

#### DATA-DRIVEN TASKS AND THEIR IMPLEMENTATION





# Fork/Join graphs constraint ||-ism

Fork/Join models restrict task graphs to be series-parallel 



without hampering ||-ism

- Fork/Join models constrain control and data dependences
  - Tasks can only be created after all data dependences satisfied
  - Necessitates ordering task creation to conform to that restriction
- May hamper performance

# Macro-dataflow for intuitive ||-ism



# Futures [Baker & Hewitt 1977]





# **DDF/DDT Code Sample**

}

DataDrivenFuture left = new DataDrivenFuture ();
DataDrivenFuture right = new DataDrivenFuture();
finish {

async await ( left ) useLeftChild(left); // Task<sub>1</sub> async await ( right ) useRightChild(right); // Task<sub>2</sub> async await ( left, right ) useBothChildren( left, right ); // Task<sub>3</sub> async left.put(leftChildCreator()); // Task<sub>4</sub> async right.put(rightChildCreator()); // Task<sub>5</sub>



# DDTs provide

- Non-series-parallel task dependence graph support
  - Less restricted parallelism
  - Better scheduling opportunities



- Single assignment (SA)
  - Race-freedom on DDF accesses
  - Determinism if all shared data is expressed as DDFs
- SA-value lifetime restriction
  - Smaller than graph lifetime
  - DDF creator:
    - Provides DDF reference to producers and consumers
  - DDF lifetime depends on
    - Creator lifetime
    - Resolver lifetime
    - Consumers' lifetimes

## **Data-Driven Scheduling**

Steps register self to items wrapped into DDFs **DDF**right **DDF**<sub>left</sub> Task Platelue glerright Plac da lo da rieft X-Task<sub>3</sub> **Fask**2 DDF<sub>left</sub> DDF<sub>right</sub> DDFright Taskc \_ DDF left = new DDF(); ready queue DDF right = new DDF(); Task<sub>9</sub> **Task**<sub>2</sub> Task **<---**async await (left) use(left); // Task async await (right) use(right); // Task<sub>2</sub> Tasksk4 async await (left,right) use(left,right); // Task<sub>3</sub> rest de la company async builder(left); // Task<sub>4</sub> async builder(right); // Task<sub>5</sub>

#### Mapping Macro-Dataflow to Task-Parallelism

- Control & data dependences as first level constructs
  - Task-parallel frameworks have them coupled e.g., OpenMP, Cilk
- Kernel instantiations may have multiple predecessors
  - Need to wait for all
  - Staged readiness concepts
    - Created (control dependence satisfied)
    - Data dependences satisfied
    - Schedulable / Ready
- DDTs provide a natural implementation for Macro-Dataflow
  - Every kernel instantiation is a DDT
  - Data dependences between DDTs are expressed through DDFs
  - Provides race freedom

## **Experimental Results**

Compared DDT implementation with four macrodata schedulers from past work

that used Concurrent Collections (CnC)

- CnC uses global data collections to synchronize tasks
- DDT/DDF results obtained at task-parallel level
   without allocating global data collections
  - CnC can be automatically translated to DDFs (ongoing work)

# **Blocking Schedulers**

Ш

- Use Java wait/notify for premature data access
- Blocking granularity
  - Instance level vs Collection level (fine-grain vs. coarsegrain)
- A blocked task blocks an entire worker thread
  - Need to create more worker threads to avoid deadlock



# Delayed async Scheduling

Every kernel instantiation is a guarded execution
 Guard condition is the availability of input data
 Task can be created eagerly before input data is available
 Promoted to ready when data provided
 Value left = new Value ();
 Value right = new Value ();
 finish {

```
async when ( left.isReady() ) useLeftChild(left); // Task<sub>1</sub>
async when ( right.isReady()) useRightChild(right); // Task<sub>2</sub>
async when ( right.isReady() && left.isReady() )
useBothChildren( left, right ); // Task<sub>3</sub>
async left.put(leftChildCreator()); // Task<sub>4</sub>
async right.put(rightChildCreator()); // Task<sub>5</sub>
```



# Data Driven Rollback & Replay



# **Experimental Setup**

- 14
- 4-socket Xeon quad-core Intel E7730 2.4 GHz
  - □ Shared 3MB L2 cache per pair of cores.
  - Main memory 32 GBs.
  - #worker threads: I6
- 8-way SMT 8-core Niagara Sun UltraSPARC T2
  - Shared 4MB L2 cache
  - #worker threads: 64
- 32-bit Sun Hotspot JDK 1.6 JVM
   GCC 4.1.2 for JNI
- 30 runs for statistical soundness
- □ Read 'Serial' as single-threaded execution of || code

## Cholesky decomposition



Average execution times and 90% confidence interval of 30 runs of single threaded and 16threaded executions for blocked Cholesky decomposition CnC application with Habanero-Java steps on 16-core Xeon with input matrix size 2000 × 2000 and with tile size 125 × 125

# Black-Scholes formula (PARSEC)



Average execution times and 90% confidence interval of 30 runs of single threaded and 16-threaded executions for blocked Black-Scholes CnC application with Habanero-Java steps on 16-core Xeon with input size 1,000,000 and with tile size 62,500

## Rician Denoising (Medical Imaging)



**Coarse Grain Blocking \* Fine Grain Blocking \* Delayed Async \* Data Driven Tasks** Average execution times and 90% confidence interval of 30 runs of single threaded and 16-threaded executions for blocked Rician Denoising CnC application with Habanero-Java steps on Xeon with input image size 2937 × 3872 and with tile size 267 × 484

\* Explicit memory management required for non-DDT schedules to avoid out-of-memory exception

### Heart Wall Tracking Dependence Graph



# Heart Wall Tracking (Rodinia)



Delayed AsyncData Driven Rollback&ReplayData Driven TasksMinimum execution times of 13 runs of single threaded and 16-threaded executions for<br/>Heart Wall Tracking CnC application with C steps on Xeon with 104 frames

# **Related Work**

#### Futures

Can build arbitrary task graphs

get()/force() is usually a blocking operation

future task creation is bound to container at creation time

#### Dataflow

■ Typically blocks on one datum (lvar) at a time, unlike async await (...)

#### Nabbit (Cilk library)

- Can build arbitrary task graphs, more explicit than DDTs
- No garbage collection and unwinding of task graph

#### Concurrent Collections (CnC)

- Globalized data collections and general tags (keys) makes memory management challenging
- DDTs can be used to obtain more efficient implementations of CnC

### Conclusions

#### Data-Driven Futures and Data-Driven Tasks

- help build arbitrary task graphs and extend task-parallel frameworks
- introduce the more-intuitive macro-dataflow to programmers on task-parallel frameworks
- support Data-Driven scheduling that outperforms alternative schedulers in both execution time and memory requirements
- help to implement blocking in tasks without blocking workers

## Future Work

- 22
- Compile Concurrent Collections down to DDTs
- Compiler optimizations to move DDF allocations to further reduce lifetimes
- Hierarchical DDTs for granularity optimizations
- Work-stealing support for DDTs
- Use DDTs to implement all blocking synchronizations without blocking worker, i.e. replace each waiting continuation as a DDT
- Locality aware scheduling with DDTs

For a hands-on trial, visit http://habanero.rice.edu/hj

http://habanero.rice.edu/cnc