Data Collection, Storage, Management, and Processing

(*centralized* and *distributed*)

GE461 - Introduction to Data Science

Spring 2022

Last update: Feb 18, 2022

Outline

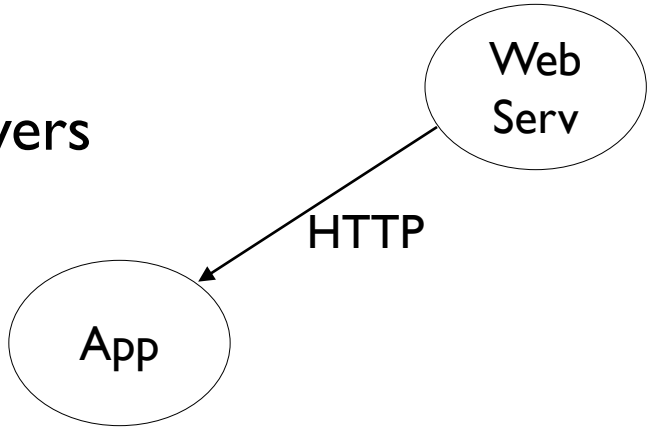
- Getting data
- Storing data
- Data management
- RDBMs and SQL
- Pandas
- Other data models
- Key-Value Stores and Column Stores
- Distributed storage
- Parallel processing frameworks
  - MapReduce
  - Spark

Getting data

- Download file (simply via browser)
  - Various formats (txt, binary, CSV, JSON, XMLS, xls,…)
- Web scraping via programs
- Query data from a database (DB) via a client program
  - Issue SQL requests to a DB server
- Query an API (usually web based) via a client program
  - REST API
  - SOA (service oriented architecture)
  - Source of data can be a DB server or some other program

Web scraping: HTTP queries

- We can download pages from web servers
- Underlying protocol is HTTP



- Below is a python code

```
import requests
response = requests.get("http://w3.cs.bilkent.edu.tr")
# some relevant fields
print (response.status_code)
print (response.content)  # or response.text
print (response.headers)
print (response.headers['Content-Type'])
```

Page address

Page is downloaded to local disk

Web scraping: HTTP queries – Parameters

- Uses the GET method of the HTTP protocol
- A URL can have parameters
  - http://www.google.com/search?**q**=bilkent&**num**=5
  - **q** and **num** are parameters

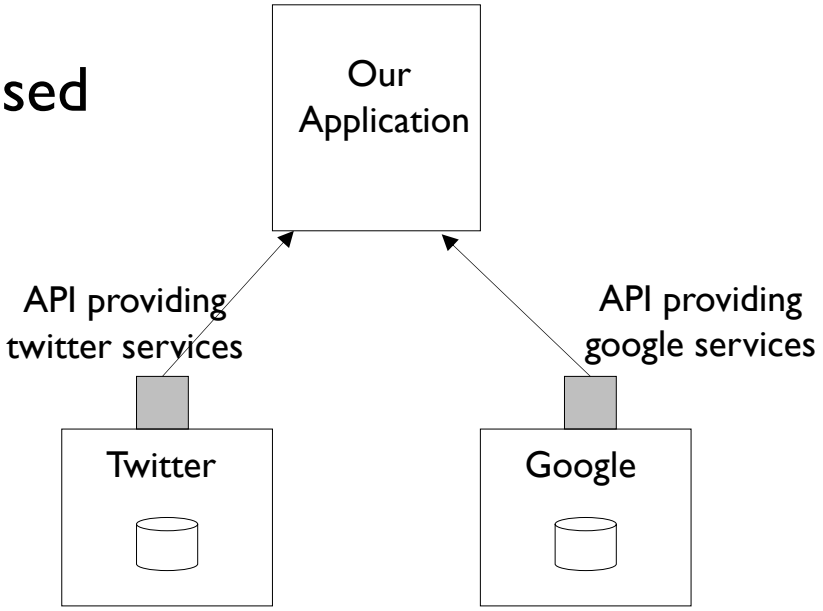
- In python we do:

```
plist = {"q":"bilkent", "num":"5"}     # parameter list
resp = requests.get("http://www.google.com/search" , params=plist)
print (resp.status_code)
print (resp.content)
```

Web API: HTTP commands

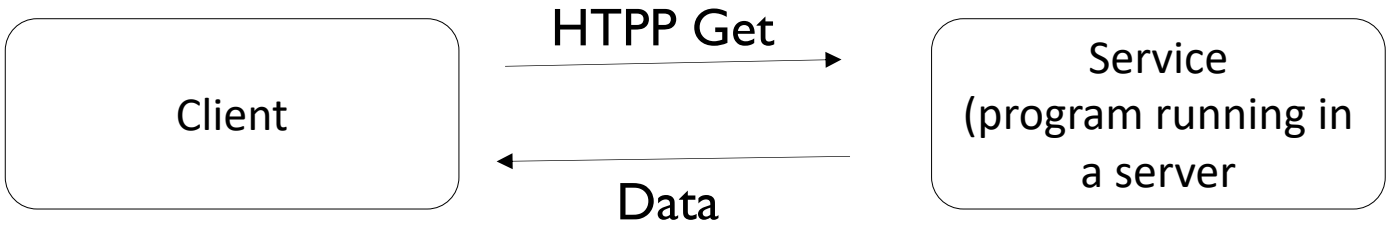
- We can query *web applications* via **Web API** and get data.

- HTTP commands (methods) used
  - GET is the most common
    - URL specified
  - But there are other HTTP methods that can change some state on the server
    - HTTP POST
    - HTTP PUT
    - HTTP DELETE



Web API

- There are web APIs for a lot of Services
- Services: applications running in remote servers and accessed via web servers.
- We can query a server (service) as if we are querying a web page server.
- The *service* running on a server should be *programmed to provide such an API.*
- *REST* is the name of such an *API standard*



REST

- REST (Representational State Transfer) API is commonly used.
- Set of rules that developers follow when they create their API.
- REST is a simple architecture style to transfer data (resource) over HTTP.
  - 1. Uses standard HTTP interface and methods (GET, PUT, POST, DELETE)
  - 2. Stateless – the server doesn't remember what you were doing

REST

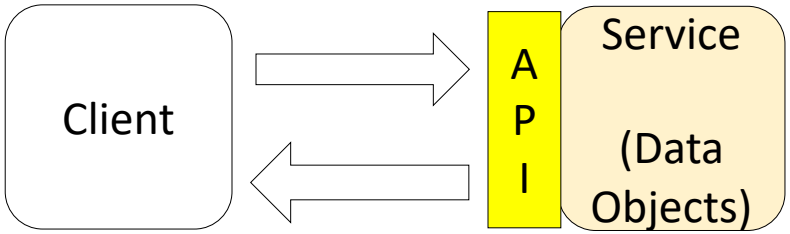
- You query a REST API with standard HTTP requests
  - You include parameters in the query.
- For example, GitHub API uses GET/PUT/DELETE to let you query or update elements in your GitHub account automatically

RESTful key elements

- Resources (and URI)
  - Data objects
- Request Verbs
  - What to do with data
- Request headers
  - Additional instructions
- Request Body
  - Data
- Response Body
  - Data

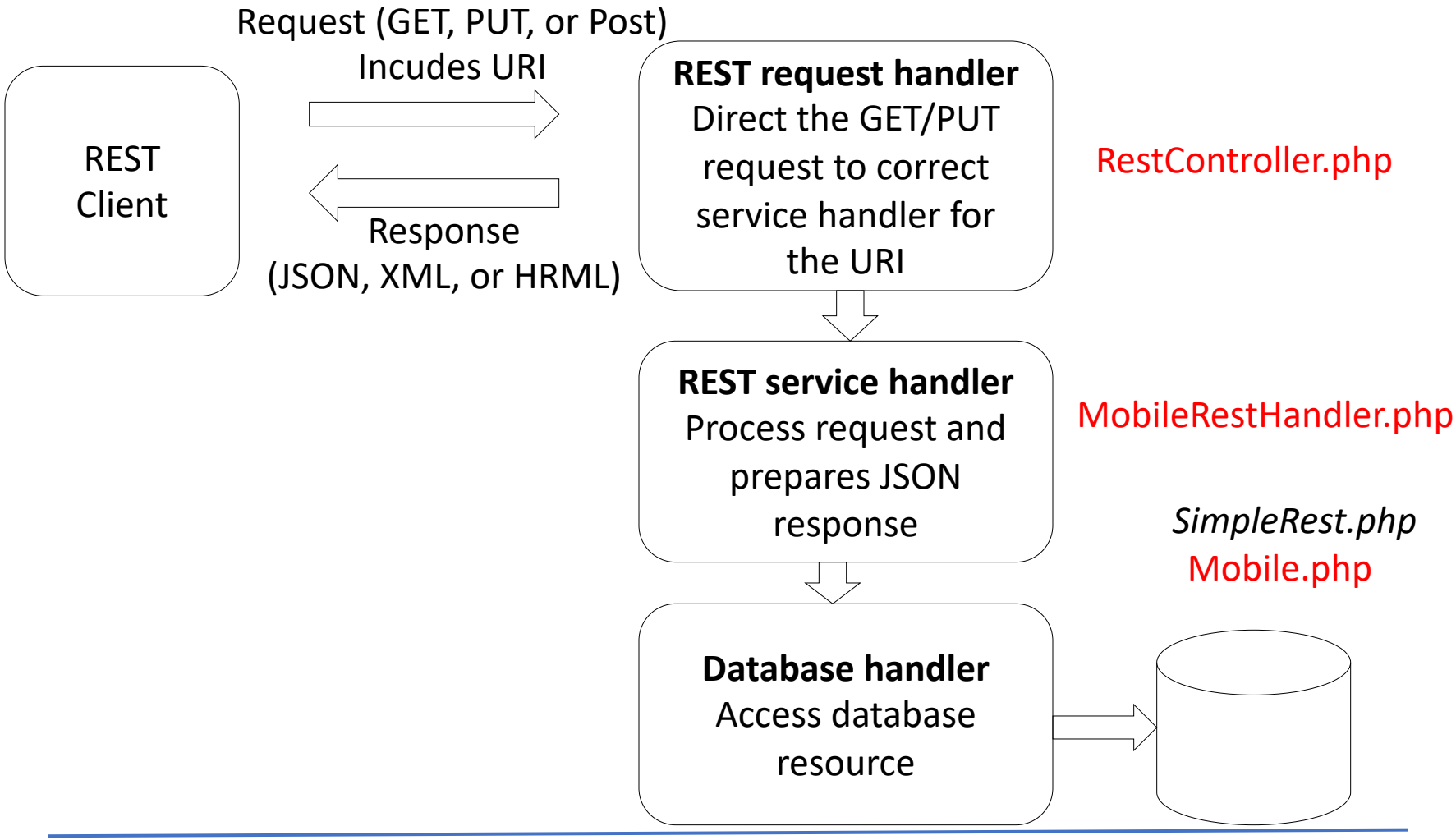
We identify our resources with URIs

We map them to service endpoints (request handlers)



We write code to process GET, PUT, POST, DELETE (service handlers)

RESTful Service



- In .htaccess file in the server, we put the following rules:

- #RewriteRule ^mobile/list/$ RestController.php?view=all
- #RewriteRule ^mobile/show/([0-9]+)/$ RestController.php?view=single&id=$1 [nc,qsa]

In this way we redirect the query to the correct handler function

RestController.php

```php
<?php
require_once("MobileRestHandler.php");

$view = "";
if(isset($_GET["view"]))
        $view = $_GET["view"];
/*
controls the RESTful services
URL mapping
*/
switch($view){

        case "all":
                // to handle REST Url /mobile/list/
                $mobileRestHandler = new MobileRestHandler();
                $mobileRestHandler->getAllMobiles();
                break;

        case "single":
                // to handle REST Url /mobile/show/<id>/
                $mobileRestHandler = new MobileRestHandler();
                $mobileRestHandler->getMobile($_GET["id"]);
                break;

        case "" :
                //404 - not found;
                break;
}
?>
```

One parameter in GET is “view”

“view” can be ”all” or single”

another parameter is “id”

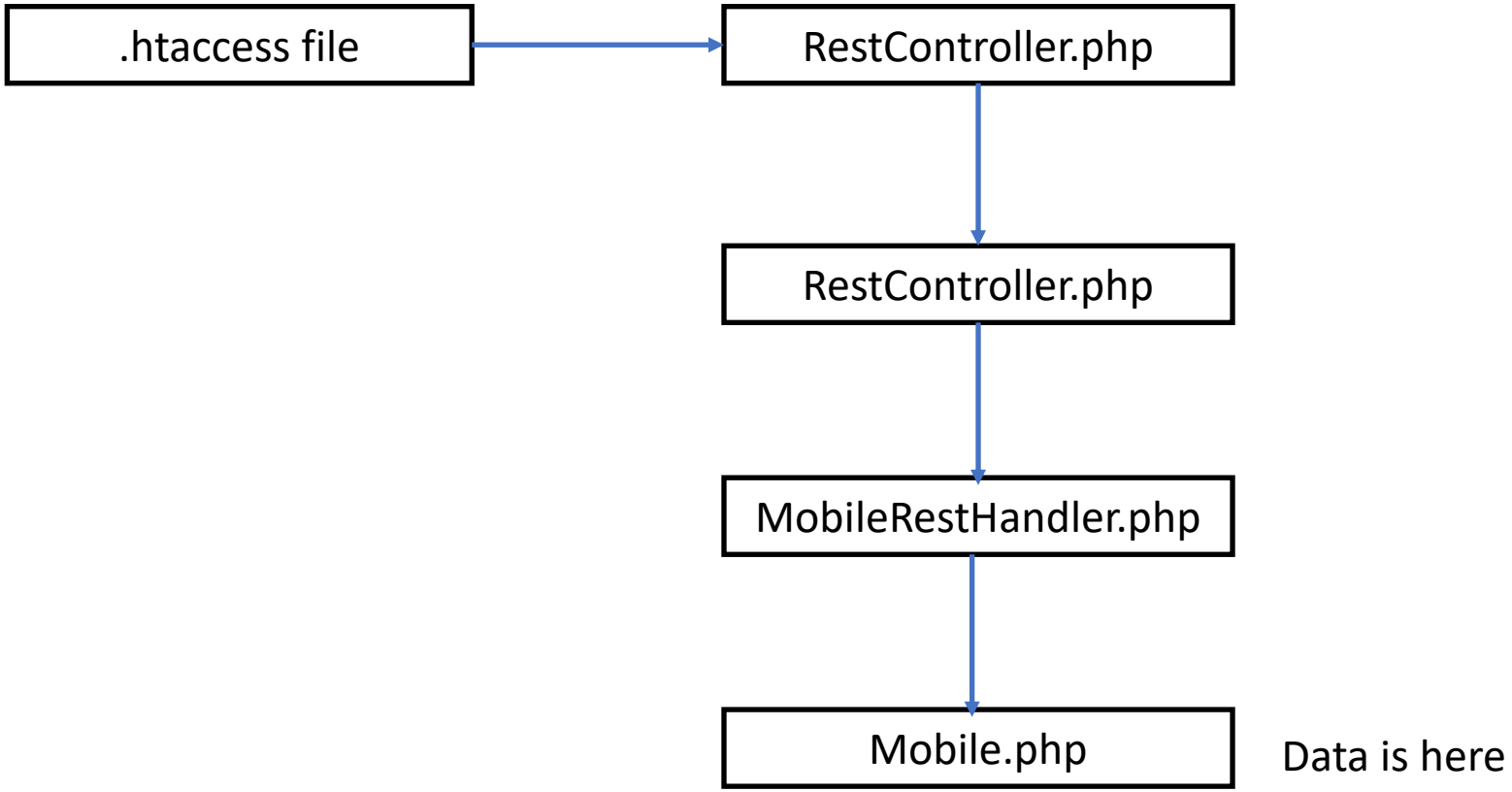
MobileRestHandler.php

```php
<?php
require_once("SimpleRest.php");
require_once("Mobile.php");

class MobileRestHandler extends SimpleRest {

	function getAllMobiles() {

		$mobile = new Mobile();
		$rawData = $mobile->getAllMobile();

		if(empty($rawData)) {
			$statusCode = 404;
			$rawData = array('error' => 'No mobiles found!');
		} else {
			$statusCode = 200;
		}

		$requestContentType = $_SERVER['HTTP_ACCEPT'];
		$this ->setHttpHeaders($requestContentType, $statusCode);

		if(strpos($requestContentType,'application/json') !== false){
			$response = $this->encodeJson($rawData);
			echo $response;
		} else if(strpos($requestContentType,'text/html') !== false){
			$response = $this->encodeHtml($rawData);
			echo $response;
		} else if(strpos($requestContentType,'application/xml') !== false){
			$response = $this->encodeXml($rawData);
			echo $response;
		}
	}
```

