



SCILIB-Accel: Performant Automatic BLAS Offload for NVIDIA Grace-Hopper

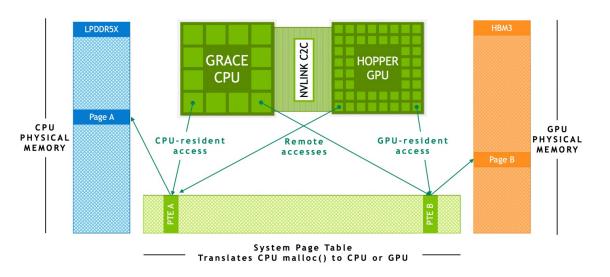
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Grace-Hopper: Key features



- single system page table for LPDDR5 + HBM
- conventional GPU managed page table for HBM
- coherent memory at cache line level
- fast C2C NVLink
- active research to utilize these new features

Allocator	Initial Page Table Entry	Cache Coherent
malloc	CPU	yes
cuda Malloc Managed	CPU	yes
cudaMalloc	GPU	no
cudaMallocHost	CPU	no



GH200: Stream & HPL

STREAM TRIAD Bandwidth (GB/s)

	CPU	GPU
LPDDR5X	418	610
НВМ	142	3680

Astonishing bandwidth. Data locality still matters.

Highly FP64 capable GPU Recent driver + recent cuBLAS: dgemm can use tensor core.

HPL (FP64)

	Rmax (Tflops)
Grace (72C)	2.8
Hopper	52.9



Porting PARSEC to GPU

- real-space DFT code at UT Austin by Prof. Chelikowsky
- PARSEC heavily relies on dgemm (77% runtime)
- Most dgemm comes from ScaLAPACK (pdgemm, pdtrsm)
- Never run on GPU before
- BLAS -> cuBLAS?
 - no way to rewrite ScaLAPACK
 - cuBLAS: different interface
 - no intent to rewrite user code
 - symbols interception and automatic offload?

total				
I	group	function	count	time
1	BLAS	dgemm_	43481	524.512
2	PBLAS	pdtrsm_	750	25.975
3 j	PBLAS İ	pdgemm_	1505	13.446
4	PBLAS İ	pdsymv_	23840	4 . 680
5 j	BLAS İ	dcopy_	28194164 İ	3.236
6 j	BLAS İ	dtrsm_	427 j	1.686
7 j	BLAS	dgemv_	1157095	1 . 389
	·	<u> </u>		4



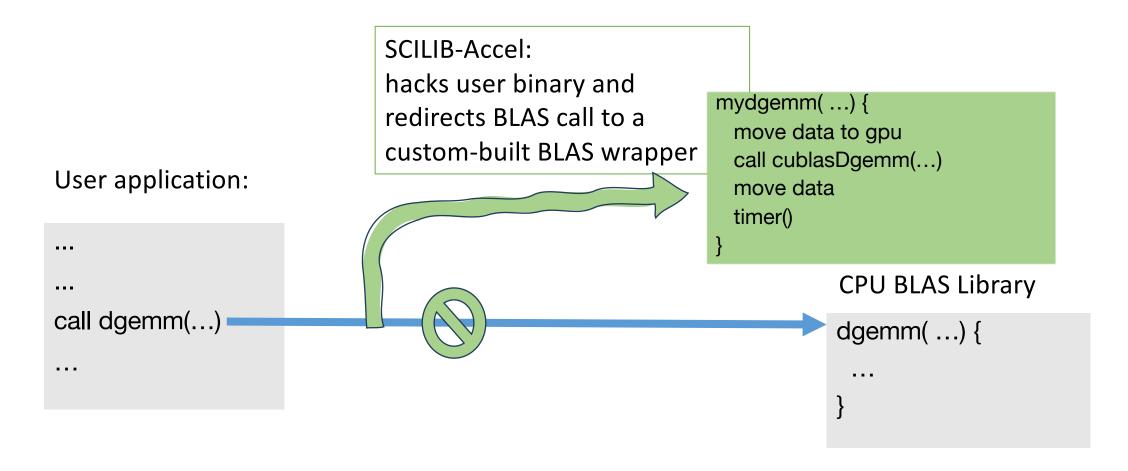
Auto BLAS Offload Attempts

- Cray LIBSci (since Titan), IBM ESSL, NVidia NVBLAS (heavy overheads)
- Some require relink, or only work for dynamically linked BLAS
- All performs mandatory data copies to/from GPU
 - copy data costs more time than compute
- hardly useful in practice.

