DataCutter: Middleware for Filtering Very Large Scientific Datasets on Archival Storage Systems

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Multi-dimensional Datasets

Spatial/multi-dimensional multi-scale, multi-resolution datasets

- Satellite data processing
- Coupled simulation systems
- The Virtual Microscope

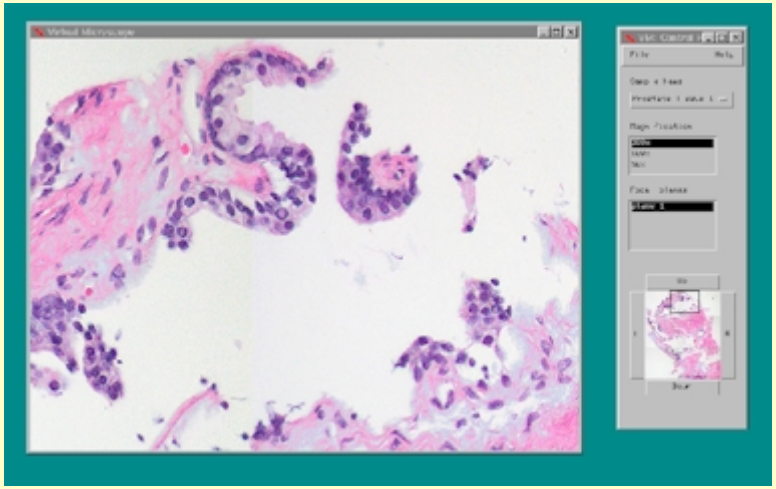
Applications access a subset of the dataset

- Subsetting done by using spatial indexes (e.g., R-trees)

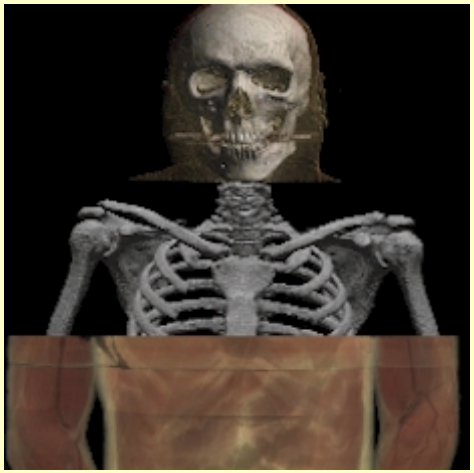
Processing can be performed before returning data to client

- often to reduce volume of data

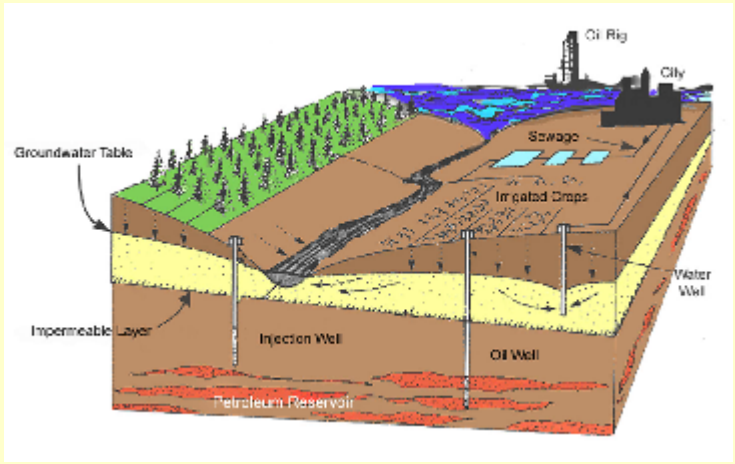
Applications



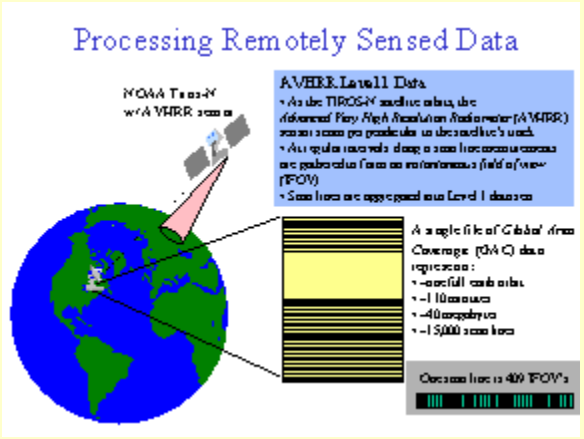
Pathology



Volume Rendering



Surface Groundwater Modeling



Satellite Data Analysis

A Motivating Scenario

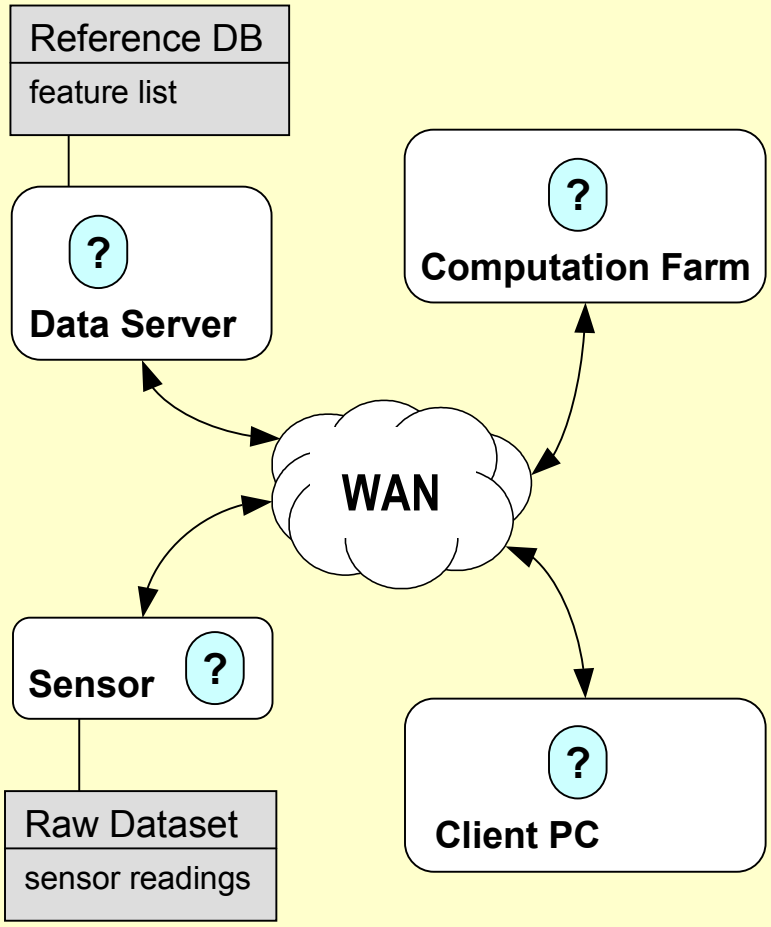
Sample Application:

- generate 3D reconstructed view from new set of sensor readings (computationally intensive)
- compare features with reference db

Configuration:

- remote data server - reference db
- sensor host - large raw readings
- parallel computation farm available

How to design application?