Mobile.php

```php
<?php
/*
A domain Class to demonstrate RESTful web services
*/
Class Mobile {

	private $mobiles = array(
		1 => 'Apple iPhone 6S',
		2 => 'Samsung Galaxy S6',
		3 => 'Apple iPhone 6S Plus',
		4 => 'LG G4',
		5 => 'Samsung Galaxy S6 edge',
		6 => 'OnePlus 2');

	/*
		you should hookup the DAO here
	*/
	public function getAllMobile(){
		return $this->mobiles;
	}

	public function getMobile($id){

		$mobile = array($id => ($this->mobiles[$id]) ? $this->mobiles[$id] : $this->mobiles[1]);
		return $mobile;
	}
}
?>
```

Server side – request processing



JSON

- JavaScript Object Notation
- Open-standard file and data format
- Uses human-readable text to transfer data objects that consists of **attribute-value pairs** or array data types

```
{
  "firstName": "John",
  "lastName": "Smith",
  "isAlive": true,
  "age": 27,
  "address": {
    "streetAddress": "21 2nd Street",
    "city": "New York",
    "state": "NY",
    "postalCode": "10021-3100"
  },
  "phoneNumbers": [
    {
      "type": "home",
      "number": "212 555-1234"
    },
    {
      "type": "office",
      "number": "646 555-4567"
    },
    {
      "type": "mobile",
      "number": "123 456-7890"
    }
  ],
  "children": [],
  "spouse": null
}
```

https://en.wikipedia.org/wiki/JSON

XML

- Extensible Markup Language
- XML defines a set of rules for encoding documents and data in a format that is both human readable and machine-readable.
- Textual data format
- Arbitrary data structures can be represented in XML.

```
<?xml version="1.0" encoding="UTF-8"?>
<note>
  <to>Tove</to>
  <from>Jani</from>
  <heading>Reminder</heading>
  <body>Don't forget me this weekend!</body>
</note>
```

https://en.wikiversity.org/wiki/XML

Structure of the data

- Structured data (has *schema* describing the structure)
  - DB Tables
- Semi-structured data
  - Documents
  - XML, JSON
- Unstructured data (no schema)
  - Text files, plain text, media (images, videos)

Databases and data management systems

- Database: A collection of data
- Database Management Systems
  - Software that stores, manages and facilitates access to data. (Oracle, MySql, Sqlite, …)
- Traditionally, relational databases
  - Transactions
  - Bank accounts, student records, customer records, inventory records.
- Modern needs and usage varies (NoSQL databases, etc.)
  - Hadoop, Spark
- Cloud databases

File system

- We can store data in files.
- This may be good enough for a lot of applications.
  - But not all applications.
- File system is not a database
  - Two people accessing a file may cause inconsistency.
  - Sudden power off will cause loss of data
  - No query support
  - No transaction concept

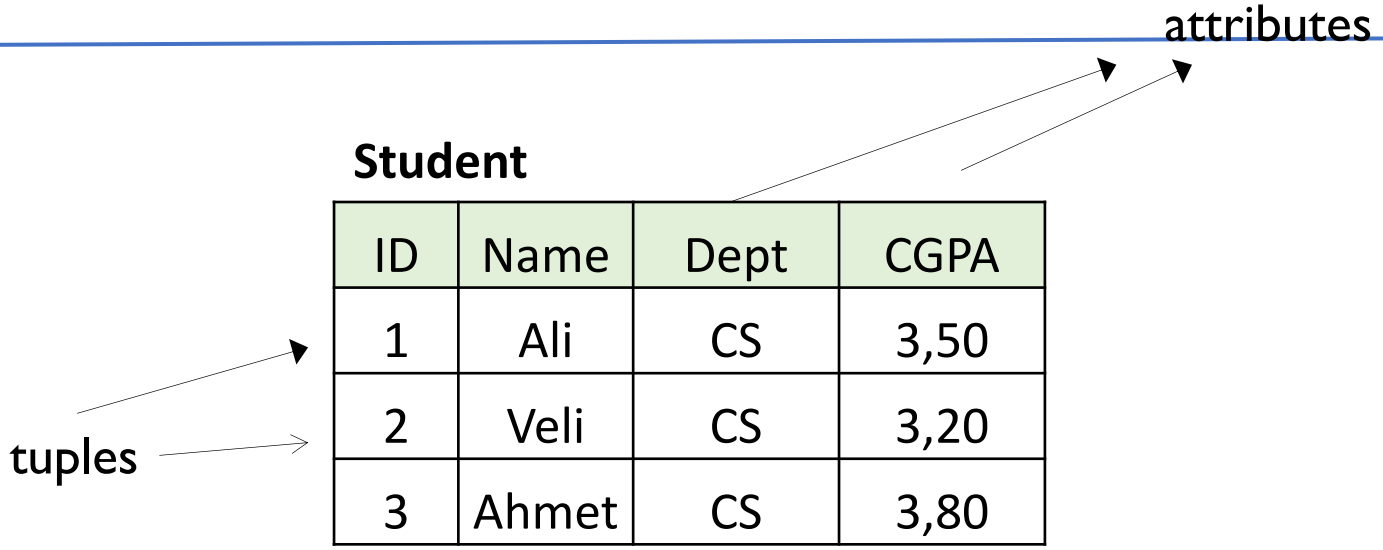
Relational DBMSs and SQL

Relational Database

- Models a real world data environment
- Entities (students, courses, instructors)
- Relationships (taking the course, giving the course, is advisor of, etc.)

- RDMBs works with tables (relations)
  - Relation: a table (with rows and columns)
  - Schema: describes columns, fields.
- A *table (also called a relation)* stores information about objects or relations of the same kind (same set of attributes)
  - Rows are called tuples (records); must be unique
  - Columns are attributes

Table



- Rows (tuples). A relation is a set of tuples.
- Columns (attributes)
- Relation (Table) name is Student.
- It has 4 attributes
- It has 3 tuples.
- These 3 tuples are an instance of the Student Relation.

Multiple Tables

- A database typically has multiple tables.
- Student table,
  Course table,
  Department table,
  Instructor Table,
  Offerings table,
  Enrollment table, ..

Course

ID	Name	Dept	Credits
CS342	Operating Systems	CS	4
GE461	Data Science	GE	3
EEE202	Circuit Theory	EEE	4
CS202	Data Structures	CS	3
IE202	Optimization	IE	3
ME101	Mechanical Systems	ME	4

Schema

- Schema for a database describes the tables and their attributes.
- It is fixed.
- It is the logical design.
- It is then populated with data (instances)
- Data + Schema = Database

Schema

- Example Schema
  - Department (name, building, chair)
  - Student (id, name, dept, CGPA)
  - Course (id, name, dept, credits)
- Some tables are for objects: Student table
- Some tables are for relations: Enrollment

Keys

- Primary Key: the attributes used to identify tuples in a table uniquely
- Foreign Key: an attribute in a table that is the primary key in another table.

Course

Foreign key

Primary key

ID	Name	Dept	Credits
CS342	Operating Systems	CS	4
GE461	Data Science	GE	3
EEE202	Ciruit Theory	EEE	4
CS202	Data Structures	CS	3
IE202	Optimization	IE	3
ME101	Mechanical Systems	ME	4

Primary key

Department

ID	Name	Building
CS	Computer Science	EA
EE	Electrical Engineering	EE
IE	Industrial Engineering	EA
ME	Mechanical Engineering	EA
MATH	Mathematics	SC

Query Language

- Query language is language to request information from a database
- *Procedural* or *declarative*
- SQL : structured query language (declarative)
  - Most common, but not the only one.

Query Language

- Can be used to
  - Create / delete a database (data definition)
  - Create / delete a table (data definition)
  - Insert, delete, update tuples (data manipulation)
  - Query table(s) (retrieve data) (data manipulation)
    - Select some set of tuples from a table
    - Join multiple tables

SQL

- SQL has two main parts:
  - DDL (data definition language);
  - DML (data manipulation language)
- Supported data types
  - char(n)
  - varchar(n)
  - int
  - real, float(n)
  - …

SQL

- CREATE TABLE Department (id varchar(20),
  name varchar(20),
  building varchar(20),
  primary key (id));

- CREATE TABLE Student (id int,
  name varchar(20),
  dept varchar(20),
  cgpa float,
  primary key (id),
  foreign key (dept) references Department;

- INSERT INTO Student VALUES (4, 'Can', 'CS', 3,75);

SQL

- To retrieve data from a table or from multiple tables, we can form and execute SQL queries.

- Basic structure for SQL queries:

  SELECT <columns> FROM <tables> where <predicate>

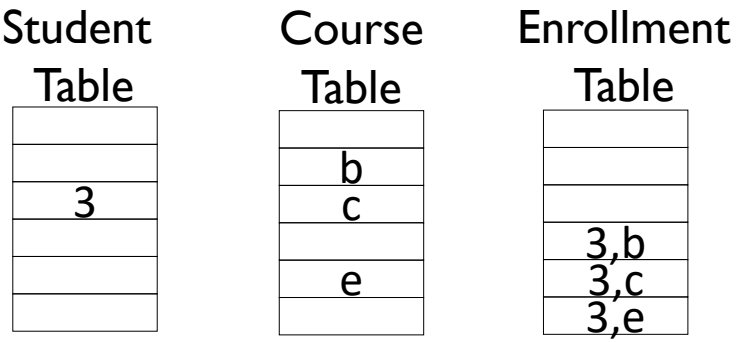
- SELECT name FROM Course
- SELECT dept FROM Course
- SELECT name, dept FROM Course
- SELECT name FROM Course WHERE dept == 'CS'

Inter-table relationships

- Several types of inter-table relationships
- 1. One-to-one
- 2. (One-to-zero/one)
- 3. One-to-many (and many-to-one)
- 4. Many-to-many

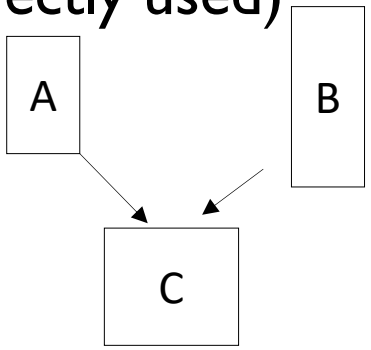
These relate one (or more) rows in a table with one (or more) rows in another table,

- via a foreign key



Joins

- Merge information in multiple tables together.
- Join operations merge multiple tables into a single relation (can be then saved as a new table or just directly used)
- Four typical types of joins:
  - Inner
  - Left
  - Right
  - Outer



- You join two tables on columns from each table, where these columns specify which rows are kept

Example: joining instructor and department

Instructor

ID	Name	Department	Title
id101	Cem	CS	C
id102	Mustafa	CS	A
id103	Emre	EE	B
id103	Ayse	CS	A
id105	Ozgur	IE	C
id106	Dilek	ME	A
id107	Ahmet	POLS	B
id108	Atakan	IR	C
id109	Remzi	PSYC	A

Department

ID	Name	Building
CS	Computer Science	Building-X
EE	Electrical Engineering	Building-X
IE	Industrial Engineering	Building-X
ME	Mechanical Engineering	Building-X
MATH	Mathematics	Building-Y
PHYS	Physics	Building-Y
ECON	Economy	Building-Z

Example: joining instructor and department

```
SELECT * FROM Instructor  INNER JOIN Department
ON Instructor.dept == Department.id;
```

Or

```
SELECT * FROM Instructor, Department
WHERE Instructor.dept == Department.id;
```

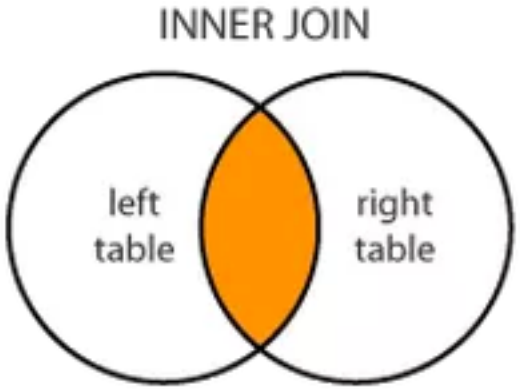
Resulting relation (can be used or can be saved)

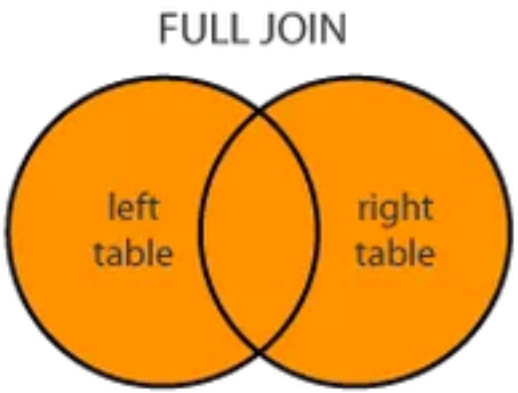
ID	Name	Dept	Title	Name (Department)	Building
id101	Cem	CS	C	Computer Science	Building-X
id102	Mustafa	CS	A	Computer Science	Building-X
id103	Emre	EE	B	Electrical Engineering	Building-X
id103	Ayse	CS	A	Computer Science	Building-X
id105	Ozgur	IE	C	Industrial Engineering	Building-X
id106	Dilek	ME	A	Mechanical Engineering	Building-X

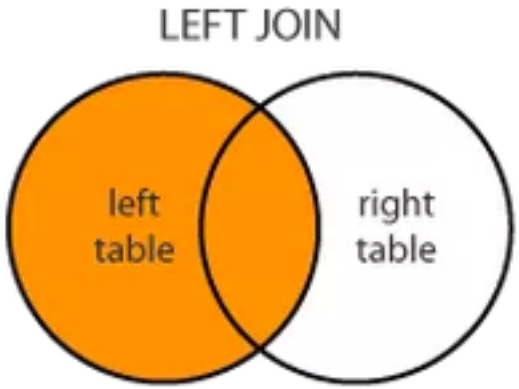
Example: left joining instructor and department

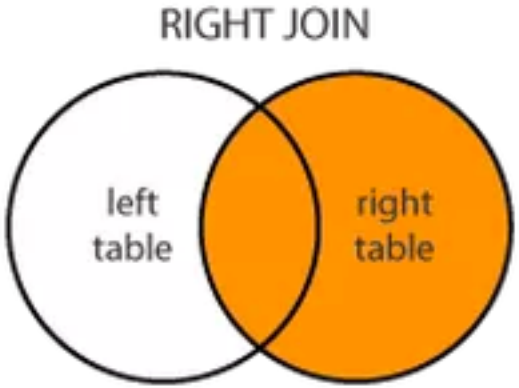
ID	Name	Dept	Title	Name (Department)	Building
id101	Cem	CS	C	Computer Science	Building-X
id102	Mustafa	CS	A	Computer Science	Building-X
id103	Emre	EE	B	Electrical Engineering	Building-X
id103	Ayse	CS	A	Computer Science	Building-X
id105	Ozgur	IE	C	Industrial Engineering	Building-X
id106	Dilek	ME	A	Mechanical Engineering	Building-X
id107	Ahmet	POLS	B	NULL	NULL
id108	Atakan	IR	C	NULL	NULL
id109	Remzi	PSYC	A	NULL	NULL

Join alternatives









Google image search for left join

SQL Lite

- SQLite: an actual relational database management system (RDBMS)
- Unlike most systems, it is a server-less model, applications directly connect to a file.
- Allows for simultaneous connections from many applications to the same database file (but not quite as much concurrency as client-server systems)
- All operations in SQLite use SQL (Structured Query Language) commands issued to the database object.

