

# GRID and evolution algorithms for critical slowing down

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Frontiers in Lattice quantum field theory  
2018 – IFT Madrid May 31<sup>th</sup>



# Computing resources



EXASCALE COMPUTING PROJECT

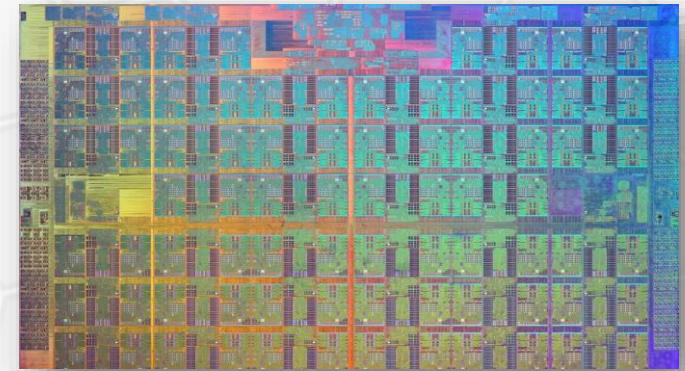


National Energy Research  
Scientific Computing Center

**DiRAC** Distributed Research utilizing Advanced Computing



Science & Technology  
Facilities Council



# GRID library



Modern C++ library for Cartesian mesh problems  
**P. Boyle, G. Cossu, A. Portelli, A. Yamaguchi**

Grid github pages [github.com/paboyle/Grid](https://github.com/paboyle/Grid)  
(partial) documentation [paboyle.github.io/Grid/](https://paboyle.github.io/Grid/)  
CI: Travis, TeamCity <https://ci.cliath.ph.ed.ac.uk/>



## Design goals

- performance portability
- zero code replication

Source code: C++11, autotools

+ HADRONs physics measurement framework based on Grid (A. Portelli)

Intense work in progress, production stage on Tesseract

# GRID architecture support

## Current support

- SSE4.2 (128 bit)
- AVX, AVX2 (256 bit) (e.g. Intel Haswell, Broadwell, AMD Ryzen/EPYC)
- AVX512F (512 bit, Intel KNL, Intel Skylake)
- QPX (BlueGene/Q), experimental
- NEON ARMv8 (thanks to Nils Meyer from Regensburg University)
- Generic vector width support

## Work in progress for

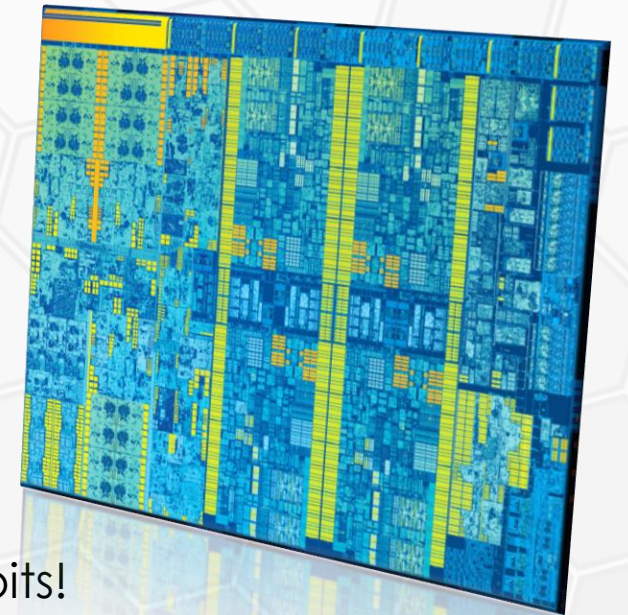
- CUDA threads (Nvidia GPUs) (GRID team & [ECP collaboration](#))
- ARM SVE (Scalable Vector Extensions - [Fujitsu post-K](#)), from 128 up to 2048 bits!

## Exploiting all levels of parallelism

- Vector units, Threading, MPI

## Work on optimising communications triggered **3 major updates** for

- Intel MPI stack (library and PSM2 driver)
- HPE-SGI Message Passing Toolkit (MPT)
- Mellanox HPC-X







# GRID features (selection)

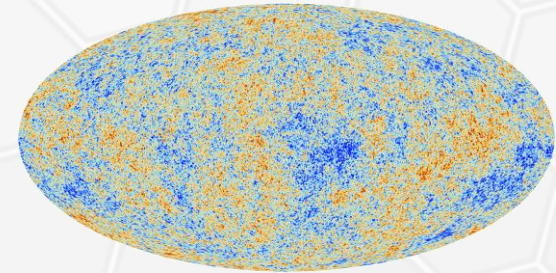
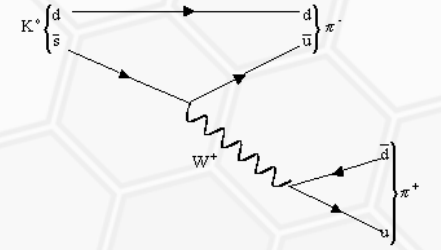
- Actions
  - Gauge: Wilson, Symanzik, Iwasaki, RBC, DBW2, generic Plaquette + Rectangle
  - Fermion: Two Flavours, One Flavour (RHMC), Two Flavours Ratio, One Flavour Ratio, Exact one-flavour. All with the EO variant.
  - Kernels: Wilson, Wilson TM, Wilson Clover + anisotropy, generalised DWF (Shamir, Scaled Shamir, Mobius, Z-mobius, Overlap, ... ), Staggered
  - Scalar Fields
  - Integrators: Leapfrog, 2<sup>nd</sup> order minimum-norm (Omelyan), force gradient, + implicit versions
- Fermion representations
  - [Fundamental](#), [Adjoint](#), [Two-index symmetric](#), [Two-index antisymmetric](#), and all possible mixing of [these](#). Any number of colours. All fermionic actions are compatible.
- Stout smeared evolution with APE kernel (for SU(3) fields). Any action can be smeared.
- Serialisation: XML, JSON
- Algorithms: GHMC, [RMHMC](#), [LAHMC](#), density of states LLR (not public) easily implemented
- File Formats: Binary, NERSC, ILDG, SCIDAC (for confs). MPI-IO for efficient parallel IO
- Measurements:
  - Hadrons (2,3 point functions), Several sources, QED, Implicitly Restarted Lanczos, and many more...
- Split Grids: 3x speedup + deflation for extreme scalability

*Some HMC features inherited from Irolo++*

# GRID current physics



- RBC-UKQCD
  - This work on algorithms...
  - Kaon decay with G-parity  $K \rightarrow \pi\pi$
  - QED corrections to Hadron Vacuum Polarization
  - Non Perturbative Renormalization
  - Holographic cosmology
  - BSM, composite Higgs with mixed representations
- Numerical Stochastic PT (Wilson Fermions) G. Filaci (UoE)
- Axial symmetry at finite temperature, Semi-leptonic B-decays (GC with JLQCD)
- Density of states (GC with A. Rago, Plymouth U.)
- ...



# GRID/Intel paper and on the tech news!



On the optimization of comms and how to drive the Intel Omni-Path

[arXiv:1711.04883](https://arxiv.org/abs/1711.04883)

## Accelerating HPC codes on Intel® Omni-Path Architecture networks: From particle physics to Machine Learning

Peter Boyle,<sup>1</sup> Michael Chuvelev,<sup>2</sup> Guido Cossu,<sup>3</sup> Christopher Kelly,<sup>4</sup> Christoph Lehner,<sup>5</sup> and Lawrence Meadows<sup>2</sup>

<sup>1</sup>The University of Edinburgh and Alan Turing Institute

<sup>2</sup>Intel

<sup>3</sup>The University of Edinburgh

<sup>4</sup>Columbia University

<sup>5</sup>Brookhaven National Laboratory

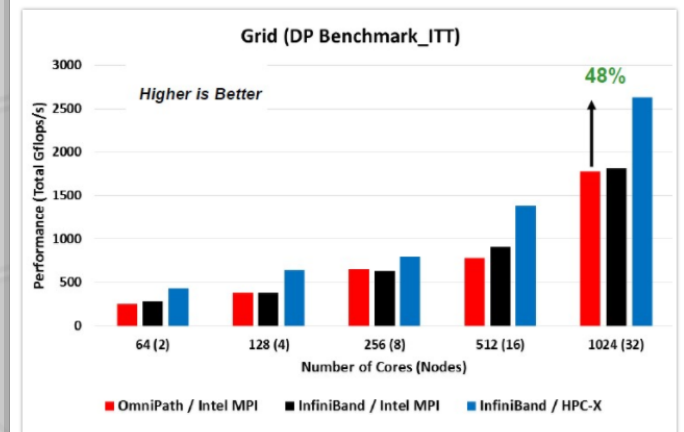
<sup>2</sup>Brookhaven National Laboratory

