

Applications of machine-learned flows to lattice QCD

The background features two faint, light-gray diagrams. On the left is a neural network diagram with three layers of nodes: the first layer has 4 nodes, the second has 4 nodes, and the third has 4 nodes, with dense connections between adjacent layers. On the right is a lattice QCD diagram showing a 4x4 grid of nodes. Each node is connected to its four nearest neighbors (up, down, left, right) by arrows pointing outwards, representing the lattice structure used in QCD simulations.

Dan Hackett (MIT → FNAL)

Probing the Frontiers of Nuclear Physics with AI at the EIC

Stony Brook / CFNS

September 25, 2023

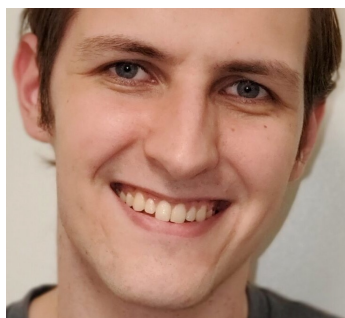
Collaborators (non-exhaustive)



Phiala Shanahan



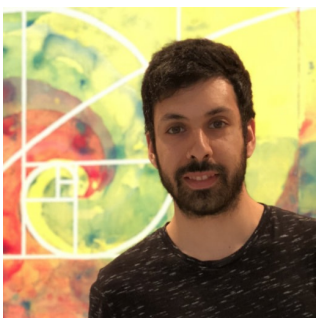
Denis Boyda



Ryan Abbott



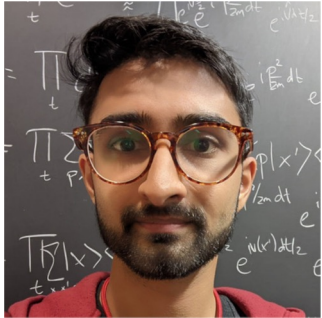
Julian Urban



Fernando Romero-López



Michael Albergo



Gurtej Kanwar



Kyle Cranmer



Sébastien Racanière



Danilo Rezende



Alex Matthews



Aleksandar Botev



Ali Razavi

Quantum Chromodynamics (QCD)

Part of the Standard Model of particle physics

QFT that describes the strong force

Dynamics of quarks & gluons

$SU(3)$ gauge theory

Pen-and-paper calculations don't work

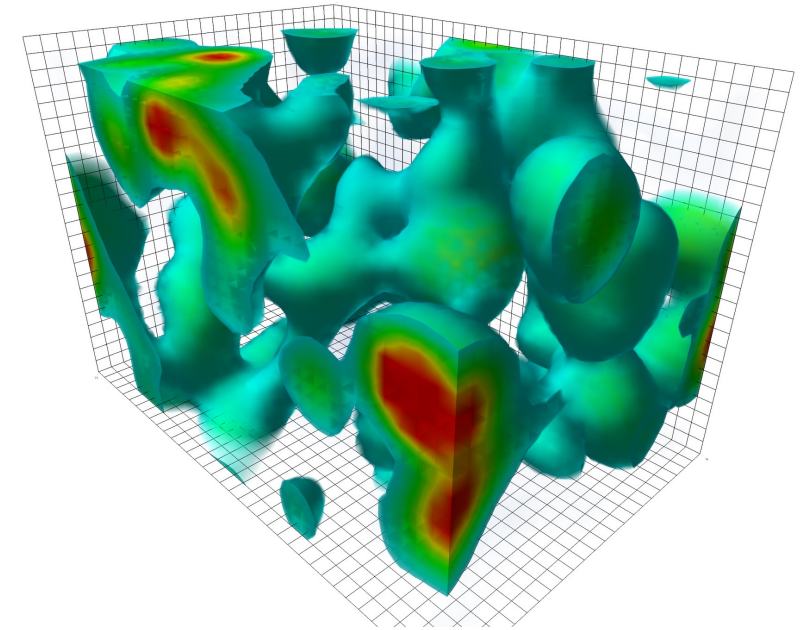
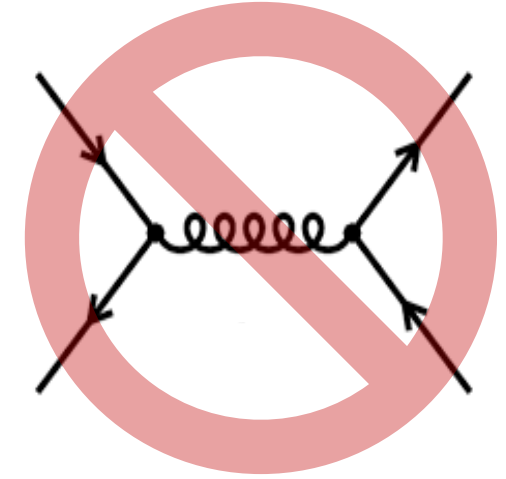
Strongly interacting QFT

Non-perturbative dynamics

Instead: lattice QCD!

Evaluate discretized QCD path integral w/ (MC)MC

Integral part of nuclear/particle theory toolkit



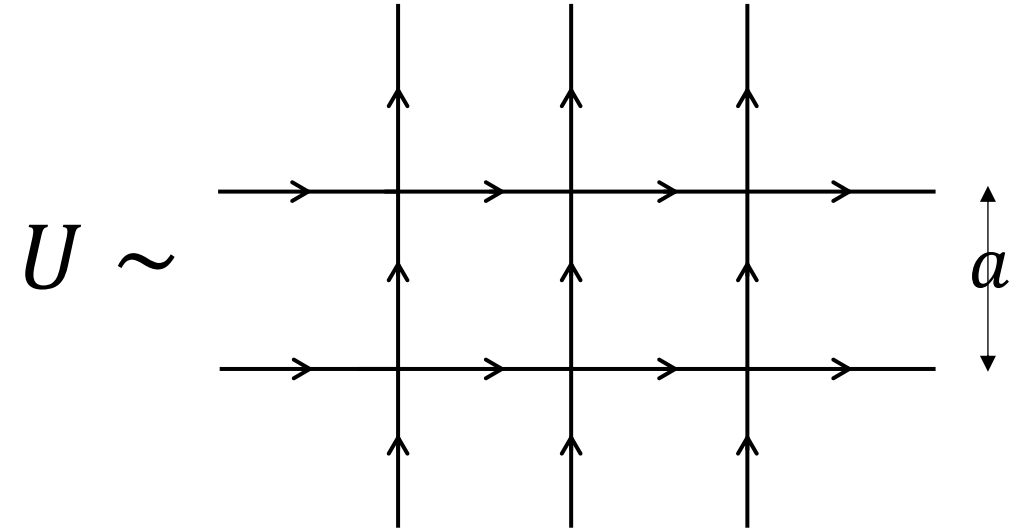
[Visualizations of Quantum Chromodynamics](#)

Lattice QCD

Setup:

- (3+1)d QFT \Rightarrow 4d Stat Mech
- Restrict to finite volume
- Discretize spacetime

Discretized gluon (gauge) field



Use Monte Carlo to (path) integrate over discretized fields:

$$\langle \mathcal{O} \rangle = \int d[U] \frac{1}{Z} e^{-S[U]} \mathcal{O}(U) \equiv \int d[U] p(U) \mathcal{O}(U) \approx \frac{1}{N} \sum_{i=1}^N \mathcal{O}(U_i)$$

\rightarrow Numerical QFT on supercomputers!

Workflow of a lattice calculation

1. Configuration generation

Sample ensembles of gauge fields w/ MCMC
...for different lattice spacings, m_q , V

2. Observable measurements

Evaluate n -point functions on e/a config
→ compute expectations

3. Analysis

Extract hadronic properties (masses, matrix elements, etc)
Extrapolate to physical limit

Workflow of a lattice calculation

1. Configuration generation

Sample ensembles of gauge fields w/ MCMC
...for different lattice spacings, m_q , V

2. Observable measurements

Evaluate n -point functions on e/a config
→ compute expectations

3. Analysis

Extract hadronic properties (masses, matrix elements, etc)
Extrapolate to physical limit



Expensive!

Workflow of a lattice calculation

1. Configuration generation

Sample ensembles of gauge fields w/ MCMC
...for different lattice spacings, m_q , V

2. Observable measurements

Evaluate n -point functions on e/a config
→ compute expectations

3. Analysis

Extract hadronic properties (masses, matrix elements, etc)
Extrapolate to physical limit

Accelerate
with ML?

Expensive!

Topological freezing

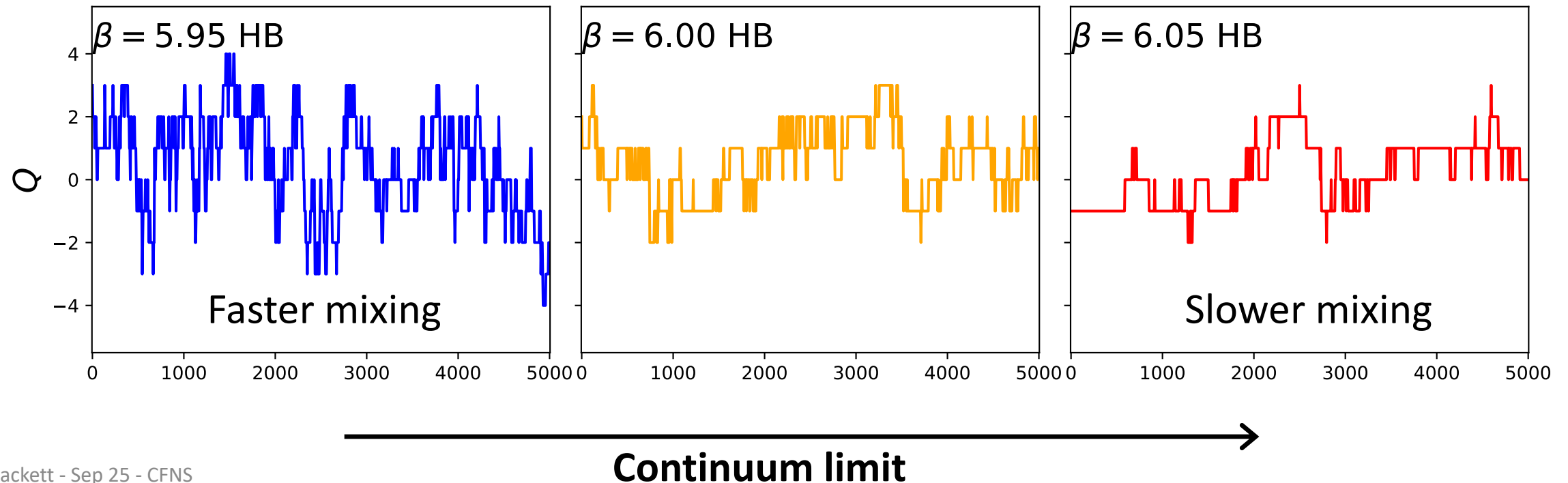
Problem: gauge field distribution is multimodal

