# Storing and Processing Multi-dimensional Scientific Datasets

#### Alan Sussman

UMIACS & Department of Computer Science



http://www.cs.umd.edu/~als

### Data Exploration and Analysis

- Large data collections emerge as important resources
  - Data collected from sensors and large-scale simulations
  - Multi-resolution, multi-scale, multi-dimensional
    - data elements often correspond to points in multi-dim attribute space
    - medical images, satellite data, hydrodynamics data, etc.
  - Terabytes to petabytes today
- Low-cost, high-performance, high-capacity commodity hardware
  - 5 PCs, 5 Terabytes of disk storage for << \$10,000</li>

### Large Data Collections

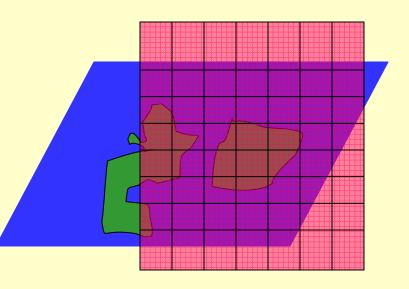
- Scientific data exploration and analysis
  - To identify trends or interesting phenomena
  - Only requires a portion of the data, accessed through spatial index
    - e.g., Quad-tree, R-tree
- Spatial (range) query often used to specify iterator
  - computation on data obtained from spatial query
  - computation aggregates data (MapReduce) resulting data product size significantly smaller than results of range query

