Data-Intensive Computing: Massive Data Processing

DIC Systems

- Google MapReduce
  - Yahoo Hadoop/PIG
  - Data parallel computing
- IBM Research System S
  - InfosphereStream product
  - Continuous data stream processing
- Microsoft Dryad/Dryad LINQ
  - DAG processing
  - Some SQL query support

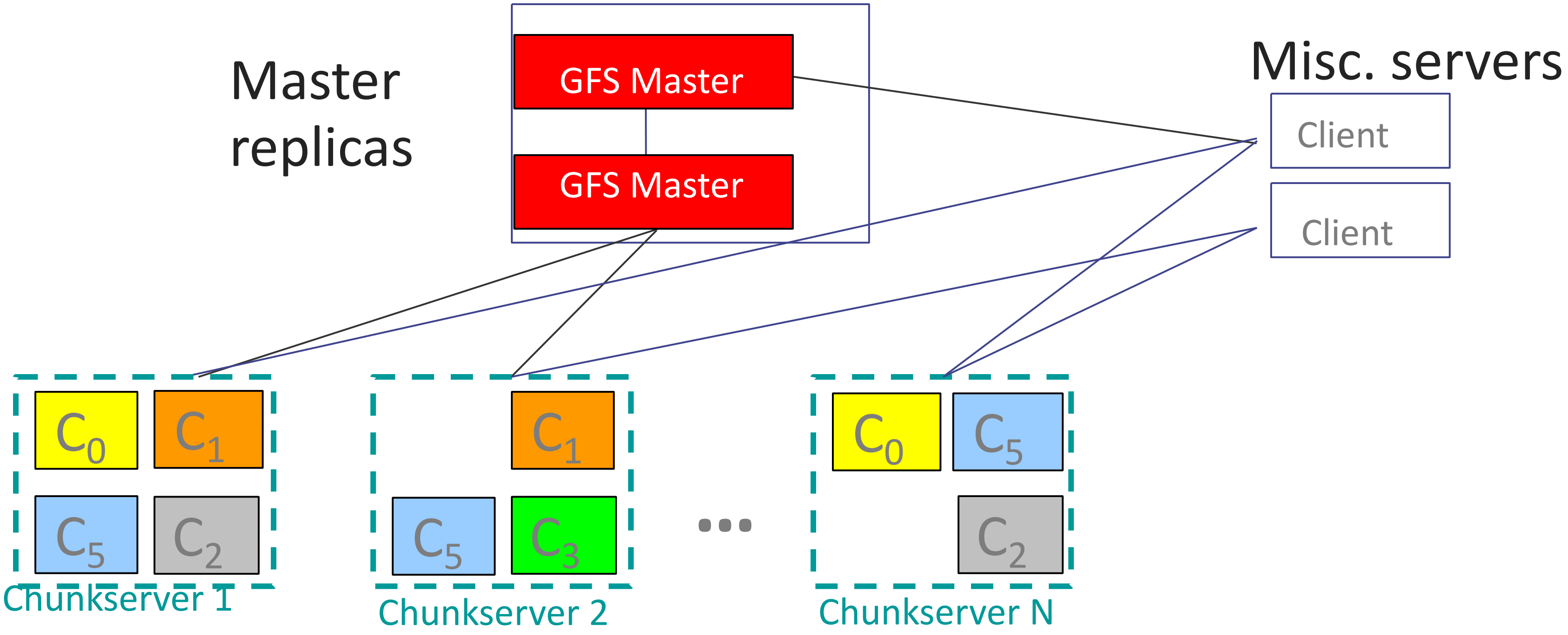
The Building Blocks of DIC at Google

- Distributed file systems: GFS
- Distributed storage: BigTable
- Job scheduler: the workqueue
- Parallel computation: MapReduce
- Distributed lock server: chubby

GFS: The Google File System

- Reliable distributed storage system for petabyte scale filesystems.
- Data kept in 64-megabyte “chunks” stored on disks spread across thousands of machines
- Each chunk replicated, usually 3 times, on different machines so that GFS can recover seamlessly from disk or machine failure.
- A GFS cluster consists of a single *master server*, multiple *chunkservers*, and is accessed by multiple *clients*.

GFS: The Google File System



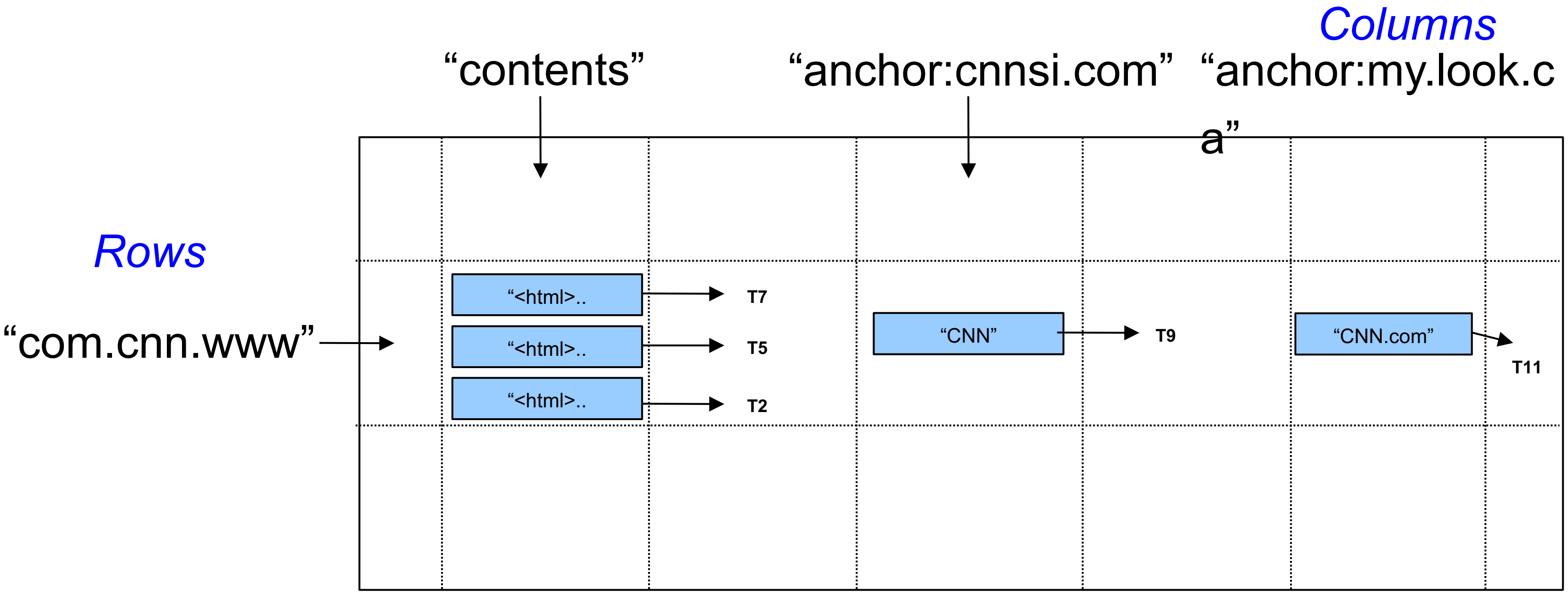
- Master manages metadata
- Data transfers happen directly between clients/chunkservers
- Files broken into chunks (typically 64 MB)
- Chunks triplicated across three machines for safety

BigTable

- A distributed storage system for managing structured data
  - Designed to scale to a very large size: petabytes of data across thousands of commodity servers.
- Built on top of GFS
- Used by more than 60 Google products and projects
  - Google Earth, Google Finance, Orkut, …

Basic Data Model

- Triple (row, column, timestamp) -> keys for lookup, insert, and delete API
- Arbitrary “columns” on a row-by-row basis
  - Column “family:qualifier”: Family is heavyweight, qualifier lightweight
  - Column-oriented physical store: rows are sparse!



Rows

- Name is an arbitrary string.
  - Access to data in a row is atomic.
  - Row creation is implicit upon storing data.
  - Transactions within a row
- Rows ordered lexicographically
  - Rows close together lexicographically usually on one or a small number of machines.
- Does not support relational model
  - No table wide integrity constants
  - No multirow transactions

MapReduce

- A parallel programming model and an associated implementation for processing and generating large data sets.
- A user specified **map** function processes a key/value pair to generate a set of intermediate key/value pairs.
- A user specified **reduce** function merges all intermediate values associated with the same intermediate key.
- Programs written in this functional style are automatically parallelized and executed on a large cluster of commodity machines.