A Motivating Scenario (2)

Application :

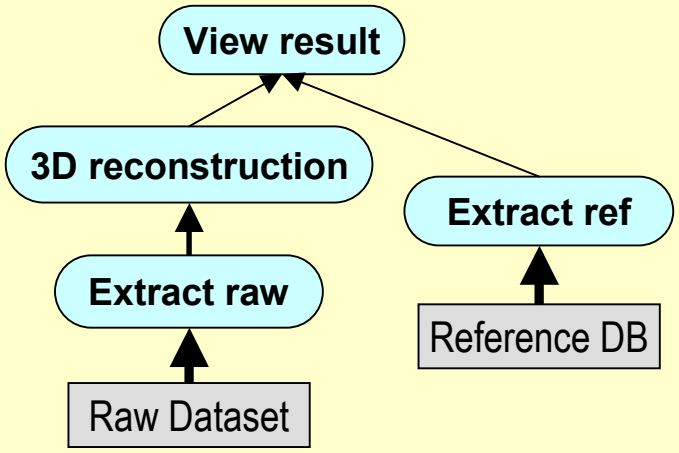
// process relevant raw readings

// generate 3D view

// compute features of 3D view

// find similar features in reference db

// display new view and similar cases



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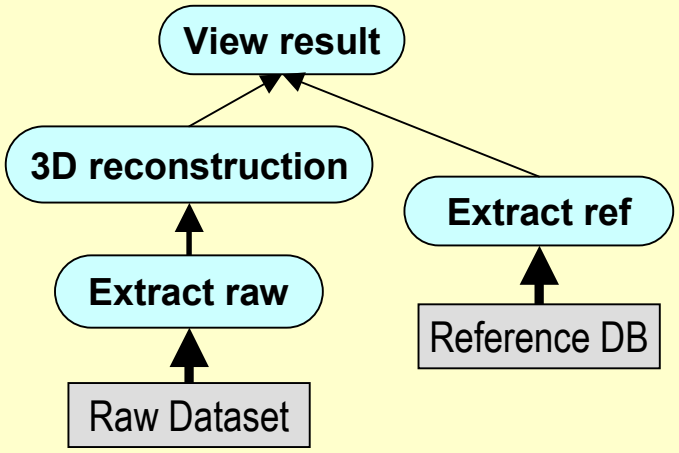
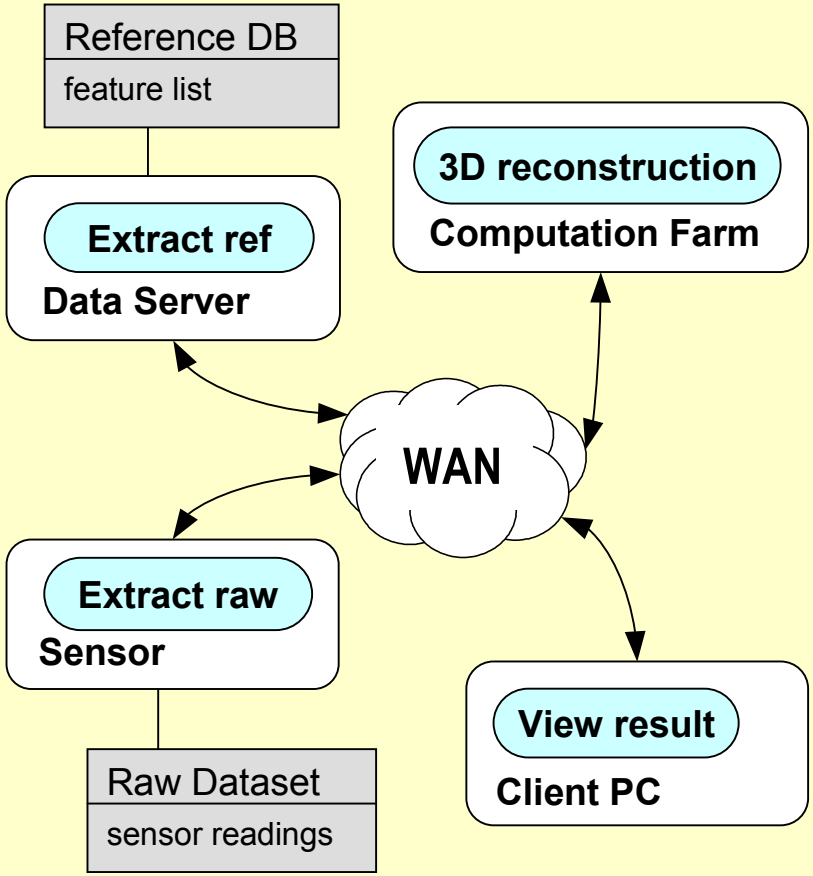




Tools to Manage Storage Hierarchy

Mass Storage:

- Load subset of data from tertiary storage into disk cache or client
- Access data from distributed data collections
- Preprocess close to data sources

Fast secondary storage:

- Tools for on-demand data product generation, interactive data exploration, visualization
- Target closely coupled sets of processors/disks

