are scaling properties of L-CNN FP action?
- Availability of derivatives is the stepping stone for further developments:
 - HMC, Langevin, GF (all based on derivatives)
 - apply exact RGT step(s)



Part III: Classically perfect gradient flow

Gradient flow

Use renormalized GF couplings as scaling quantities:

$$\frac{dA_{\mu}(t)}{dt} = D_{\nu}G_{\nu\mu} \qquad \langle t^{2}E(t)\rangle = \frac{3(N^{2}-1)g^{2}}{128\pi^{2}} \left(1+O(g^{2})\right), \qquad E = \frac{1}{4}G_{\mu\nu}G_{\mu\nu}$$

On the lattice, artifacts are introduced through discretization of S^g, S^f, S^e :

$$\langle t^2 E(t) \rangle_a = \frac{3(N^2 - 1)g_0^2}{128\pi^2}$$

$$\frac{2}{0} \left(C(a^2/t) + O(g_0^2) \right)$$

Gradient flow

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On the lattice, artifacts are introduced through discretization of S^g, S^f, S^e :

$$\langle t^2 E(t) \rangle_a = \frac{3(N^2 - 1)g_0^2}{128\pi^2}$$

 \Rightarrow turns out that GF with FP action is classically perfect!

$$\left(C(a^2/t) + O(g_0^2)\right)$$

Gradient flow at tree level

At tree level, the flow equation reads:

 $\frac{dA_{\mu}(p,t)}{dt} =$

with the solution

 $A_{\mu}(p,t) = \exp$

leading to

 $\langle t^2 E(t) \rangle_a = \frac{(N^2 - 1)}{2} g_0^2 t^2$

and with $S^f = S^g = S^e$:

[Fodor, Holland, et al., *JHEP* 09 (2014) 018, 1406.0827]

$$-\left(S^f_{\mu\nu}(p) + \mathcal{G}_{\mu\nu}\right) A_{\nu}(p,t)$$

$$\left\{-t\left(S^{f}(p)+\mathcal{G}\right)\right\}\right]_{\mu\nu}A_{\nu}(p,0)$$

$${}^{2}\int_{-\pi/a}^{\pi/a} \frac{d^{4}p}{(2\pi)^{4}} \operatorname{Tr}\left[e^{-t(S^{f}+\mathscr{G})}(S^{g}+\mathscr{G})^{-1}e^{-t(S^{f}+\mathscr{G})}\cdot S^{e}\right]$$

$$C(a^{2}/t) = \frac{64\pi^{2}}{3}t^{2} \int_{-\pi/a}^{\pi/a} \frac{d^{4}p}{(2\pi)^{4}} \operatorname{Tr}\left[e^{-2t(S^{f}+\mathscr{G})}\right]$$



Gradient flow at tree level

$$S^{cutoff} \stackrel{}{=} \delta_{\mu\nu} p^2 - p_{\mu} p_{\nu}$$
:

$$\Rightarrow C(a^2/t) = \frac{64}{\pi^2} \left(\frac{t}{a^2}\right)^2 \left(\int_{-\pi/a}^{\pi/a} \frac{dp}{2\pi} e^{-2p^2 t}\right)^4$$



Choose $S^f = S^g = S^e$

Gradient flow at tree level Choose $S^f = S^g = S^e$

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$$S^{Wilson} \stackrel{\circ}{=} \delta_{\mu\nu} \hat{p}^2 - \hat{p}_{\mu} \hat{p}_{\nu}, \quad \hat{p}_{\mu} = 2/a \sin(ap_{\mu}/2)$$

$$\Rightarrow C(a^2/t) = \frac{64}{\pi^2} \left(\frac{t}{a^2}\right)^2 \left(e^{-4t/a^2} I_0\left(4t/a^2\right)\right)^4$$







Gradient flow with FP action Choose $S^f = S^g = S^e = S^{FP}$

Iterating the FP equation in the quadratic approximation:

$$D'_{\mu\nu}(p) = \frac{1}{16} \sum_{l=0}^{1} \left[\omega \left(\frac{p+2\pi l}{2} \right) D \left(\frac{p+2\pi l}{2} \right) \right]$$

After *n* iterations:

$$D_{\mu\nu}^{(n)}(p) \sim \left[\Omega^{(n)}\left(\frac{p+2\pi l}{2^n}\right)\Omega^{(n)\dagger}\left(\frac{p+2\pi l}{2^n}\right)\right]$$

The poles determine the dispersion relation: 0 1 $\forall p$ sums over l generate tower of poles \Rightarrow full relativistic spectrum recovered

$$\Rightarrow C^{FP}(a^2/t) = \frac{64}{\pi^2} \left(\frac{t}{a^2}\right)^2 \left(\int_{-\infty}^{\infty} \frac{dp}{2\pi} e^{-2p^2 t}\right)^4 = 1$$