<sup>4</sup>Columbia University

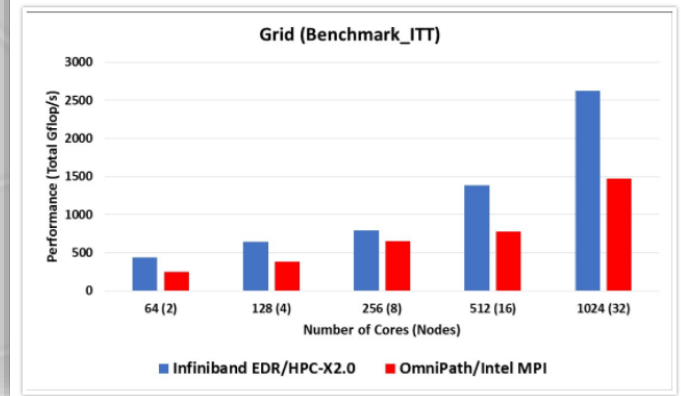
HPC Tech news site reported GRID benchmarks in a [Battle of the InfiniBands](#) article (Nov 29) from the [HPC Advisory Council](#) slides



Here is a set of tests on the GRID benchmark that Intel ran (in the red and black columns again) that showed Omni-Path 100 and EDR InfiniBand essentially neck and neck; then Mellanox did a rerun of its EDR InfiniBand with the HPC-X transport tweaks, and got a pretty significant jump in performance. The processors in the two socket servers were Intel's "Broadwell" Xeon E5-2697A chips. Take a gander:



Here is another test that Mellanox did, pitting the InfiniBand/HPC-X combo against Omni-Path with Intel's MPI implementation. In this test, Mellanox ran on clusters with from two to 16 nodes, and the processors were the Xeon SP-6138 Gold chips:



# Critical slowing down

Continuum limit of lattice QFT: second order critical point

$$\tau_{\text{int}}(O) \propto a^{-\varepsilon}$$

The exponent depends on the:

- algorithm to generate the Markov Chain
- observable (if not universal)

Some observables couple more tightly to the slow modes of the transition matrix, e.g. the **topological charge**



# Markov Chain Monte Carlo

Problem: sampling of a target probability distribution  $p(x) = \frac{1}{Z} \exp(-S(x))$

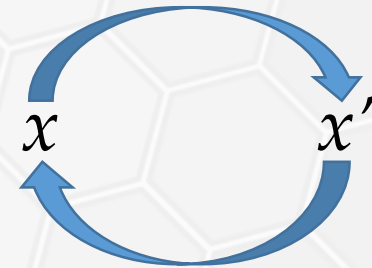
Generate a Markov chain  $x_0 \rightarrow x_1 \rightarrow \dots \rightarrow x_N$

such that  $\int p(x)T(x'|x)dx = p(x')$

$p(x)$  is a **fixed point** of the transition matrix  $T$ , or eigenmode for a discrete set of states

$$\hookrightarrow \langle O \rangle = \frac{1}{Z} \int O \exp(-S(x))dx \approx \frac{1}{N} \sum O(x_n)$$

Detailed balance  $p(x)T(x'|x) = p(x')T(x|x')$   
→ fixed point equation



Note: detailed balance is a sufficient but NOT a necessary condition

# Generalised Hybrid Monte Carlo

Hamiltonian evolution  
Duane et al. 1987

$$H(x) = \frac{1}{2}p^T p + S(x)$$

$$p(x) \propto \exp(-H(x))$$

$$x' = FL(M, \epsilon)x^{(t,0)}$$

$$x^{(t,1)} = x'$$

Accept

$$x^{(t,1)} = x^{(t,0)}$$

Reject

$$x^{(t,2)} = Fx^{(t,1)}$$

$$\pi_{\text{accept}} = \min\left(1, \frac{p(x')}{p(x)}\right)$$

$$x^{(t+1,0)} = R(\alpha)x^{(t,2)}$$

## Markov transitions

Hamiltonian integration

M steps,  $\epsilon$  step size

Symplectic, reversible

$$L(M, \epsilon)$$

Momenta flip  $F$

Momenta randomization

$\alpha$  mixing angle

$$R(\alpha)$$

Note:  $(FL)^{-1} = L^{-1}F = FL$

simplifying the Metropolis-Hastings step  $\pi_{\text{accept}} = \min\left(1, \frac{p(x')}{p(x)} \frac{T(x|x')}{T(x'|x)}\right)$

See e.g. Kennedy, Pendleton hep-lat/0008020

# Generalised Hybrid Monte Carlo

Hamiltonian evolution  $H(x) = \frac{1}{2}p^T p + S(x)$   
Duane et al. 1987

$$p(x) \propto \exp(-H(x))$$

Some special cases

- complete randomization of momenta:  
Standard HMC
- no momenta randomization: microcanonical  
integration (non ergodic)
- single step integration and complete momenta  
randomization: Langevin Monte Carlo

Markov transitions

Hamiltonian integration  
M steps,  $\epsilon$  step size  
Symplectic, reversible

$$L(M, \epsilon)$$

Momenta flip  $F$

Momenta randomization  
 $\alpha$  mixing angle

$$R(\alpha)$$



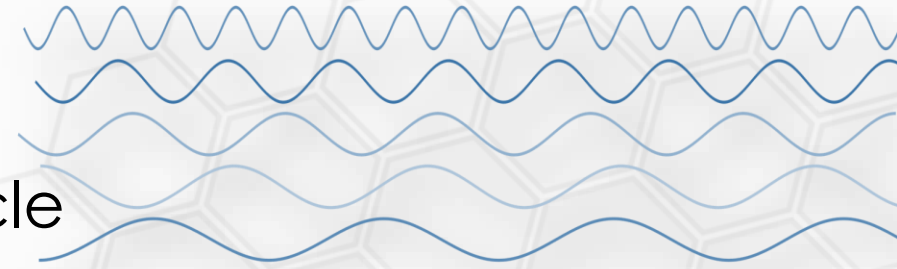
# Riemannian Manifold Hybrid Monte Carlo RMHMC



# Accelerating slow modes

Transition matrix:

- **Fastest modes** limit the integration step size
- **Slow modes** take longer time to complete a cycle and decorrelate



Increasing ratio of frequencies determines the critical slowing down

Simple scalar free field example: characteristic frequency  $\omega(p)^2 = m^2 + p^2$

Consider the Hamiltonian evolution of

$$H(\pi, \psi) = \frac{1}{2} \pi^T (M^2 - \partial^2)^{-1} \pi + S(\phi) \quad \longrightarrow \quad \omega(p)^2 = \frac{m^2 + p^2}{M^2 + p^2}$$

Extend this idea to gauge theories

# Gauge invariant Fourier acceleration

Duane, Pendleton et al. 1986, 1988

Formulated in geometric terms recently by Girolami, Calderhead 2011

Covariant modifications of the kinetic term (metric in a Riemannian Manifold: [RM-HMC](#))

$$\frac{1}{2} \pi^T M^{-1} \pi \quad M \phi(x) = (1 - \kappa) \phi(x) - \frac{\kappa}{4d} \nabla^2 \phi(x) \quad \text{Covariant laplacian}$$

$\kappa \rightarrow 1$  max acceleration  
for free fields

The resulting Hamilton equations are [non-separable](#)

Leapfrog-like schemes do not work anymore as non reversible and non volume conserving.

