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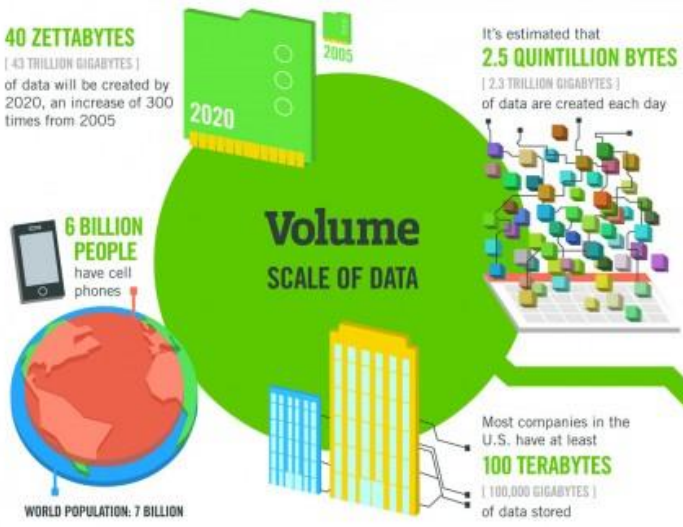
▷ Department of Computational and Data Sciences

▷ Indian Institute of Science, Bangalore



# Big Data Processing with Apache Spark

# Motivation



# The FOUR V's of Big Data

From traffic patterns and music downloads to web history and medical records, data is recorded, stored, and analyzed to enable the technology and services that the world relies on every day. But what exactly is big data, and how can these massive amounts of data be used?

As a leader in the sector, IBM data scientists break big data into four dimensions: **Volume, Velocity, Variety and Veracity**

Depending on the industry and organization, big data encompasses information from multiple internal and external sources such as transactions, social media, enterprise content, sensors and mobile devices. Companies can leverage data to adapt their products and services to better meet customer needs, optimize operations and infrastructure, and find new sources of revenue.

By 2015  
**4.4 MILLION IT JOBS**  
will be created globally to support big data, with 1.9 million in the United States

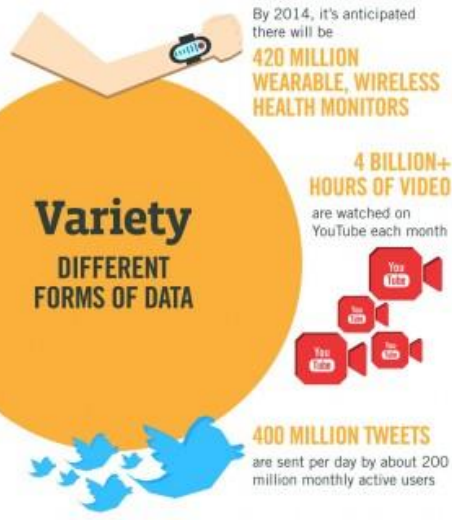


As of 2011, the global size of data in healthcare was estimated to be

**150 EXABYTES**  
[ 161 BILLION GIGABYTES ]



**30 BILLION  
PIECES OF CONTENT**  
are shared on Facebook every month



The New York Stock Exchange captures **1 TB OF TRADE INFORMATION** during each trading session



Modern cars have close to **100 SENSORS** that monitor items such as fuel level and tire pressure

