Big Data Analytics
Map-Reduce and Spark

Slides by:

Joseph E. Gonzalez

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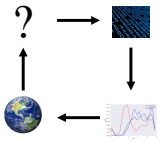


Data in the Organization
A little bit of buzzword bingo!

Inventory

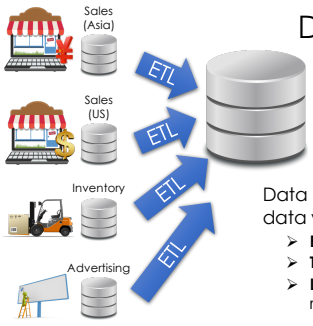
It is tempting to think of data as being organized in a single source-of-truth database.

Operational Data Stores

- Capture **the now**
- Many different databases across an organization
- Mission critical … be careful!
  - Serving live ongoing business operations
  - Managing inventory
- Different formats (e.g., currency)
  - Different schemas (acquisitions …)
- Live systems often don't maintian history

We would like a consolidated, clean, historical snapshot of the data.

Data Warehouse



Collects and organizes historical data from multiple sources

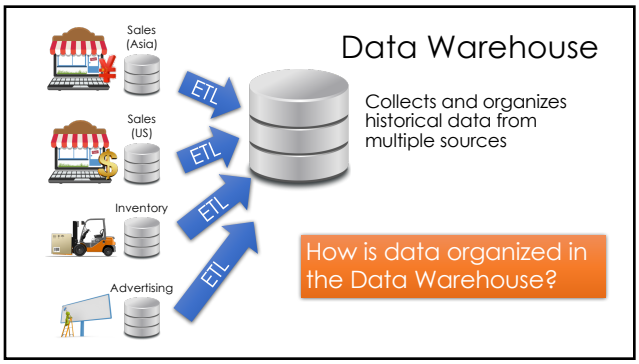
Data is *periodically* **ETL**ed into the data warehouse:

- **Extracted** from remote sources
- **Transformed** to standard schemas
- **Loaded** into the (typically) relational (SQL) data system

Extract → Transform → Load (ETL)

Extract & Load: provides a snapshot of operational data
- Historical snapshot
- Data in a single system
- Isolates analytics queries (e.g., Deep Learning) from business critical services (e.g., processing user purchase)
- Easy!

Transform: clean and prepare data for analytics in a unified representation
- **Difficult** → often requires specialized code and tools
- Different schemas, encodings, granularities



Example Sales Data

pname	category	price	qty	date	day	city	state	country
Corn	Food	25	25	3/30/16	Wed.	Omaha	NE	USA
Corn	Food	25	8	3/31/16	Thu.	Omaha	NE	USA
Corn	Food	25	15	4/1/16	Fri.	Omaha	NE	USA
Galaxy 1	Phones	18	30	3/30/16	Wed.	Omaha	NE	USA
Galaxy 1	Phones	18	20	3/31/16	Thu.	Omaha	NE	USA
Galaxy 1	Phones	18	50	4/1/16	Fri.	Omaha	NE	USA
Galaxy 1	Phones	18	8	3/30/16	Wed.	Omaha	NE	USA
Peanuts	Food	2	45	3/31/16	Thu.	Seoul		Korea

- **Big** table: many *columns* and *rows*
  - Substantial redundancy → expensive to store and access
- Could we organize the data more efficiently?

Multidimensional Data Model

Sales **Fact Table**

pid	timeid	locid	sales
11	1	1	25
11	2	1	8
11	3	1	15
12	1	1	30
12	2	1	20
12	3	1	50
12	1	1	8
13	2	1	10
13	3	1	10
11	1	2	35
11	2	2	22
11	3	2	10
12	1	2	26

Locations

locid	city	state	country
1	Omaha	Nebraska	USA
2	Seoul		Korea
5	Richmond	Virginia	USA

Products

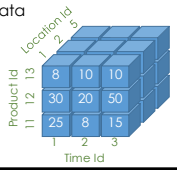
pid	pname	category	price
11	Corn	Food	25
12	Galaxy 1	Phones	18
13	Peanuts	Food	2

Time

timeid	Date	Day
1	3/30/16	Wed.
2	3/31/16	Thu.
3	4/1/16	Fri.

Dimension Tables

- Multidimensional "Cube" of data



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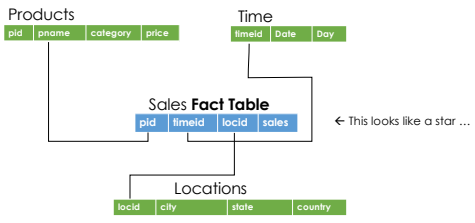
Dimension Tables

- Normalized Representation
- Fact Table
  - minimizes redundant info.
  - Reduces data errors
- Dimensions
  - easy to manage and summarize
  - Rename: Galaxy1 → Phablet
- How do we do analysis?
  - **Joins!!!!**

The Star Schema



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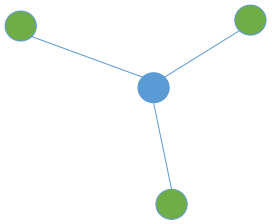

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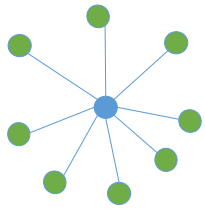
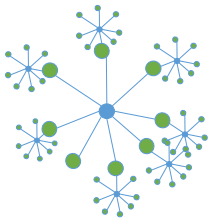


← This looks like a star …

The Snowflake Schema



← This looks like a snowflake …?

Data Warehouse

Collects and organizes historical data from multiple sources

How is data organized in the Data Warehouse?

Star Schemas

Data Warehouse

Collects and organizes historical data from multiple sources

- How do we deal with semi-structured and unstructured data?
- Do we really want to force a schema on load?

Data Warehouse

Collects and organizes historical data from multiple sources

How do we load and process this data in a relational system?

Depends on use …
Can be difficult …
Requires thought …

Data Lake*

Store a copy of all the data

- in one place
- in its original "natural" form

Enable data consumers to choose how to transform and use data.

- *Schema on Read*

Enabled by new Tools:
Map-Reduce & Distributed Filesystems

What could go wrong?