Integration procedure by [implicit integration](#) (Leimkuhler, Reich 2004)

$$\pi^{n+\frac{1}{2}} = \pi^n - \frac{\epsilon}{2} \frac{\delta H}{\delta \phi}(\phi^n, \pi^{n+\frac{1}{2}})$$

$$\phi^{n+1} = \phi^n + \frac{\epsilon}{2} \left[ \frac{\delta H}{\delta \pi}(\phi^n, \pi^{n+\frac{1}{2}}) + \frac{\delta H}{\delta \pi}(\phi^{n+1}, \pi^{n+\frac{1}{2}}) \right]$$

$$\pi^{n+1} = \pi^{n+\frac{1}{2}} - \frac{\epsilon}{2} \frac{\delta H}{\delta \phi}(\phi^{n+1}, \pi^{n+\frac{1}{2}})$$

# RM-HMC evolution

Another modification is necessary

- The new kinetic term introduces the **inverse determinant of  $M$**  in the distribution: it must be cancelled

Two solutions

- a set of **auxiliary fields** (scalars in the adjoint representation) with action  $\frac{1}{2} p_\theta^T M^2 p_\theta + \theta^2$  and include this in the Hamiltonian integration
- Use pseudofermion-like fields and update only at the refresh step

New parameters:  $\kappa$

Choice of operator  $M$  not unique.

We can imagine also operators with a bounded spectral content

**Overhead: inversion of the Laplacian, implicit integration**

Should be irrelevant once fermions are included

Tested originally in 2d SU(2) pure gauge (with non exact Runge-Kutta integration)

**Now testing on 4d SU(3) pure gauge and CP<sup>N</sup> models (Jüttner, Sanfilippo)**

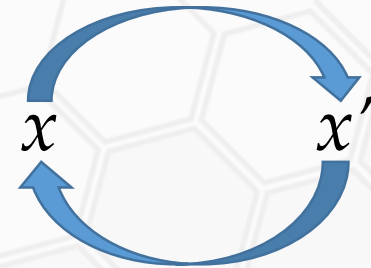


# Look Ahead Hybrid Monte Carlo LAHMC



# Dropping detailed balance

$$p(x)T(x'|x) = p(x')T(x|x')$$



a **sufficient** but NOT a **necessary** condition

Can introduce a random walk behaviour to the evolution

Rejection, in general, leads to momentum reversal, wasteful

We would like to

- move further in the integration
- reduce the rejection steps optimizing the costs

# Look Ahead HMC

Repeat the integration accepting with modified probabilities up to a maximum number  $K$  of times

$$x^{(t,1)} = \begin{cases} Lx^{(t,0)} & \text{prob } \pi_{L^1}(x^{(t,0)}) \\ L^2x^{(t,0)} & \text{prob } \pi_{L^2}(x^{(t,0)}) \\ \dots & \\ L^Kx^{(t,0)} & \text{prob } \pi_{L^K}(x^{(t,0)}) \\ Fx^{(t,0)} & \text{prob } \pi_F(x^{(t,0)}) \end{cases}$$

Randomize momenta:  $x^{(t+1,0)} = R(\alpha)x^{(t,1)}$

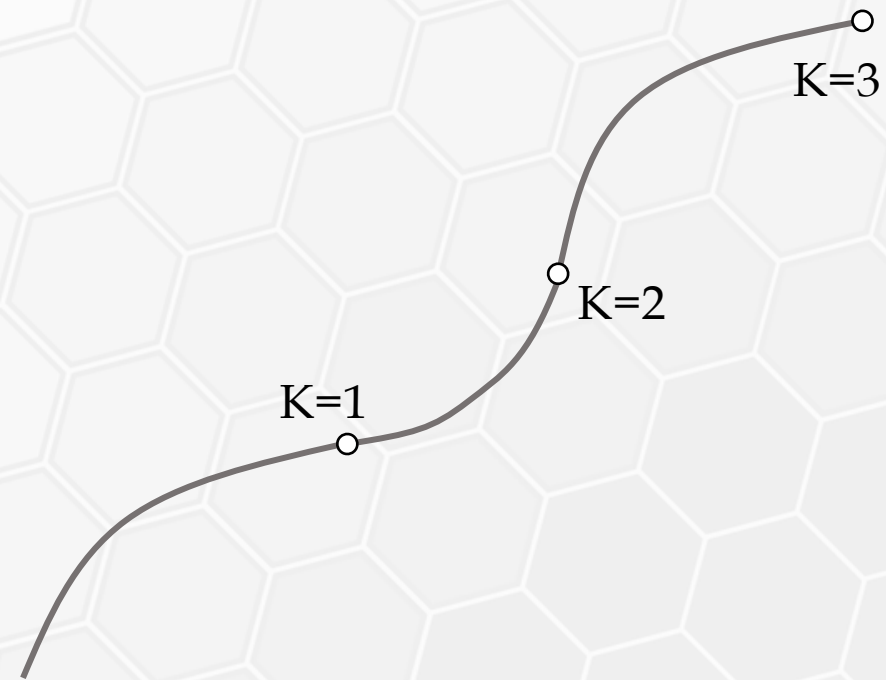
$$\pi_{L^a}(x) = \min \left[ 1 - \sum_{b < a} \pi_{L^b}(x), \frac{p(FL^a x)}{p(x)} \left( 1 - \sum_{b < a} \pi_{L^b}(FL^a x) \right) \right]$$

Same as HMC (generalized) for  $K=1$

Target distribution is a fixed point of the evolution

Sohl-Dickstein et al. (for machine learning) 2016

$$\begin{aligned} x' = FL(M, \epsilon)x^{(t,0)} & \quad x^{(t,1)} = x' \quad \text{Accept} \\ & \quad x^{(t,1)} = x^{(t,0)} \quad \text{Reject} \\ x^{(t,2)} = Fx^{(t,1)} & \quad \pi_{\text{accept}} = \min\left(1, \frac{p(x')}{p(x)}\right) \\ x^{(t+1,0)} = R(\alpha)x^{(t,2)} & \end{aligned}$$



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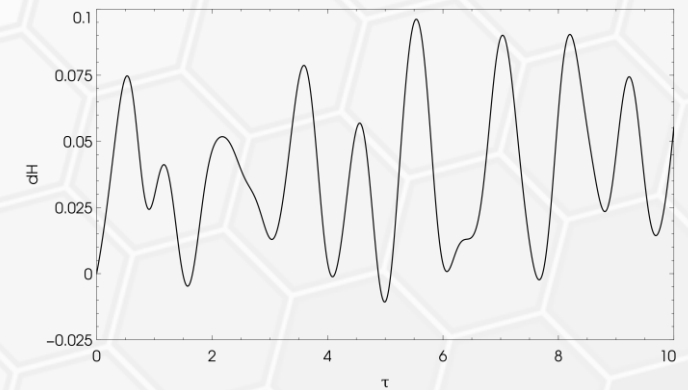
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Same as HMC (generalized) for  $K=1$

Target distribution is a fixed point of the evolution

Sohl-Dickstein et al. (for machine learning) 2016

Symplectic integrators:  
H oscillates around the original value during evolution,  $dH$  same order even after long trajectories



Hopefully more work per chain pays in terms of sample quality

# Simulations: current status

## Pure gauge SU(3)

Implemented both algorithm prototypes in Grid

- Few days of work for RMHMC (for any gauge theory w/o fermions)
- One day for LAHMC

Nice example of the higher level flexibility of Grid

Reference runs: HMC in Grid with 2<sup>nd</sup> order minimum norm integration.

Two volumes  $16^4$  and  $32^4$ , Wilson Gauge action at  $\beta = 6.2, 6.4$  respectively.

## CP<sup>N</sup> model (Jüttner, Sanfilippo)

Model has severe slowing down at small lattice spacing

Simulating N=10

several  $\beta$ s and  $\kappa$  to check the acceleration efficiency in the continuum limit