Client-Server DBMS vs Serverless DBMS

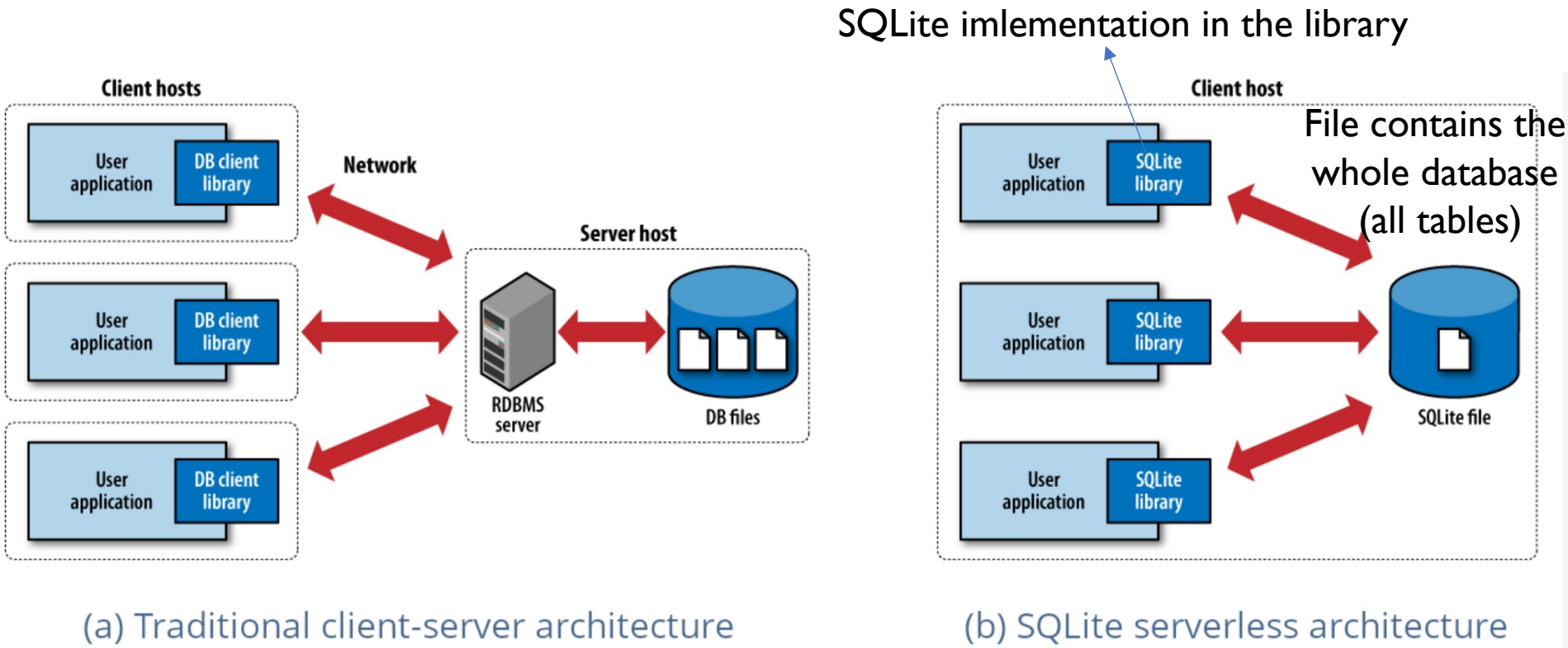


Figure from : developia.org/sqlite

Client – Server Architecture
For example: MySQL server

Serverless DBMS
For example: SQLite

Use of SQL in Python

```
import sqlite3

 conn = sqlite3.connect('ders.db') / # create or open db
 c = conn.cursor()  # obtain a handle to the connection

query = "CREATE TABLE Student (id varchar(10) \
 PRIMARY KEY, name varchar(20), dept varchar(10), \
 cgpa REAL NOT NULL);"

c.execute(query)
conn.commit()

query = "INSERT INTO Student VALUES (?, ?, ?, ?);"
c.execute(query, '2222', 'Ali' , 'CS', '3.5'))
conn.commit()
```

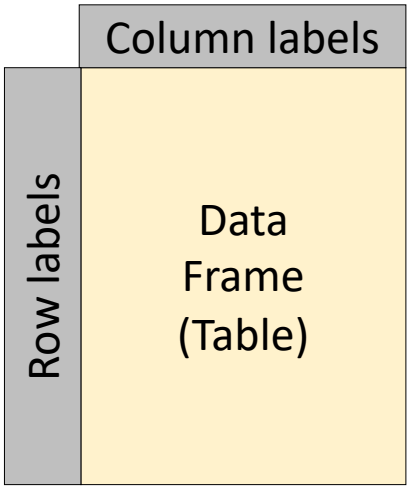
SQL in Python

```
query = "SELECT * FROM Student;”
c.execute(query)

rlist = c.fetchall()    # fetch the rows in a list
for i in range(len(rlist)):       # print the list
        print (rlist[i][1])              # one row at a time


query = "SELECT * FROM Student  WHERE Student.dept == ‘CS’ ;”
c.execute(query)
conn.commit()

query = "SELECT * FROM Instructor, Department WHERE   \
      Instructor.dept == Department.id;”          # JOIN
c.execute(query)
conn.commit()
```

Pandas

- Pandas is a "Data Frame" library in Python, developed for manipulating in-memory data with row and column labels (as opposed to, e.g., matrices, that have no row or column labels)

- Pandas is not a relational database system, but it contains functions that mirror some functionality of relational databases. For example: merge mimics join.



Important data structures of Pandas

- Series:
  - Array (of objects of the same type) (1D)
  - Homogenous array that can be indexed.
- Data Frame:
  - Table structure (2D)
  - Columns
  - Column types can be different
  - For one column: all values are of the same type (a Series)

Pandas

- Fast and efficient DataFrame object with default and customized indexing.
- Tools for loading data into in-memory data objects from different file formats.

From: https://www.tutorialspoint.com/python_pandas/

Pandas

- Label-based slicing, indexing and subsetting of large data sets.
- Columns from a data structure can be deleted or inserted.
- Group by data for aggregation and transformations.
- High performance merging and joining of data.
- Time Series functionality.

Pandas

```
import pandas as pd

df = pd.DataFrame([('id1', 'Ali', 'CS', '3.4'),
('id2', 'Ahmet', 'EE', '3.3'),
('id3', 'Ayse', 'IE', '3.7'),
('id4', 'Begum', 'ME', '3.5'),
('id5', 'Mehmet', 'CS' '3.5'),
('id6', 'Ramazan', 'EE', '3.6')],
columns=["Stu ID", "Name", "Dept", "CGPA"])


print (df)
```

Column index

Row index

	Stu ID	Name	Dept	CGPA
0	id1	Ali	CS	3.4
1	id2	Ahmet	EE	3.3
2	id3	Ayse	IE	3.7
3	id4	Begum	ME	3.5
4	id5	Mehmet	CS	3.5
5	id6	Ramazan	EE	3.6

Pandas

- Pandas is not RBMS, no primary key concept
- It has index concept.
- Operations in Pandas are typically not in place (that is, they return a new modified DataFrame, rather than modifying an existing one; by default)
- We can use the "inplace" flag to make them done in place
- If we select a single row or column in a Pandas DataFrame, it will return a "Series" object,
- A Series object is like a one-dimensional indexed array (sequence of values and their indices).

Pandas: some data frame methods

df.head(): some number of rows from beginning.

df.tail(): some number of rows from end.

df.iloc[i,j]: access the entry (value) at the ith row and jth column

x = df.iloc[0,1] for example.
It will access "Ali". [0,0] will access "id1".

df.loc[rowindexlabel, columnindexlabel]: access the entry at the specified row and column

x = df.loc[3,"Dept"]

will access "ME"

	Stu ID	Name	Dept	CGPA
0	id1	Ali	CS	3.4
1	id2	Ahmet	EE	3.3
2	id3	Ayse	IE	3.7
3	id4	Begum	ME	3.5
4	id5	Mehmet	CS	3.5
5	id6	Ramazan	EE	3.6

Other and Bigger Data

Other Data Models

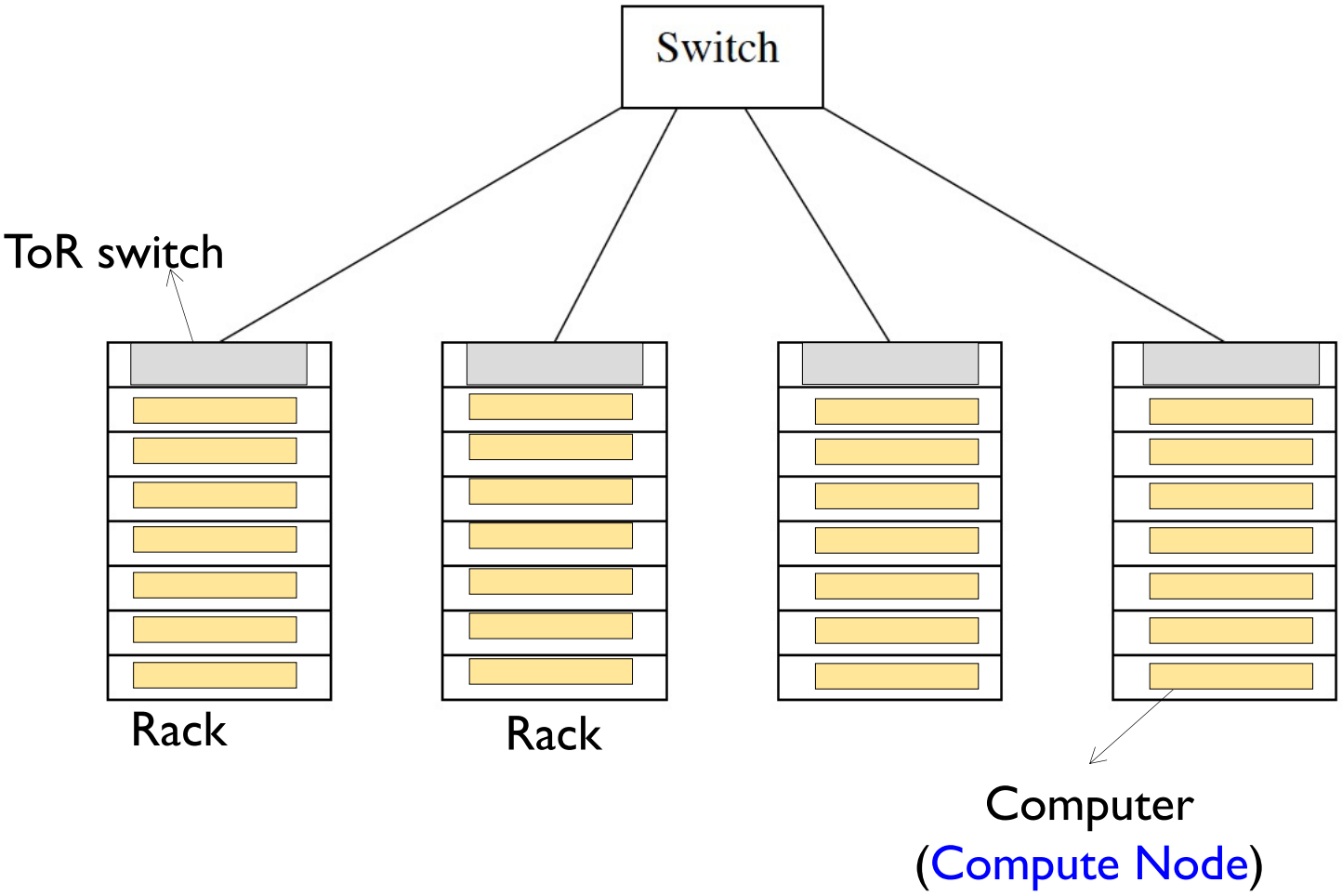
- RDMS is good for storing transactional and/or structured data.
  - Bank account data
  - Employee data
  - Student data
  - Customer data
- New classes of applications
  - Search
  - Email
  - Browsing
  - Instant messaging
  - Social media
  - Online retail
- NoSQL databases (not only SQL)

Big Data

- If data is fitting in a single machine disk/RAM, this is not that big data.
  - GB data can fit into a single computer (PC)
  - Singe machine solutions are good.
- If data is big (TeraBytes, PetaBytes, ..), then we need small or large cluster of machines to process data.

- How can we store and process data in a cluster?

What is a Cluster?



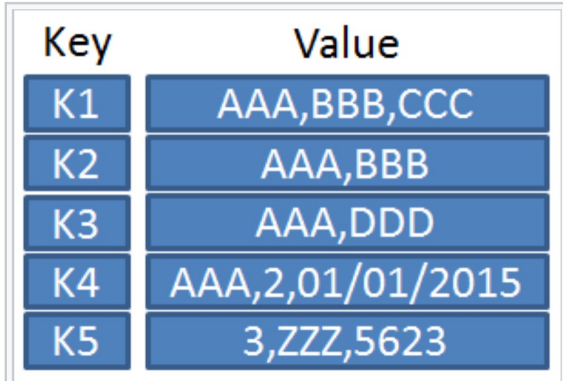
Compute node: processor, with its main memory, cache, and local disk (storage)

Distributed File System (DFS)

- To exploit cluster computing, files must look and behave somewhat differently from the conventional file systems found on single computers (Linux FS, NTFS, FAT32 are local file systems).
- This new file system, often called a **distributed file system** or DFS is typically used as follows.
  - Files can *be enormously big*, possibly terabytes in size. If you have only small files, there is no point using a DFS for them.
  - Files are *rarely updated.* Rather, they are read as data for some calculation, and possibly additional data is appended to files from time to time.
- Example: *HDFS* (Hadoop File System)

Other data stores: Key-Value Stores

- Key/Value Stores (NoSQL)
  - Large data
  - Key-value sets stored
    - Example: customer id, date, purchased items
  - Performance is critical
  - Eventual consistency is fine.
  - No fancy reports.
  - Data analysis and recommendation
  - Query set depends on the application
  - Just keys and values, no schema
- Amazon Dynamo DB
- Apache Cassandra



Key	Value
K1	AAA,BBB,CCC
K2	AAA,BBB
K3	AAA,DDD
K4	AAA,2,01/01/2015
K5	3,ZZZ,5623

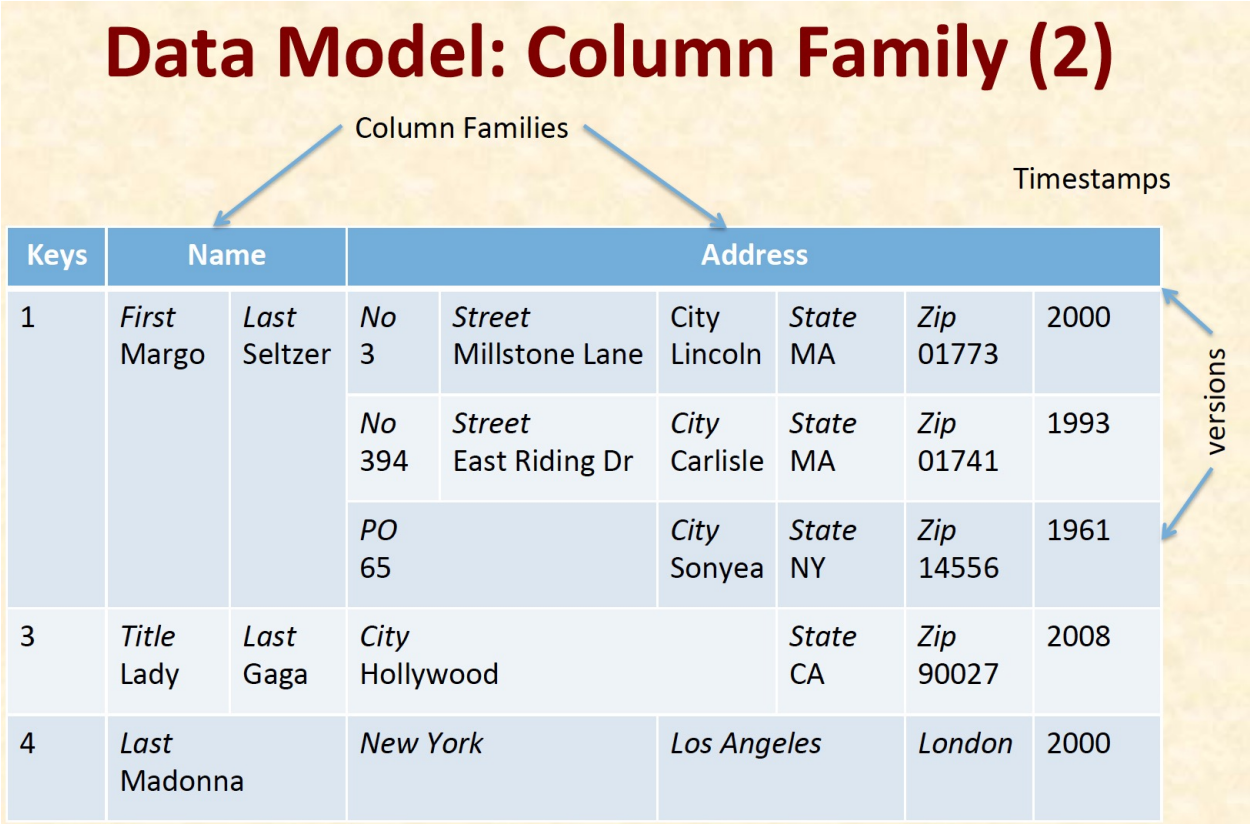
From wikipedia

Other data stores: Column Family Stores

- A big table of rows and columns (billions of rows, billions of columns possible): sparse
- Columns are grouped into Column Families
- Column Families:
  - Typically stored together
  - Can have *different columns for each row*
  - Can have duplicate items in any column
- No schema or type enforcement
  - All data treated as byte strings
- Indexed by row (***row key***)
  - Rows are grouped into tables (chunks)
- Rows usually kept in *sorted order* *wrt row key*

Example: Google BigTable

Other data stores: Column Family Stores



Keys	Name		Address					
1	*First* Margo	*Last* Seltzer	*No* 3	*Street* Millstone Lane	City Lincoln	*State* MA	*Zip* 01773	2000
			No 394	*Street* East Riding Dr	*City* Carlisle	*State* MA	*Zip* 01741	1993
			PO 65		*City* Sonyea	*State* NY	*Zip* 14556	1961
3	*Title* Lady	*Last* Gaga	*City* Hollywood			*State* CA	*Zip* 90027	2008
4	*Last* Madonna		*New York*		*Los Angeles*		*London*	2000

from: CS109 Harvard

How data internally stored

Logical View

CF1 CF2

	C1	C2	C3
R1	X (t3, t2, t1)		
R2		X	X
R3	X (t1)		X
R4	X (t2, t1)	X	
R5			X

Table

X denotes an existing value

Ri is a row key (string)

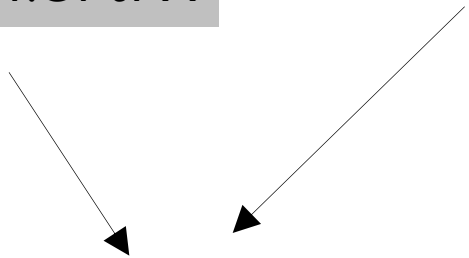
CFi: is a column family name

Ci is a column name (string) (also called column key)

Physical View

R1 CF1:C1 t3 X
R1 CF1:C1 t2 X
R1 CF1:C1 t1 X
R3 CF1:C1 t1 X
R4 CF1:C1 t2 X
R4 CF1:C1 t1 X

R2 CF2:C2 t1 X
R2 CF2:C3 t1 X
R3 CF2:C3 t1 X
R4 CF2:C2 t1 X
R5 CF2:C3 t1 X



This is how data can be stored internally in two files.

