

JACC: An OpenACC Runtime Framework with Kernel-Level and Multi-GPU Parallelization

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Introduction

```
__global__ void kernel(  
    float *m, float3 *p, float3 *v){  
    int tid = blockIdx.x *  
        blockDim.x + threadIdx.x;  
    int offset = tid * THREAD_SIZE;  
    for (int j = 0; j < THREAD_SIZE; j++) {  
        int i = offset + j;  
        p[i].x += v[i].x * DT;  
        p[i].y += v[i].y * DT;  
        p[i].z += v[i].z * DT;  
    }  
}
```



```
#pragma acc data copyin (p_x[N], p_y[N], p_z[N], m[N])  
#pragma acc data copyout (v_x[N], v_y[N], v_z[N])  
for (int t = 0; t < TIME_STEP; t++) {  
    #pragma acc parallel loop independent  
        for (int i = 0; i < N; i++) { /* ... */ }  
  
    #pragma acc parallel loop independent  
        for (int i = 0; i < N; i++) {  
            p_x[i] += v_x[i] * DT;  
            p_y[i] += v_y[i] * DT;  
            p_z[i] += v_z[i] * DT;  
        }  
}
```



- **Modern supercomputers often have heterogeneous designs**

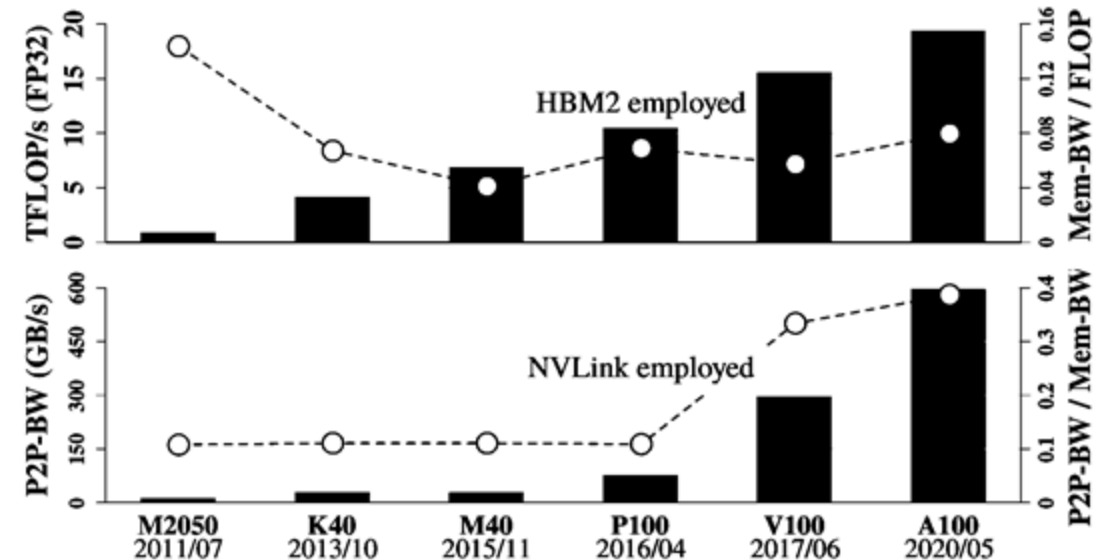
- Execution performed on CPUs & *Accelerators* (e.g. GPUs/FPGAs)

- **Utilizing accelerators poses additional programming cost**

- Through primitives (CUDA/OpenCL) or *Abstract Models* (DSL/Directive)
- The latter introduces less engineering efforts w/ limited interfaces → *Less Efficiency*

Introduction

- Exploiting better performance on accelerators is not straightforward
 - Higher compute performance, *Lower Bandwidth/FLOP Ratio*
 - Global/local memory access, synchronization, on-chip resource use and little parallelism might limit the performance
 - GPU's parallelism: instruction-level, thread-level, kernel-level or device-level
- Currently, the NVLink interconnect is enhancing peer-to-peer communication among multi-GPU
 - *Increased P2P-Bandwidth/Mem-Bandwidth*
 - This allows not only compute-intensive but memory-intensive applications to utilize several devices



```
#pragma acc data copyin (p_x[N], p_y[N], p_z[N], m[N])
#pragma acc data copyout (v_x[N], v_y[N], v_z[N])
for (int t = 0; t < TIME_STEP; t++) {
  #pragma acc parallel loop independent
    for (int i = 0; i < N; i++) { /* ... */ }

  #pragma acc parallel loop independent
    for (int i = 0; i < N; i++) {
      p_x[i] += v_x[i] * DT;
      p_y[i] += v_y[i] * DT;
      p_z[i] += v_z[i] * DT;
    }
}
```

OpenACC
Directives for Accelerators

- OpenACC offers compiler directives to program accelerators in existing languages
- Without introducing vendor-specific languages such as CUDA, users are allowed to parallelize their code and rely on the compiler for generating device-specific application code

- OpenACC = **kernels** + **routines**

- An OpenACC kernel is the unit of program execution on accelerators launched with a specified parallelism
- The environment for kernel execution can be controlled by OpenACC routines (e.g. data copies and sync behaviors)

```
acc_set_device_num(...);  
acc_copyin(...);
```

- **OpenACC directives** are provided for specifying a portion of code as a kernel and defining data

- Data-related directives can be replaced by routine calls
- Kernel directives have to be embedded with original code for pre-execution compilation

```
#pragma acc data copyin(...)  
#pragma acc kernels ...
```