# Current status: RMHMC, CP<sup>N</sup>

N=10

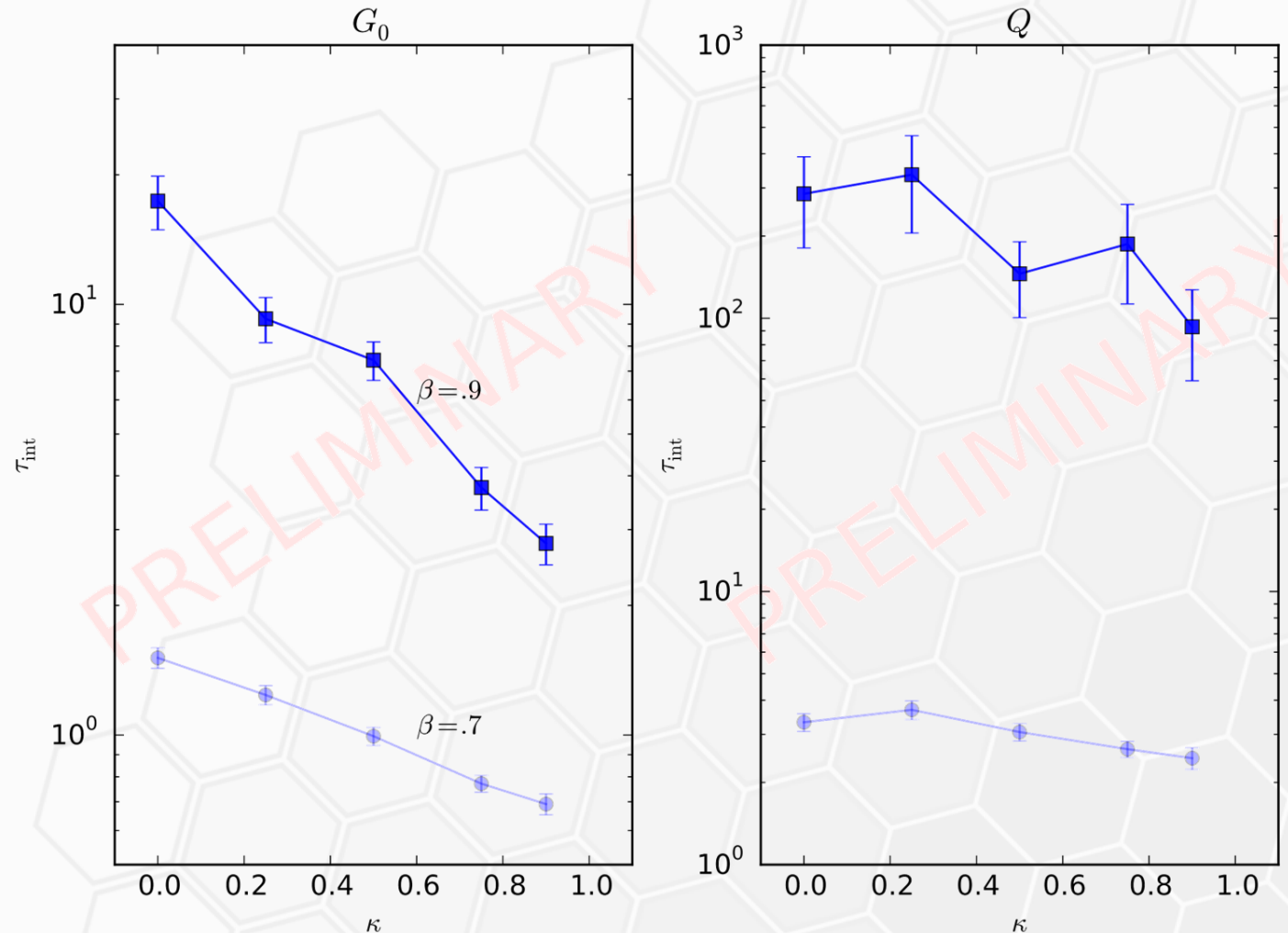
Showing 2 lattice spacings

$\beta = 0.7$  L=42

$\beta = 0.9$  L=90 statistics to be increased

Order of magnitude reduction  
of autocorrelation time  
observed in  $G_0$

$G_0$  is the 2-point correlator  
(projected at zero momentum)  
 $Q$  is the topological charge



# Current status: SU(3)

RMHMC reminder: modification of the kinetic term in Hamiltonian

$$\frac{1}{2}\pi^T M^{-1}\pi$$

$$M\phi(x) = (1 - \kappa)\phi(x) - \frac{\kappa}{4d}\nabla^2\phi(x)$$

Pure gauge, Wilson action

$\beta = 6.2$  ( $a = 2.9 \text{ GeV}^{-1} = 0.068 \text{ fm}$ ),  $L=16$

$\beta = 6.4$  ( $a = 3.8 \text{ GeV}^{-1} = 0.051 \text{ fm}$ ),  $L=32$ .

Reference: HMC 83-84% acceptance (Grid)

RMHMC overhead:

- Laplacian inversion  $\sim 20$  iterations. Almost independent of  $k$
- Implicit steps converge after 4-5 iterations

Observables:

- Topological charge and susceptibility
- $T_0 = 2\tau_{\text{flow}}^2 \frac{\langle E \rangle}{V}$

# Current status: SU(3)

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Observables:

- Topological charge and susceptibility
- $T_0 = 2\tau_{\text{flow}}^2 \frac{\langle E \rangle}{V}$

Definition of cost related to the number of force computations (with an eye on simulations including fermions)

$$C(\mathcal{O}) = \frac{N_{\text{traj}} N_{\text{MD}}}{N_{\text{conf}}} \tau_{\text{acorr}}(\mathcal{O})$$

$\tau_{\text{acorr}}(\mathcal{O})$  is the integrated autocorrelation time for observable  $\mathcal{O}$

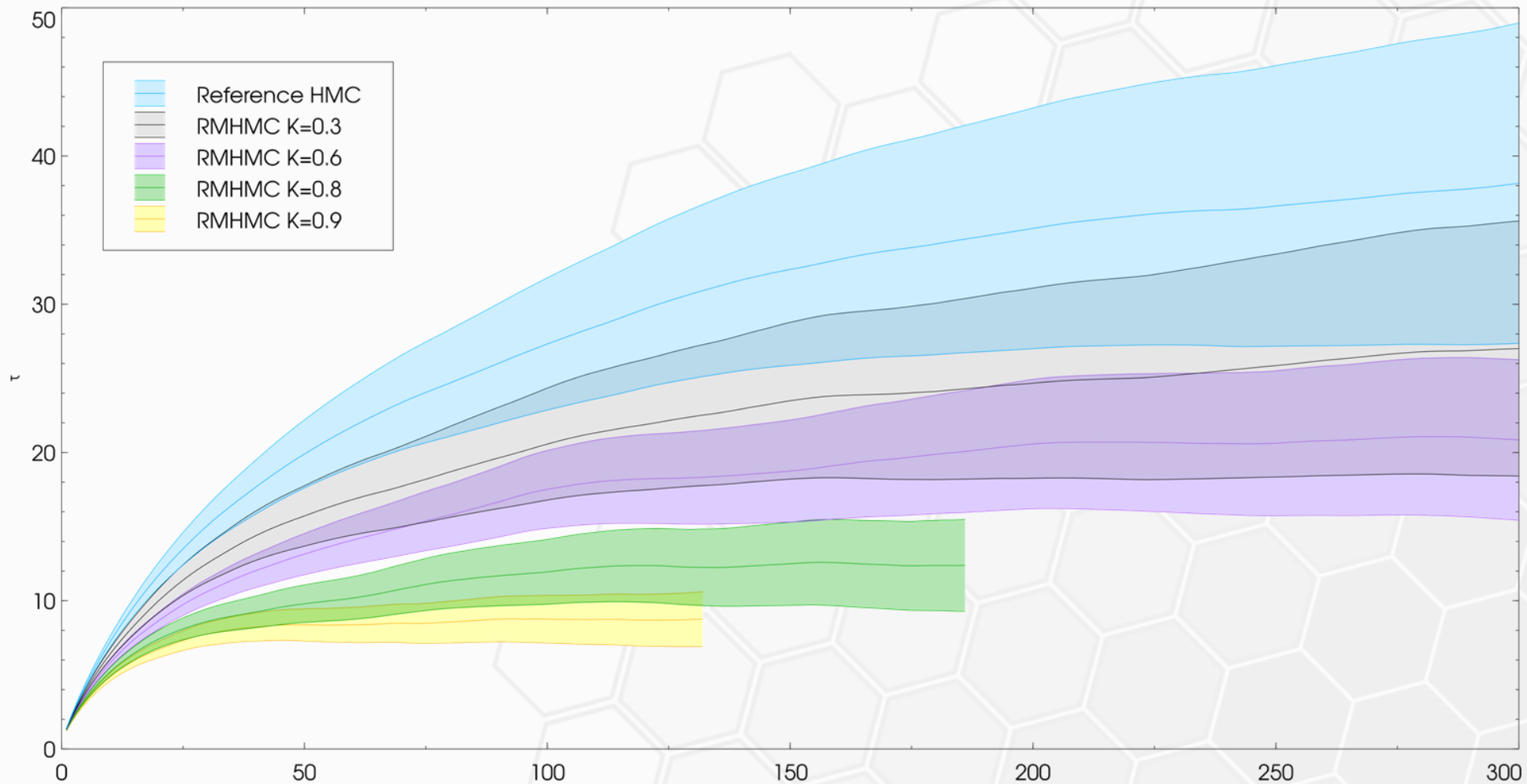
Trivial for HMC and RMHMC ( $N_{\text{traj}} = N_{\text{conf}}$ ) but not for LAHMC.