How data internally stored

- Bigtable cells which do not contain a value consume no disk space.
  - Sparse table.
- For each valid cell value, we store the column name as well, not only the row key.
- For each cell, we can keep different versions of cell data (time stamped)
- To learn which column names are there in the table, we have to do a full scan of the table. Schema just gives created column families, not column keys.
- For each key-value pair, we keep the associated lengths as well.
  - *key length, value length* (both variable size)

Example from HBase

HBase: Open source Hadoop implementation of Bigtable. It is a NoSQL database system.

Conceptual

Row Key	Time Stamp	ColumnFamily contents	ColumnFamily anchor
"com.cnn.www"	t9		anchor:cnnsi.com = "CNN"
"com.cnn.www"	t8		anchor:my.look.ca = "CNN.com"
"com.cnn.www"	t6	contents:html = "<html>..."	
"com.cnn.www"	t5	contents:html = "<html>..."	
"com.cnn.www"	t3	contents:html = "<html>..."	

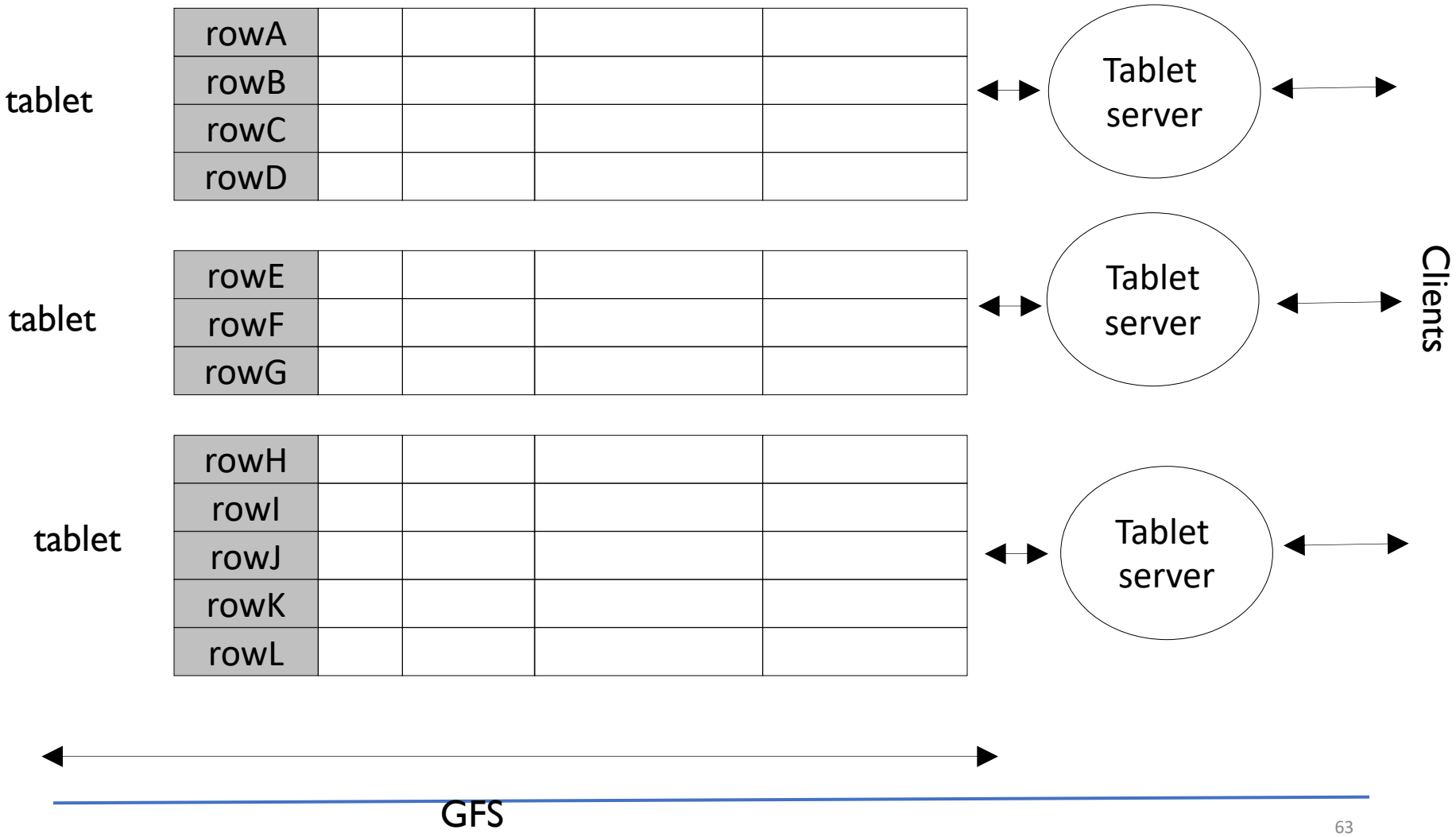
Physical

Row Key	Time Stamp	Column Family anchor
"com.cnn.www"	t9	anchor:cnnsi.com = "CNN"
"com.cnn.www"	t8	anchor:my.look.ca = "CNN.com"

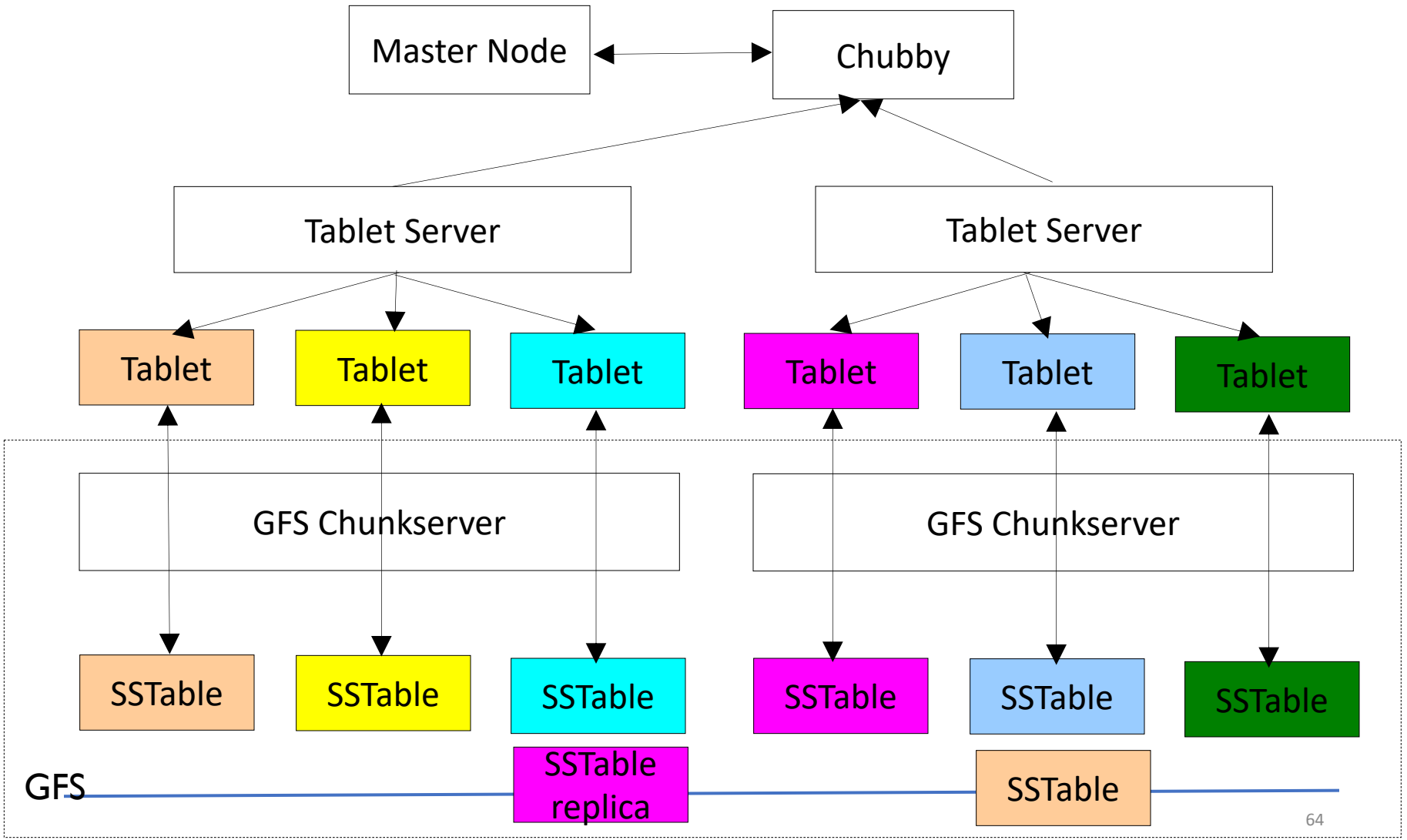
Row Key	Time Stamp	ColumnFamily "contents:"
"com.cnn.www"	t6	contents:html = "<html>..."
"com.cnn.www"	t5	contents:html = "<html>..."
"com.cnn.www"	t3	contents:html = "<html>..."

Table and Tablets

Table and Tablets

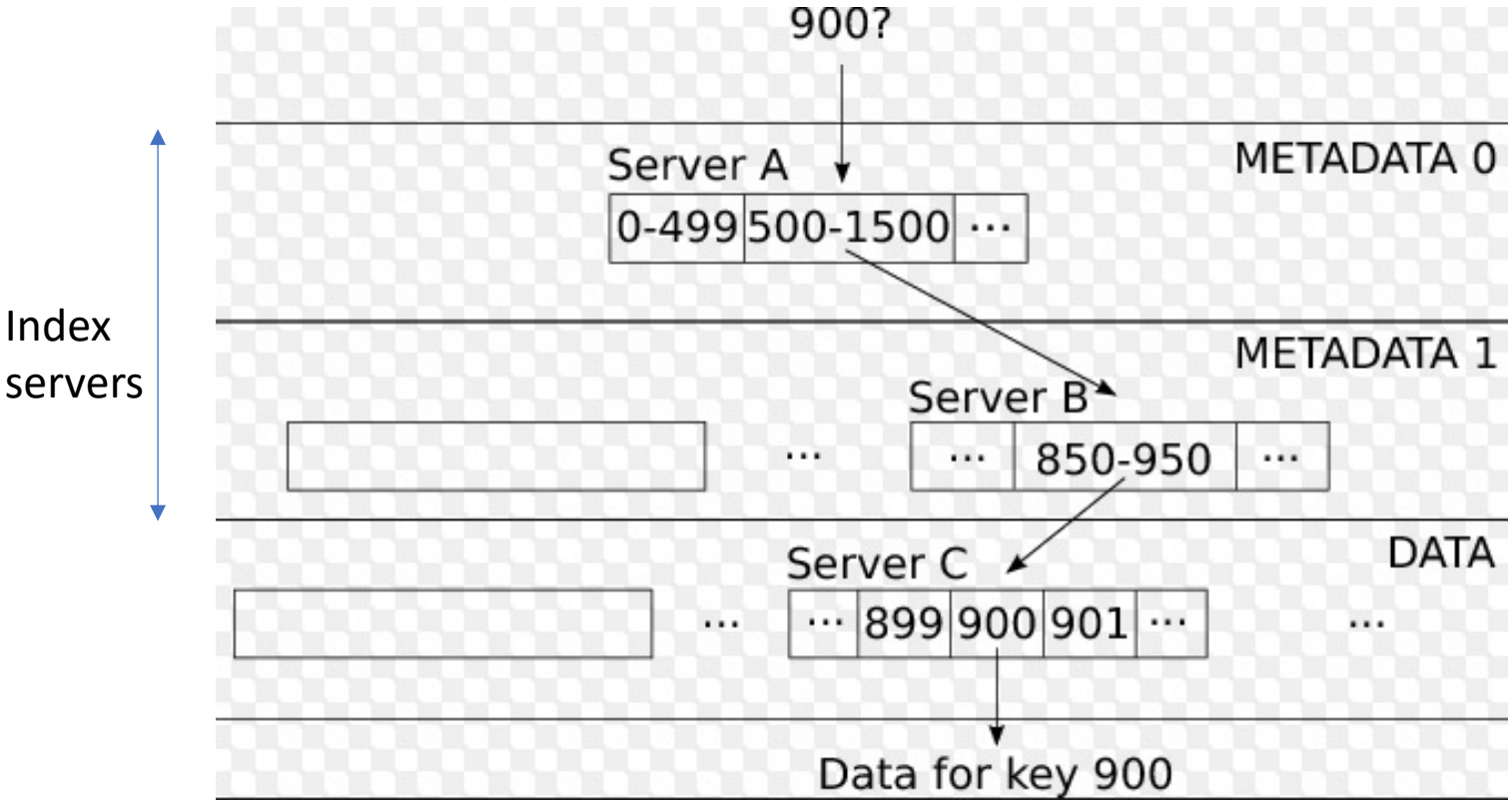


BigTable Architecture



Tablet Location

Example: locating data with row key = 900



Document Stores

- A Key/Value store where value is a document with structure
- Structures for documents:
  - JSON
  - XML
  - PDF
  - DOC
- Search for and within documents possible.

MapReduce

Distributed Big Data Processing

- Big Data is distributed on many machines
  - Local processing preferable, but not always sufficient and possible.
- MPI was used in the past
  - Explicit data handling
- New frameworks are available
- MapReduce Framework (Google, Hadoop)
  - Distributed data storage file system (GFS or HDFS)
  - Distributed data table (BigTable or HBASE)
  - Distributed processing language (MapReduce)
- Spark framework

MapReduce

- MapReduce:
  - A programming model and associated implementation for processing and generating large datasets
- Hadoop system has it as its programming model.
  - Hadoop system has also a file system (HDFS) and a NoSQL database system (Hbase)
- App specifies Map function and Reduce Function for a computation to be done
- Many real world tasks expressible with this model
- A program written with this model is automatically parallelized and executed on a large cluster of machines.

