# Programming at Scale: Dataflow

cs378h

# Today

Questions?

Administrivia

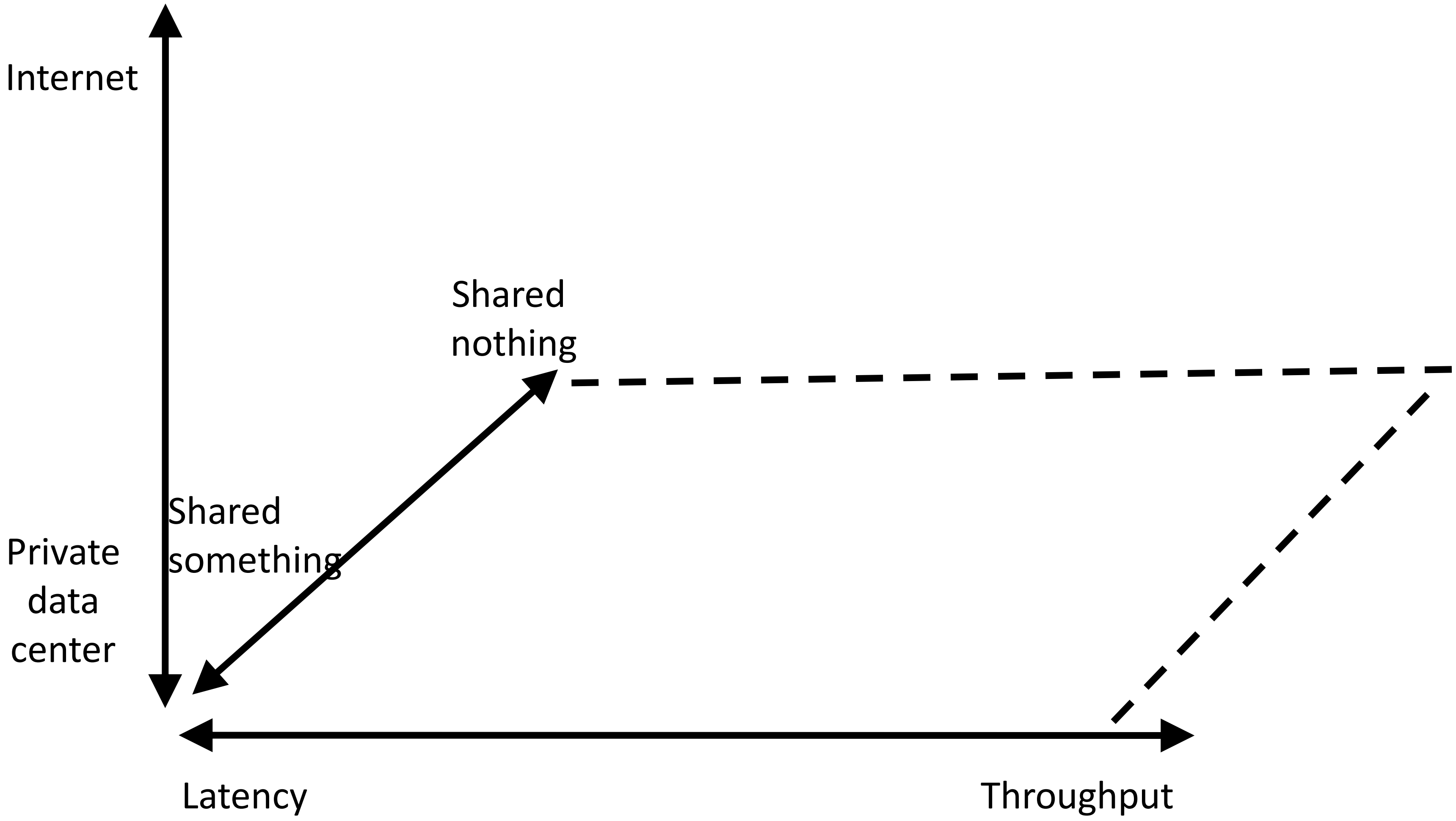
- Project Proposal Due Soon!

Agenda:

- MPI Wrapup
- Dataflow

# Review: Scale: Goal

# Review: Design Space



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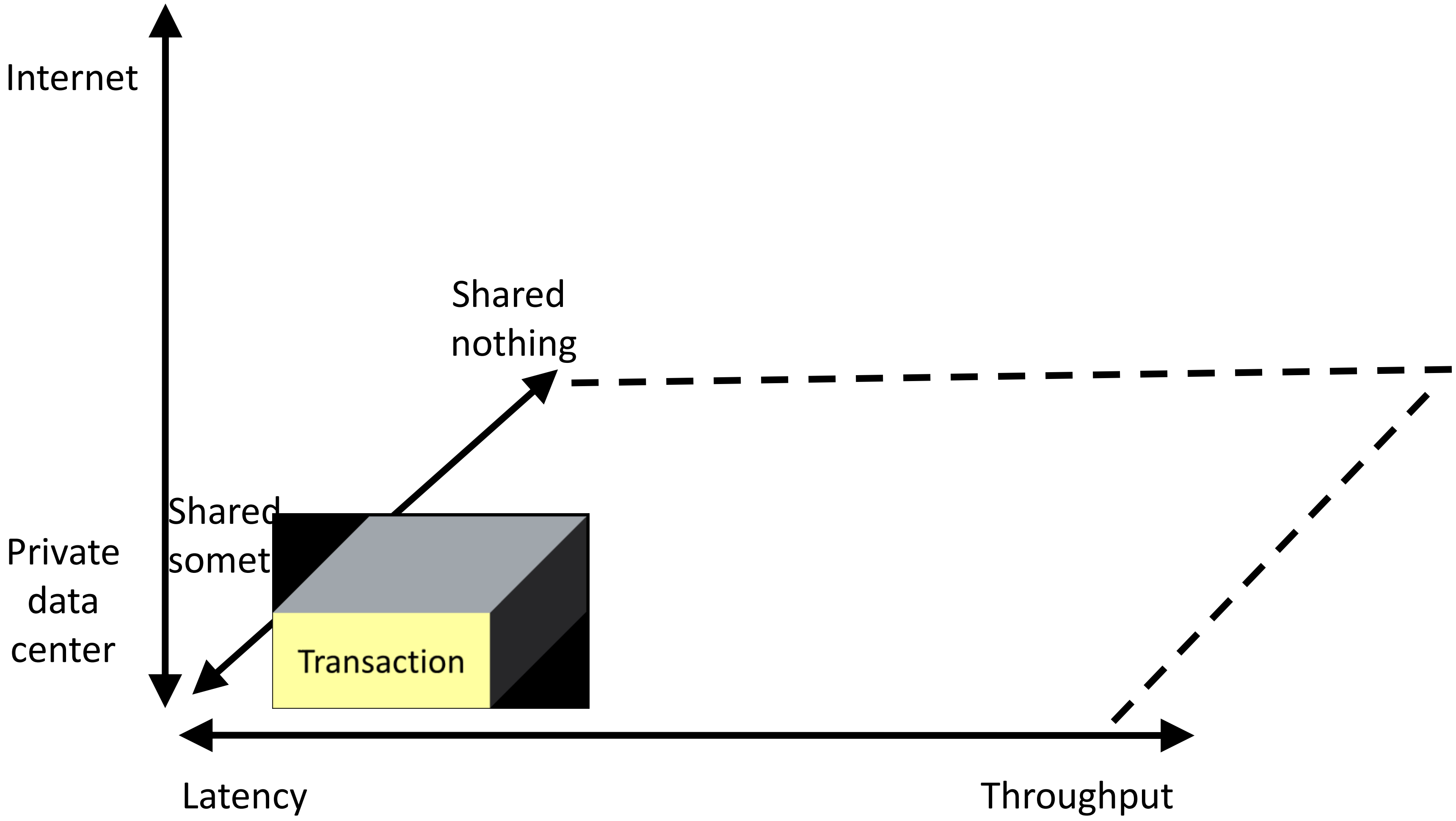

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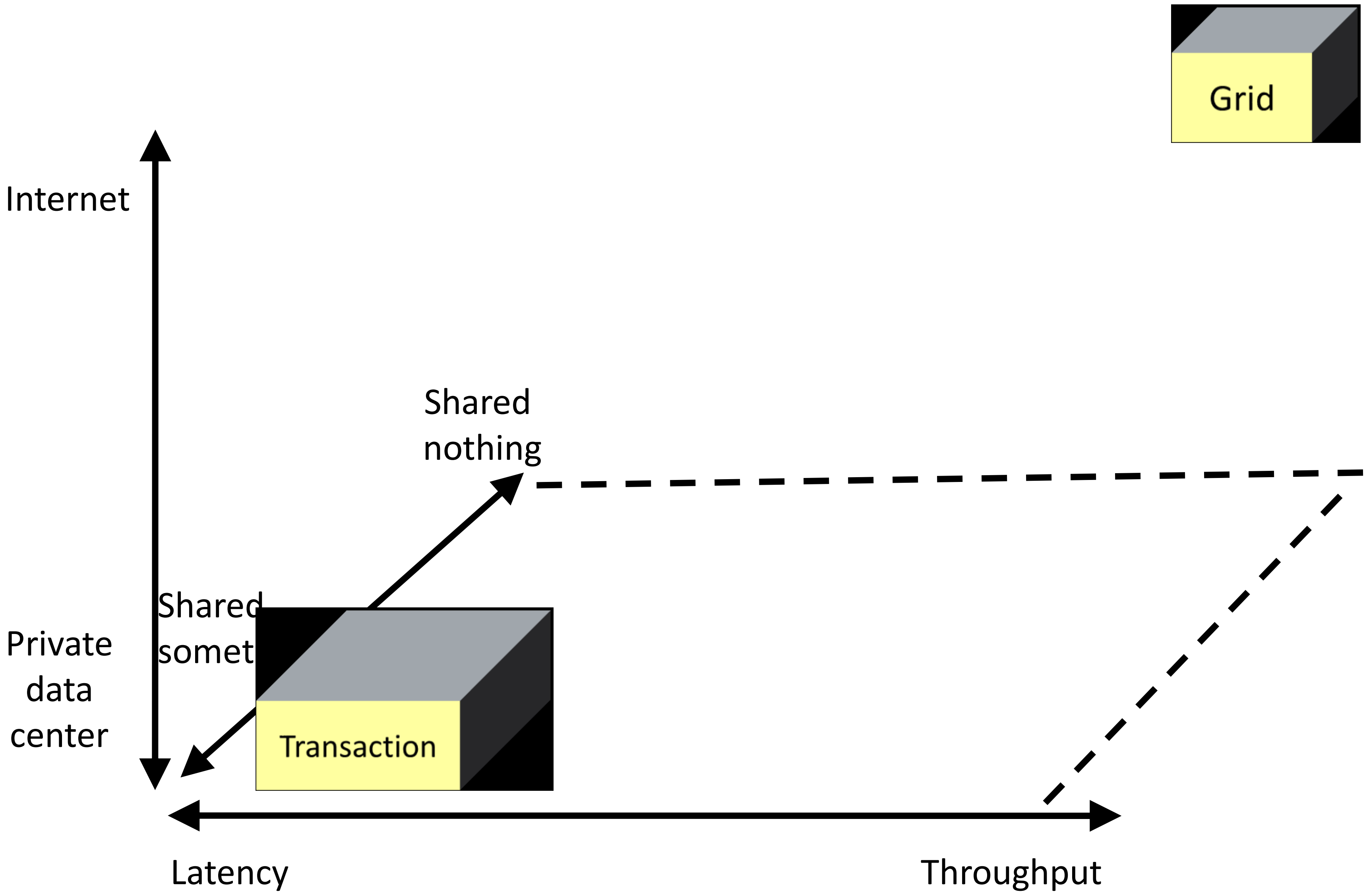

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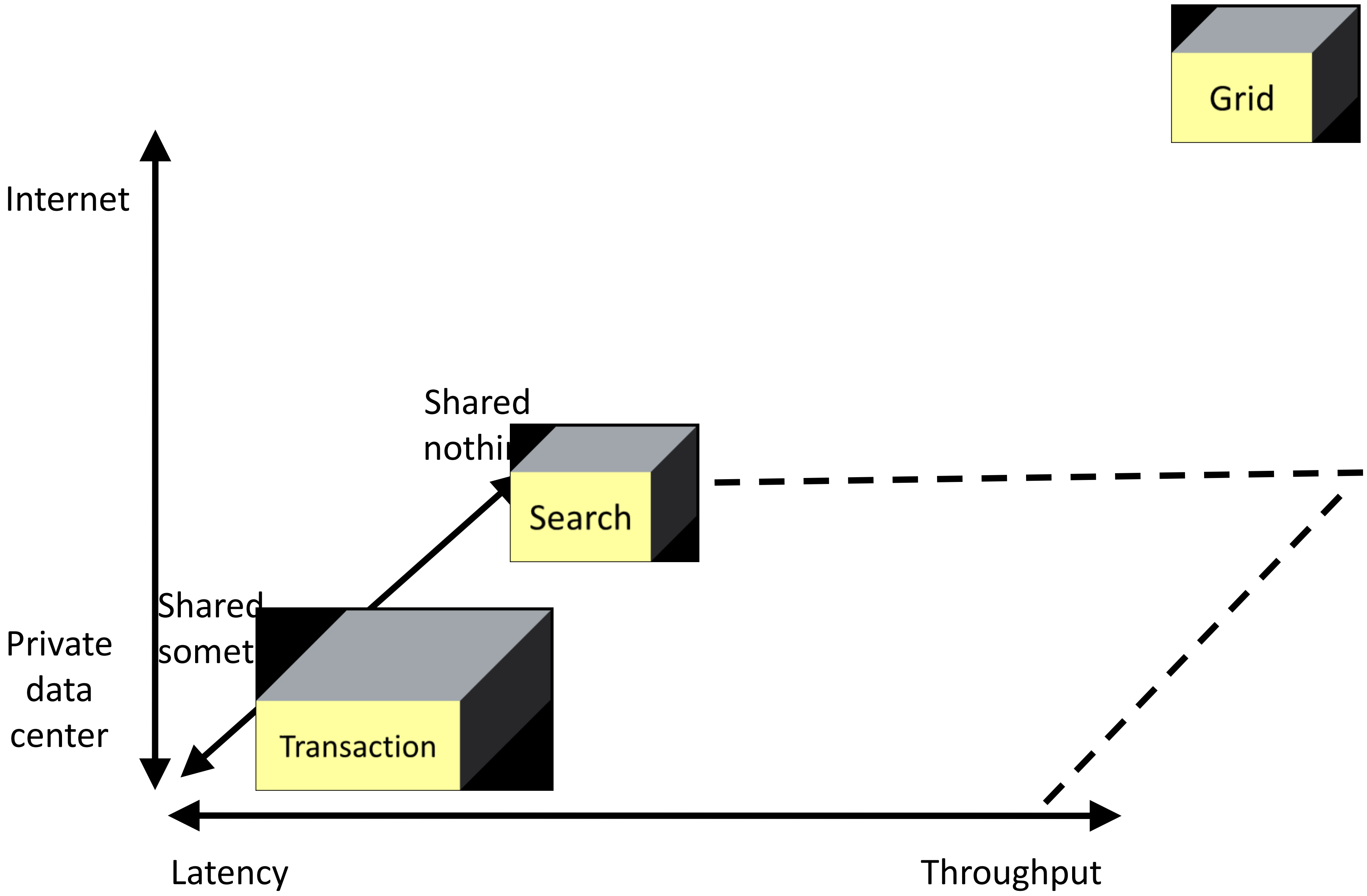

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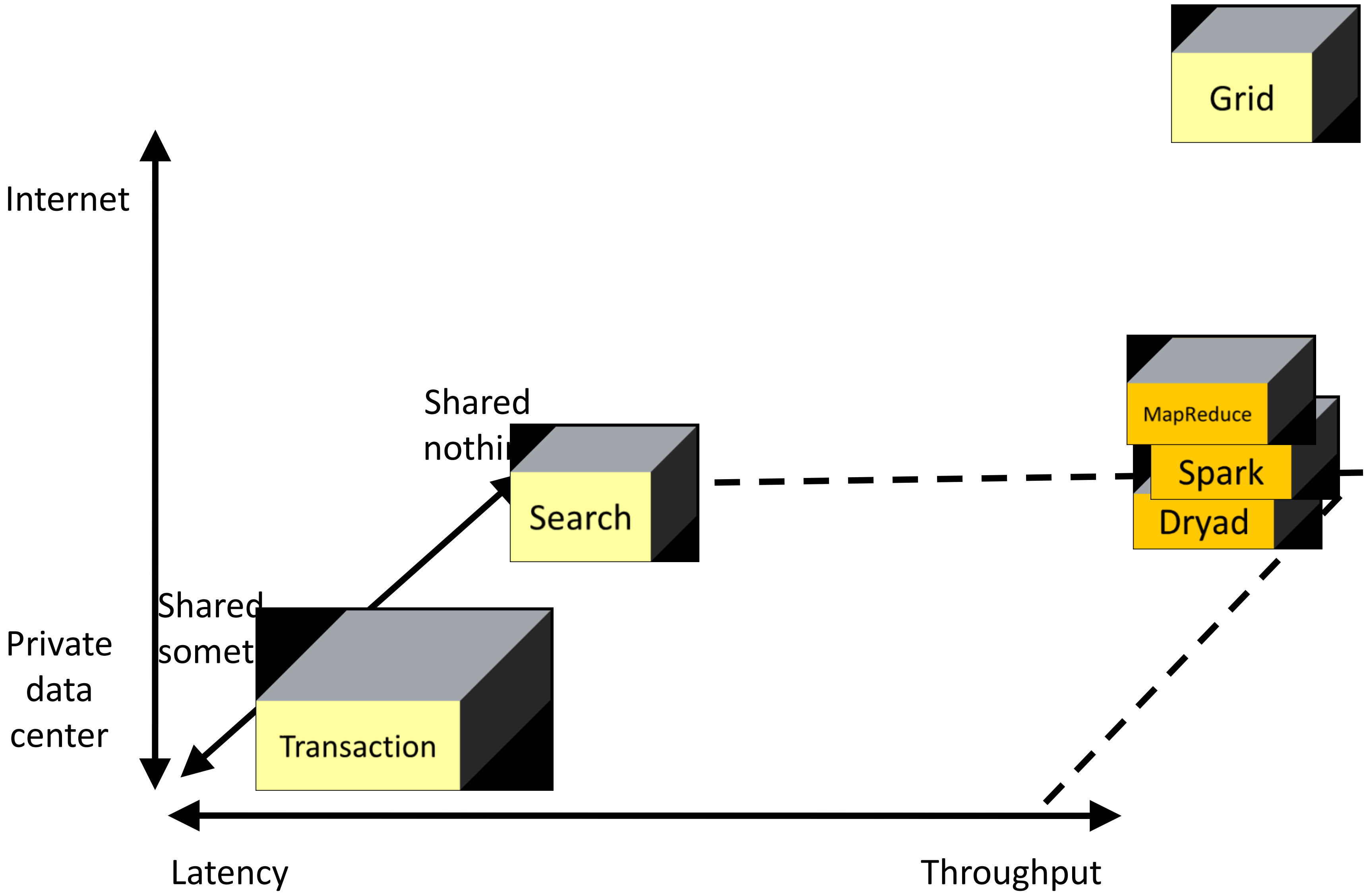

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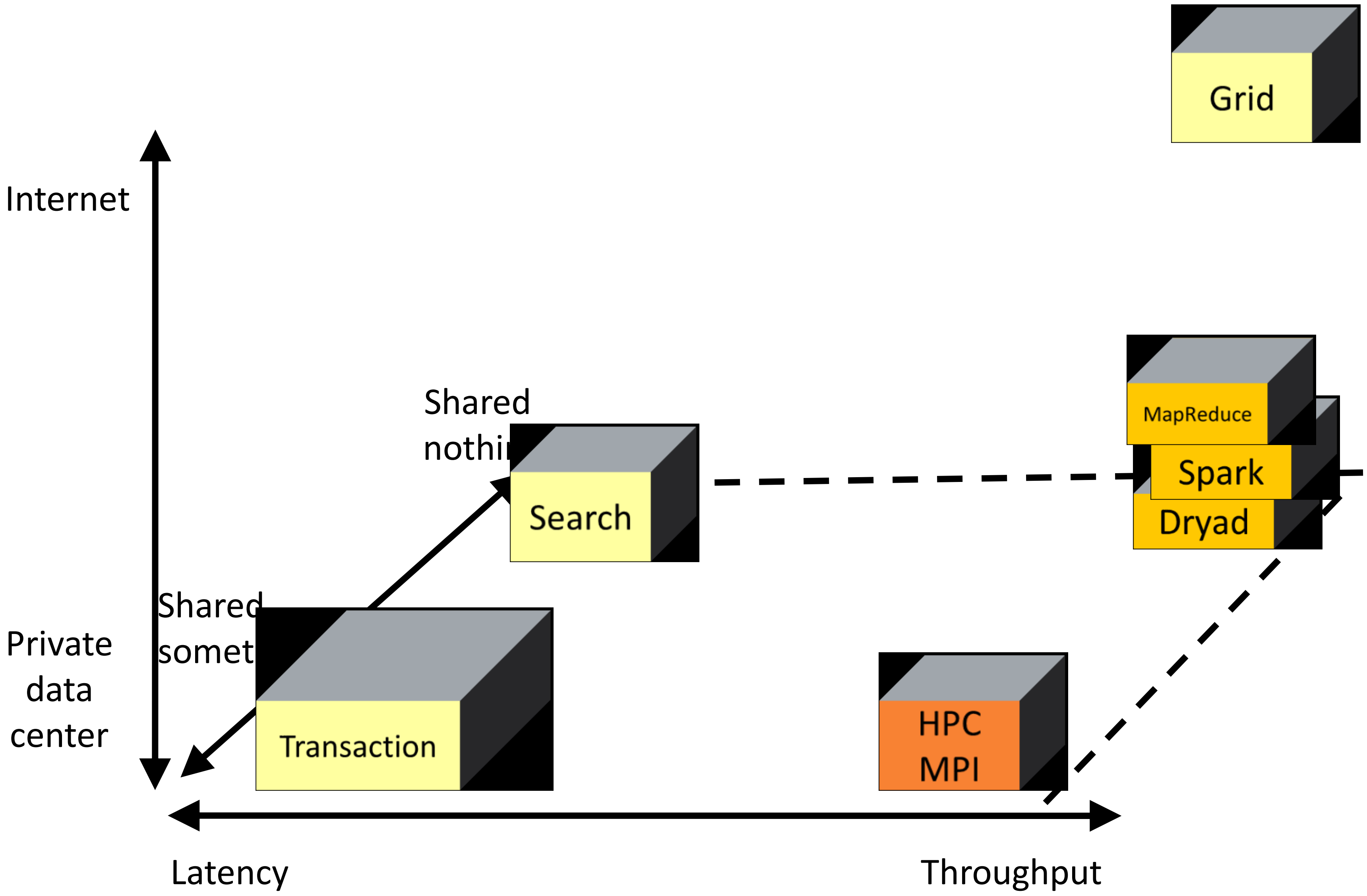

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# Hare-brained-scheme.com

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> *"We're going to be super rich! We just need a program to search for strings in text files..."*

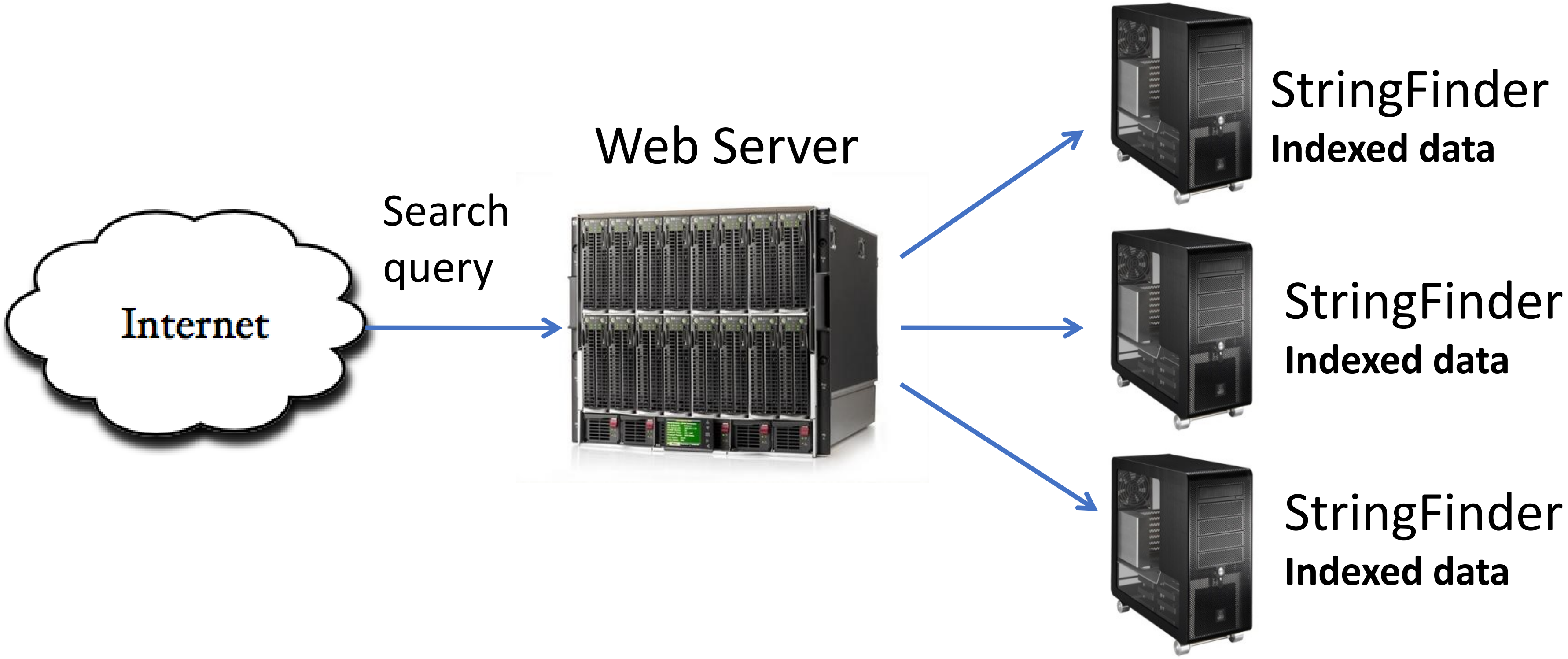
Input: <search_term>, <files>

Output: list of files containing <search_term>

# One Solution

```
public class StringFinder {
    int main(…) {
            foreach(File f in getInputFiles()) {
                if(f.contains(searchTerm))
                    results.add(f.getFileName());
            }
            System.out.println("Files:" + results.toString());
     }
}
```

# Infrastructure is hard to get right



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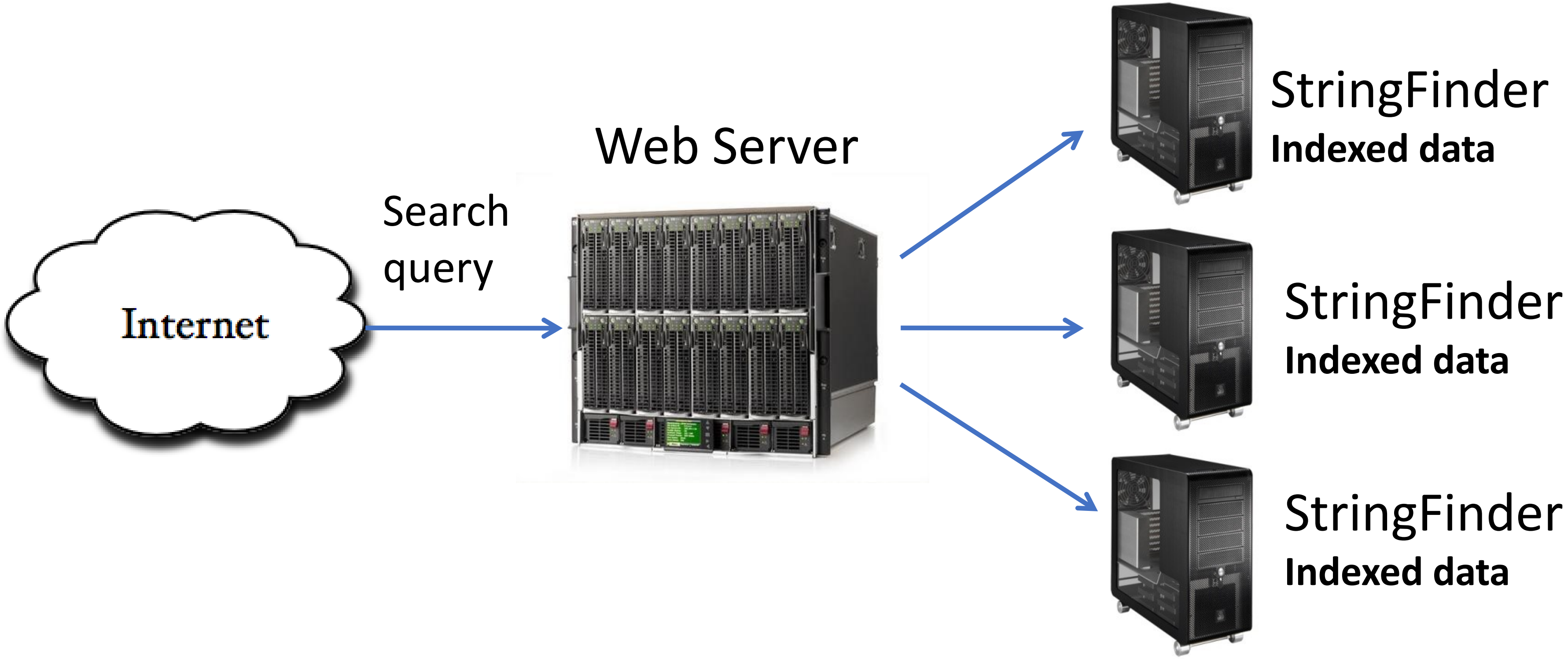