Motivation

- Large-Scale Data Processing
  - Want to use 1000s of CPUs
    - But don’t want hassle of ***managing*** things
- MapReduce runtime provides
  - Automatic parallelization & distribution
  - Fault tolerance
  - I/O scheduling
  - Monitoring & status updates

Map/Reduce

- Map/Reduce
  - Programming model from Lisp
  - (and other functional languages)
- Many problems can be phrased this way
- Easy to distribute across nodes
- Failure/retry semantics

Map in Lisp (Scheme)

- (map ***f list [list***$_2$ ***list***$_3$ ***…]***)

Unary operator

- (map square ‘(1 2 3 4))
  - (1 4 9 16)

Binary operator

- (reduce + ‘(1 4 9 16))
  - 30
- (reduce + (map square (map – l$_1$ l$_2$))))

Map/Reduce at Google

- map(key, val) is run on each item in set
  - emits new-key / new-val pairs

- reduce(key, vals) is run for each unique key emitted by map()
  - emits final output

count words in docs

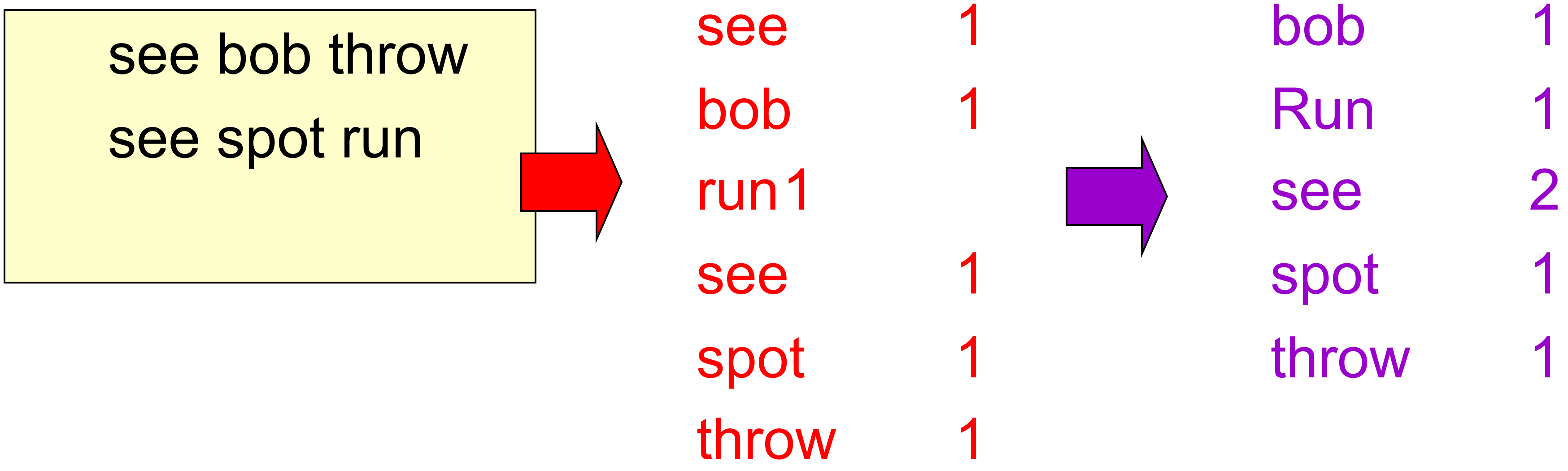
- – Input consists of (url, contents) pairs

- – map(key=url, val=contents):
  - For each word *w* in contents, emit (w, “1”)

- – reduce(key=word, values=uniq_counts):
  - Sum all “1”s in values list
  - Emit result “(word, sum)”

Count, Illustrated

```
map(key=url, val=contents):
    For each word w in contents, emit (w, "1")
reduce(key=word, values=uniq_counts):
    Sum all "1"s in values list
    Emit result "(word, sum)"
```



see bob throw
see spot run

see	1
bob	1
run1	
see	1
spot	1
throw	1

bob	1
Run	1
see	2
spot	1
throw	1

Grep

- – Input consists of (url+offset, single line)
- – map(key=url+offset, val=line):
  - If contents matches regexp, emit (line, “1”)
- – reduce(key=line, values=uniq_counts):
  - Don’t do anything; just emit line

Reverse Web-Link Graph

- Map
  - – For each URL linking to target, …
  - – Output <target, source> pairs
- Reduce
  - – Concatenate list of all source URLs
  - – Outputs: <target, ***list*** (source)> pairs

Implementation Overview

Typical cluster:

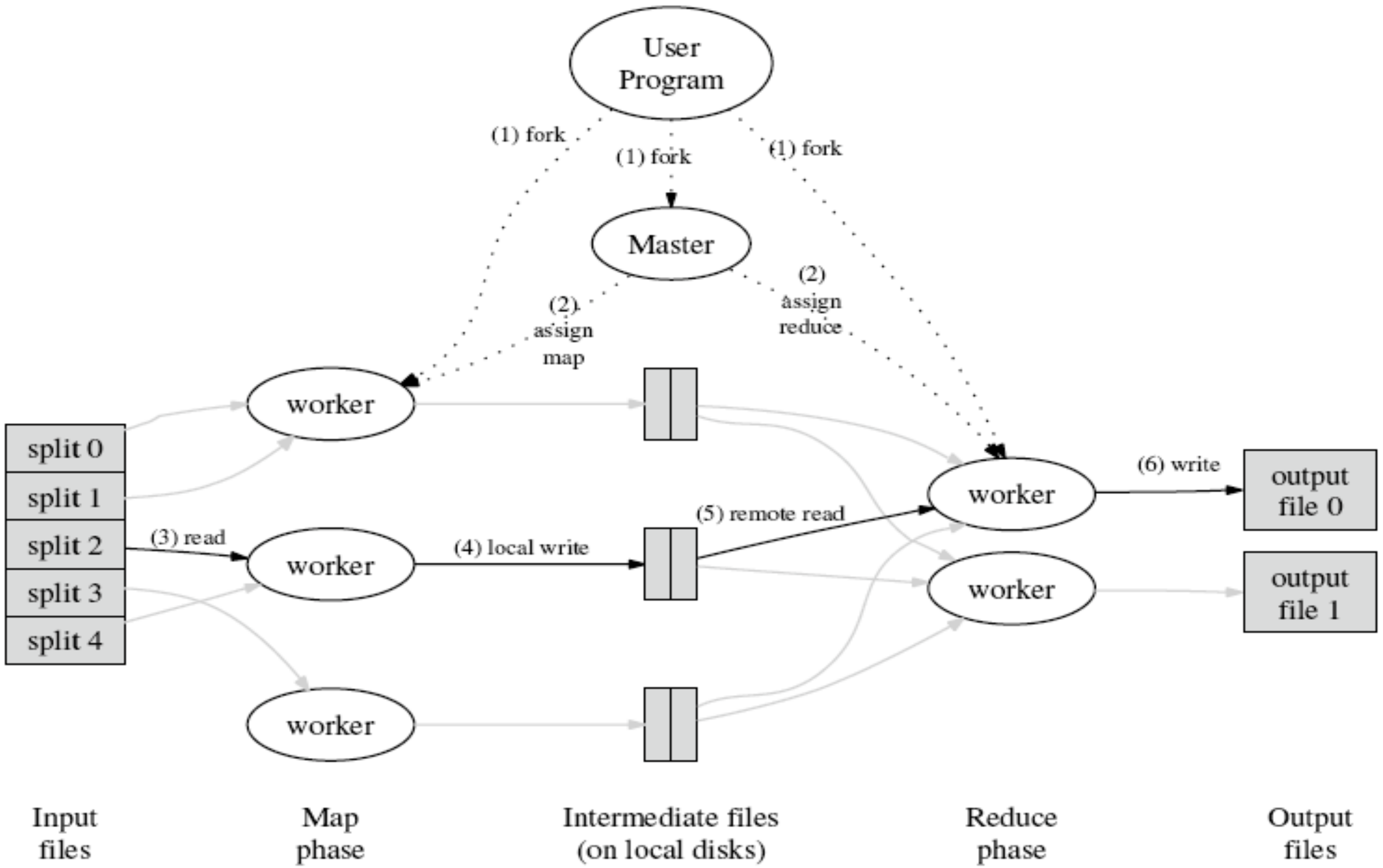
- 100s/1000s of 2-CPU x86 machines, 2-4 GB of memory
- Limited bisection bandwidth
- Storage is on local IDE disks
- GFS: distributed file system manages data
- Job scheduling system: jobs made up of tasks, scheduler assigns tasks to machines

Implementation is a C++ library linked into user programs

MapReduce Runtime System

- How is this distributed?
  - Partition input key/value pairs into chunks, run map() tasks in parallel
  - After all map()s are complete, consolidate all emitted values for each unique emitted key
  - Partition space of output map keys, and run reduce() in parallel
- If map() or reduce() fails, reexecute!

