

On the sparse grid combination method for $SU(2)$ lattice problems

Michael Griebel

University of Bonn and Fraunhofer SCAI

Joint work with Heinz-Jürgen Flad, U. Bonn

1. The lattice model $SU(2)$
2. The sparse grid combination method
3. Numerical experiments

The lattice model SU(2)

- Non-abelian **SU(2)** Yang-Mills theory in **d dimensions**
 - $d - 1$ spatial and one imaginary time dimension
 - Wick-rotated into Euclidean space with Euclidean metric

- Uniform **lattice** of size N , i.e

$$\Lambda_{d,N} := \{n = (n_0, \dots, n_{d-1}) \in \mathbb{N}_0^d : n_\mu = 0, \dots, N - 1\}$$

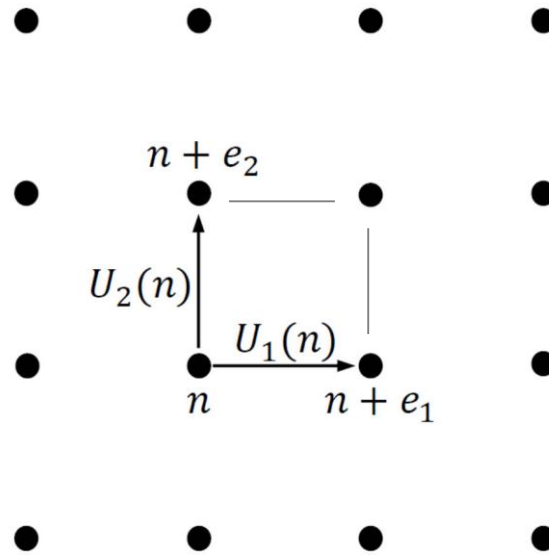
- On each lattice **site** $n \in \Lambda_{d,N}$, place **d link variables**

$$U_\mu(n) \in SU(2), \mu = 0, \dots, d - 1$$

- **Matrices** $U_\mu(n) \in \mathbb{C}^{2 \times 2}$ with $U_\mu(n)U_\nu^\dagger(n) = 1$ and $\det U_\mu(n) = 1$
- **Connect** site n to sites $n + e_\mu$ in **forward** directions $\mu = 0, \dots, d - 1$, with e_μ the d -dimensional **unit** vector in coordinate direction μ .

The lattice model SU(2)

- Example



- Set of all such matrices

$$\mathcal{U}_{d,N} = \{ U_\mu(n) \in SU(2), n \in \Lambda_{d,N}, \mu = 0, \dots, d-1 \}$$

- Plaquette operator in site n is the closed loop

$$P_{\mu,\nu}(n) := U_\mu(n) U_\nu(n + e_\mu) U_\mu^\dagger(n + e_\nu) U_\nu^\dagger(n)$$

The lattice model SU(2)

- For each element in $\mathcal{U}_{d,N}$ we have Wilson's **lattice action**

$$S_{\Lambda_{d,N}} := -\frac{\beta}{2} \sum_{n \in \Lambda_{d,N}} \sum_{\mu < \nu} \text{Re Tr } P_{\mu,\nu}(n)$$

with $\beta = \frac{1}{g_0^2}$ the inverse squared gauge **coupling constant**

- Produce a **Markov chain** of M samples $\mathcal{U}_{d,N,i}, i = 1, \dots, M$ via rejection sampling by the Metropolis algorithm distributed as

$$\mathbb{P}(\mathcal{U}_{d,N}) \propto \exp(-S(\mathcal{U}_{d,N}))$$

- Tune the **rejection rate** to about 50%
- For given parameters N, M, β , we employ the **code `su2`** of C. Urbach, HISKP, see

<https://github.com/urbach/su2/tree/EducationalVersion>

The lattice model SU(2)

- The main **observable** is the empirical **plaquette expectation**

$$\hat{P}_{d,N,M} := \langle P \rangle_M := \frac{1}{M} \sum_{i=1}^M P(\mathcal{U}_{d,N;i})$$

where

$$P(\mathcal{U}_{d,N;i}) = \frac{2}{d(d-1)N^d} \sum_{n \in \Lambda_{d,N}} \sum_{\mu < \nu} \operatorname{Re} \operatorname{Tr} U_{\mu,\nu;i}(n)$$

with the **sampled** matrices

$$U_{\mu,\nu;i}(n), \quad n \in \Lambda_{d,N}, \mu, \nu = 0, \dots, d-1, \mu < \nu$$

that together comprise **one sample** $\mathcal{U}_{d,N,i}$

- The **cost** is $\operatorname{cost}_{d,N,M} = O(MN^d)$ with β -dependent constant
- The **error** is $|\hat{P}_{d,\infty,\infty} - \hat{P}_{d,N,M}|$