1. How do we distribute the searchable files on our machines?

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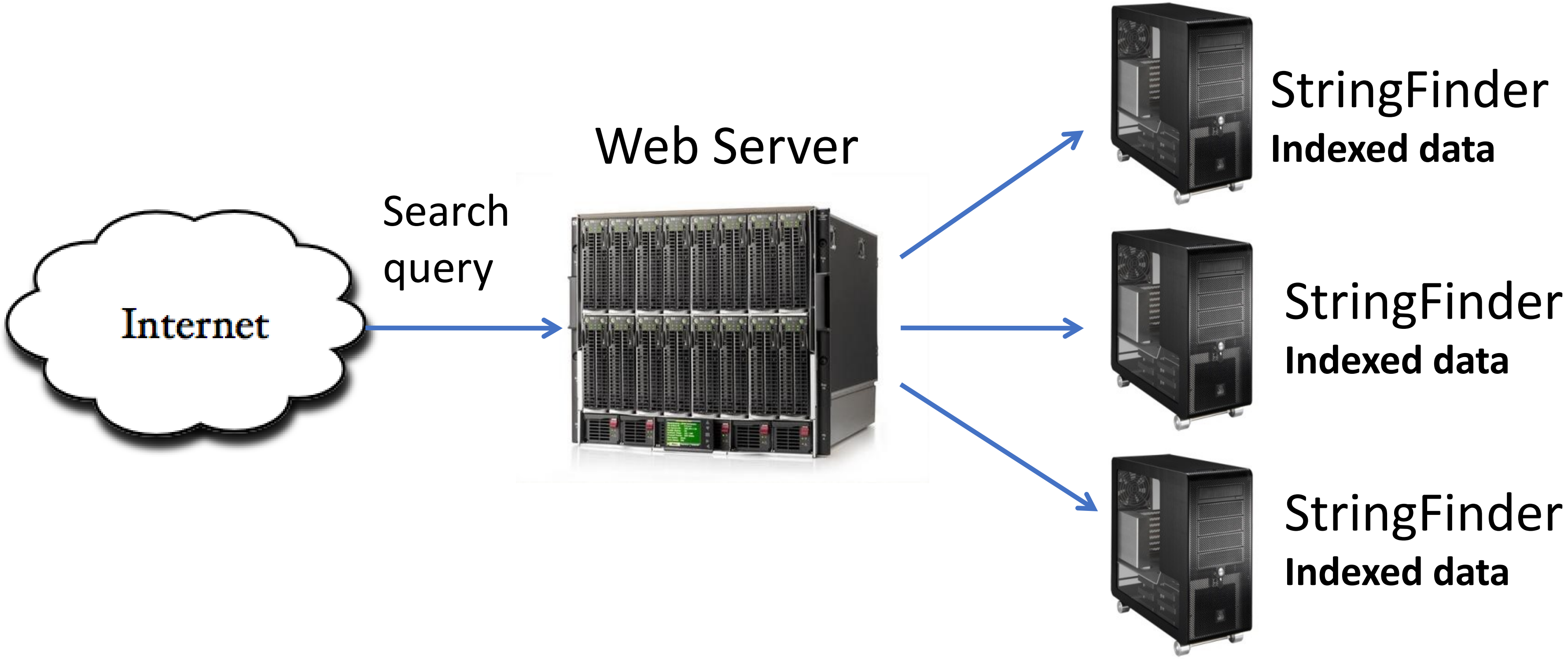


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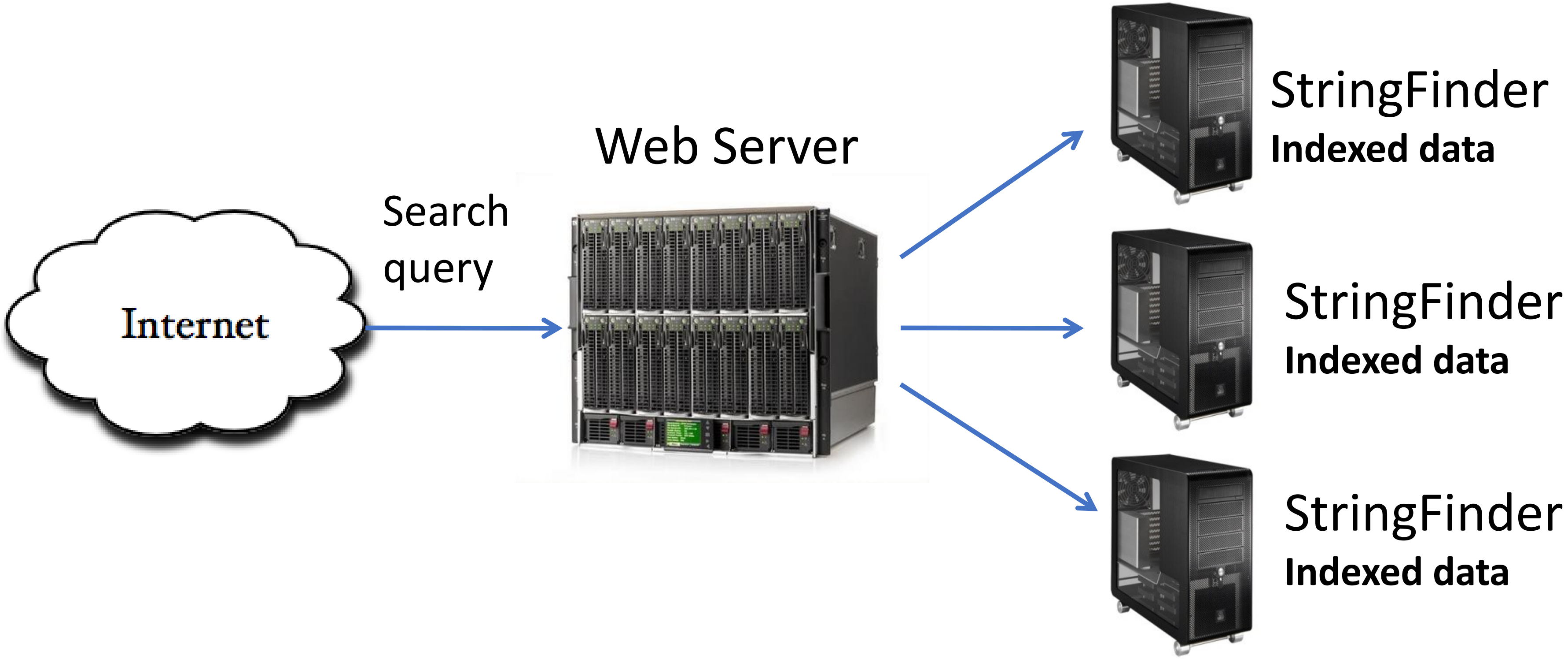


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3. What if a StringFinder machine dies? How would you know it was dead?

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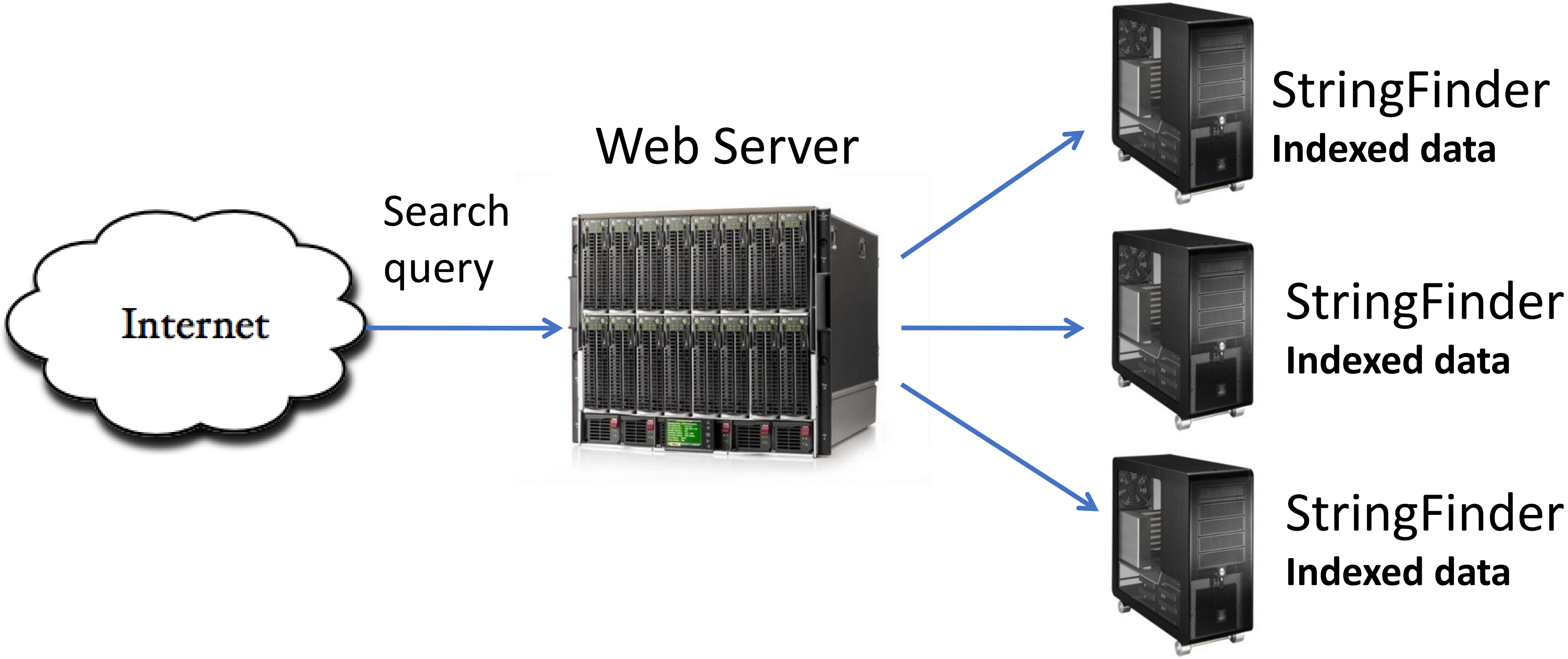


1. How do we distribute the searchable files on our machines?
2. What if our webserver goes down?
3. What if a StringFinder machine dies? How would you know it was dead?
4. **What if marketing comes and says, “well, we also want to show pictures of the earth from space too! Ooh..and the moon too!”**

# StringFinder was the easy part!

**You really need general infrastructure.**

Many different tasks

Want to use hundreds or thousands of PC’s

Continue to function if something breaks

Must be easy to program…

# 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

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**Key Ideas:**

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

Differences:

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

# MapReduce

- Input & Output: sets of <key, value> pairs
- Programmer writes 2 functions:

```
map (in_key, in_value) -> list(out_key,
  intermediate_value)
```

  - Processes <k,v> pairs
  - Produces intermediate pairs

```
reduce (out_key, list(interm_val)) ->
    list(out_value)
```

  - Combines intermediate values for a key
  - Produces a merged set of outputs

# Indexing (1)

```
public void map() {
  String line = value.toString();
  StringTokenizer itr = new StringTokenizer(line);
    if(itr.countTokens() >= N) {
      while(itr.hasMoreTokens()) {
        word = itr.nextToken()+"|"+key.getFileName();
              output.collect(word, 1);
    }
  }
}
```

Input: a line of text, e.g. "**mistakes were made**" from **myfile.txt**

Output:

**mistakes|myfile.txt**
**were|myfile.txt**
**made|myfile.txt**

# Indexing (2)

```
public void reduce() {
      int sum = 0;
      while(values.hasNext()) {
            sum += values.next().get();
      }
      output.collect(key, sum);
}
```

Input: a <term,filename> pair, list of occurrences (e.g. {1, 1,..1})
Output:

**mistakes|myfile.txt 10**
**were|myfile.txt 45**
**made|myfile.txt 2**

# Review: K-Means

```
public void kmeans() {
  while(…) {
    for each point
      find_nearest_center(point);
    for each center
      compute_new_center(center)
  }
}
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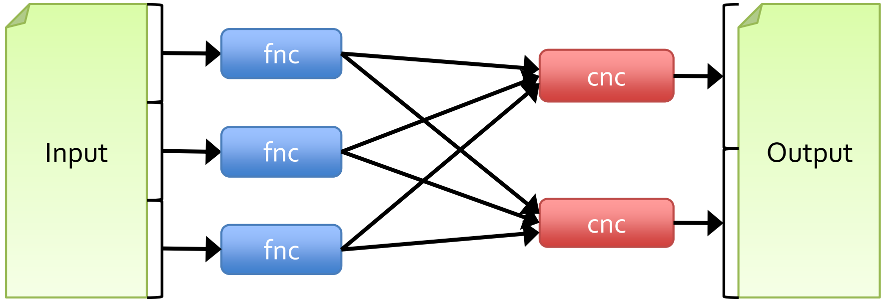

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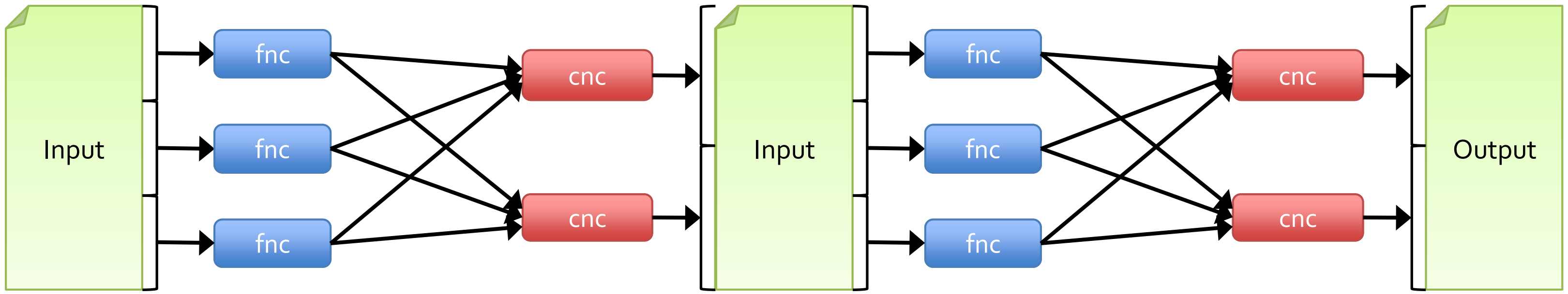

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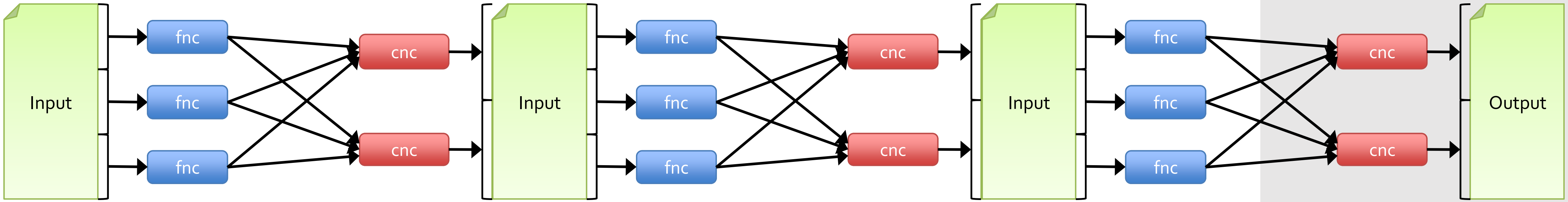


# Example: K-Means Mapper

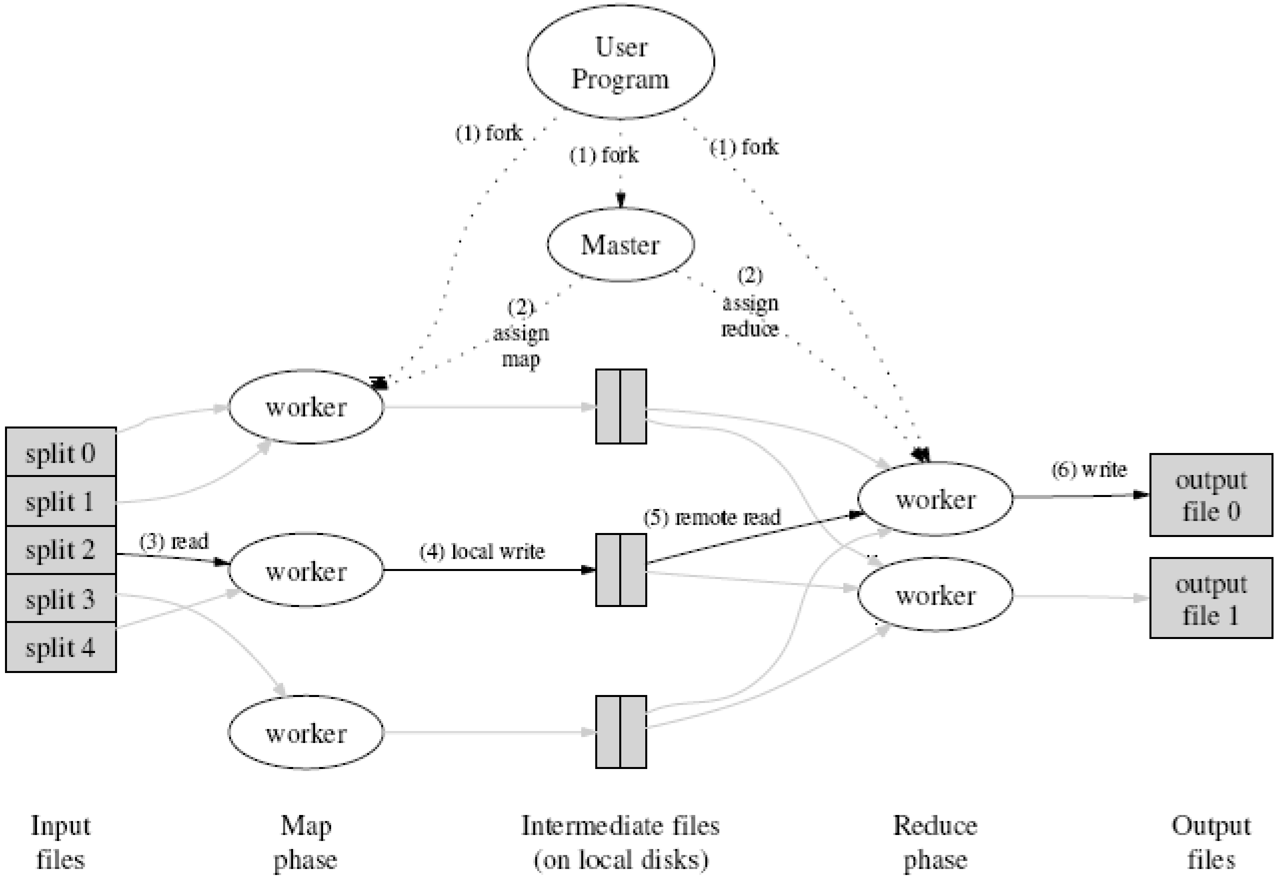
```java
/*
 * Map: find minimum distance center for point, emit to reducer
 */
@Override
public void map(LongWritable key, Text value,
                OutputCollector<DoubleWritable, DoubleWritable> output,
                Reporter reporter) throws IOException {
    String line = value.toString();
    double point = Double.parseDouble(line);
    double min1, min2 = Double.MAX_VALUE, nearest_center = mCenters.get(0);
    // Find the minimum center from a point
    for (double c : mCenters) {
        min1 = c - point;
        if (Math.abs(min1) < Math.abs(min2)) {
            nearest_center = c;
            min2 = min1;
        }
    }
    // Emit the nearest center and the point
    output.collect(new DoubleWritable(nearest_center),
            new DoubleWritable(point));
}
```

# Example: K-Means Reducer

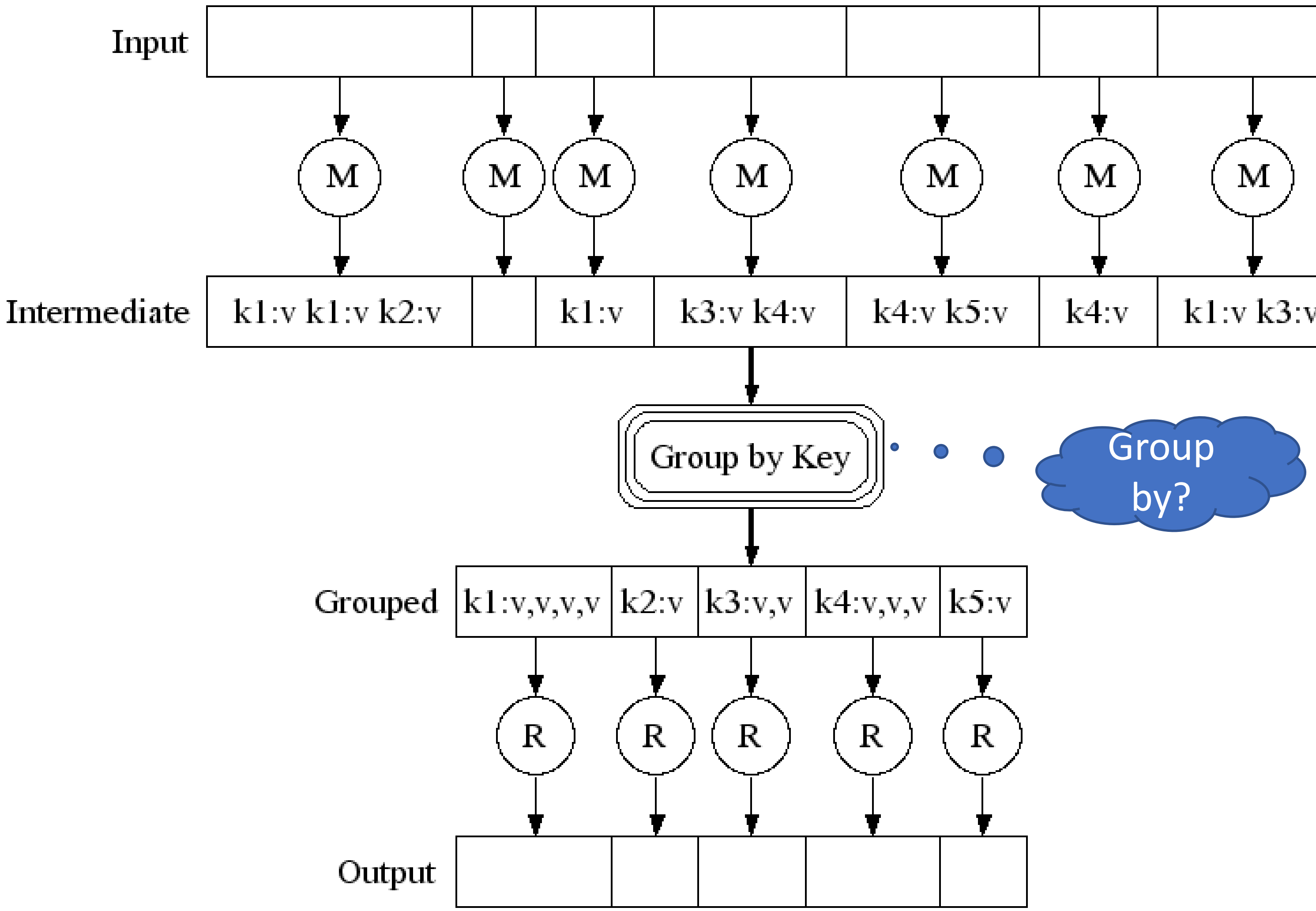
```java
/*
 * Reduce: collect all points per center and calculate
 * the next center for those points
 */
@Override
public void reduce(
        DoubleWritable key, Iterator<DoubleWritable> values,
        OutputCollector<DoubleWritable, Text> output, Reporter reporter)
        throws IOException {
    double newCenter;
    double sum = 0;
    int no_elements = 0;
    String points = "";
    while (values.hasNext()) {
        double d = values.next().get();
        points = points + " " + Double.toString(d);
        sum = sum + d;
        ++no_elements;
    }

    // We have a new center now
    newCenter = sum / no_elements;