*Still being defined…(Buzzword Disclaimer)

The Dark Side of Data Lakes

- Cultural shift: *Curate → Save Everything!*
  - Noise begins to dominate signal
- Limited data governance and planning
  - **Example:** *hdfs://important/joseph_big_file3.csv_with_json*
  - **What** does it contain?
  - **When** and **who** created it?
- No cleaning and verification → lots of dirty data
- New tools are more complex and old tools no longer work

Enter the data scientist

A Brighter Future for Data Lakes

Enter the data scientist

- Data scientists bring new skills
  - Distributed data processing and cleaning
  - Machine learning, computer vision, and statistical sampling
- Technologies are improving
  - SQL over large files
  - Self describing file formats & catalog managers
- Organizations are evolving
  - Tracking data usage and file permissions
  - Data engineers and managers

Distributed File Systems
Storing very large files

Fault Tolerant Distributed File Systems (e.g., HDFS)

How do we **store** and **access** very **large files** across **cheap** commodity devices ?

[Ghemawat et al., SOSP'03]

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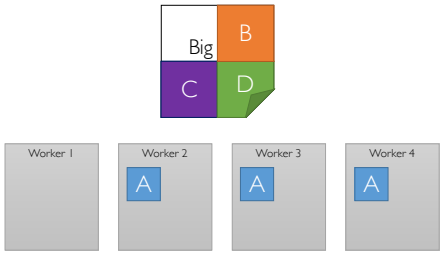

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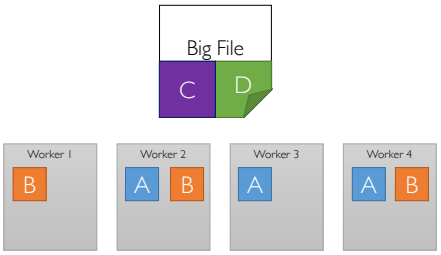

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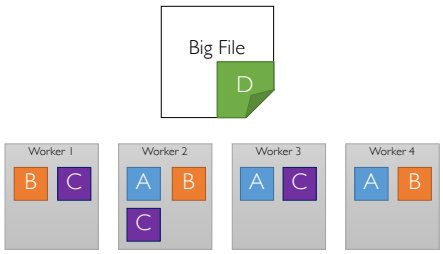

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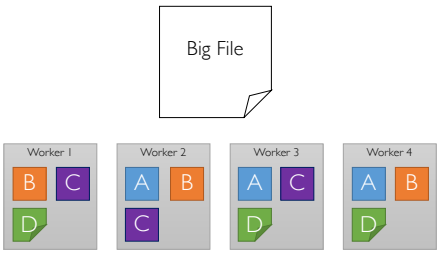
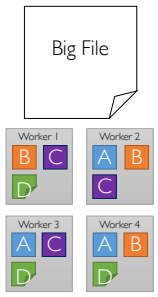


[Ghemawat et al., SOSP'03]

Fault Tolerant Distributed File Systems (e.g., HDFS)

- Split large files over multiple machines
  - Easily support very massive files spanning
- Read parts of file in parallel
  - Fast reads of large files
- Often built using cheap commodity storage devices

Cheap commodity storage devices will fail!



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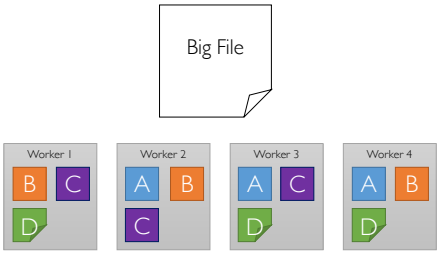

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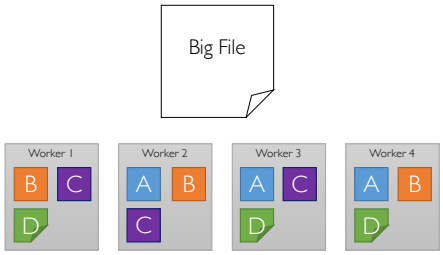
Fault Tolerant Distributed File Systems
Failure Event



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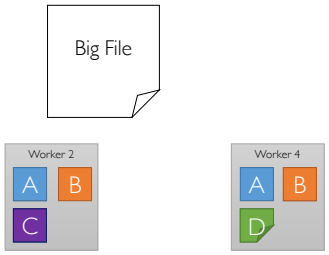

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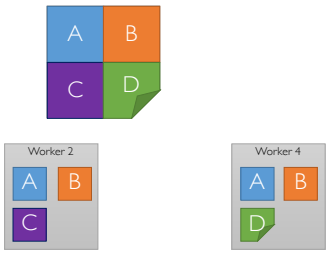

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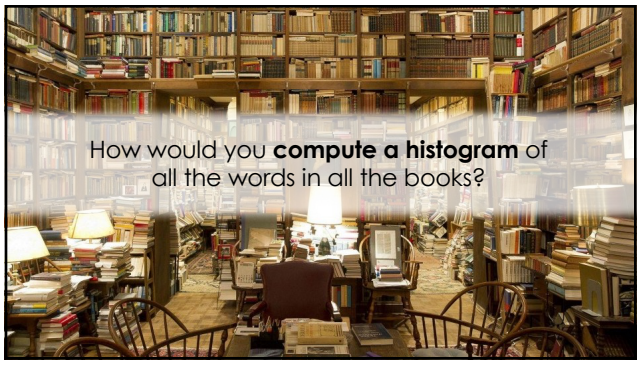
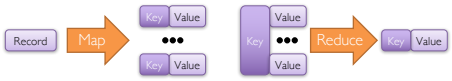
Map-Reduce Distributed Aggregation

Computing are very large files



The Map Reduce Abstraction



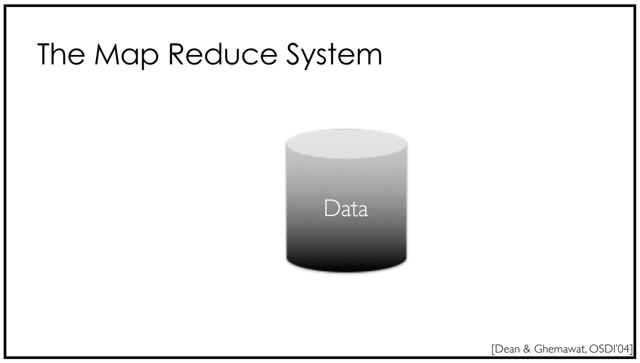
Example: *Word-Count*

```
Map(docRecord) {
  for (word in docRecord) {
    emit (word, 1)
  }
}
```

```
Reduce(word, counts) {
  emit (word, SUM(counts))
}
```