DataCutter Middleware

Targets multi-dim datasets in archival storage systems

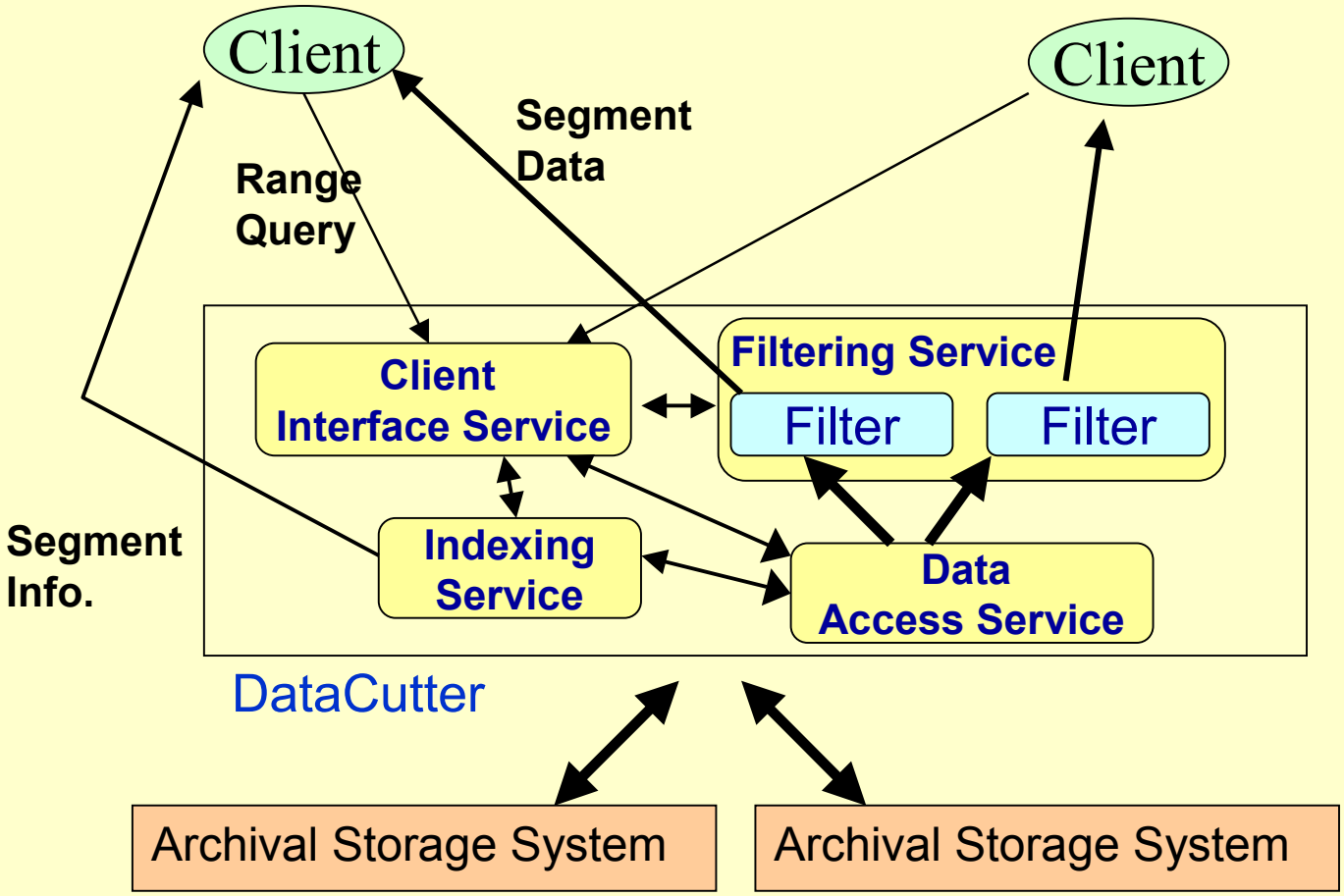
Subsetting through *Range Queries*

- range defines a hyperbox in the multi-dimensional attribute space underlying the dataset
- retrieve items whose coordinates fall within box

Restricted application processing as *Filters*

- intended to execute near (LAN) storage system
- purpose is to reduce amount of data transmitted to client

DataCutter Architecture



Subsetting

Datasets are partitioned into segments

- used to index the dataset, unit of retrieval

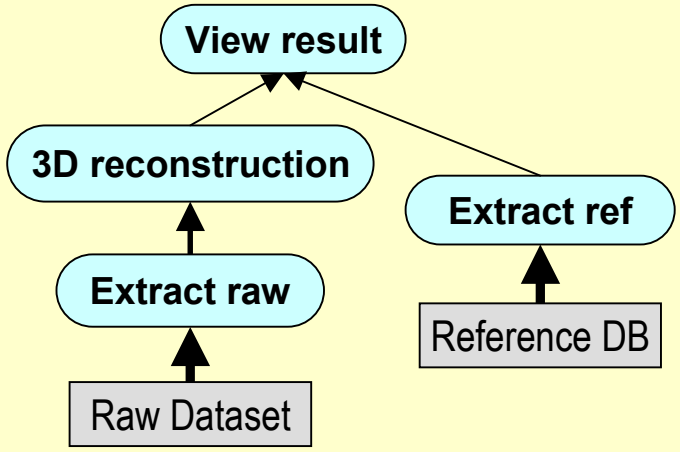
Indexing very large datasets

- Multi-level hierarchical indexing scheme
- Summary index files -- for a collection of segments or detailed index files
- Detailed index files -- to index the individual segments

Application Filters

Purpose: Specialized user code for processing data segments before returning them to the client

- based on Active Disks [Acharya, Uysal, Saltz]
- filters are the unit of computation
  - high level tasks
  - init,process,finalize interface
- streams are how filters communicate
  - unidirectional buffer pipes



Placement

The dynamic assignment of filters to particular hosts for execution is placement (mapping)

Possible Optimization Goals:

Communication

- leverage filter affinity to dataset (contrast with Distributed Storage)
- minimize communication volume on slower connections
- co-locate filters with large communication volume

Computation

- expensive computation on faster, less loaded hosts

Current Software Infrastructure

Prototype implementation of filter framework

- C++ language binding
- one thread for each instantiated filter
- manual placement; wide-area execution service

Prototype indexing/data access service

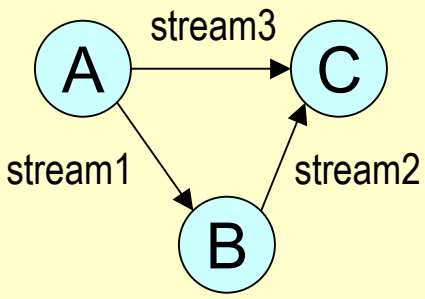
- UNIX filesystem, HPSS archival storage
- R-tree indexes supported
- being integrated with NPACI Storage Resource Broker (SRB)

Filter Framework

```
class MyFilter : public Filter_Base {
public:
        int init(int argc, char *argv[ ]) { … };
        int process(stream_t st[ ]) { … };
        int finalize(void) { … };
}
```

