Practical applications of machinelearned flows on gauge fields

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Lattice 2023

July 3, 2023

Collaborators (non-exhaustive)



Flows

f: learned, invertible map between gauge fields



...with a tractable Jacobian determinant $J_f(U) = \left| \det \frac{\partial f(U)}{\partial U} \right|$

...maybe equivariant w/r/t symmetries g of interest f(g(U)) = g(f(U))

...with many tunable parameters

Flows

Flows are "bridges" between different distributions/theories/actions



Exact bridge between r and q

Choose r, but flow induces q

For sampling applications: variationally optimize f so $q \approx p \propto e^{-S_p}$

 \rightarrow *Approximate* bridge between r and p

(Approximate) direct sampling with flows Apply f to Haar uniform to get model q, tune f so $q \approx p \propto e^{-S_{\text{target}}}$



Reweight from $q \rightarrow p$ w(U) = p(U) / q(U) $\langle O \rangle_p = \langle wO \rangle_q$

Measure of sampling quality: $ESS = 1/\langle w^2 \rangle_q \in [0,1]$ Intuition: $Var_q[wO] \approx Var_p[O]/ESS$ $ESS \sim 1/2 \tau_{AC}$ (Approximate) direct sampling with flows Apply f to Haar uniform to get model q, tune f so $q \approx p \propto e^{-S_{\text{target}}}$



Numerical details

Wilson pure gauge SU(3)

Sample w/ heatbath (HB) + overrelaxation (OR)

Topological charges

Wilson flow to $t/a^2 = 2$, compute w/ clover definition, round to integer

Residual flows [2305.02402]

Each layer applies a step of gradient flow w/r/t a learned action to a subset of links

 \rightarrow tractable/inexpensive exact Jacobian

Reverse KL self-training

Sample base distribution r w/ HB+OR Train on smaller volumes, then transfer







App 1: Correlated ensembles

Flow an ensemble

→ $\{U\}$ and $\{f(U)\}$ are correlated This is useful!

e.g. for noise cancellation in differences

 $\langle 0 \rangle_p - \langle 0 \rangle_r$

 $= \langle wO \rangle_q - \langle O \rangle_r$ = $\langle w(f(U)) O(f(U)) - O(U) \rangle_{U \sim r}$

Application: Feynman-Hellmann

$$S \to S + \lambda O$$

$$\frac{\partial E_h}{\partial \lambda}\Big|_{\lambda=0} \sim \langle h|O|h\rangle$$

(Complication: involves fits for E_h , but same idea)

See also [Bacchio 2305.07932]



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[QCDSF-UKQCD 1205.6410] 0.584 ε reweighting Flowed & reweighted $\delta S = -\lambda \frac{\beta}{N_c} \left[\sum_i P_{ti} - \sum_{i < j} P_{ij} \right]$ 0.582 Independent ensemble 0.580 ع 0.578 $\langle x \rangle_g^{\text{lat}} = -\frac{2}{3m} \frac{\partial m}{\partial \lambda} \Big|_{\lambda=0} \approx -\frac{2}{3m} \frac{1}{\lambda} [m(\lambda) - m(0)]$ 0.576 0.01 0ε λ Parameters: 8.0 $8^3 \times 16$ $\beta = 6$ $\kappa = 0.132$ (quenched) 0.6 Flow: 0.4 ESS ≈ 0.84 $\langle x \rangle_{g,\pi}^{\text{latt}}$ 0.2 $\lambda = 0.01$ 0.0 $\lambda = 0$ ε reweighting -0.2 Φ Flow -0.4Φ Compute $m(\lambda)$ from $\langle w C^{2\text{pt}} \rangle_q$ Multi-ensemble Dan Hackett - Aug 3 - Lattice 2023

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8

App 2: Transformed Replica EXchange (T-REX)

(REX a.k.a. parallel tempering)

Simultaneously sample chains for different targets



Flow and propose swap

[Invernizzi Krämer Clemente Noé 2210.14104]

App 2: T-REX Results



1 step = 5 HB + 2 OR, propose swaps every 5 steps

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Speed-up for multi-ensemble calculation

T-REX streams correlated (useful!)

Neglecting flow costs!



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Break-even for sampling $\beta = 6.05$

Neglecting flow costs!

T-REX HB only $\beta = 6.05$ 250 -200 \times 3 chains $\tau_{int}(Q)$ (Cost overhead if only keeping $\beta = 6.05$) 50 0 -200 400 600 800 1000 200 400 600 800 0 1000 0

App 3: Parallel Tempering on Boundary Conditions (PTBC)

[Hasenbusch 1706.04443] [Bonnano Bonati D'Elia 2012.14000]

[Boyle T 9:00] [Nada M 14:30]

Introduce localized OBC defect "Poke a hole in the boundary"

→ Faster topological mixing Remove defect w/ REX

Note: **J** other options than OBC defects Other geometries $\beta_{defect} > 0$ May work better(?)



App 3: Defect Repair Replica EXchange (DR-REX)

Train flow to repair defect (Or, multiple flows for several steps of partial repair)

Defect has localized physical effects

Flow acts on subvolume

- \rightarrow No ESS volume scaling
- \rightarrow Volume-independent computational cost







Target: $\beta = 6.3$ on 16^4 Swap AR ~ 23% 2³ OBC defect DR-REX $\beta_d = 0$ DR-REX $\beta_d = 3$ Two flows to repair $\beta_d = 0 \rightarrow 3 \rightarrow 6.3$ 2 animi in Flows act on 8^4 subvolume -2 · -4 PTBC $\beta_d = 0$ PTBC $\beta_d = 3$ Similar swap AR w/o flows 2 · requires 7-8 chains -2 -4



1 step = 1 HB + 5 OR, propose swaps every 10 steps

Target: $\beta = 6.3$ on 16^4 Two flows to repair a 2^3 OBC defect $\beta_d = 0 \rightarrow 3 \rightarrow 6.3$

Flows act on 8⁴ subvolume



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Closing Thoughts

Flows can give useful correlations between ensembles Feynman-Hellmann, continuum/chiral limits, ...

REX makes natural use of flows

Limiting case: direct sampling

See also: CRAFT [Matthews Arbel Rezende Doucet 2201.13117] → SNFs [Nada M 14:30]

- Straightforward generalizations to (pseudo)fermions / QCD Flows for fermions [2106.05934] PFs for gauge fields [2207.08945] QCD [2207.08945]
- PTBC \rightarrow DR-REX: very promising

Flows can make deeper/wider defects practical than w/ REX alone

Stay tuned!