Optimizing Example: Multi-GPU Use

```
Config {  
    for (int d = 0; d < NUM_DEV; d++) {  
        acc_set_device_num(d , 0);  
        int length = N / NUM_DEVICES;  
        int init = length * d;  
        int until = length * (d + 1);  
    }  
  
Kernel {  
    #pragma acc parallel loop\  
        independent async(d)  
    for (int i = init; i < until; i++) {  
        /* ... */  
    }  
  
Comm {  
    for (int d2 = 0; d2 < NUM_DEV; d2++) {  
        cudaMemcpyAsync( ... );  
    }  
}
```

- **Each kernel needs code extension**

- Loop splitting / Async / Communication
- Many other factors such as runtime information are concerned in real applications

→ *In-situ kernel declarations bring much complexities*

- **Once kernels are declared, they do not allow any update**

→ *has to prepare adjusted kernels before the compilation*

Proposed Framework: JACC

- Our framework JACC is designed to serve as a **transparent layer between runtime and compiler**
 - All the components of OpenACC, here, are provided as runtime routines
 - Having the ability to perform dynamic analysis and runtime compilation, allowing further efforts at runtime
- We adapt several **automated optimization techniques** on JACC
 - Asynchronous execution / On-the-fly kernel optimization / Multi-GPU utilization

Execution Flow of JACC

Input Code

```
#pragma acc data copyout(x[0:N])
#pragma acc parallel loop
for (int i=0; i<N; i++)
    x[i]=y[i] * y[i];
```

JACC Code

```
/* Entry of #pragma acc data */
jacc_create(x, N * sizeof (float));

/* #pragma acc parallel loop */
jacc_kernel_push(
    "#pragma acc parallel present (x, y)\n"
    "#pragma acc loop\n"
    "for (int i=0; i<N; i++) /* ... */",
    /* args */ , /* flags */ );

/* Exit of #pragma acc data */
jacc_copyout(x, N * sizeof(float));
```

Dynamic Code

```
void kernel0(float *x,
             float *y, size_t N) {
    #pragma acc parallel present(x, y)
    #pragma acc loop
    for (int i=0; i<N; i++)
        x[i]=y[i] * y[i];
}
```

② Exec

JACC Runtime

Data Management

- Array Mapping
- CPU-to/from-Device Communication

Kernel Execution

- Code Gen/Compile
- Parameter Calculation
- Extended Execution

① Routine Use

③ Generate Code

④ Compile (PGI/GCC)
Link
Caching Binary
Execution

Automated Asynchronous Execution

Input Code

```
#pragma acc kernels create(a, b) copyout(c)
{ for (...) a[i] = i; for (...) b[i] = i;
  for (...) c[i] = a[i] + b[i];
  for (...) c[i] = b[i] + c[i]; }
```

JACC Code

```
jacc_create(...);      // Create a/b/c
jacc_kernel_push(...); // Initialize a
jacc_kernel_push(...); // Initialize b
jacc_kernel_push(...); // Update c from a/b
jacc_kernel_push(...); // Update c from b/c
jacc_copyout(...);     // Copyout c; Del a/b
```

Dynamic Code

```
void kernel0(..., int async) {
// ...
#pragma acc parallel ... async(async)
  for (...) {
    a[i] = i;
  }
}
```

JACC Runtime

Async	(Cr)	(K1)	(K2)	(K3)	(K4)	(Out)
0	a	a	Sync			
1	b					
2	c			c	c	c

On-the-Fly Kernel Specialization

Input Code



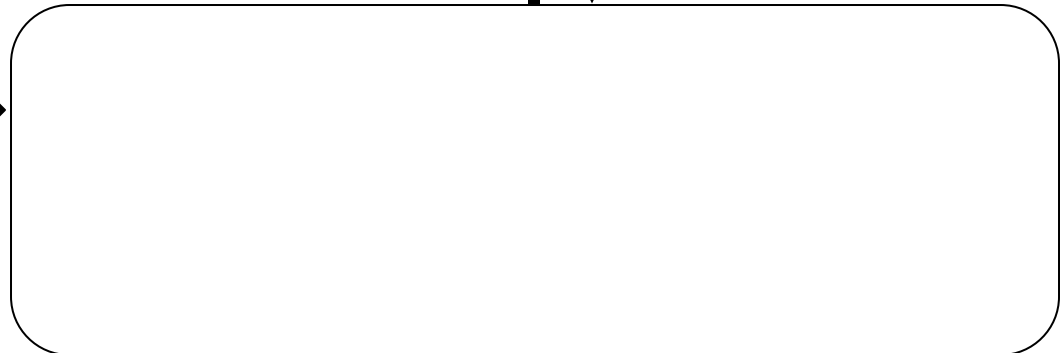
JACC Code

```
kernel(); // contains #pragma  
jacc_optimize();  
kernel();
```