Map: Idempotent
Reduce: Commutative and Associative

[Dean & Ghemawat, OSDI'04]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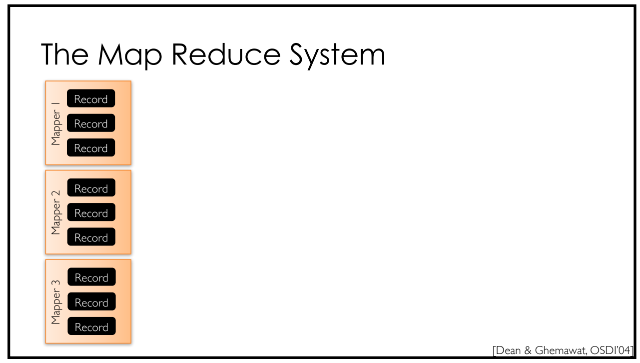
[Dean & Ghemawat, OSDI'04]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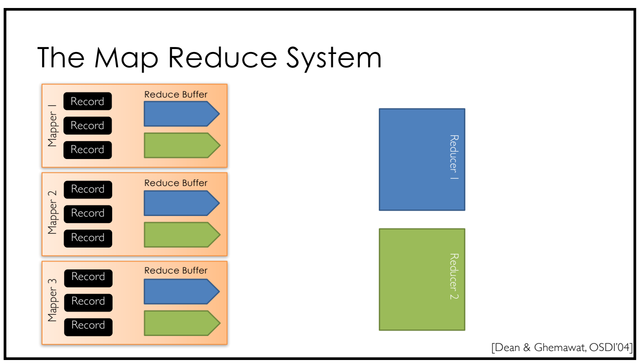
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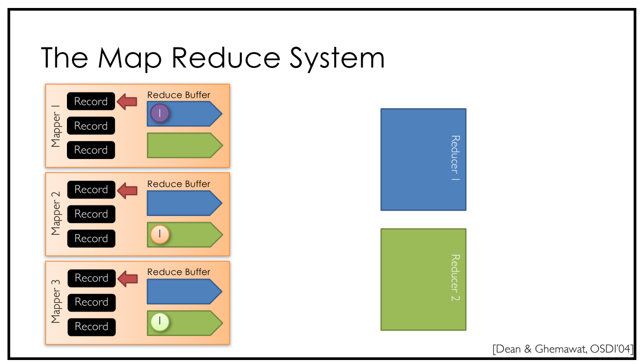
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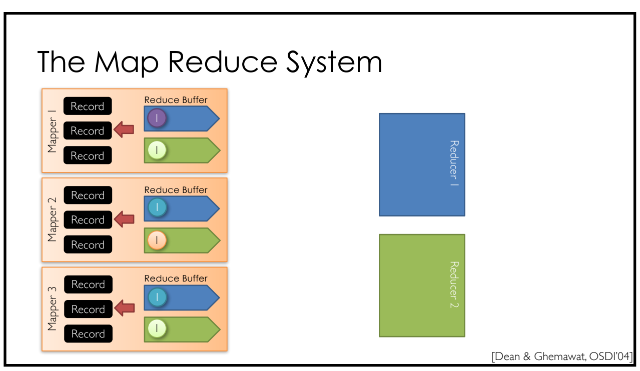
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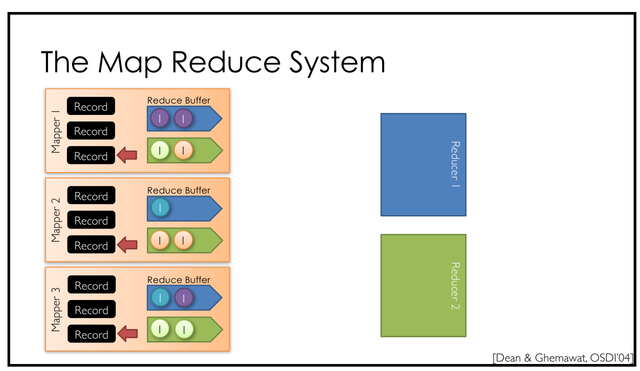
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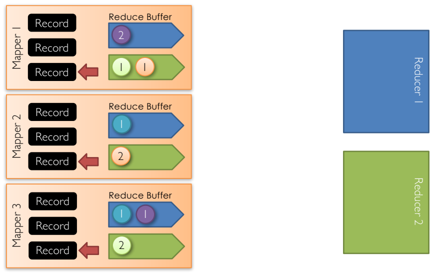

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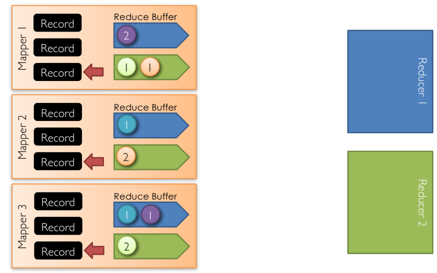

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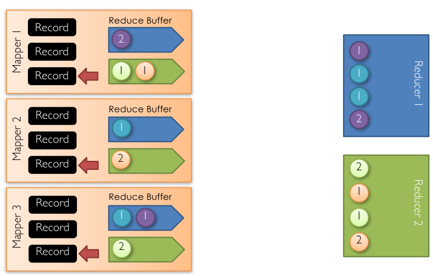

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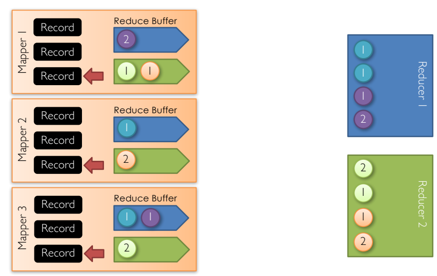

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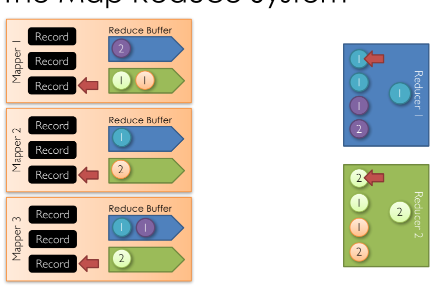

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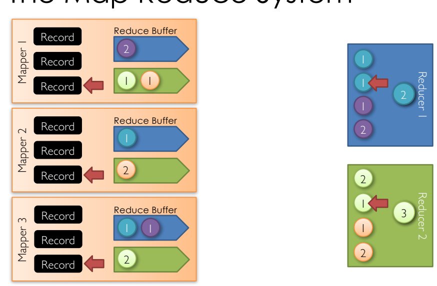