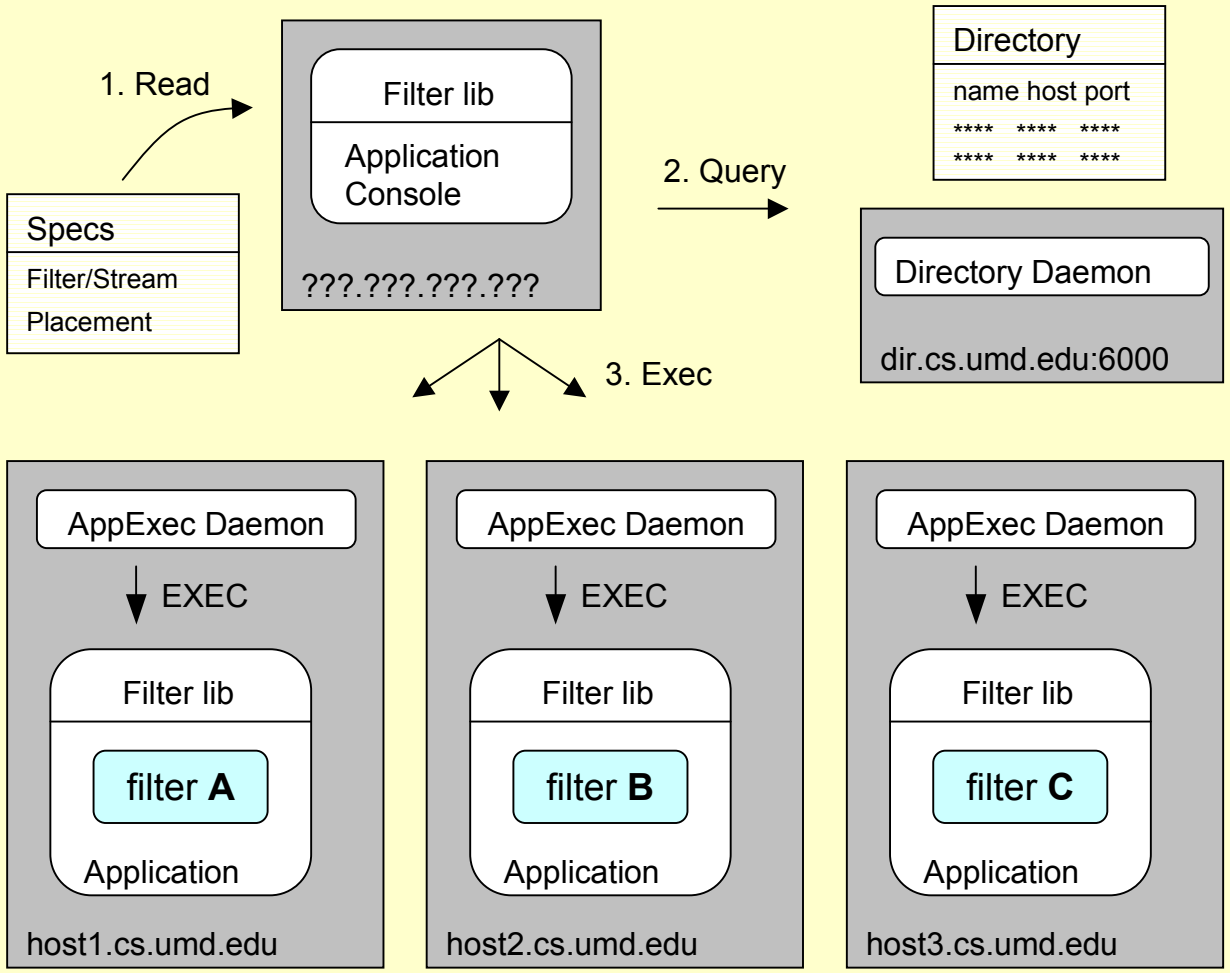
Filter Connectivity / Placement

[filter.A]
outs = stream1 stream3
[filter.B]
ins = stream1
outs = stream2
[filter.C]
ins = stream2 stream3



[placement]
A = host1.cs.umd.edu
B = host2.cs.umd.edu
C = host3.cs.umd.edu

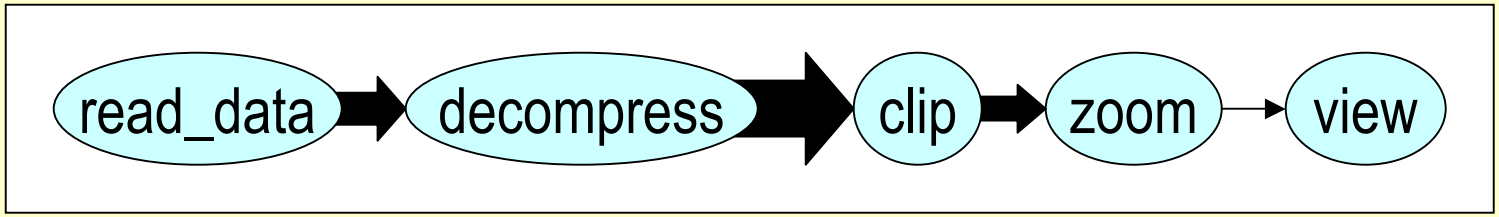
Execution Service



Application: Virtual Microscope

- Interactive software emulation of high power light microscope for processing/visualizing image datasets
- 3-D Image Dataset (100MB to 5GB per focal plane)
- Client-server system organization
- Rectangular region queries, multiple data chunk reply

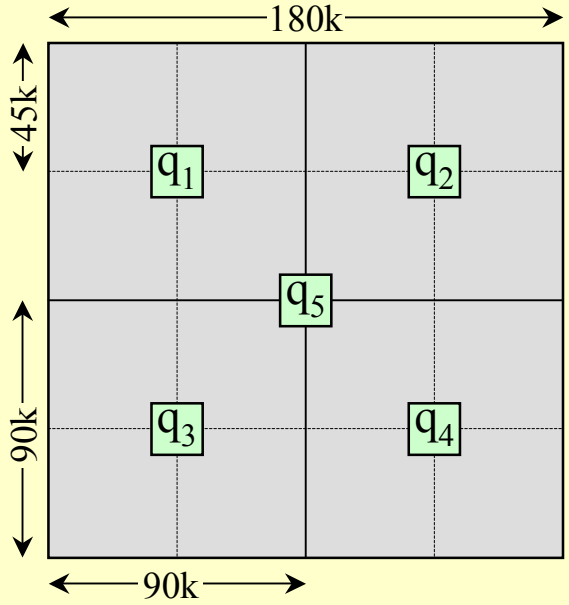
- pipeline style processing



Experimental Setup

- UMD 10 node IBM SP (1 4CPU, 3 2CPU, 6 1CPU)
- HPSS system (10TB tape storage, 500GB disk cache)
- 4GB JPEG compressed dataset (90GB uncompressed), 180k x 180k RGB pixels (200 x 200 image chunks)
- 250GB JPEG compressed dataset (5.6TB uncompressed), 1440k x 1440k RGB pixels (1600 x 1600 image chunks)
- Queries: 4500x4500 q1-q5,q6; 9000x9000 q7; 18000x18000 q8 pixels
- {server}--{client}
  - server host = SP node (1CPU or 2CPU nodes)
  - client host = User Workstation (SPARC 10 or Ultra1)

Experimental Setup (2)

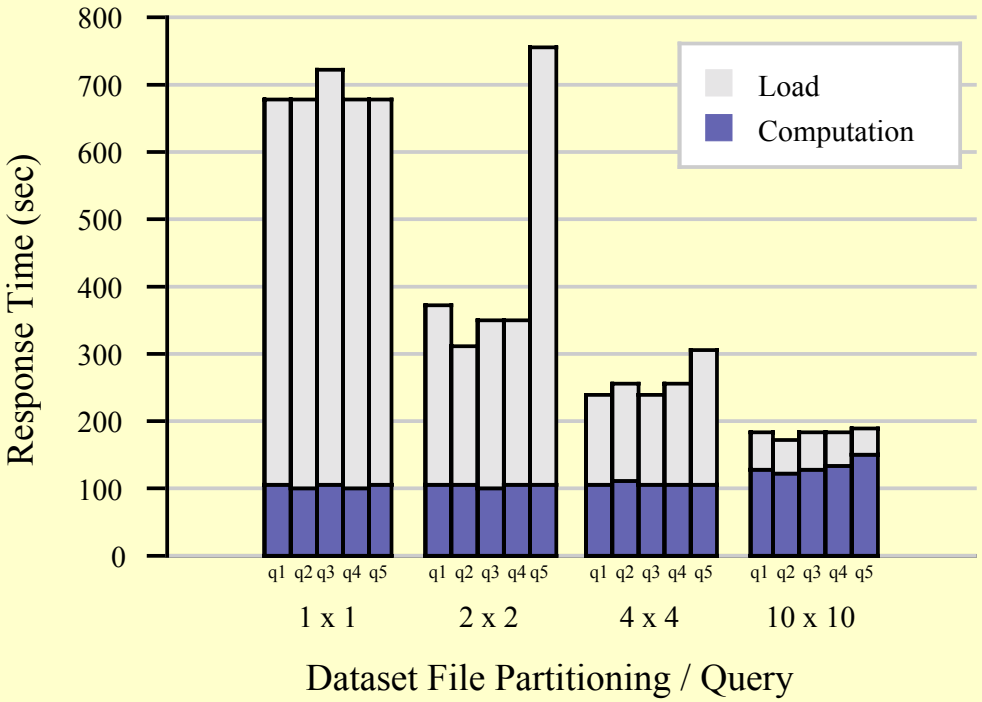


4GB dataset

Filter	*Total Volume*	*Volume / Chunk*
read_data	3.60 MB	102.52 KB
decompress	83.42 MB	2373.04 KB
clip	57.83 MB	1645.02 KB
zoom (no)	57.83 MB	1645.02 KB
zoom (8)	.90 MB	25.70 KB