Dynamic Code

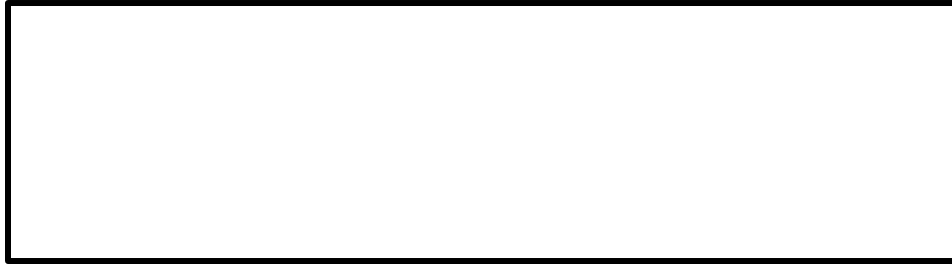
```
void kernel0(float *x, float *y,  
             size_t N, float *sum_out) {  
    float sum;  
    #pragma acc parallel ...  
    for (...) { ... }  
    *sum_out = sum;  
}
```

JACC Runtime



On-the-Fly Kernel Specialization

Input Code



JACC Code

```
kernel(); // contains #pragma
jacc_optimize();
kernel();
```

Dynamic Code

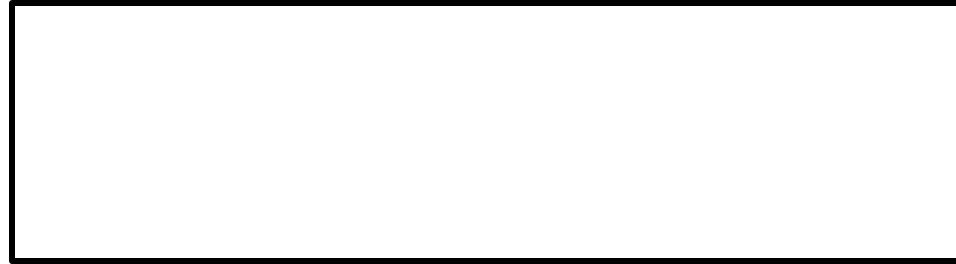
```
void kernel0(float *x, float *y,
             size_t N, float *sum_out) {
    float sum;
    #pragma acc parallel ...
    for (...) { ... }
    *sum_out = sum;
}
```

JACC Runtime

Args	(K0)	(K1)	(K2)	(K3)	...
0	0x...	0x...	0x...		
1	0x...				
2	1024				
3	Varied				

On-the-Fly Kernel Specialization

Input Code



JACC Code

```
kernel(); // contains #pragma  
jacc_optimize();  
kernel();
```

Dynamic Code

Specialized Code

```
#define N 1024  
void kernel0_opt(  
    float (* restrict x),  
    float (* restrict y),  
    float *sum_out) {  
    // The same as profiled code  
}
```

JACC Runtime

Args	(K0)	(K1)	(K2)	(K3)	...
0	0x...	0x...	0x...		
1	0x...				
2	1024				
3	Varied				

¿Multi-GPU Utilization?

- Previous work have persistently focused on loop splitting over plural GPUs or required manual efforts
- Mere loop splitting causes *unsolvable dependencies* among devices in real applications
- Unified memory can be employed among GPUs, but memory thrashing is inevitable
- **Key ideas to automate multi-GPU use**
 - Increased P2P-Bandwidth/Mem-Bandwidth
 - Less overheads of computation compared to memory accesses

Predicate-Based Filtering

- We duplicate the program structure on all the GPUs
- Our technique **predicate-based filtering** limits memory accesses depending on data regions to which the GPU writes
- GPU-to-GPU communication after each kernel execution

`a[i]*=2;`



`(a_lb <= i && a_ub >= i) ? a[i]*=2 : a[i];`

lb: lower-bound, ub: upper-bound

```
1  a[i]=x; b[i]=a[i]; x=c[j]
2  a[k]=x; b[k]=a[k];
```

```
1  /* a[i]=x */
2  ((a_lb<=i && a_ub>=i)||
3   (b_lb<=i && b_ub>=i)) ? a[i]=x:a[i];
4  /* b[i]=a[i] */
5  ((b_lb<=i && b_ub>=i)) ? b[i]=a[i]:b[i];
6  /* x=c[j] */
7  x=((a_lb<=k && a_ub>=k)||
8     (b_lb<=k && b_ub>=k)) ? c[j]:0;
9  /* a[k]=x */
10 ((a_lb<=k && a_ub>=k)||
11   (b_lb<=k && b_ub>=k)) ? a[k]=x:a[k];
12 /* b[k]=a[k] */
13 ((b_lb<=k && b_ub>=k)) ? b[k]=a[k]:b[k];
```

Predicate for Multi-Dimensional Arrays

```
1  #pragma acc parallel loop gang
2  for (i = 1; i <= gp02; i++) {
3    #pragma acc loop worker vector
4    for (k = 1; k <= gp22; k++) {
5      for (m = 0; m < 5; m++)
6        for (n = 0; n < 5; n++) {
7          lhsY[n][m][BB][jsize][i][k] =
8            lhsY[n][m][BB][jsize][i][k]
9            - lhsY[n][0][AA][jsize][i][k]
10             * lhsY[0][m][CC][jsize-1][i][k]
11             /* - lhsY[n][1..3][AA][jsize][i][k]
12                * lhsY[1..3][m][CC][jsize-1][i][k] */
13             - lhsY[n][4][AA][jsize][i][k]
14             * lhsY[4][m][CC][jsize-1][i][k];
15        }}}
```

Kernel code from NPB-BT

(Two inner loops are unrolled in actual code)

- Linear splits cause all-to-all dependencies among statements
→ all statements are *duplicated on all the GPUs*
- **We divide a specific dimension**
 - The dimension should contain the most parallel iterators (such as i and k)
 - The leftmost dimension is preferred in the C language and the rightmost dimension in Fortran