    // Emit new center and point
    output.collect(new DoubleWritable(newCenter), new Text(points));
}
```

# How Does Parallelization Work?

INPUT FILE(s)

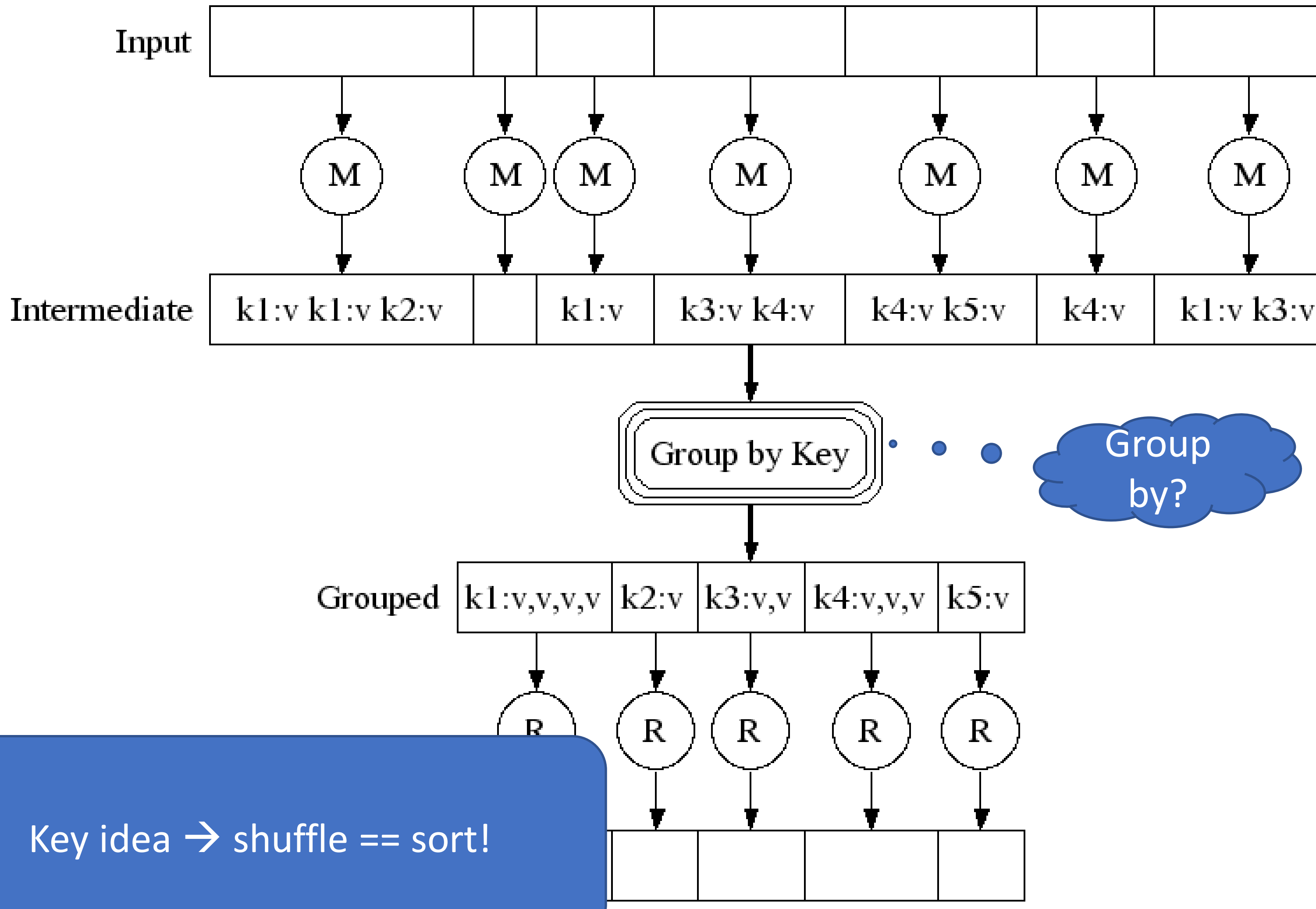


# Execution



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
Group by?
Grouped
k1:v,v,v,v
k2:v
k3:v,v
k4:v,v,v
k5:v
R
R
R
R
R
Output

# Execution




Key idea → shuffle == sort!

# Task Granularity And Pipelining

|map tasks| >> |machines| -- why?

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Minimize fault recovery time

Pipeline map with other tasks

Easier to load balance dynamically

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Why might he say this?

# MapReduce: not without Controversy

## MapReduce: A major step backwards | The Database Column

http://databasecolumn.vertica.com/database-innovation/mapreduce-a-major-step-backwards/ September 6, 2011

on Jan 17 in Database architecture, Database history, Database innovation posted by DeWitt

*[Note: Although the system attributes this post to a single author, it was written by David J. DeWitt and Michael Stonebraker]*

On January 8, a Database Column reader asked for our views on new distributed database research efforts, and we'll begin here with our views on MapReduce. This is a good time to discuss it, since the recent trade press has been filled with news of the revolution of so-called "cloud computing." This paradigm entails harnessing large numbers of (low-end) processors working in parallel to solve a computing problem. In effect, this suggests constructing a data center by lining up a large number of "jelly beans" rather than utilizing a much smaller number of high-end servers.

For example, IBM and Google have announced plans to make a 1,000 processor cluster available to a few select universities to teach students how to program such clusters using a software tool called MapReduce [1]. Berkeley has gone so far as to plan on teaching their freshman how to program using the MapReduce framework.

As both educators and researchers, we are amazed at the hype that the MapReduce proponents have spread about how it represents a paradigm shift in the development of scalable, data-intensive applications. MapReduce may be a good idea for writing certain types of general-purpose computations, but to the database community, it is:

1. A giant step backward in the programming paradigm for large-scale data intensive applications

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So why is it such a big success?

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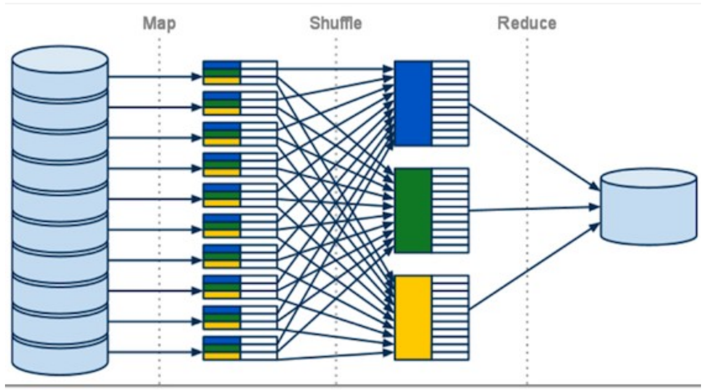
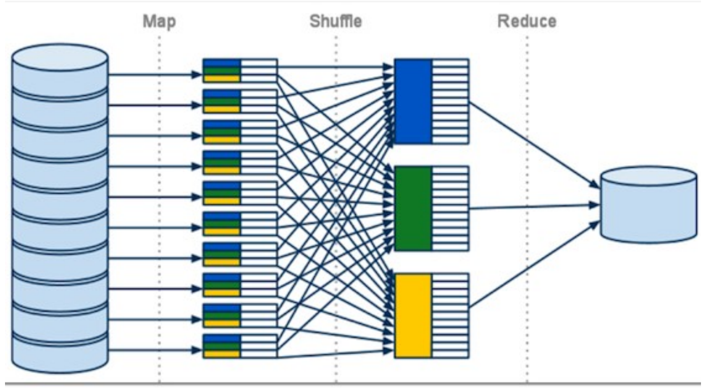


# MapReduce and Dataflow

- MR is a ***dataflow*** engine
- Lots of others
  - Dryad
  - DryadLINQ
  - Dandelion
  - CIEL
  - GraphChi/Pregel
  - Spark



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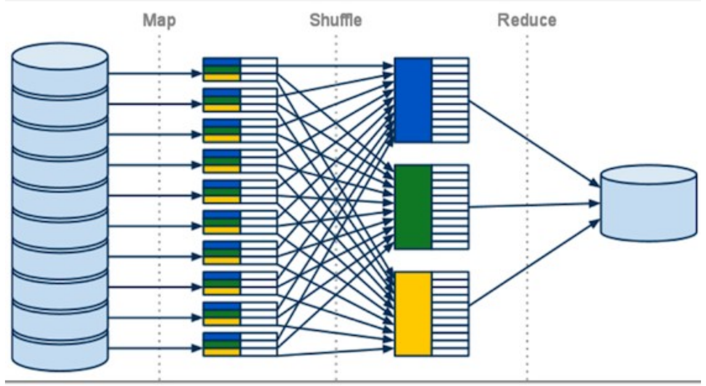
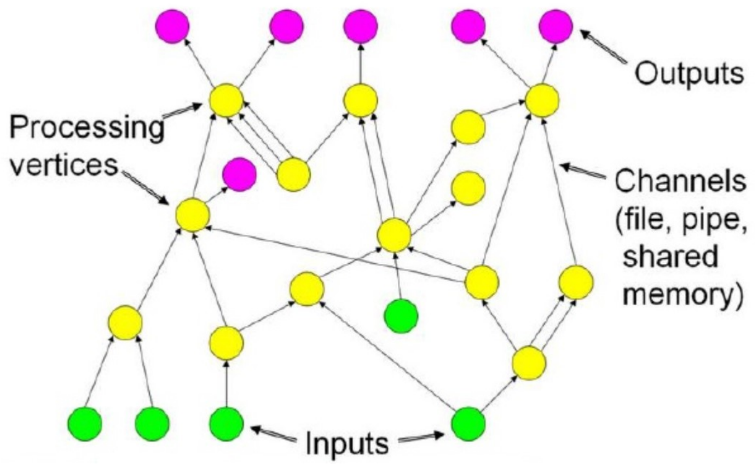


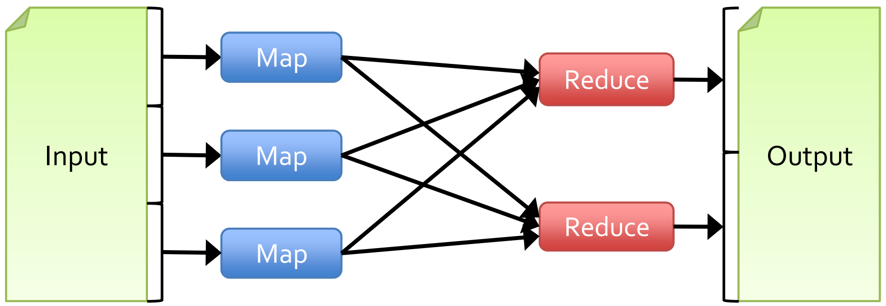
# MapReduce vs Dryad (and others…)

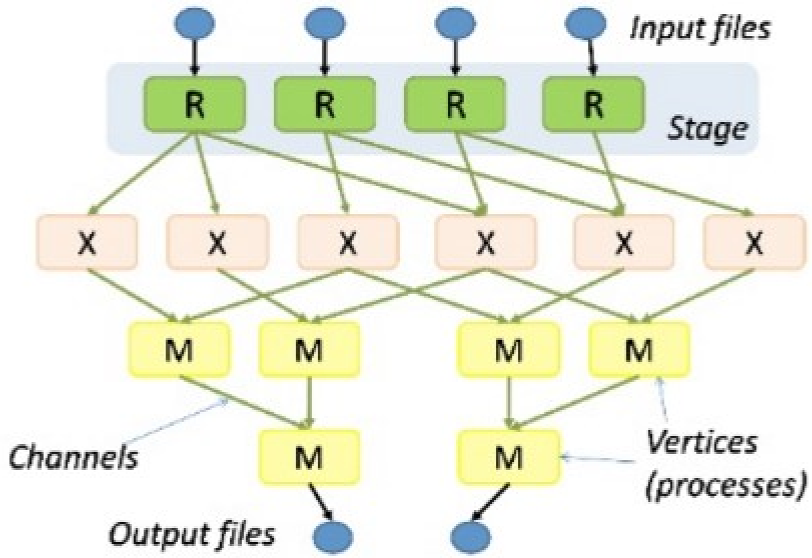
DAG instead of BSP

Interface variety

- Memory FIFO
- Disk
- Network

Flexible Modular Composition



# Dryad (2007): 2-D Piping

- Unix Pipes: 1-D

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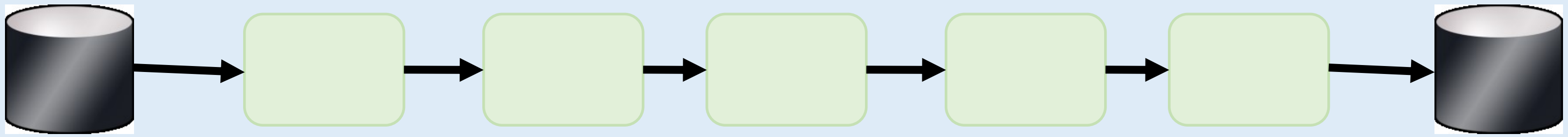

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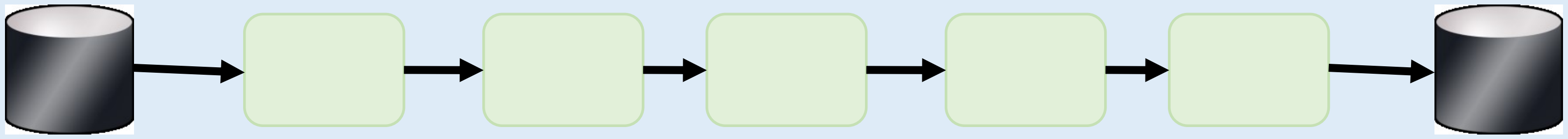

- Dryad: 2-D

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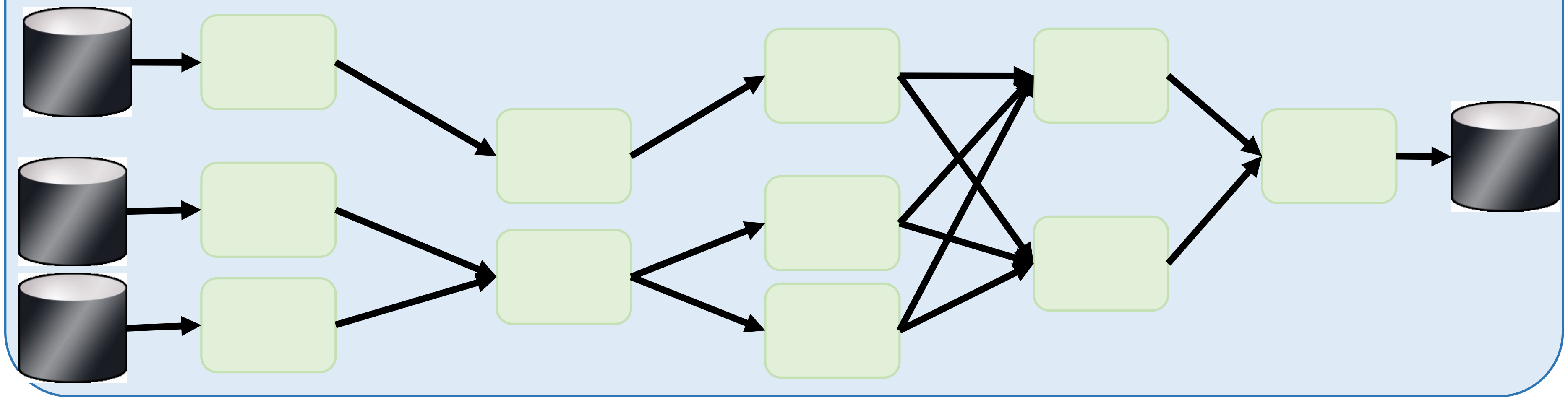
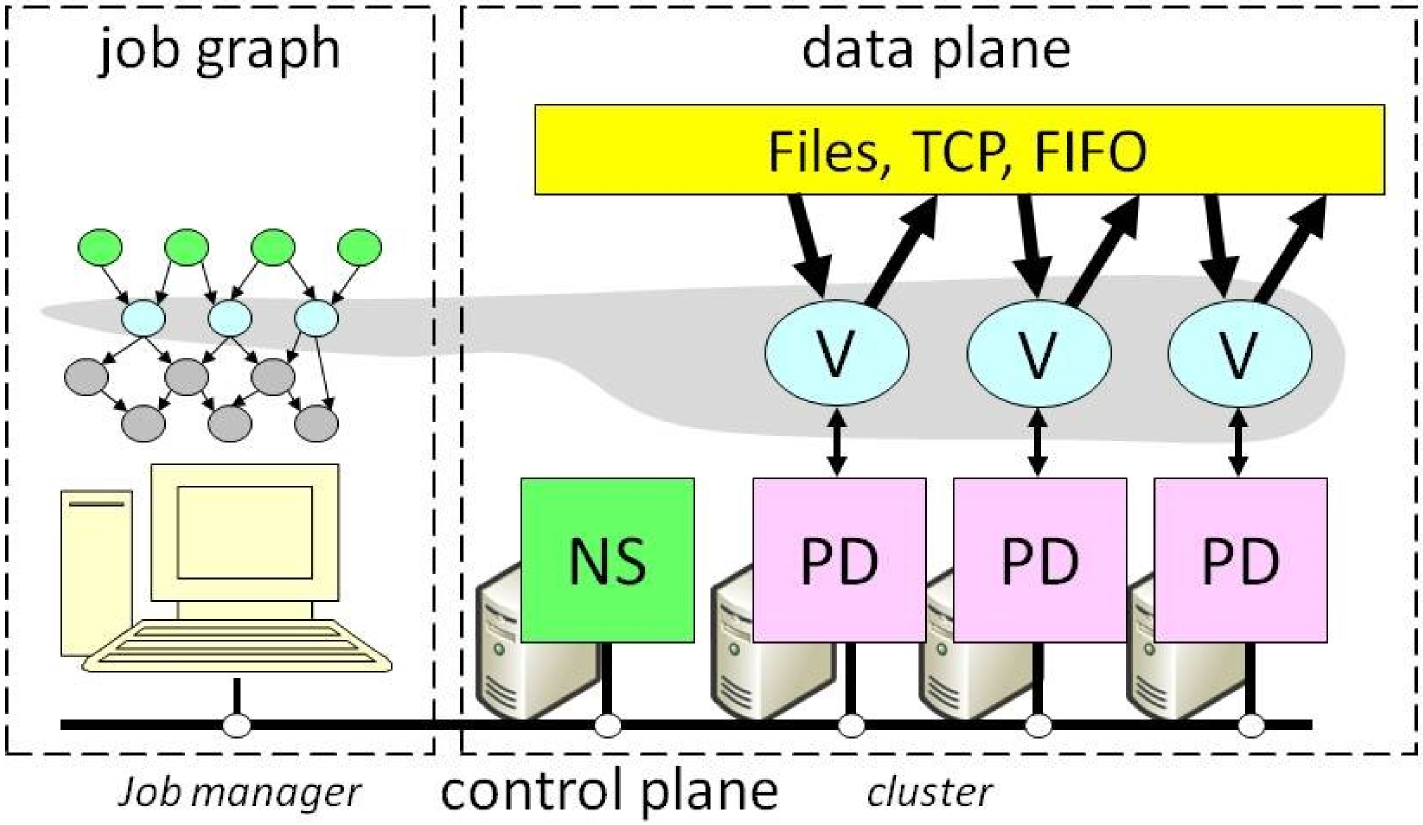
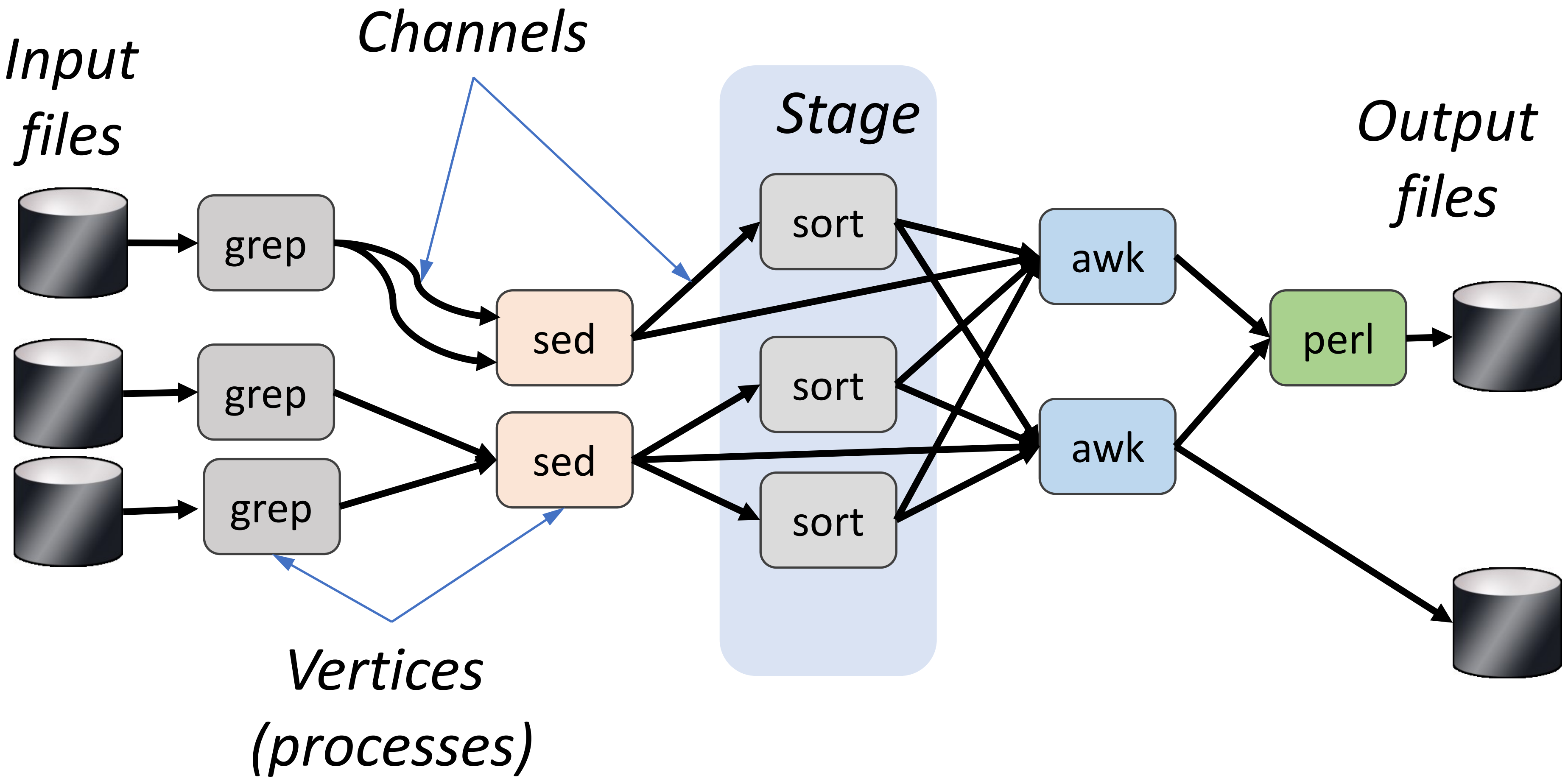


# Dataflow Engines



# Dataflow Job Structure



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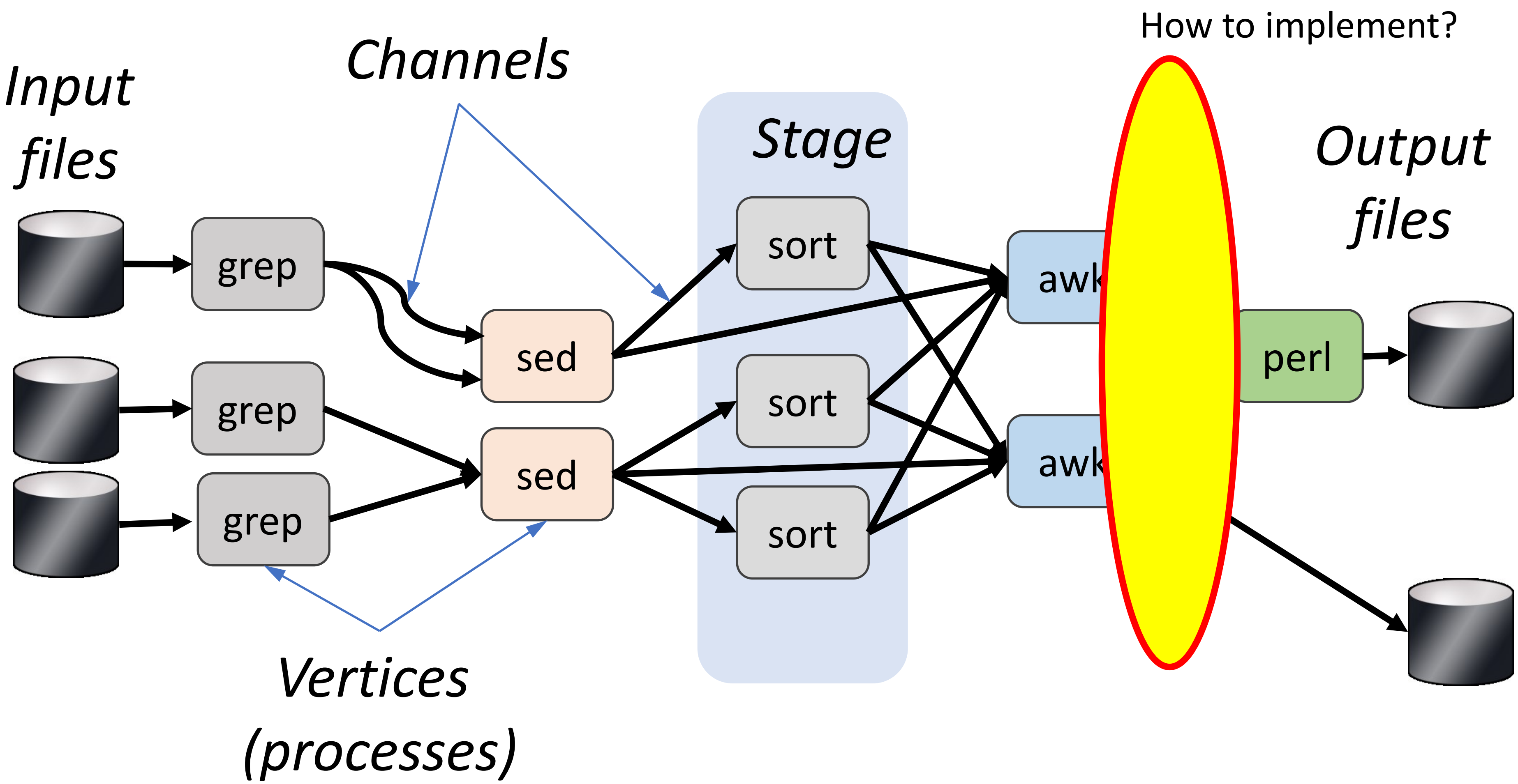
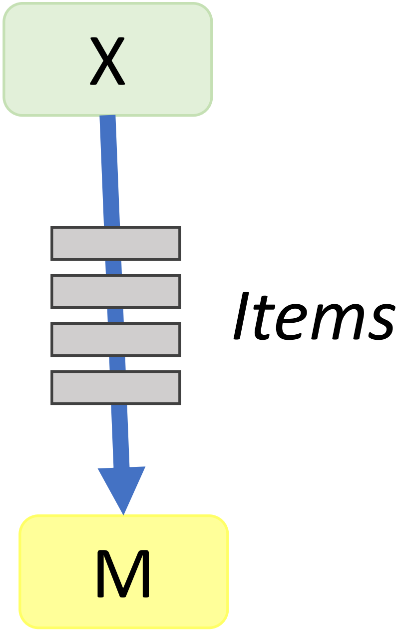


# Channels




Finite streams of items

- distributed filesystem files
  (persistent)
- SMB/NTFS files
  (temporary)
- TCP pipes
  (inter-machine)
- memory FIFOs
  (intra-machine)

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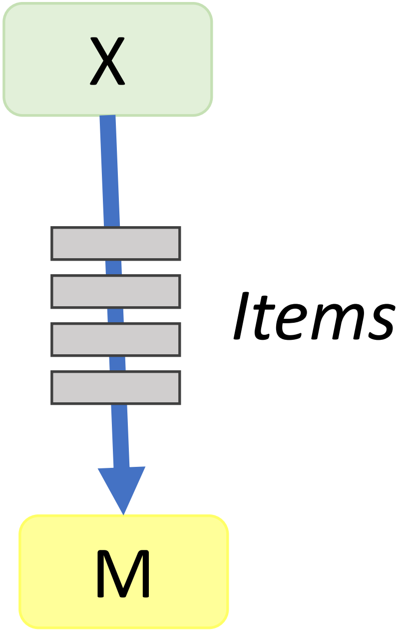


Key idea:
Encapsulate data movement behind channel abstraction → gets programmer out of the picture

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# 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

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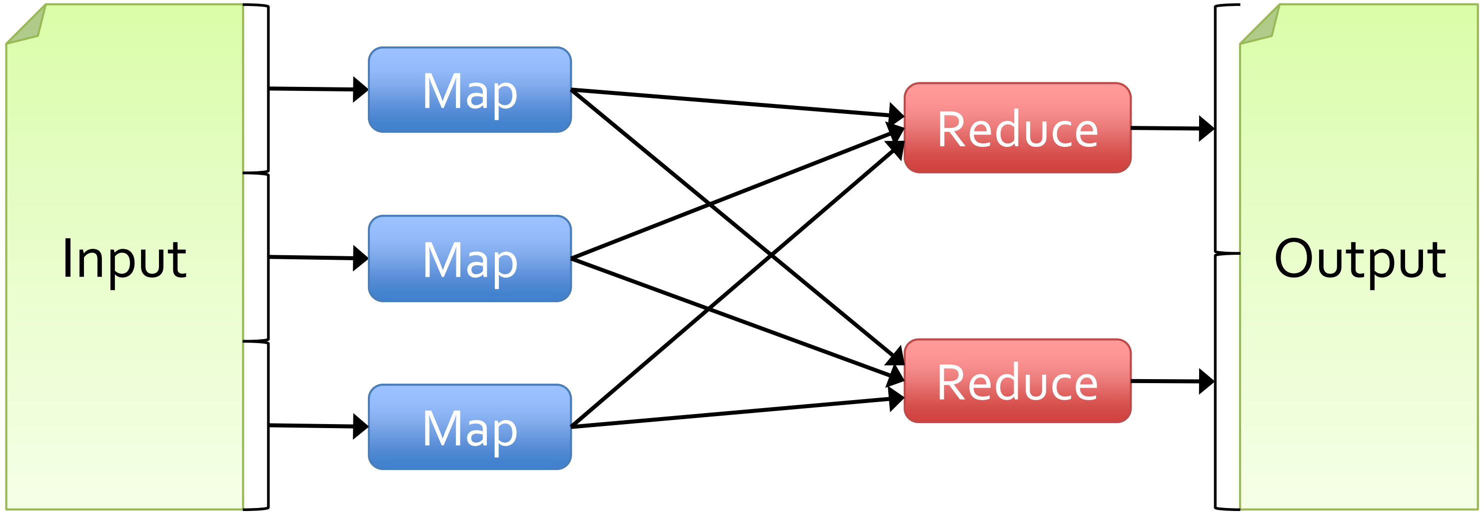
Multi-core

Iteration

# Motivation

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

E.g., MapReduce:



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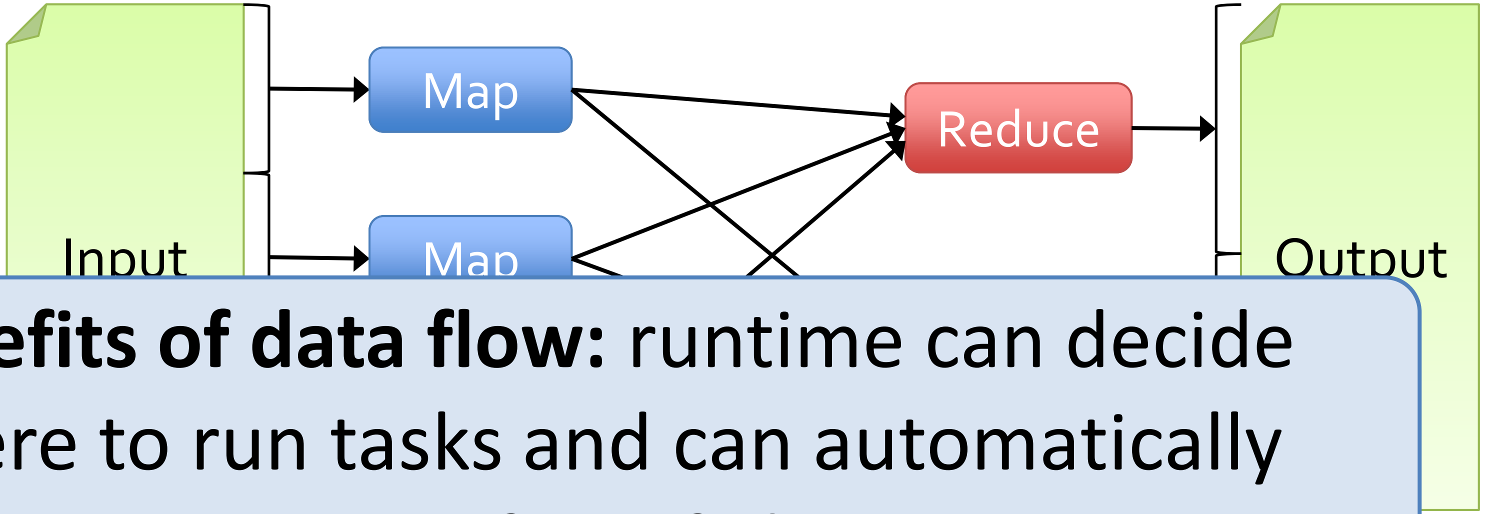



**Benefits of data flow:** runtime can decide where to run tasks and can automatically recover from failures

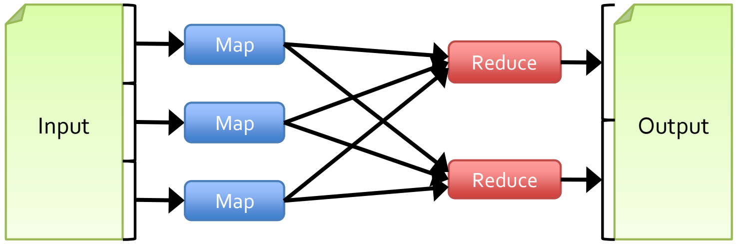
# Iterative Computations: PageRank

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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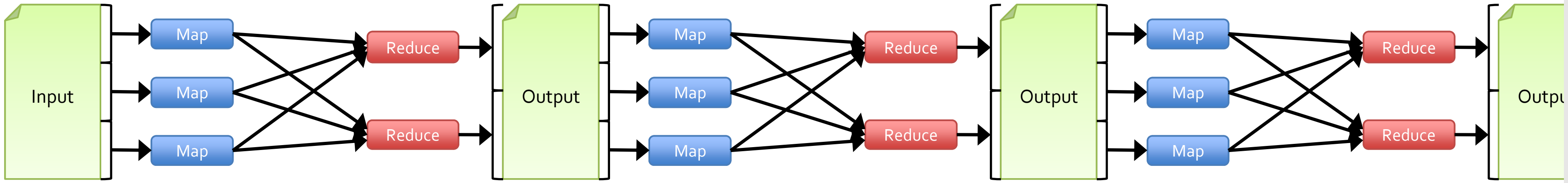

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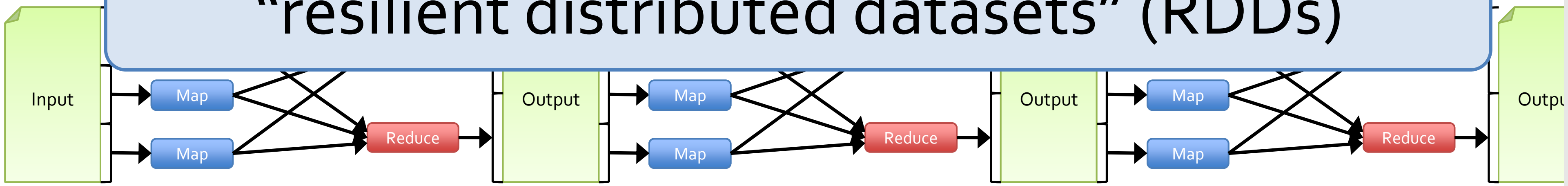
2. On each iteration, update each page's rank to

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

