Programming at Scale: Dataflow

cs378

Today

Questions?

Administrivia

- Project Proposal Due Soon!

Agenda:

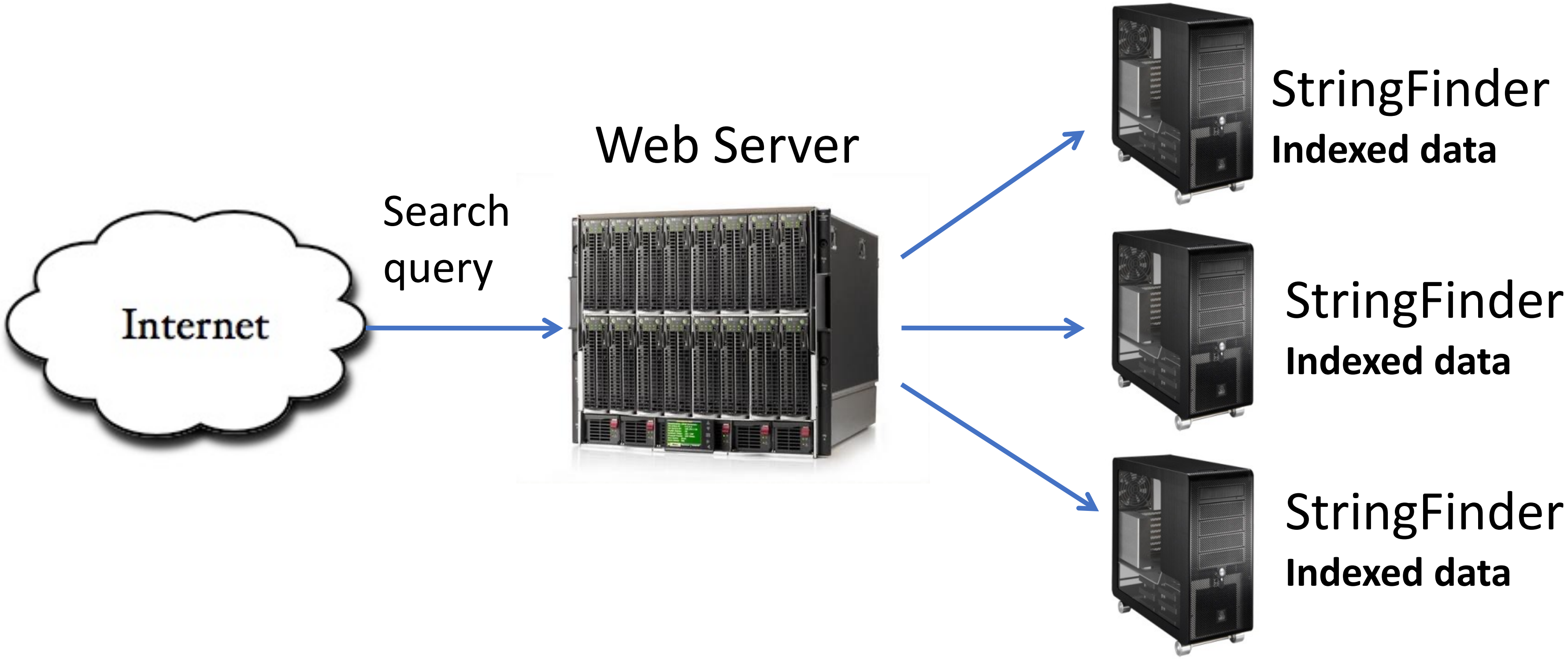
- Dataflow Wrap up
- Start talking about Consistency at scale

Spark faux quiz (5 min, any 2):

- What is the difference between *transformations* and *actions* in Spark?
- Spark supports a persist API. When should a programmer want to use it? When should she [not] use use the "*RELIABLE*" flag?
- List aspects of Spark's design that help/hinder multi-core parallelism relative to MapReduce. If the issue is orthogonal, explain why.
- Compare and contrast fault tolerance guarantees of Spark to those of MapReduce. How are[n't] the mechanisms different?
- Compare/contrast the *abstractions* for parallelism in Spark/MapReduce
- For what kinds of workloads will Spark/MR have different/similar performance?
- Why does Spark expose control over caching RDDs in memory to the programmer?
- What's a "wide" dependence? A "narrow" one? How do these ideas relate to fault tolerance in Spark?
- Is Spark a good system for indexing the web? For computing page rank over a web index? Why [not]?