Translation for Predicate (NPB-CG)

Original

```
1 #pragma acc parallel/  
2   num_gangs(end) num_workers(4)  
3   vector_length(32)  
4 {  
5   #pragma acc loop gang  
6   for (j = 0; j < end; j++) {  
7     tmp1 = rowstr[j];  
8     tmp2 = rowstr[j+1];  
9     sum = 0.0;  
10    #pragma acc loop worker/  
11      vector reduction(+:sum)  
12    for (k = tmp1; k < tmp2; k++) {  
13      tmp3 = colidx[k];  
14      sum = sum + a[k]*p[tmp3];  
15    }  
16    q[j] = sum;  
17  }  
18 }
```

Basic Idea:

- **Split Array-Writes Evenly**
- **Filter Access to Dependencies**
- **All-to-All Communication**

Predicated

```
1 #pragma acc parallel num_gangs (end)/  
2   num_workers(4) vector_length(32)  
3 #pragma acc loop gang  
4 for(j = 0; j < end; j++) {  
5   tmp1 = ((r_lb <= j) && (r_ub >= j)) ?  
6           rowstr[j] : 0;  
7   tmp2 = ((r_lb <= j) && (r_ub >= j)) ?  
8           rowstr[j + 1] : 0;  
9   sum = 0.0;  
10  #pragma acc loop worker vector/  
11      reduction(+:sum)  
12  for (k = tmp1; k < tmp2; k++) {  
13    tmp3 = ((r_lb <= j) && (r_ub >= j)) ?  
14           colidx[k] : 0;  
15    sum = sum +  
16          (((r_lb <= j) && (r_ub >= j)) ?  
17            a[k] : 0) *  
18          (((r_lb <= j) && (r_ub >= j)) ?  
19            p[tmp3]:0);  
20  }  
21  ((r_lb <= j) && (r_ub >= j)) ?  
22      (r[j] = sum) : r[j];  
23 }
```

Predicate with Adaptive Algorithm

- **Expected performance degradation by:**

- Large GPU-to-GPU communication latency
- Failure of parallelization due to intra-kernel dependencies or less memory accesses

- **Enable multi-GPU execution for each kernel after satisfying the condition below five times:**

$$time_{\text{Kernel}} > time_{\text{Kernel}}/n_{\text{GPUs}} + \text{WriteSize}/peak_{\text{P2P}}$$

- **Disable multi-GPU execution after satisfying one of conditions five times and when (left-right) > 0 on average**

$$time_{\text{Kernel}} + time_{\text{Comm}} > time_{\text{Kernel}} \times n_{\text{GPUs}}$$

$$time_{\text{Kernel}} + time_{\text{Comm}} > eff_{\text{dup}} \times \text{WriteSize}$$

Implementation of Predicate

Input Code

```
#pragma acc kernels ..
```

JACC Code

```
jacc_kernel_push(..);
```

JACC Runtime

Data Management

- Array Mapping
- GPU-to-GPU or CPU-to/from-GPU Communication

Kernel Execution

- Code Gen/Compile
- Parameter Calculation
- Switching GPUs
- Adaptive Running

Dynamic Code

```
void kernel0(...)  
{ //Declarations  
  //Kernel Code  
  //Reduction  
}
```

Read
x=c[j]; a[k]=x; b[k]=a[k];
Read **Read**

Iterative Dataflow Analysis

①

②

③

④

⑤

Fortran Example

Input Code CloverLeaf calc_dt_kernel.f90

```
1 !$ACC KERNELS
2 ! ...
3 !$ACC LOOP INDEPENDENT REDUCTION(min:dt_min_val)&
4 !$ACC GANG(128)
5   DO k=y_min,y_max
6 !$ACC LOOP INDEPENDENT REDUCTION(min:dt_min_val)
7     DO j=x_min,x_max
8       IF(dt_min(j,k).LT.dt_min_val) &
9 &           dt_min_val=dt_min(j,k)
10    ENDDO
11  ENDDO
12 !$ACC END KERNELS
```

