### **Exercise 1 C Solution**

while ( dt > MAX\_TEMP\_ERROR && iteration <= max\_iterations ) {</pre>

}

```
Generate a GPU kernel
#pragma acc kernels
for(i = 1; i <= ROWS; i++) {</pre>
    for(j = 1; j <= COLUMNS; j++) {</pre>
        Temperature[i][j] = 0.25 * (Temperature_last[i+1][j] + Temperature_last[i-1][j] +
                                      Temperature_last[i][j+1] + Temperature_last[i][j-1]);
    }
}
dt = 0.0; // reset largest temperature change
                                                                                      Generate a GPU kernel
#pragma acc kernels
for(i = 1; i <= ROWS; i++){</pre>
    for(j = 1; j <= COLUMNS; j++){</pre>
        dt = fmax( fabs(Temperature[i][j]-Temperature_last[i][j]), dt);
        Temperature_last[i][i] = Temperature[i][i];
    }
}
if((iteration % 100) == 0) {
    track_progress(iteration);
}
iteration++;
```

### **Exercise 1 Fortran Solution**

do while ( dt > max\_temp\_error .and. iteration <= max\_iterations)</pre>

enddo

```
Generate a GPU kernel
!$acc kernels
do j=1,columns
   do i=1, rows
      temperature(i,j)=0.25*(temperature_last(i+1,j)+temperature_last(i-1,j)+ &
                             temperature_last(i,j+1)+temperature_last(i,j-1) )
   enddo
enddo
!$acc end kernels
dt=0.0
                                                                                    Generate a GPU kernel
!$acc kernels
do j=1,columns
   do i=1,rows
      dt = max( abs(temperature(i,j) - temperature_last(i,j)), dt )
      temperature_last(i,j) = temperature(i,j)
   enddo
enddo
!$acc end kernels
if( mod(iteration, 100).eq.0 ) then
   call track_progress(temperature, iteration)
endif
iteration = iteration+1
```



### Exercise 1: Compiler output (C)

instr009@h2ologin2:~/Update> cc -acc -Minfo=accel laplace\_bad\_acc.c main: 62, Generating present\_or\_copyout(Temperature[1:1000][1:1000]) Generating present\_or\_copyin(Temperature\_last[0:][0:]) Generating NVIDIA code Compiler was able to Generating compute capability 1.3 binary parallelize Generating compute capability 2.0 binary Generating compute capability 3.0 binary 63, Loop is parallelizable 64, Loop is parallelizable Accelerator kernel generated 63, #pragma acc loop gang /\* blockIdx.y \*/ 64, #pragma acc loop gang, vector(128) /\* blockIdx.x threadIdx.x \*/ 73, Generating present\_or\_copyin(Temperature[1:1000][1:1000]) Generating present\_or\_copy(Temperature\_last[1:1000][1:1000]) Generating NVIDIA code Compiler was able to Generating compute capability 1.3 binary parallelize Generating compute capability 2.0 binary Generating compute capability 3.0 binary 74. Loop is parallelizable 75, Loop is parallelizable Accelerator kernel generated 74, #pragma acc loop gang /\* blockIdx.y \*/ 75, #pragma acc loop gang, vector(128) /\* blockIdx.x threadIdx.x \*/ 76. Max reduction generated for dt

## Exercise 1: Performance

3372 steps to convergence

Execution	Time (s)	Speedup
CPU Serial	18	
CPU 2 OpenMP threads	9.4	1.99
CPU 4 OpenMP threads	4.7	3.98
CPU 8 OpenMP threads	2.5	7.48
CPU 16 OpenMP threads	1.4	13.4
CPU 28 OpenMP threads	0.9	21.5
OpenACC GPU	29	0.6x



## What's with the OpenMP?

We can compare our GPU results to the <u>best</u> the multi-core CPUs can do.

If you are familiar with OpenMP, or even if you are not, you can compile and run the OpenMP enabled versions in your OpenMP directory as:

pgcc -mp laplace\_omp.c or pgf90 -mp laplace\_omp.f90

then to run on 8 threads do:

```
export OMP_NUM_THREADS=8
a.out
```

Note that you probably only have 8 real cores if you are still on a GPU node. Do something like "interact -n28" if you want a full node of cores.