Review: Scale: Goal

Infrastructure is hard to get right



1. How do we distribute the searchable files on our machines?
2. What if our webserver goes down?
3. What if a StringFinder machine dies? How would you know it was dead?
4. **What if marketing comes and says, "well, we also want to show pictures of the earth from space too! Ooh..and the moon too!"**

Dataflow Engines

Programming model + infrastructure

Write programs that run on lots of machines

Automatic parallelization and distribution

Fault-tolerance

I/O and jobs Scheduling

Status and monitoring

Key Ideas:

*All modern "big data" platforms are **dataflow engines!***

Differences:

1. what graph structures are allowed?
2. How does this impact programming model?

Spark (2012) Background

Commodity clusters: important platform

- **In industry:** search, machine translation, ad targeting, …
- **In research:** bioinformatics, NLP, climate simulation, …

Cluster-scale models (e.g. MR) de facto standard

- Fault tolerance through replicated durable storage
- Dataflow is the common theme

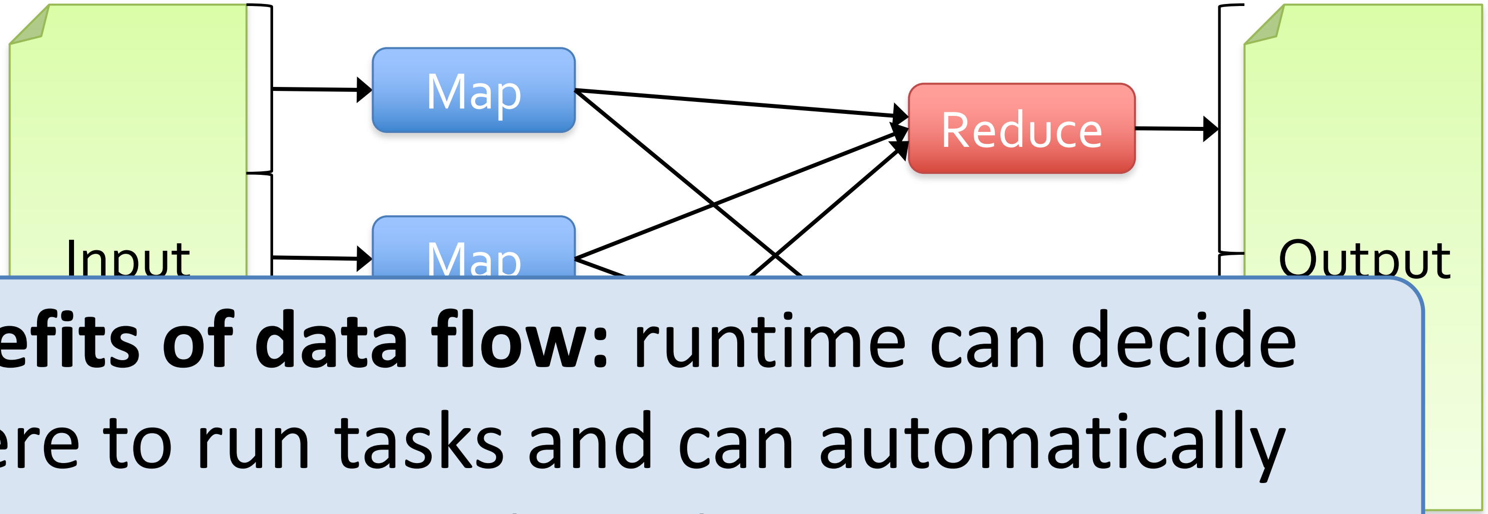
Multi-core

Iteration

Motivation

Programming models for clusters transform data flowing from stable storage to stable storage

E.g., MapReduce:



Benefits of data flow: runtime can decide where to run tasks and can automatically recover from failures