Must sample different **topological sectors**

Exponential slowdown of tunneling between sectors w/ standard MCMC algos

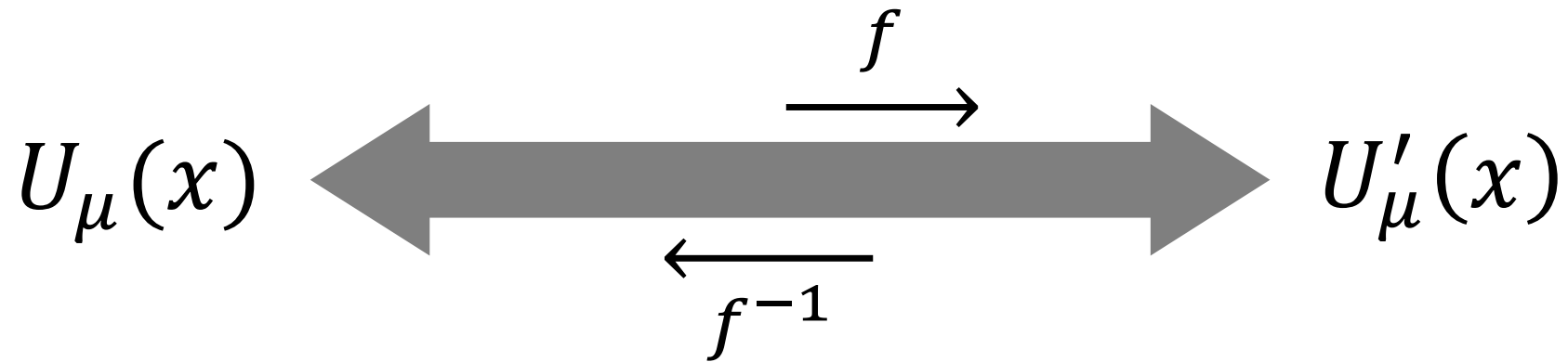
Can result in *effective* loss of ergodicity [2202.1172]

→ Apparent convergence to wrong answers at achievable sample sizes



A New Tool: Machine-learned Flows

f : learned, invertible (diffeomorphic) map between gauge field configs




...with many tunable parameters \rightarrow ML

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

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

A New Tool: Machine-learned Flows

Flows are “bridges” between different distributions/theories/actions

$$r(U) = \frac{e^{-S_r(U)}}{Z_r} \quad \begin{array}{c} \xrightarrow{f} \\ \xleftarrow{f^{-1}} \end{array} \quad q(U') = \frac{r(U)}{J_f(U)}$$


Exact bridge between r and q

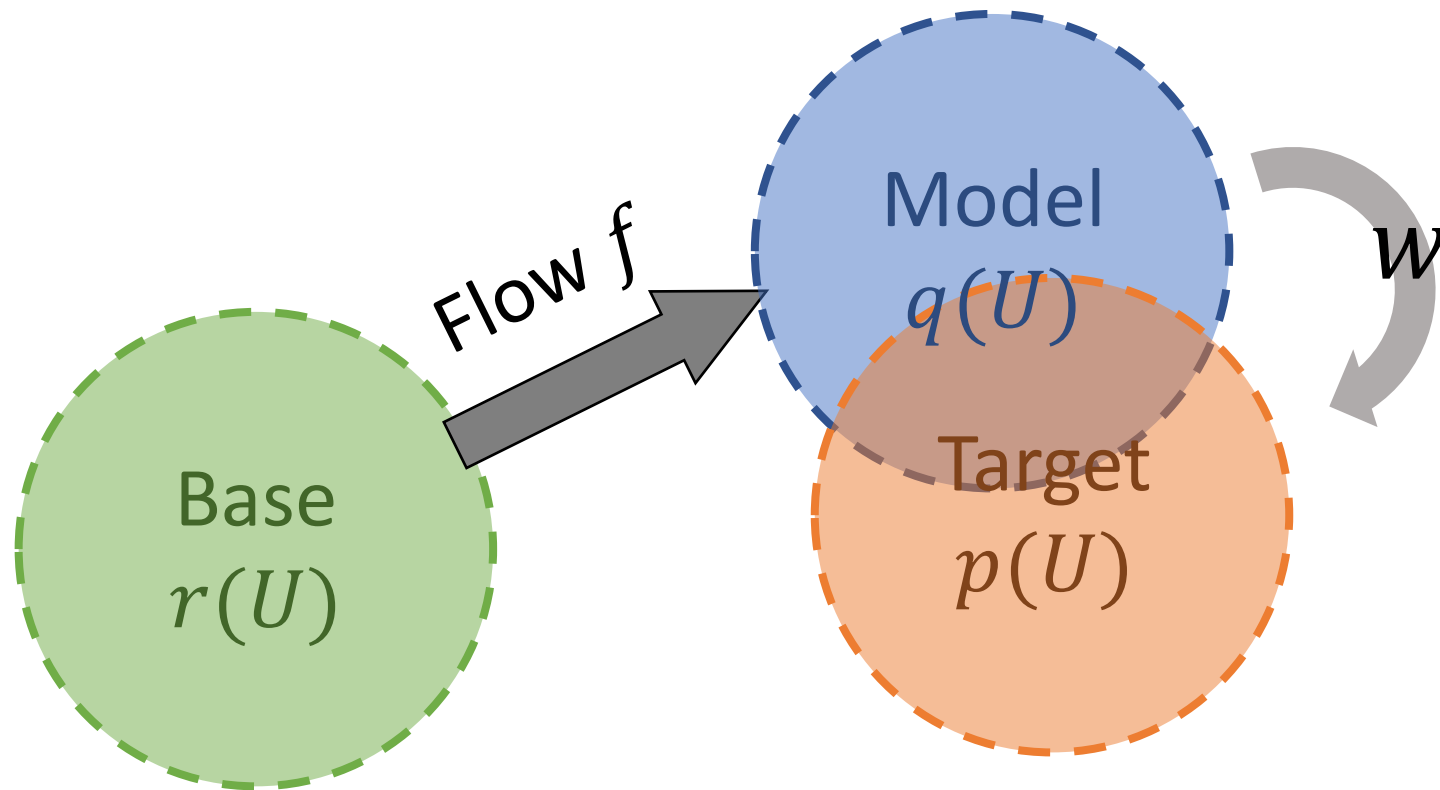
Choose r , but flow induces q

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

→ *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 $q \rightarrow p$

$$w(U) = p(U) / q(U)$$

$$\langle O \rangle_p = \langle wO \rangle_q$$

Or, \sim equivalently,
Metropolize

→ Flow-based MCMC

a.k.a. neural MCMC

a.k.a. ...

Progress so far

Flows for LQFT (scalar field theories)

[\[1904.12072\]](#) [\[2107.00734\]](#) [\[2211.07541\]](#)

Gauge-equivariant flows

U(1) [\[2003.06413\]](#)

SU(N) [\[2003.06413\]](#) [\[2305.0242\]](#)

Flows for fermionic theories

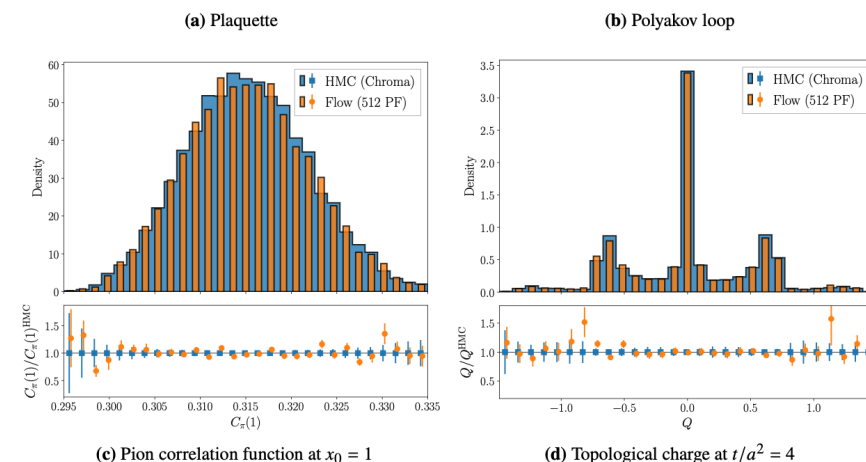
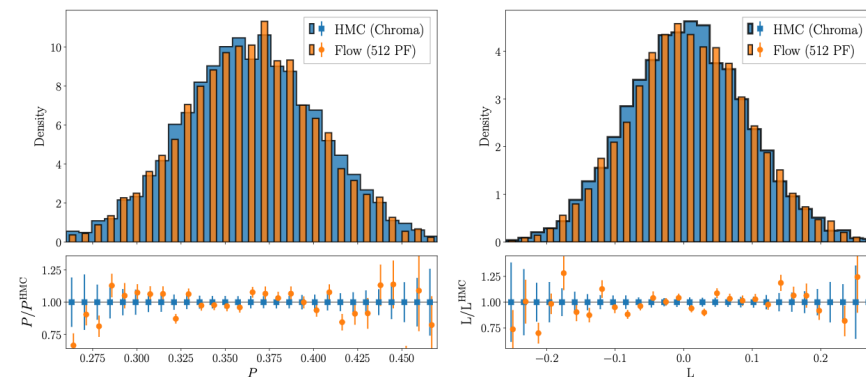
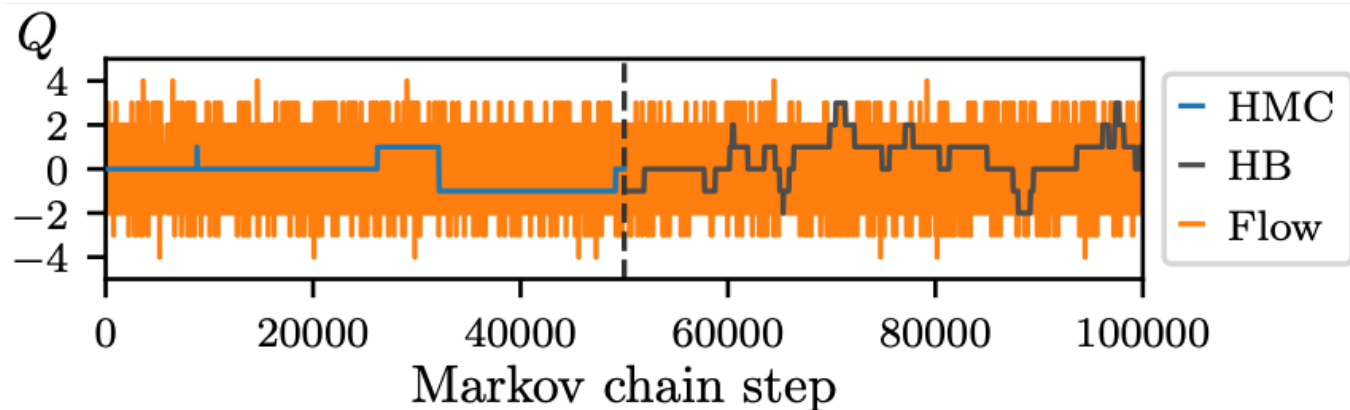
Yukawa model [\[2106.05934\]](#)

Schwinger model [\[2202.11712\]](#)

Stochastic methods for fermions [\[2207.08945\]](#)

→ First demonstration for QCD! [\[2208.03832\]](#)

Result: Improved sampling in (1+1)d U(1) gauge theory



Progress so far

Flows for LQFT (scalar field theories)

[\[1904.12072\]](#) [\[2107.00734\]](#) [\[2211.07541\]](#)

Gauge-equivariant flows

U(1) [\[2003.06413\]](#)

SU(N) [\[2003.06413\]](#) [\[2205.0242\]](#)