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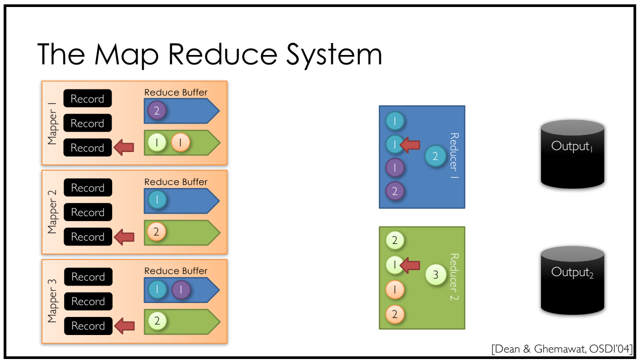
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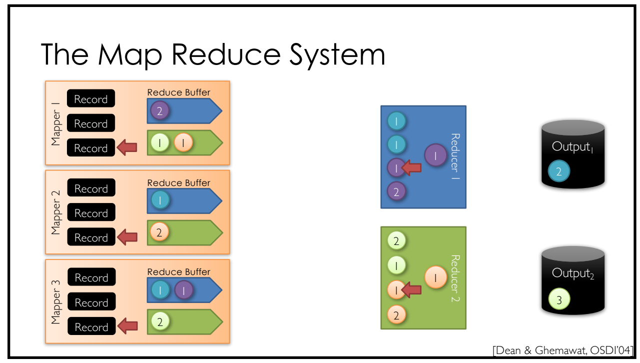
[Dean & Ghemawat, OSDI'04]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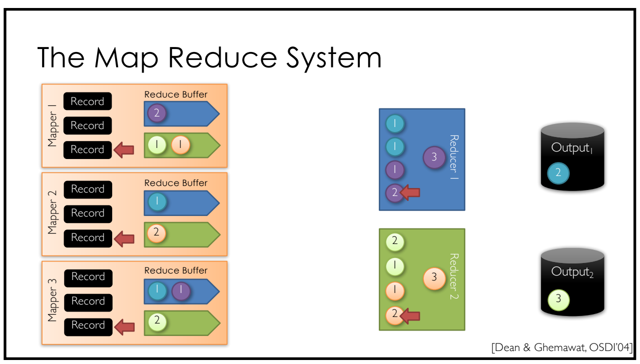
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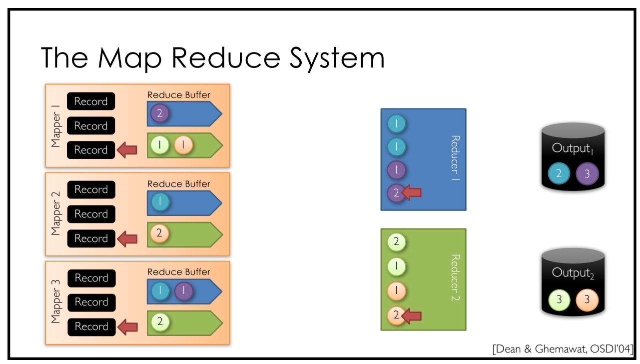
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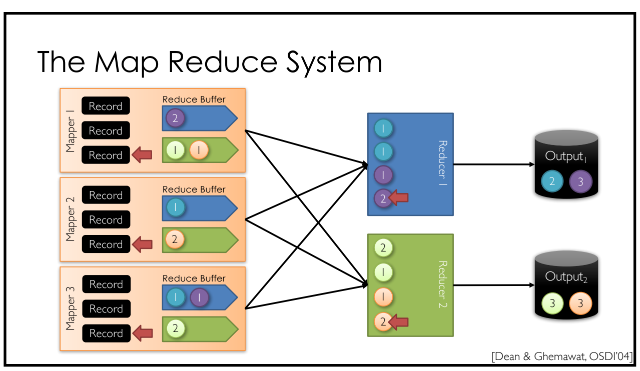
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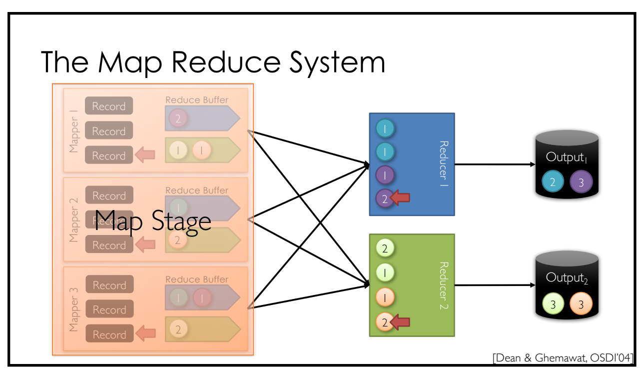
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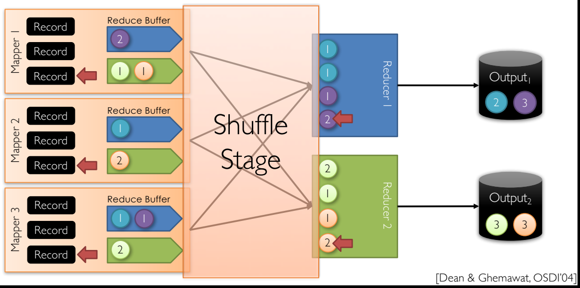

[Dean & Ghemawat, OSDI'04]

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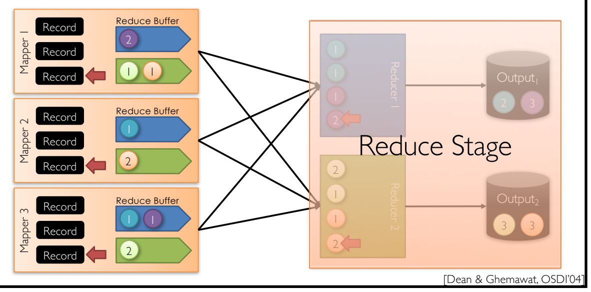
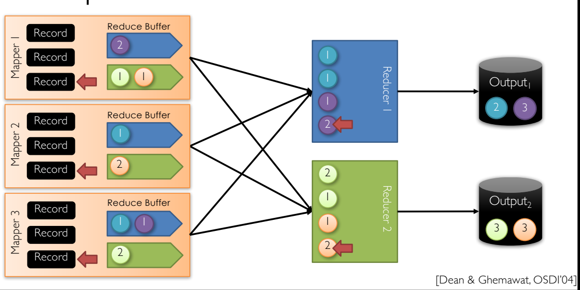


[Dean & Ghemawat, OSDI'04]

The Map Reduce: **Fault Tolerance**



[Dean & Ghemawat, OSDI'04]

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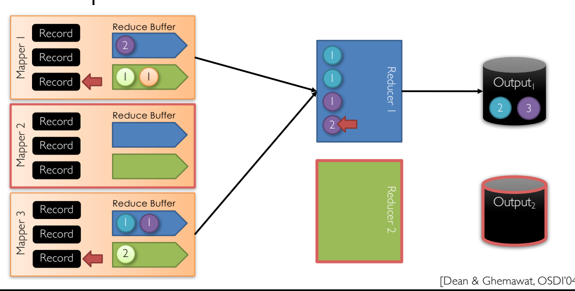