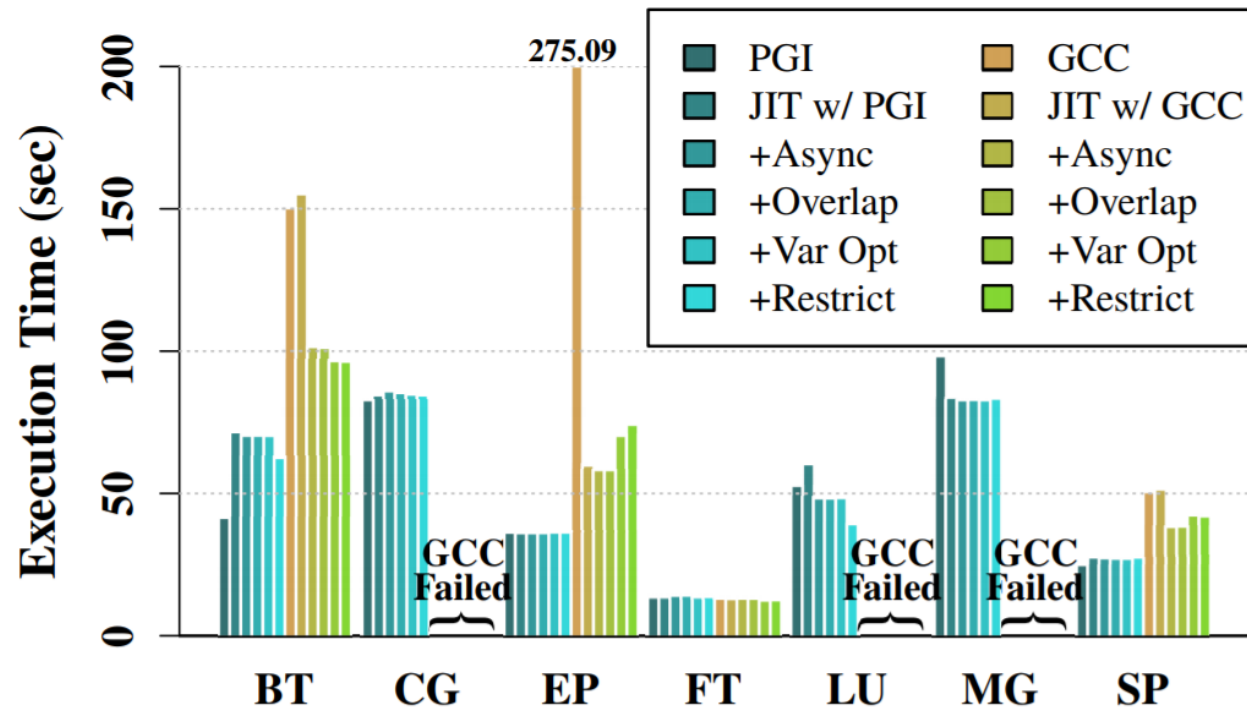
JACC Code

```
1 BLOCK
2   INTEGER(KIND=8) :: arg = 0
3   CALL jacc_arg_build(&
4     &"real\0", "dt_min\0",           &! Type, Symbol
5     & c_loc(dt_min), sizeof(dt_min), &! Address, Size
6     & ..., &! Analysis Info (e.g. WRITE, PRESENT, REDUCTED)
7     & lbound(dt_min), ubound(dt_min), &! Boundary
8     & arg)
9   CALL jack_arg_build(...)
10  ...
11  CALL jacc_kernel_push(&
12    && ! Kernel Code
13    "  !$ACC PARALLEL PRESENT(dt_min) NUM GANGS(128)\n &
14    & # 139 "calc_dt_kernel.f90"\n &
15    & ... !$ACC END PARALLEL\0", arg)
16 END BLOCK
```

- The JACC translator is implemented as a XcodeML converter (C/Fortran \rightarrow XML \rightarrow C/Fortran). Compiler: PGI/GCC
- The evaluation is performed on NVIDIA DGX-1 w/ Tesla V100 SXM2 (16GB Memory) x 8
 - We use tightly-coupled four GPUs where each link offers a unidirectional bandwidth of 25GB/s
- Benchmarks: Manually-tuned NAS Parallel Benchmarks (NPB) in C & CloverLeaf/CCS-QCD/Himeno in Fortran

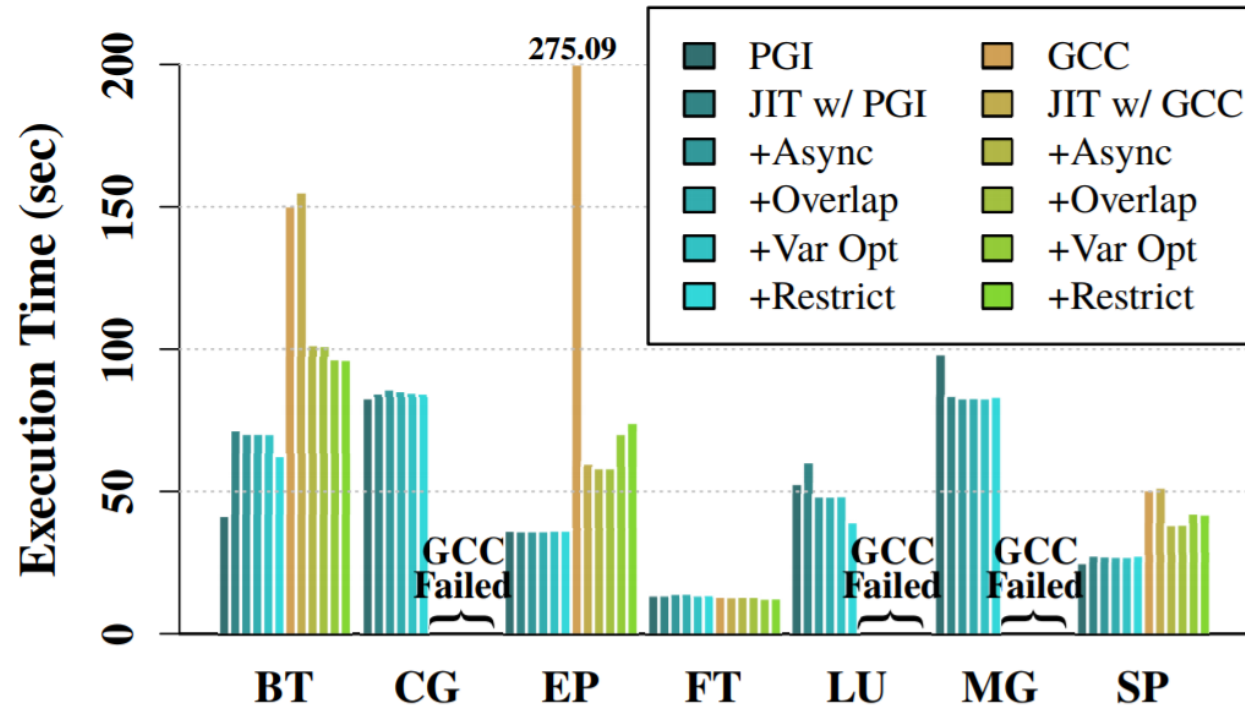
Name	Description	Dependency	Problem Size	Memory	Num Kernels
BT	CFD with Block Tri-Diagonal Solver	Halo (3D)	Class C: 162x162x162 (FP64), iter=200	4.915 GB	46
CG	Minimum-Eigenvalue Calculation	Irregular	Class C: size=150000 (FP64), iter=3750	0.747 GB	16
EP	Random-Number Generation in Parallel	None	Class D: size=137438953472 (FP64)	2.305 GB	4
FT	Discrete 3D Fast Fourier Transform	All-to-All	Class C: 512x512x512 (FP64), iter=20	9.317 GB	12
LU	CFD with Lower-Upper Gauss-Seidel Solver	Halo (3D)	Class C: 162x162x162 (FP64), iter=250	1.471 GB	59
MG	Multigrid Discrete Poisson Equation	Long & Short	Class C: 512x512x512 (FP64), iter=1000	6.114 GB	16
SP	CFD with Scalar Penta-Diagonal Solver	Halo (3D)	Class C: 162x162x162 (FP64), iter=400	1.700 GB	65
CloverLeaf	2D Euler Equations Solver	Halo (2D)	3840x1920 (FP64), step=1800	1.749 GB	114
CCS-QCD	Lattice QCD Simulation	Halo (3D)	32x32x32x128 (FP64), iter=1000 for BiCGStab	15.255 GB	27
Himeno	19-point Jacobian Stencil Computation	Halo (3D)	Size XL:1024x512x512 (FP32), iter=1000	14.409 GB	2