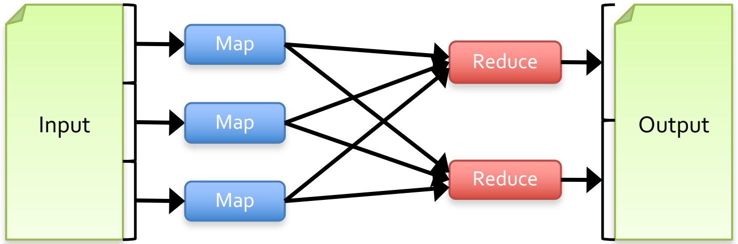
Iterative Computations: PageRank

1. Start each page with a rank of 1
2. On each iteration, update each page's rank to

$$\Sigma_{i \in \text{neighbors}} \text{rank}_i / |\text{neighbors}_i|$$

```
links = // RDD of (url, neighbors) pairs
ranks = // RDD of (url, rank) pairs

for (i <- 1 to ITERATIONS) {
  ranks = links.join(ranks).flatMap {
    (url, (links, rank)) =>
      links.map(dest => (dest, rank/links.size))
  }.reduceByKey(_ + _)
}
```



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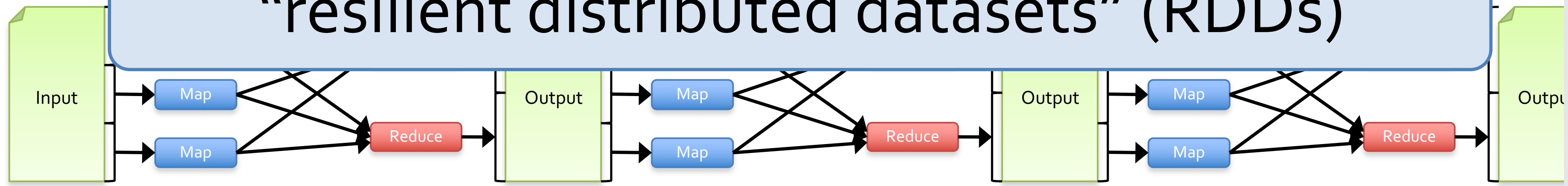
Solution: augment data flow model with "resilient distributed datasets" (RDDs)



Programming Model

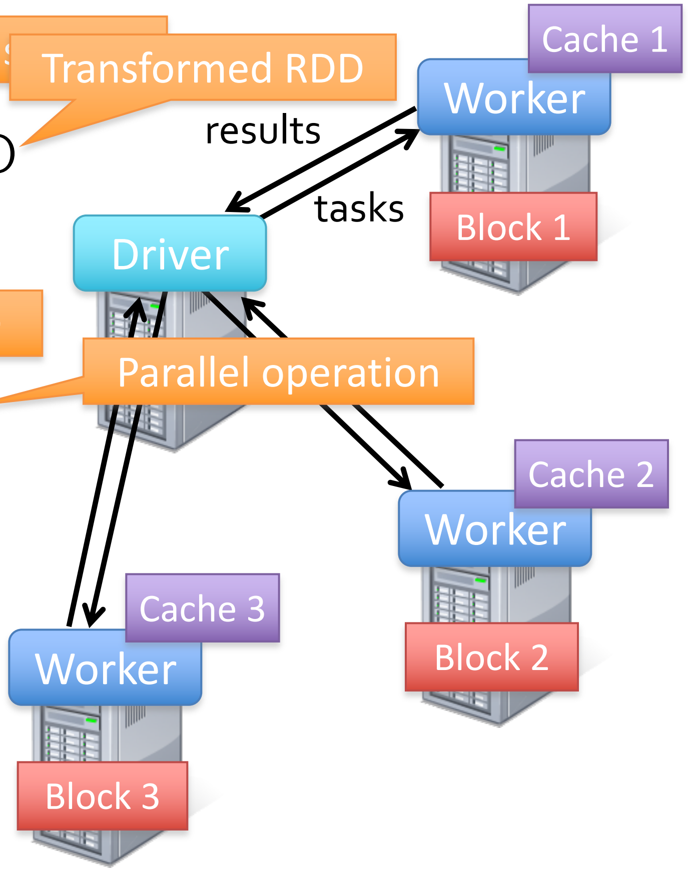
- Resilient distributed datasets (RDDs)
  - Immutable collections partitioned across cluster that can be rebuilt if a partition is lost
  - Created by transforming data in stable storage using data flow operators (map, filter, group-by, …)
  - Can be *cached* across parallel operations
- Parallel operations on RDDs
  - Reduce, collect, count, save, …
- Restricted shared variables
  - Accumulators, broadcast variables