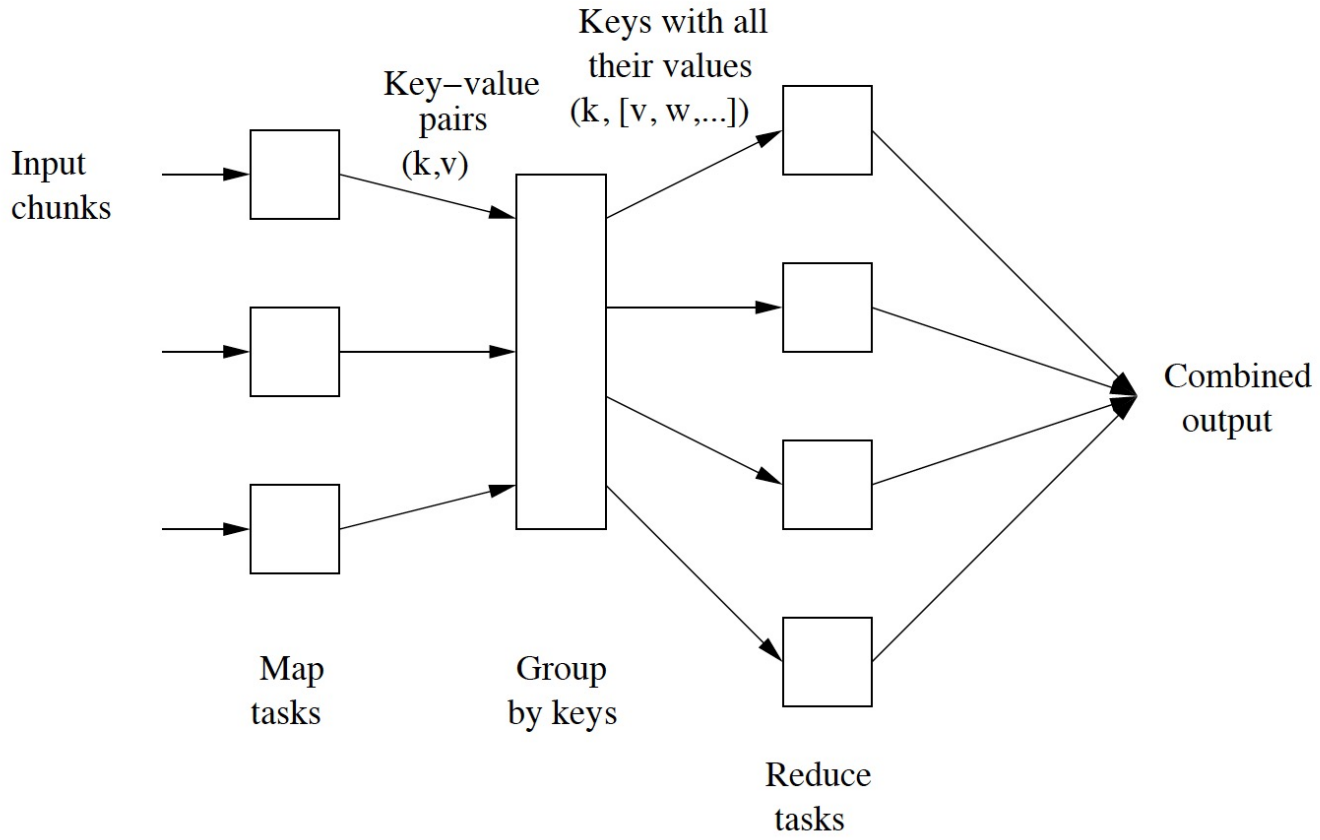
Programming Model

- Computation
  - Input: A set of input key/value pairs
  - Output: a set of output key/value pairs
- User of MapReduce library specifies
  - a Map function
  - a Reduce function

Programming Model

- Map function:
  - Takes: an input key/value pair
  - Produces: a set of intermediate key/value pairs
  - All intermediate values with the same intermediate key are grouped
- Reduce function:
  - Takes: accepts an intermediate key and a set of values for that
  - Merges all the values to form a smaller set of values (for example, sum, count, etc.)

MapReduce Computation



map (k1,v1) → list(k2,v2)
reduce (k2,list(v2)) → list(v2)

Example: word count

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

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

Programming

- We can write an application program in which
  - We write map() and reduce() functions
  - Specify the input files
  - Specify the number of map workers (machines) (N)
  - Specify the number of reduce workers (machines) (R)
  - Specify output files
- Framework will do the rest (parallel processing)
  - Partition the input into M splits
  - Handle each split via the map() as a task
  - Schedule tasks to machines (workers)
  - Sort at the reduce workers before the reduce()
  - Write the results to output files (sorted order)

Application Examples

- Distributed Grep:
  - Map() function emit a line if it matches a supplied pattern
  - The reduce() function is an identity function
- Count of URL access frequency
  - Logs of web page request
  - Map() output <URL, 1>.
  - Reduce() adds together all values for the same URL and emits <URL, total-count> pair
- Distributed Sort
  - Files containing records processed
  - Map() extracts key from each record and emits <key, record>
  - Reduce() emits all pairs unchanged (framework sorts)

Application Examples

- Reverse Web-Link Graph
  - Map() outputs <target,source> pairs for each link to a target URL found in a page names source
  - Reduce() concatenates the list of all source URLs associated with a given target URL and emits the pair: <target, list(sources)>
- Inverted Index
  - Map() parses each document and emits a sequence of <word, document ID> pairs. Reduce() accepts all pairs for a given word, sorts the corresponding document IDs and emits a <word, list(document ID)> pair.

Execution Overview

- 1) SPLIT: MapReduce library in user program splits the input files into M pieces of typically 16-64 MB each. Starts up many copies of the program on a cluster of machines.

- 2) SCHEDULE: One of the copies of the program is special – master. The rest are workers that are assigned work by the master. M map tasks, R reduce tasks to be assigned. Master picks up idle workers and assign each either map or reduce task.

- 3) MAP: A worker that is assigned map task reads the content of the corresponding input split, parses key value pairs and passes each pair to the user defined Map function. Map function produces intermediate key-value pairs and buffers them.

Execution Overview

- 4) INTERMEDIATE FILES: Periodically, buffered pairs are written to local disk, partitioned into R regions by the partitioning function. The location of these files are passed to master, which forwards them later to the reduce workers.

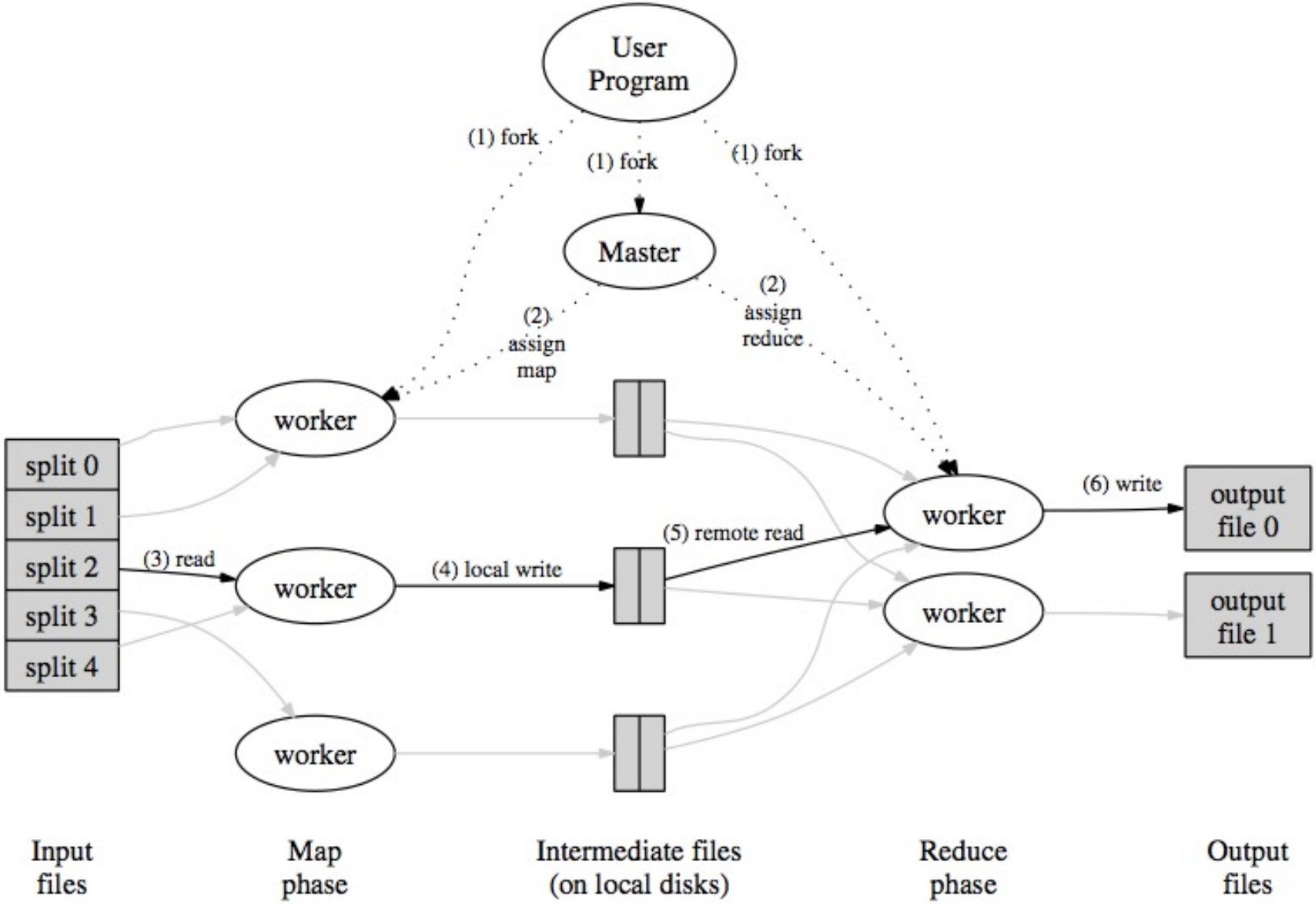
- 5) SORT AND GROUP: When a reduce worker is notified by the master about these locations (assigned a reduce task), it uses RPC to read the buffered regions (files) from map worker local disks. When a reduce worker has read all data, it sorts by intermediate key so that all occurrences of the same key are grouped together. If memory is not enough, external sort can be used.

Execution Overview

- 6) REDUCE: The reduce worker iterates over the sorted intermediate key-value pairs and for each unique intermediate key encountered, it passes the key and the corresponding set of values to the user's Reduce function. The output of Reduce is appended to a final output file for this reduce partition.

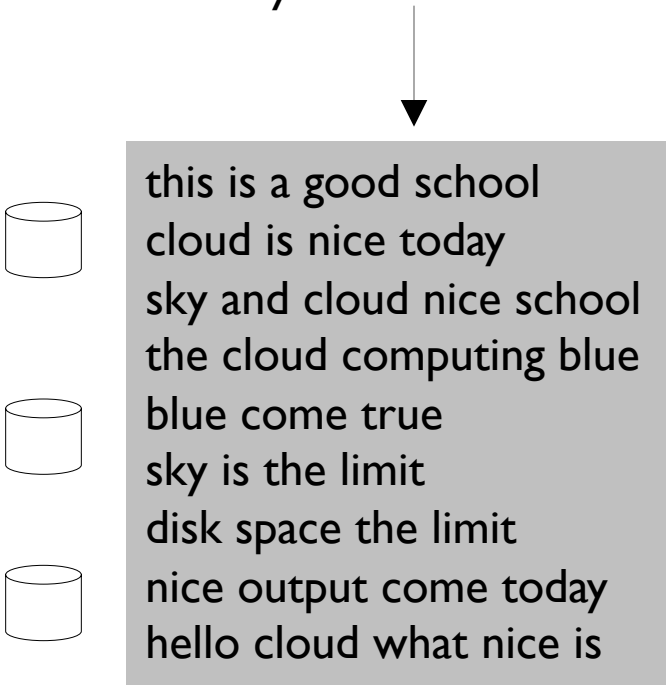
- 7) FINISH: When all map and reduce tasks have been completed, the master wakes up the user program. At this point, the MapReduce() call in the user program returns back to the user code.

At the end, R final output files are there (one per reduce task).

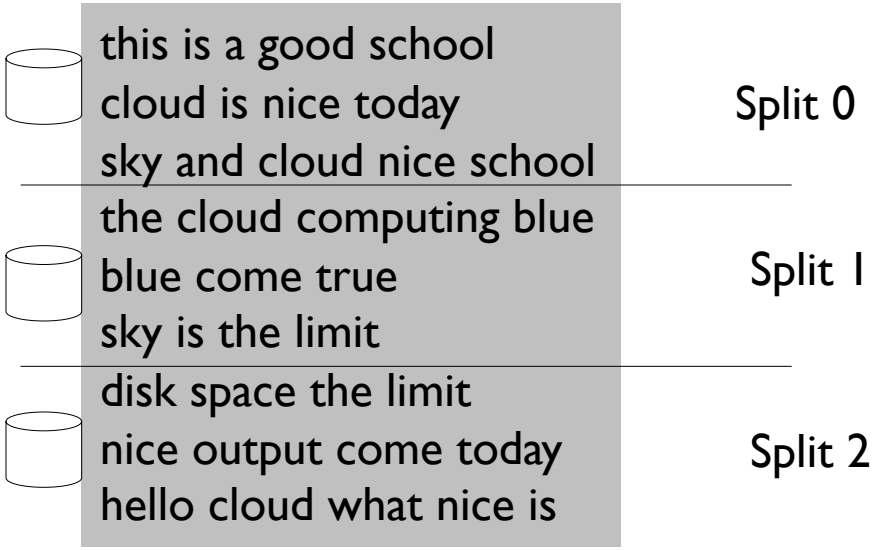

User Program
(1) fork
(1) fork
(1) fork
Master
(2) assign map
(2) assign reduce
worker
worker
worker
worker
worker
split 0
split 1
split 2
split 3
split 4
(3) read
(4) local write
(5) remote read
(6) write
output file 0
output file 1
Input files
Map phase
Intermediate files (on local disks)
Reduce phase
Output files

Small Example

Assume we have the following input data which is a sequence of lines of arbitrary words.