Distributed Execution



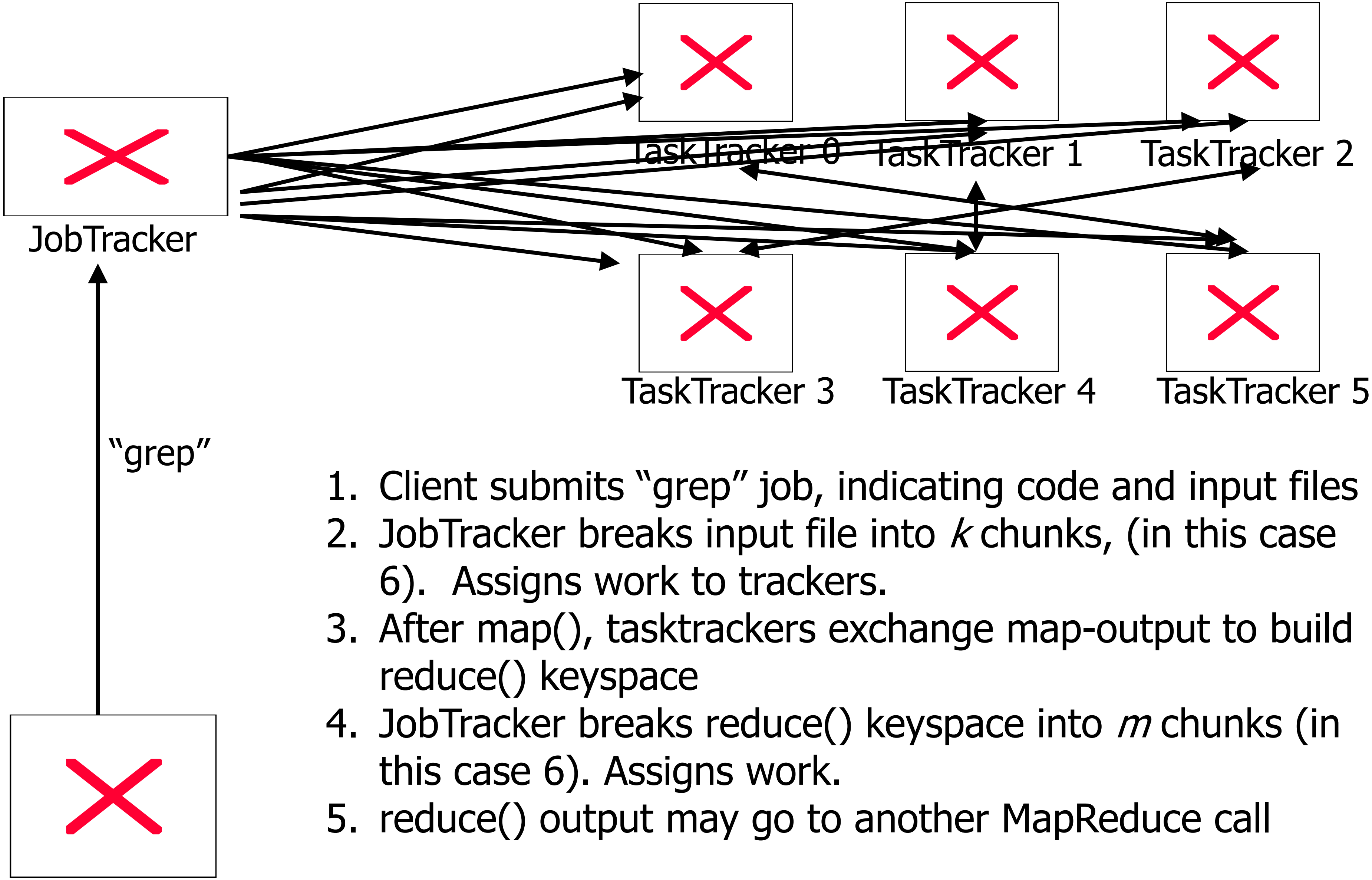
Example: Count word occurrences

```
map(String input_key, String input_value):
  // input_key: document name
  // input_value: document contents
  for each word w in input_value:
    EmitIntermediate(w, "1");


reduce(String output_key, Iterator
  intermediate_values):
  // output_key: a word
  // output_values: a list of counts
  int result = 0;
  for each v in intermediate_values:
    result += ParseInt(v);
 Emit(AsString(result));
```

Example vs. Actual Source Code

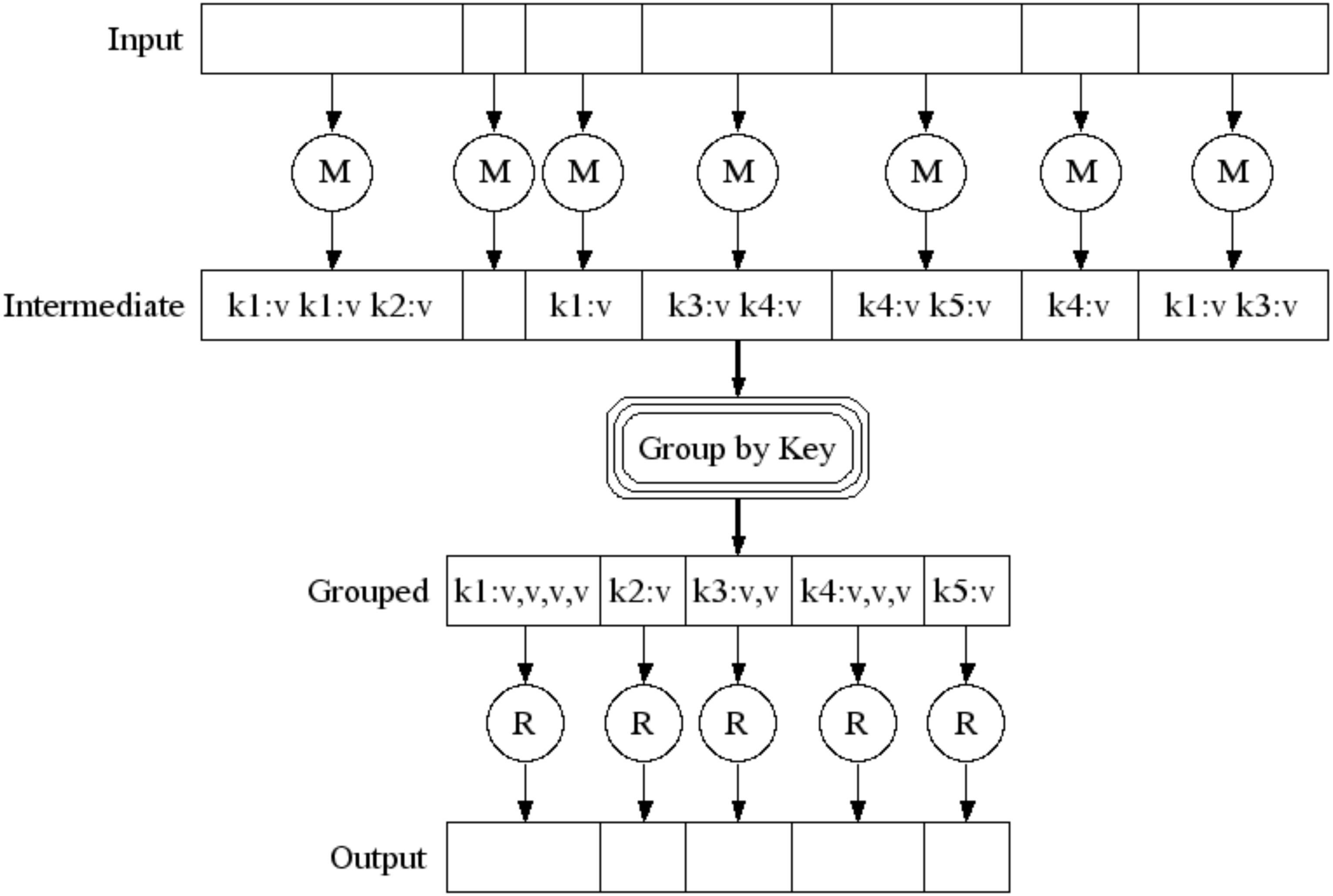
- Example is written in pseudo-code
- Actual implementation is in C++, using a MapReduce library
- Bindings for Python and Java exist via interfaces
- True code is somewhat more involved (defines how the input key/values are divided up and accessed, etc.)