Example: Log Mining

- Load error messages from a log into memory, then interactively search for various patterns

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t')(2))
cachedMsgs = messages.cache()

cachedMsgs.filter(_.contains("foo")).count
cachedMsgs.filter(_.contains("bar")).count
. . .
```

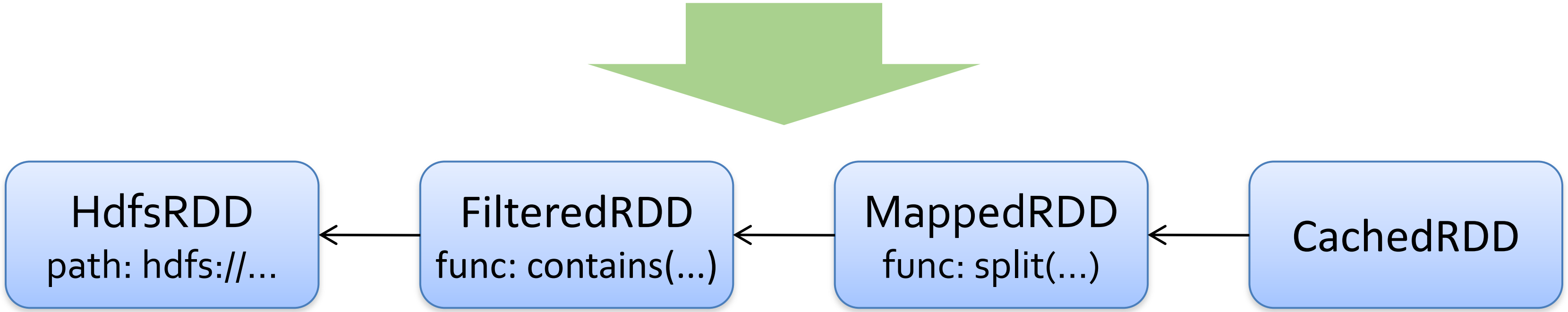


Result: full-text search of Wikipedia in <1 sec (vs 20 sec for on-disk data)

RDD Fault Tolerance

- RDDs maintain *lineage* information that can be used to reconstruct lost partitions
- Ex:

```
cachedMsgs = textFile(...).filter(_.contains("error"))
                          .map(_.split('\t')(2))
                          .persist()
```



Systems

```
lines = LOAD '/user/hadoop/HDFS_File.txt' AS (line:chararray);
words = FOREACH lines GENERATE FLATTEN(TOKENIZE(line)) as word;
grouped = GROUP words BY word;
wordcount = FOREACH grouped GENERATE group, COUNT(words);
DUMP wordcount;
```

App

	SQL	Sawzall	≈SQL	LINQ, SQL
Language		Sawzall	Pig, Hive	DryadLINQ
Execution	Parallel Databas			
Storage		BigTable	S3	SQL Server

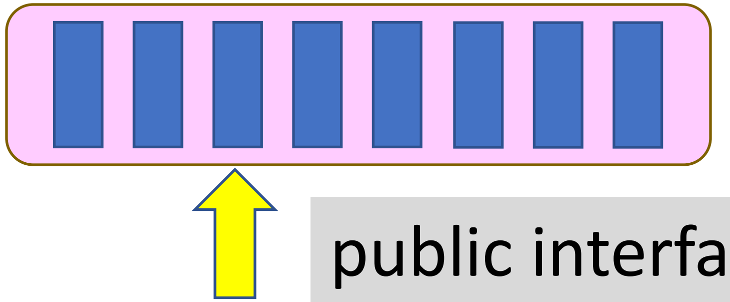
```
-- import the file as lines
CREATE EXTERNAL TABLE lines(line string)
LOAD DATA INPATH 'books' OVERWRITE INTO TABLE lines;