Flows for fermionic theories

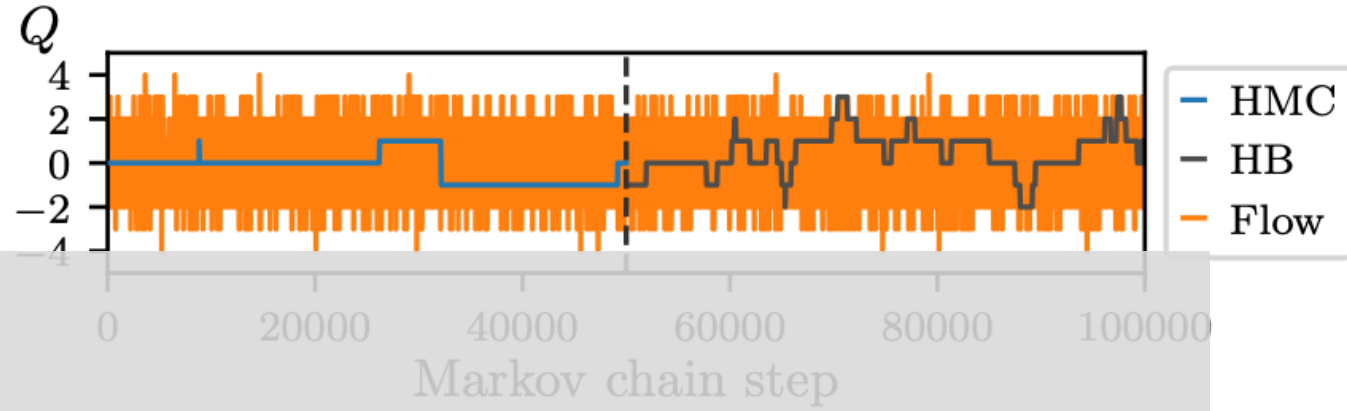
Yukawa model [\[2109.05954\]](#)

Schwinger model [\[2207.11712\]](#)

Stochastic methods for fermions [\[2207.08945\]](#)

→ First demonstration for QCD! [\[2208.03832\]](#)

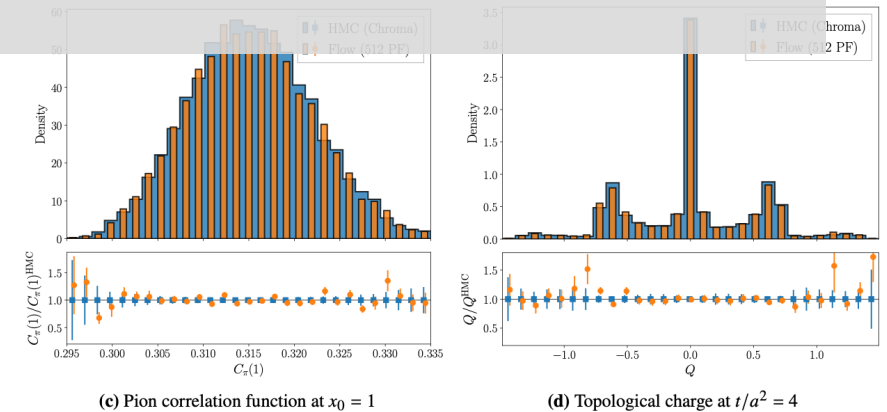
Result: Improved sampling in (1+1)d U(1) gauge theory



Towards state-of-the-art scales:

1. Better QCD models (Denis's talk)

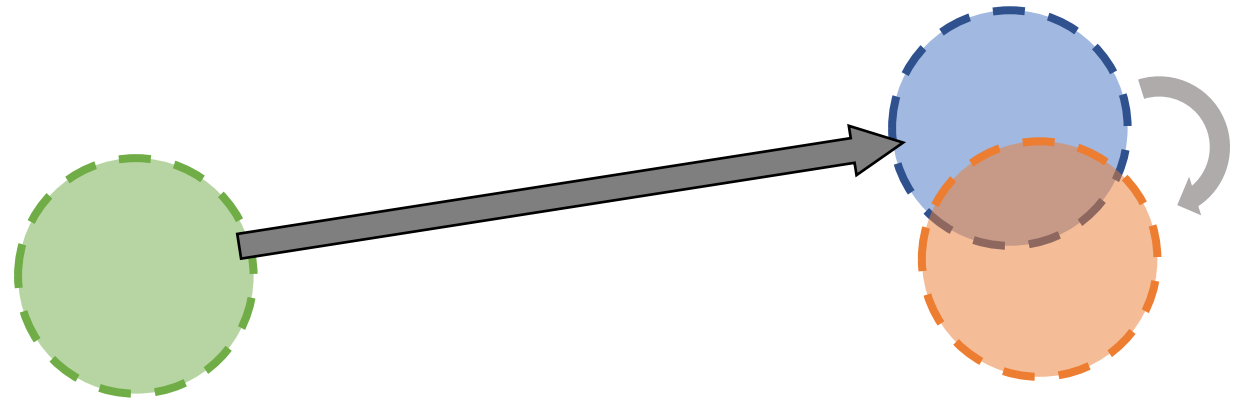
2. Different algorithmic use cases for flows



Applications

Basic idea: don't flow as far

→ 3x demos



Target theory: $SU(3)$ gluodynamics

Avoid fermionic complications (for now)

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

“Residual flows” [2305.02402]

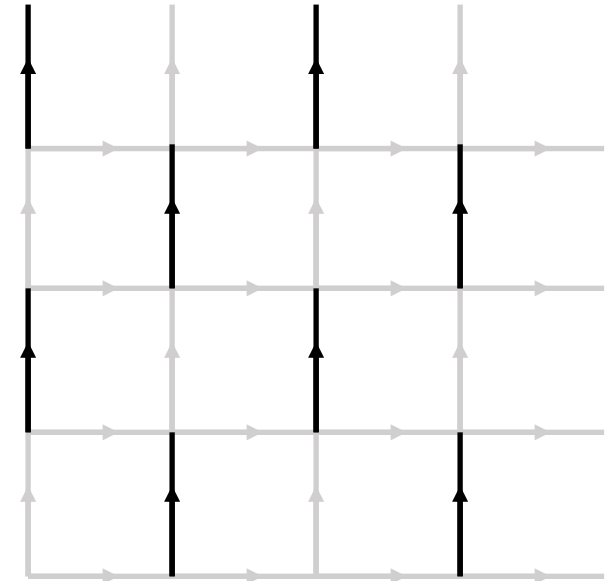
~ ODE flow + variable partitioning (cf. coupling layers)

→ tractable/inexpensive exact Jacobian

Features:

Gauge equivariant flows

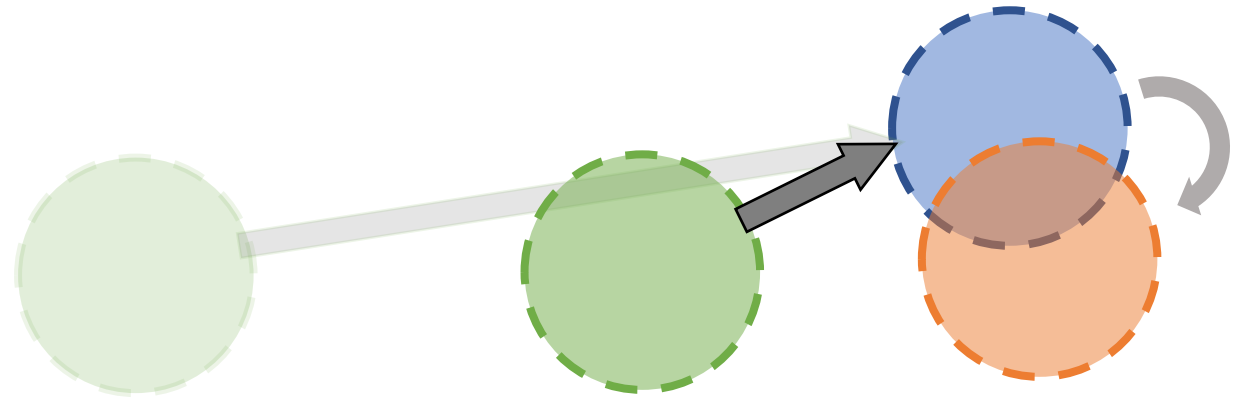
Translationally invariant \leftrightarrow volume transferrable



Applications

Basic idea: don't flow as far

→ 3x demos



Target theory: $SU(3)$ gluodynamics

Avoid fermionic complications (for now)

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

“Residual flows” [2305.02402]

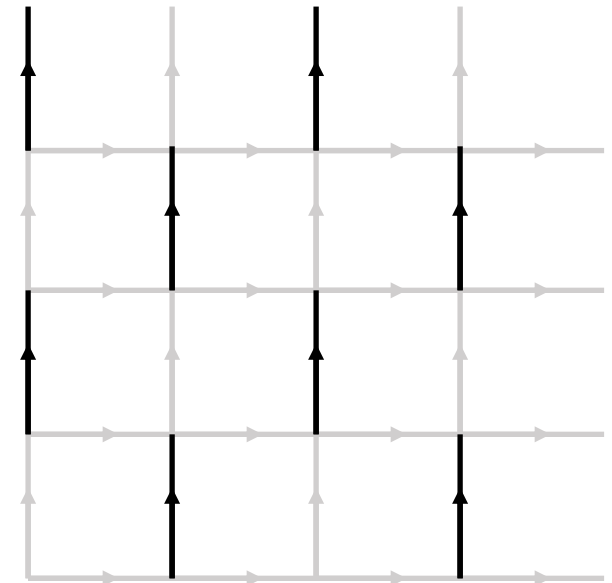
~ ODE flow + variable partitioning (cf. coupling layers)

→ tractable/inexpensive exact Jacobian

Features:

Gauge equivariant flows

Translationally invariant \leftrightarrow volume transferrable



App 1: Correlated ensembles

Flow an ensemble

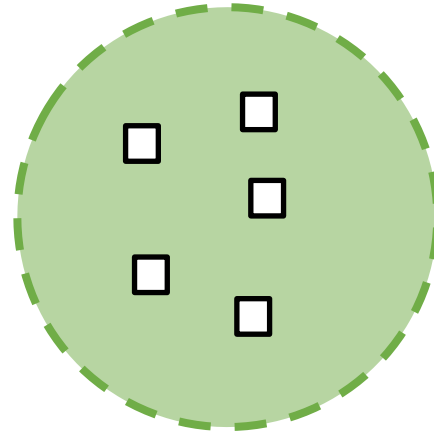
→ $\{U\}$ and $\{f(U)\}$ are correlated

This is useful!

e.g. for noise cancellation in differences

$$\begin{aligned} & \langle O \rangle_p - \langle O \rangle_r \\ &= \langle wO \rangle_q - \langle O \rangle_r \\ &= \langle w(f(U)) O(f(U)) - O(U) \rangle_{U \sim r} \end{aligned}$$

$$\{U\} \sim r$$



Application: Feynman-Hellmann

$$S \rightarrow S + \lambda O$$

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

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

See also [Bacchio 2305.07932]