 SCILIB-Accel: a new tool to overcome all these issues!



SCILIB-Accel: workflow

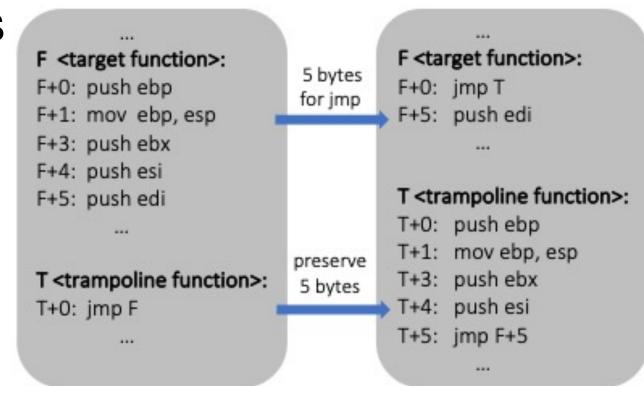




SCILIB-Accel: intercept BLAS calls

Replace BLAS calls with CUBLAS calls (level-3 for now)

- Symbol interception by trampoline-based Dynamic Binary Instrumentation
- No user code recompile
- Effective for both dynamically and statically linked BLAS.
- Negligible overhead when replacing function with same signature.





SCILIB-Accel: data movements strategy 1/3

1. Mem-copy: cudaMemCpy Matrices between CPU mem to GPU mem for every CUBLAS call (all other tools do this)

```
cudaMemCpy matrix A, B, C to GPU

cublasDgemm(..., device_A, .., device_B, .., device_C, ..)

cudaMemCpy matrix C back to CPU
```

Method		application total runtime	dgemm time	data movement
CPU, single Grad	ce	776.5s	608s	0
Auto offload S1: data copy		425.7s	12.4s	220.7s



SCILIB-Accel vs NVBLAS

- NVBLAS is supposed to be equivalent to SCILIB-Accel Strategy 1
- but NVBLAS has ridiculous overhead, not usable at all.

Runtime of cublasDgemm w/ cudaMemCpy (transA='T', transB='N', M=32, N=2400, K=93536)

	GH200	H100-PCIe	GH200	H100-PCIe
Offload Strategy	Strategy 1	Strategy 1	NVBLAS	NVBLAS
Total time	5.50ms	32.80ms	54.8 ms	134.0ms
 cudaMemcpy[†] 	4.96 ms	31.79ms	-	-
cublasDgemm	0.52 ms	0.99ms	-	-
3. other	0.02 ms	0.02ms	-	-

[†] Including copying matrices A, B and C to GPU memory and C back to host memory.



SCILIB-Accel: data movements strategy 2/3

2. Coherent Access: just pass the CPU malloc pointer to GPU kernel let counter-based migration or compiler optimization (-gpu=unified) to move data

cublasDgemm(..., host_A, .., host_B, .., host_C, ..)

Method		application total runtime	dgemm time	data movement
CPU, single Gra	ce	776.5s	608s	0
	S1: data copy	425.7s	12.4s	220.7s
Auto offload	S2: cuda runtime	470.0s	234.0s	in dgemm CUDA counter-based migration
	S2: -gpu=unified*	246.8s	56.6s	in dgemm