q_5 sample volume

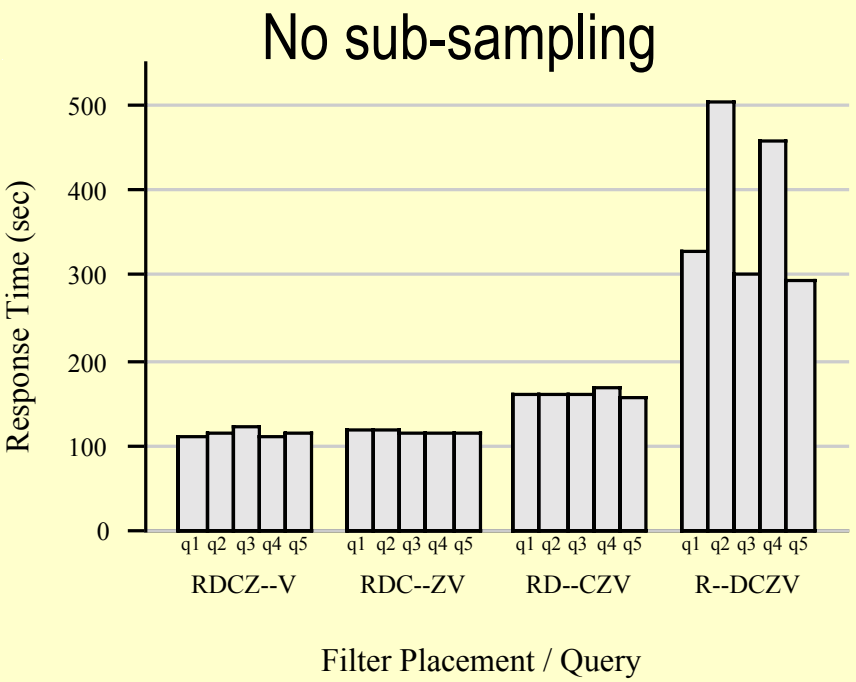
Experiment: Dataset Tiling

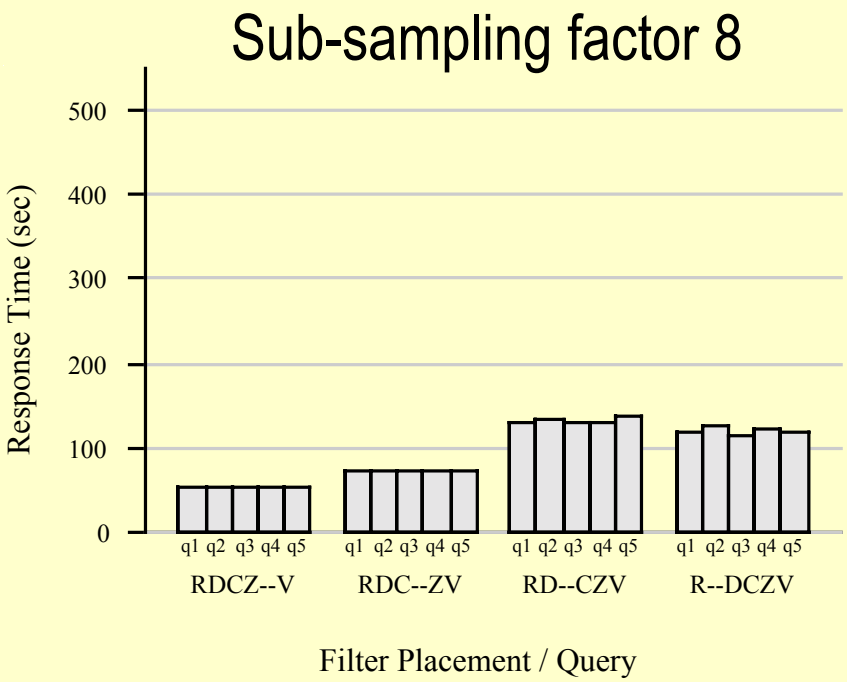


Setup: 4GB dataset, cold cache

Point: dataset organization can be controlled, and affects performance

Experiment: Computation / Volume

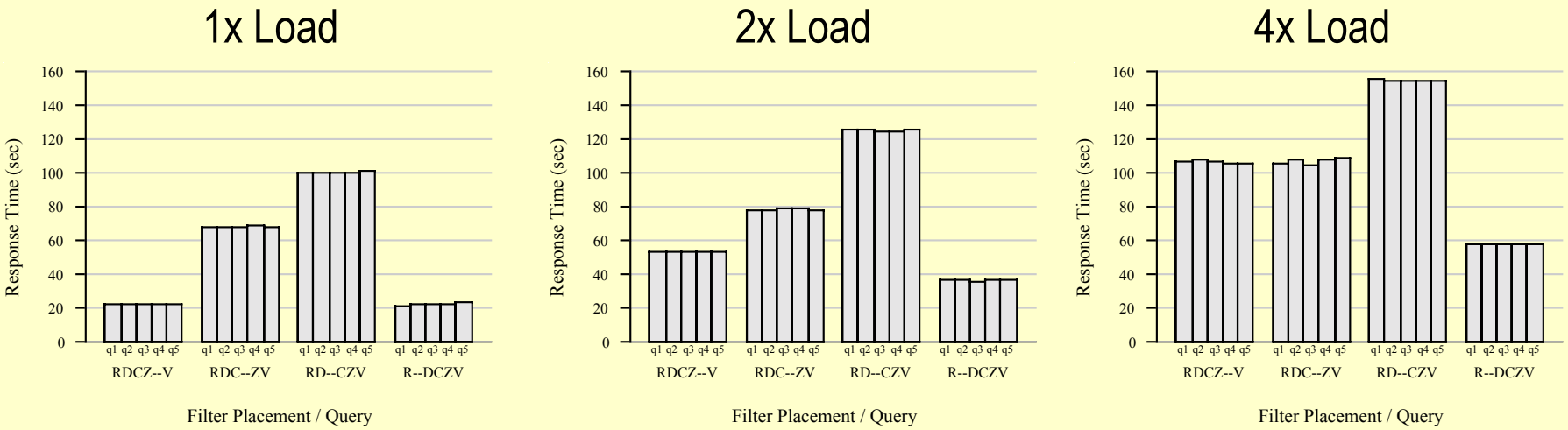




Setup: 4GB dataset, warm cache

Point: amount of computation and communication makes a significant difference for efficient placement.