### What went wrong?

#### **export PGI\_ACC\_TIME=1** to activate profiling and run again:



#### Basic Concept Simplified, but sadly true





### **Multiple Times Each Iteration**





### **Excessive Data Transfers**

#### while ( dt > MAX\_TEMP\_ERROR && iteration <= max\_iterations ) {</pre>





### Data Management

The First, Most Important, and possibly Only OpenACC Optimization



### First, about that "reduction"





### Data Construct Syntax and Scope

#### Fortran

!\$acc data [clause ...]
 structured block
!\$acc end data

С

}

#pragma acc data [clause ...]
{
 structured block



### **Data Clauses**

copy( list )

Allocates memory on GPU and copies data from host to GPU when entering region and copies data to the host when exiting region. Principal use: For many important data structures in your code, this is a logical default to input, modify and return the data.

copyin( list ) Allocates memory on GPU and copies data from host to GPU when
entering region.
Principal use: Think of this like an array that you would use as just
an input to a subroutine.

copyout( list ) Allocates memory on GPU and copies data to the host when exiting
region.
Principal use: A result that isn't overwriting the input data structure.

create( list ) Allocates memory on GPU but does not copy.
Principal use: Temporary arrays.



# Array Shaping

Compilers sometimes cannot determine the size of arrays, so we must specify explicitly using data clauses with an array "shape". The compiler will let you know if you need to do this. Sometimes, you will want to for your own efficiency reasons.

#pragma acc data copyin(a[0:size]), copyout(b[s/4:3\*s/4])

Fortran

C

!\$acc data copyin(a(1:size)), copyout(b(s/4:3\*s/4))

- Fortran uses start:end and C uses start:length
- Data clauses can be used on data, kernels or parallel



### Compiler will (increasingly) often make a good guess...

```
int main(int argc, char *argv[]) {
```

```
int i;
double A[2000], B[1000], C[1000];
#pragma acc kernels
for (i=0; i<1000; i++){</pre>
```

```
A[i] = 4 * i;
B[i] = B[i] + 2;
C[i] = A[i] + 2 * B[i];
```



pgcc -acc -Minfo=accel loops.c
main:

- 6, Generating present\_or\_copyout(C[:])
  - Generating present\_or\_copy(B[:])
  - Generating present\_or\_copyout(A[:1000])
  - Generating NVIDIA code
- 7, Loop is parallelizable Accelerator kernel generated



### **Data Regions Have Real Consequences**

#### Simplest Kernel



#### With Global Data Region



### Data Regions Are Different Than Compute Regions



### **Data Movement Decisions**

- Much like loop data dependencies, sometime the compiler needs your human intelligence to make high-level decisions about data movement. Otherwise, it must remain conservative - sometimes at great cost.
- You must think about when data truly needs to migrate, and see if that is better than the default.
- Besides the scope based data clauses, there are OpenACC options to let us manage data movement more intensely or asynchronously. We could manage the above behavior with the update construct:

Fortran :
!\$acc update [host(), device(), ...]

C: #pragma acc update [host(), device(), ...]

Ex: #pragma acc update host(Temp\_array) //Gets host a current copy



# Exercise 2: Use acc data to minimize transfers

(about 40 minutes)

Q: What speedup can you get with data + kernels directives?

- Start with your Exercise 1 solution or grab laplace\_bad\_acc.c/f90 from the Solutions subdirectory. This is just the solution of the last exercise.
- Add data directives where it helps.
  - Think: when *should* I move data between host and GPU? Think how you would do it by hand, then determine which data clauses will implement that plan.
  - Hint: you may find it helpful to ignore the output at first and just concentrate on getting the solution to converge quickly (at 3372 steps). Then worry about *updating* the printout.



### Exercise 2 C Solution

#pragma acc data copy(Temperature\_last), create(Temperature)
while ( dt > MAX\_TEMP\_ERROR && iteration <= max\_iterations ) {</pre>

```
dt = 0.0; // reset largest temperature change
```

```
// copy grid to old grid for next iteration and find latest dt
#pragma acc kernels
for(i = 1; i <= ROWS; i++){
    for(j = 1; j <= COLUMNS; j++){
        dt = fmax( fabs(Temperature[i][j]-Temperature_last[i][j]), dt);
        Temperature_last[i][j] = Temperature[i][j];
    }
}</pre>
```

```
// periodically print test values
if((iteration % 100) == 0) {
    #pragma acc update host(Temperature)
    track_progress(iteration);
}
```

iteration++;