**Velocity  
ANALYSIS OF  
STREAMING DATA**

By 2016, it is projected there will be

**18.9 BILLION NETWORK CONNECTIONS**

— almost 2.5 connections per person on earth



**1 IN 3 BUSINESS LEADERS**

don't trust the information they use to make decisions



**27% OF RESPONDENTS**

In one survey were unsure of how much of their data was inaccurate

**Veracity  
UNCERTAINTY OF DATA**

Poor data quality costs the US economy around

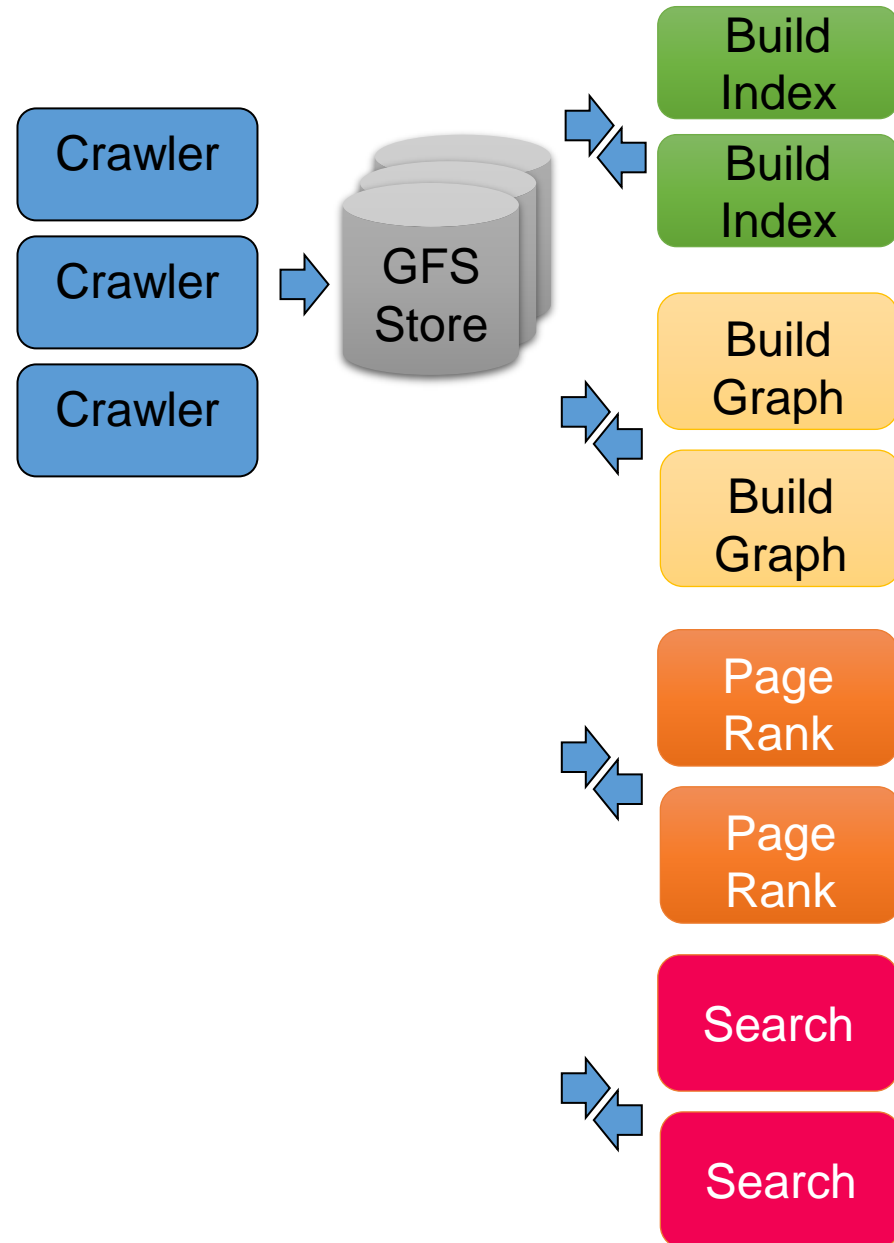
**\$3.1 TRILLION A YEAR**



Sources: McKinsey Global Institute, Twitter, Cisco, Gartner, EMC, SAS, IBM, MEPTec, QAS