Limits

- For $M \rightarrow \infty$ we have **convergence** $\hat{P}_{d,N,M} \rightarrow \hat{P}_{d,N,\infty}$
 - Is due to the law of large numbers and the Metropolis algorithm
- **Infinite volume limit:** $N \rightarrow \infty$.
 - It exists for $\beta > 0$, the system converges to a Young-Mills theory in discrete space-time with lattice spacing $a = 1$
 - If the **confinement** property holds we have fast convergence in N and need practically only moderate values of N
- **Continuum limit:**
 - Hope: By making N larger while making the lattice spacing a smaller and smaller, a continuous theory is obtained with $a \rightarrow 0$.
 - Renormalization group transform, Callan-Symanzik equation, Low-Gell-Mann functions, improved actions
- **For now:** We stick to the **infinite volume limit** only

Sparse grid combination method

- **So far:** With d, N, M, β fixed, we can compute $\hat{P}_{d,N,M}$ by the code *su2* with cost of $O(MN^d)$, certain accuracy and convergence rate
 - Can we **improve** on the relation of error versus cost ?
- **Sparse grids:**
 - For function approximation, quadrature, PDE solution, uncertainty quantification, machine learning, we can apply the sparse grid idea and have substantial cost complexity gains
 - This is due to higher **regularity** of the underlying functions which possess bounded mixed derivatives.
 - Can we find a related property for lattice problems, and can we exploit it to gain faster algorithms ?
- We try to first find out for the **SU(2)**
- Note: **Multilevel MC** and **multi-fidelity UQ** are just **special cases** of a sparse grid method, sparse grids are more general

Sparse grid combination method

- Consider **dyadic levels** $l_1, l_2 \geq 1$, i.e. $N = 2^{l_1}, M = 2^{l_2}$ and, with

$$\tilde{P}_{l_1, l_2} := \hat{P}_{d, 2^{l_1}, 2^{l_2}}$$

the associated table of **results** of the code *su2*

$$\{\tilde{P}_{l_1, l_2}\}_{l_1, l_2} \quad l_1, l_2 \in \mathbb{N}^2$$

which is trivially extended to zero levels by $\tilde{P}_{0, l_2} = \tilde{P}_{l_1, 0} = \tilde{P}_{0, 0} = 0$

- Define the table $\{\Delta_{l_1, l_2}\}_{l_1, l_2}$ of the **hierarchical surplus/benefit**

$$\Delta_{l_1, l_2} := \tilde{P}_{l_1, l_2} - \tilde{P}_{l_1-1, l_2} - \tilde{P}_{l_1, l_2-1} + \tilde{P}_{l_1-1, l_2-1}$$

- Telescopic sum identities**

$$\tilde{P}_{L_1, L_2} = \sum_{l_1=1}^{L_1} \sum_{l_2=1}^{L_2} \Delta_{l_1, l_2} \quad \text{and} \quad \tilde{P}_{\infty, \infty} = \sum_{l_1=1}^{\infty} \sum_{l_2=1}^{\infty} \Delta_{l_1, l_2}$$

Sparse grid combination method

- Take the **cost** $cost_{l_1, l_2}$ of each Δ_{l_1, l_2} into account, which is up to a small constant that of the cost of \tilde{P}_{l_1, l_2}
- Define the table $\{bcr_{l_1, l_2}\}_{l_1, l_2}$ with the **benefit/cost ratios**

$$bcr_{l_1, l_2} := \frac{|\Delta_{l_1, l_2}|}{cost_{l_1, l_2}}$$

- The **optimal** index set Γ_K can be determined by a simple **knapsack problem**: Sort the benefit/cost ratios and take the first K indices with the **largest** bcr_{l_1, l_2} into account
- For rising K it involves a **truncation** of the bcr table along its level set lines
- Leads to the associated **general sparse grid** approximation

$$\tilde{P}_{L_1, L_2} = \sum_{l_1, l_2 \in \Gamma_K} \Delta_{l_1, l_2}$$

with minimal overall cost $\sum_{l_1, l_2 \in \Gamma_K} cost_{l_1, l_2}$ and minimal error