## Typical Query

Output grid onto which a projection is carried out

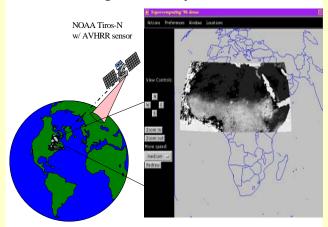


Specify portion of raw sensor data corresponding to some search criterion



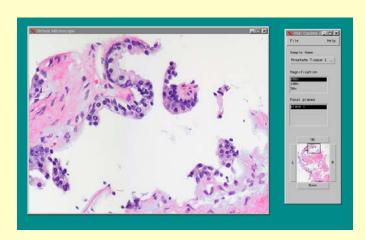
### Target example applications

#### Processing Remotely-Sensed Data



Pathology

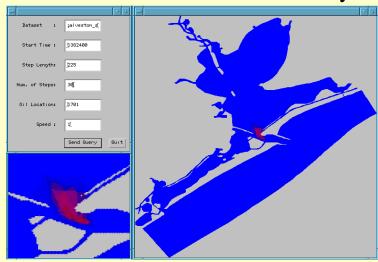
Satellite Data Processing



#### Water Contamination Study



Multi-perspective volume reconstruction



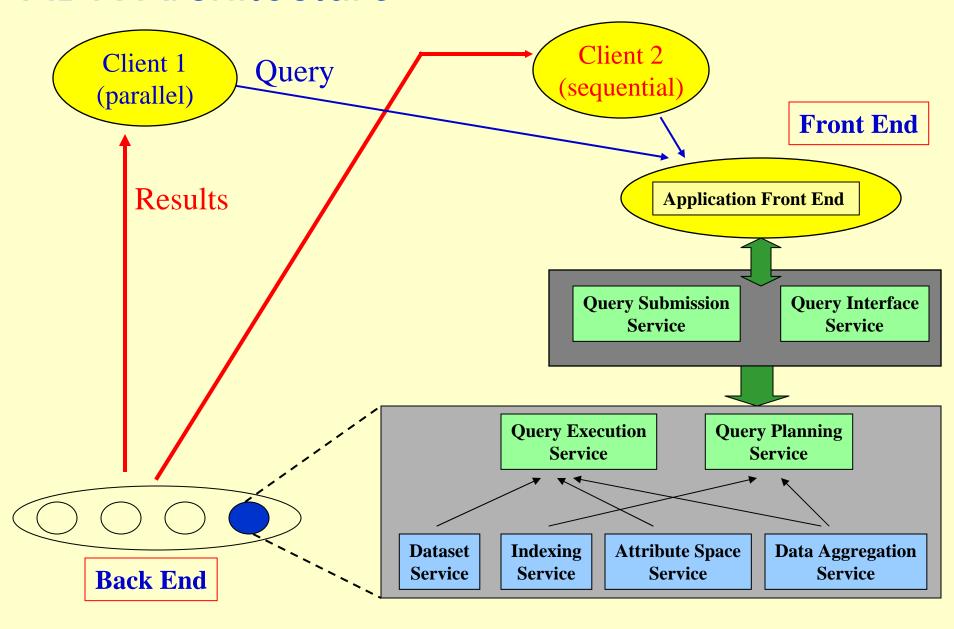
### Outline

- Active Data Repository
  - Overall architecture
  - Query planning
  - Query execution
  - Experimental Results
- DataCutter

### Active Data Repository (ADR)

- An object-oriented framework (class library + runtime system) for building parallel databases of multi-dimensional datasets
  - enables integration of storage, retrieval and processing of multidimensional datasets on distributed memory parallel machines.
  - can store and process multiple datasets.
  - provides support and runtime system for common operations such as
    - data retrieval,
    - memory management,
    - scheduling of processing across a parallel machine.
  - customizable for application specific processing.

### **ADR Architecture**



### Active Data Repository (ADR)

- Dataset is collection of user-defined data chunks
  - a data chunk contains a set of data elements
  - multi-dim bounding box (MBR) for each chunk, used by spatial index
  - chunks declustered across disks to maximize aggregate I/O bandwidth
- Separate planning and execution phases for queries
  - Tile output if too large to fit entirely in memory
  - Plan each tile's I/O, data movement and computation
    - Identify all chunks of input that map to tile
    - Distribute processing for chunks among processors
  - All processors work on one tile at a time

### **Query Planning**

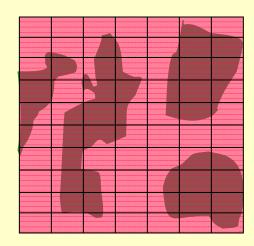
- Index lookup
  - Select data chunks of interest
  - Compute mapping between input and output chunks
- Tiling
  - Partition output chunks so that each tile fits in memory
  - Use Hilbert curve to minimize total length of tile boundaries
- Workload partitioning
  - Each aggregation operation involves an input/output chunk pair
  - Want good load balance and low communication overhead

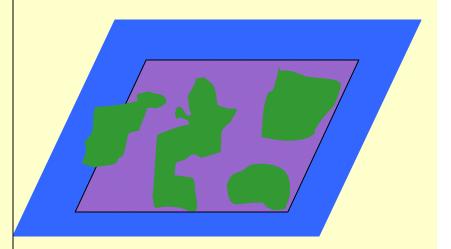
### **Query Execution**

- Broadcast query plan to all processors
- For each output tile:
  - Initialization phase
     Read output chunks into memory, replicate if necessary
  - Reduction phase
     Read and process input chunks that map to current tile
  - Combine phase
     Combine partial results in replicated output chunks, if any
  - Output handling
     Compute final output values

### ADR Processing Loop

```
O \leftarrow Output dataset, I \leftarrow Input dataset
A \leftarrow Accumulator (for intermediate results)
[S_I, S_O] \leftarrow Intersect(I, O, R_{query})
foreach o<sub>e</sub> in S<sub>O</sub> do
              read o<sub>e</sub>
              a_e \leftarrow Initialize(o_e)
foreach ie in S<sub>I</sub> do
              read i<sub>e</sub>
              S_A \leftarrow Map(i_e) \cap S_O
              foreach ae in SA do
                             a_e \leftarrow Aggregate(i_e, a_e)
foreach a<sub>e</sub> in S<sub>O</sub> do
               o_e \leftarrow Output(a_e)
              write o<sub>e</sub>
```