[Dean & Ghemawat, OSDI'04]

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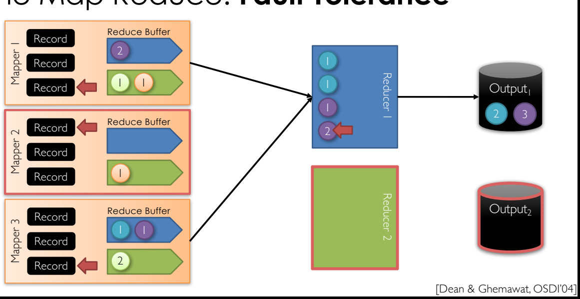

[Dean & Ghemawat, OSDI'04]

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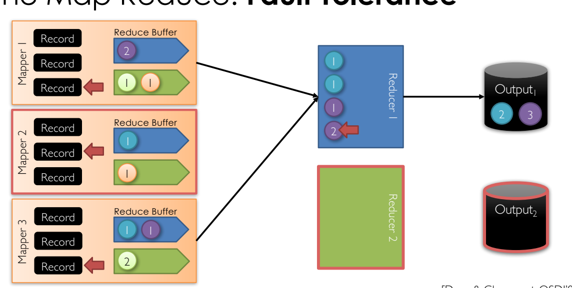

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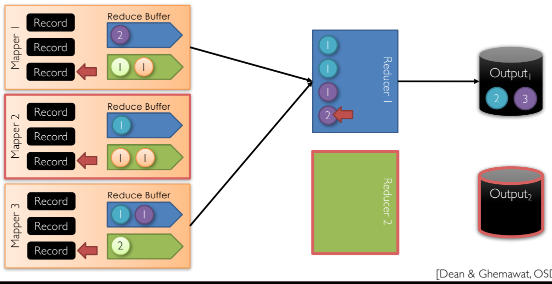

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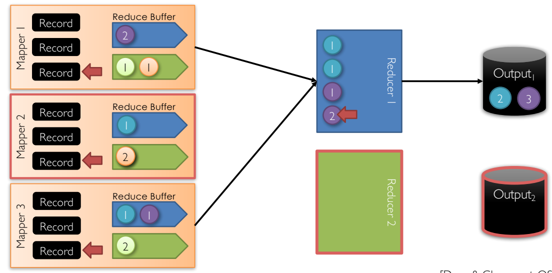

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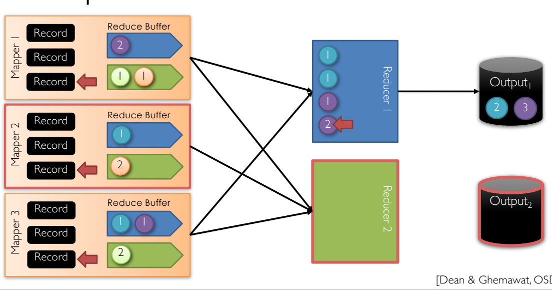

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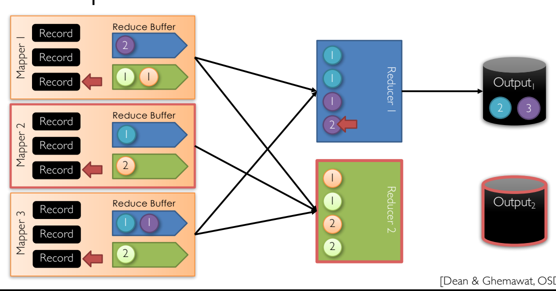

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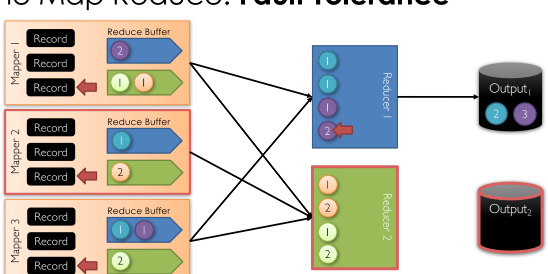

[Dean & Ghemawat, OSDI'04]

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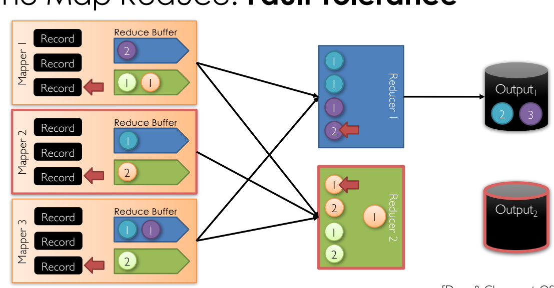

[Dean & Ghemawat, OSDI'04]

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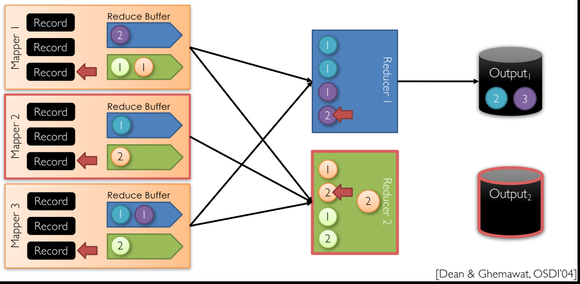

[Dean & Ghemawat, OSDI'04]

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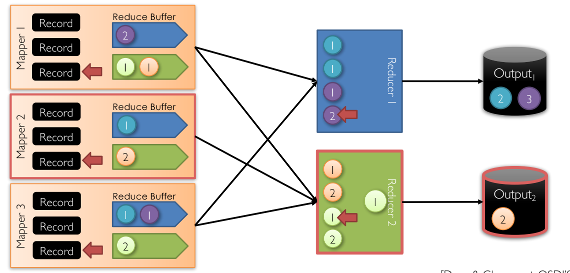

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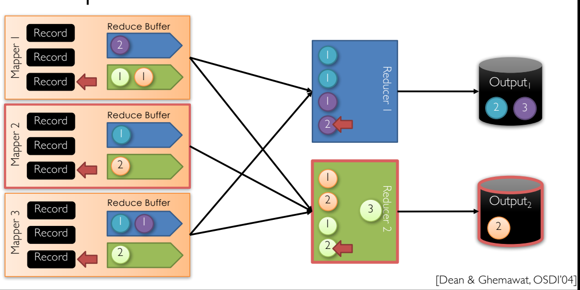