Job Processing

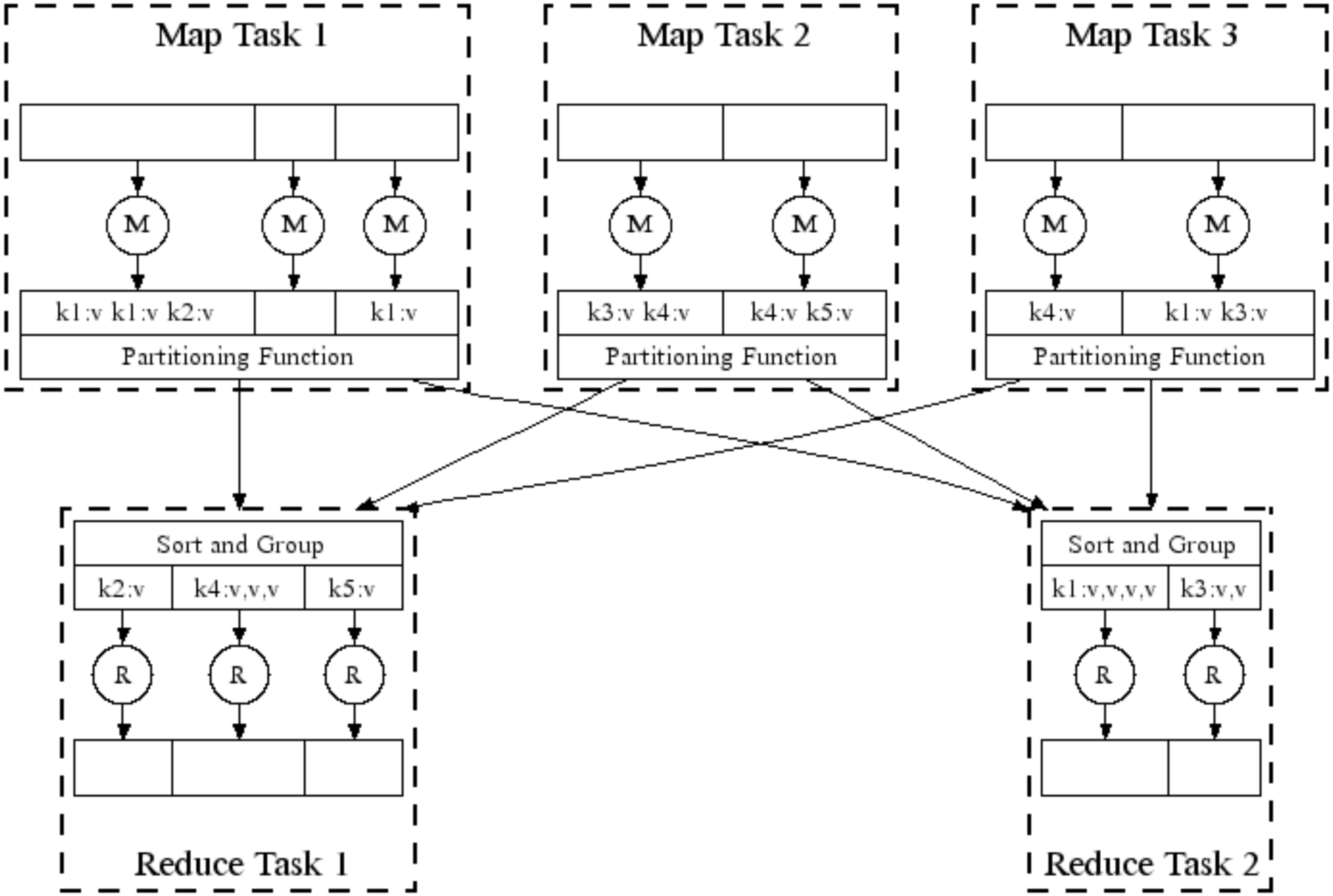


1. Client submits "grep" job, indicating code and input files
2. JobTracker breaks input file into *k* chunks, (in this case 6). Assigns work to trackers.
3. After map(), tasktrackers exchange map-output to build reduce() keyspace
4. JobTracker breaks reduce() keyspace into *m* chunks (in this case 6). Assigns work.
5. reduce() output may go to another MapReduce call

Execution


Input
M
M
M
M
M
M
M
Intermediate
k1:v k1:v k2:v
k1:v
k3:v k4:v
k4:v k5:v
k4:v
k1:v k3:v
Group by Key
Grouped
k1:v,v,v,v
k2:v
k3:v,v
k4:v,v,v
k5:v
R
R
R
R
R
Output

Parallel Execution



Fault Tolerance

Handled via re-execution

- Detect failure via periodic heartbeats
- Re-execute completed + in-progress *map* tasks (why?)
- Re-execute in progress *reduce* tasks (why?)
- Task completion committed through master

Robust: lost 1600/1800 machines once → finished ok

Refinement: Redundant Execution

Slow workers significantly delay completion time

- Other jobs consuming resources on machine
- Bad disks w/ soft errors transfer data slowly
- Weird things: processor caches disabled (!!)

Solution: Near end of phase, spawn backup tasks

- Whichever one finishes first "wins"

Dramatically shortens job completion time

Refinement: Locality Optimization

- Master scheduling policy
  - Ask GFS for locations of replicas of input file blocks
  - Map tasks typically split into 64MB (GFS block size)
  - Map tasks scheduled so GFS input block replica are on same machine or same rack
- Effect
  - Thousands of machines read input at local disk speed
    - Without this, rack switches limit read rate

Refinement
Skipping Bad Records

- Map/Reduce functions sometimes fail for particular inputs
  - Best solution is to debug & fix
    - Not always possible ~ third-party source libraries
  - On segmentation fault:
    - Send UDP packet to master from signal handler
    - Include sequence number of record being processed
  - If master sees two failures for same record:
    - Next worker is told to skip the record

Performance

Tests run on cluster of 1800 machines:

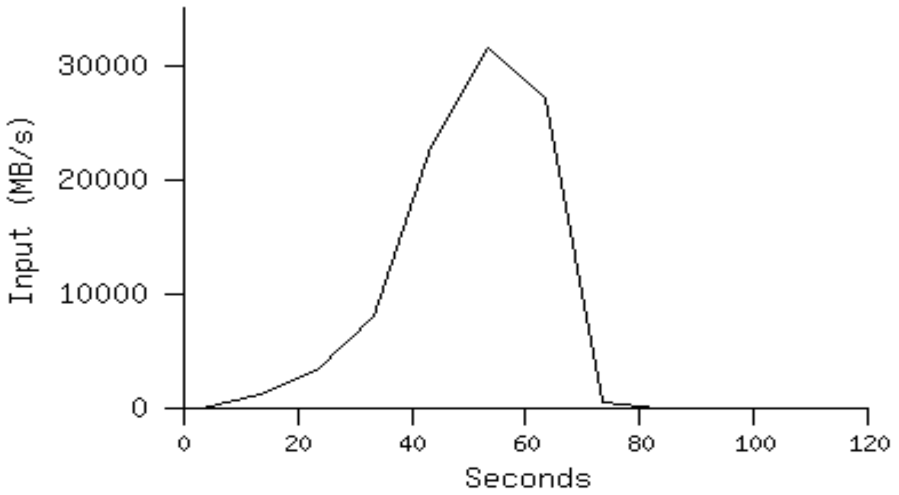
- 4 GB of memory
- Dual-processor 2 GHz Xeons with Hyperthreading
- Dual 160 GB IDE disks
- Gigabit Ethernet per machine
- Bisection bandwidth approximately 100 Gbps

Two benchmarks:

MR_GrepScan 1010 100-byte records to extract records matching a rare pattern (92K matching records)

MR_SortSort 1010 100-byte records (modeled after TeraSort benchmark)

MR_Grep

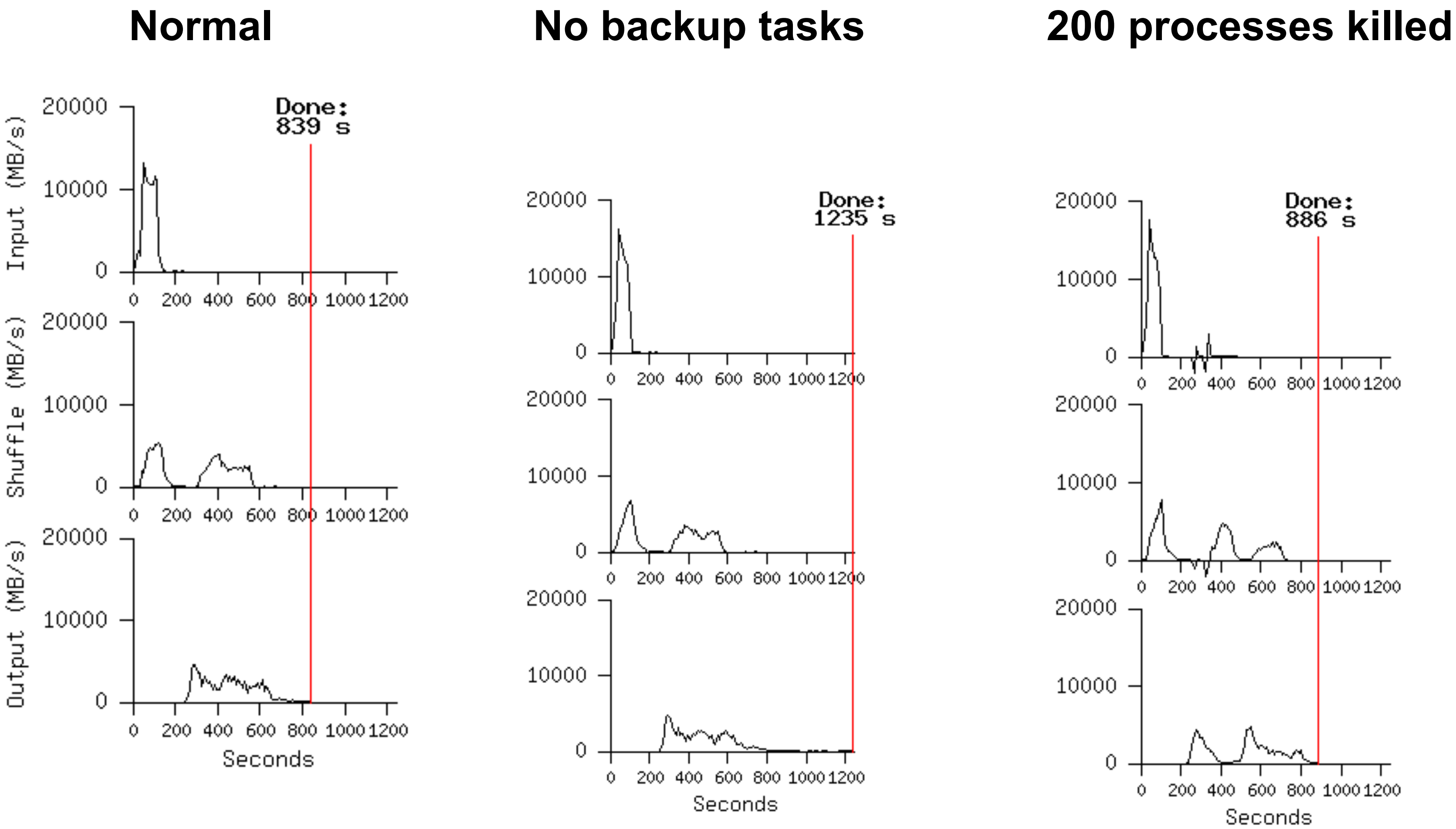


Locality optimization helps:

- 1800 machines read 1 TB at peak ~31GB/s
- W/out this, rack switches would limit to 10 GB/s