# Current status: RMHMC, SU(3)

Pure gauge, Wilson action,  $\beta = 6.2$   $L=16$ . Reference: HMC  $\sim 83\%$  acceptance

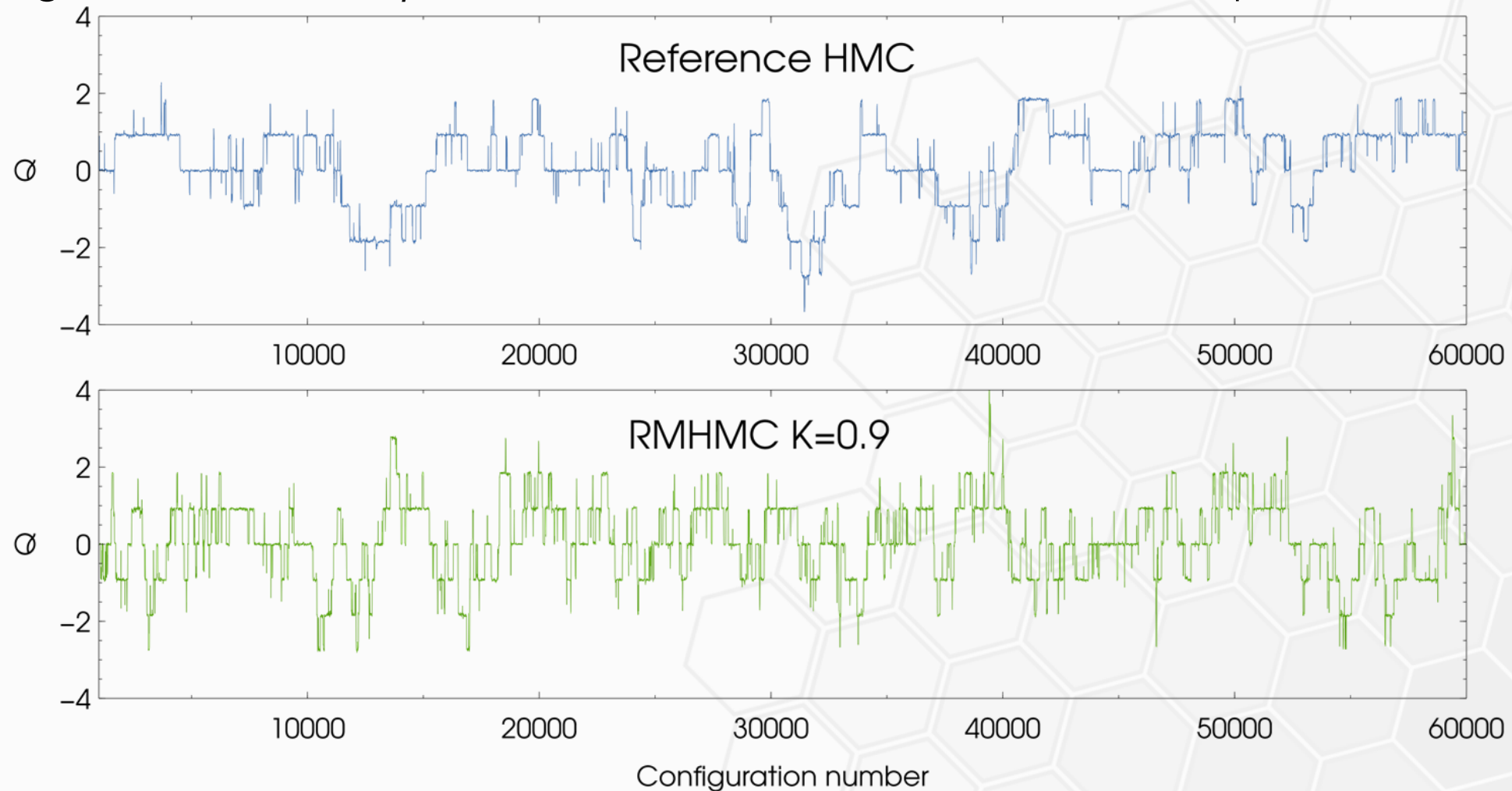
$T_0$

Integrated autocorrelation time



# Current status: RMHMC, SU(3)

Pure gauge, Wilson action,  $\beta = 6.2$  L=16. Reference: HMC ~83% acceptance

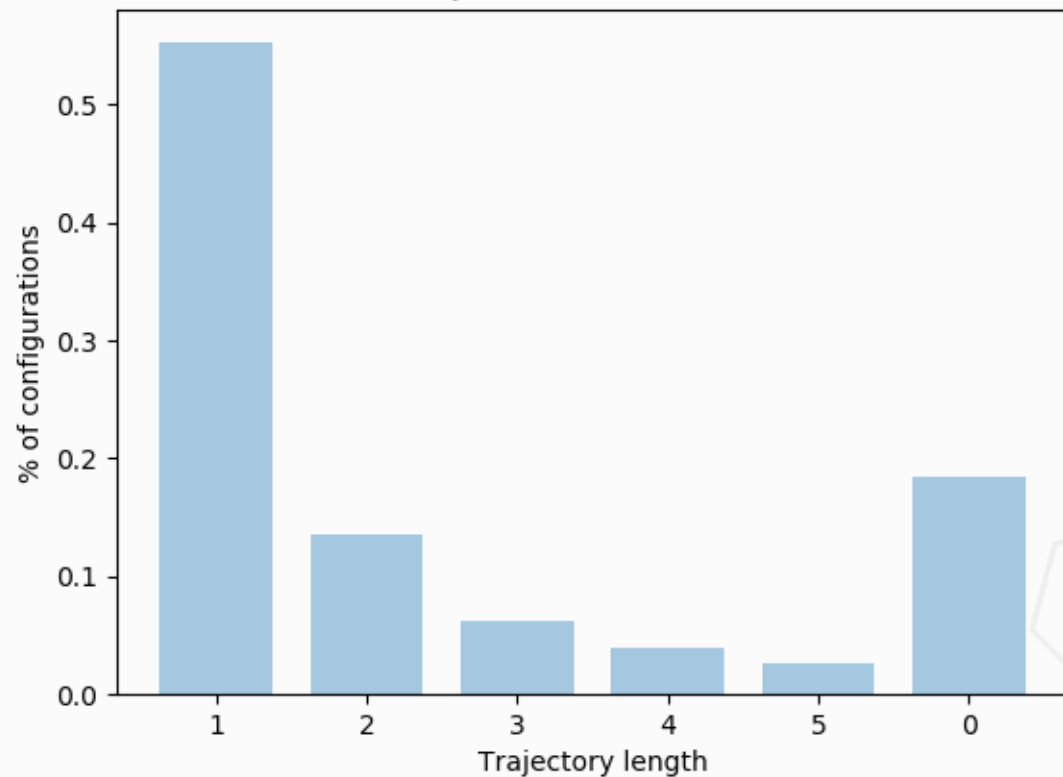


# Current status: LAHMC

Pure gauge, Wilson action,  $\beta = 6.2$   $L=16$ , several pairs  $(K, \alpha)$   
Effect on acceptance/rejection rate