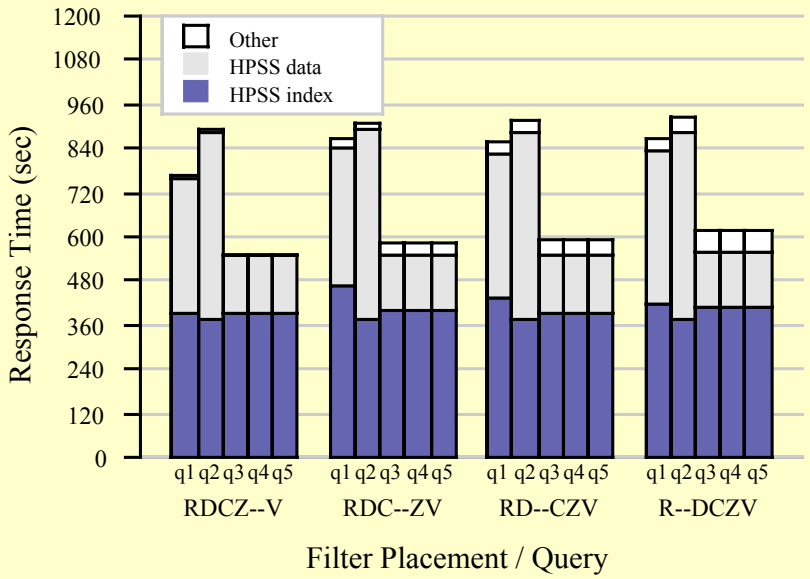
Experiment: Server Load

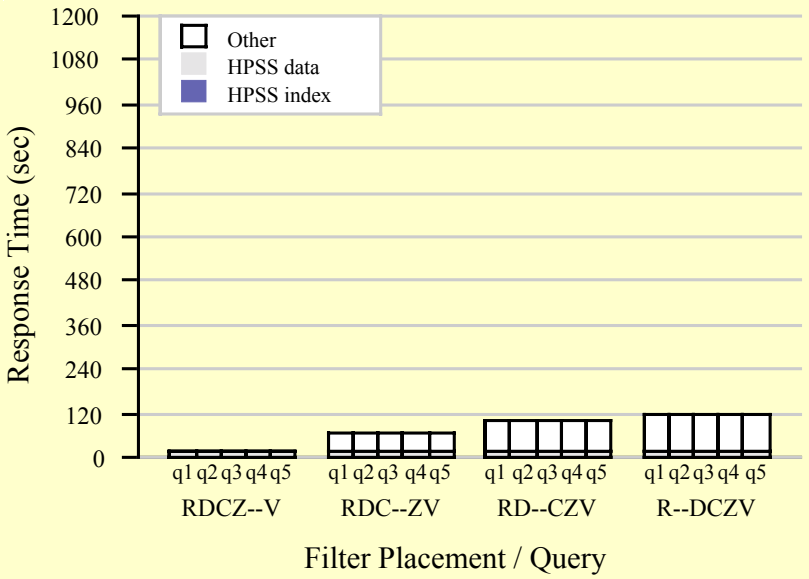


Setup:4GB dataset, zoom 8, warm cache

Point: server load has a dramatic effect on efficient placement.

Experiment: Cold vs. Warm Cache

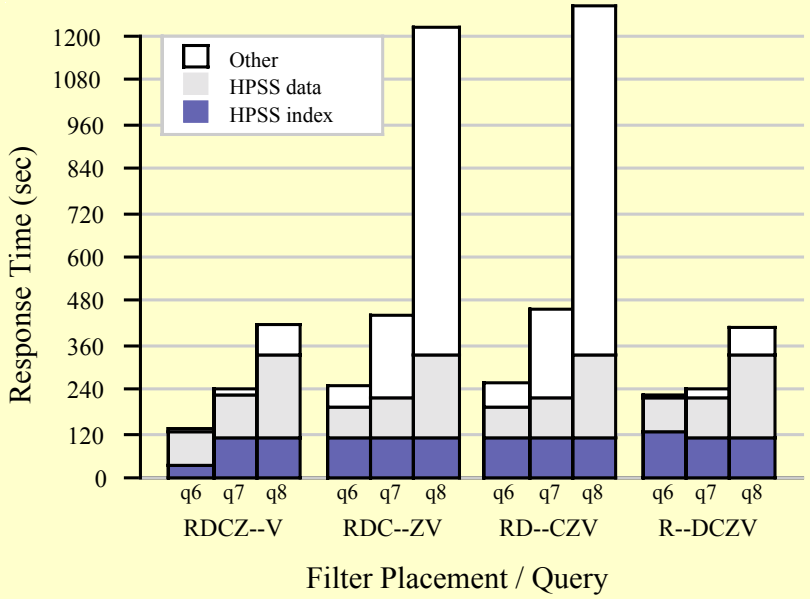


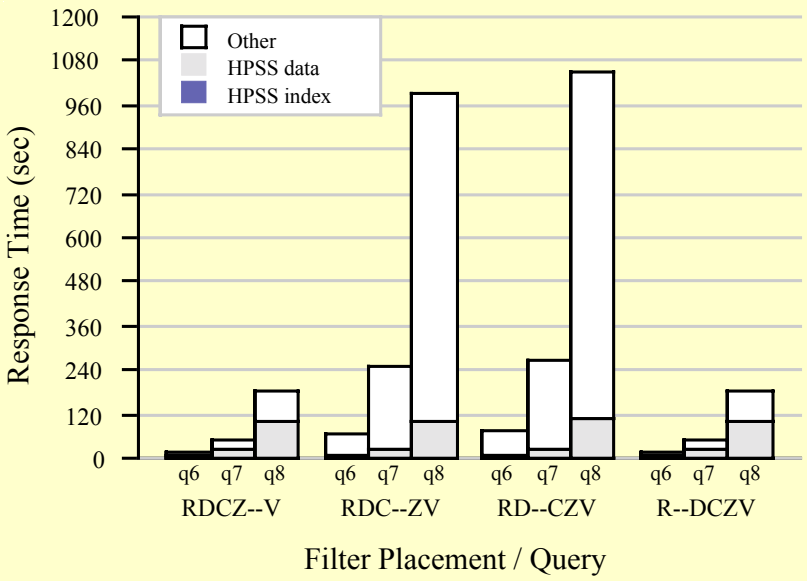


Setup: 250GB dataset, zoom 8

Point: q1-q5 dominated by HPSS access, tape storage location dependent

Experiment: Scaling Query Size





Setup: 250GB dataset, zoom 8

Point: q6-q8 larger, but not dominated as much HPSS access, network volume still important