### **Query Execution Strategies**

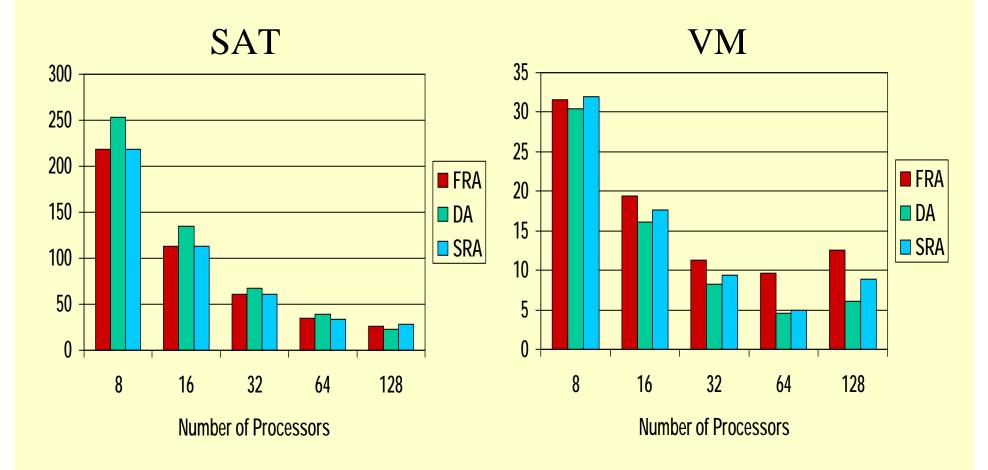
- Distributed Accumulator (DA)
  - Assign aggregation operation to owner of output chunk
- Fully Replicated Accumulator (FRA)
  - Assign aggregation operation to owner of input chunk
  - Requires *combine* phase
- Sparsely Replicated Accumulator (SRA)
  - similar to FRA, but only replicate output chunk when needed

### Performance Evaluation

- 128-node IBM SP, with 256MB memory per node
- Datasets generated by Application Emulators
  - Satellite Data Processing (SAT) non-uniform mapping
  - Virtual Microscope (VM)

Арр	Input	Output	Fan-in	Fan-out (avg)	Comp (ms) t <sub>init</sub> -t <sub>red</sub> -t <sub>comb</sub>
SAT	1.6-26GB	25MB	161-1307	4.6	1-40-20
VM	1.5-24GB	192MB	16-128	1.0	1-5-1

### **Query Execution Time (sec)**



(Fixed input size)

Alan Sussman - 3/5/08

### Summary of Experimental Results

- Communication volume
- DA may have computational load imbalance due to non-uniform mapping
- Relative performance depends on
  - Query characteristics (e.g., fan-in, fan-out)
  - Machine configurations (e.g., number of processors)
- No strategy always outperforms the others

### ADR queries vs. Other Approaches

- Similar to out-of-core reductions (more general MapReduce)
  - Commutative & associative
  - Most reduction optimization techniques target in-core data
  - Out-of-core techniques require data redistribution
- Similar to relational group-by queries
  - Distributive & algebraic [Gray96]
  - spatial-join + group-by
  - For ADR, output data items and extents known prior to processing Alan Sussman - 3/5/08

```
double x[max_nodes],
    y[max_nodes];
integer ia[max_edges],
    ib[max_edges];
for (i=0; i<max_edges; i++)
    x[ia[i]] += y[ib[i]];
```

```
Select Dept, AVG(Salary)
From Employee
Group By Dept
```

### Outline

- Active Data Repository
- DataCutter
  - Architecture
  - Filter-stream programming
  - Group Instances
  - Transparent copies

### Distributed Grid Environment

#### Heterogeneous Shared Resources:

- Host level: machine, CPUs, memory, disk storage
- Network connectivity

#### Many Remote Datasets:

- Inexpensive archival storage
- Islands of useful data
- Too large for replication

### **DataCutter**

Target same classes of applications as ADR

#### **Indexing Service**

- Multi-level hierarchical indexes based on spatial indexing methods – e.g., R-trees
  - Relies on underlying multi-dimensional space
  - User can add new indexing methods

#### Filtering Service

- Distributed C++ (and Java) *component* framework
- Transparent tuning and adaptation for heterogeneity
- Filters implemented as threads 1 process per host