Result: Async/Kernel-Opt



- Performance changes of **Original** → **JACC** due to less static information
- **JACC** → **+Async** Performance improve 3.43% with PGI and 22.08% with GCC on average
 - **+Async** → **+Overlap** No improvement because of little inter-kernel parallelism
- With **+Restrict**, better performance up to 23.39% in BT/LU with PGI and 5.59% less in EP with GCC

Result: Async/Kernel-Opt

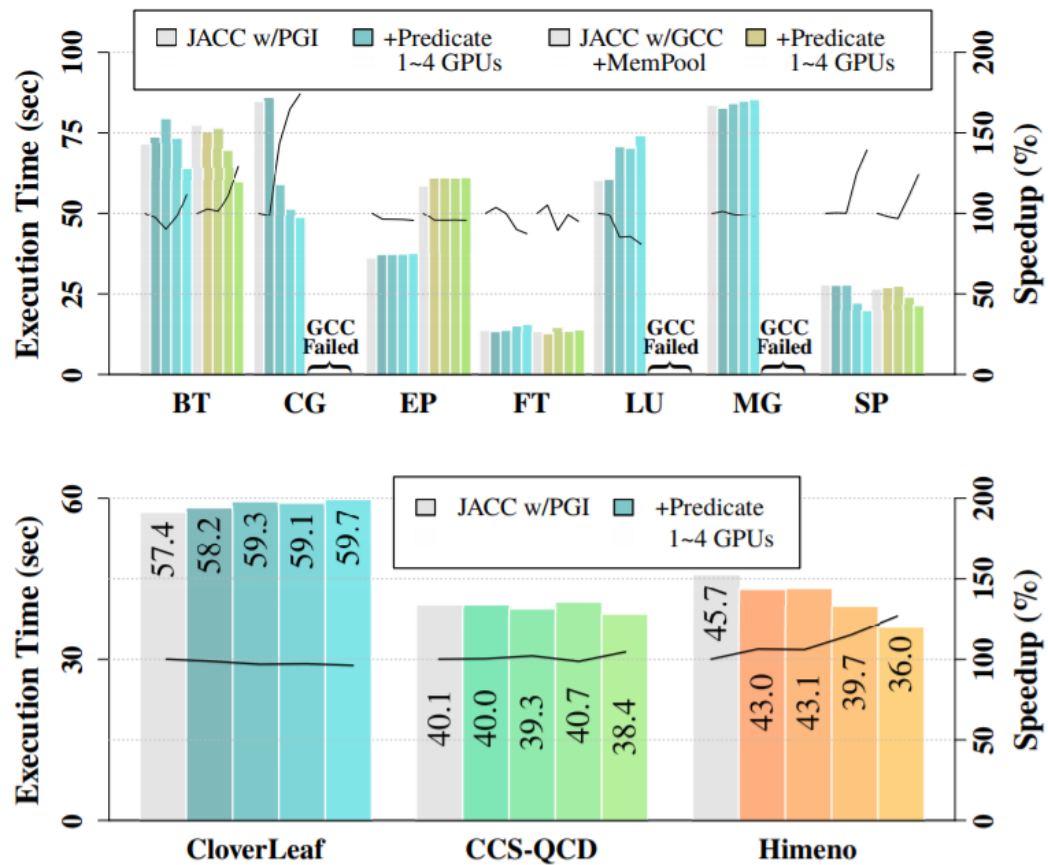


- With **+Var Opt**, no performance change in most cases and worsen efficiencies in EP/SP with GCC
 - Suffered from low utilization by ineffective threads which are created due to reduced register use
 - On the other hand, performance improvements of **+Restrict** are achieved by parallelized memory accesses which require additional registers