-- create a virtual view that splits the lines
SELECT word, count(*) FROM lines
      LATERAL VIEW explode(split(text, ' ' )) lTable as word
      GROUP BY word;
```

```
count: table sum of int;
total: table sum of float;
sum_of_squares: table sum of float;
x: float = input;
emit count <- 1;
emit total <- x;
emit sum_of_squares <- x * x;
```

Background: Collections and Iterators

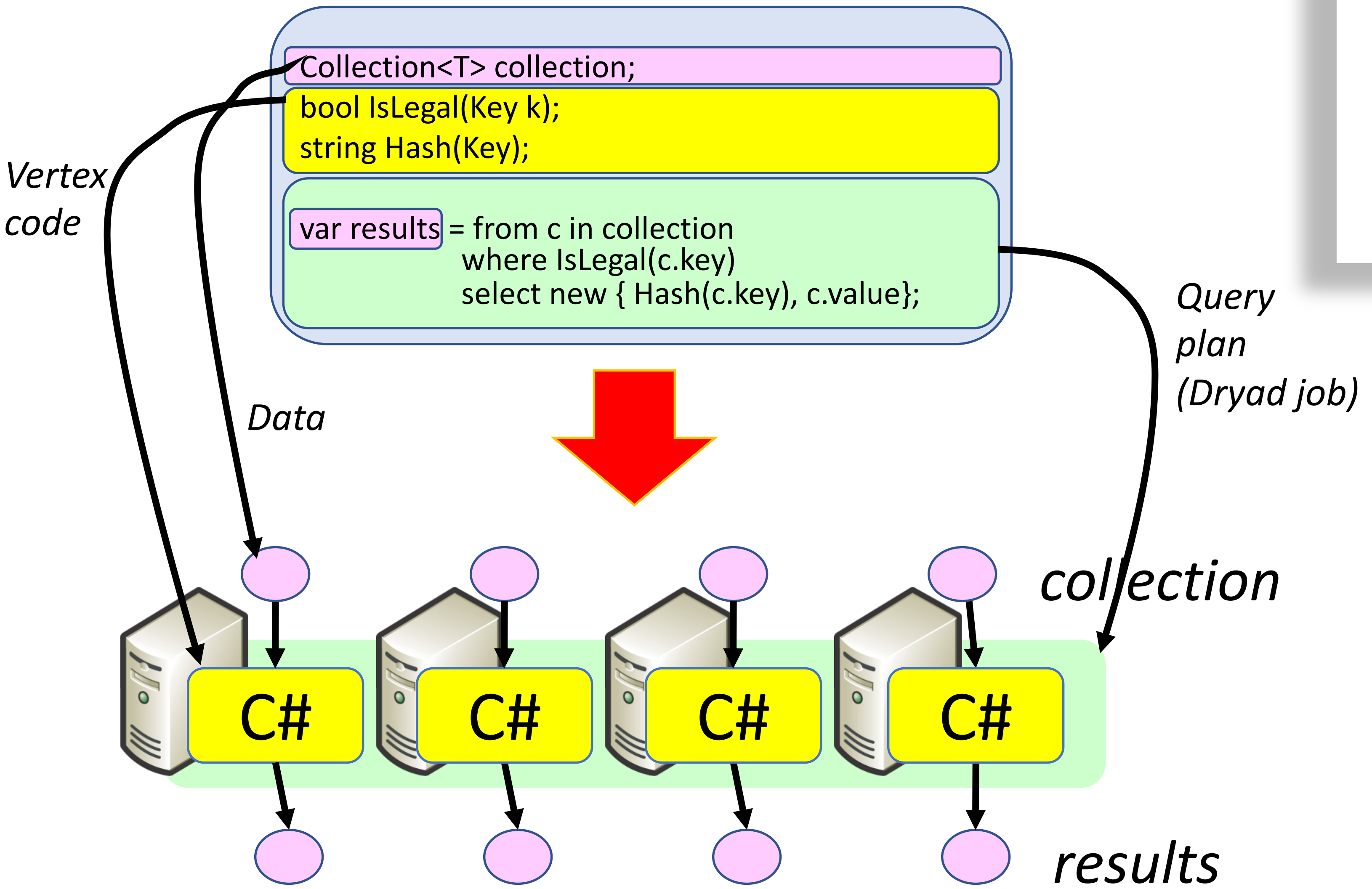
```
class Collection<T> : IEnumerable<T>;
```

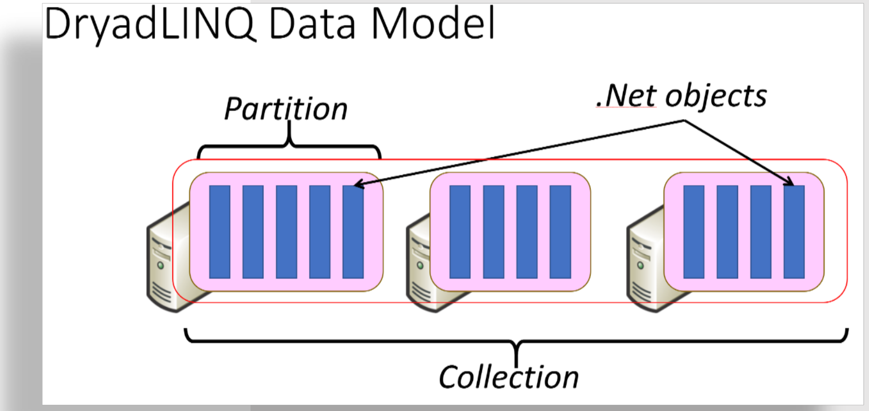