Startup overhead is significant for short jobs

MR_Sort



Normal

No backup tasks

200 processes killed

- Backup tasks reduce job completion time a lot!
- System deals well with failures

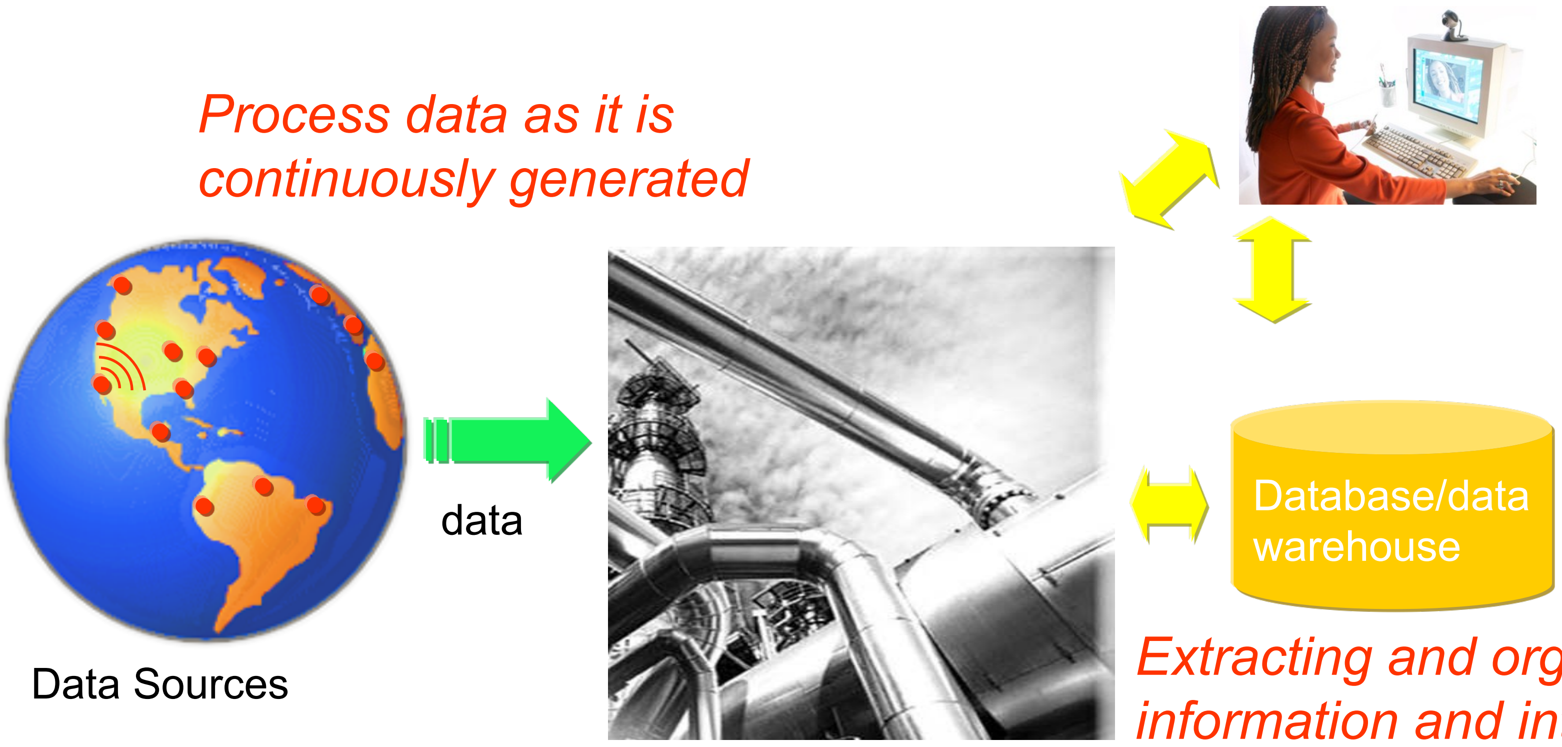
MapReduce Summary

- MapReduce has proven to be a useful distributed programming abstraction
- Greatly simplifies large-scale data-intensive computing
- Functional programming paradigm can be applied to many data analysis applications
- Fun to use: focus on problem, let library deal with messy details

What is Stream Processing?

Minimizing time to react

Process data as it is continuously generated



data

Data Sources

Database/data warehouse

Extracting and organizing information and intelligence

Stream Processing System

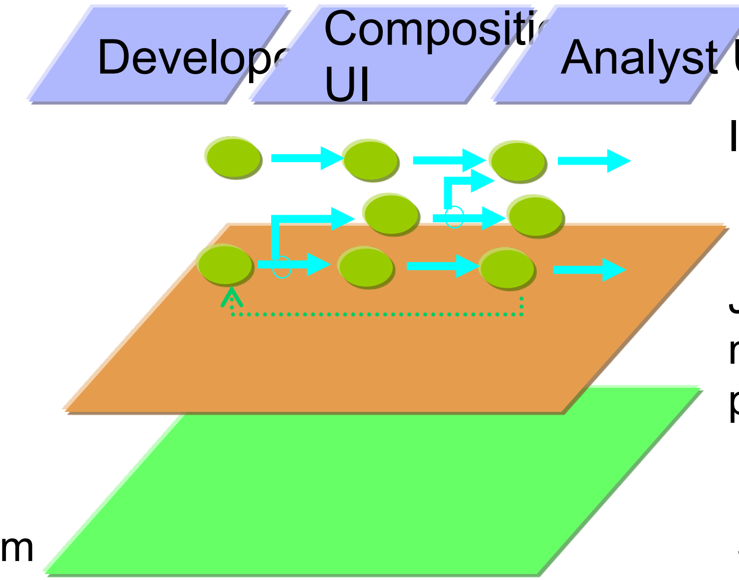
What Makes a Stream Processing System?

Tooling

Application

Runtime Environment

Hardware Platform



Interconnection of operators

Job management, resource management, content routing, programming model, object store

Servers, networks, storage, operating system, file system

Stream Processing System

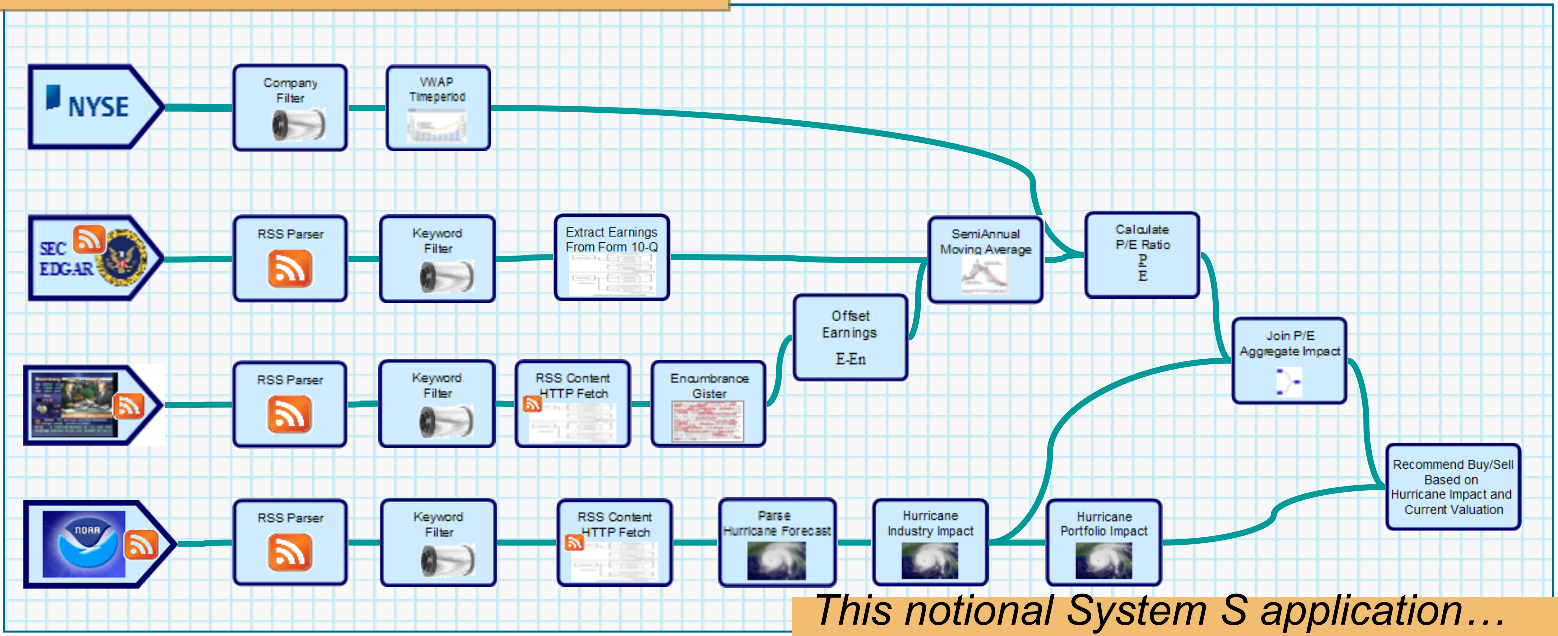
System S Stream Processing

- New *stream* computing paradigm
- Pull information from anywhere in real time
- Ultra-low latency, ultra-high throughput
- Scalable