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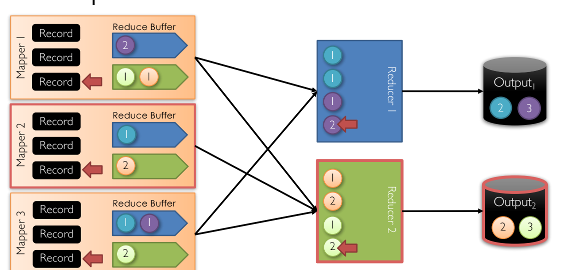
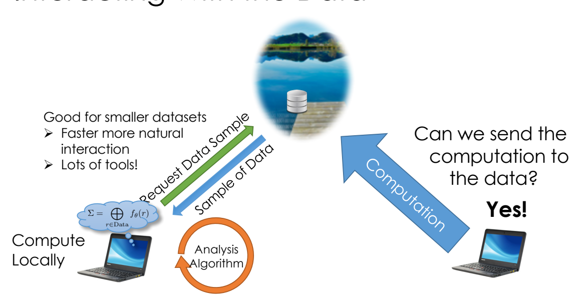


[Dean & Ghemawat, OSDI'04]

Interacting with Data @ Scale

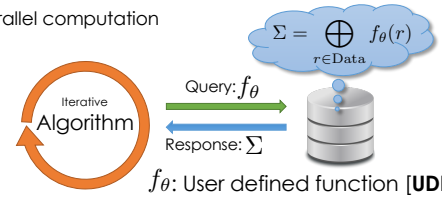
Map-Reduce

Interacting With the Data



Statistical Query Pattern
Common Machine Learning Pattern

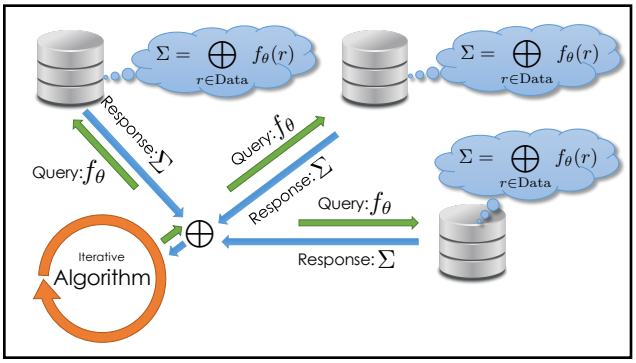
- Computing aggregates of user defined functions
- Data-Parallel computation



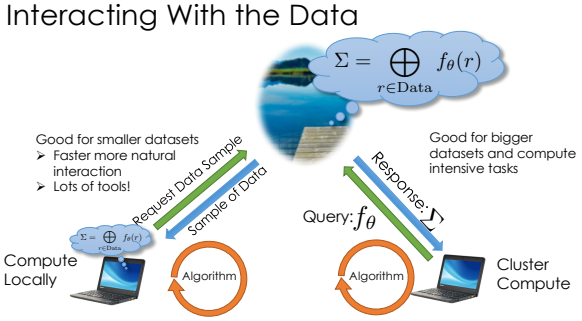
f_θ: User defined function [**UDF**]

$\bigoplus$: User defined aggregate [**UDA**]

D. Caragea et al., A Framework for Learning from Distributed Data Using Sufficient Statistics and Its Application to Learning Decision Trees, Int. J. Hybrid Intell. Syst. 2004



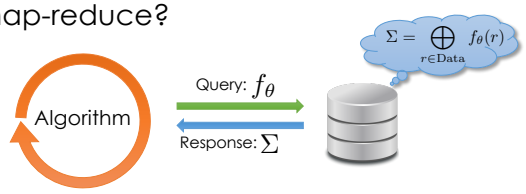
Interacting With the Data



Can we compute

$$\hat{\theta} = (X^T X)^{-1} X^T Y$$

using the statistical query pattern in map-reduce?



Can we compute

$$\hat{\theta} = (X^T X)^{-1} X^T Y$$

using the statistical query pattern in map-reduce?

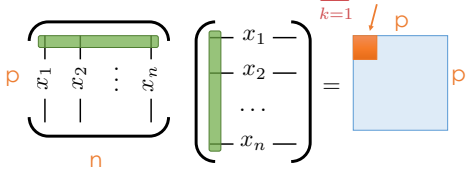
Query 1

Query 2

Break computation into two queries

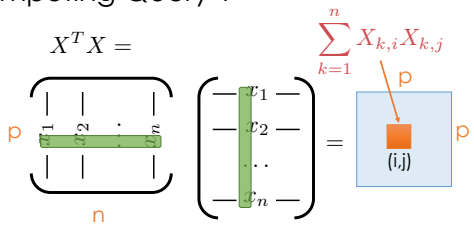
Computing Query 1

$$X^T X = \sum_{k=1}^{n} X_{k,1} X_{k,1}$$



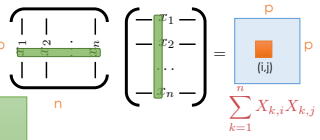
Computing Query 1

$$X^T X = \sum_{k=1}^{n} X_{k,i} X_{k,j}$$



Computing Query 1

$X^T X =$



$\sum_{k=1}^{n} X_{k,i} X_{k,j}$

```
def map_xtx(x, y):
   p = len(x)
   for i in range(p):
      for j in range(p):
         yield ([i,j], x[i] * x[j])
```

```
def sum(k, values):
   return (k, np.sum(values)
```

Computing Query 2 ($X^T Y$)

```
def map_xty(x, y):
   for i in range(len(x)):
      yield (i, x[i] * y[i])
```

```
def sum(k, values):
   return (k, np.sum(values)
```

```
def map_xtx(x, y):
   p = len(x)
   for i in range(p):
      for j in range(p):
         yield ([i,j], x[i] * x[j])
```

```
def map_xty(x, y):
   for i in range(len(x)):
      yield (i, x[i] * y[i])
```

```
def sum(k, values):
   return (k, np.sum(values)
```

$O(nd^2)$ #mappers

Run Locally:

```
XtX_pairs = data.map(map_xtx).reduce(sum)
XtX = np.zeros(p,p)
for ((i,j), v) in XtX_pairs: XtX[i,j] = v
```

```
XtY_pairs = data.map(map_xty).reduce(sum)
XtY = np.zeros(p,1)
for (i,v) in XtY_pairs: XtY[i] = v
```

Algorithm

$O(d^3)$

```
theta = np.linalg.solve(XtX, XtY)
```

Map Reduce Technologies

Hadoop

- First open-source map-reducesoftware system
  - Managed by Apache foundation
- Based on Google's
  - Map-Reduce
  - Google File System
- Several key technologies
  - **HDFS:** Hadoop File System
  - **Yarn:** Yet another resource negotiator
  - **MapReduce:** map-reduce compute framework