Experiment: Filter Overhead

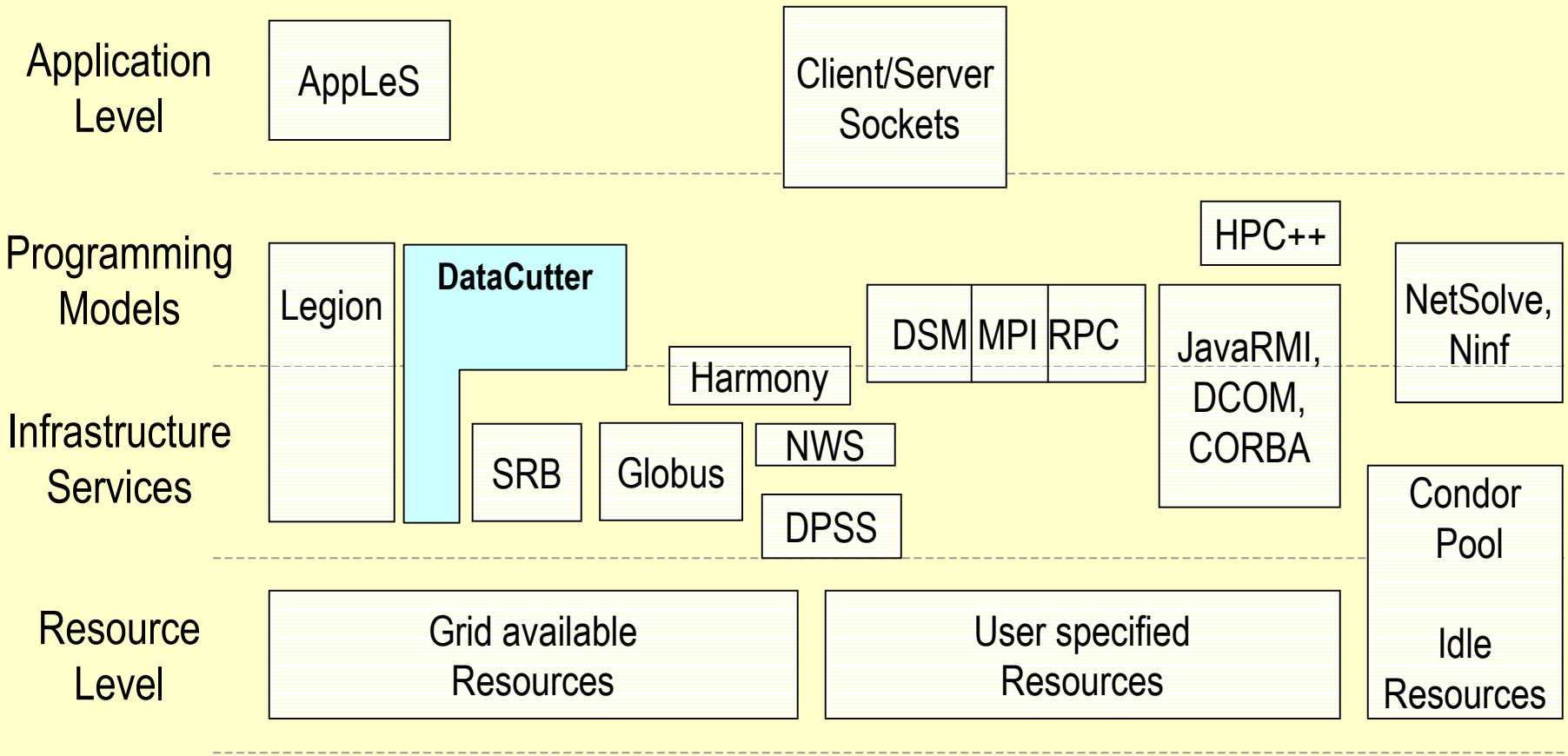
6% - 30% overhead

Point: overhead is not very large for the unoptimized filter prototype

Future Work

- New applications
  - Database (Sort, Select/Project/Join)
  - Visualization
  - Satellite data processing
- Automated placement of filters
- Tighter integration with NPACI Storage Resource Broker (SRB)

Related Work



<End of Talk>

Filter Environment

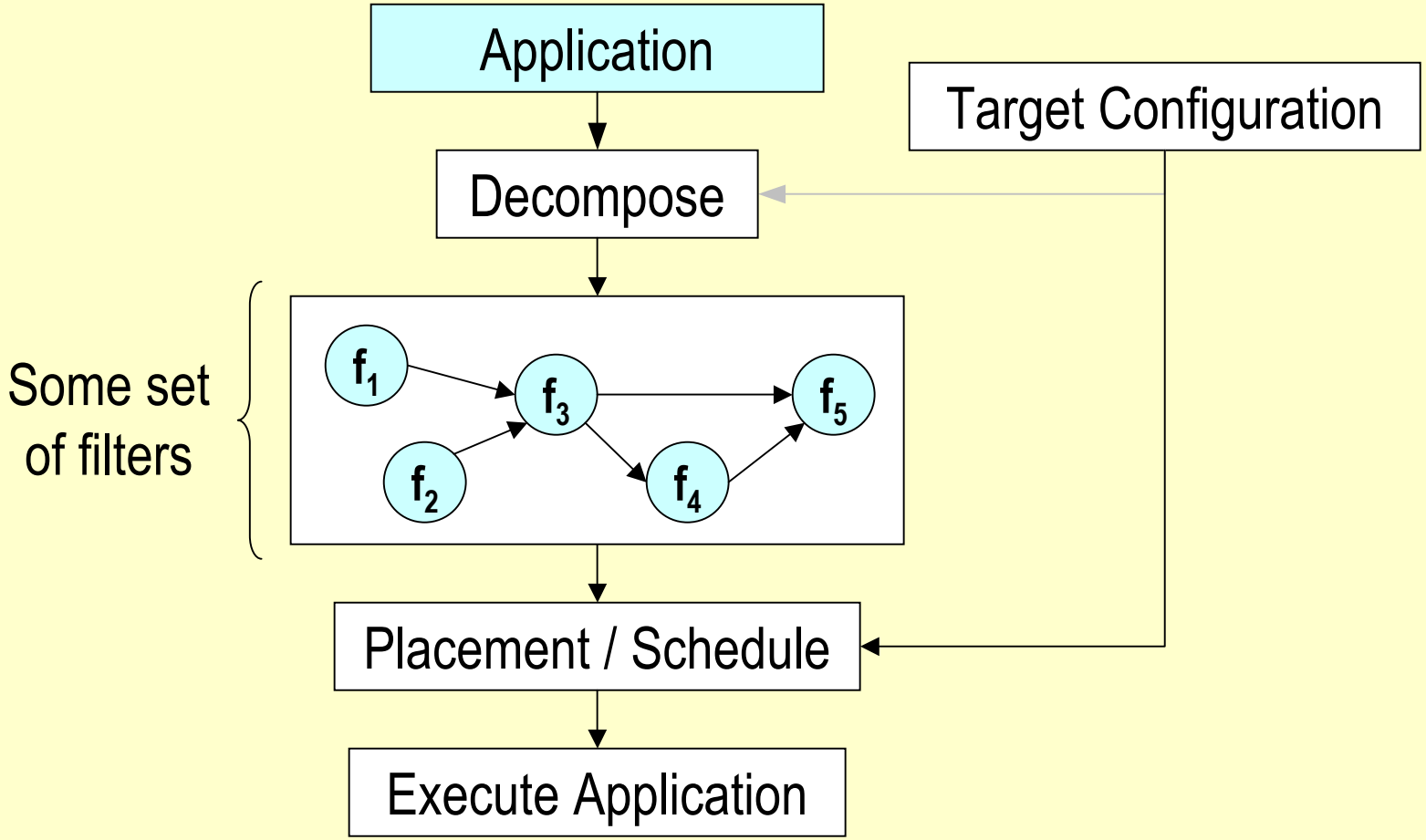
Filter constraints

- communicate with other filters *only* using streams
- cannot change stream endpoints
- may disclose dynamic allocation of memory/scratch space before execution