```
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(_ + _)
```

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



# Programming Model

- Resilient distributed datasets (RDDs)
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- Parallel operations on RDDs
  - Reduce, collect, count, save, …
- Restricted shared variables
  - Accumulators, broadcast variables

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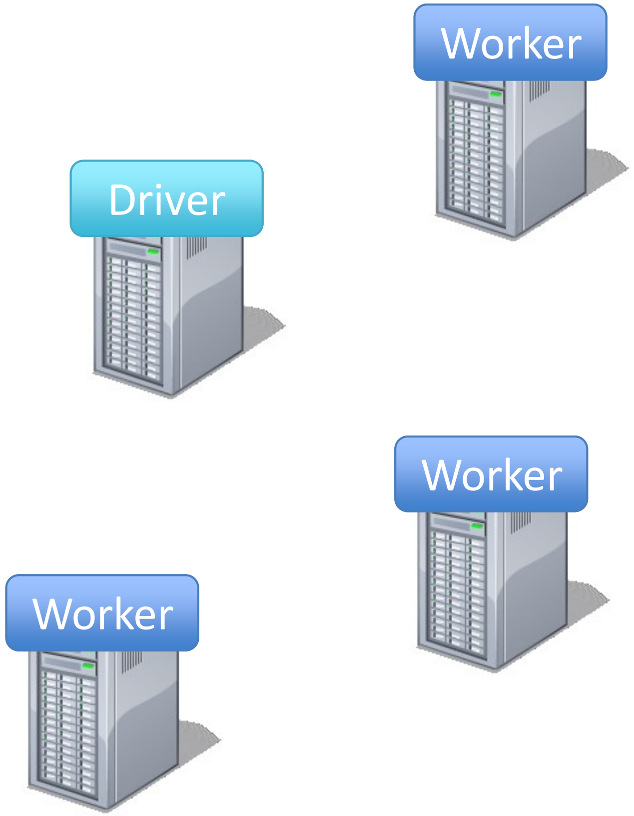

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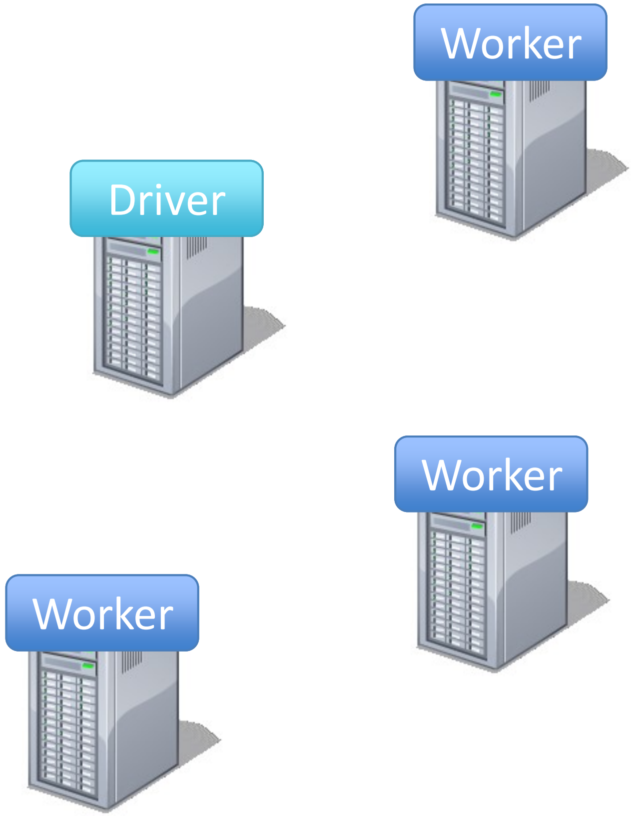

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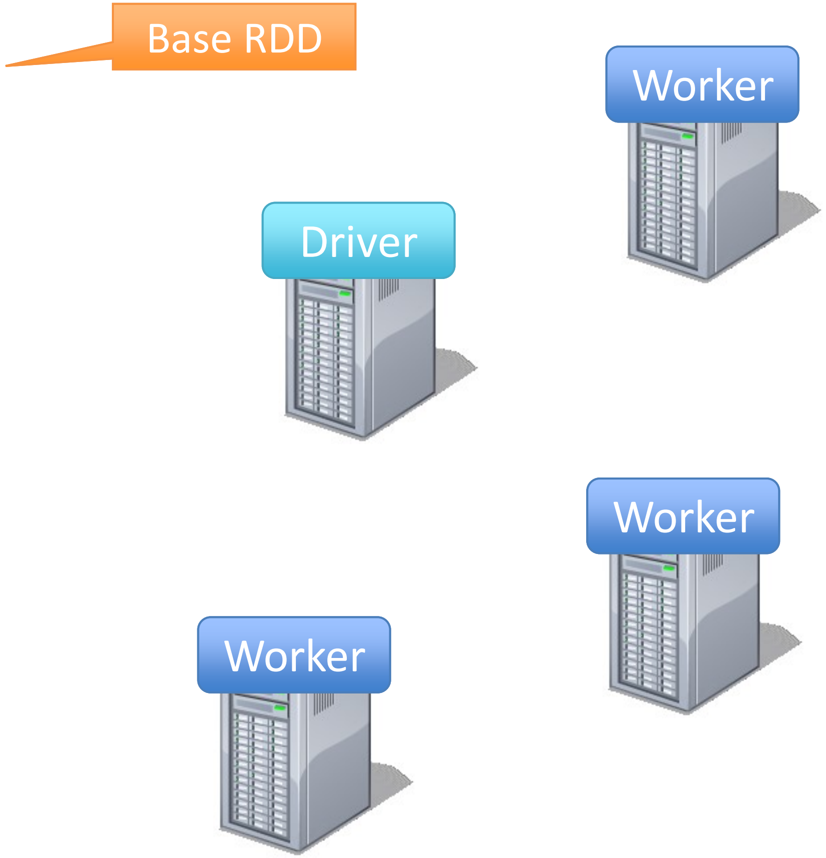

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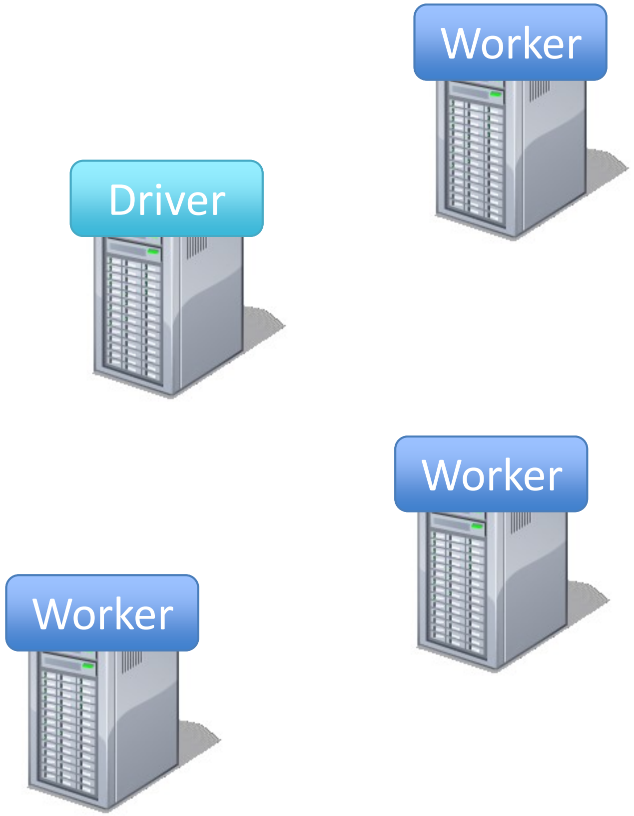

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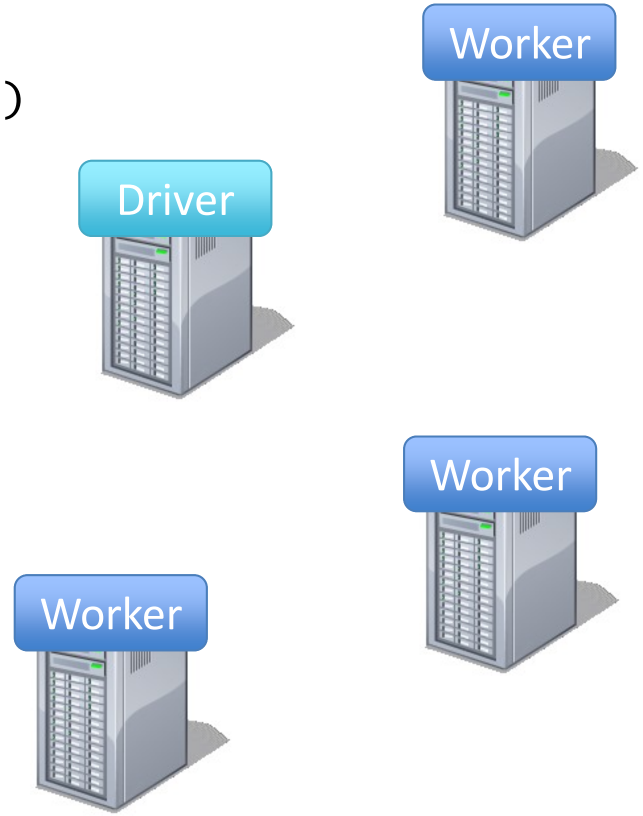

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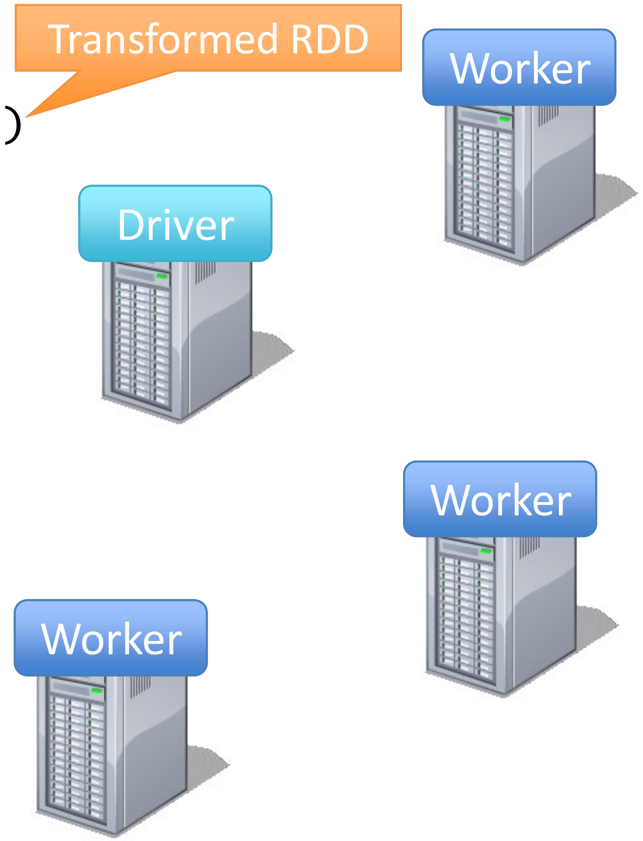

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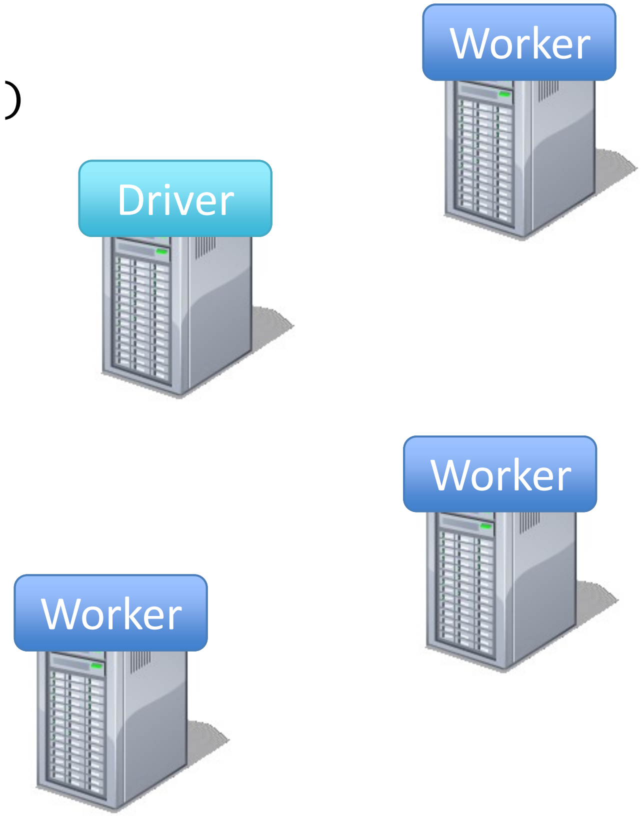

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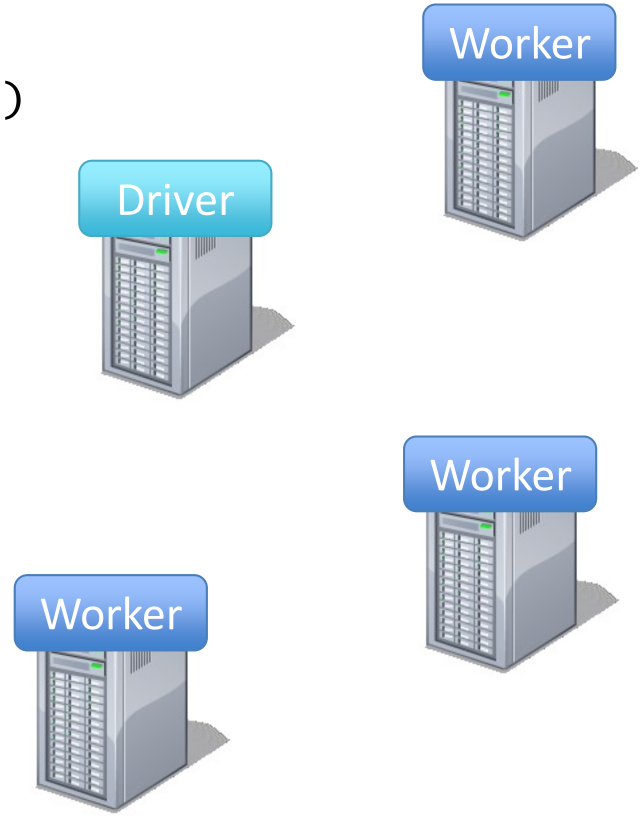

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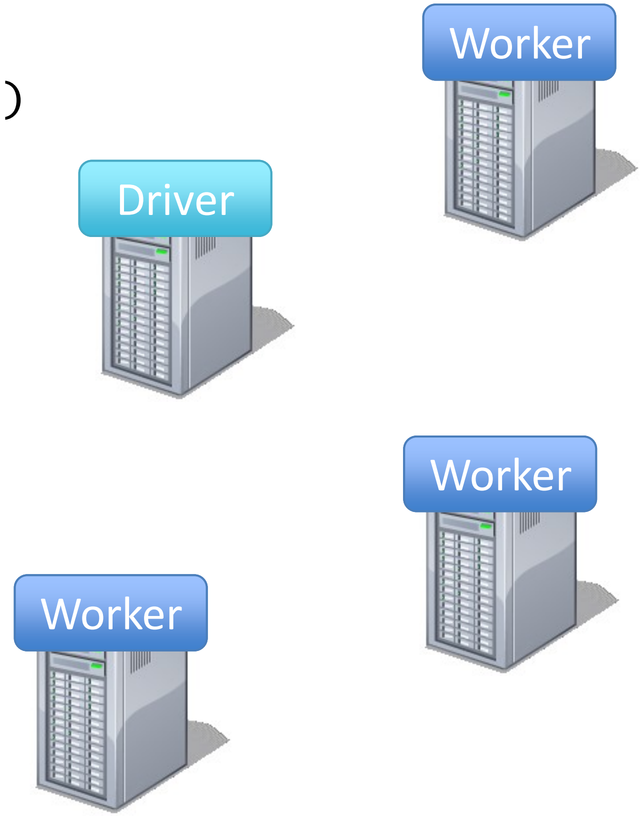

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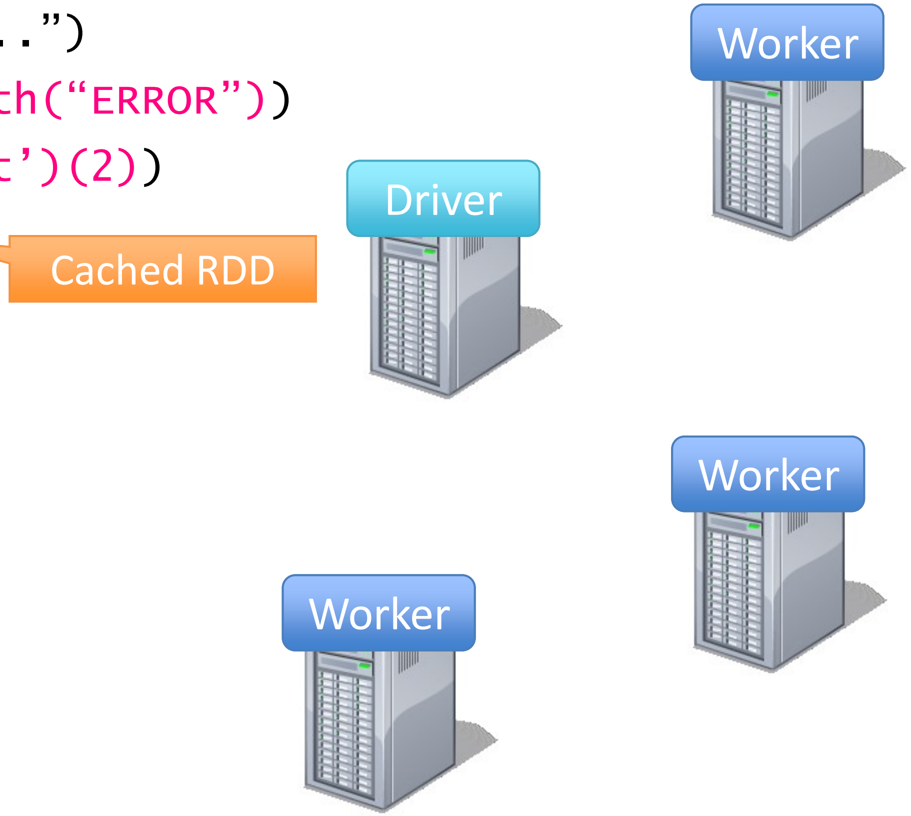

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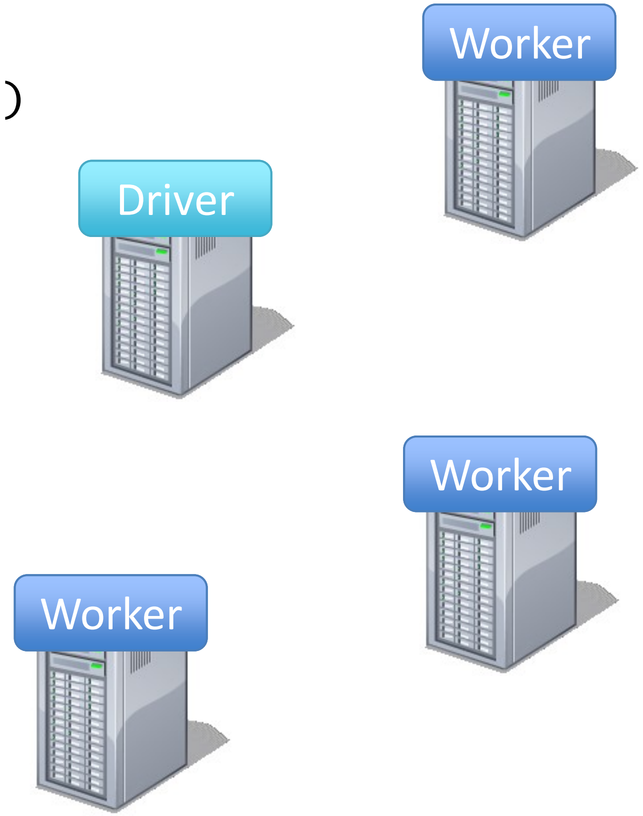

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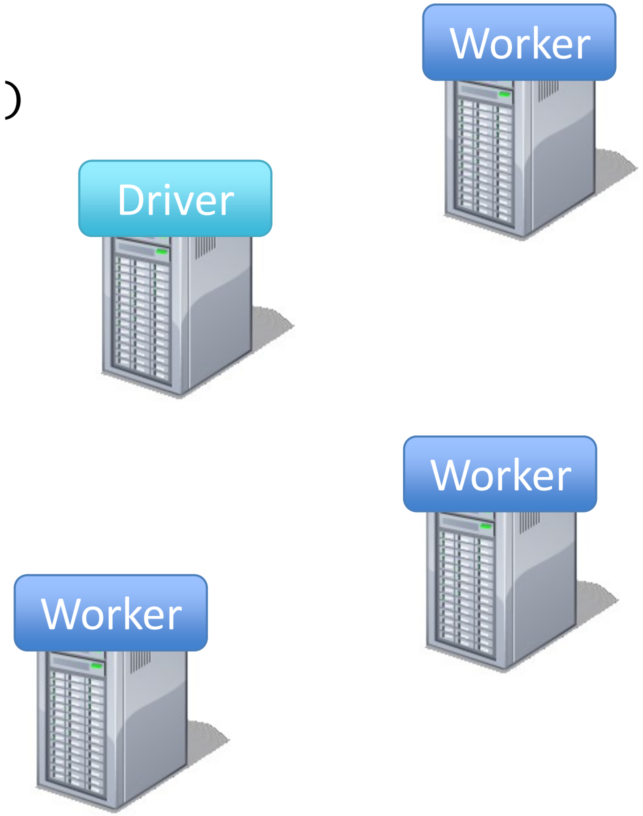

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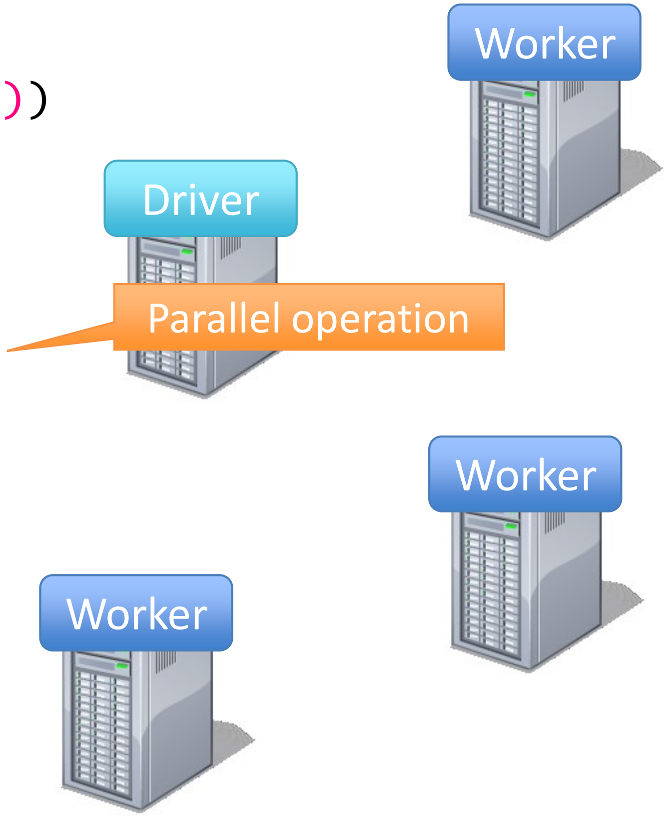

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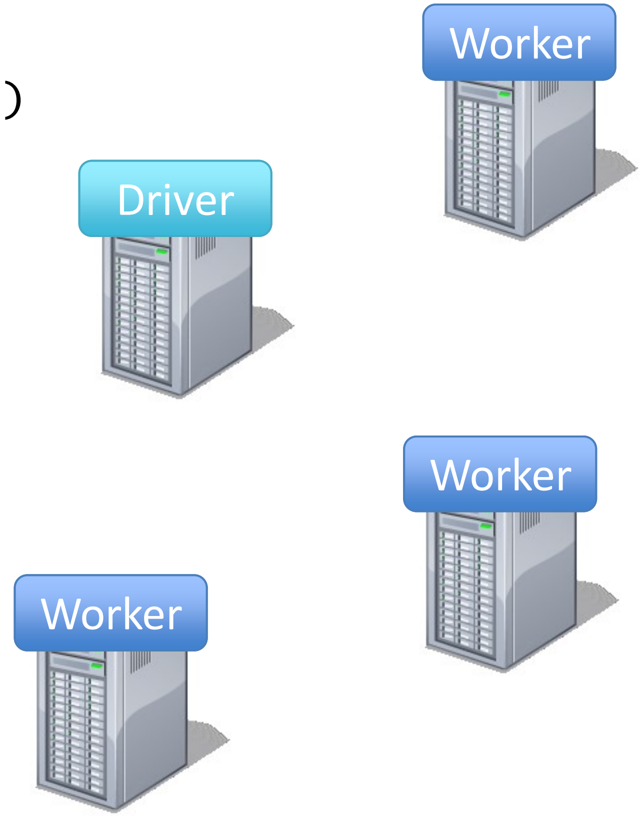

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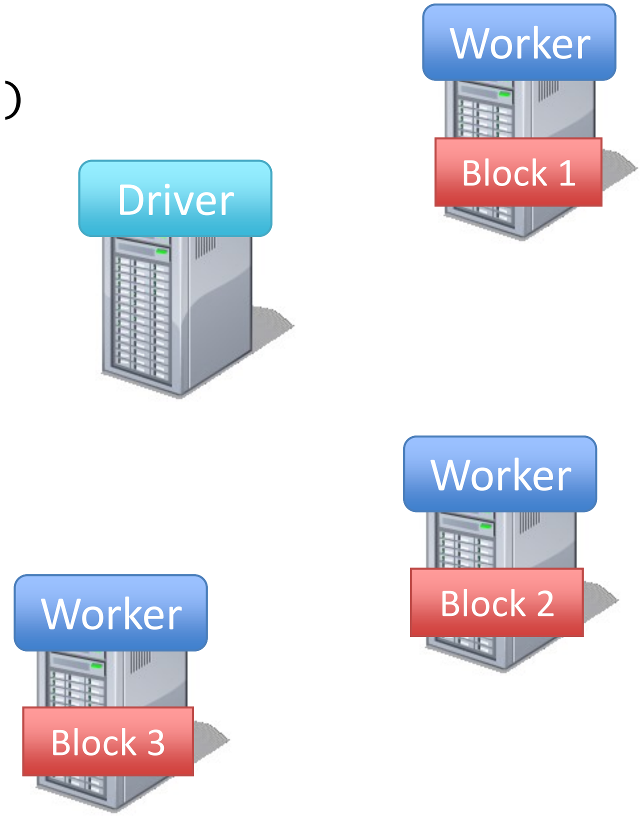

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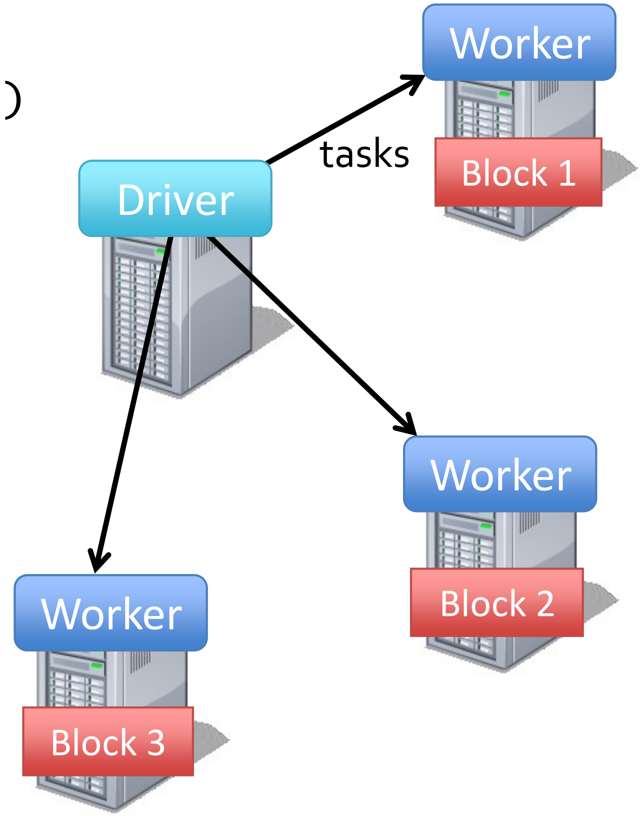

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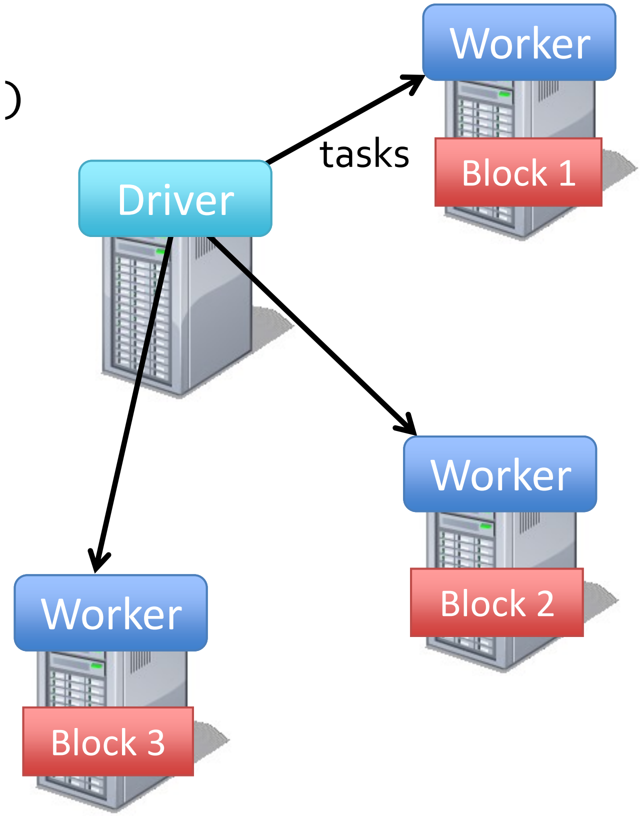

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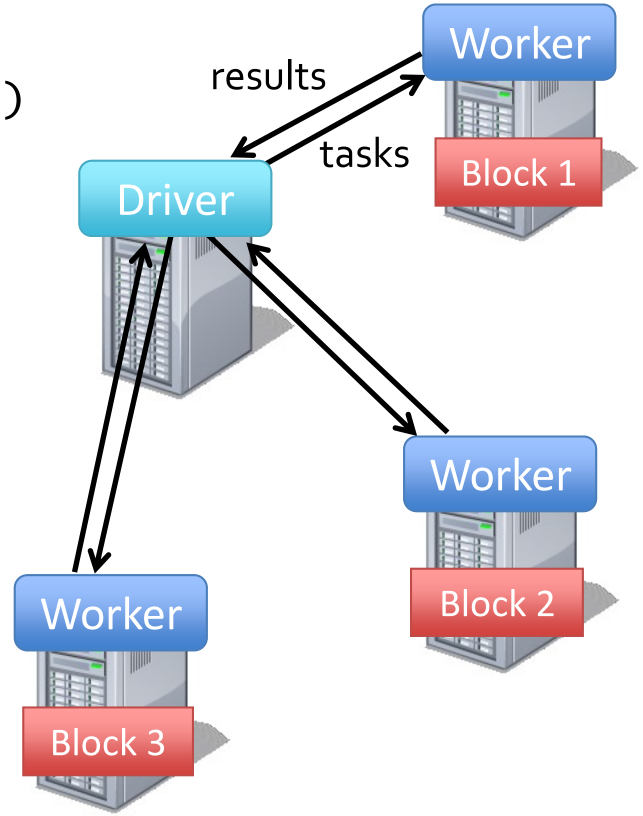

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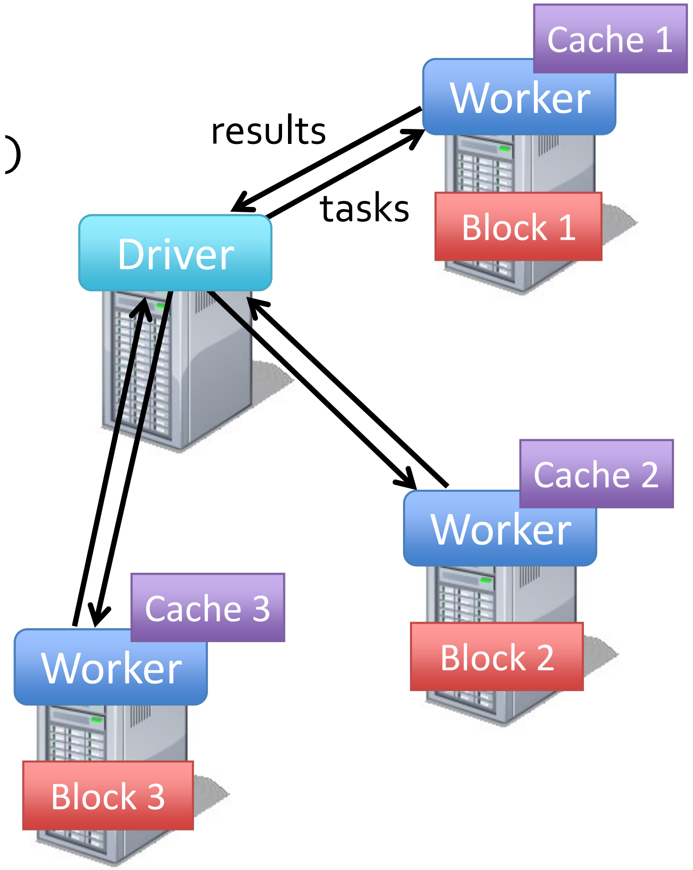

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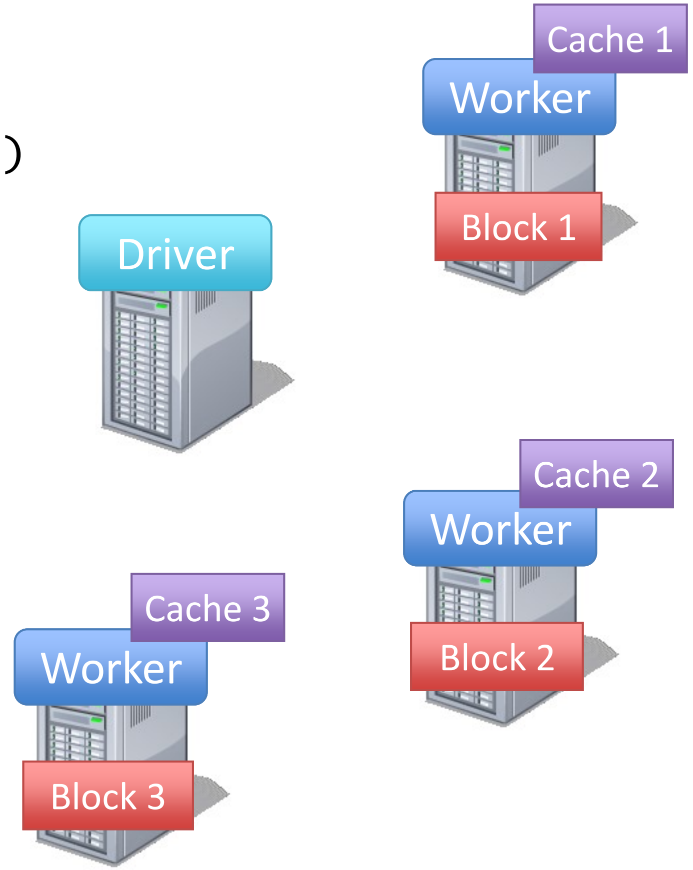

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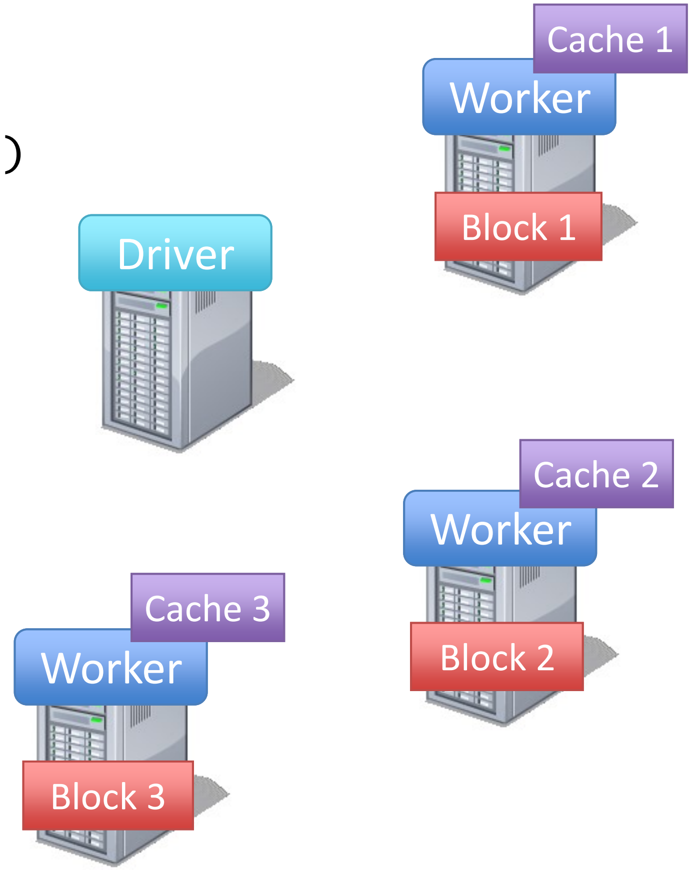

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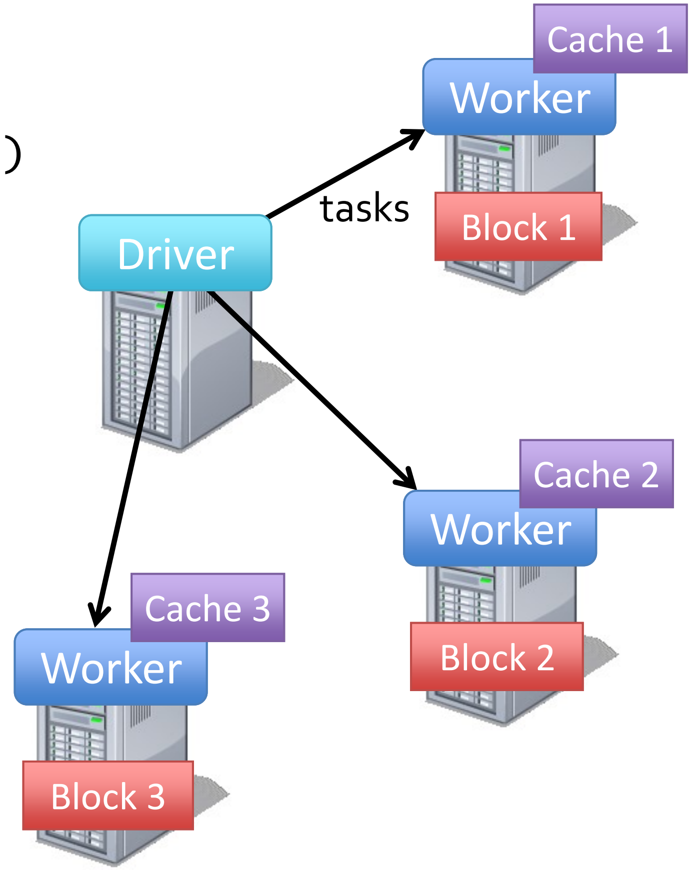

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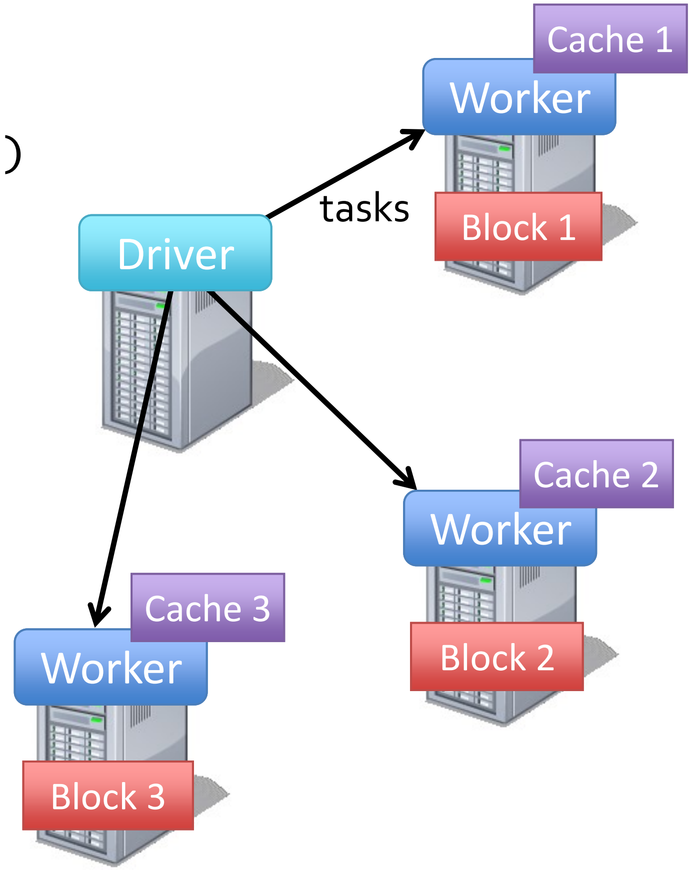

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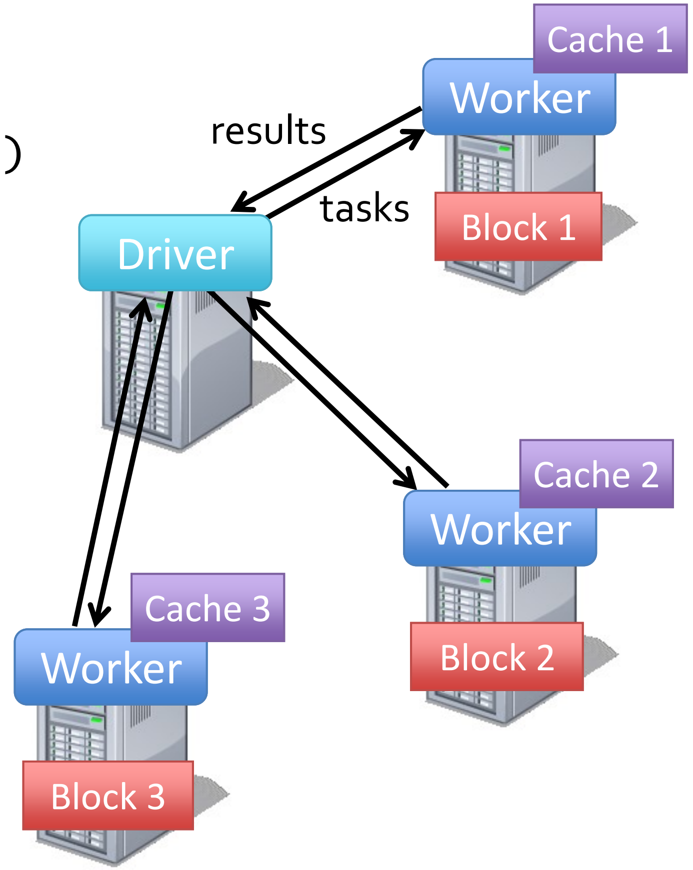

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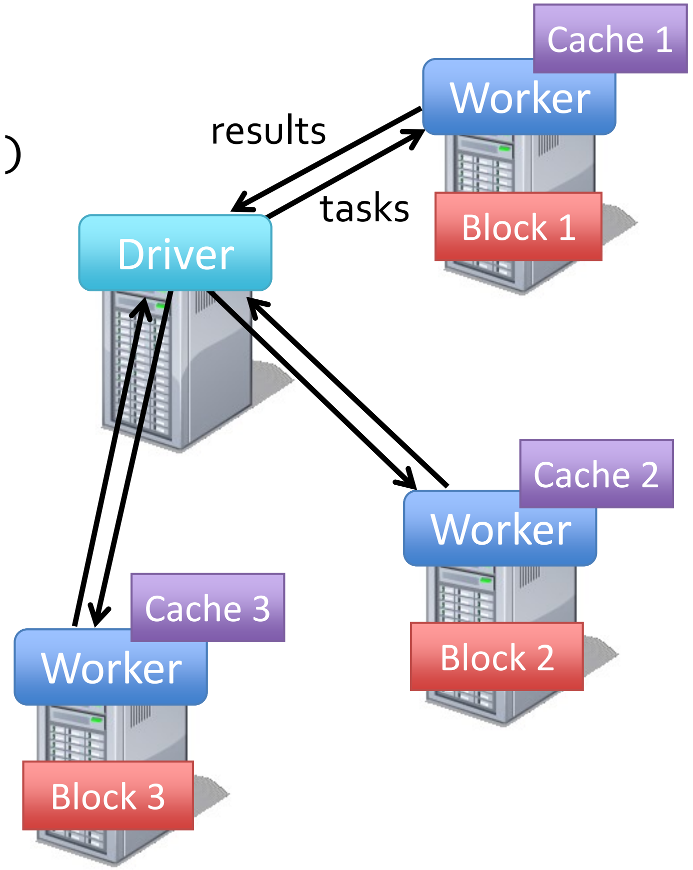

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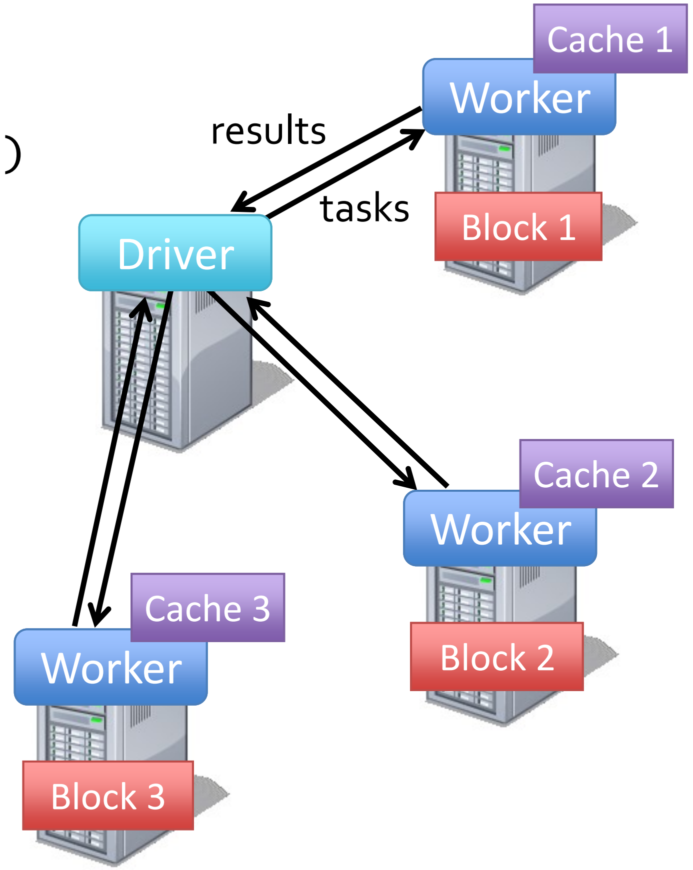


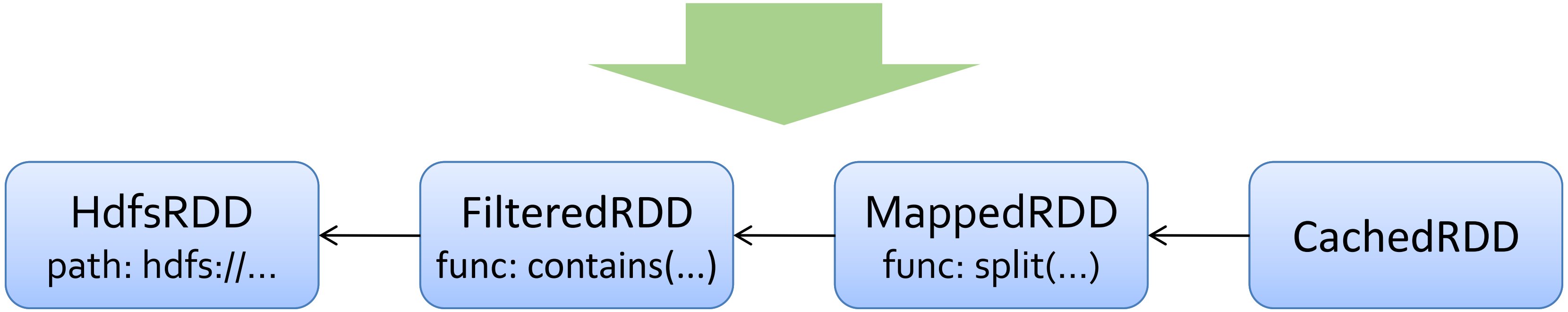

**Result:** full-text search of Wikipedia in <1 sec (vs 20 sec for on-disk data)

# 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()
```