App 1: Correlated ensembles

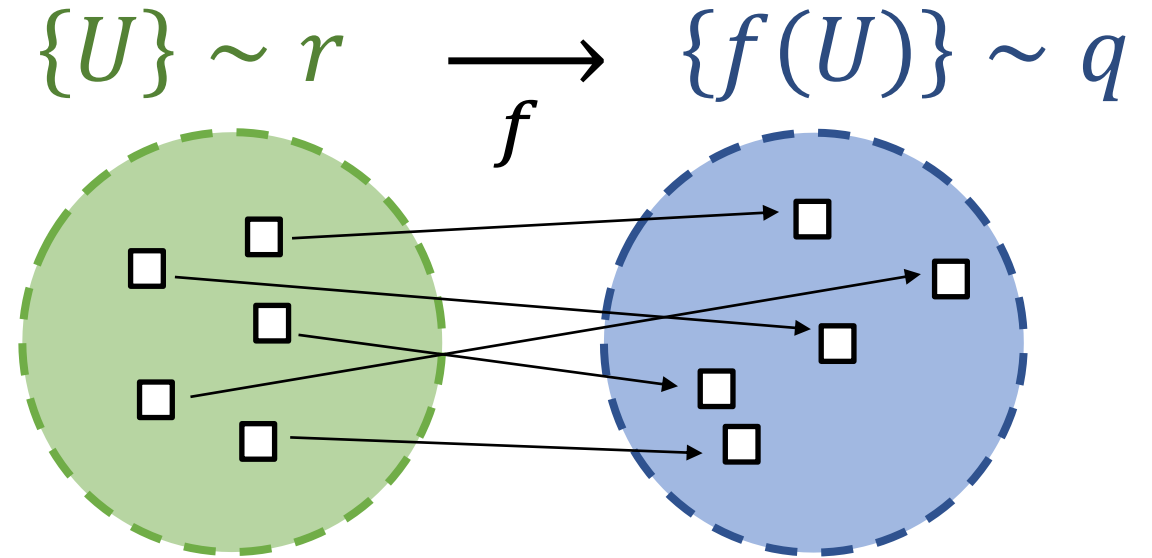
Flow an ensemble

→ $\{U\}$ and $\{f(U)\}$ are correlated

This is useful!

e.g. for noise cancellation in differences

$$\begin{aligned} & \langle O \rangle_p - \langle O \rangle_r \\ &= \langle wO \rangle_q - \langle O \rangle_r \\ &= \langle w(f(U)) O(f(U)) - O(U) \rangle_{U \sim r} \end{aligned}$$



Application: Feynman-Hellmann

$$S \rightarrow S + \lambda O$$

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

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

See also [Bacchio 2305.07932]

App 1: Correlated ensembles

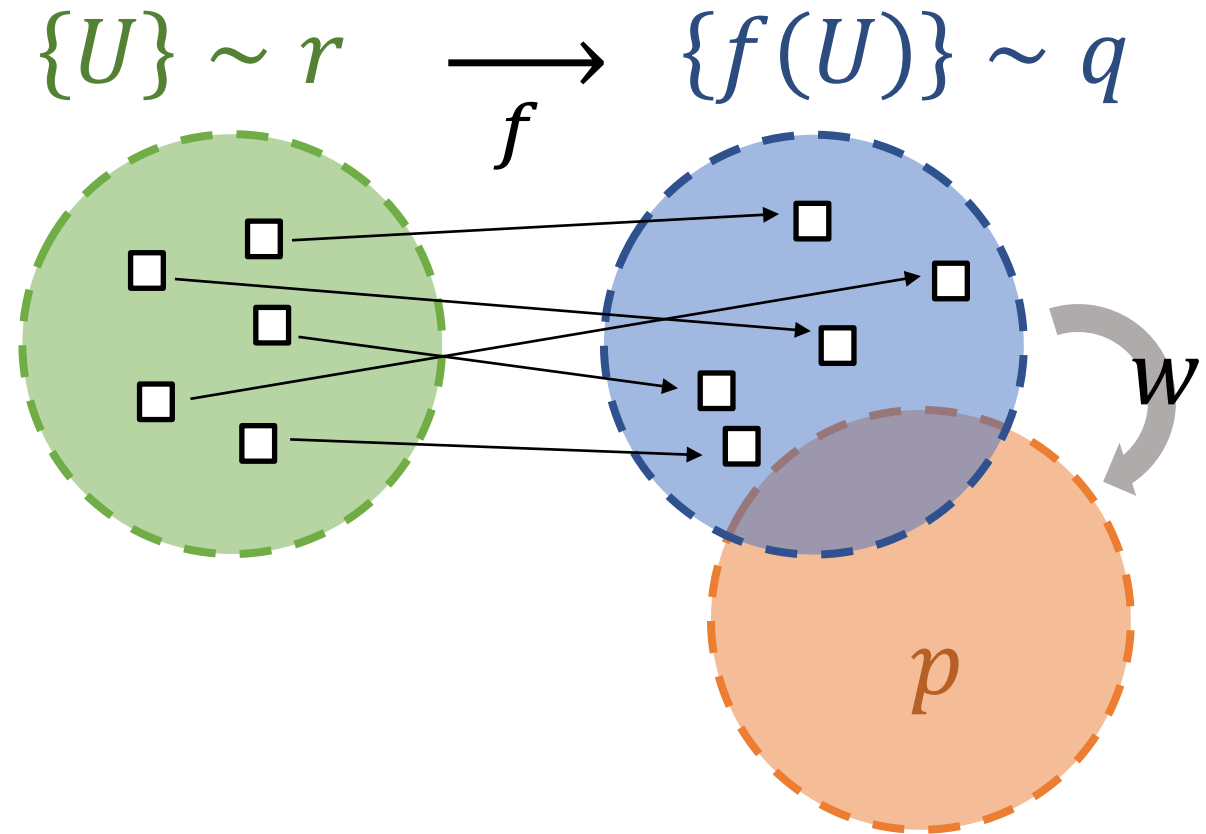
Flow an ensemble

→ $\{U\}$ and $\{f(U)\}$ are correlated

This is useful!

e.g. for noise cancellation in differences

$$\begin{aligned} & \langle O \rangle_p - \langle O \rangle_r \\ &= \langle wO \rangle_q - \langle O \rangle_r \\ &= \langle w(f(U)) O(f(U)) - O(U) \rangle_{U \sim r} \end{aligned}$$



Application: Feynman-Hellmann

$$S \rightarrow S + \lambda O$$

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

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

See also [Bacchio 2305.07932]

App 1: Pion $\langle x \rangle_g$ w/ flowed Feynman-Hellmann

[QCDSF-UKQCD 1205.6410]

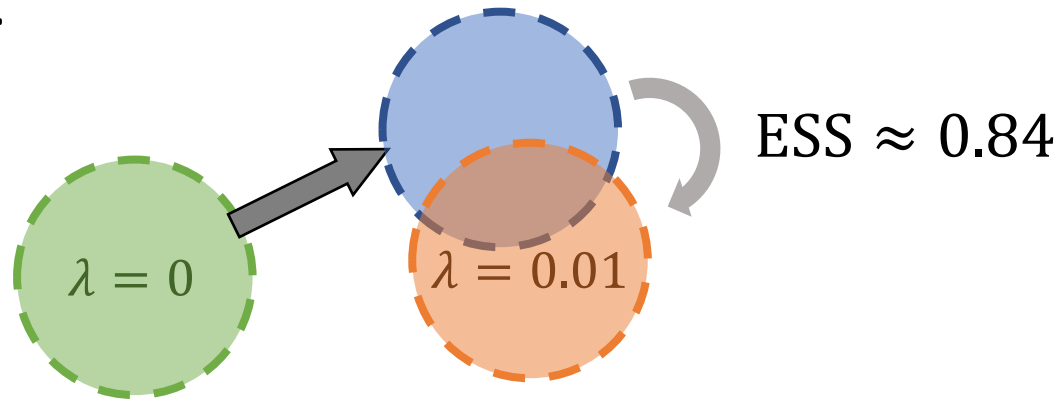
Spatial-temporal anisotropy: $\delta S = -\lambda \frac{\beta}{N_c} [\sum_i P_{ti} - \sum_{i<j} P_{ij}]$

$$\langle x \rangle_g^{\text{lat}} = -\frac{2}{3m} \frac{\partial m}{\partial \lambda} \Big|_{\lambda=0} \approx -\frac{2}{3m} \frac{1}{\lambda} [m(\lambda) - m(0)]$$

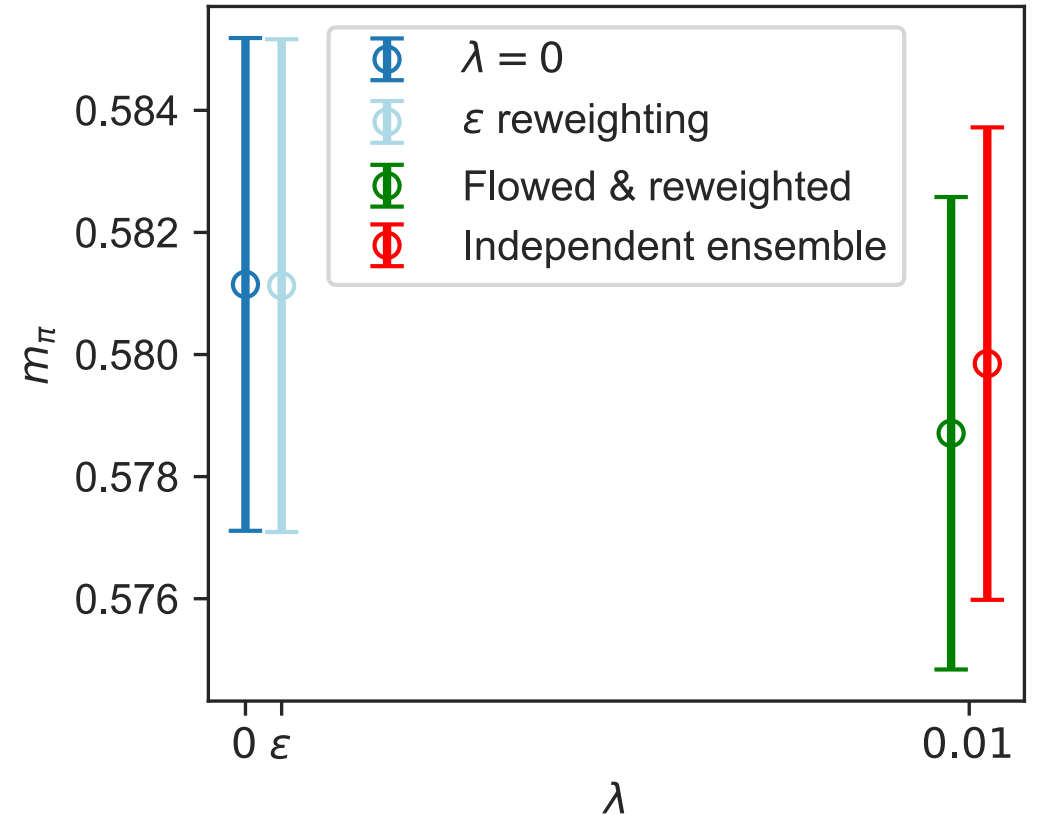
Parameters:

$$8^3 \times 16 \quad \beta = 6 \quad \kappa = 0.132 \text{ (quenched)}$$

Flow:



Compute $m(\lambda)$ from $\langle w C^{2\text{pt}} \rangle_q$



App 1: Pion $\langle x \rangle_g$ w/ flowed Feynman-Hellmann

[QCDSF-UKQCD 1205.6410]