Advantages

- location independence
- easier scheduling of resources
- filter stop and restart is defined explicitly in model

Manual Restructuring Process

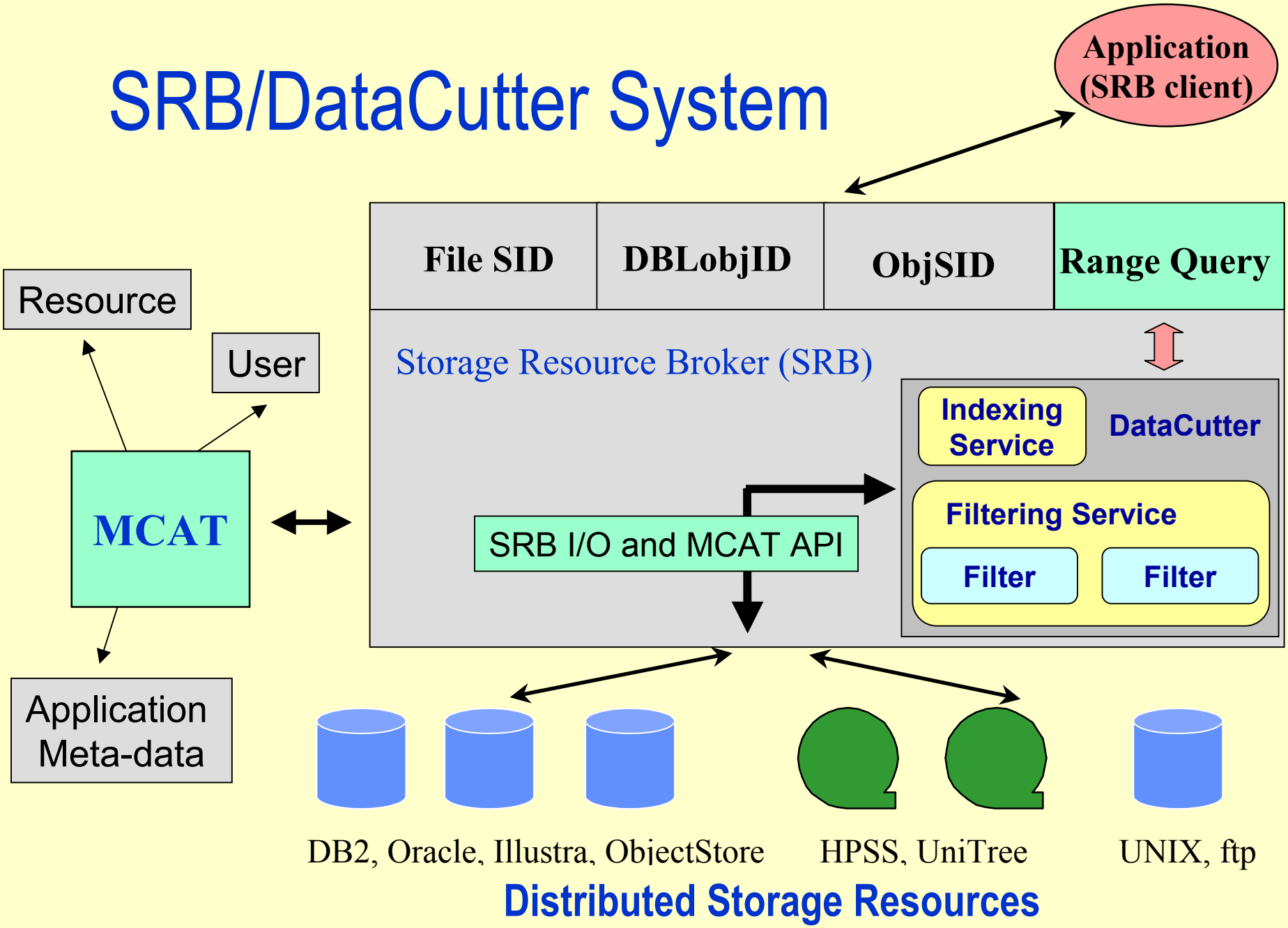


SRB/DataCutter integration

API for SRB clients to

- create indexes (R-tree index)
- subset data sets
- carry out restricted filter operations on portions of files (data segments) before returning them to the client (to perform filtering or aggregation to reduce data volume)
- only one filter can run per query

SRB/DataCutter System



Extensions to Filter Framework

- cost model based placement 1
- externalize filter library (inter-application) 2
- dynamic attachment 2
  partial filter graphs left running (server applications)
- history feedback into cost models 2
- parallel filters 3

Adaptive Placement

- Applications expose unit-of-work
  - unit of work boundaries are when decisions are made
  - a decision to modify placement is made globally
    - new instance created, and all *new* work uses it
    - for filters with state, model defines explicit state transfer
      old instance sends data over temporary special stream to new instance from <old>:finalize() to <new>:init()
    - not really “migrated”, but effect is similar without high cost
  - ex: many clients or server load high, push filters toward clients

Why not XXX programming model?

- Ex: MPI, PVM, etc. (can be used instead)
  - decide which machines to use based on dataset affinity
  - detect where running and use functional parallelism to control which filters runs
  - add disclosure of comm. pattern and resource usage
  - add mechanism for shutting down nodes and adding new during computation for adaptation
- Why use filter-stream programming model
  - because it provides these services in a natural way
  - encourages minimized state and resource usage

What will not work well?

- Fine grained tasks
- Fine coordination between filters
- Long request-response chains with dependencies between queries

Annotation Detail

- Static annotations
  - host (cpu_power, cost)
  - filter (cpu_time, size_transform, num_transform, content_transform)
  - stream (size_unit)
- Runtime properties
  - host (cpu_load, memory_free, scratch_space_free)
  - network (bw, latency, jitter)

Related Projects

- ADR (Active Data Repository) [Chang et al.]
  - Support optimized associative access and processing of persistent multi-dimensional data
  - Customizable for various applications
  - Integrate and overlap a wide range of order-independent user-defined aggregation operations with data retrieval
  - Target a shared-nothing architecture with disk farm
  - Compiler to generate ADR code from Titanium, a Java dialect
  - Caching proxy for co-located clients

Related Projects

- Active Disks [Uysal, Acharya, Saltz]
  - Putting significant processing and memory on disks
  - Execution of data-intensive parts of algorithms on disk resident processors
  - Stream-based programming model