# Data-Parallel Computation Systems

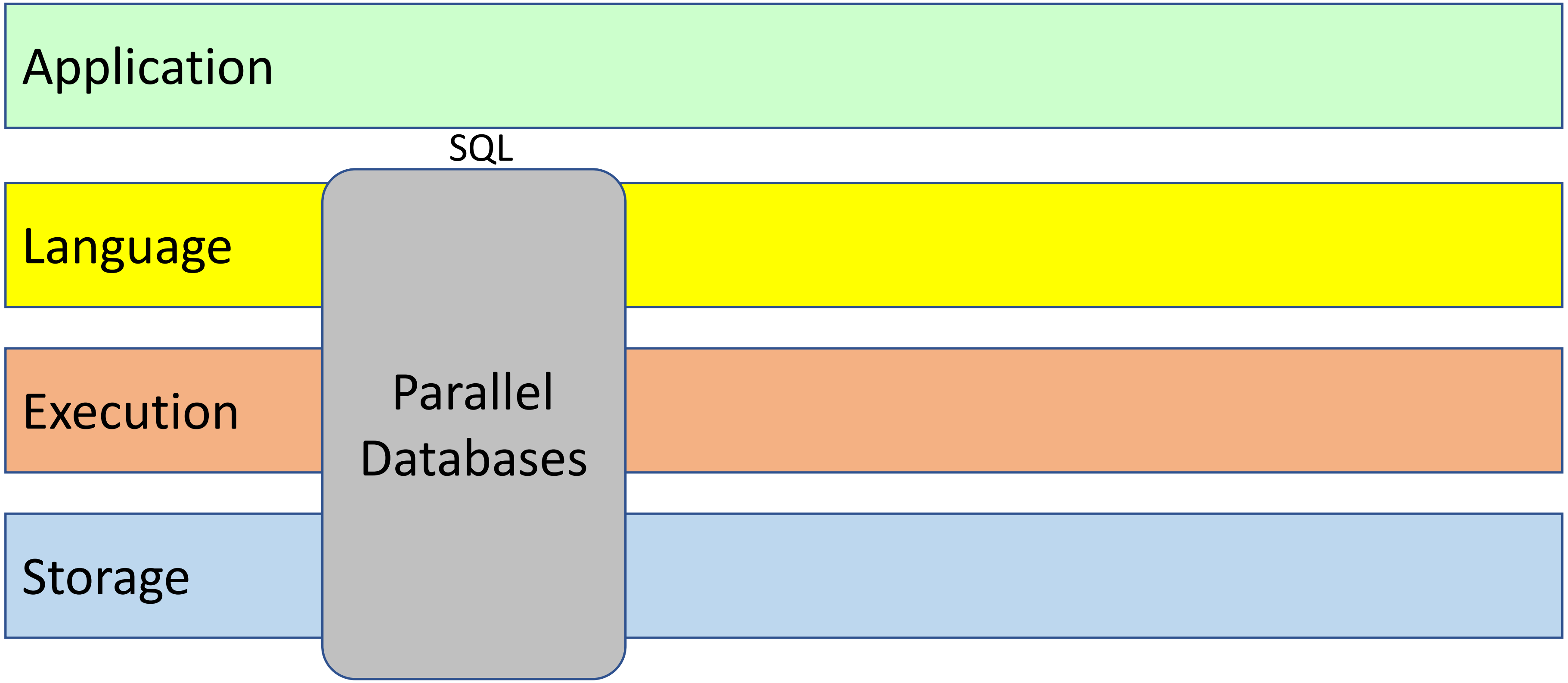
Application

Language

Execution

Storage

# Data-Parallel Computation Systems



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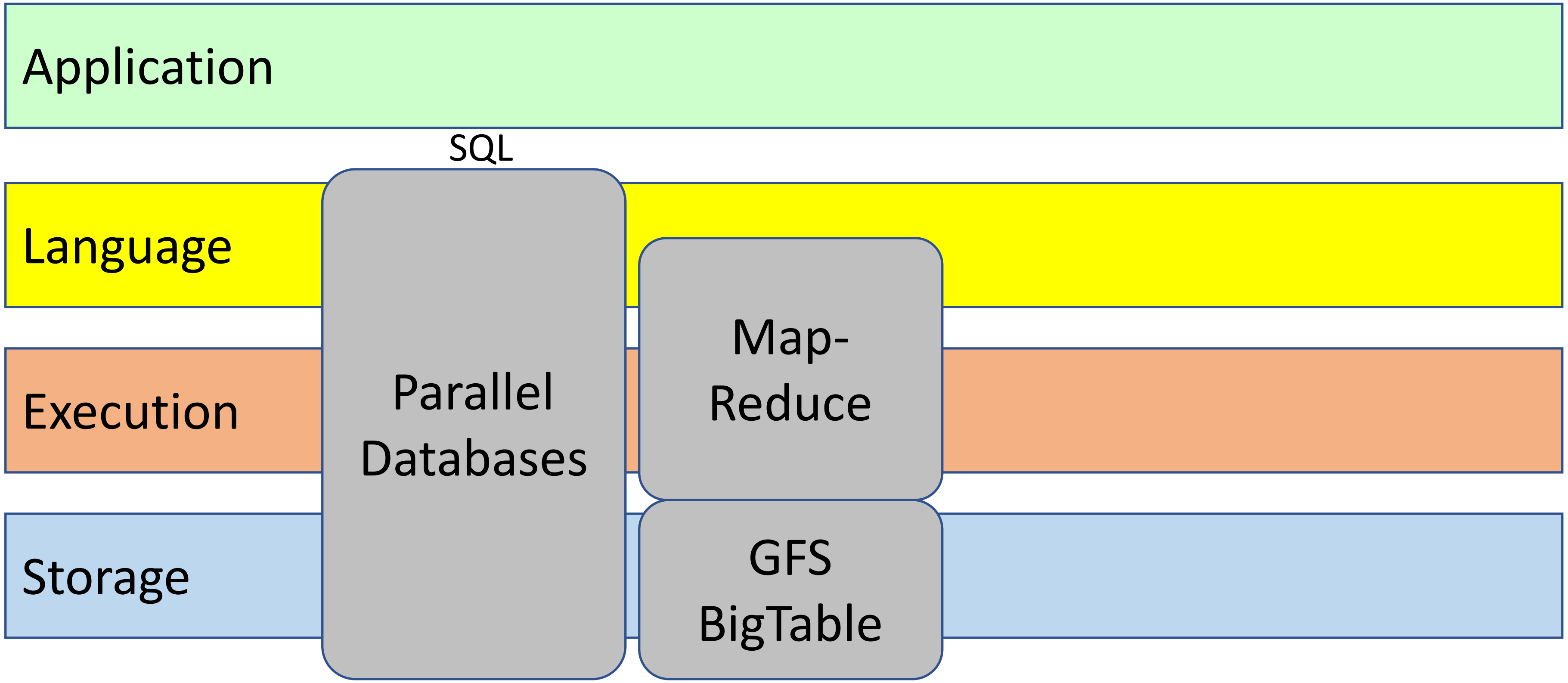

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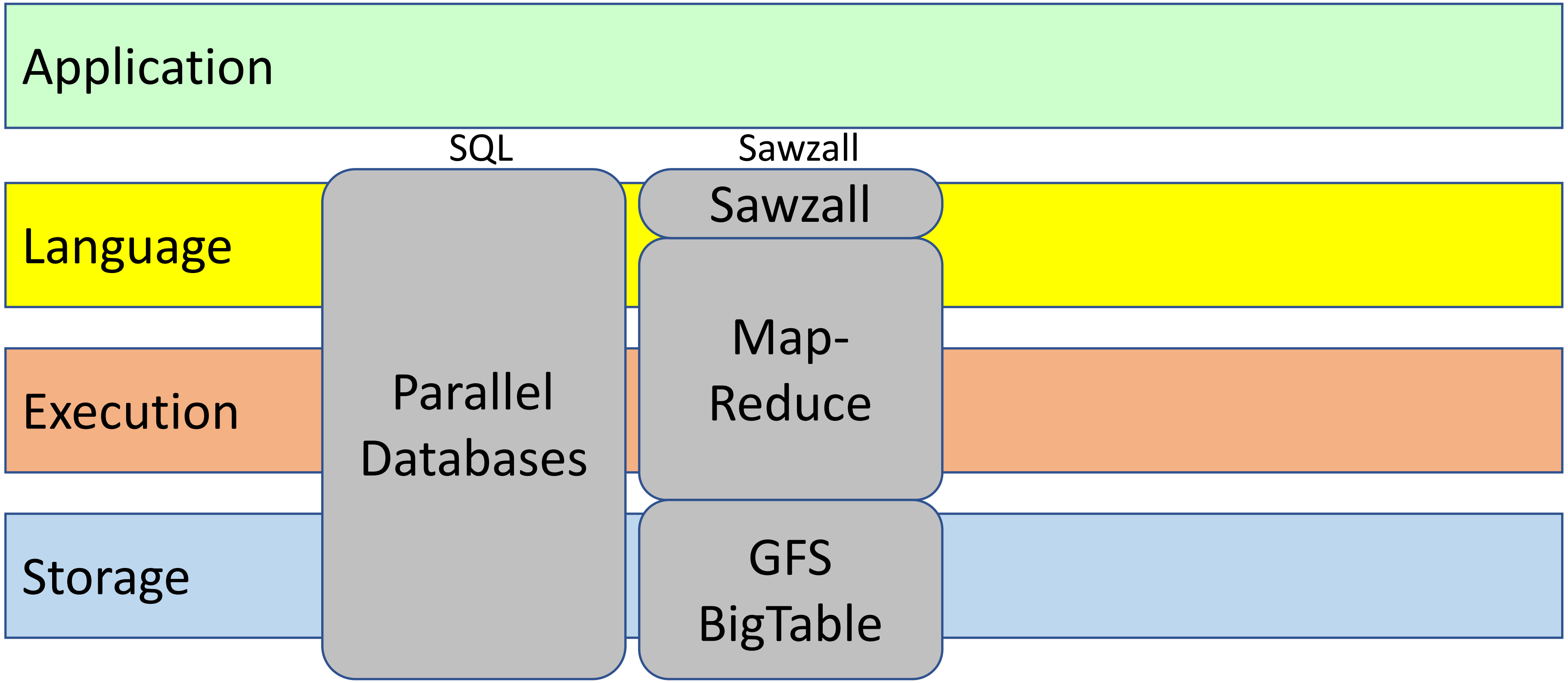