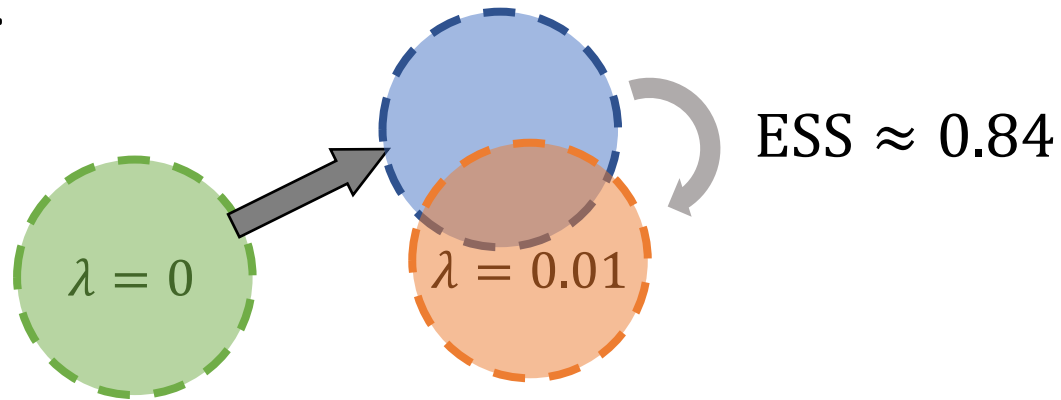
Spatial-temporal anisotropy: $\delta S = -\lambda \frac{\beta}{N_c} [\sum_i P_{ti} - \sum_{i<j} P_{ij}]$

$$\langle x \rangle_g^{\text{lat}} = -\frac{2}{3m} \frac{\partial m}{\partial \lambda} \Big|_{\lambda=0} \approx -\frac{2}{3m} \frac{1}{\lambda} [m(\lambda) - m(0)]$$

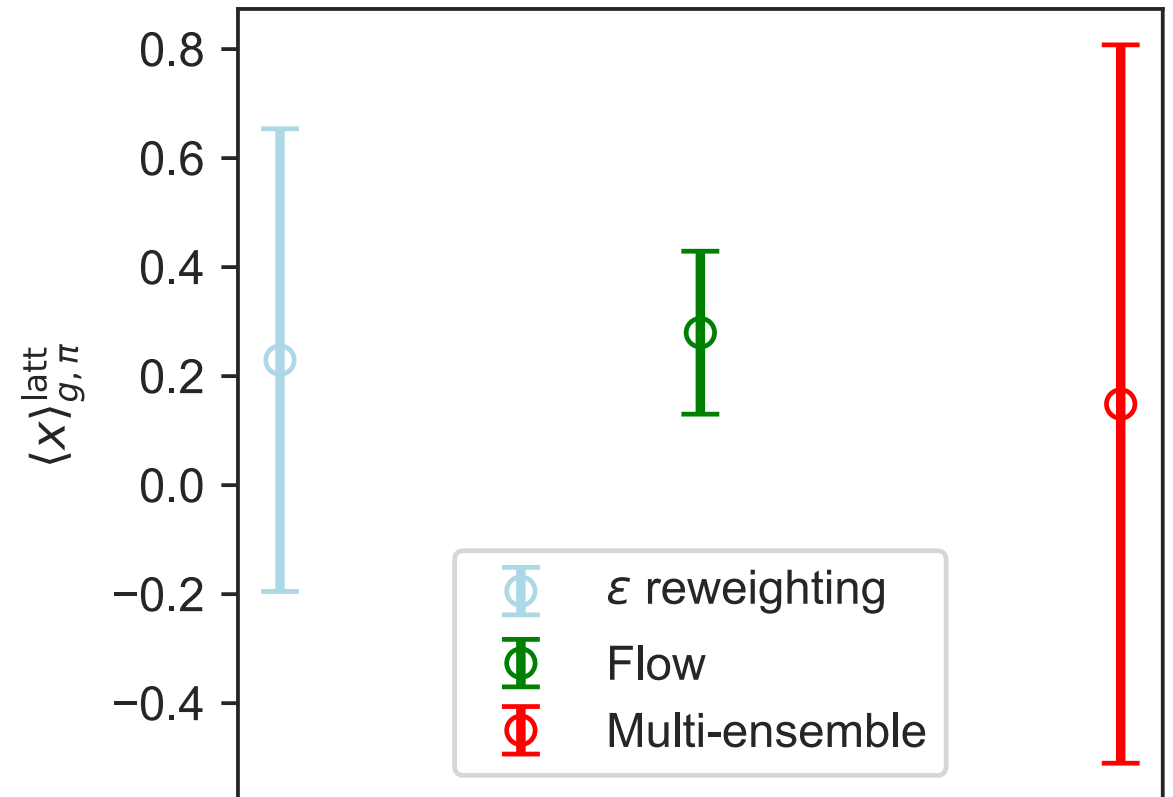
Parameters:

$$8^3 \times 16 \quad \beta = 6 \quad \kappa = 0.132 \text{ (quenched)}$$

Flow:



Compute $m(\lambda)$ from $\langle w C^{2\text{pt}} \rangle_q$



App 1: Pion $\langle x \rangle_g$ w/ flowed Feynman-Hellmann

[QCDSF-UKQCD 1205.6410]

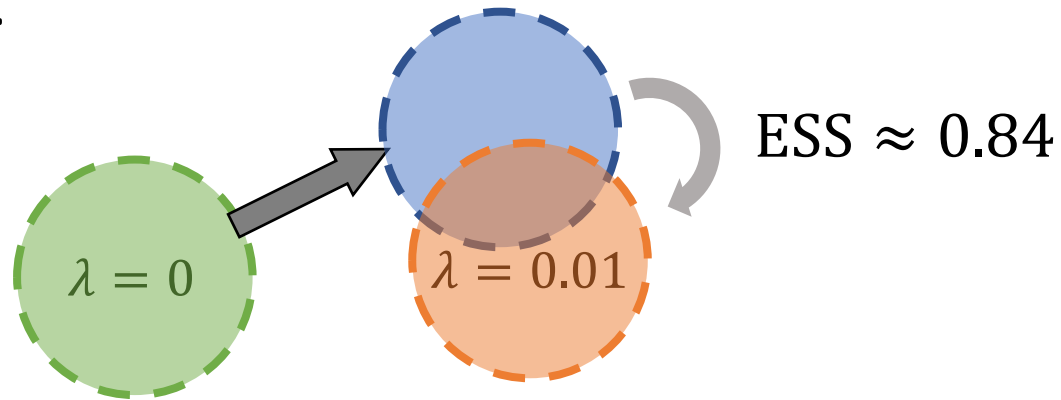
Spatial-temporal anisotropy: $\delta S = -\lambda \frac{\beta}{N_c} [\sum_i P_{ti} - \sum_{i<j} P_{ij}]$

$$\langle x \rangle_g^{\text{lat}} = -\frac{2}{3m} \frac{\partial m}{\partial \lambda} \Big|_{\lambda=0} \approx -\frac{2}{3m} \frac{1}{\lambda} [m(\lambda) - m(0)]$$

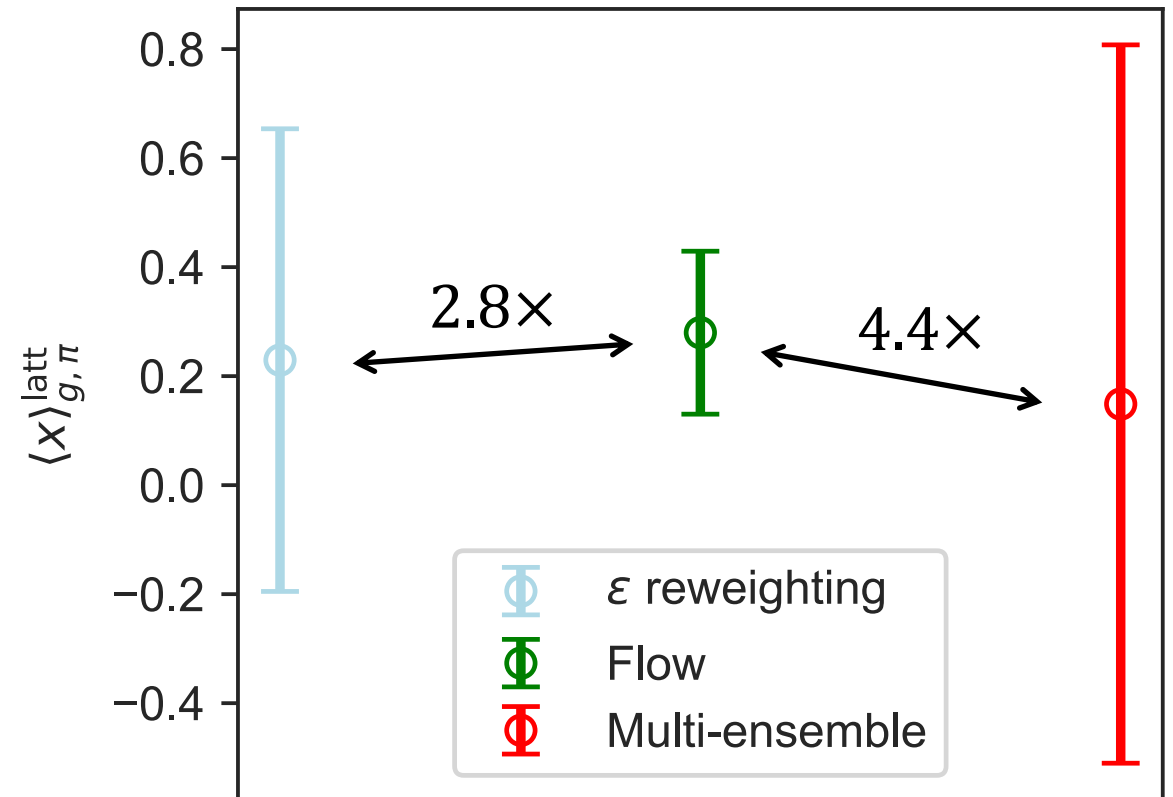
Parameters:

$$8^3 \times 16 \quad \beta = 6 \quad \kappa = 0.132 \text{ (quenched)}$$

Flow:



Compute $m(\lambda)$ from $\langle w C^{2\text{pt}} \rangle_q$

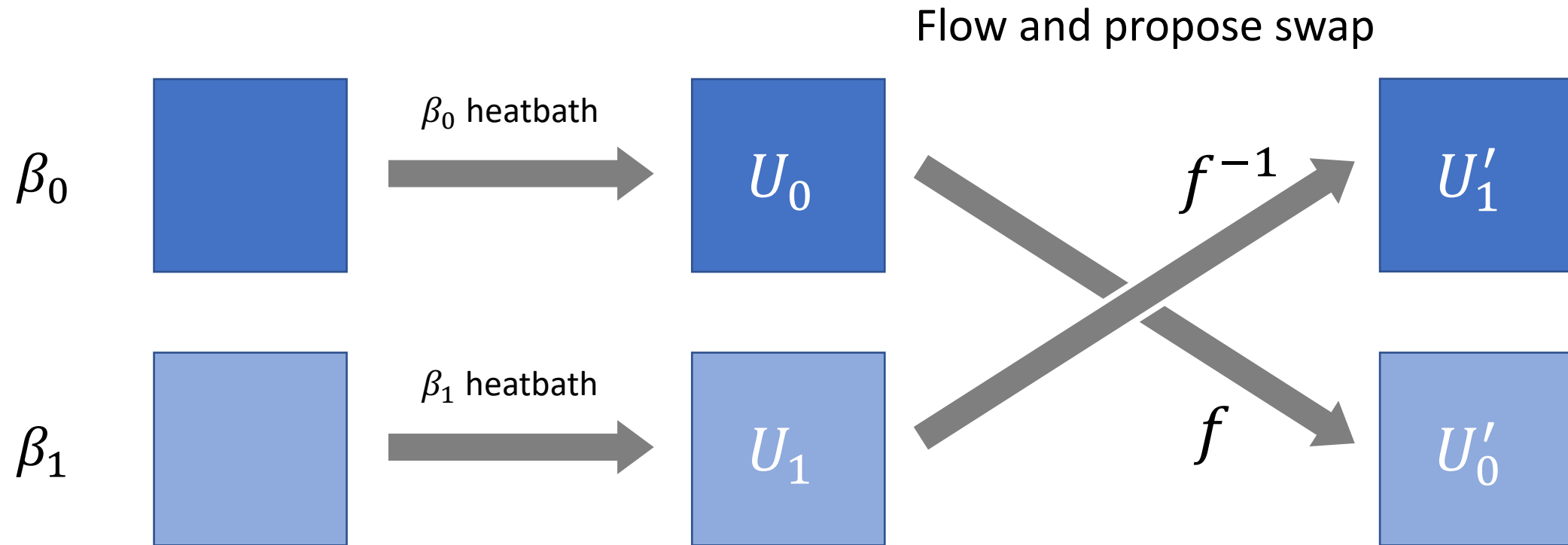


App 2: Transformed Replica EXchange (T-REX)