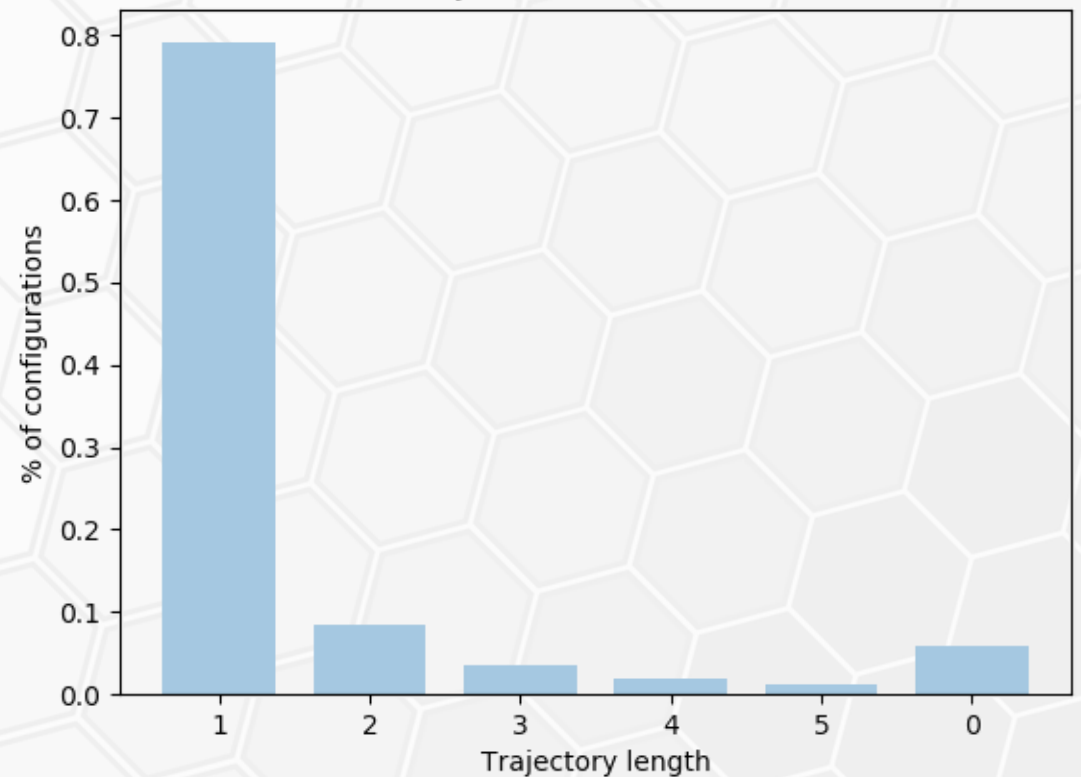
MD steps = 10,  $K = 5$

Trajectories distribution



MD steps = 15,  $K = 5$

Trajectories distribution





# Current status: LAHMC

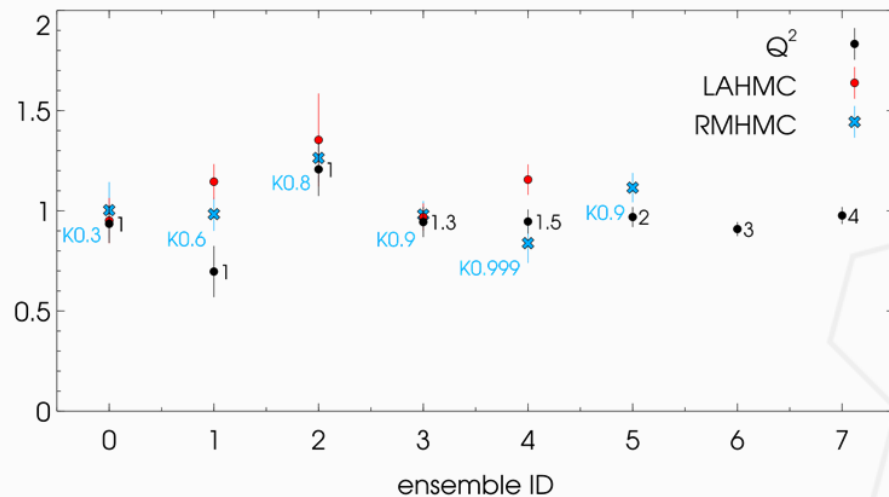
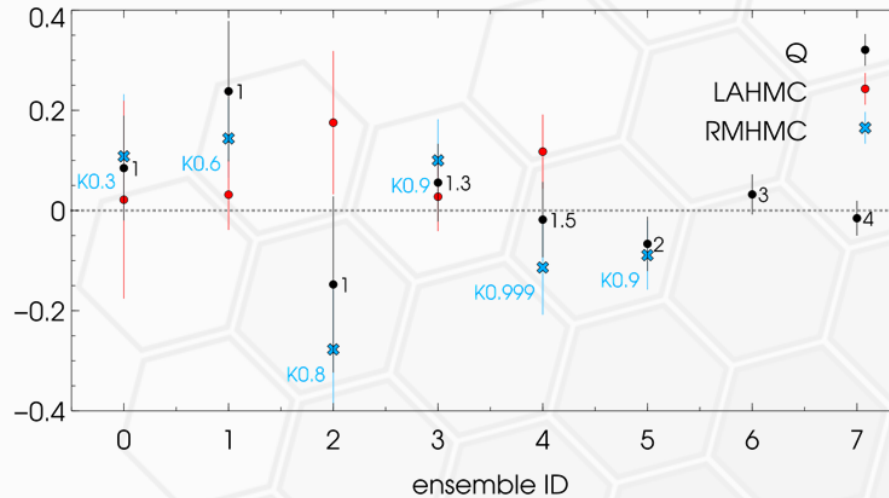
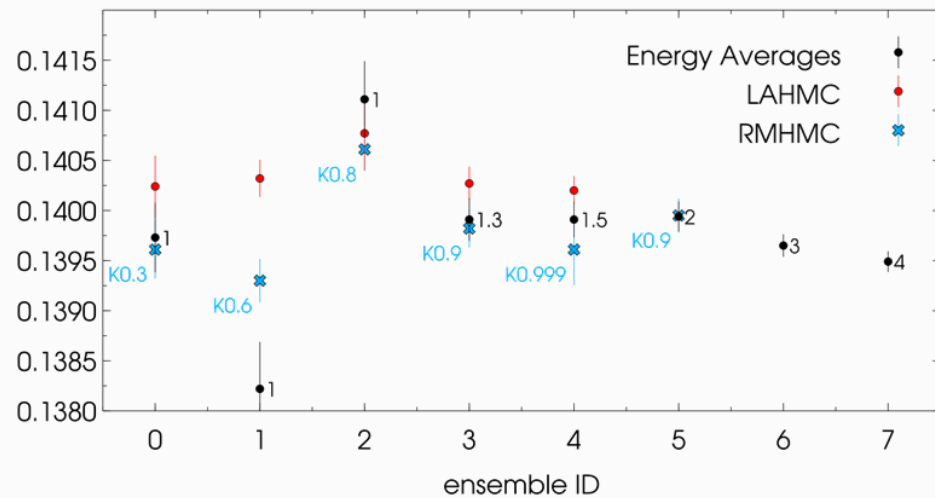
Pure gauge, Wilson action,  $\beta = 6.2$   $L=16$ , several pairs  $(K, \alpha)$

Effect on acceptance/rejection rate

ID	L	$\beta$	$N_{MD}$	$\tau$	K	$\alpha$	dH 1	Acc.	Acc. 1	Avg $\tau$	Avg $N_{MD}$
LA0	16	6.2	10	1.0	5	0.6	$0.704 \pm 0.0080$	0.81	0.55	1.31	22.26
LA1	16	6.2	10	1.0	5	1.0	$0.697 \pm 0.0061$	0.81	0.55	1.3	22.23
LA2	16	6.2	15	1.0	5	1.0	$0.140 \pm 0.0026$	0.94	0.79	1.21	22.47
LA8	32	6.4	10	1.0	5	1.0	$1.080 \pm 0.0044$	0.82	0.55	1.31	22.35
LA9	32	6.4	20	2.0	5	1.0	$1.102 \pm 0.0072$	0.82	0.55	2.63	44.7