System S: A Closer Look

System S continually adapts to new inputs, new modalities

Analytics may be a combination of provided and user-developed/legacy operators



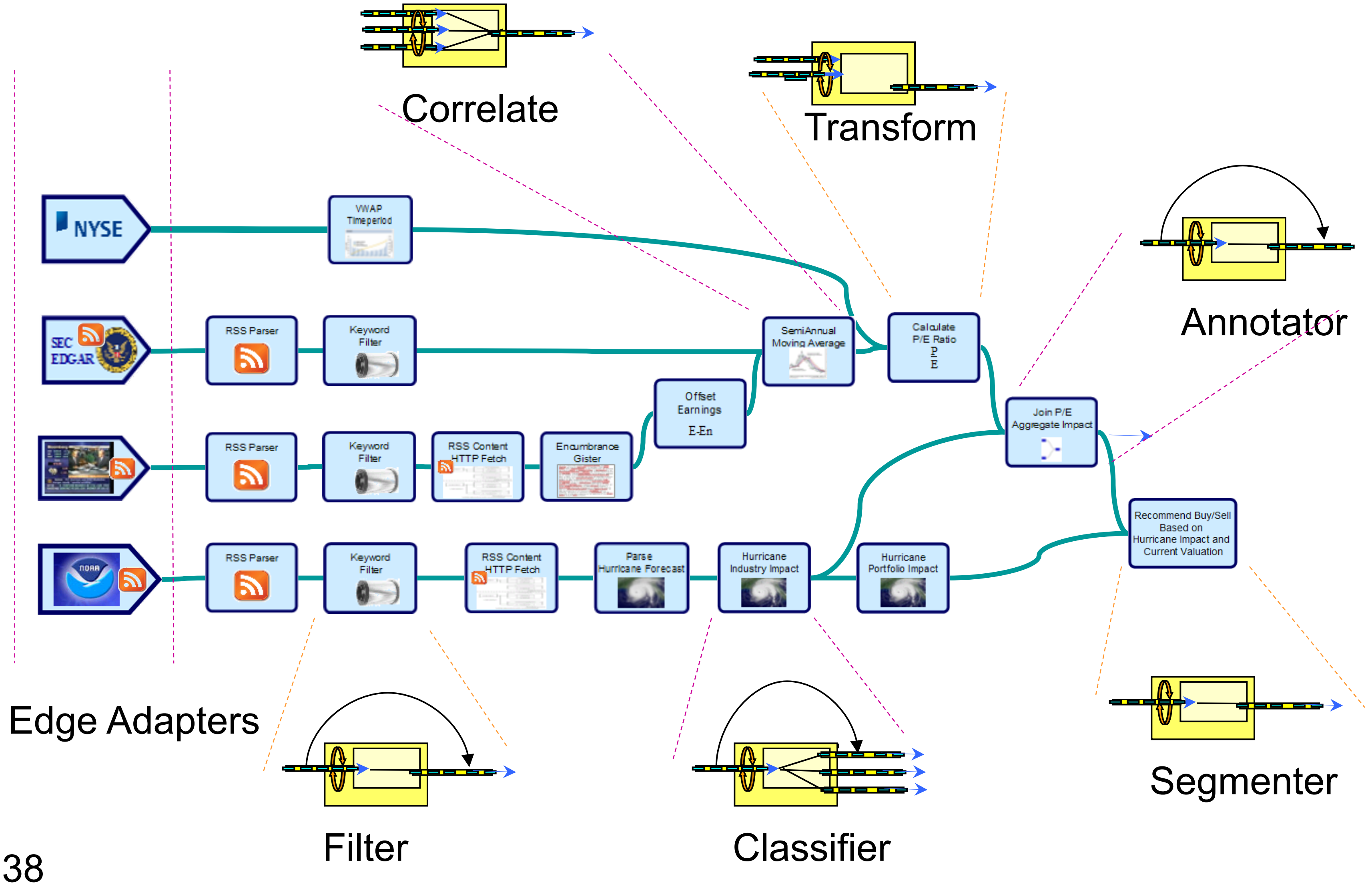
System S applications can seamlessly process structured (event) and unstructured data

This notional System S application…

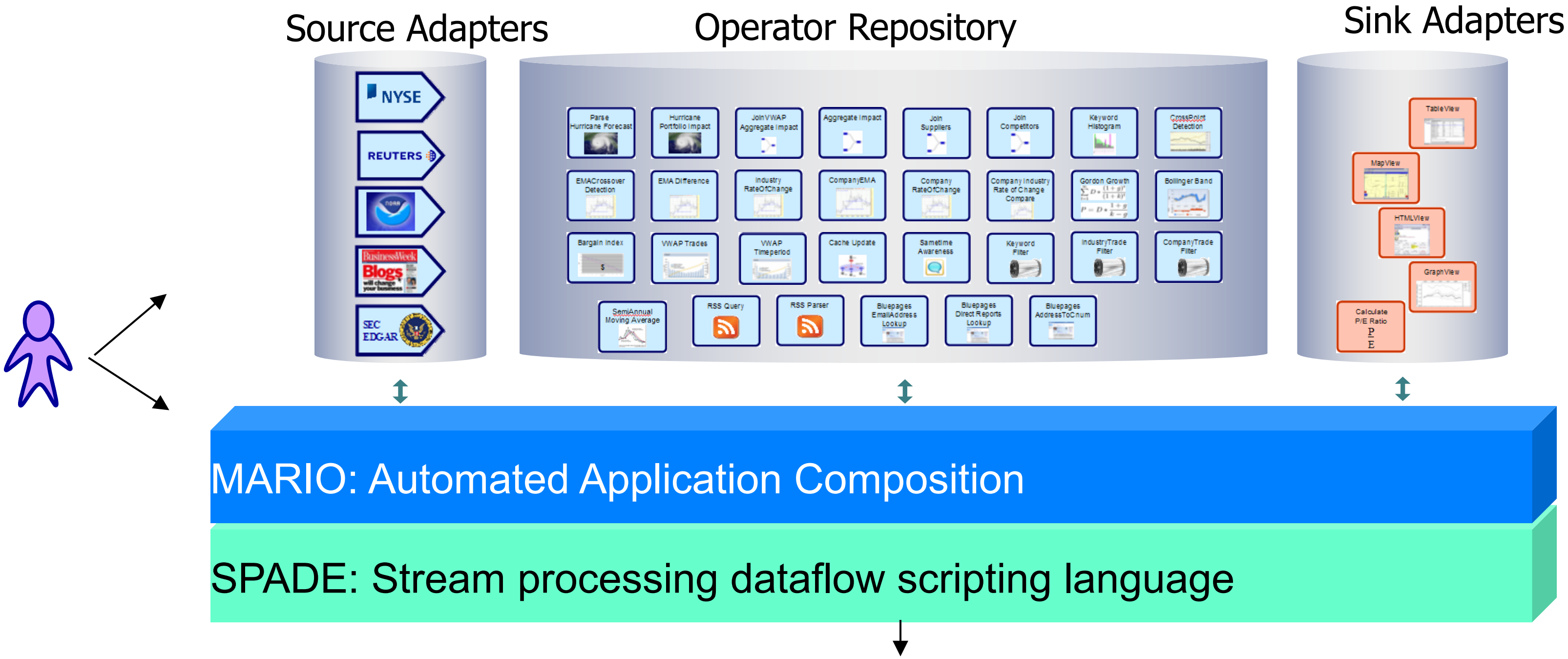
- *Calculates VWAP*
- *Calculates P/E, based earnings from Edgar*
- *Refines earnings based on encumbrances identified in newsfeeds*

SPADE Building Blocks

Classifiers, Annotators, Correlators, Filters, Aggregators



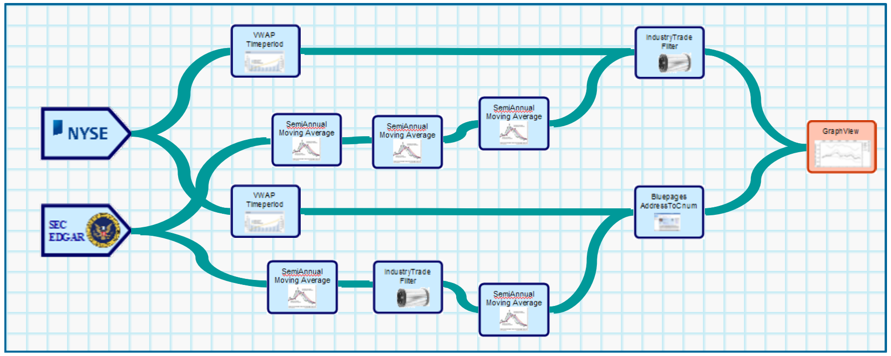
Application Programming



MARIO: Automated Application Composition

SPADE: Stream processing dataflow scripting language

- Consumable
- Reusable set of operators
- Connectors to external static or streaming data sources and sinks

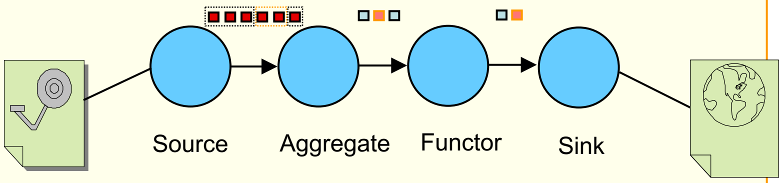


NYSE
SEC EDGAR
VWAP Timeperiod
SemiAnnual Moving Average
SemiAnnual Moving Average
SemiAnnual Moving Average
VWAP Timeperiod
SemiAnnual Moving Average
IndustryTrade Filter
SemiAnnual Moving Average
IndustryTrade Filter
Bluepages AddressToCnum
GraphView

Platform Optimized Compilation

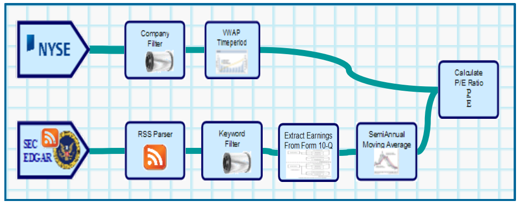
SPADE

- SPADE (*Stream Processing Application Declarative Engine*) is an intermediate language for streaming applications.
  - Simplifies design of applications used by System S
  - Hides complexities of
    - manipulating data streams (e.g., contains generic language support for data types and building block operations)
    - fanning out applications to distributed heterogeneous nodes
    - transporting data through diverse computer infrastructures (ingesting external data, routing intermediate results, looping in feedback, branching, outputing the results, ...)