# Filter-Stream Programming (FSP)

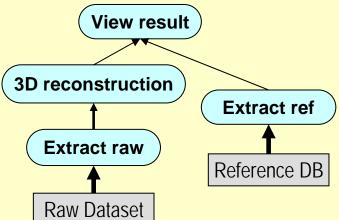
#### Purpose: Specialized components for processing data

based on Active Disks research [Acharya, Uysal, Saltz: ASPLOS'98],

macro-dataflow, functional parallelism

filters – logical unit of computation

- high level tasks
- init,process,finalize interface
- streams how filters communicate
  - unidirectional buffer pipes
  - uses fixed size buffers (min, good)
- users specify filter connectivity and filter-level characteristics



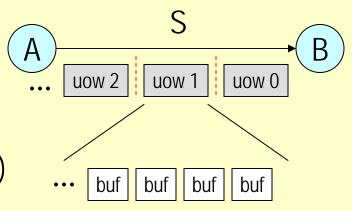
### FSP: Abstractions

#### Filter Group

- logical collection of filters to use together
- application starts filter group instances

#### Unit-of-work cycle

- "work" is application defined (ex.: a query)
- work is appended to running instances
- init(), process(), finalize() called for each uow
- process() returns { EndOfWork | EndOfFilter }
- allows for adaptivity



### **Optimization Techniques**

### Mapping filters to hosts

allow components to execute concurrently

#### Multiple filter group instances

allow work to be processed concurrently

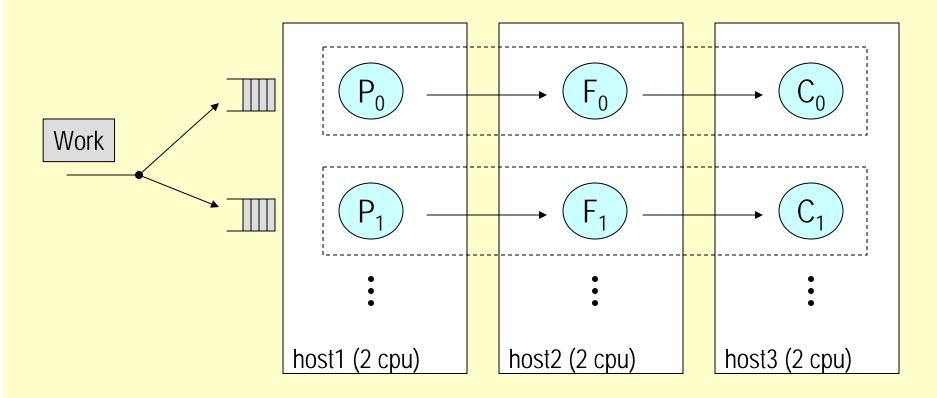
#### Transparent copies

 keep pipeline full by avoiding filter processing imbalance and use write policies to deal with dynamic buffer distribution

### Application memory tuning

minimize resource usage to allow for copies

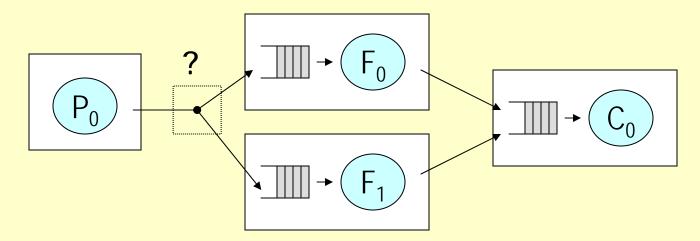
### Optimization - Group Instances



Match # instances to environment (CPU capacity, network)

### **Transparent Copies**

- replicate filters within an instance (intra-work)
- write policy to distribute work buffers to copies
  - shared queue within host
  - across hosts round robin (RR), weighted RR (WRR), demand-driven (DD), user-defined (UD)
- single stream illusion, UOW<sub>i</sub> < UOW<sub>i+1</sub>
- state consistency problems addressed by a merge step