Part IV: HMC results and GF data





- sample momenta *p*
- integrate eqs of motion (leapfrog, Omelyan)
- correct for *H* non-conservation

$$\langle \exp(-\Delta H) \rangle = 1$$





Gradient Flow (GF)

continuum

$$\frac{dA_{\mu}}{dt} = D_{\nu}G_{\nu\mu} \qquad G_{\mu\nu} = \partial_{\mu}A_{\nu} - \partial_{\nu}A_{\mu} + [A_{\mu}, A_{\nu}] \qquad A_{\mu}(t) \qquad E = \frac{1}{4}G^{a}_{\mu\nu}G^{a}_{\mu\nu}$$

scale definition

 $t^2 \langle E \rangle |_{t_0} = 0.3$



 $t_0 = 0.167 \text{ fm}$ SU(3) gauge theory

$$t\frac{d}{dt}\left(t^2\langle E\rangle\right)|_{t=w_0^2} = 0.3$$

universal value in the continuum limit $a^2/t_0 \rightarrow 0$

Gradient Flow (GF)

how does FP action perform?

ongoing part of project

comparison with independent Wilson gauge action simulations

continuum limit $a^2/t_0 \to 0$

Wilson action: artifacts $O(a^2)$

FP action: artifacts appear to be smaller, consistent with continuum limit at lattice spacing ~ 0.1 fm

Part V: The quantum perfect RG action

The effective action $\beta A_{RT}[V]$ is described by infinitely many couplings $\{c_{\alpha}^{RT}\}$:

 $\exp\left\{-\beta' A'_{RT}[V]\right\} = \left[\mathscr{D}U \exp\left\{-\left(\beta A_{RT}[U] + T[U, V]\right)\right\}\right]$

Two practical problems:

- how to parametrize RT, i.e., which set $\{c_{\alpha}^{RT}\}$?
- how to determine $\{c_{\alpha}^{RT}\}$?

The effective action $\beta A_{RT}[V]$ is described by infinitely many couplings $\{c_{\alpha}^{RT}\}$:

$$\exp\left\{-\beta'\left(A_{RT}'[V^{\epsilon}] - A_{RT}'[V]\right)\right\} = \left\langle \exp\left\{-\left(T[U, V^{\epsilon}] - T[U, V]\right)\right\}\right\rangle_{V}$$

 $\exp\left\{-\beta' A'_{RT}[V]\right\} = \left[\mathscr{D}U \exp\left\{-\left(\beta A_{RT}[U] + T[U, V]\right)\right\}\right]$

Two practical problems:

• how to parametrize RT, i.e., which set $\{c_{\alpha}^{KI}\}$?

• how to determine
$$\{c_{\alpha}^{RT}\}$$
?

 \Rightarrow change of action from change of configuration $V \rightarrow V_{\epsilon}$ via MC simulation:

 \Rightarrow change of action from change of configuration $V \rightarrow V_{c}$:

$$\exp\left\{-\beta'\left(A_{RT}'[V_{\epsilon}] - A_{RT}'[V]\right)\right\} = \left\langle e^{-\left(T[U, V^{\epsilon}] - T[U, V]\right)}\right\rangle_{V}$$

with

$$\left< \mathcal{O} \right>_V = \frac{\int \mathcal{D}Ue^{-\left(\beta A\right)}}{\int \mathcal{D}Ue^{-\left(\beta A\right)}}$$

Note: difference $T[U, V_e] - T[U, V]$ only depends on the blocked link $Q_{\mu}(x_B)[U]$:

 $A_{RT}[U] + T[U, V]) \cdot \mathcal{O}$

 $\left(\beta A_{RT}[U] + T[U,V]\right)$

$$\operatorname{\mathsf{ReTr}}\left(\left\{V_{\mu}^{\epsilon}(x_B) - V_{\mu}(x_B)\right\} \cdot Q_{\mu}^{\dagger}(x_B)\right)$$

 \Rightarrow change of action from change of configuration $V \rightarrow V_{\epsilon}$:

$$\exp\left\{-\beta'\left(A_{RT}'[V^{\epsilon}] - A_{RT}'[V]\right)\right\} = \left\langle e^{-\left(T[U, V^{\epsilon}] - T[U, V]\right)}\right\rangle$$

In practice:

- 1. generate $\{V\}$, e.g., with $\beta' A^{FP}$, at fine lattice spacing a'
- 2. $\forall V$ simulate U with βA^{FP} at finer lattice spacing a = a'/2

3. store $Q_{\mu}(x_B)[U]$ and calculate –

4. repeat with β'' at coarser a'' and simulate $\beta' A'_{RT}$ at a' = a''/2

$$\frac{\delta(\beta' A'_{RT}[V])}{\delta V^a_{x,\mu}} \text{ from } V \to V_{\epsilon}$$
training data for L-CNN!

Conclusions: RG from ML

New technologies enable old ideas:

