Performance optimizations for porting the openQ*D package to GPUs

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Introduction/Motivation

Other talks involving OpenQ*D [Campos et al. arXiv:1908.11673]:

- Jens Luecke: An update on *QCD* + *QED* simulations with *C** boundary conditions (July 29)
- Madeleine Dale: Baryon masses from full *QCD* + *QED_C* simulations (July 29)
- Lucius Bushnaq: Implementing noise reduction techniques into the OpenQxD package (July 30)

Introduction/Motivation

$$D\psi = \eta \tag{1}$$

- source spinor $\eta \in \mathbb{C}^n$, given
- Dirac operator D, sparse, $n \times n$ -matrix, complex, given
- Wilson Dirac Operator with a clover term
- Lattice QCD: $n = 4 \cdot 3 \cdot V$, with $V = L_0 L_1 L_2 L_3$

Example: 96×64^3 -lattice $n = 3 \cdot 10^8$



Conjugate Gradient with different real number formats

Conjugate Gradient - Convergence analysis



Conclusions:

- binary16 or bfloat16 are sufficient
- use binary64 in reduction variables (norms)

$$\|\vec{x}\| = \sqrt{\sum_i x_i^2}$$

- implement a general mixed precision solver
- solver-kernel consists of norms, scalar products, applications of D,

 $\mathsf{axpys} \implies \mathsf{memory} \ \mathsf{bound} \ \mathsf{operations}$

- Residue: $\rho_i = \eta D\psi_i$
- binary16: 5 exponent, 10 mantissa bits
- bfloat16: 8 exponent, 7 mantissa bits

SAP-preconditioned GCR algorithm

SAP-preconditioned GCR algorithm (SAP+GCR)

Ω_1	Ω_2	Ω_3	Ω_4
Ω_5	Ω_6	$Ω_6$ $Ω_7$ $Ω_8$	
Ω_9	Ω_{10}	Ω_{11}	Ω_{12}
Ω_{13}	Ω_{14}	Ω_{15}	Ω_{16}

Figure 1: A d = 2 dimensional example of a decomposition of a lattice Ω into domains named Ω_i . [Lüscher arXiv:hep-lat/0304007]

- \bullet Only nearest-neighbour interaction \implies blocks of same color are independent
 - solve gray blocks
 - update boundaries
 - solve white blocks
 - update boundaries

 \implies one Schwarz-cycle (alternate between black and white blocks)

- Preconditioning phase:
 - n_{cy} Schwarz-cycles
 - *n_{mr}* MR-steps on each blocked problem

SAP-preconditioned GCR algorithm (SAP+GCR)



Figure 2: Machine: Intel(R) 6130 @ 2.10GHz with 1.5 TB memory, an NVIDIA V100 (via PCIe) GPU with 16 GB memory.

SAP+GCR - Conclusions

- Heavy and non-intuitive run-time dependence on input parameters (*n_{cy}*, *n_{mr}*)
- Existence of exceptional configurations with extremely long run-times, non-convergence
- Adaptive variant (tries to find the optimal config every GCR-iteration anew, avoiding exceptional configs, suitable long running simulations, where D vastly changes its condition)
 - upper bound: $n_{cy} = 20$ and $n_{mr} = 20$
 - lower bound: $n_{cy} = 1$ and $n_{mr} = 4$
 - after every Schwarz cycle, exit if residual satisfies

$$\|\rho_i\| \ge \|\rho_{i-1}\|$$

• after every MR-step, exit if **blocked** residual satisfies

$$\|\rho_i\| \ge \alpha \|\rho_{i-1}\|$$
 where $\alpha \in \{0.7, 0.9\}$

SAP-preconditioned GCR algorithm (SAP+GCR)



Figure 3: Machine: Intel(R) 6130 @ 2.10GHz with 1.5 TB memory, an NVIDIA V100 (via PCIe) GPU with 16 GB memory.

Summary

- Dirac-operator in reduced precision, mixed precision solvers, expected speedup ≤ 2x
- GPU gives significant performance increase, 2x 10x
- Hybrid solution gives significant performance increase, up to 8x
- Adaptive SAP+GCR, more versatile, suitable long running simulations (no fixed choice of n_{cy}, n_{mr})
- Future: heterogeneous computing, speedup unknown
- Thanks for listening!
- We acknowledge access to Piz Daint at the Swiss National Supercomputing Centre, Switzerland under the ETHZ's share with the project IDs s299 and c21.

Backup slides

Floating-point format limits						
name	f _{max}	f _{min}	f _{smin}	sign.		
binary64	$1.8 imes10^{308}$	$2.2 imes10^{-308}$	$4.9 imes10^{-324}$	≤ 15.9		
binary32	$3.4 imes10^{38}$	$1.2 imes10^{-38}$	$1.4 imes10^{-45}$	\leq 7.2		
binary16	$6.6 imes10^4$	$6.1 imes10^{-5}$	$6.0 imes10^{-8}$	\leq 3.3		
bfloat16	$3.4 imes10^{38}$	$1.2 imes10^{-38}$	$9.2 imes10^{-41}$	≤ 2.4		
tensorfloat32	$3.4 imes10^{38}$	$1.2 imes10^{-38}$	$1.1 imes10^{-41}$	\leq 7.2		
binary24	$1.8 imes10^{19}$	$2.2 imes10^{-19}$	$3.3 imes10^{-24}$	≤ 5.1		
binary128	$1.2 imes 10^{4932}$	$3.4 imes 10^{-4932}$	$6.5 imes10^{-4966}$	\leq 34		
binary256	$1.6 imes 10^{78,913}$	$1 imes 10^{-78,912}$	$1 imes 10^{-78,983}$	\leq 71.3		

Table 1: Summary of highest representable numbers, minimal subnormal and non-subnormal representable numbers above 0 in any IEEE 754 floating-point format together with their approximated precision in decimal.

SAP+GCR - ill-conditioned system



Figure 4: Time measurements for the SAP_GCR kernel on different configurations. Node: AMD EPYC 7742 CPU @ 2.25GHz, 512 GB memory, NVIDIA A100 (via SXM4) GPU with 40 GB memory.

Floating-point formats					
name	S	е	m	comment	
binary64	1	11	52	double precision, IEEE 754	
binary32	1	8	23	single precision, IEEE 754	
binary16	1	5	10	half precision, IEEE 754	
bfloat16	1	8	7	Googles Brain Float	
tensorfloat32	1	8	10	NVIDIAs TensorFloat-32	
binary24	1	7	16	AMDs fp24	
binary128	1	15	112	IEEE 754	
binary256	1	19	236	IEEE 754	

Table 2: Commonly used floating-point formats, where *s* is the number of sign bits, *e* the number of exponent bits and *m* the number of mantissa bits.

Dirac-matrix



Figure 5: An example plot of a Dirac-matrix of an 8⁴-lattice with SF-boundary conditions. Every pixel consists of 192×192 real numbers. If the average over that numbers is non-zero the pixel is drawn black, else the pixel is drawn white. The density gives the overall percentage of non-zero values.

Scheme of Dirac-matrix



Figure 6: Schematic of the Dirac-operator in terms of a large sparse matrix.

The arithmetic intensity I is the ratio of the work W and the memory traffic T appearing in a considered piece of code,

$$V = \frac{W}{T}.$$

The work W needs to be given as number of floating-point operations and the memory traffic T in terms of stored and loaded bytes. The unit of arithmetic intensity I is then floating-point operations per byte and depends on the data type of the involved quantities.