Result: GCC Custom Allocation

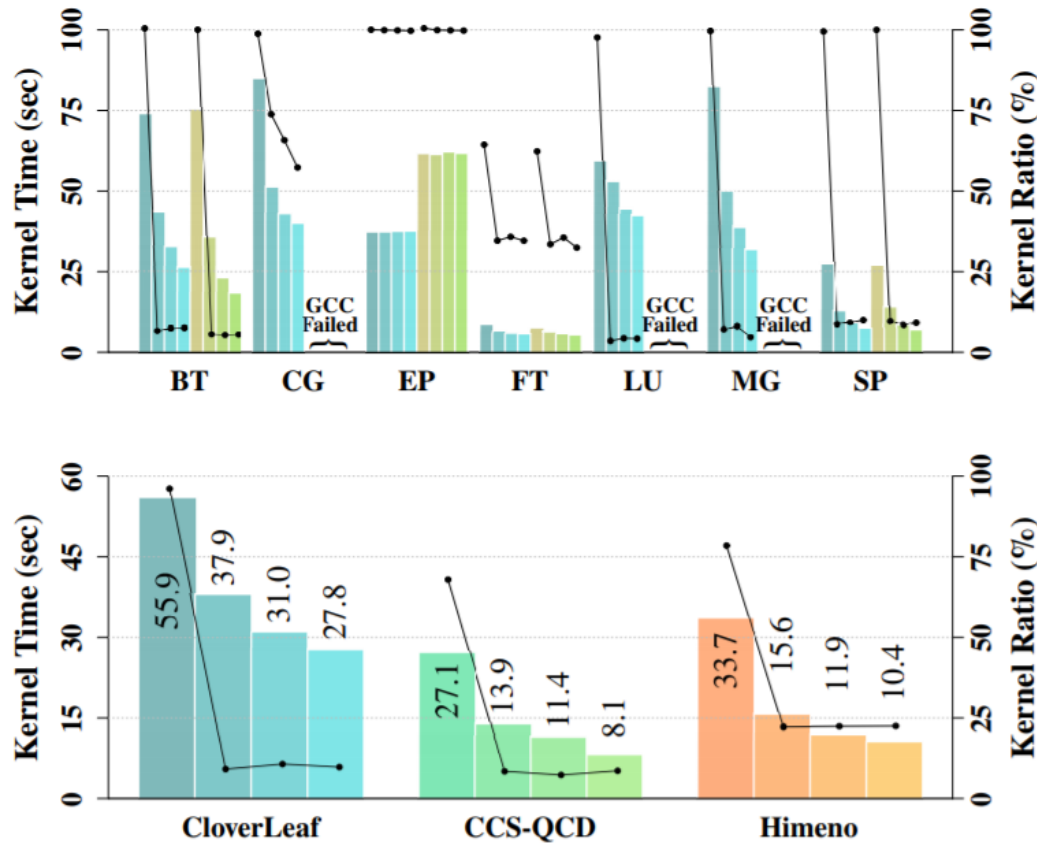
- The performance difference between PGI and GCC is primarily caused by the latency of memory allocation; PGI owns memory pools for device memory, while GCC does not
- For our multi-GPU experiments to explicitly show the performance improvements by kernel parallelization, we **integrate two pools for device memory** into the GCC library libgomp
 - One for user-invoked allocation, another for the GCC's internal allocation which tends to be smaller
 - With the memory-pool integration, GCC's efficiency becomes competitive to PGI while having -7.83% ~ 5.05% better throughputs
 - Except the case of EP, where the kernel execution poses a 38.31% overhead due to GCC's device-code

Result: Multi-GPU Utilization in Total



- Five of 10 applications improved by 4.05% ~ 43.43% when enabling four GPUs compared one GPU use
- When only the kernel execution and GPU-to-GPU transfers are concerned, six benchmarks improved by 23.9% on average
 - Other factors necessary for multi-GPU such as memory allocation and synchronization causes some overheads

Result: Multi-GPU Utilization in Kernel



- Using the memory-intensive benchmarks BT/SP, PGI achieves 2.83x and 3.59x improvements on four GPUs and GCC does 4.13x and 3.85x, respectively
- For LU, the shorter running time of each kernel execution than 1ms limits acceleration to 1.40x, involving overheads for duplicating program
- EP does not improve due to its compute-bound nature
- The 20% execution of CloverLeaf is distributed over multi-GPU but those kernels are not well enhanced