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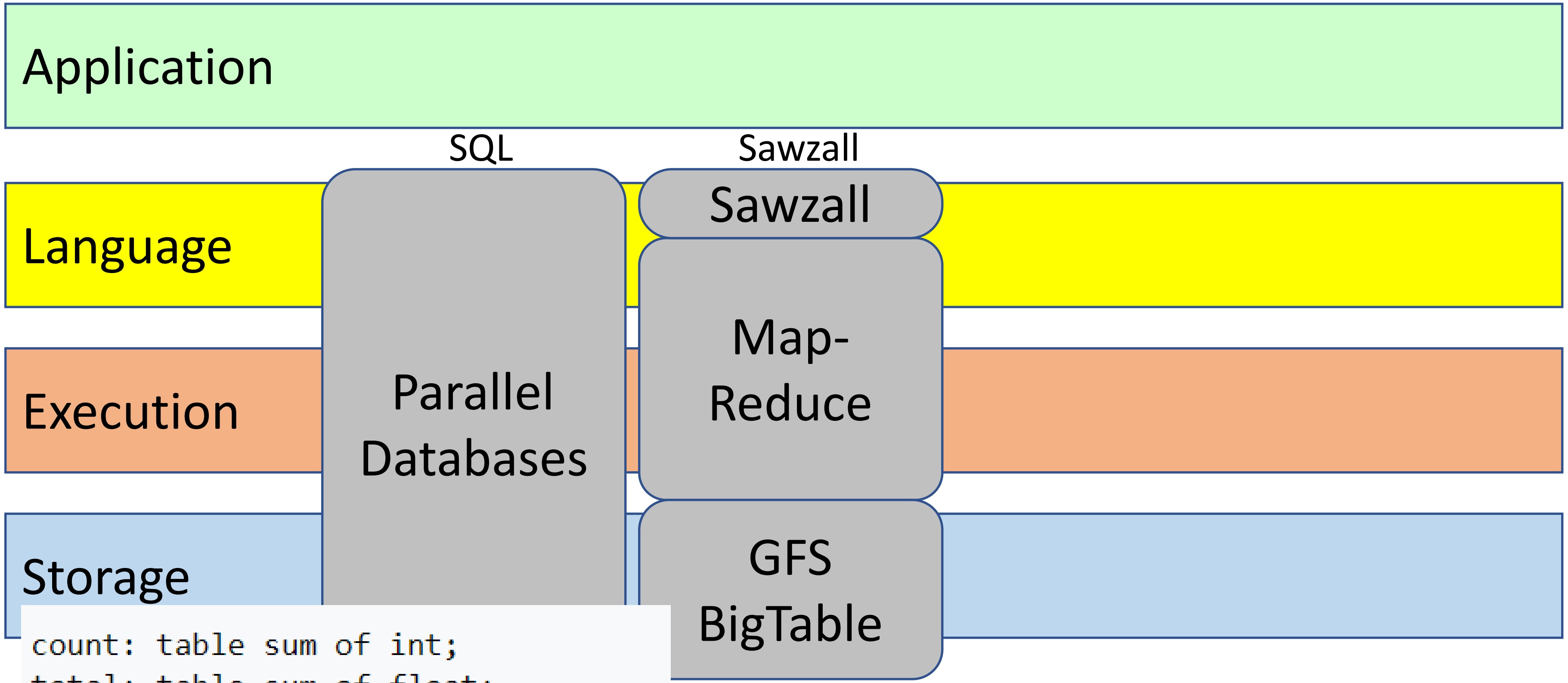


```
count: table sum of int;
total: table sum of float;
sum_of_squares: table sum of float;
x: float = input;
emit count <- 1;
emit total <- x;
emit sum_of_squares <- x * x;
```

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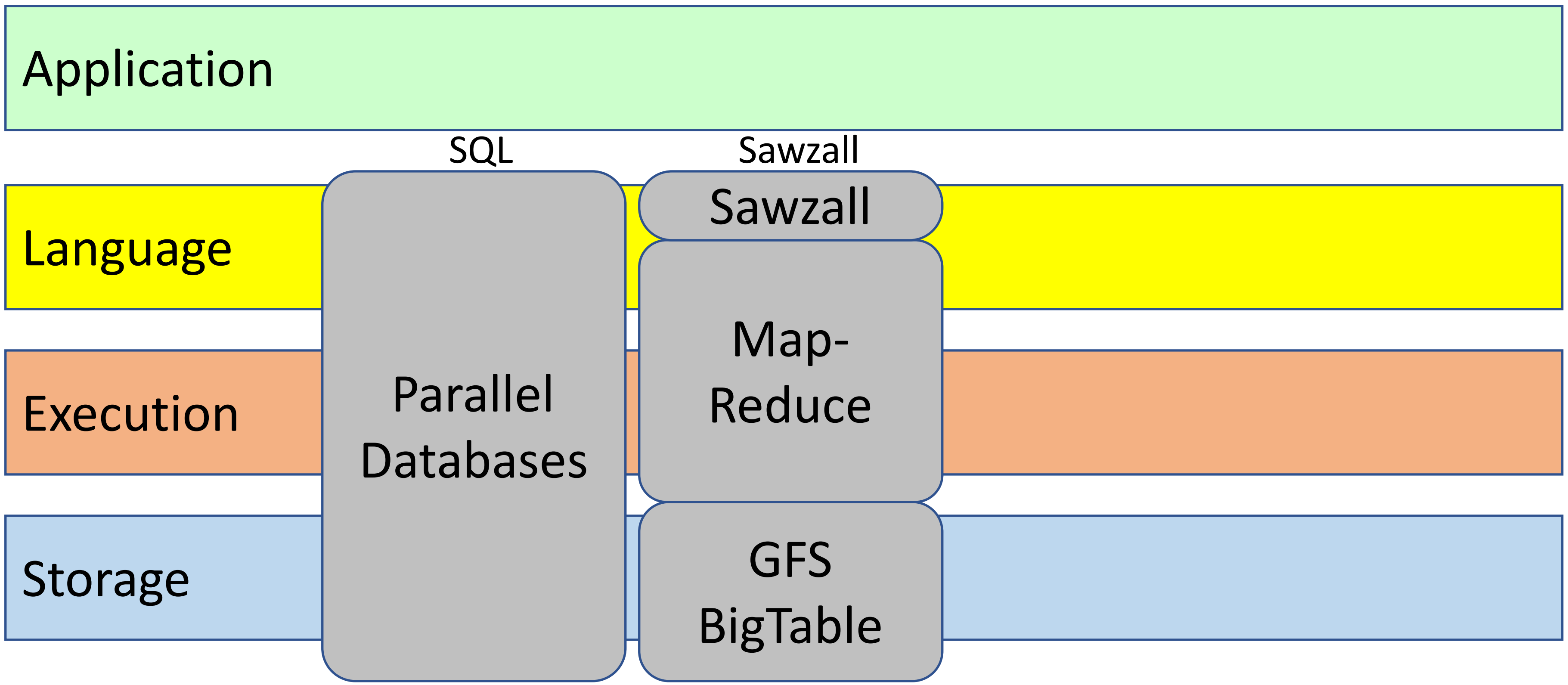

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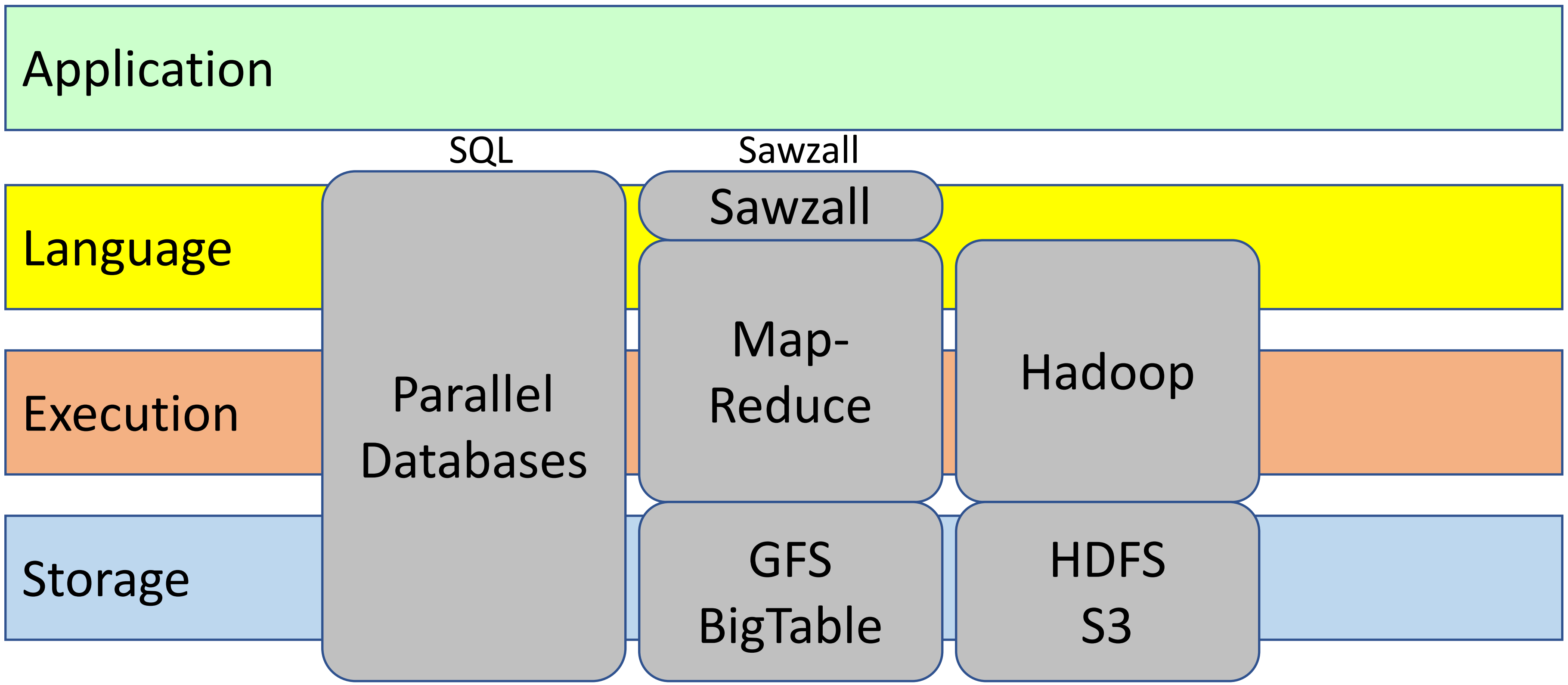

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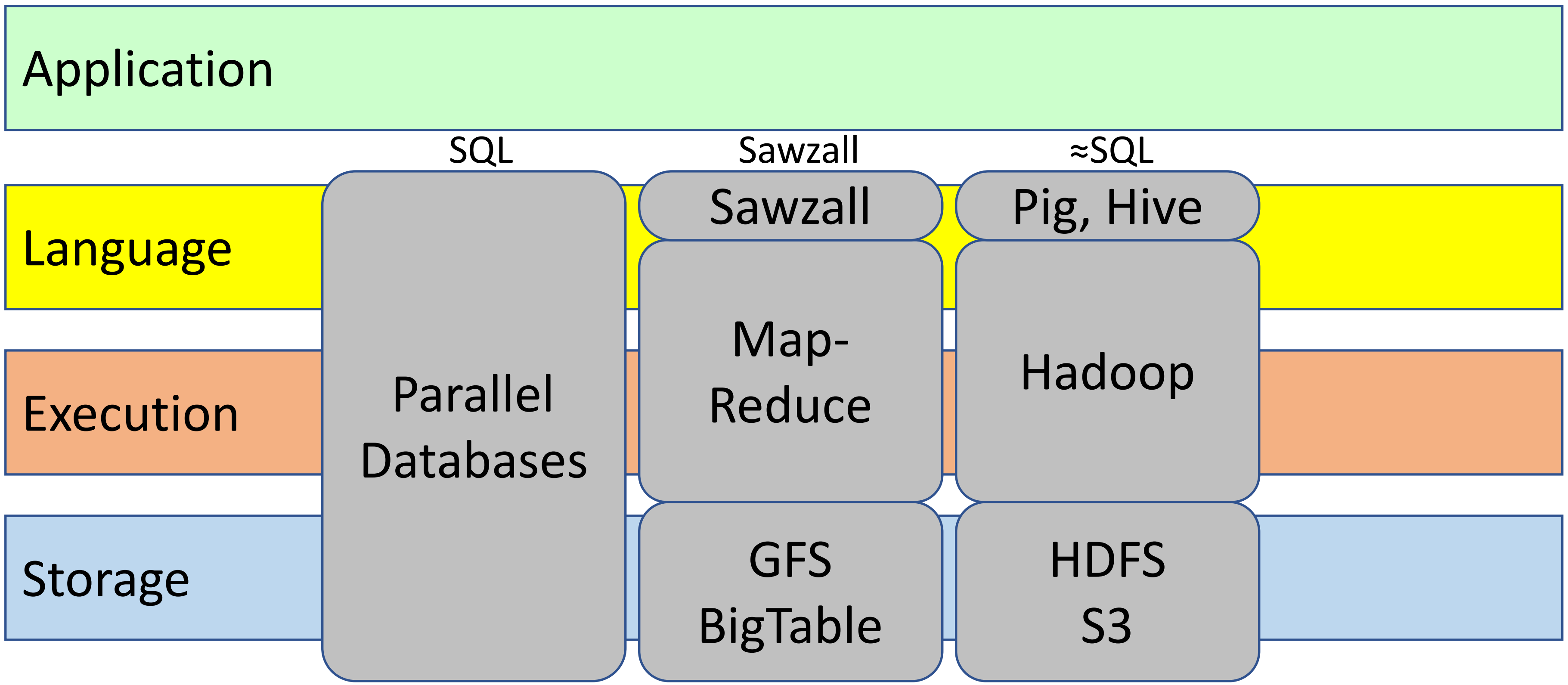

# Systems

```
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

Language

Sawzall

Pig, Hive

Execution

Paralle
Databas

Storage

BigTable

S3

```
-- 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;
```

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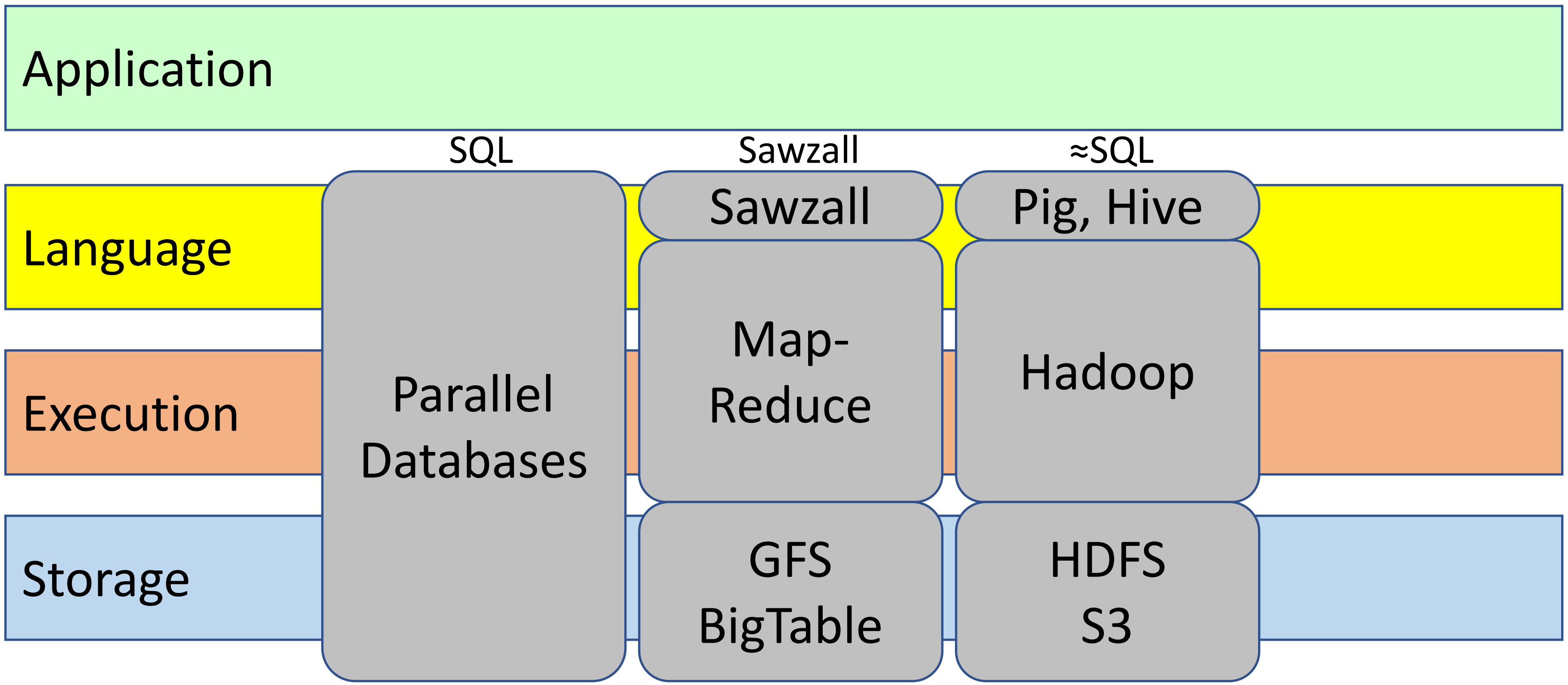

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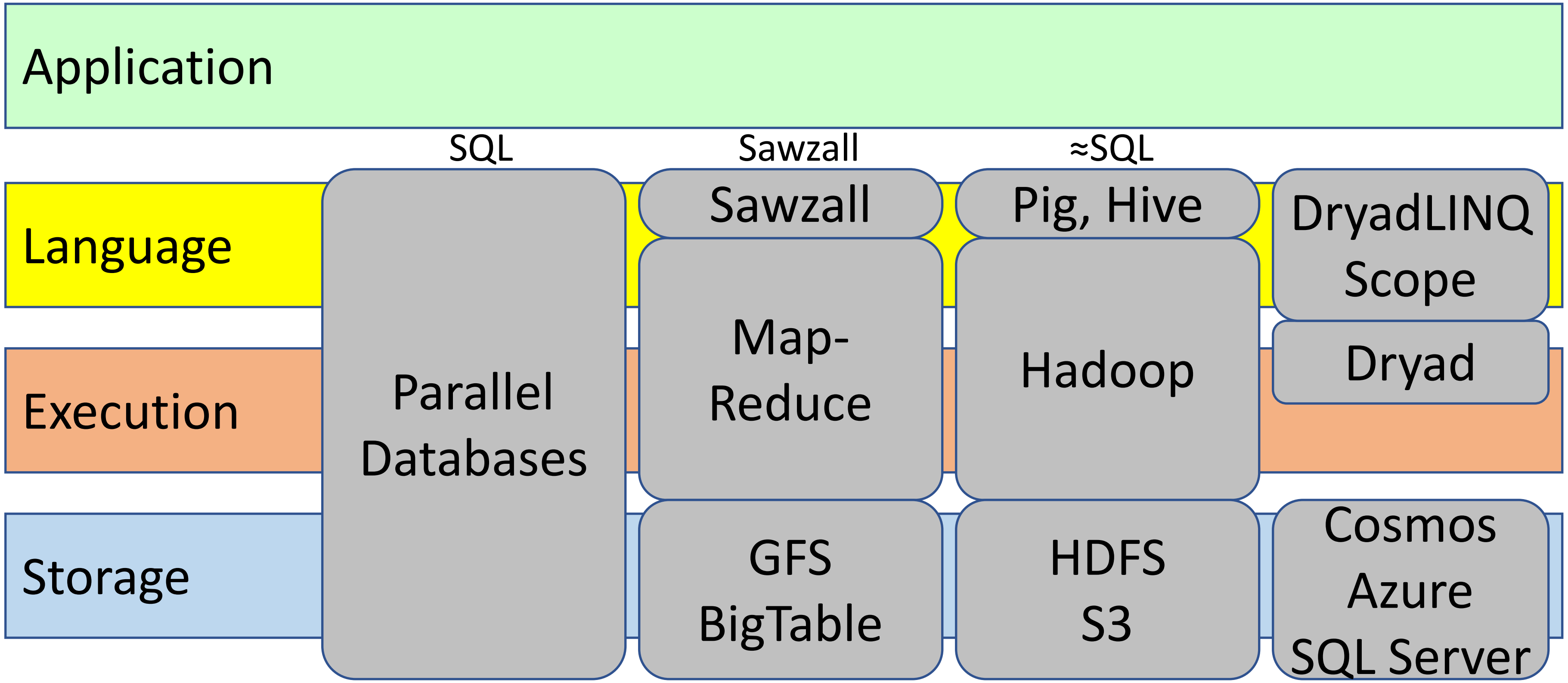

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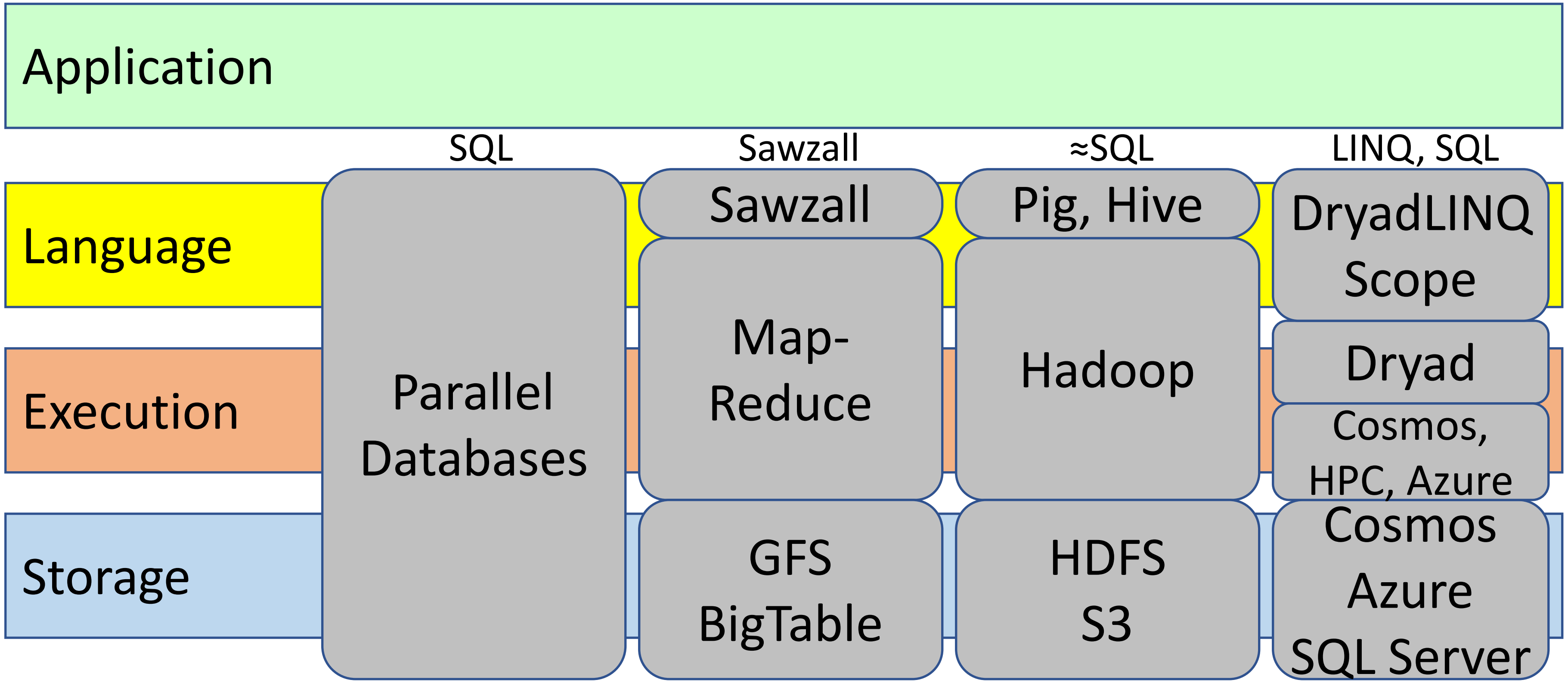

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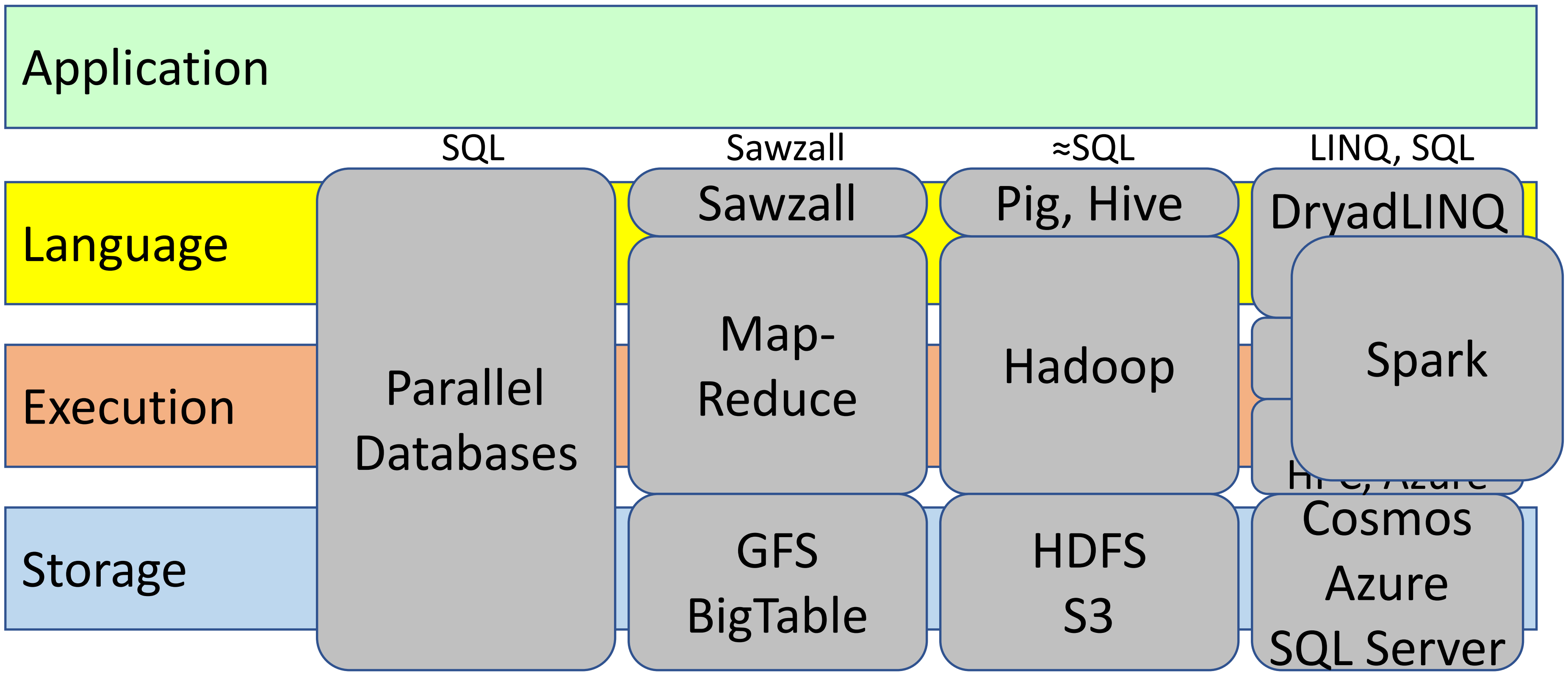

# Summary

Dataflow key enabler for cluster-scale parallelism

Key issues become runtime's responsibility

- Data movement
- Scheduling
- Fault-tolerance

# Example: Counting Words...