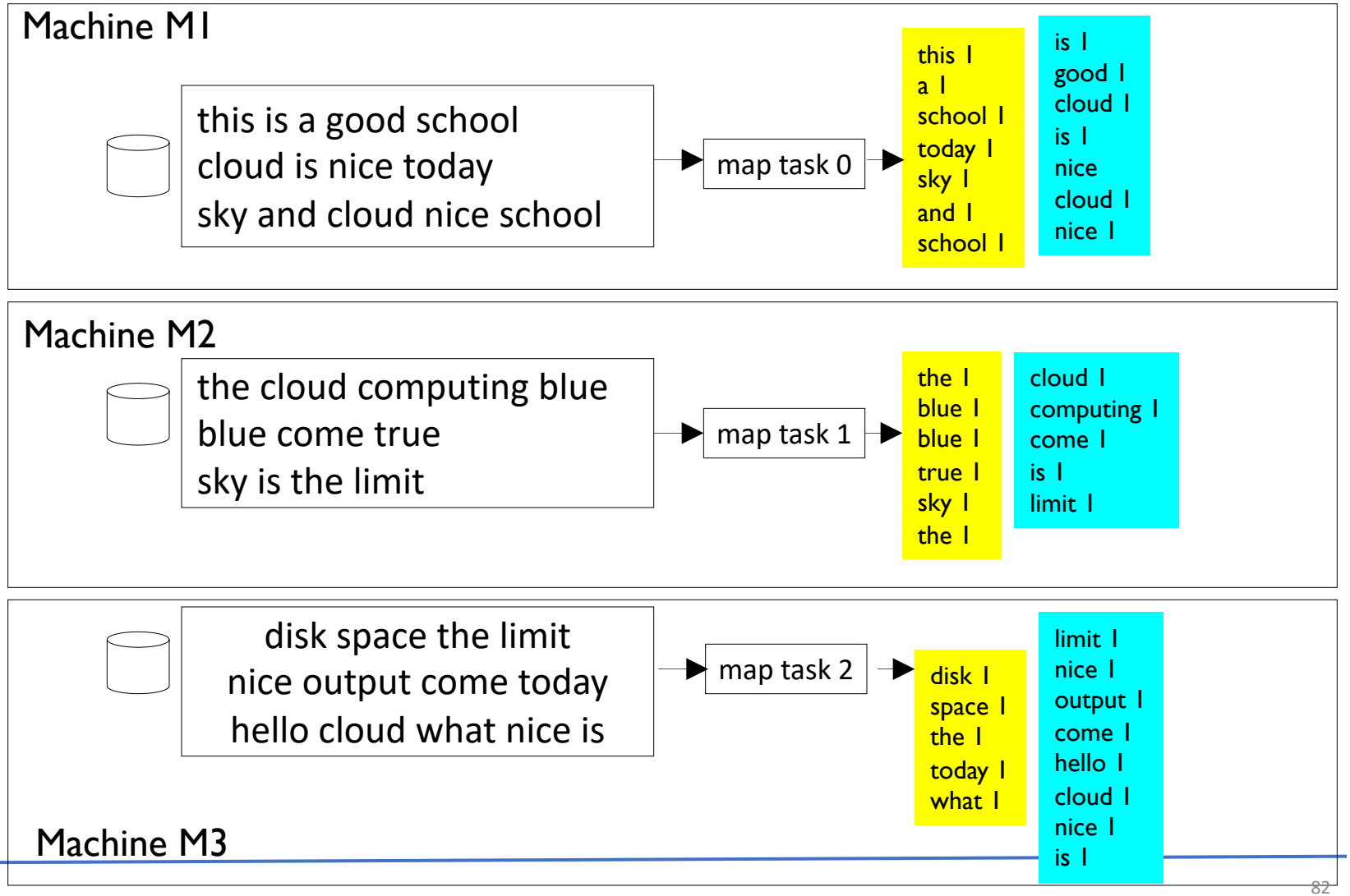


Input Data

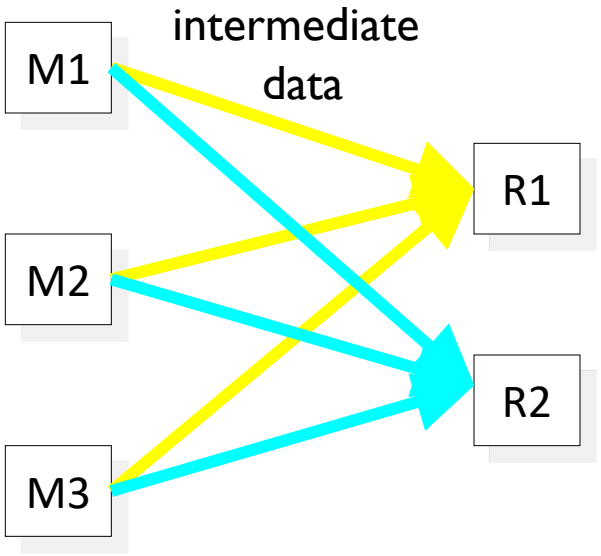


Splitting the Input Data

Small Example

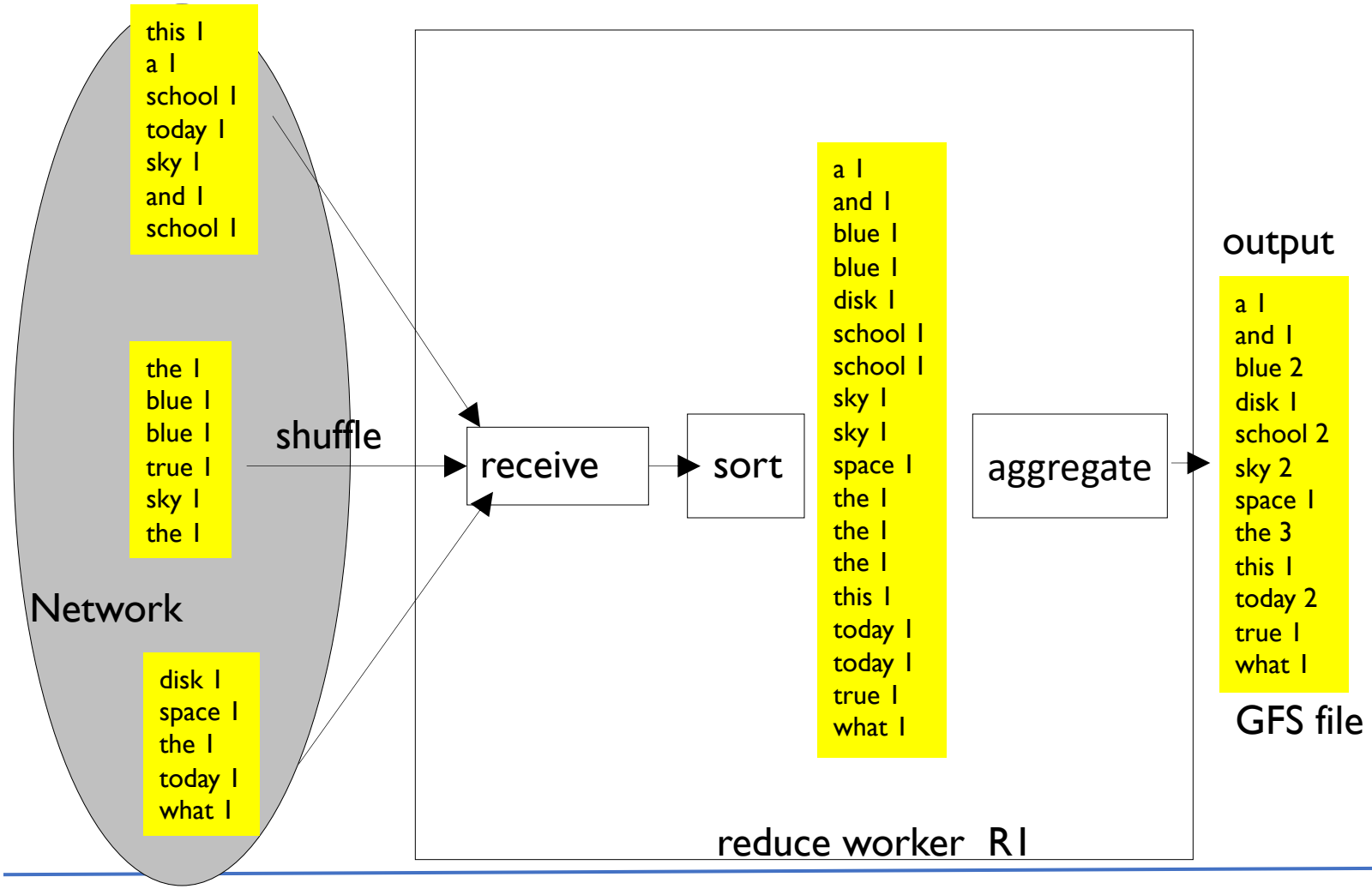


Small Example

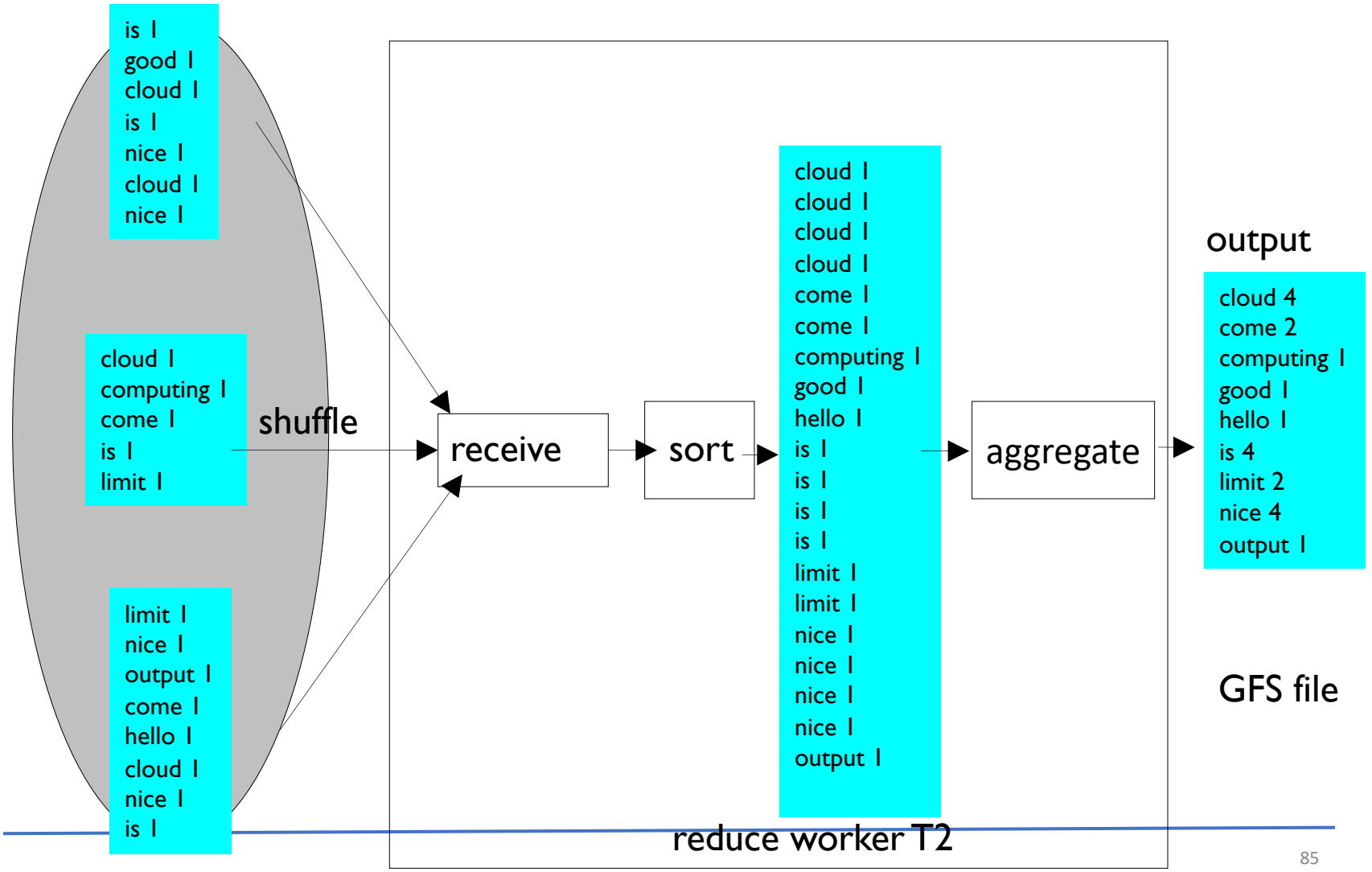


Shuffle over Network

Small Example



Small Example



Small Example

Result (Output) Files

a 1
and 1
blue 2
disk 1
school 2
sky 2
space 1
the 3
this 1
today 2
true 1
what 1

cloud 4
come 2
computing 1
good 1
hello 1
is 4
limit 2
nice 4
output 1

Sorted. Stored in DFS.

Partitioning Function

- User specifies the number of reduce tasks (i.e., output files) that he desires: R.
- Data gets partitioned across these tasks using a partitioning function on the intermediate key
- Default function: hash(key) mod R
- User can specify a different function.
- Example:
  - hash(hostname(URLkey)) mod R
  - to have all entries belonging to a host in the same output file.

Additional Study Material (optional)

Spark

- MapReduce limitations (processing for big data)
  - Not good for iterative operations (Machine Learning algorithms): slow
  - Not good for interactive big data applications: slow
  - Difficulty in programming directly
  - Not good for every application
  - Good for batch applications working on big data
- Specialized systems built
  - Pregel, GraphLab, Storm.
- Spark's goal was: to generalize MapReduce to support new apps with same engine
  - Still can work like map-reduce
  - But can do much more very efficiently (x10 or more)

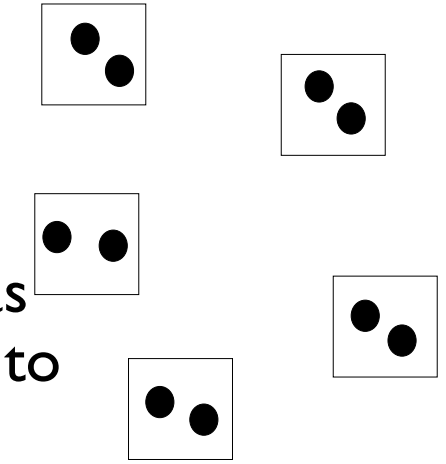
Spark features

- Handles batch, interactive and real-time jobs with a single framework
- Native integration with Java, Scala, Python
- Programming at a higher level of abstraction
- More general
  - Map/reduce is just one set of constructs

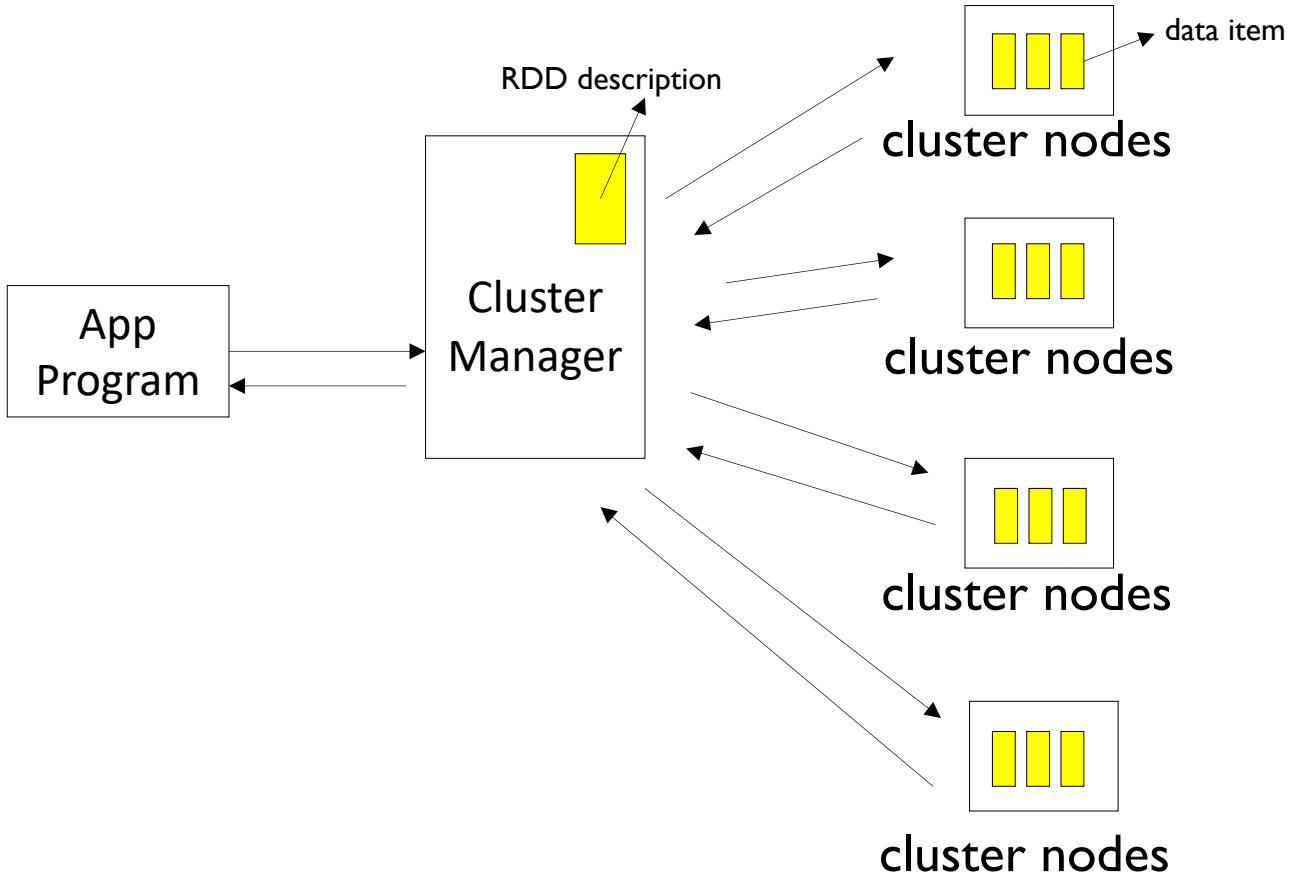
- It is a cluster computing framework. But can run on a single node (machine) as well.
  - Scalable (more nodes can be added to the cluster and Spark can utilize them)
  - Fault tolerant (node failures handled transparently)

Spark

- Main abstraction in Spark is RDD (**resilient distributed dataset**)
- RDD represents a read-only collection of objects (data items) *partitioned* across a set of machines. Partition can be rebuilt if it is lost.
  - Data item (element) can be of various types.
- Users can explicitly cache an RDD across machines and reuse it in multiple MapReduce-like parallel operations.
- RDD has enough information about how it was derived from other RDDs (lineage) to be able to rebuild just that partition. Fault tolerance.
- There is a base RDD (on disk)



Spark


data item
RDD description
cluster nodes
App
Program
Cluster
Manager
cluster nodes
cluster nodes
cluster nodes

RDD

- RDDs can only be created through deterministic *operations* (*transformations*) on either (1) data in stable storage or (2) other RDDs.
  - *map, flatmap, filter, join*
- RDDs do not need to be materialized at all times. RDD has enough information about how it was derived from other datasets (its lineage) to compute its partitions from data in stable storage.
- Users can control two other aspects of RDDs: *persistence* and *partitioning*.
  - Caching
  - Partitioning across machines on a key, etc.

Programming Interface

- For the programmer, each dataset (RDD) is represented as an object (language object) and transformations are invoked using methods on these objects.
  - Scala can be used.
  - Python can be used.
  - Java can be used
- Programmers start by defining one or more RDDs through *transformations* on data in stable storage
  - *map, fiter, …*
    - >>> linesRDD = sc.textFile ("world.txt")
- They can then use these RDDs in *actions*, which are operations that return a value to the application or export data to a storage system.
  - *count, collect, save, …*

RDDs can be stored or cached

- Programmers can call a *persist*() method to indicate which RDDs they want to reuse in future operations.
  - Spark keeps persistent RDDs in memory by default, but it can spill them to disk if there is not enough RAM.
  - Or can just put into the disk.
- The *cache*() method is similar, but default is Memory_Only.