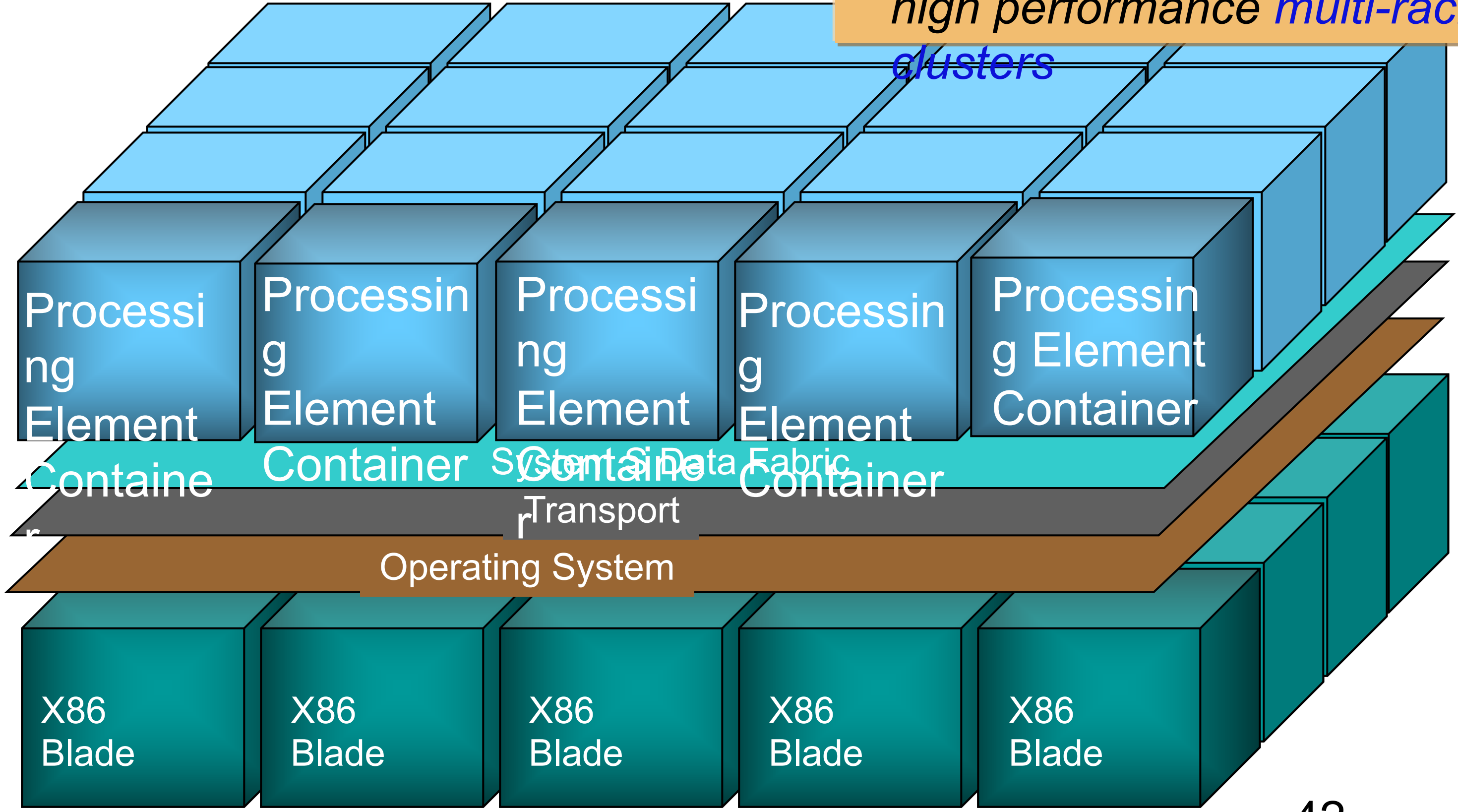
```
[Application]
SourceSink trace

[Typedefs]
typespace sourcesink

typedef id_t Integer
typedef timestamp_t Long

[Program]
// virtual schema declaration
vstream Sensor (id : id_t, location : Double, light : Float, temperature : Float, timestamp :
timestamp_t)

// a source stream is generated by a Source operator – in this case tuples come from an input file
stream SenSource ( schemaFor(Sensor) )
        := Source( ) [ “file:///SenSource.dat” ] {}

// this intermediate stream is produced by an Aggregate operator, using the SenSource stream as
input
stream SenAggregator ( schemaFor(Sensor) )
        := Aggregate( SenSource <count(100),count(1)> ) [ id . location ]
                              { Any(id), Any(location), Max(light), Min(temperature), Avg(timestamp) }

// this intermediate stream is produced by a functor operator
stream SenFunctor ( id: Integer, location: Double, message: String )
        := Functor( SenAggregator ) [ log(temperature,2.0)>6.0 ]
                         { id, location, “Node ”+toString(id)+ “ at location ”+toString(location) }

// result management is done by a sink operator – in this case produced tuples are sent to a socket
Null := Sink( SenFunctor ) [ “cudp://192.168.0.144:5500/” ] {}
```

System S Runtime Services



Optimizing scheduler assigns operators to processing nodes, and continually manages resource allocation

Runs on commodity hardware – from single node to blade centers to high performance multi-rack clusters

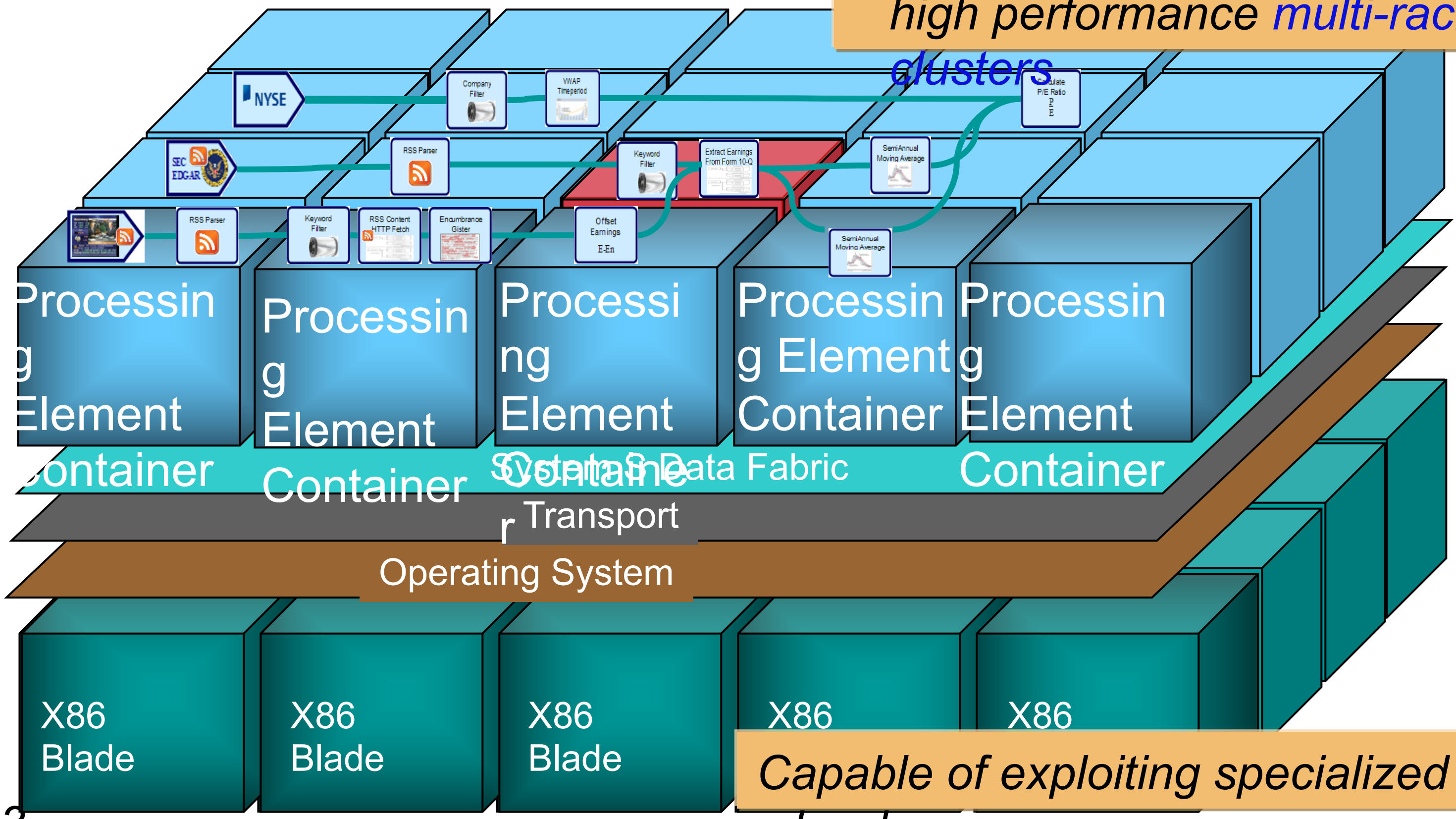

Processing Element Container
Processing Element Container
Processing Element Container
Processing Element Container
Processing Element Container
System S Data Fabric
Transport
Operating System
X86 Blade
X86 Blade
X86 Blade
X86 Blade
X86 Blade