Sparse grid combination method

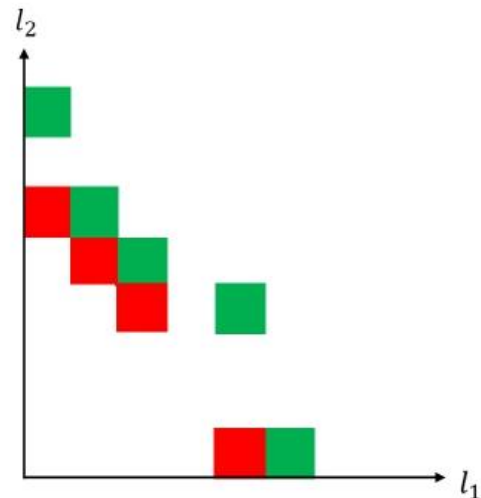
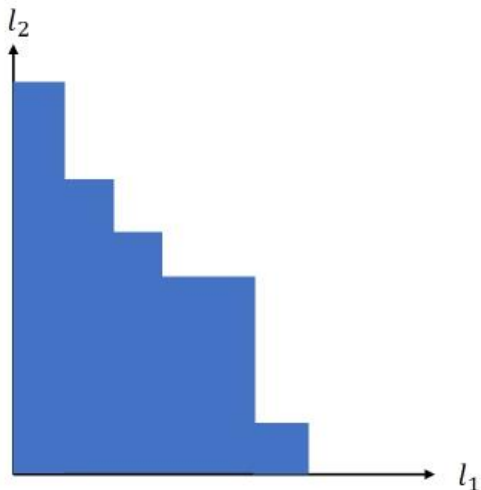
- The telescopic sum for Γ_K can be partially reversed. This leads to the **general sparse grid combination method**

$$\tilde{P}_{\Gamma_K} = \sum_{l_1, l_2 \in \Gamma_K} \Delta_{l_1, l_2} = \sum_{l_1, l_2 \in \Gamma_K} c_{l_1, l_2} l_{1, l_2} \tilde{P}_{l_1, l_2}$$

with the combination **coefficients**

$$c_{l_1, l_2} := \sum_{z_1, z_2=0,0}^{l_1, l_2} (-1)^{z_1 + z_2} \chi_{\Gamma_K}((l_1, l_2) + (z_1, z_2))$$

and the **characteristic** function $\chi_{\Gamma_K}(l_1, l_2) := \begin{cases} 1 & \text{if } (l_1, l_2) \in \Gamma_K \\ 0 & \text{else} \end{cases}$



Sparse grid combination method

- Involves now only certain \tilde{P}_{l_1, l_2} , i.e. **calls** of the **code *su2***, with different parameters and the linear combination of its results
- Can be tried analogously with other theories and codes
- Can also be tried for code involving renormalization, Callan-Symanzik corrections, etc. provided that there is code and that the limit exists at all ?
- Can be seen as a **two-variate extrapolation** method between the lattice size/spacing and the number of MC samples

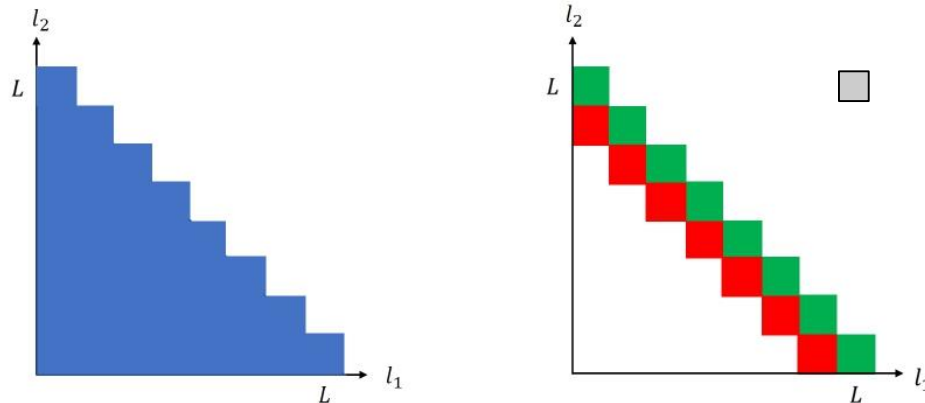
Sparse grid combination method

- Most simple example: **Isotropic sparse grid**, $d = 2$
- **Index set**: $\Gamma_{isp,L} = \{(l_1, l_2) \in \mathbb{N}^2, l_1 + l_2 \leq L + 1\}$
- Isotropic sparse grid approximation

$$\tilde{P}_{isp,L} = \sum_{l_1, l_2 \in \Gamma_{sparse,L}} \Delta_{l_1, l_2}$$

- **Isotropic combination technique**

$$\tilde{P}_{isp,L} = \sum_{l_1+l_2=L+1} \tilde{P}_{l_1, l_2} - \sum_{l_1+l_2=L+1} \tilde{P}_{l_1, l_2}$$



- **Cost complexity gain** in contrast to full grid \square :
 $O(L2^L)$ instead of $O(2^{2L})$

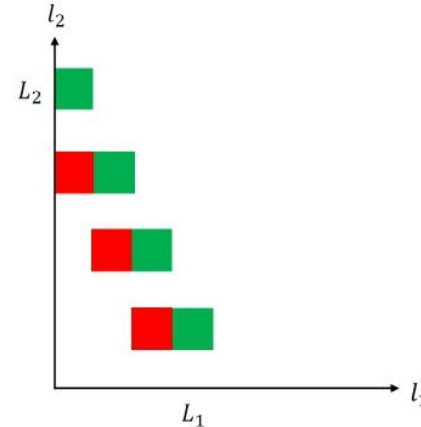
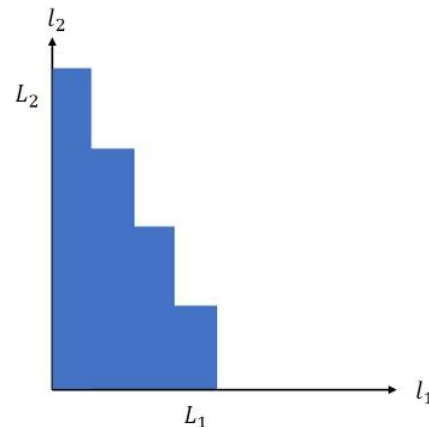
Sparse grid combination method

- Isotropic situation **rarely** encountered: Slow rate of MC in l_1 -direction, much faster rate in l_2 -direction, product decay unclear
- **Anisotropic** index set associated to L_1, L_2

$$\Gamma_{asp,L_1,L_2} = \{(l_1, l_2) \in \mathbb{N}^2, (L_2 - 1)l_1 + (L_1 - 1)l_2 \leq L_1L_2 - 1\}$$

- Anisotropic sparse grid approximation $\tilde{P}_{asp,L_1,L_2} = \sum_{l_1, l_2 \in \Gamma_{asp,L_1,L_2}} \Delta_{l_1, l_2}$
- **Anisotropic combination technique**

$$\tilde{P}_{asp,L_1,L_2} = \sum_{(L_2-1)l_1+(L_1-1)l_2=L_1L_2} \tilde{P}_{l_1, l_2} - \sum_{(L_2-1)l_1+(L_1-1)l_2=L_1L_2-1} \tilde{P}_{l_1, l_2}$$

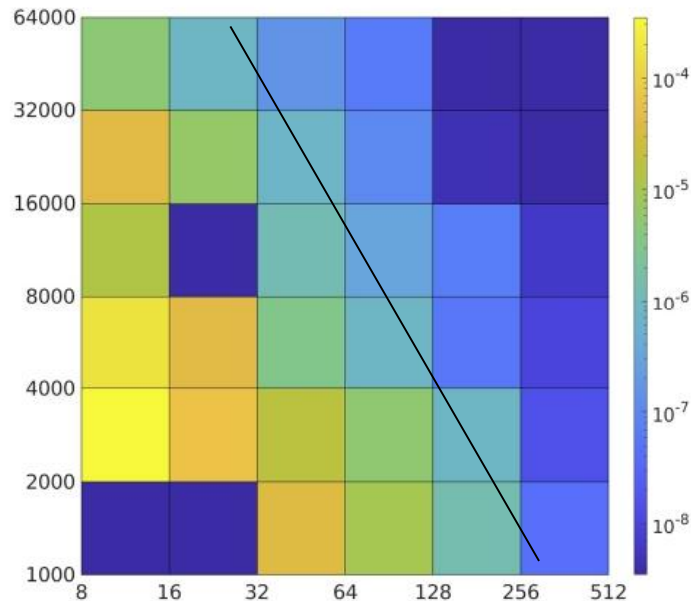


- Cost complexity gain in contrast to full grid:

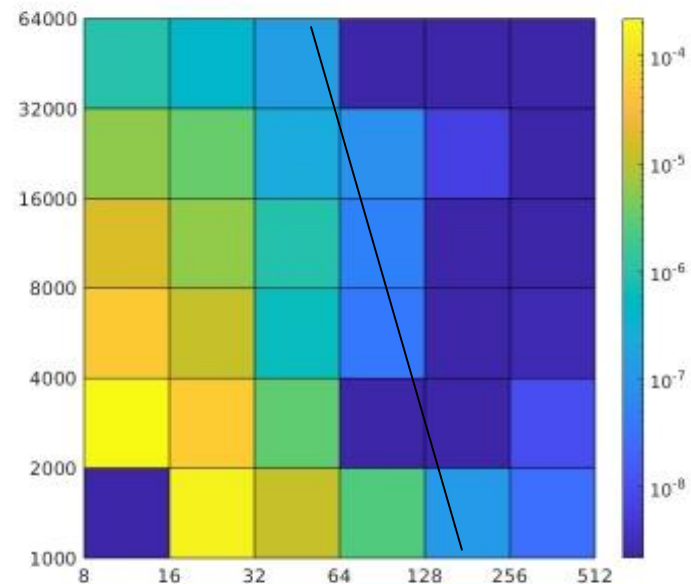
$$O(2^{\max(L_1, L_2)}) \text{ instead of } O(2^{L_1+L_2})$$

Numerical experiments

- For simplicity, set $d = 2$
- We consider $\beta = 0,5$ and $\beta = 10$
- Benefit cost ratios for N, M of different level indices



$\beta = 0,5$



$\beta = 10.0$

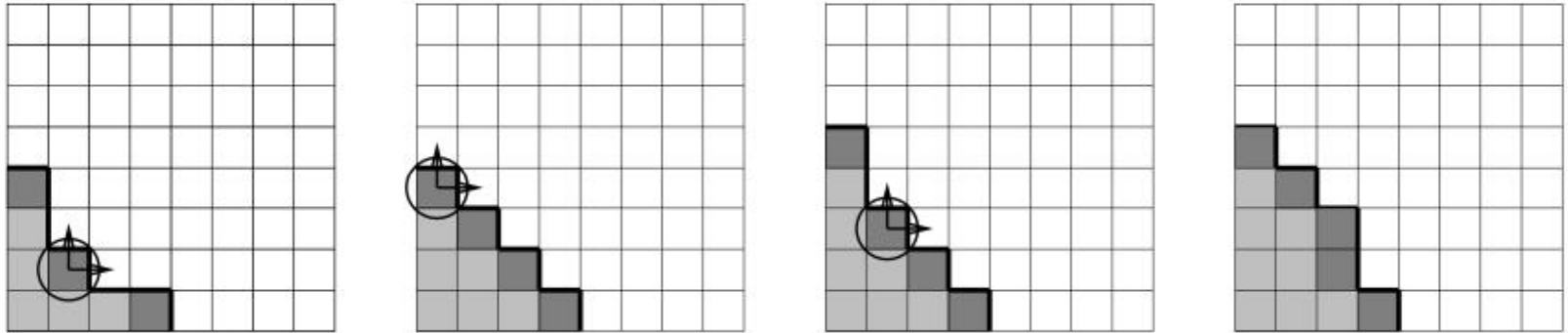
- We see an **anisotropic sparse grid** structure in both cases and **NOT** a full grid structure

Numerical experiments

- This is **good news**:
 - We have a kind of product type behavior of the convergence and a **sparse grid effect** for the SU(2).
 - Allows substantially **faster** algorithms by means of the sparse grid combination method
- The diagonal cut off isoline of the isotropic case for optimal complexity is **rotated**
 - Anisotropy reflects the slower convergence rate in sampling direction versus the faster rate in lattice size direction
 - Gets **more profound** for the larger value of β
- How can we **detect** this algorithmically and how can we practically **construct** an optimal index set ?

Algorithmic remarks

- **Dimension-adaptive method** builds the index set successively adapted to a specific problem under consideration
- Example:



- **Adaptive method**: Error indicator $bcr_{l_1, l_2} > \varepsilon$ involving the Δ_{l_1, l_2} , largest value marks the index for refinement, refinement in two directions, and repeat
- Associated combination method involves only the \tilde{P}_{l_1, l_2}
- Note again: Just **code** to be called for different lattice resolutions and different samplings/chain lengths

Concluding remarks

- We studied SU(2) lattice problems for the most **simple** case $d=2$ and the **infinite volume limit**
 - Wanted to find out if there is a kind of product decay/sparse grid effect or not
 - **Yes !** Allows to substantially speed up calculations
- Next:
 - Consider the cases $d = 3, 4$
 - Try to consider the continuum limit case, code ?
 - Consider other problems than just SU(2), code ?
 - Note: Other codes can be simply **plugged into** our method
- Instead with MCMC, our approach could work for quasi MC-type techniques of higher order as well ?