Example: mining console logs

- Suppose that a web service is experiencing errors and an operator wants to search terabytes of logs in the Hadoop filesystem (HDFS), a distributed file system, to find the cause. Using Spark, the operator can load just the error messages from the logs into RAM across a set of nodes and query them interactively. The operator would first type the following Scala code:

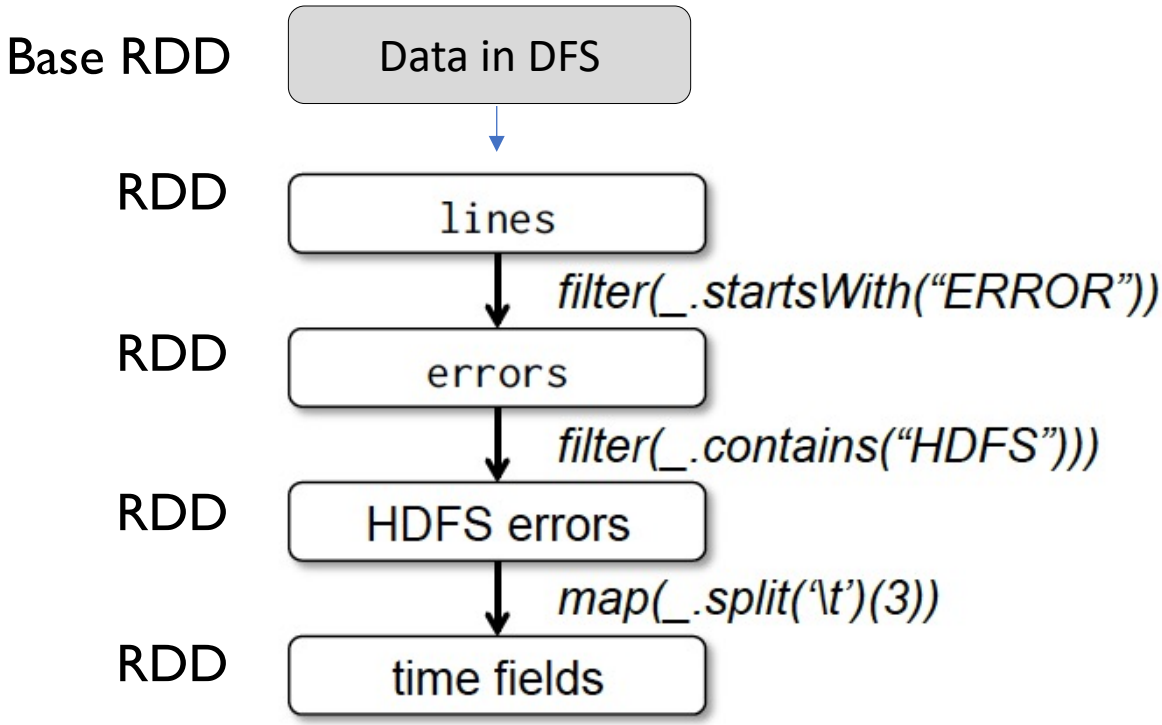
Example: mining console logs

Extract and load error messages

querying

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
errors.persist()

errors.count()

// Count errors mentioning MySQL:
errors.filter(_.contains("MySQL")).count()

// Return the time fields of errors mentioning
// HDFS as an array (assuming time is field
// number 3 in a tab-separated format):
errors.filter(_.contains("HDFS"))
      .map(_.split('\t')(3))
      .collect()
```

Lineage Graph



Extracting and querying error messages (illustrated)

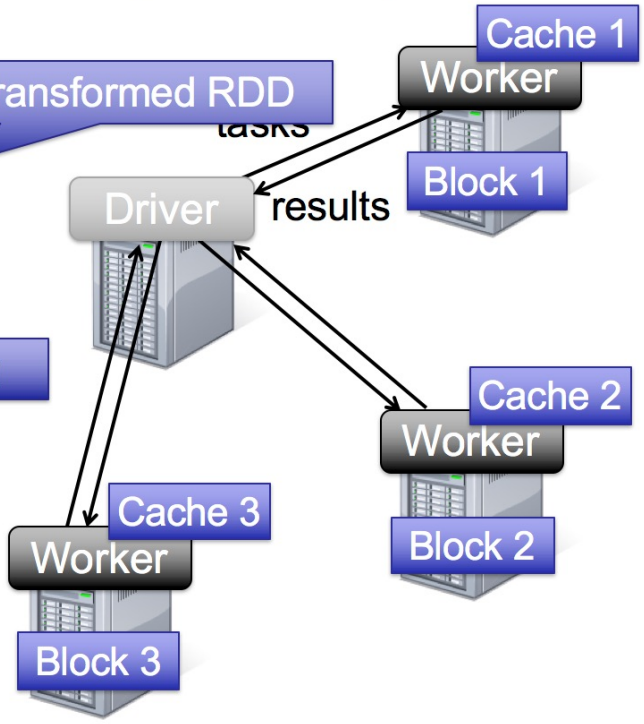
- Load error messages from a log into memory, then interactively search for patterns

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

Base RDD

Transformed RDD

Action

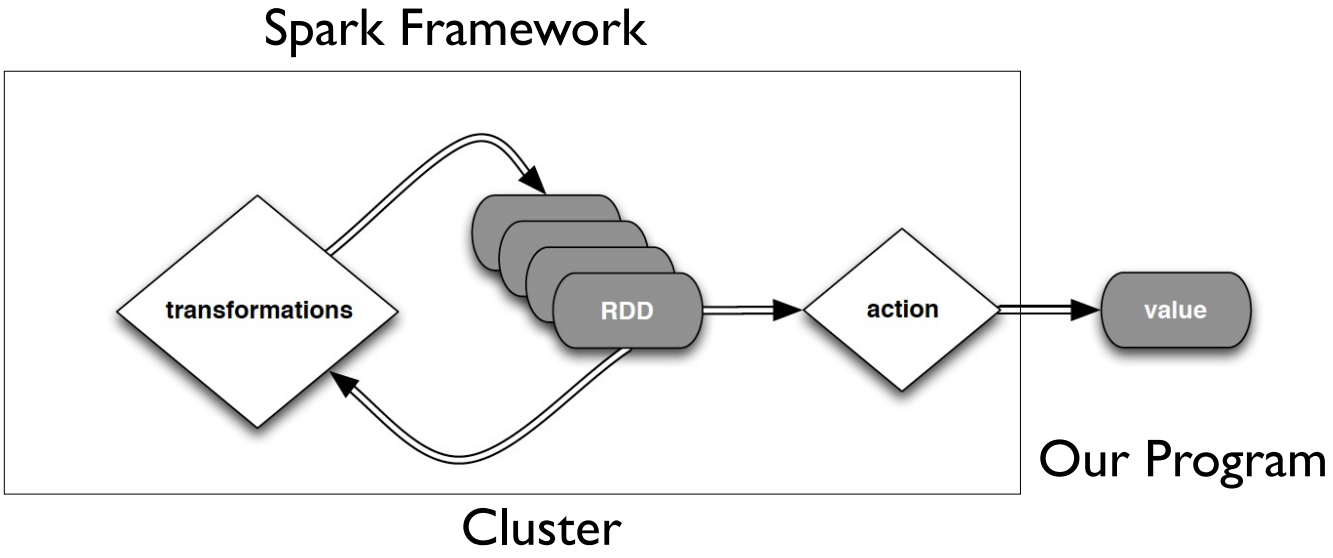


Result: scaled to 1 TB data in 5-7 sec
(vs 170 sec for on-disk data)

Strata conference slides, 2013

RDD generation

- Spark can create RDDs from any file stored in HDFS or other storage systems supported by Hadoop, e.g., local file system, Amazon S3, Hypertable, HBase, etc.
- Spark supports text files, SequenceFiles, and any other Hadoop InputFormat, and can also take a directory or a glob (e.g. /data/201404*)



Generating RDDs in Python

```
# Turn a local collection into an RDD
sc.parallelize([1, 2, 3, 4, 5, 6, 7, 8])

# Load text file from local FS, HDFS, or S3
sc.textFile("file.txt")
sc.textFile("directory/*.txt")
sc.textFile("hdfs://namenode:9000/path/file")

# Use any existing Hadoop InputFormat
sc.hadoopFile(keyClass, valClass, inputFmt, conf)
```

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RDD from another other RDD

- Transformations create a new dataset from an existing one
- All transformations in Spark are lazy: they do not compute their results right away – instead they remember the transformations
- applied to some base dataset
- optimize the required calculations
- recover from lost data partitions

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```
nums = sc.parallelize([1, 2, 3])
# Pass each element through a function
squares = nums.map(lambda x: x*x)   # => {1, 4, 9}
# Keep elements passing a predicate
even = squares.filter(lambda x: x % 2 == 0) # => {4}
# Map each element to zero or more others
nums.flatMap(lambda x: range(0, x))  # => {0, 0, 1, 0, 1, 2}
```

Operations: Transformations

transformation	*description*
map(*func***)**	return a new distributed dataset formed by passing each element of the source through a function *func*
filter(*func***)**	return a new dataset formed by selecting those elements of the source on which *func* returns true
flatMap(*func***)**	similar to map, but each input item can be mapped to 0 or more output items (so *func* should return a Seq rather than a single item)
sample(*withReplacement, fraction, seed***)**	sample a fraction *fraction* of the data, with or without replacement, using a given random number generator *seed*
union(*otherDataset***)**	return a new dataset that contains the union of the elements in the source dataset and the argument
distinct([*numTasks***]))**	return a new dataset that contains the distinct elements of the source dataset

Operations: Transformations

transformation	*description*
groupByKey([*numTasks*])	when called on a dataset of (K, V) pairs, returns a dataset of (K, Seq[V]) pairs
reduceByKey(*func*, [*numTasks*])	when called on a dataset of (K, V) pairs, returns a dataset of (K, V) pairs where the values for each key are aggregated using the given reduce function
sortByKey([*ascending*], [*numTasks*])	when called on a dataset of (K, V) pairs where K implements Ordered, returns a dataset of (K, V) pairs sorted by keys in ascending or descending order, as specified in the boolean ascending argument
join(*otherDataset*, [*numTasks*])	when called on datasets of type (K, V) and (K, W), returns a dataset of (K, (V, W)) pairs with all pairs of elements for each key
cogroup(*otherDataset*, [*numTasks*])	when called on datasets of type (K, V) and (K, W), returns a dataset of (K, Seq[V], Seq[W]) tuples – also called groupWith
cartesian(*otherDataset*)	when called on datasets of types T and U, returns a dataset of (T, U) pairs (all pairs of elements)

Operations: Actions

action	description
reduce(*func***)**	aggregate the elements of the dataset using a function *func* (which takes two arguments and returns one), and should also be commutative and associative so that it can be computed correctly in parallel
collect()	return all the elements of the dataset as an array at the driver program – usually useful after a filter or other operation that returns a sufficiently small subset of the data
count()	return the number of elements in the dataset
first()	return the first element of the dataset – similar to *take(1)*
take(*n***)**	return an array with the first *n* elements of the dataset – currently not executed in parallel, instead the driver program computes all the elements
takeSample(*withReplacement, fraction, seed***)**	return an array with a random sample of *num* elements of the dataset, with or without replacement, using the given random number generator seed

Operations: Actions

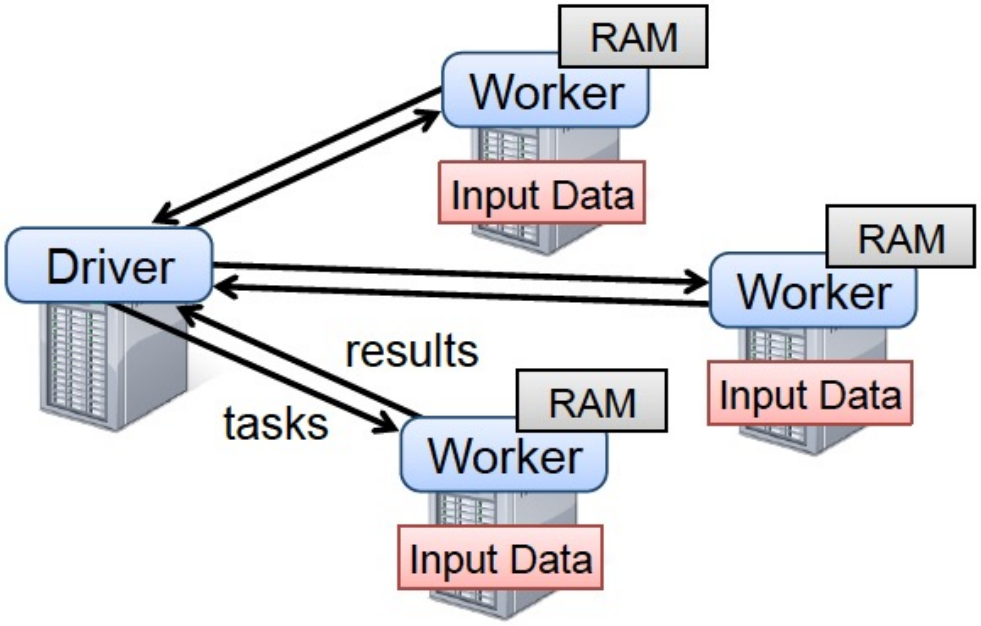
action	*description*
saveAsTextFile(*path*)	write the elements of the dataset as a text file (or set of text files) in a given directory in the local filesystem, HDFS or any other Hadoop-supported file system. Spark will call `toString` on each element to convert it to a line of text in the file
saveAsSequenceFile(*path*)	write the elements of the dataset as a Hadoop `SequenceFile` in a given path in the local filesystem, HDFS or any other Hadoop-supported file system. Only available on RDDs of key-value pairs that either implement Hadoop's `Writable` interface or are implicitly convertible to `Writable` (Spark includes conversions for basic types like `Int`, `Double`, `String`, etc).
countByKey()	only available on RDDs of type `(K, V)`. Returns a `Map` of `(K, Int)` pairs with the count of each key
foreach(*func*)	run a function *func* on each element of the dataset – usually done for side effects such as updating an accumulator variable or interacting with external storage systems

RDD operations (Summary)

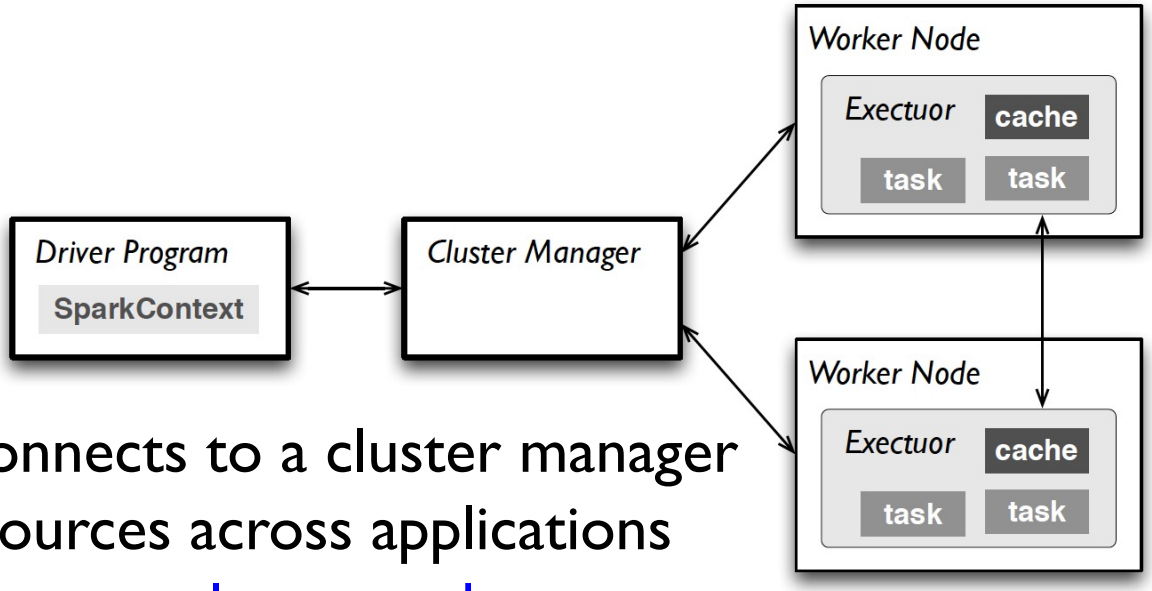
Transformations	$map(f : \mathrm{T} \Rightarrow \mathrm{U})$	:	RDD[T] ⇒ RDD[U]
	$filter(f : \mathrm{T} \Rightarrow \mathrm{Bool})$	:	RDD[T] ⇒ RDD[T]
	$flatMap(f : \mathrm{T} \Rightarrow \mathrm{Seq[U]})$	:	RDD[T] ⇒ RDD[U]
	$sample(fraction : \mathrm{Float})$	:	RDD[T] ⇒ RDD[T] (Deterministic sampling)
	$groupByKey()$	:	RDD[(K, V)] ⇒ RDD[(K, Seq[V])]
	$reduceByKey(f : (\mathrm{V}, \mathrm{V}) \Rightarrow \mathrm{V})$	:	RDD[(K, V)] ⇒ RDD[(K, V)]
	$union()$	:	(RDD[T], RDD[T]) ⇒ RDD[T]
	$join()$	:	(RDD[(K, V)], RDD[(K, W)]) ⇒ RDD[(K, (V, W))]
	$cogroup()$	:	(RDD[(K, V)], RDD[(K, W)]) ⇒ RDD[(K, (Seq[V], Seq[W]))]
	$crossProduct()$	:	(RDD[T], RDD[U]) ⇒ RDD[(T, U)]
	$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	:	RDD[(K, V)] ⇒ RDD[(K, W)] (Preserves partitioning)
	$sort(c : \mathrm{Comparator[K]})$	:	RDD[(K, V)] ⇒ RDD[(K, V)]
	$partitionBy(p : \mathrm{Partitioner[K]})$	:	RDD[(K, V)] ⇒ RDD[(K, V)]
Actions	$count()$	:	RDD[T] ⇒ Long
	$collect()$	:	RDD[T] ⇒ Seq[T]
	$reduce(f : (\mathrm{T}, \mathrm{T}) \Rightarrow \mathrm{T})$	:	RDD[T] ⇒ T
	$lookup(k : \mathrm{K})$	:	RDD[(K, V)] ⇒ Seq[V] (On hash/range partitioned RDDs)
	$save(path : \mathrm{String})$	:	Outputs RDD to a storage system, *e.g.*, HDFS

Transformations and actions available on RDDs in Spark. Seq[T] denotes a sequence of elements of type T.