```
public interface IEnumerable<T>  {
        IEnumerator<T> GetEnumerator();
}
```

```
public interface IEnumerator <T> {
        T Current { get; }
        bool MoveNext();
        void Reset();
}
```

DryadLINQ = LINQ + Dryad





Programming Model

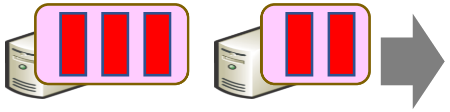
Where

Select

GroupBy

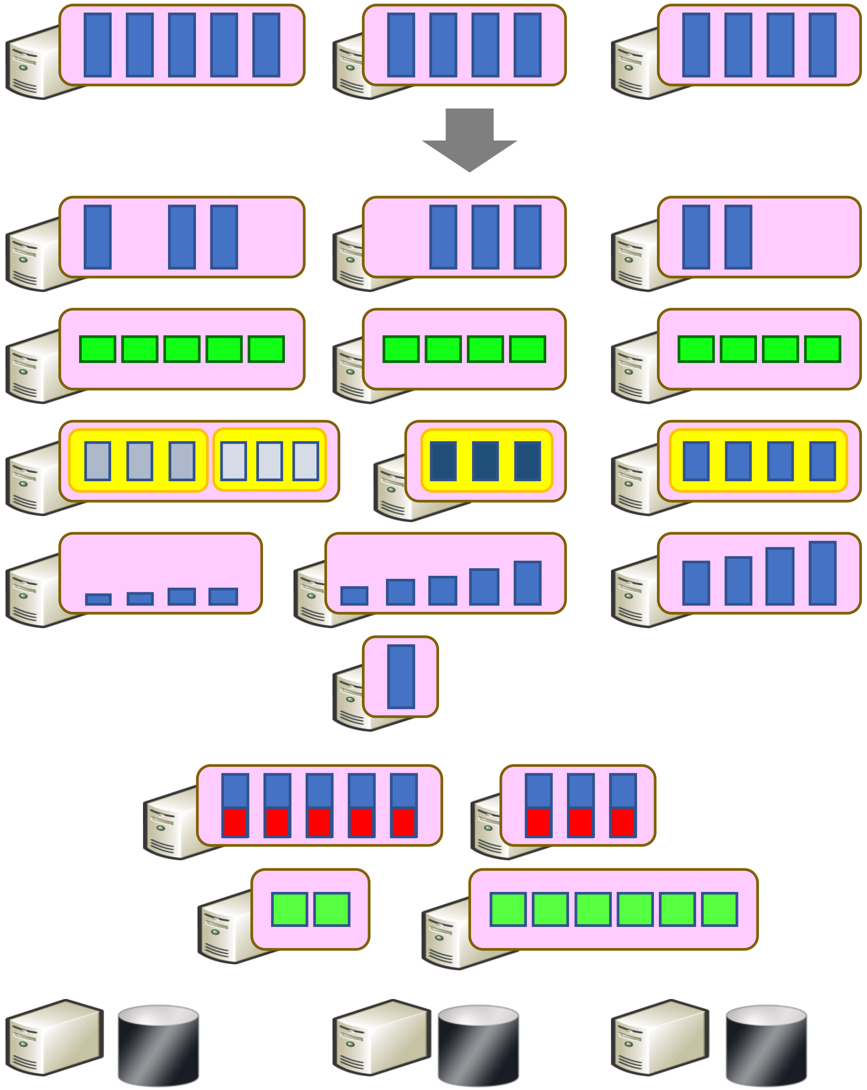
OrderBy

Aggregate

Join 

Apply

Materialize



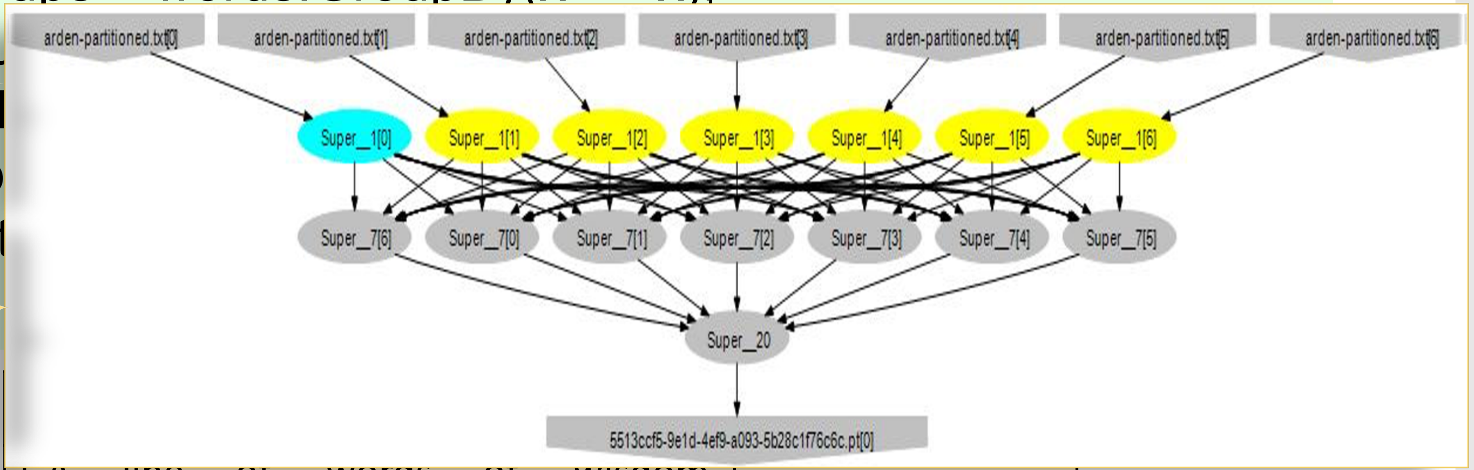
Example: Histogram