# SU(3), coarse lattices summary

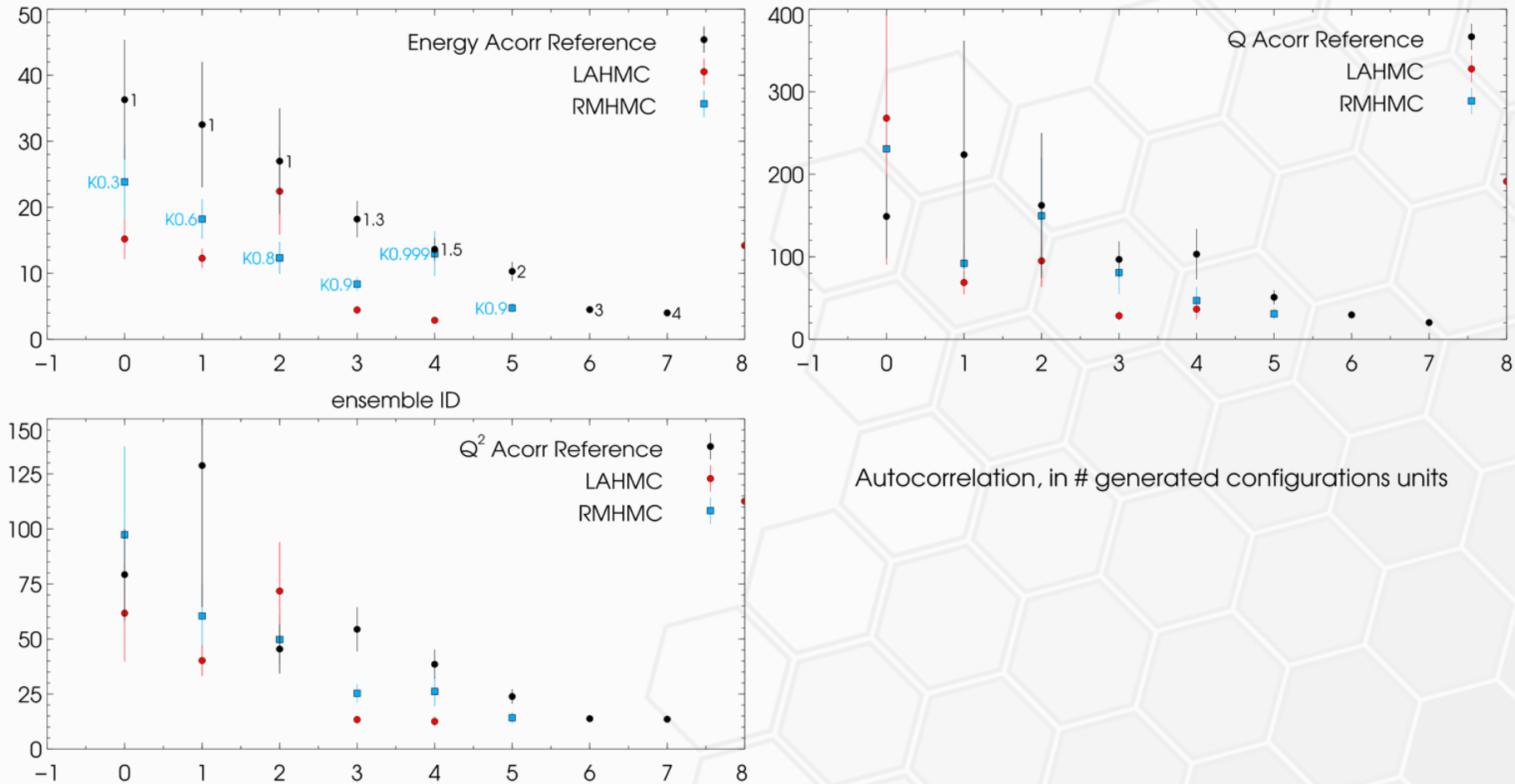
Pure gauge, Wilson action,  $\beta = 6.2$  L=16. Reference: HMC ~83% acceptance



Averages: no biases  
(ref runs 1,2 low stat. Not considered)

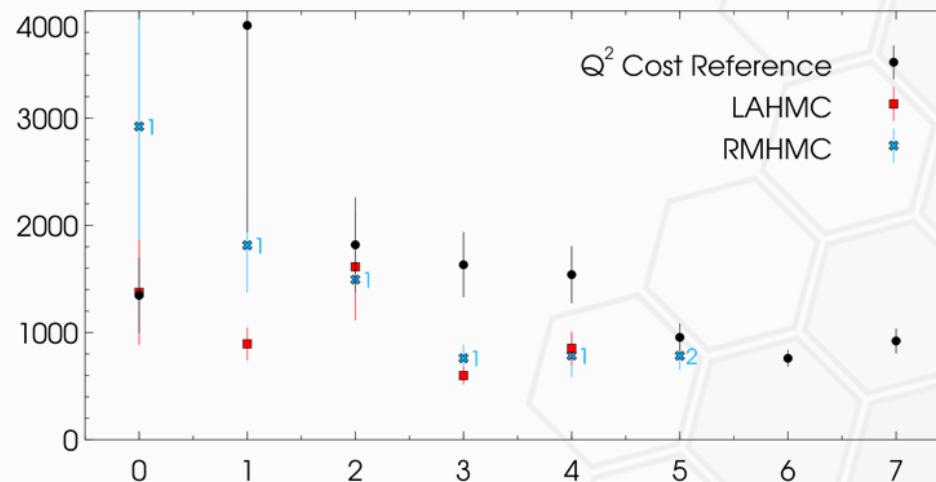
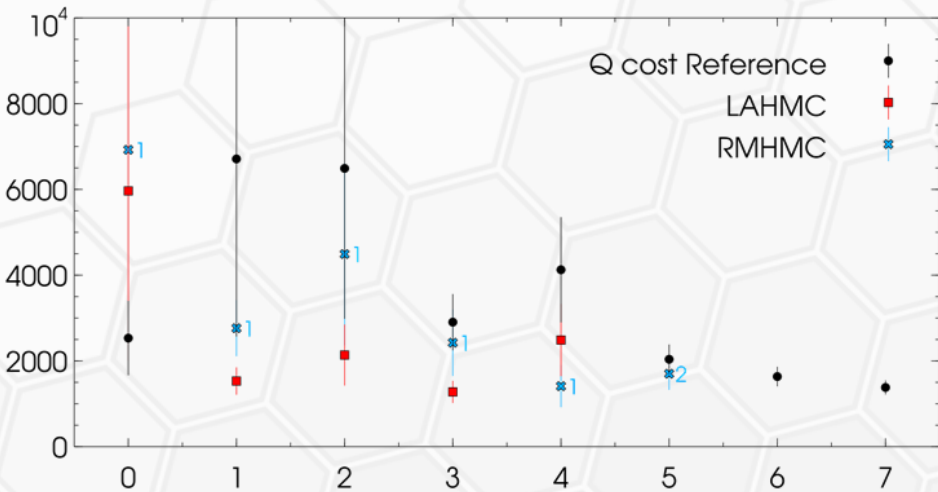
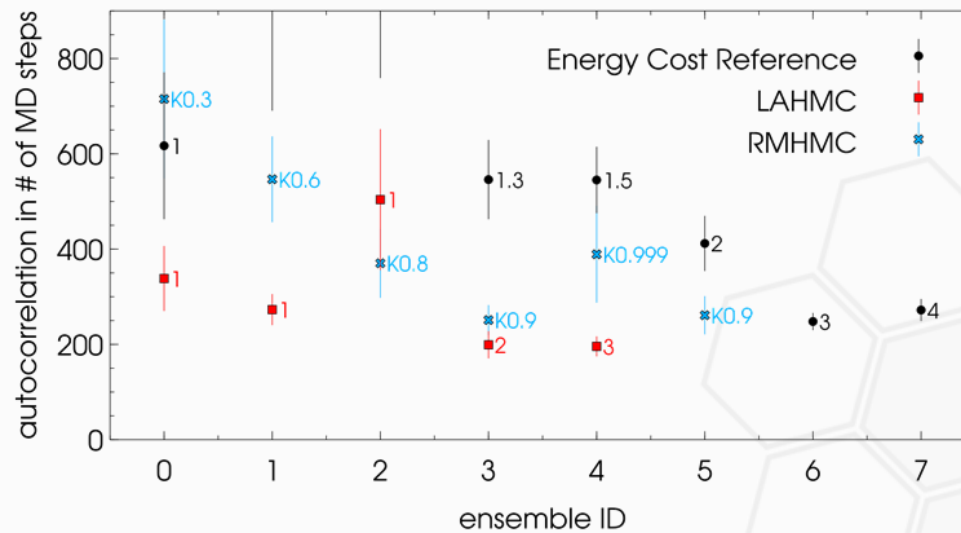
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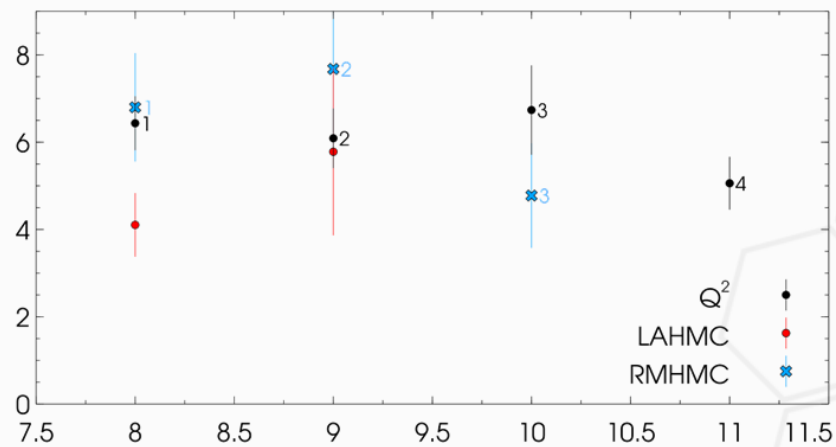
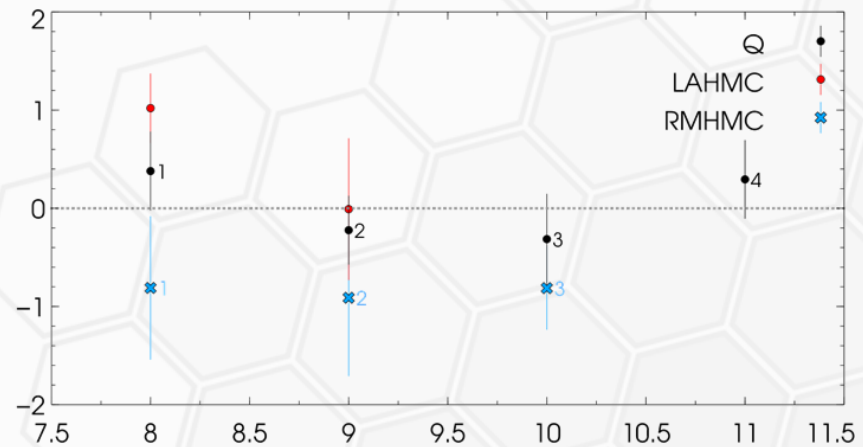
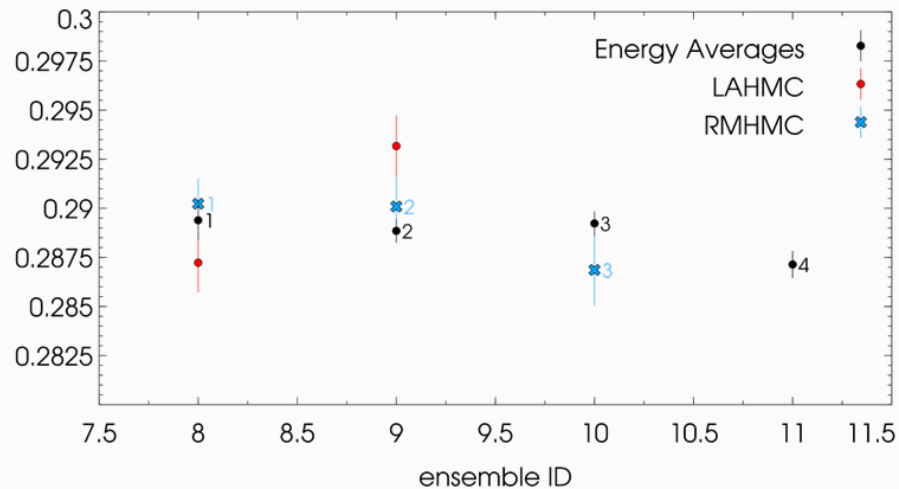
Pure gauge,  
Wilson action  
 $\beta = 6.2$   $L=16$