### **Exercise 2 Fortran Solution**

!\$acc data copy(temperature\_last), create(temperature)
do while ( dt > max\_temp\_error .and. iteration <= max\_iterations)</pre>

```
!$acc kernels
do i=1.columns
   do i=1, rows
      temperature(i,j)=0.25*(temperature_last(i+1,j)+temperature_last(i-1,j)+ \&
                             temperature_last(i,j+1)+temperature_last(i,j-1) )
   enddo
enddo
!$acc end kernels
dt=0.0
!copy grid to old grid for next iteration and find max change
!$acc kernels
do j=1.columns
   do i=1,rows
      dt = max( abs(temperature(i,j) - temperature_last(i,j)), dt )
      temperature_last(i,j) = temperature(i,j)
   enddo
enddo
                                                         !$acc update host(temperature(columns-5:columns,rows-5:rows))
!$acc end kernels
!periodically print test values
                                                                                                      Except bring back a copy
if( mod(iteration, 100).eq.0 ) then
   !$acc update host(temperature)
                                                                                                                    here
   call track_progress(temperature, iteration)
endif
iteration = iteration+1
```

enddo !\$acc end data





## Exercise 2: Performance

3372 steps to convergence

Execution	Time (s)	Speedup
CPU Serial	18	
CPU 2 OpenMP threads	9.4	1.99
CPU 4 OpenMP threads	4.7	3.98
CPU 8 OpenMP threads	2.5	7.48
CPU 16 OpenMP threads	1.4	13.4
CPU 28 OpenMP threads	0.9	21.5
OpenACC GPU	1.5	12



## **OpenACC or OpenMP?**

Don't draw any grand conclusions yet. We have gotten impressive speedups from both approaches. But our problem size is pretty small. Our main data structure is:

1000 x 1000 = 1M elements = 8MB of memory

We have 2 of these (temperature and temperature\_last) so we are using roughly 16 MB of memory. Not very large. When divided over cores it gets even smaller and can easily fit into cache.

The algorithm is very realistic, but the memory bandwidth stress is very low.



## **OpenACC or OpenMP on Larger Data?**

We can easily scale this problem up, so why don't I? Because it is nice to have exercises that finish in a few minutes or less.

We scale this up to  $10K \times 10K$  (1.6 GB problem size) for the hybrid challenge. These numbers start to look a little more realistic. But the serial code takes over 30 minutes to finish. That would have gotten us off to a slow start!

Execution	Time (s)	Speedup
CPU Serial	2187	
CPU 16 OpenMP threads	183	12
CPU 28 OpenMP threads	162	13.5
OpenACC	103	21

Obvious cusp for core scaling appears

#### 10K x 10K Problem Size



### Latest Happenings In Data Management

#### Unified Memory

- Unified address space allows us to pretend we have shared memory
- Skip data management, hope it works, and then optimize if necessary
- For dynamically allocated memory can eliminate need for pointer clauses



#### NVLink

One route around PCI bus (with multiple GPUs)





### **Further speedups**

OpenACC gives us even more detailed control over parallelization • Via gang, worker, and vector clauses

By understanding more about OpenACC execution model and GPU hardware organization, we can get higher speedups on this code

By understanding bottlenecks in the code via profiling, we can reorganize the code for higher performance

 But you have already gained most of any potential speedup, and you did it with a few lines of directives!



## **General Principles: Finding Parallelism In Code**

- Nested for/do loops are best for parallelization
  - Large loop counts are best
- Iterations of loops must be <u>independent</u> of each other
  - To help compiler: restrict keyword (C), independent clause
  - Use subscripted arrays, rather than pointer-indexed arrays (C)
- Data regions should avoid wasted transfers
  - If applicable, could use directives to explicitly control sizes
- Various other annoying things can interfere with accelerated regions
  - IO
  - Limitations on function calls and nested parallelism (relaxed much in 2.0)



## Is OpenACC Living Up To My Claims?

- High-level. No involvement of OpenCL, CUDA, etc.
- Single source. No forking off a separate GPU code. Compile the same program for accelerators or serial, non-GPU programmers can play along.
- Efficient. Experience show very favorable comparison to low-level implementations of same algorithms. kernels is magical!
- Performance portable. Supports GPU accelerators and co-processors from multiple vendors, current and future versions.
- Incremental. Developers can port and tune parts of their application as resources and profiling dictates. No wholesale rewrite required. Which can be <u>quick.</u>



### In Conclusion...