Spark

In-Memory Dataflow System

Developed at the UC Berkeley AMP Lab

M. Zaharia, M. Chowdhury, M. J. Franklin, S. Shenker, and I. Stoica. *Spark: cluster computing with working sets.* HotCloud'10

M. Zaharia, M. Chowdhury, T. Das, A. Dave, J. Ma, M. McCauley, M.J. Franklin, S. Shenker, I. Stoica. *Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing.* NSDI'2012

What Is Spark

- Parallel execution engine for big data processing
- **General**: efficient support for multiple workloads
- **Easy** to use: 2-5x less code than Hadoop MR
  - High level API's in Python, Java, and Scala
- **Fast**: up to 100x faster than Hadoop MR
  - Can exploit in-memory when available
  - Low overhead scheduling, optimized engine

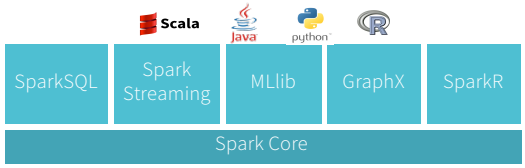
Spark Programming Abstraction

- *Write programs in terms of transformations on distributed datasets*
- Resilient Distributed Datasets (RDDs)
  - Distributed collections of objects that can stored in memory or on disk
  - Built via parallel transformations (map, filter, …)
  - Automatically rebuilt on failure

Slide provided by M. Zaharia

General

- Unifies ***batch, interactive, streaming*** workloads
- Easy to build sophisticated applications
  - Support iterative, graph-parallel algorithms
  - Powerful APIs in Scala, Python, Java, R



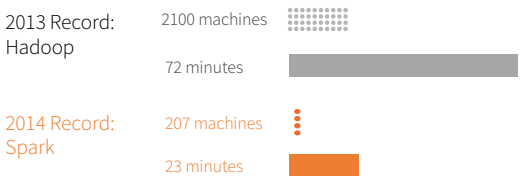
Easy to Write Code

WordCount in 50+ lines of Java MR

```
val f = sc.textFile(inputPath)
val w = f.flatMap(l => l.split(" ")).map(word => (word, 1)).cache()
w.reduceByKey(_ + _).saveAsText(outputPath)
```

WordCount in 3 lines of Spark

Fast: Time to sort 100TB



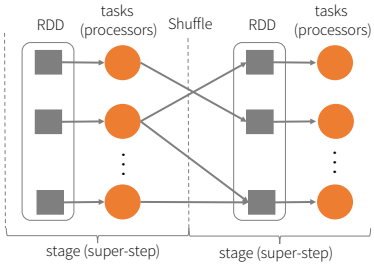
Also sorted 1PB in 4 hours (bottlenecked by network)

Source: Daytona GraySort benchmark, sortbenchmark.org

RDD: Resilient Distributed Datasets

- Collections of objects partitioned & distributed across a cluster
  - Stored in RAM or on Disk
  - Resilient to failures
- Operations
  - Transformations
  - Actions

Spark, as a BSP System



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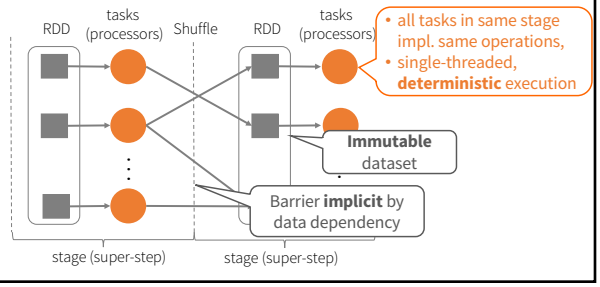

Operations on RDDs

- Transformations f(RDD) => RDD
  - Lazy (not computed immediately)
  - E.g., "map", "filter", "groupBy"
- Actions:
  - Triggers computation
  - E.g. "count", "collect", "saveAsTextFile"

Example: Log Mining

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

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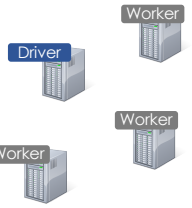
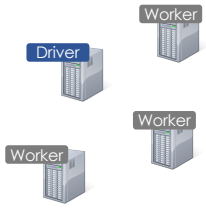


Example: Log Mining

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

```
lines = spark.textFile("hdfs://...")
```

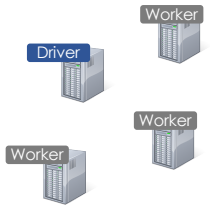


Example: Log Mining

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

Base RDD

```
lines = spark.textFile("hdfs://...")
```



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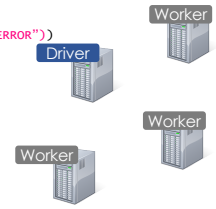
```
lines = spark.textFile("hdfs://...")
errors = lines.filter(lambda s: s.startswith("ERROR"))
```



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

Transformed RDD

```
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```

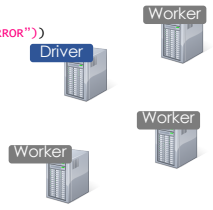

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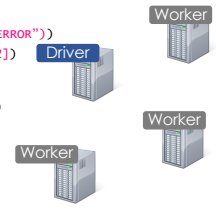
```
lines = spark.textFile("hdfs://...")
errors = lines.filter(lambda s: s.startswith("ERROR"))
messages = errors.map(lambda s: s.split("\t")[2])
messages.cache()