(REX a.k.a. parallel tempering)

[Invernizzi Krämer Clemente Noé 2210.14104]

Simultaneously sample chains for different targets



$$p_{\text{acc}} = \min \left[1, \frac{p_0(U'_1) p_1(U'_0)}{p_0(U_0) p_1(U_1)} J_f(U_0) J_{f^{-1}}(U_1) \right]$$

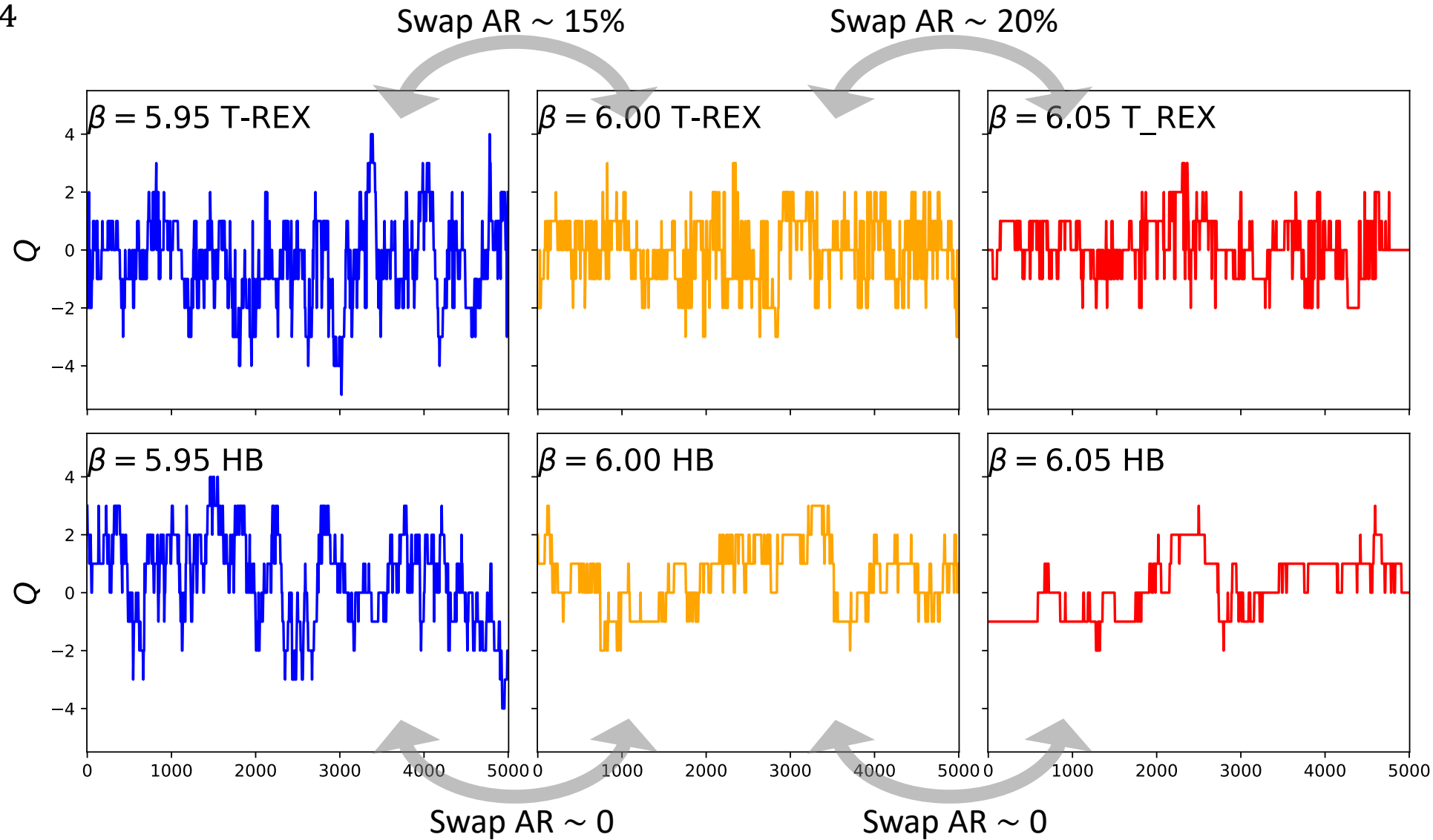
App 2: T-REX Results

Three target β s on 12^4

Two different flows

$5.95 \leftrightarrow 6$

$6 \leftrightarrow 6.05$



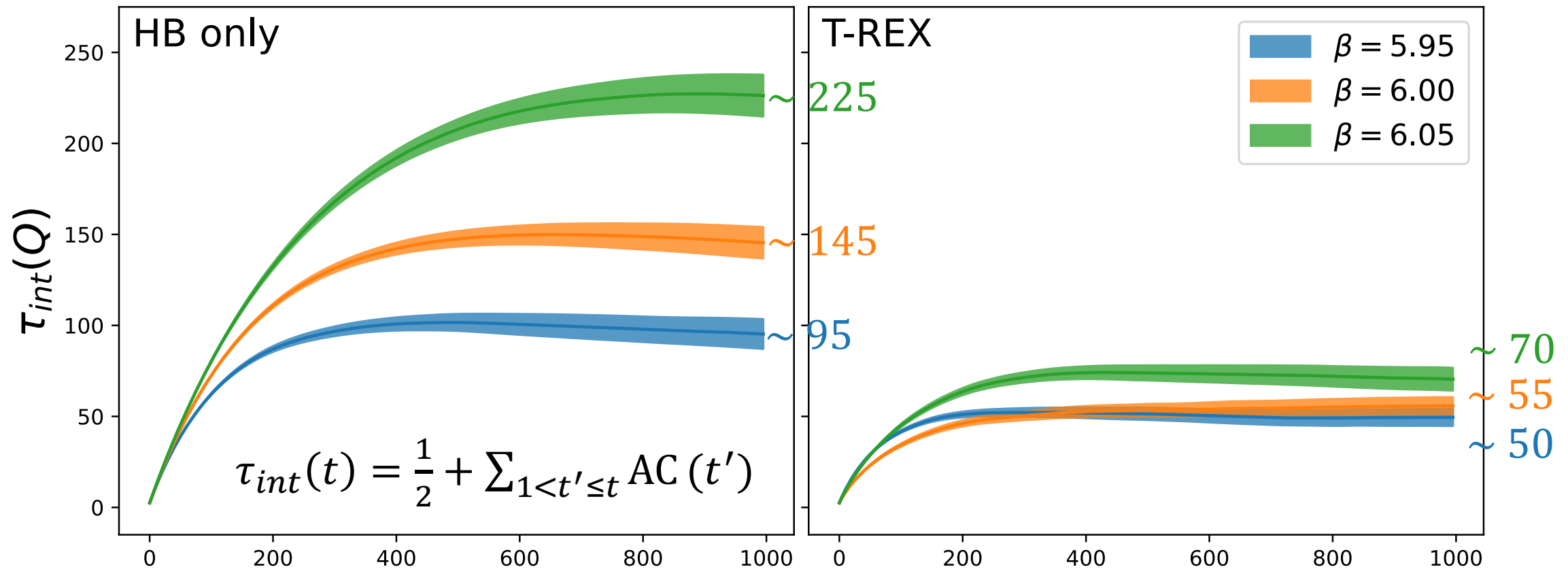
1 step = 5 HB + 2 OR, propose swaps every 5 steps

App 2: T-REX Results

Speed-up for multi-ensemble calculation

T-REX streams correlated (useful!)

Neglecting flow costs!



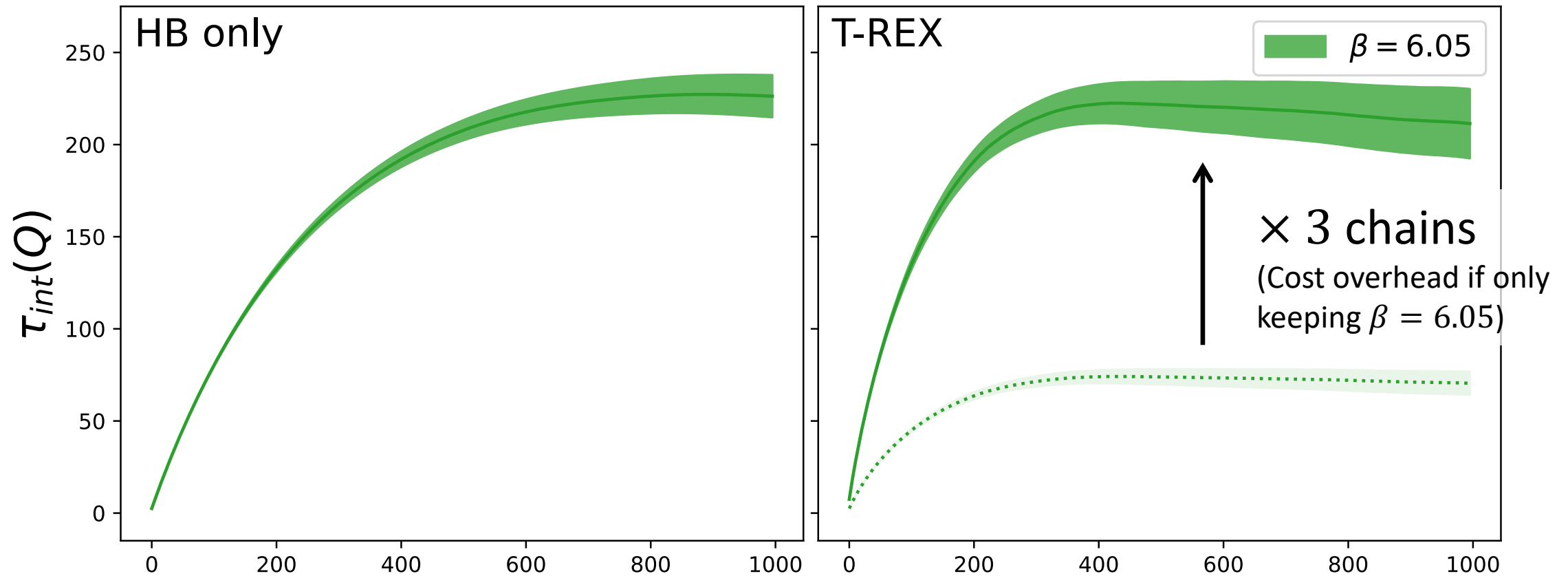
App 2: T-REX Results

Speed-up for multi-ensemble calculation

T-REX streams correlated (useful!)