Spark Runtime

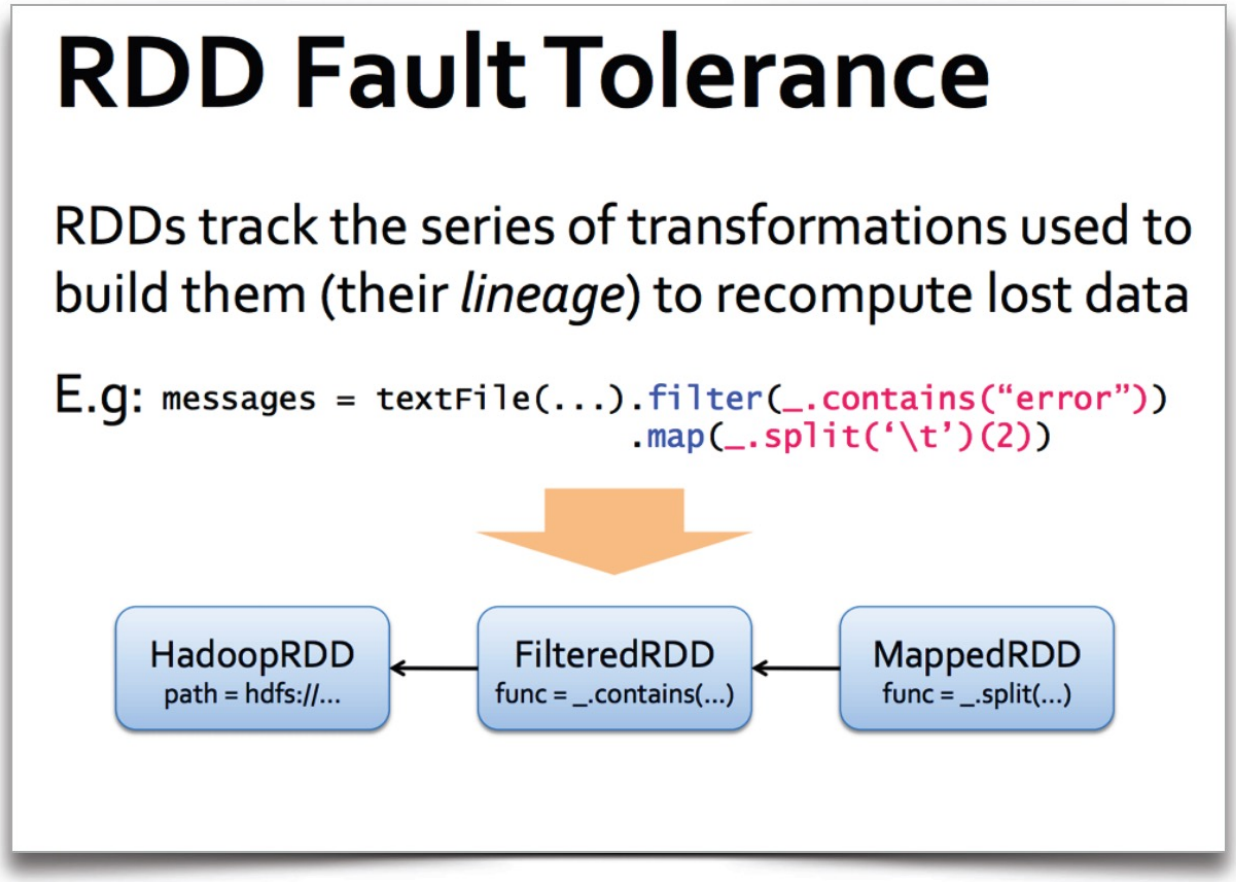


Spark Runtime



1. Our Program connects to a cluster manager which allocate resources across applications
2. acquires executors on cluster nodes – worker processes to run computations and store data
3. sends app code to the executors
4. sends tasks for the executors to run

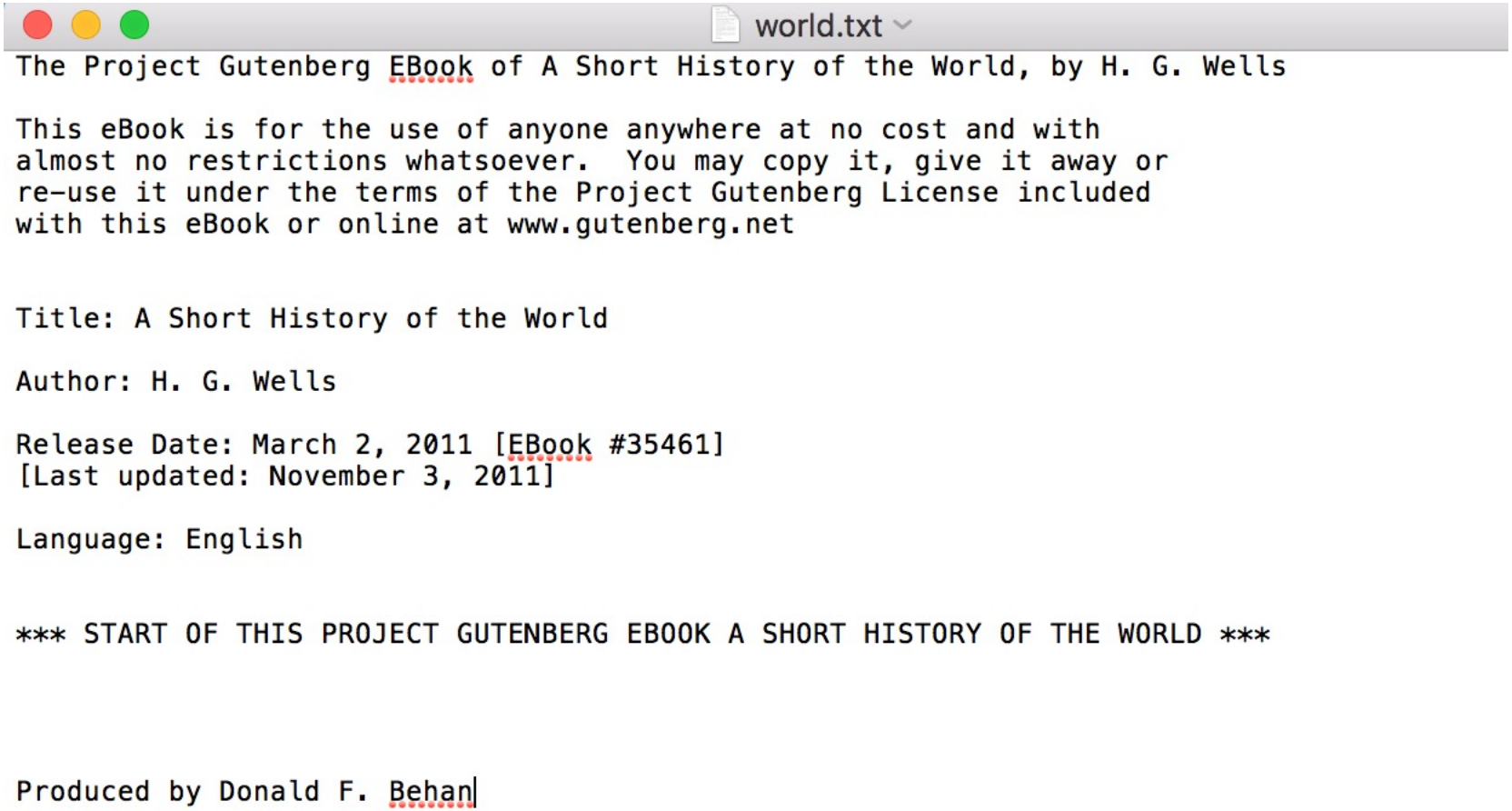
How fault tolerance achieved



A text-file example to form RDD

- We can dowload a textfile from Internet
  - Ebook from Gutenberg project.
- Assume the downloaded ebook (Short History of the World) is put into a txt file world.txt

word.txt


world.txt
The Project Gutenberg EBook of A Short History of the World, by H. G. Wells
This eBook is for the use of anyone anywhere at no cost and with
almost no restrictions whatsoever. You may copy it, give it away or
re-use it under the terms of the Project Gutenberg License included
with this eBook or online at www.gutenberg.net
Title: A Short History of the World
Author: H. G. Wells
Release Date: March 2, 2011 [EBook #35461]
[Last updated: November 3, 2011]
Language: English
*** START OF THIS PROJECT GUTENBERG EBOOK A SHORT HISTORY OF THE WORLD ***
Produced by Donald F. Behan

word.txt

world.txt

```
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PREFACE

This SHORT HISTORY OF THE WORLD is meant to be read
straightforwardly almost as a novel is read.  It gives in the most
general way an account of our present knowledge of history, shorn
of elaborations and complications.  It has been amply illustrated
and everything has been done to make it vivid and clear.  From it
the reader should be able to get that general view of history
which is so necessary a framework for the study of it particular
period or the history of a particular country.  It may be found
useful as a preparatory excursion before the reading of the
author's much fuller and more explicit _Outline of History_ is
undertaken.  But its especial end is to meet the needs of the busy
general reader, too driven to study the maps and time charts of
that _Outline_ in detail, who wishes to refresh and repair his
faded or fragmentary conceptions of the great adventure of
mankind.  It is not an abstract or condensation of that former
work.  Within its aim the _Outline_ admits of no further
condensation.  This is a much more generalized History, planned
and written afresh.

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 CONTENTS
```

Process text file

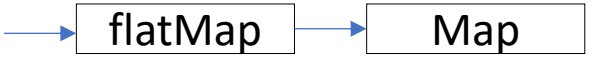
- We can now process this file. For example, to obtain all words in the book into a list, or to count the words.

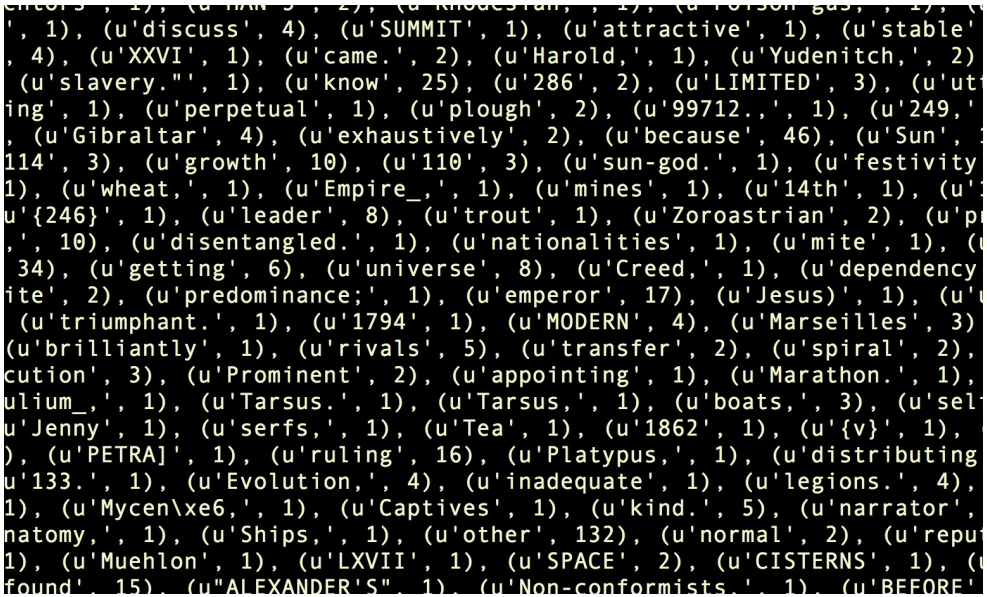
- To obtain words, in our Python program we write:
  - distFile = sc.textFile("world.txt")!
  - distFile.map(lambda x: x.split(' ')).collect()

Word count

Python code:

```
from operator import add
f = sc.textFile("world.txt")
words = f.flatMap(lambda x: x.split(' ')).map(lambda x: (x, 1))
words.reduceByKey(add).collect()
```





Word count

- Spark can persist (or cache) a dataset in memory across operations
- Each node stores in memory any slices of it that it computes and reuses them in other actions on that dataset – often making future actions more than 10x faster
- The cache is fault-tolerant: if any partition of an RDD is lost, it will automatically be recomputed using the transformations that originally created it

```
from operator import add
f = sc.textFile("README.md")
w = f.flatMap(lambda x: x.split(' ')).map(lambda x: (x, 1)).cache()
w.reduceByKey(add).collect()
```

Accumulators

- Accumulators are variables that can only be "added" to through an associative operation
- Used to implement counters and sums, efficiently in parallel
- Spark natively supports accumulators of numeric value types and standard mutable collections, and programmers can extend for new types
- Only the driver program can read an accumulator's value, not the tasks

Accumulators

- We can define and use an accumulator variable. All functions, no matter in which node they are executed, can add into the accumulator variable.

Python:

```
accum = sc.accumulator(0)
rdd = sc.parallelize([1, 2, 3, 4])
def f(x):
    global accum
    accum += x

rdd.foreach(f)

accum.value
```

Create the variable

There are 4 elements in the dataset

We define a function

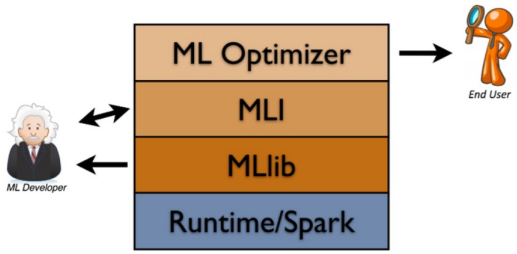
We are executing the function on each dataset element x

We are accessing to the accumulated value

Spark libraries/frameworks

- Spark Streaming
  - Stream analytics

- MLlib
  - Distributed machine learning framework



- GraphX
  - Distributed graph processing framework

References

1. Database System Concepts. Silberschatz et al. 6th edition. 2011.
2. CS109 Data Science, Harvard.
3. CMSC320 Introduction to Data Science, UMD.
4. 15-388/688 Practical Data Science, CMU.
5. CS194 Introduction to Data Science, UC Berkeley.
6. CSCI 1951A. Data Science, Brown.
7. Cloud Computing: Theory and Practice, D. Marinescu, Morgan Kaufmann, 2013.
8. MapReduce: Simplified Data Processing on Large Clusters, J. Dean and S. Ghamawat, OSDI, 2004.
9. Mining of Massive Datasets, J. Leskovec, A. Rajaraman, J. Ullman.
10. CS240A, UCSB.
11. Resilient Distributed Datasets: A Fault-Tolerant Abstraction for
12. In-Memory Cluster Computing, Zaharia et al., NSDI 2012.

References

- https://phppot.com/php/php-restful-web-service/
- Sqlite3: https://www.sqlite.org/index.html
- RDMBs and Pandas: https://www.textbook.ds100.org/ch/09/sql_intro.html
- https://www.textbook.ds100.org/ch/03/pandas_intro.html
- https://medium.com/swlh/pyspark-on-macos-installation-and-use-31f84ca61400