^{*} requires recompile of PARSEC and SCILIB-Accel



Strategy 3: Common level3 BLAS use patterns

Case 1: block matrix multiplication, e.g. ScaLAPACK.
 Every submatrix of A multiplies with submatrix of B

	bs			
bs	A ₁₁	A ₁₂		A _{1n}
	A ₂₁	A ₂₂		A _{2n}
	:	:	:	:
	A _{n1}	A _{n2}		A _{nn}

	bs			
bs	B ₁₁	B ₁₂		B _{1n}
х	B ₂₁	B ₂₂		B _{2n}
^		:	:	:
	B _{n1}	B _{n2}		B _{nn}

	bs			
bs	C ₁₁	C ₁₂		C _{1n}
	C ₂₁	C ₂₂		C _{2n}
	:	:	:	:
	C _{n1}	C _{n2}		C _{nn}

- Case 2: Self-Consistent Field calculation, calculations are performed on the same matrix until convergence is reached.
- Case 3: a sequence of matrix multiplications.
 Each matrix is involved in multiply gemm calls

- In these common cases, matrix inputs for gemm calls can be re-used
- LDDDR5 in NUMA0, HBM in NUMA1
- There will be CPU accessing the matrices (normalize, scale, trace, etc....)
 - through coherent access on GH
- Assume non-gemm CPU access of the matrices are relatively trivial, matrices can be kept resident on NUMA 1 (just like remote memory access is assumed to be relatively trivial in OpenMP first touch)
- leads to Strategy 3:
 GPU first use



SCILIB-Accel: data movements strategy 3/3

- 3. GPU First Use: matrices are moved HBM the first time they are used by CUBLAS.
 - Matrices stay on HBM throughout their lifetime
 - Implemented by migrating memory pages from NUMA0 to NUMA1, move_page function from libnuma is used.

```
if (on numa 0) move_page (host_A);
if (on numa 0) move_page (host_B);
if (on numa 0) move_page (host_C);
cublasDgemm(..., host_A, .., host_B, .., host_C, ..)
```



SCILIB-Accel: easy to use

Just LD_PRELOAD it!
All level-3 BLAS are implemented!

LD_PRELOAD=\$PATH_TO_LIB/scilib-dbi.so run your cpu code.

get code from here https://github.com/nicejunjie/scilib-accel



SCILIB-Accel: data movements strategy 3

First Use Policy, best performance!

4k page: 220.3, 64k page: 230s

PARSEC performantly runs on GPU for the first time ever!

Matrix reuse: every matrix moved to HBM gets reused 570 times on average by subsequent dgemm calls.

Method		application total runtime	dgemm time	data moveme
CPU, single Gra	ce	776.5s	608s	0
	S1: data copy	425.7s	12.4s	220.7s
A . CCl .	S2: CUDA runtime	470.0s	234.0s	in dgemm
Auto offload	S2: -gpu=unified*	246.8s	56.6s	in dgemm
	S3: GPU First Use	220.3s	29.1s	1.3s



Application Tests: MuST

MuST suite solves the Kohn-Sham equation by solving the Green's function. In contrast to solving the wave-function, it can perform KKR-CPA calculations for random structures and LSMS calculations for large systems with linear scalability to the system size. https://github.com/mstsuite/MuST

The code has a native GPU version calling cuSolver doing the critical matrix inverse. SCILIB-Accel auto offload does much better offloading more components to GPU.

MuST

Method		App Runtime	zgemm+ztrsm time	data movem time	ent
CPU, Grace		124s	82.5 + 35.2s	-	
Auto offload	GPU First Use	30.7s	15.9s+3.8s	3.6s	/latrix reuse: 7



SCILIB-Accel: Performant Auto BLAS offload

- High bandwidth C2C NVLink and coherent memory inspires new possibilities of doing auto offload.
- https://github.com/nicejunjie/scilib-accel
- automatically offload CPU BLAS calls to GPU
- no user code modification or recompilation
- Works for statically and dynamically linked BLAS
- Better performance than all other tools



Final comment

- Easy way to explore GPU capability
- Get incentives to port CPU codes to GPU
- Performance may further improve as there is still performance issue of CUDA kernel accessing malloc HBM memory.
- Let me know if this tool helps you.

https://github.com/nicejunjie/scilib-accel