Break-even for sampling $\beta = 6.05$

} Neglecting flow costs!



App 3: Parallel Tempering on Boundary Conditions (PTBC)

[Hasenbusch 1706.04443]

[Bonnano Bonati D'Elia 2012.14000]

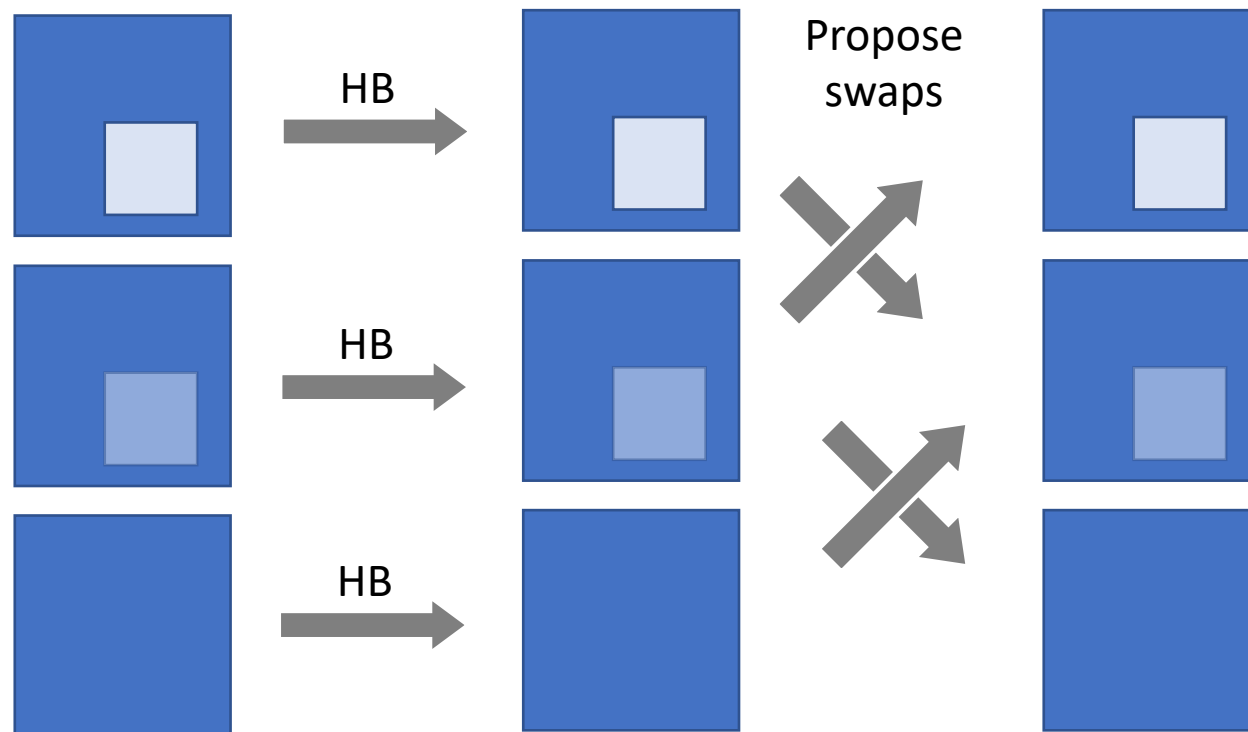
Introduce localized defect

$$\beta_{\text{defect}} < \beta_{\text{target}}$$

“Poke a hole in the boundary”

→ Faster topological mixing

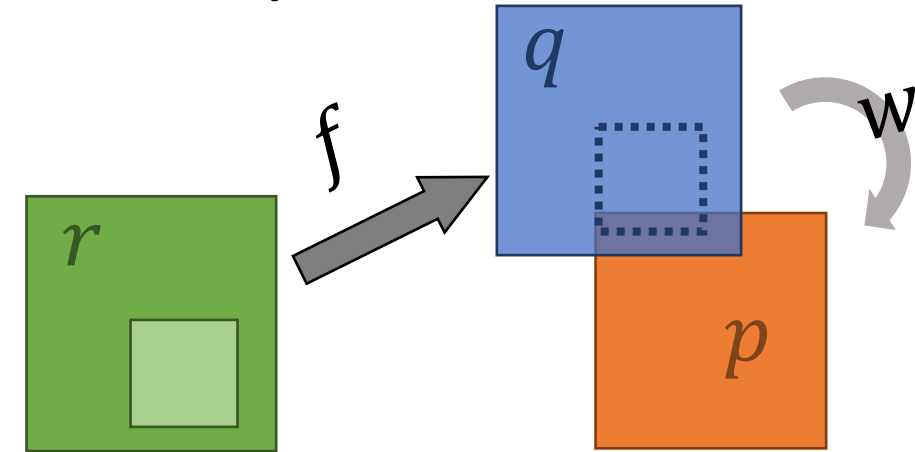
Remove defect w/ REX



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

Train flow to repair defect

(Or, multiple flows for several steps of partial repair)