System S Runtime Services

Optimizing scheduler assigns operators to processing nodes, and continually manages resource allocation

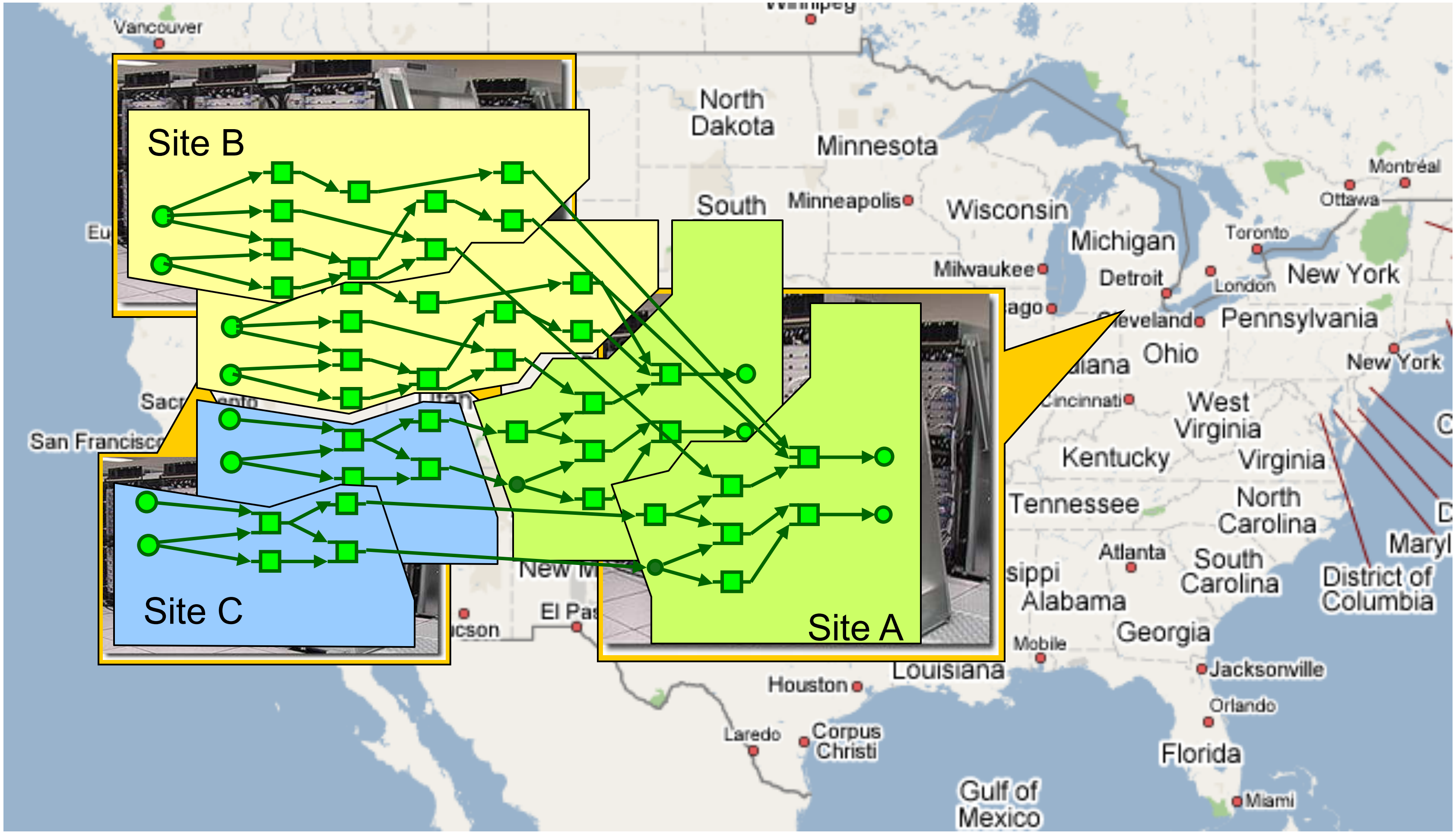
Adapts to changes in resources, workload, data rates

Runs on commodity hardware – from single node to blade centers to high performance multi-rack clusters



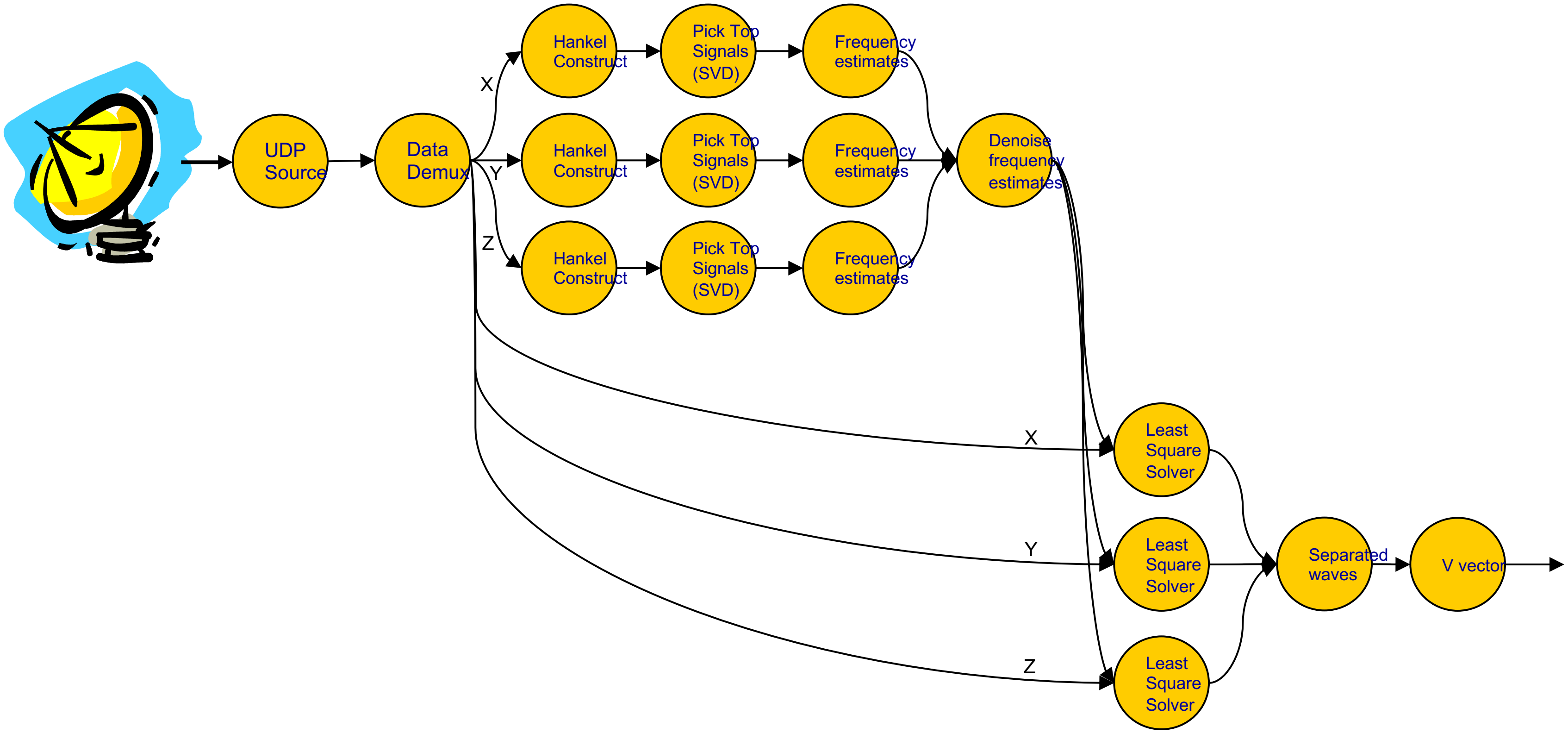
Capable of exploiting specialized hardware

Distributed operation



Summary

Simplified Processing Flow Graph


UDP Source
Data Demux
X
Y
Z
Hankel Construct
Hankel Construct
Hankel Construct
Pick Top Signals (SVD)
Pick Top Signals (SVD)
Pick Top Signals (SVD)
Frequency estimates
Frequency estimates
Frequency estimates
Denoise frequency estimates
X
Y
Z
Least Square Solver
Least Square Solver
Least Square Solver
Separated waves
V vector