messages.filter(lambda s: "mysql" in s).count()
```



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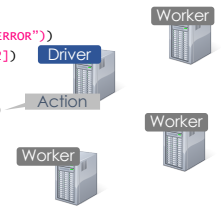
Action



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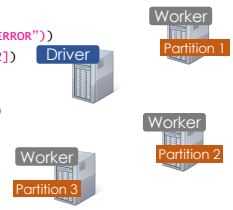

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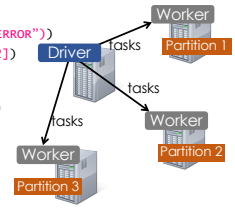

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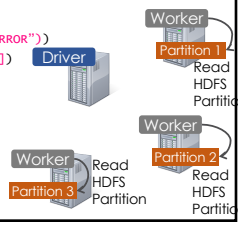

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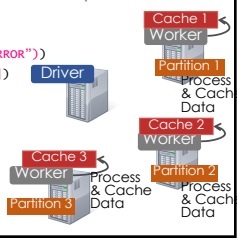

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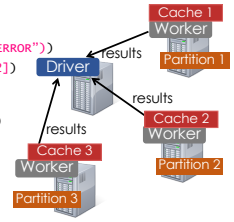

Example: Log Mining

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

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lines = spark.textFile("hdfs://...")
errors = lines.filter(lambda s: s.startswith("ERROR"))
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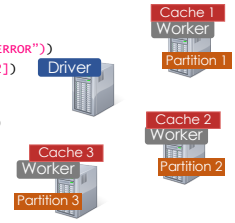

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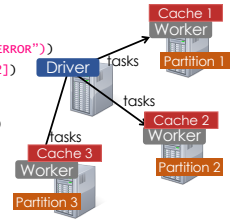

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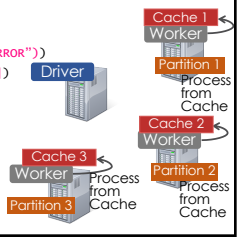

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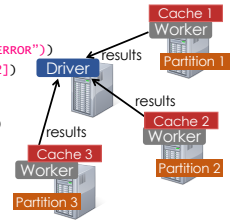

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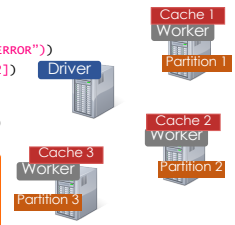

Cache your data → Faster Results

Full-text search of Wikipedia

- 60GB on 20 EC2 machines
- 0.5 sec from mem vs. 20s for on-disk

Abstraction: *Dataflow Operators*

map	reduce	sample
filter	count	take
groupBy	fold	first
sort	reduceByKey	partitionBy
union	groupByKey	mapWith
join	cogroup	pipe
leftOuterJoin	cross	save
rightOuterJoin	zip	...

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Language Support

Python

```
lines = sc.textFile(...)
lines.filter(lambda s: "ERROR" in s).count()
```

Scala

```
val lines = sc.textFile(...)
lines.filter(x => x.contains("ERROR")).count()
```

Java

```
JavaRDD<String> lines = sc.textFile(...);
lines.filter(new Function<String, Boolean>() {
  Boolean call(String s) {
    return s.contains("error");
  }
}).count();
```

Standalone Programs

Python, Scala, & Java

Interactive Shells

Python & Scala

Performance

Java & Scala are faster due to static typing

K-Means +

How do we run k-means on the data warehouse / data lake?

Can we express K-Means in the **Statistical Query Pattern?**

```
centers ← pick k initial Centers
while (centers are changing):
    // Compute the assignments (E-Step)
    asg ← [(x, nearest(centers, x)) for x in data]
    for i in range(k): // Compute the new centers (M-Step)
        centers[i] = mean([x for (x, c) in asg if c == i])
```

Query returns all the data ...

Merge with M-Step → **Statistical Query Pattern**

```
centers ← pick k initial Centers
while (centers are changing):
    for i in range(k):
        new_centers[i] =
            mean([x for x in data if nearest(centers, x) == i])
    centers = new_centers
```

K-Means in Map-Reduce (for HW)

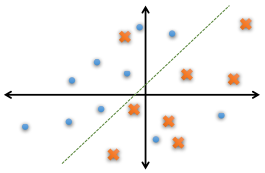
- **MapFunction**(*old_centers, x*)
  - Compute the index of the nearest old center
  - Return (**key** = *nearest_centers*, **value** = (x, 1))
- **ReduceFunction** combines values and counts
  - For each cluster center (Group By)
- Data system returns aggregate statistics:

$$s_i = \sum_{x \in \text{Cluster } i} x_i \qquad \text{and} \qquad n_i = \sum_{x \in \text{Cluster } i} 1$$

- ML algorithm computes new centers: $\mu_i = s_i / n_i$

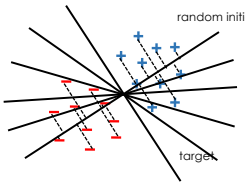
Not Covered In Class

Logistic Regression?



Logistic Regression

Iterative batch gradient descent.

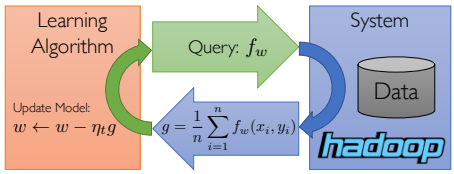


Slide provided by M. Zaharia

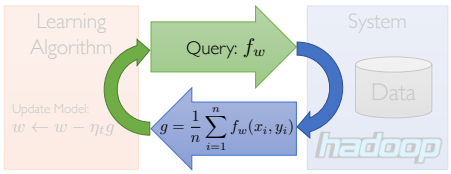
Logistic Regression in Map-Reduce

- Gradient descent:

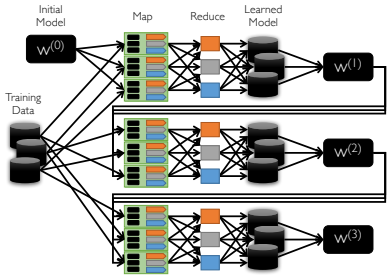
$$f_\theta(x, y) = \nabla_\theta \left(-\log \mathcal{L}\left(\theta; (x, y)\right)\right)$$



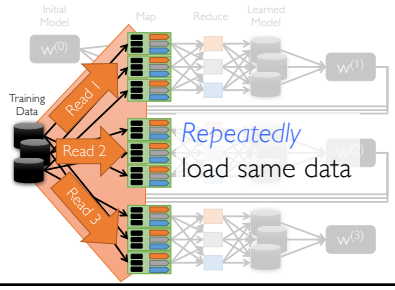
Map-Reduce is not optimized for iteration and multi-stage computation



Iteration in Map-Reduce



Cost of Iteration in Map-Reduce



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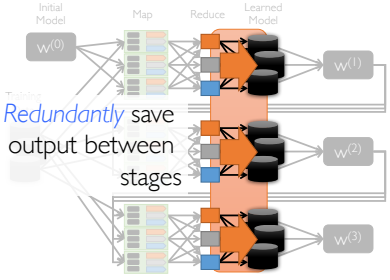
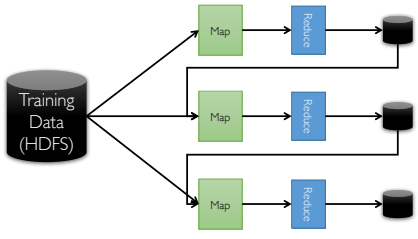
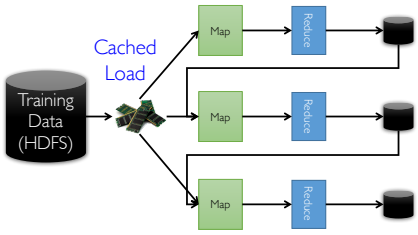


Dataflow View



Memory Opt. Dataflow



10-100× faster than network and disk

Memory Opt. Dataflow View