```
public static IQueryable<Pair> Histogram(
      IQueryable<LineRecord> input, int k)
{
    var words = input.SelectMany(x => x.line.Split(' '));
         roups = words.GroupBy(x => x);
```

SelectMany
Sort
GroupBy+Select
HashDistribute

MergeSort
GroupBy
Select
Sort
Take

MergeSort
Take



[“A”, “line”, “of”, “words”, “of”, “wisdom”]
[[“A”], [“line”], [“of”, “of”], [“words”], [“wisdom”]]
[{“A”, 1}, {“line”, 1}, {“of”, 2}, {“words”, 1}, {“wisdom”, 1}]
[{“of”, 2}, {“A”, 1}, {“line”, 1}, {“words”, 1}, {“wisdom”, 1}]
[{“of”, 2}, {“A”, 1}, {“line”, 1}]

RDDs

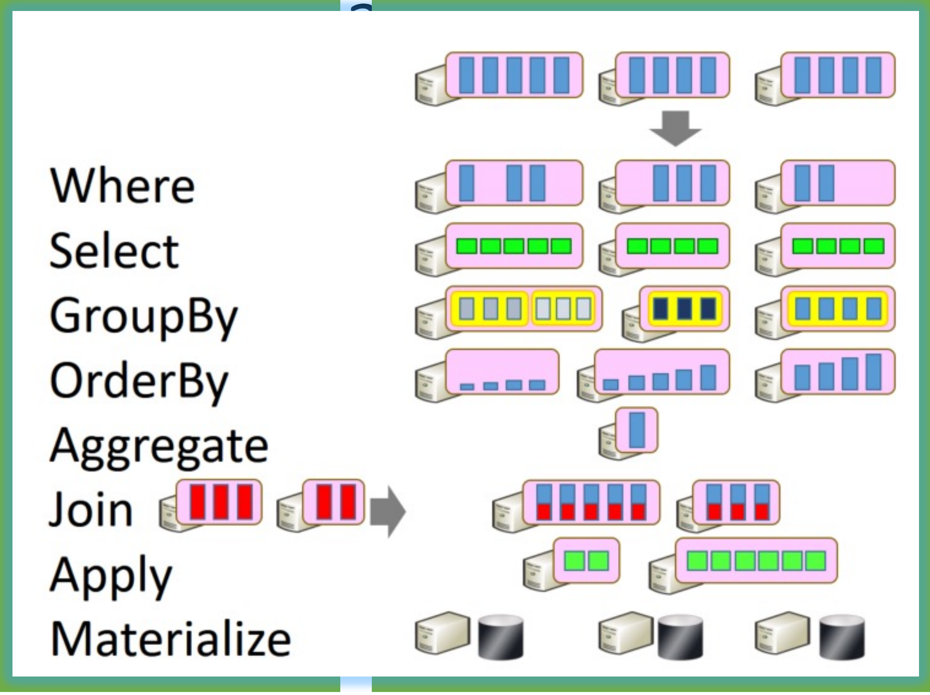
- Immutable, partitioned, logical collection of records
  - Need not be materialized

Transformations
(define a new RDD)

map
filter
sample
union
groupByKey
reduceByKey
join
persist/cache
...

Parallel operations
(return a result to driver)

reduce



RDDs vs Distributed Shared Memory

Concern	RDDs	Distr. Shared Mem.
Reads	Fine-grained	Fine-grained
Writes	Bulk transformations	Fine-grained
Consistency	Trivial (immutable)	Up to app / runtime
Fault recovery	Fine-grained and low-overhead using lineage	Requires checkpoints and program rollback
Straggler mitigation	Possible using speculative execution	Difficult
Work placement	Automatic based on data locality	Up to app (but runtime aims for transparency)

Summary

Dataflow key enabler for cluster-scale parallelism

Key issues become runtime’s responsibility

- Data movement
- Scheduling
- Fault-tolerance

MapReduce is sub-optimal

- Modern DBMSs: hash + B-tree indexes to accelerate data access.
  - Indexes are user-defined
  - Could MR do this?
- No query optimizer! (oh my, terrible…but good for researchers! ☺)
- Skew: wide variance in distribution of keys
  - E.g. “the” more common than “zyzzyva”
- Materializing splits
  - N=1000 mappers → M=500 keys = 500,000 local files
  - 500 reducer instances “pull” these files
  - DBMSs push splits to sockets (no local temp files)

MapReduce: !novel && feature-poor

- Partitioning data sets (map) == Hash join
- Parallel aggregation == reduce
- User-supplied functions differentiates from SQL:
  - POSTGRES user functions, user aggregates
  - PL/SQL: Stored procedures
  - Object databases

Absent features:

- Indexing
- Update operator
- Transactions
- Integrity constraints, referential integrity
- Views

Why is MapReduce backwards?

Map == group-by

Reduce == aggregate

```
SELECT job, COUNT(*) as "numemps"
    FROM employees
    WHERE salary > 1000
    GROUP BY job;
```

- Where is the aggregate in this example?
- Is the DBMS analogy clear?

Why is MapReduce backwards?

Schemas are good (what’s a schema?)

Separation of schema from app is good (why?)

High-level access languages are good (why?)