Result: Multi-GPU Utilization in Detail

Name	Num Kernels	Kernel Dup [ms]	Num Adapted	Comm + Kernel [ms]	Kernel Total (ave) [ms]	Kernel Adapted (ave) [ms]	Comm (ave) [ms]	Average WriteSize	GPU-to-GPU Bandwidth
BT	46	88,715	3	63,856	46,639 (0.44)	14,940 (24.75)	17,217 (28.52)	684.10 MB	23.99 GB/s
CG	16	75,178	7	44,137	38,720 (0.08)	34,365 (0.12)	5,417 (0.02)	0.10 MB	5.40 GB/s
EP	4	37,485	3	37,787	37,710 (24.55)	37,710 (24.55)	77 (0.05)	0.03 MB	0.54 GB/s
FT	12	8,472	4	8,757	6,096 (47.29)	4,983 (62.37)	2,661 (33.31)	806.92 MB	24.23 GB/s
LU	59	76,325	7	71,614	64,342 (0.09)	3,886 (0.03)	7,272 (0.06)	0.39 MB	6.28 GB/s
MG	16	83,586	3	83,654	83,654 (0.47)	5,604 (0.35)	0 (0.00)	0.00 MB	0.00 GB/s
SP	65	27,809	3	19,609	16,648 (0.64)	1,969 (1.64)	2,961 (2.47)	58.24 MB	23.60 GB/s
CloverLeaf	114	55,017	3	55,272	54,079 (0.22)	10,980 (4.27)	1,193 (0.46)	5.46 MB	11.76 GB/s
CCS-QCD	27	26,517	11	24,641	13,031 (0.97)	5,811 (1.91)	11,610 (3.82)	91.67 MB	24.02 GB/s
Himeno	2	33,726	1	23,149	11,894 (5.93)	8,318 (8.30)	11,255 (11.23)	271.47 MB	24.18 GB/s

- Better scaling can be obtained with longer kernel execution even with larger transfers
 - BT is successfully parallelized with communications of a six-dimensional array decomposed per GPU in 75 segments of 8MB size, having original kernel execution longer than 10ms

Result: Data-Size Scaling with Predicate

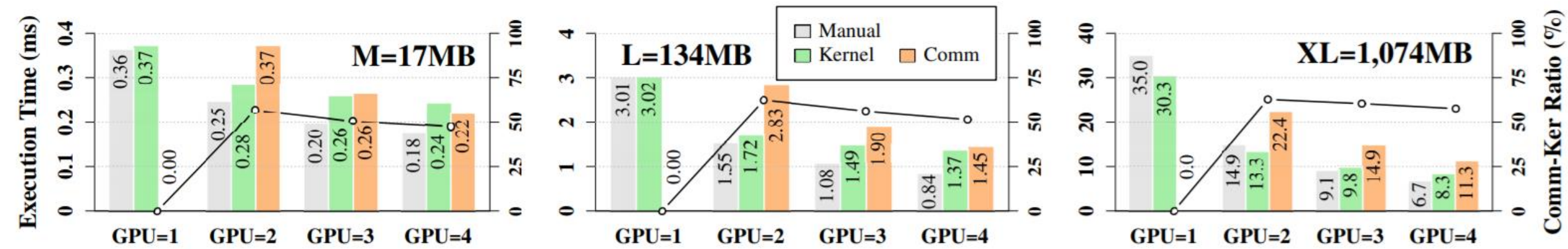


Fig. Performance of Himeno Benchmark (Stencil Code)

- Communication speed with two GPUs → four GPUs, 1.70x with size M, 1.95x with L and 1.99x with XL
- Kernel Performance with single → four GPUs, 1.53x, 2.19x and 3.64x improvements for size M, L and XL
- The optimized communication for the stencil application significantly reduces the latencies.

We consider those domain-specific approaches for future work

Result: Comparison with Predicate

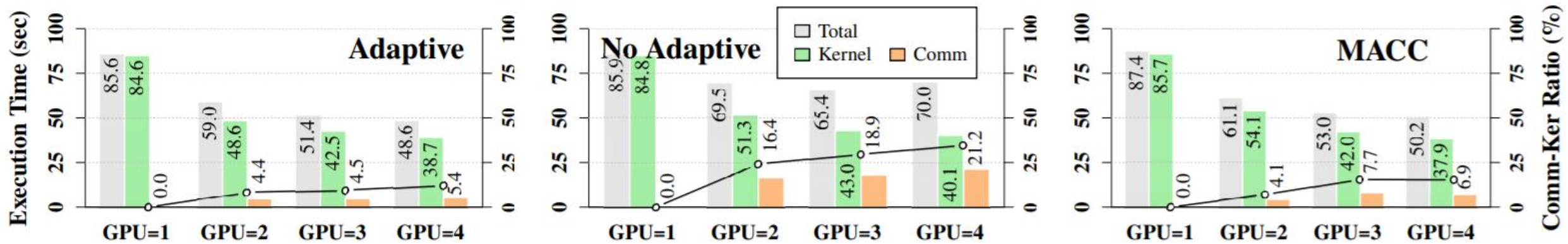


Fig. Performance of NPB-CG

- Previous work MACC can support only two of 10 benchmarks (Himeno/CG)
- MACC automates loop splitting of all the kernels in CG but employs no adaptive algorithm
- Our algorithm has better efficiency up to 3.50% by disabling multi-GPU execution for lower-latency kernels
- Compared to non-adaptive execution, we archive 44.09% better total efficiency

- We presented **JACC**, an OpenACC framework which facilitates runtime extension
 - JACC creates dynamic code from original kernels and compiles it with a specified compiler in order to support on-the-fly code extension automatically
 - Demonstrated for asynchronous execution and kernel specialization
- We proposed **predicate-based filtering**, a novel code-translation technique of multi-GPU utilization, for distributing highly-tuned applications without additional user effort
- Having many kernels parallelized on a multi-GPU environment, we showed the performance improvements of several tested benchmarks where precise data-dependency analysis is always restrained

BACK UP