## Runtime Pipeline Balancing

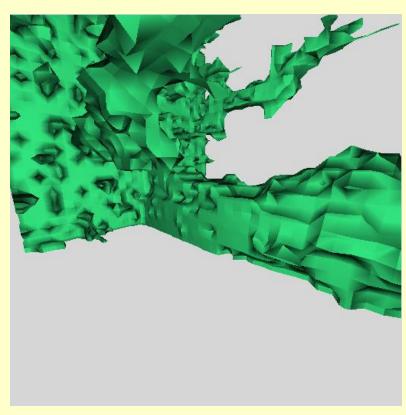
#### Use local information:

- queue size, send time / receiver acks
- Adjust number of transparent copies
- Demand based dataflow (choice of consumer)
  - Within a host perfect shared queue among copies
  - Across hosts
    - Round Robin (RR)
    - Weighted Round Robin (WRR)
    - Demand-Driven (DD) sliding window (buffer consumption rate)
    - User-defined

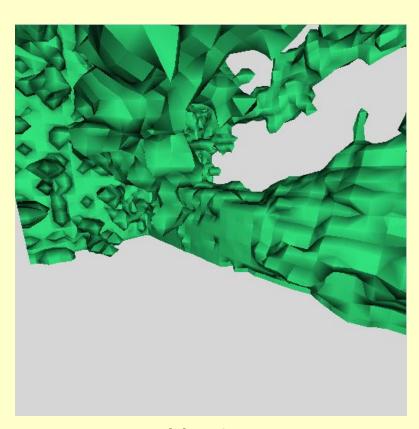
### Experiment – Isosurface Rendering

- Isosurface rendering on Red/Blue Linux cluster at Maryland
  - Red 16 2-processor PII-450, 256MB, 18GB SCSI disk
  - Blue 12 2-processor PIII-550, 1GB, 2-8GB SCSI disk + 1 8-processor PIII-550, 4GB, 2-18GB SCSI disk
  - Connected via Gigabit Ethernet
- UT Austin ParSSim chemical species transport simulation
  - Single time step 3D visualization, read all data for 1 time step
- Two implementations of Raster filter z-buffer and active pixels

### Sample Isosurface Visualization

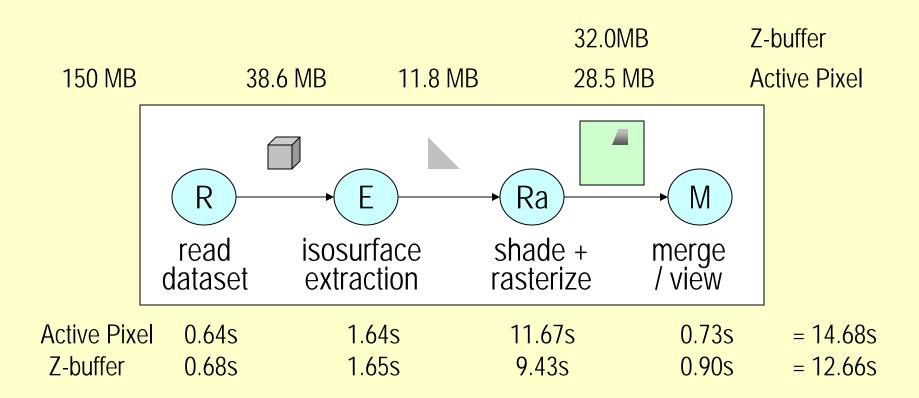


$$V = 0.35$$



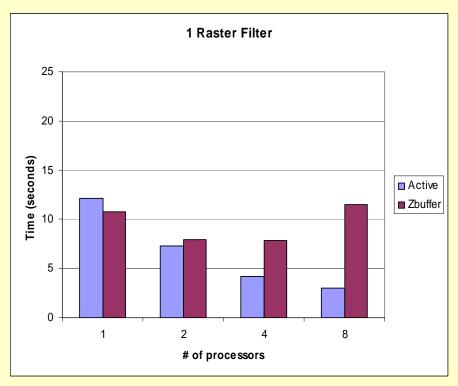
V = 0.7

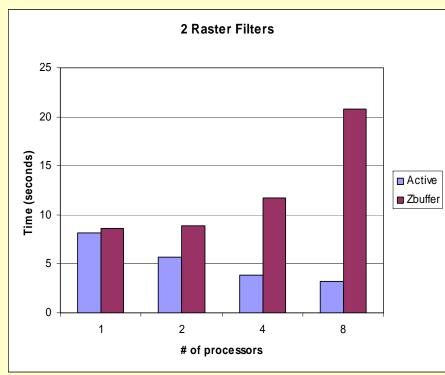
### Experimental setup



Experiment to follow combines R and E filters, since that showed best performance in experiments not shown