```
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));
```

***MapReduce handles all the other details!***

# Redundant Execution

Slow worker can throttle performance: why?

What makes a worker slow?

Solution:

# Redundant Execution

Slow worker can throttle performance: why?

What makes a worker slow?

- Other Jobs on machine (how could we fix)
- Bad disks, soft errors
- Exotica (processor caches disabled!)

Solution: spawn backups near end of phase

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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

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- Partitioning data sets (map) == Hash join

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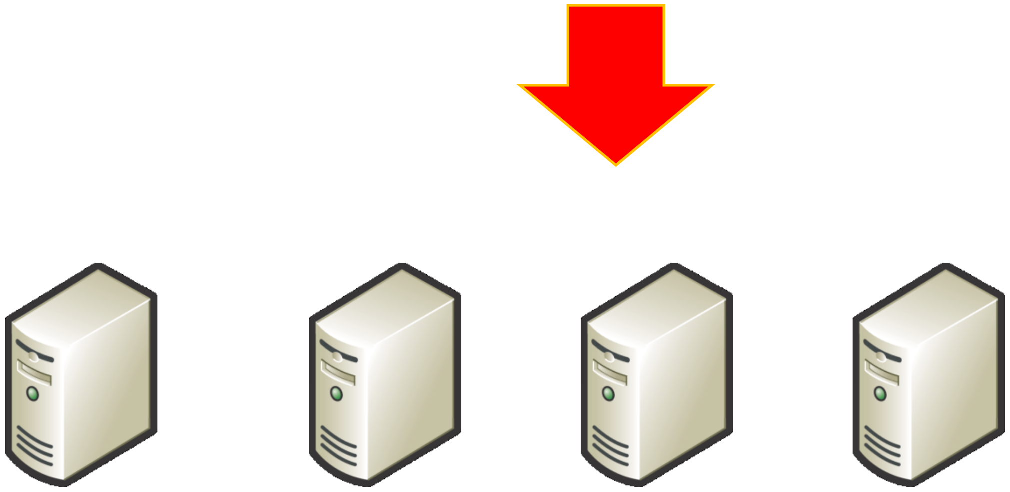
- Indexing
- Update operator
- Transactions
- Integrity constraints, referential integrity
- Views

# DryadLINQ = LINQ + Dryad

```
Collection<T> collection;
bool IsLegal(Key k);
string Hash(Key);

var results = from c in collection
              where IsLegal(c.key)
              select new { Hash(c.key), c.value};
```



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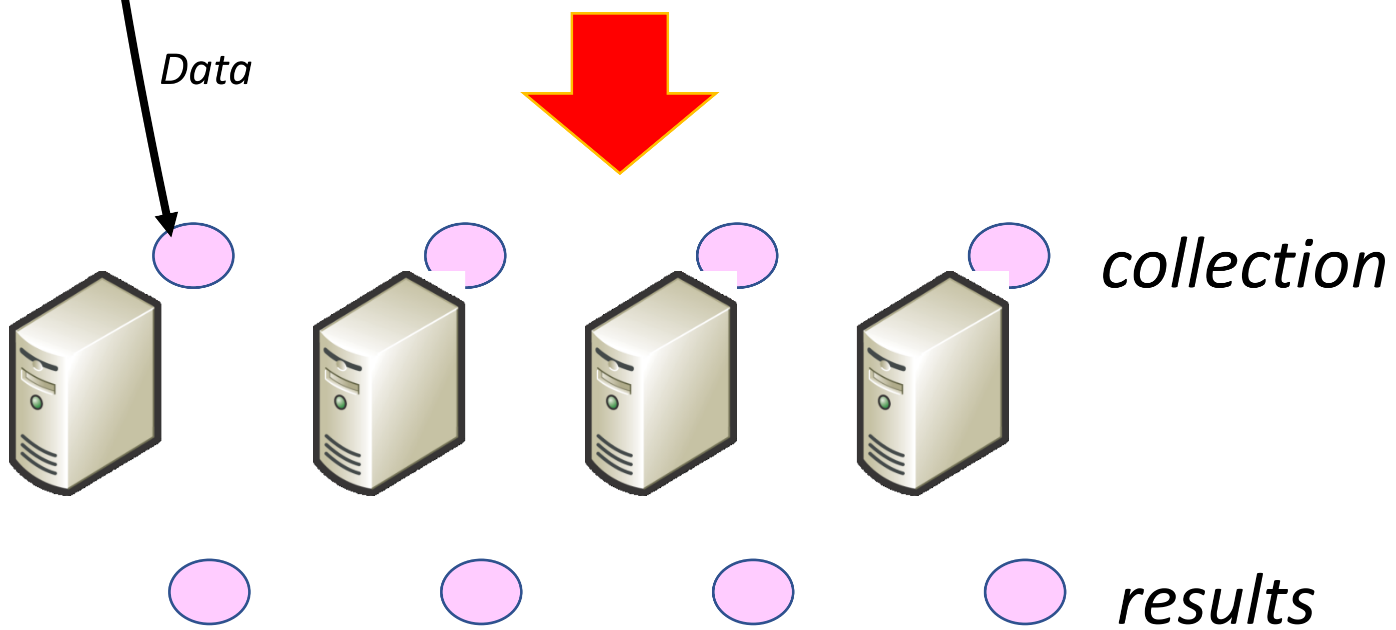

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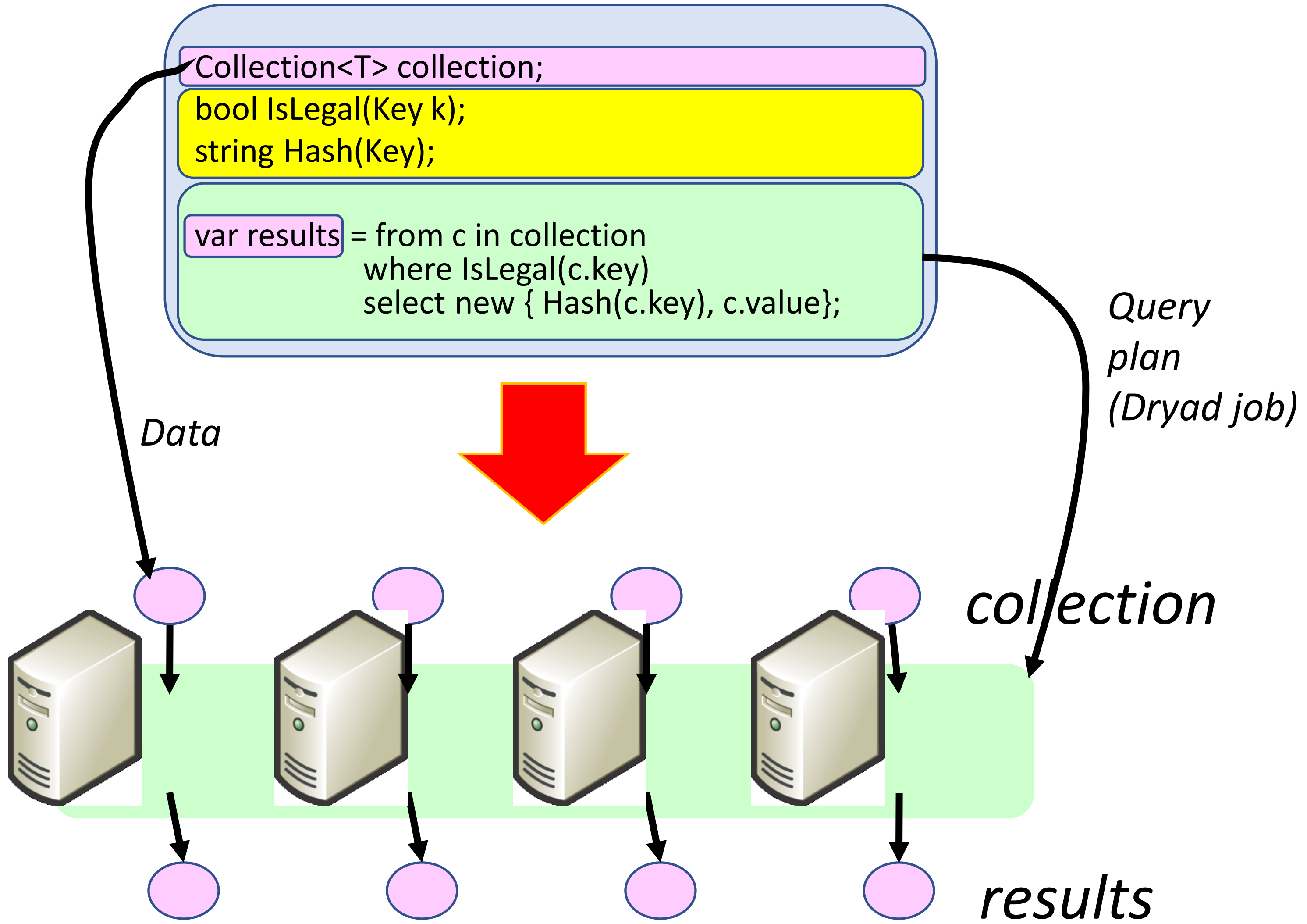

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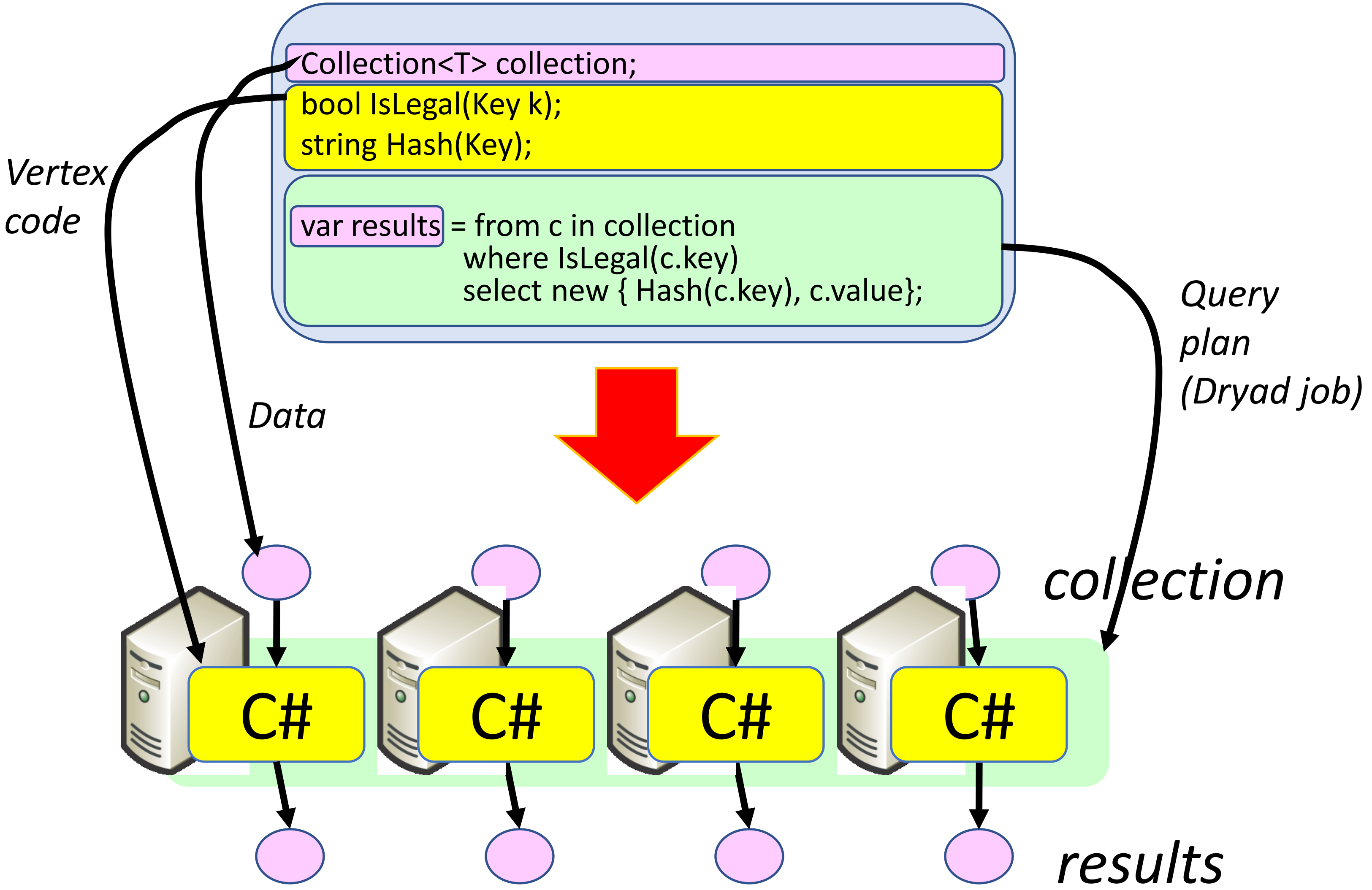
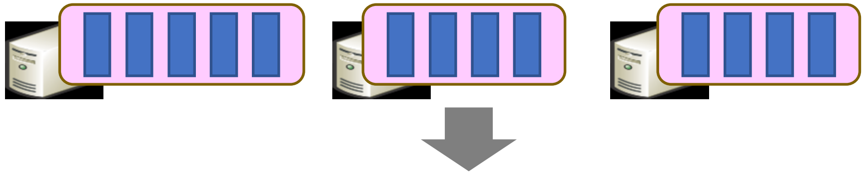


# Programming Model



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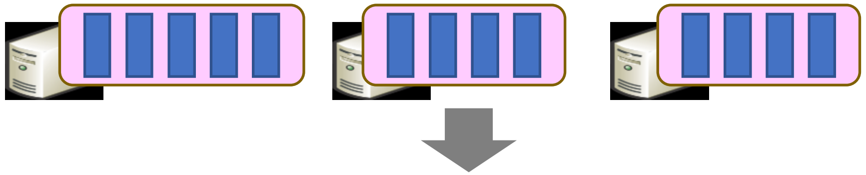

Where

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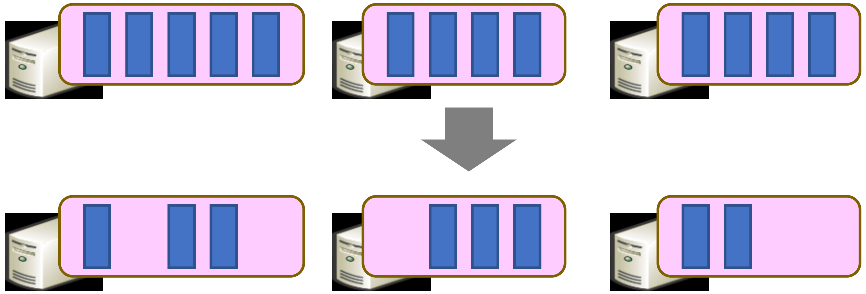
Where



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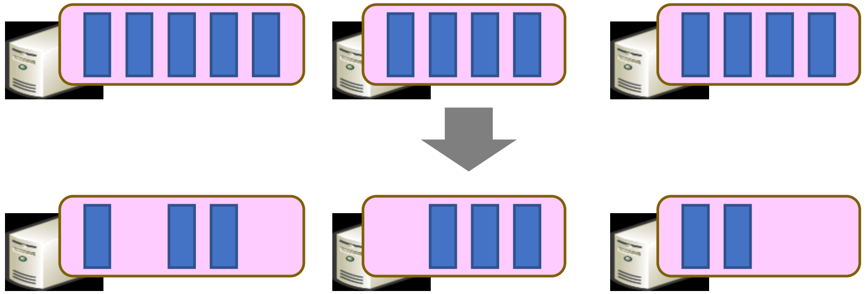

Where

Select

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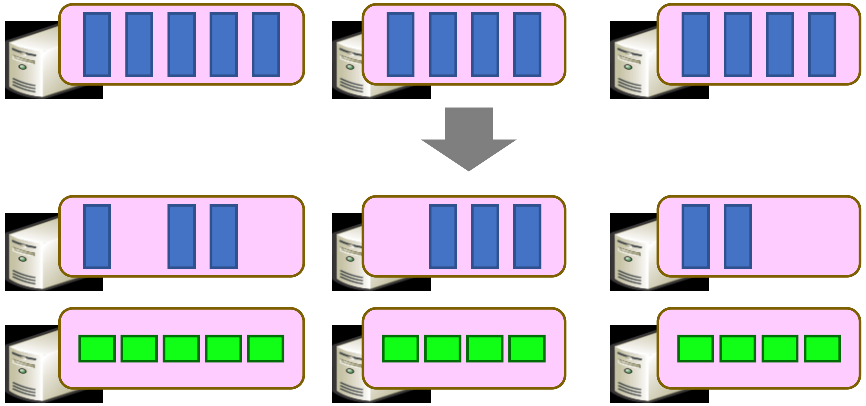

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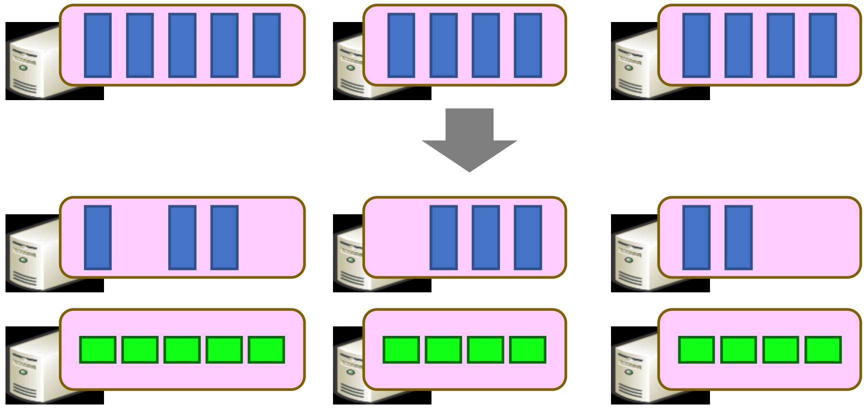
Where

Select

GroupBy



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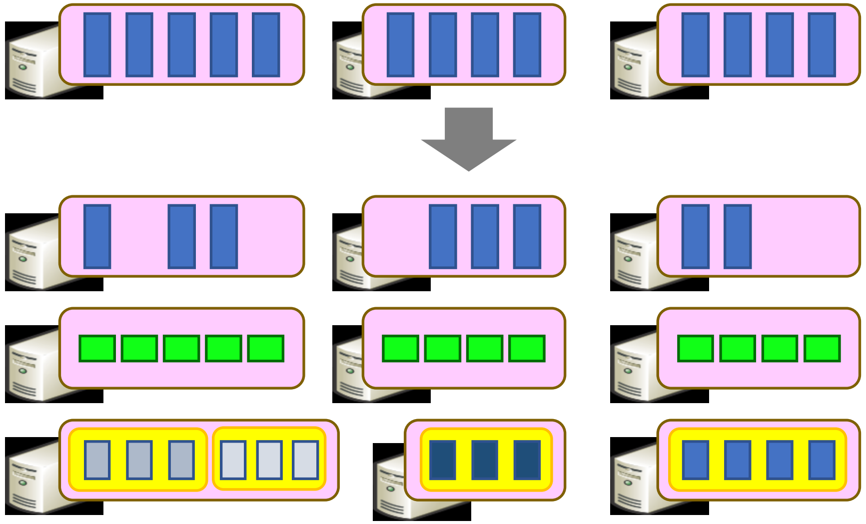


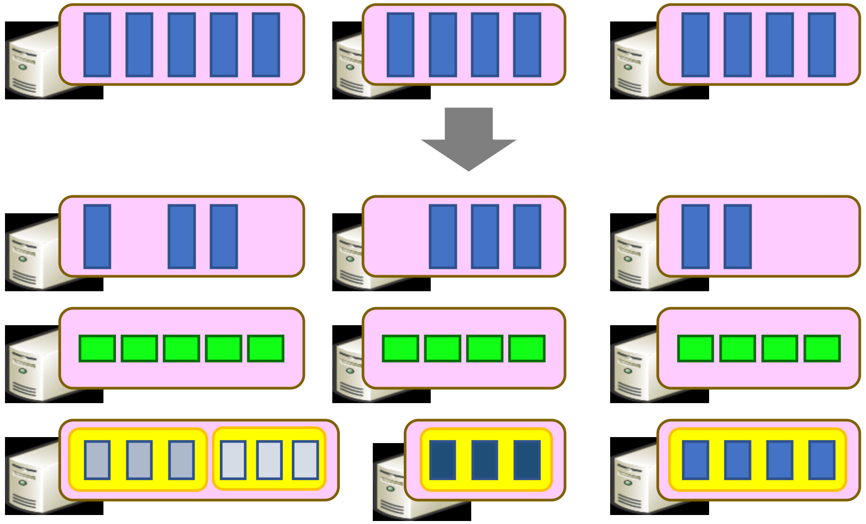
# Programming Model

Where

Select

GroupBy

OrderBy



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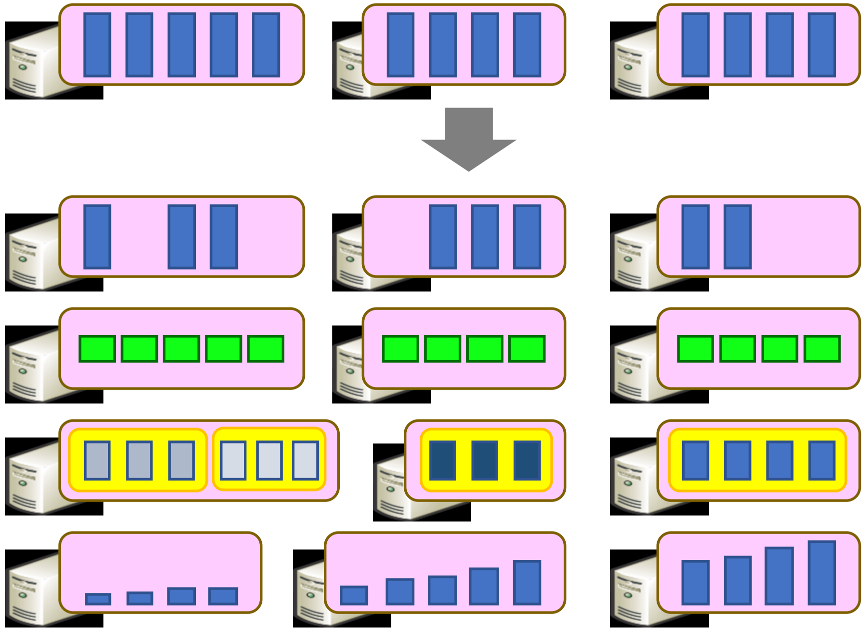


Where

Select

GroupBy

OrderBy

# Programming Model

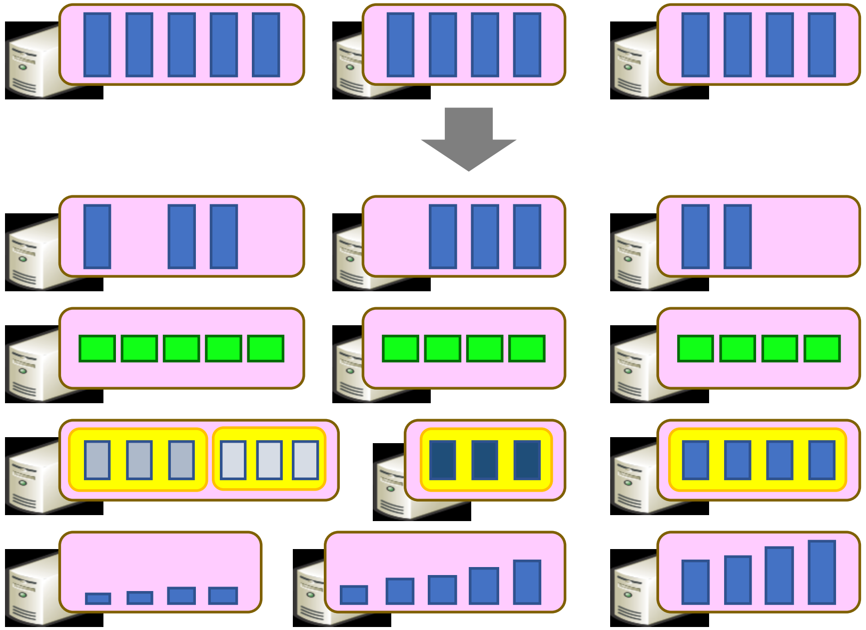
Where

Select

GroupBy

OrderBy

Aggregate



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Where

Select

GroupBy

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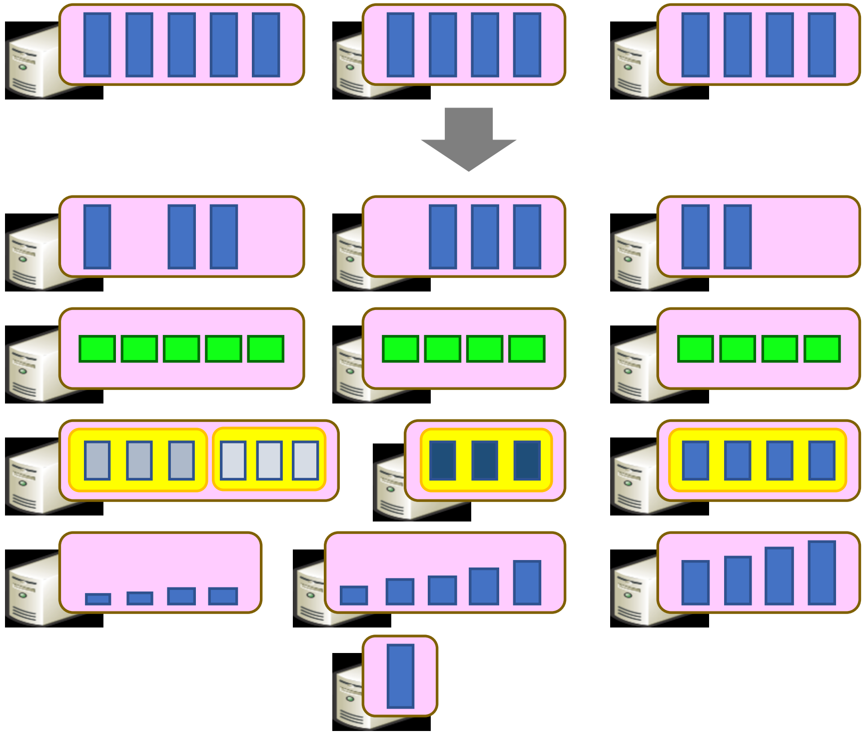
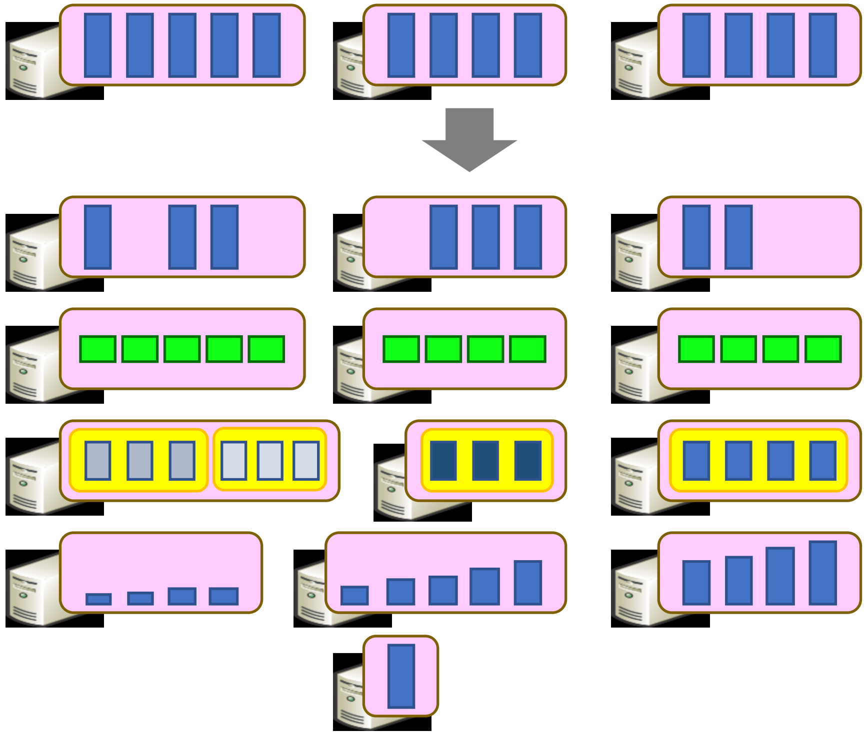


# Programming Model

Where
Select
GroupBy
OrderBy
Aggregate
Join



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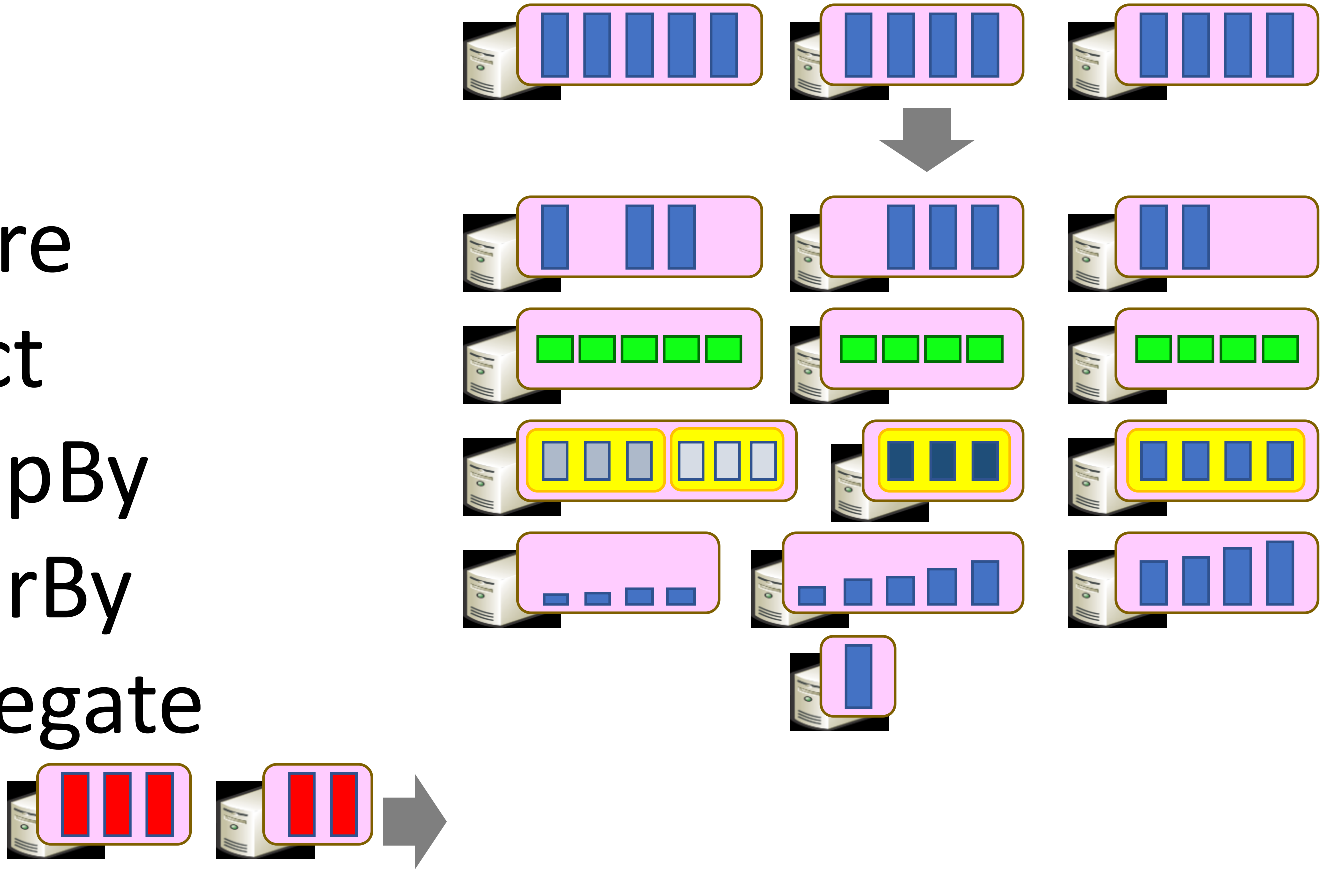
Join



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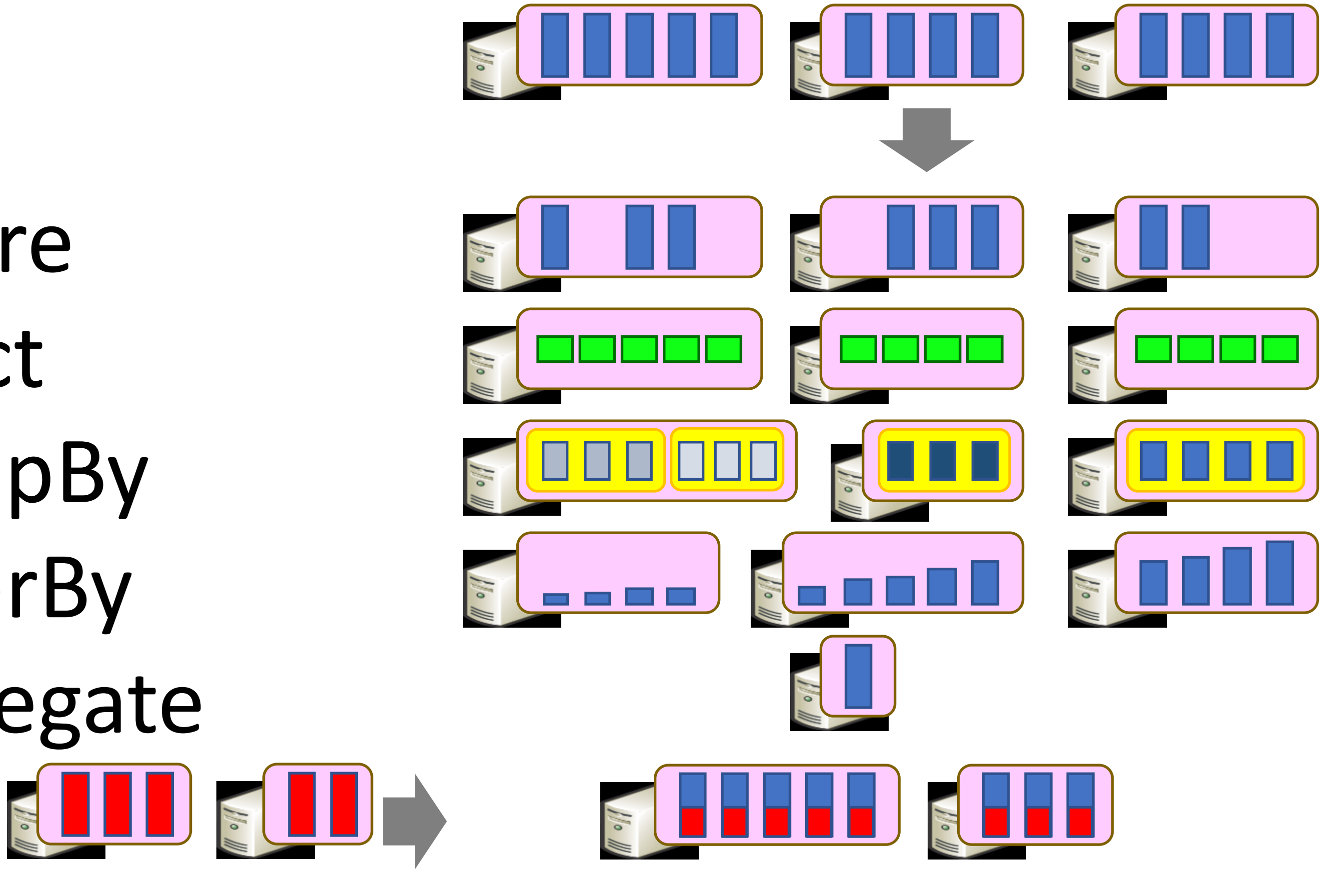


# Programming Model

Where

Select

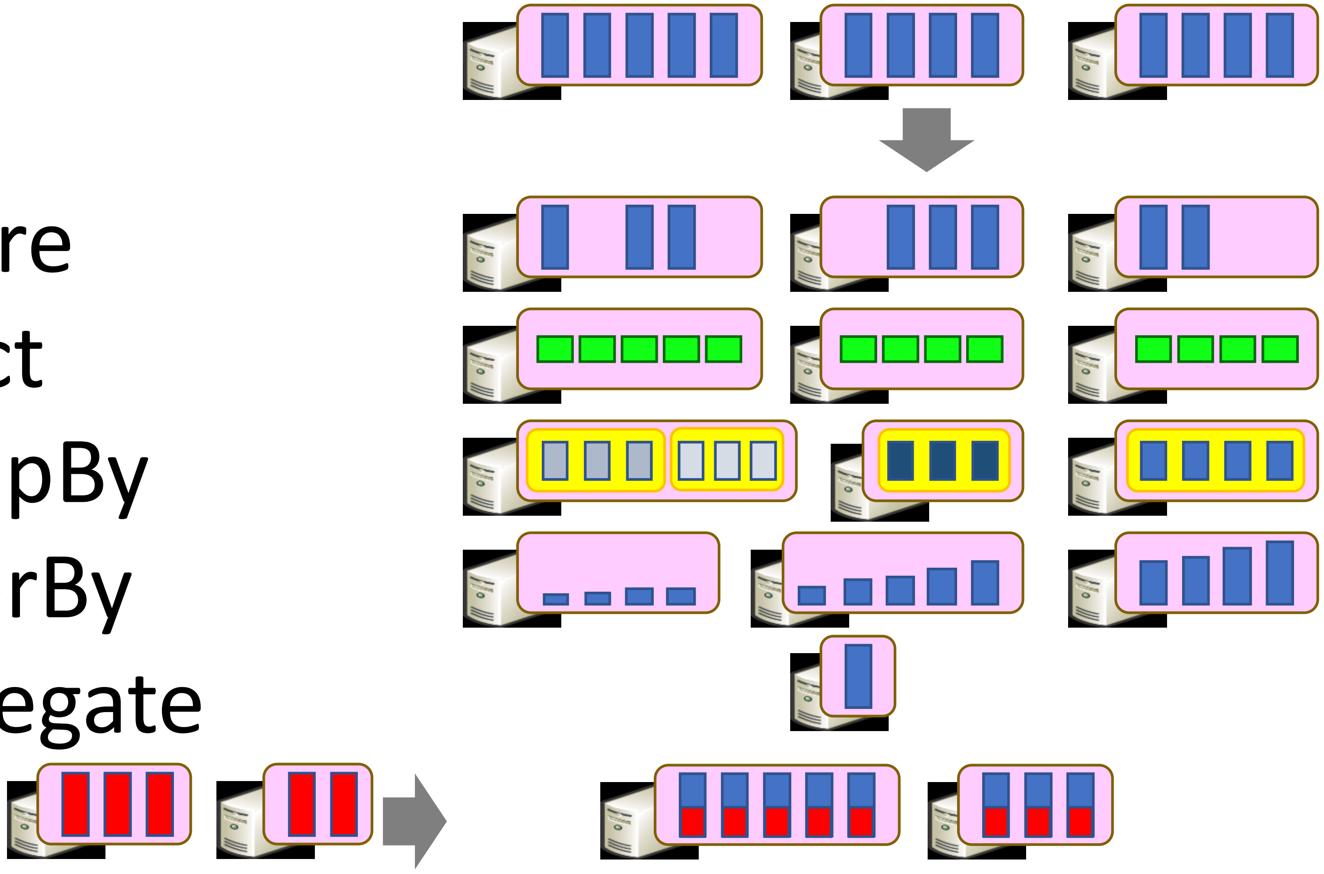
GroupBy

OrderBy

Aggregate

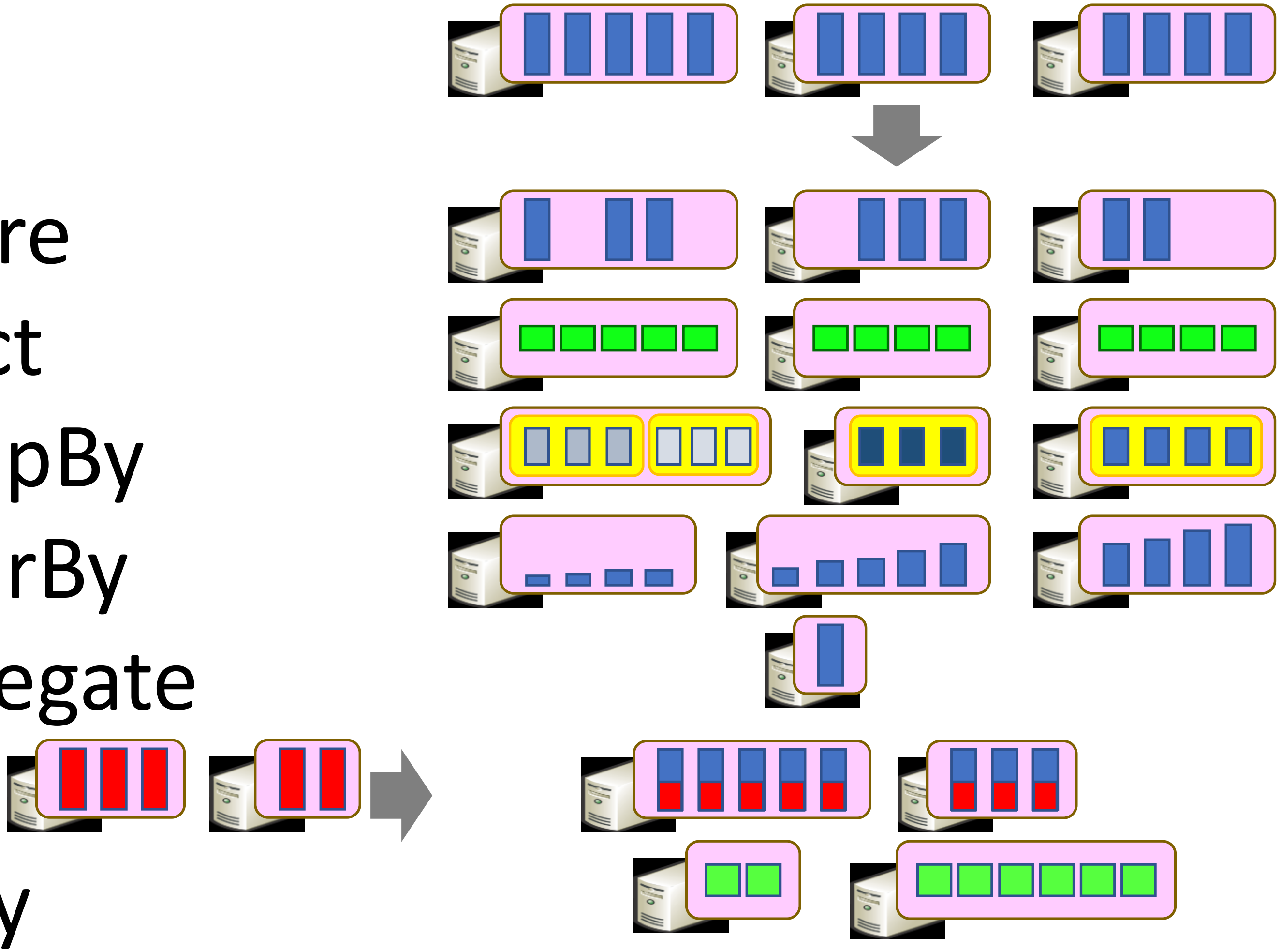
Join

Apply



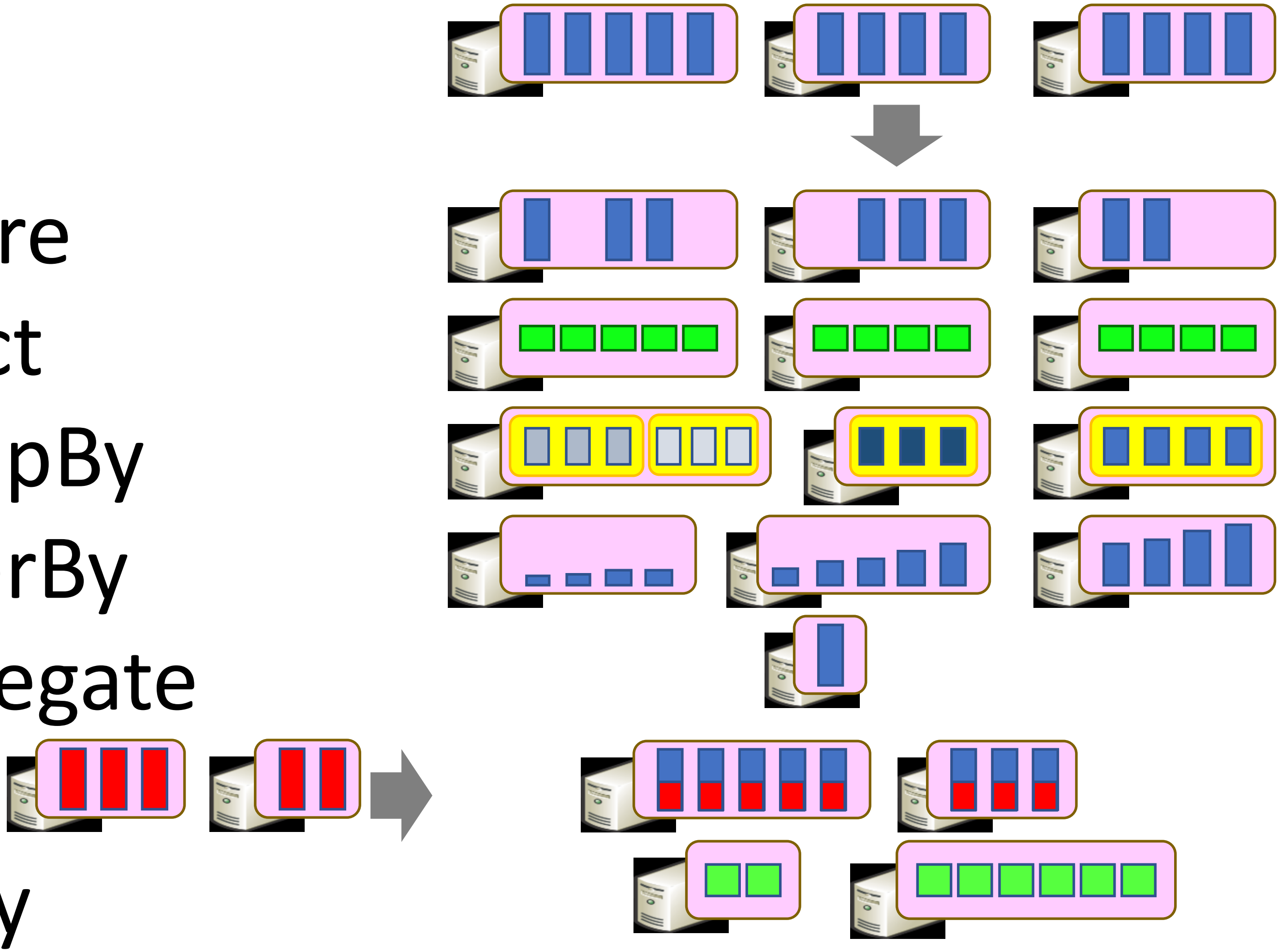
# Programming Model

Where
Select
GroupBy
OrderBy
Aggregate
Join
Apply



# Programming Model

Where
Select
GroupBy
OrderBy
Aggregate
Join
Apply
Materialize



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Where
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GroupBy
OrderBy
Aggregate
Join
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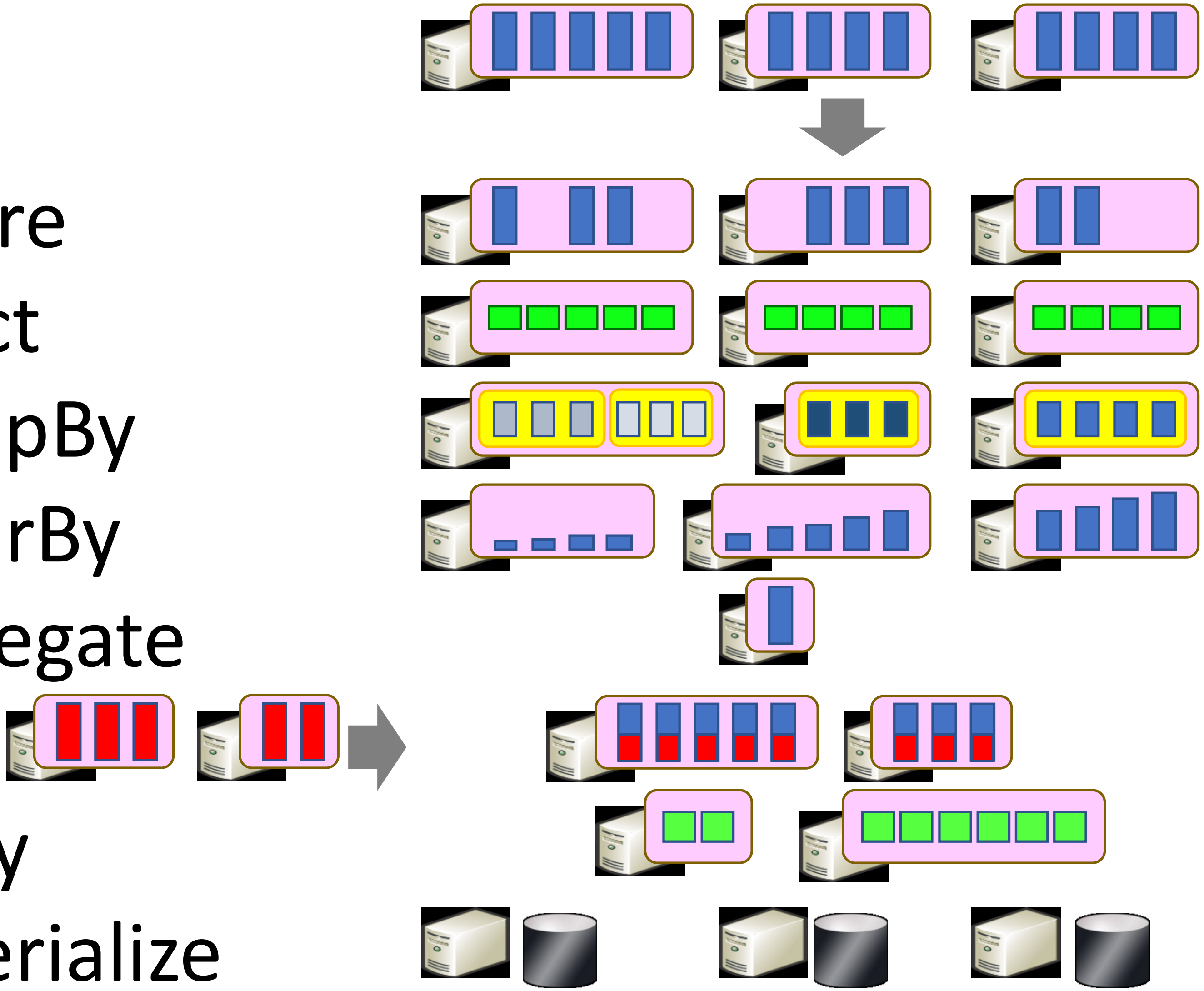
Materialize



# Example: Histogram