**COST ESTIMATE**

# SU(3), fine lattices summary

Pure gauge, Wilson action,  $\beta = 6.4$  L=32. Reference: HMC ~84% acceptance

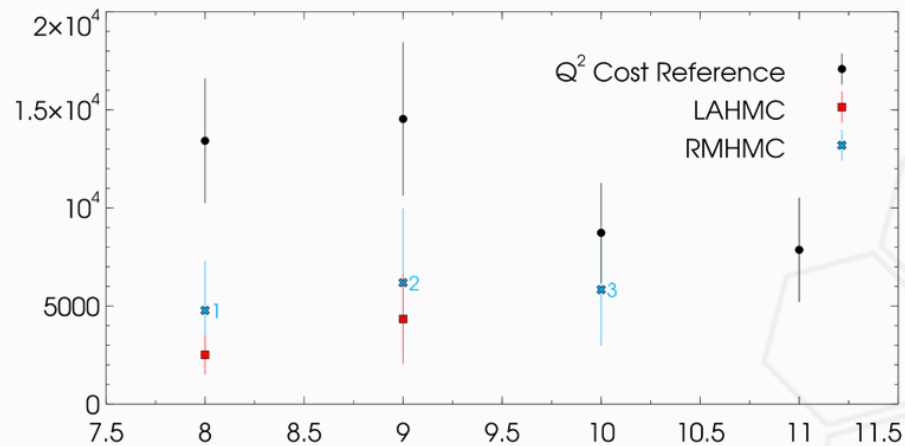
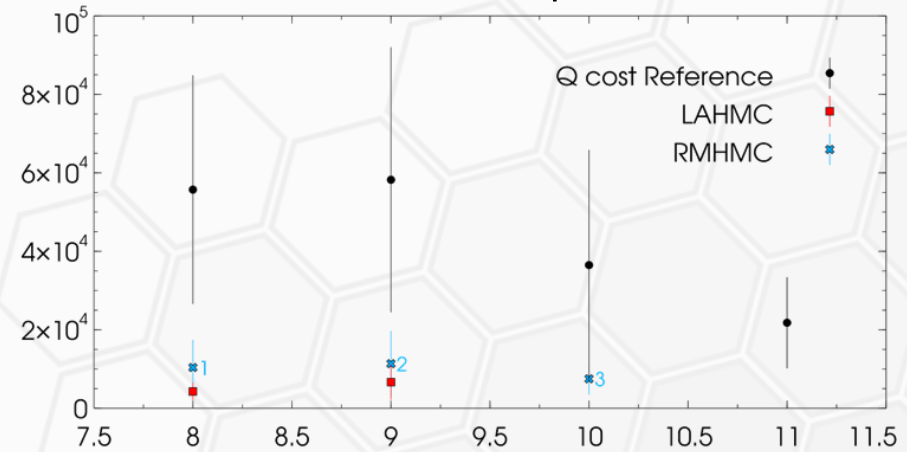
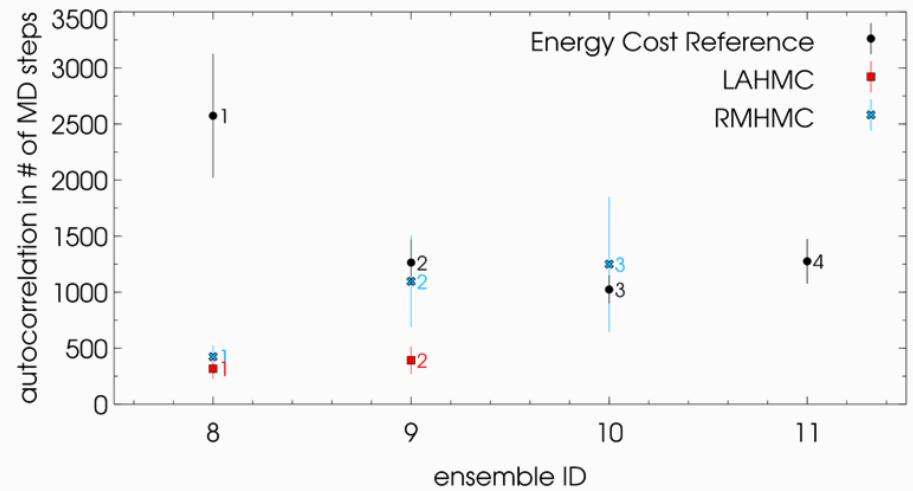


Averages L=32  $\beta=6.4$

**WORK IN PROGRESS**

# SU(3), fine lattices summary

Pure gauge, Wilson action,  $\beta = 6.4$  L=32. Reference: HMC ~84% acceptance



**WORK IN PROGRESS**



# Outlook

Currently finalizing the scaling study towards the continuum

- Positive (not yet conclusive) results, quick to implement
- RMHMC: study other “acceleration” operators, e.g. Laplacian with a spectral bound (using Chebyshev polynomials for example)
- Methods can be combined, working in “orthogonal” directions
- Useful interaction between the ML and Statistical physics community

# GRID and evolution algorithms for critical slowing down

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in collaboration with P. Boyle, N. Christ, C. Jung, A. Jüttner, F. Sanfilippo

Frontiers in Lattice quantum field theory  
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