### Active Pixel vs. Z-Buffer

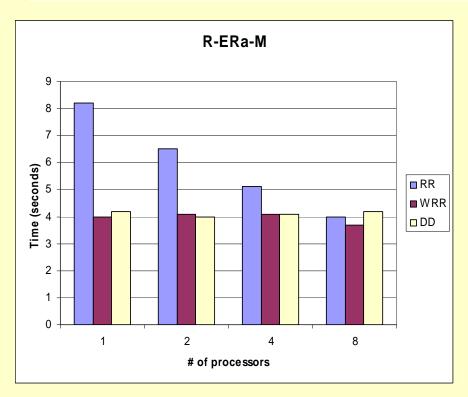


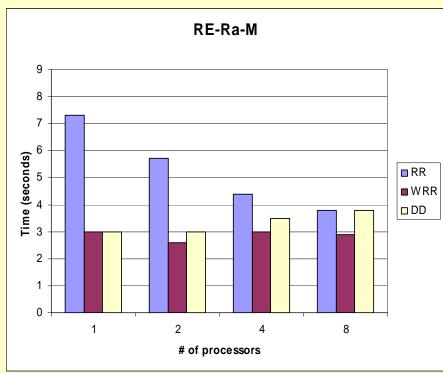


Configuration: RE-Ra-M

Only Red nodes used – each one runs 1 RE, 1 or 2 RA, and one node runs M

### Heterogeneous Nodes



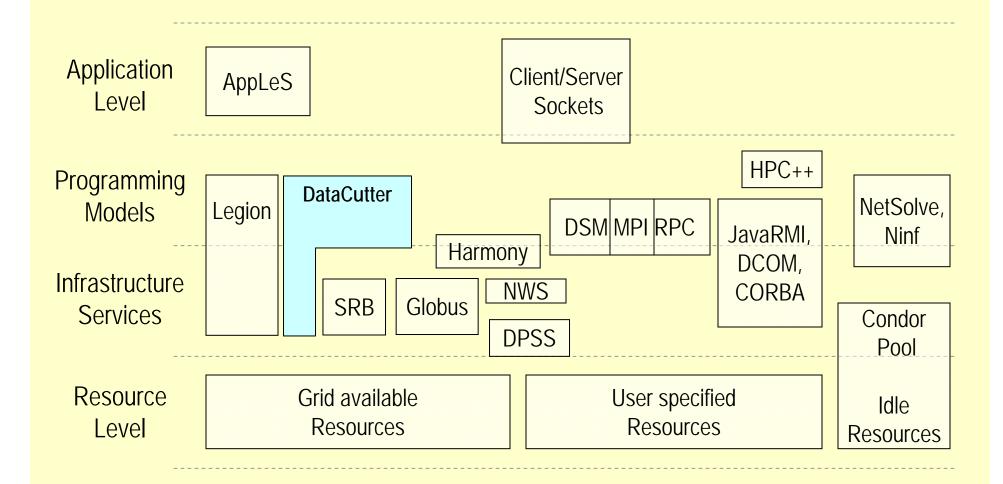


Active Pixel algorithm on 8-processor Blue node + Red data nodes Blue node runs 7 Ra or ERa copies and M, Red nodes each run 1 of each except M

### Summary of Results

- Placement matters
  - Heterogeneity of shared resources, data volume
- More instances and transparent copies
  - Balance applications for heterogeneity
- No static choice will work
  - Runtime heterogeneity and dynamic shared resources

### DataCutter as a Grid Service



### Acknowledgments

- Students
  - Chialin Chang ADR
  - Michael Beynon, Renato Ferreira DataCutter
- Other faculty and postdocs (now at Ohio State)
  - Joel Saltz
  - Tahsin Kurc
  - Umit Catalyurek