```
public static IQueryable<Pair> Histogram(
      IQueryable<LineRecord> input, int k)
{
    var words = input.SelectMany(x => x.line.Split(' '));
    var groups = words.GroupBy(x => x);
    var counts = groups.Select(x => new Pair(x.Key, x.Count()));
    var ordered = counts.OrderByDescending(x => x.count);
    var top = ordered.Take(k);
    return top;
}
```

| |
|---|
| "A line of words of wisdom" |
| ["A", "line", "of", "words", "of", "wisdom"] |
| [["A"], ["line"], ["of", "of"], ["words"], ["wisdom"]] |
| [ {"A", 1}, {"line", 1}, {"of", 2}, {"words", 1}, {"wisdom", 1}] |
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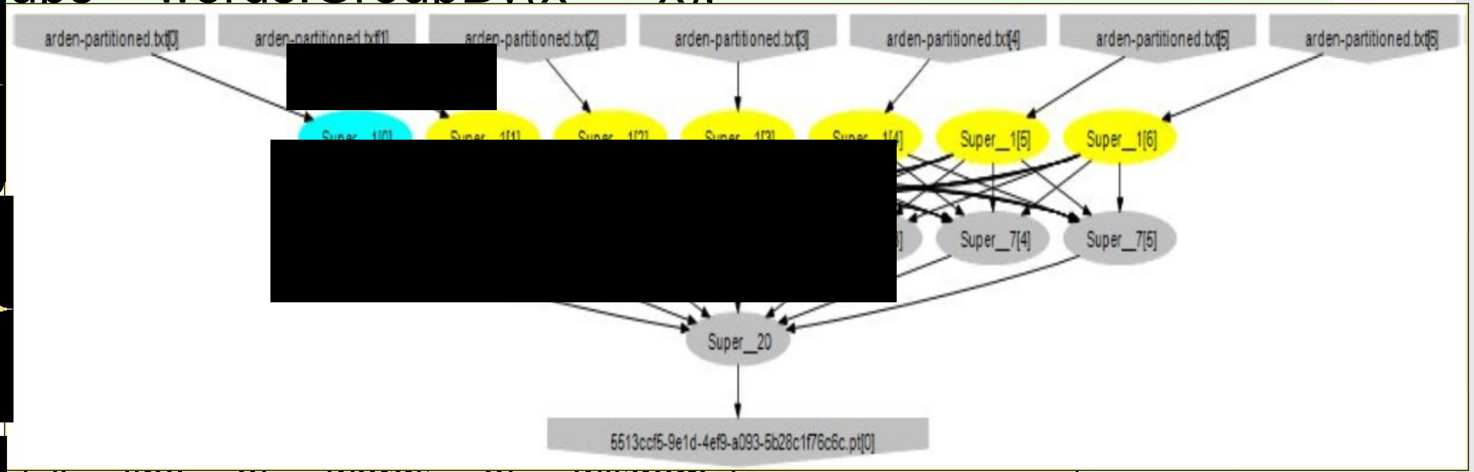
SelectMany
Sort
GroupBy+Select
HashDistribute

MergeSort
GroupBy
Select
Sort
Take

MergeSort
Take




| |
|---|
| [“A”, “line”, “of”, “words”, “of”, “wisdom”] |
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# RDDs

- Immutable, partitioned, logical collection of records
  - Need not be materialized
  - contains information to rebuild a dataset
- Partitioning can be based on a key
- Built using bulk transformations on other RDDs
- Can be cached for future reuse

# RDDs

- Immutable, partitioned, logical collection of records
  - Need not be materialized
  - build a dataset
  - on a key
  - ations on other RDDs
  - reuse

Transformations
(define a new RDD)

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

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**(define a new RDD)**

map
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union
groupByKey
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…

**Parallel operations**
**(return a result to driver)**

reduce
collect
count
save
lookupKey
…

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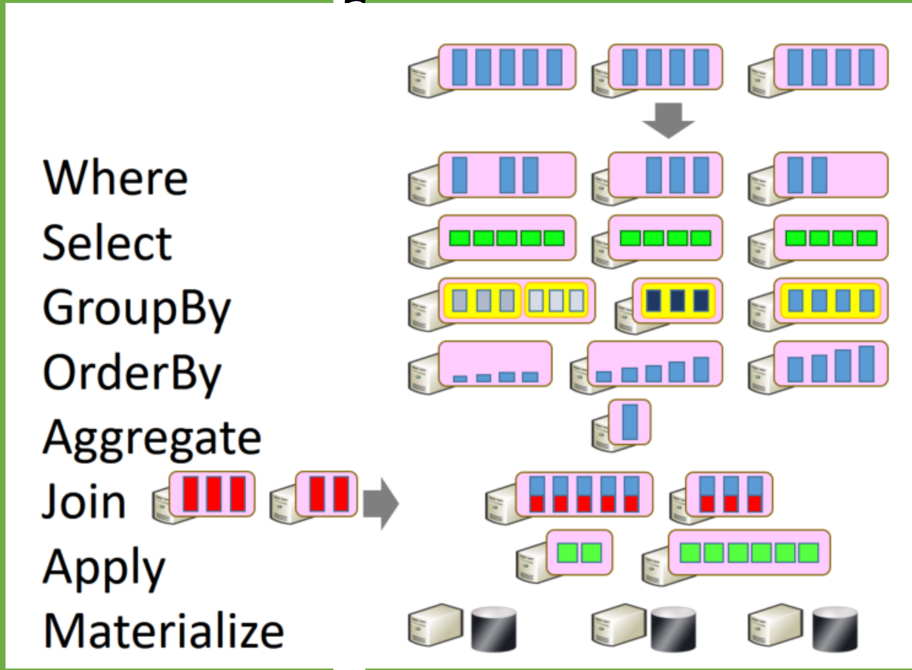
reduce



# 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) |

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| | | | | | | |
|---|---|---|---|---|---|---|
| 10 | 30 | 20 | 10 | 20 | 30 | 10 |

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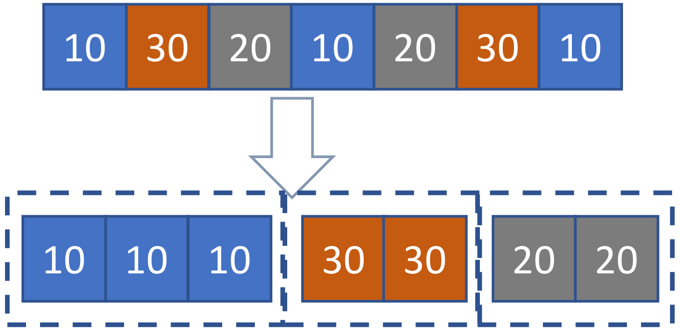

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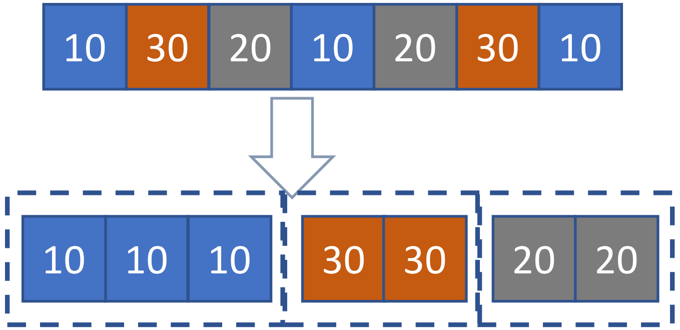


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foreach(T elem in ints)
{
   key   = KeyLambda(elem);

   group = GetGroup(key);

   group.Add(elem);
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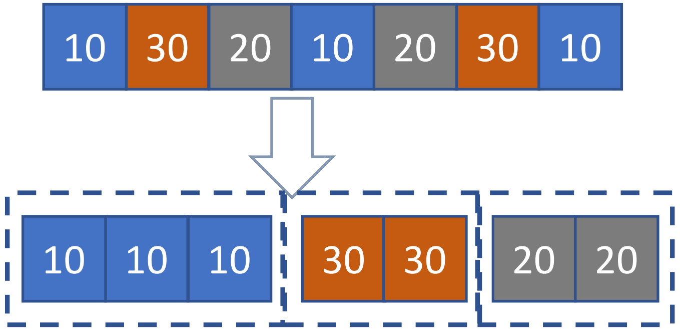


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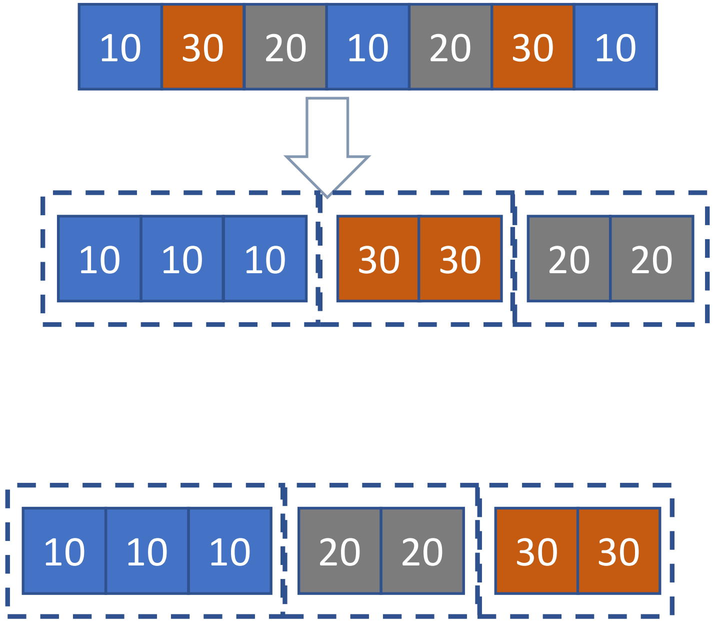


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- Where is the aggregate in this example?
- Is the DBMS analogy clear?

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