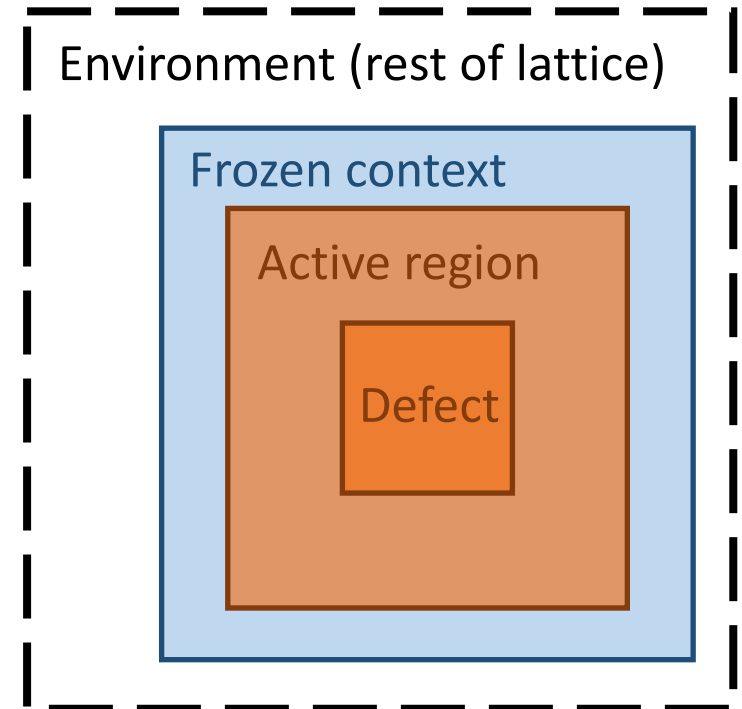


Defect has localized physical effects

Flow acts on subvolume

→ No ESS volume scaling

→ Volume-independent computational cost



App 3: DR-REX Results

Target: $\beta = 6.3$ on 16^4

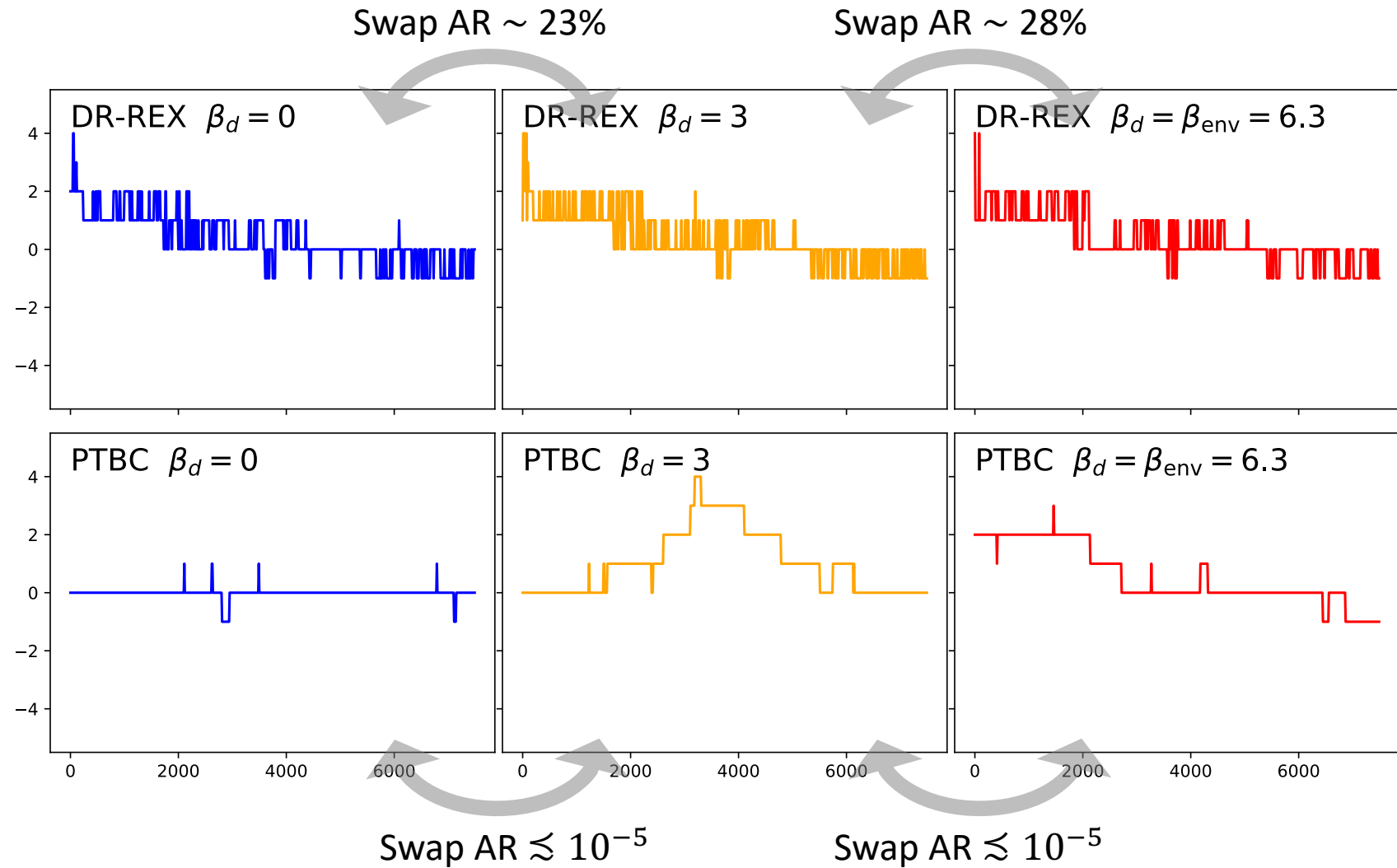
2^3 OBC defect

Two flows to repair

$$\beta_d = 0 \rightarrow 3 \rightarrow 6.3$$

Flows act on 8^4 subvolume

Similar swap AR w/o flows
requires 7-8 chains



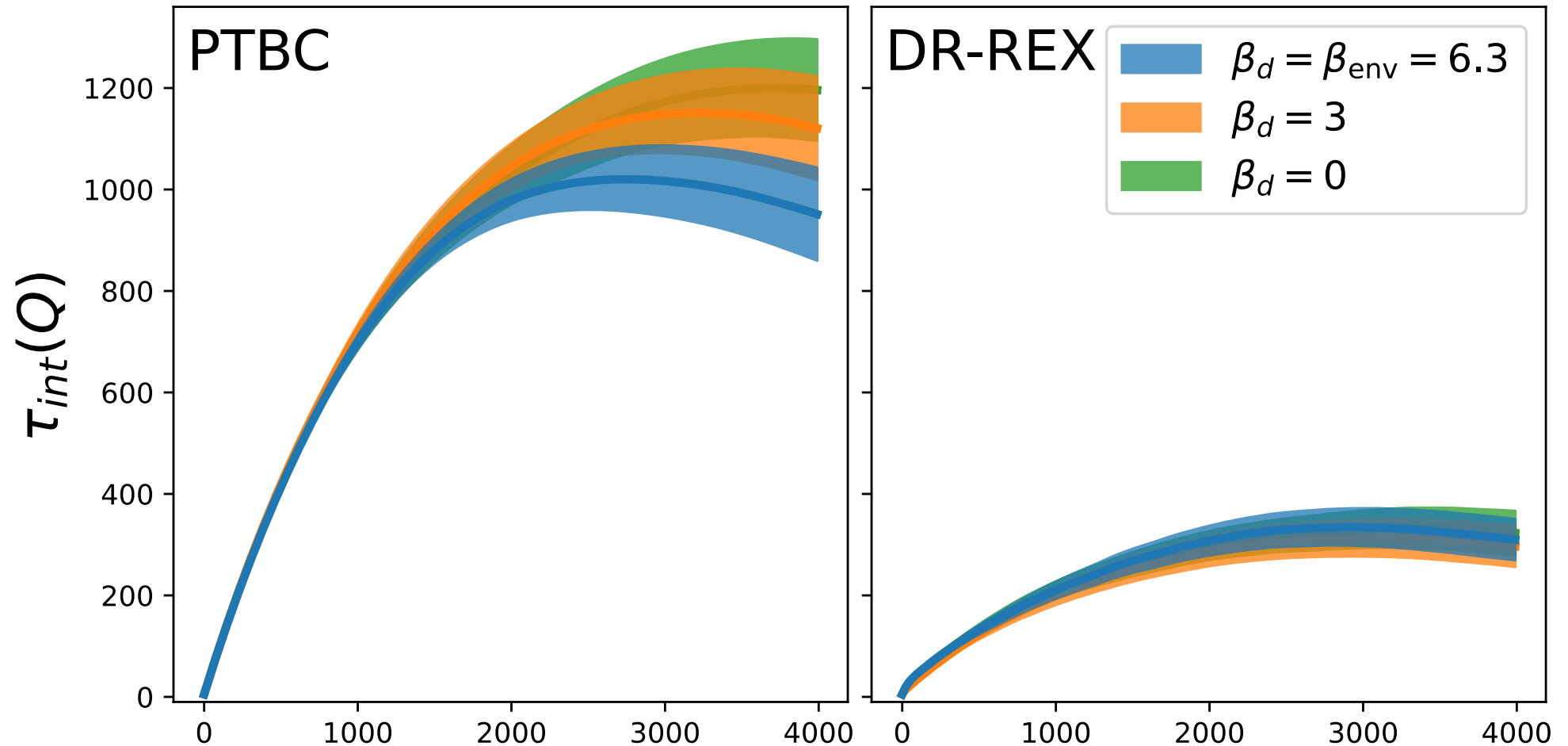
1 step = 1 HB + 5 OR, propose swaps every 10 steps

App 3: DR-REX Results

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 8^4 subvolume

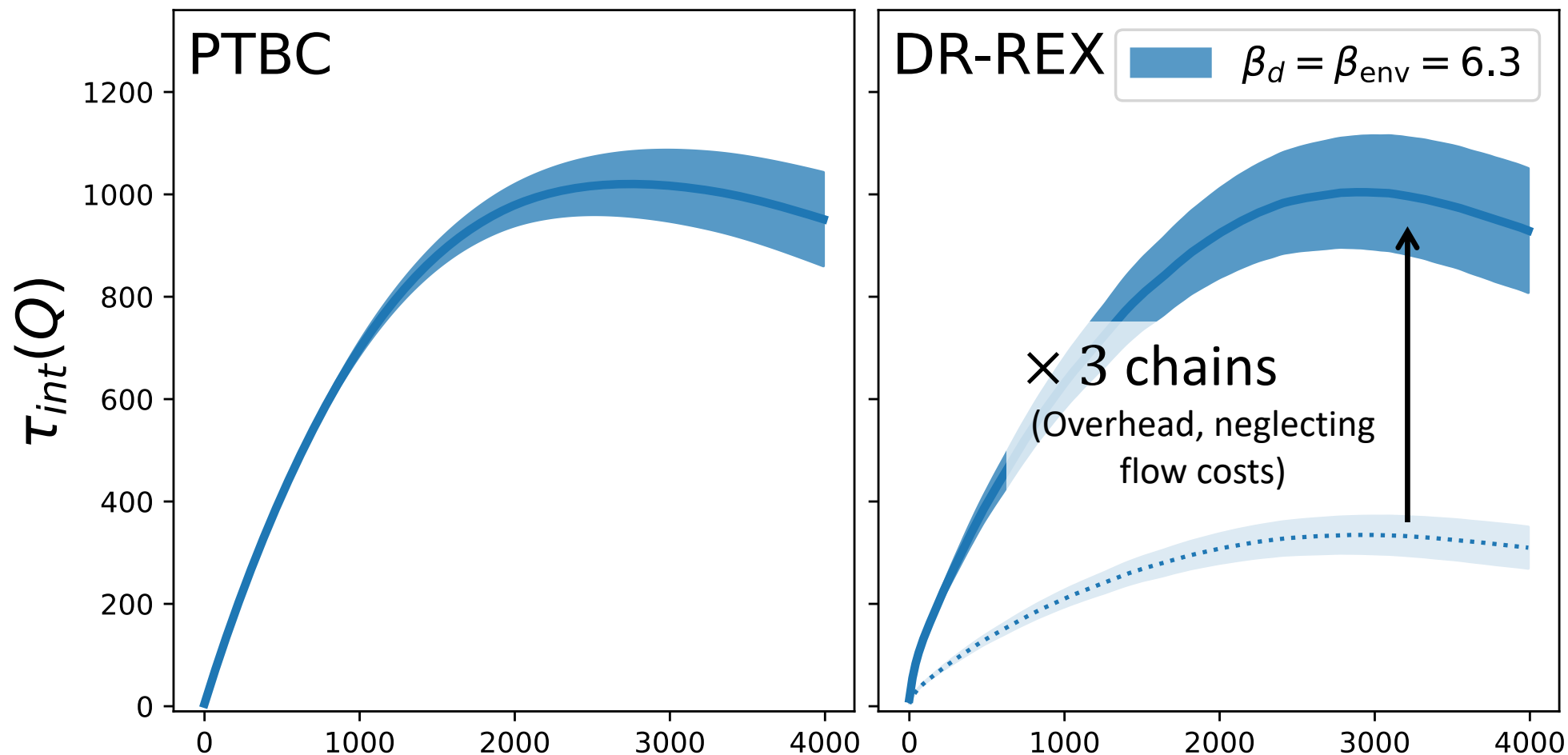


App 3: DR-REX Results

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 8^4 subvolume

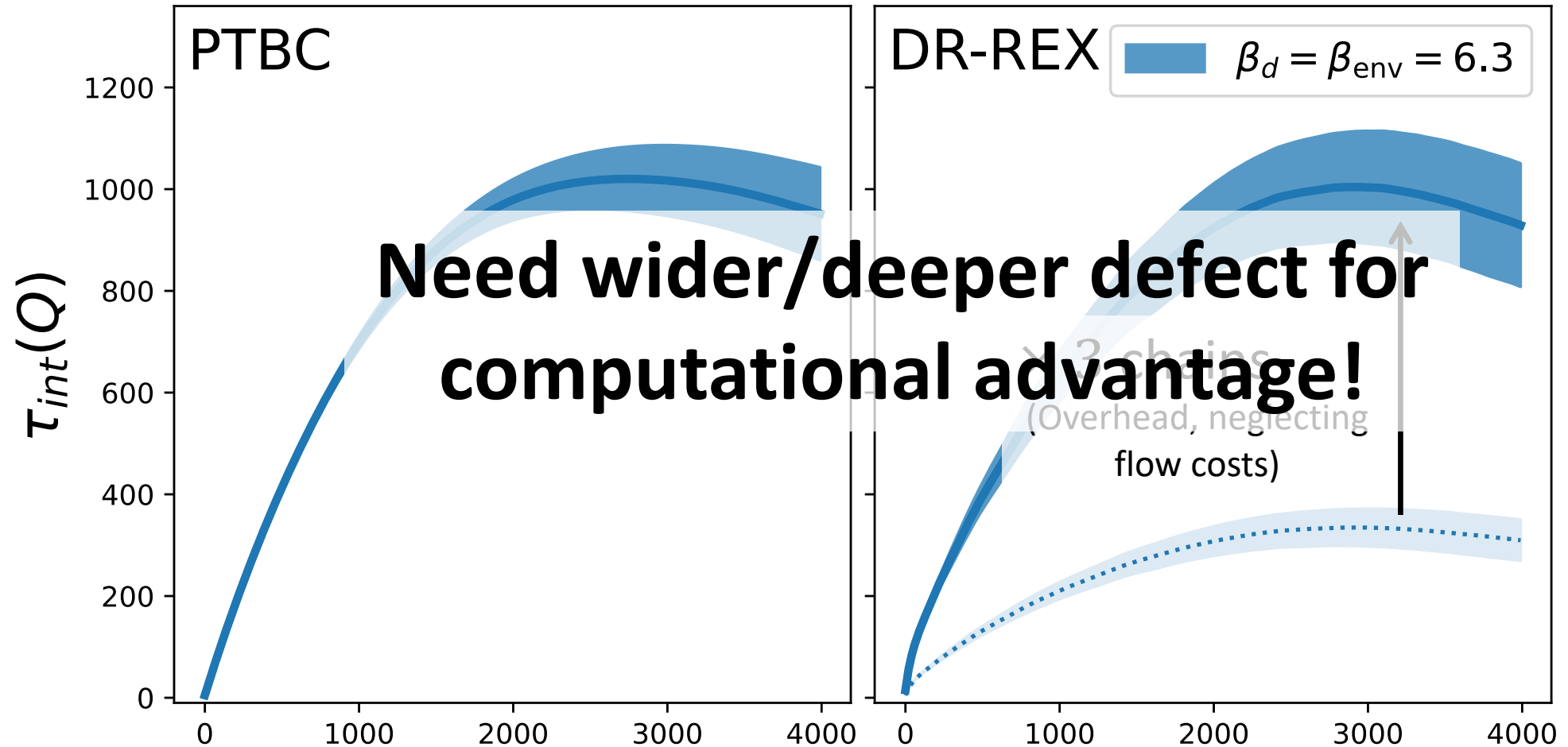


App 3: DR-REX Results

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 8^4 subvolume



Outlook

Great potential for ML acceleration of lattice QCD calcs

Opportunities for useful applications before full generative modeling

REX makes natural use of flows

Limiting case: direct sampling

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

Correlated ensembles / T-REX generally applicable in MC calcs

Straightforward generalizations to (pseudo)fermions / QCD

Flows for fermions [2106.05934] PFs for gauge fields [2207.08945] QCD [2207.08945]

PTBC → DR-REX: very promising