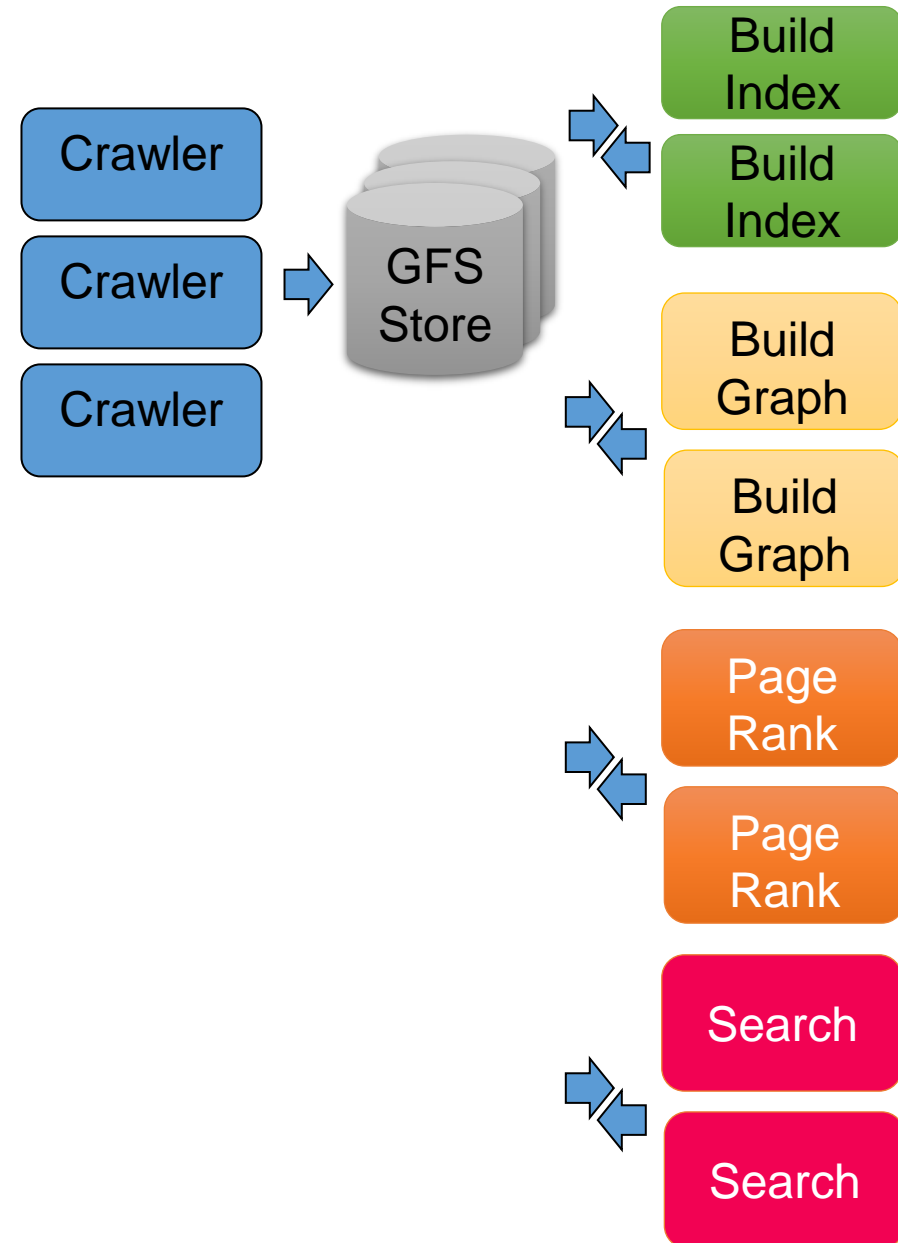
# Motivation: Store

- ▶ Google wants to search the entire WWW
- ▶ How do we store the WWW at scale?
  - “few million files, each typically 100 MB or larger in size”
  - “large streaming reads and small random reads”
  - Google File System/HDFS



# Motivation: Process

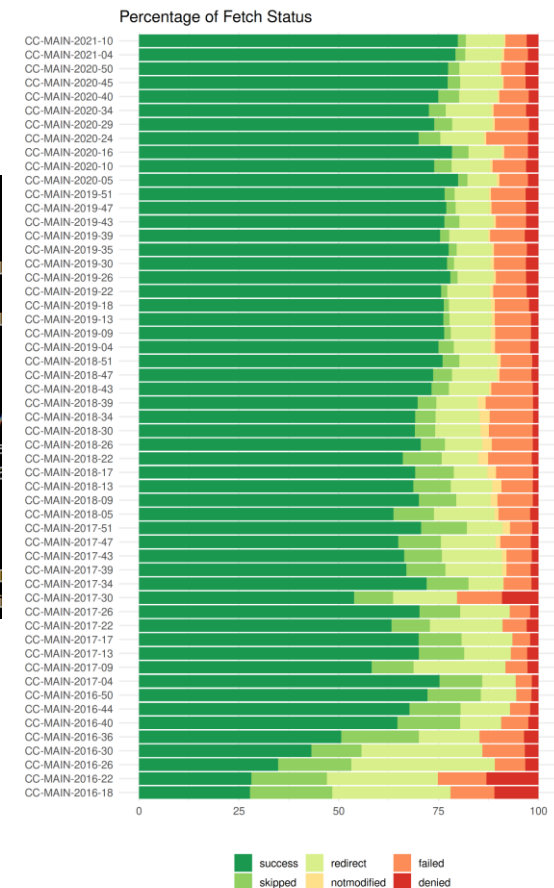
- ▶ Google wants to search the entire WWW
- ▶ How do we process this data at scale?
  - Inverted Index of Webpage keywords
  - PageRank algorithm for ranking



# Motivation: Web Crawl & Search

- ▶ HTTP Response logs (~65k per day for CDS!)
  - Lines with HTTP response codes
  - Distribution of browser types

```
10.0.7.5 - - [04/Apr/2021:03:28:11 +0000] "GET / HTTP/1.1" 200 22613 "-" "-"
10.0.7.4 - - [04/Apr/2021:03:28:23 +0000] "GET / HTTP/1.1" 301 - "-" "-"
10.0.7.4 - - [04/Apr/2021:03:28:23 +0000] "GET / HTTP/1.1" 200 22613 "-" "-"
10.0.7.5 - - [04/Apr/2021:03:28:25 +0000] "GET /robots.txt HTTP/1.1" 200 160 "-" "Mozilla/5.0 (compatibl
n/seznambot-intro/)"
10.0.7.4 - - [04/Apr/2021:03:28:30 +0000] "GET /sitemap-pt-post-2018-08.xml HTTP/1.1" 200 501 "-" "Mozil
oveda.seznam.cz/en/seznambot-intro/)"
10.0.7.5 - - [04/Apr/2021:03:28:41 +0000] "GET / HTTP/1.1" 301 - "-" "-"
10.0.7.5 - - [04/Apr/2021:03:28:41 +0000] "GET / HTTP/1.1" 200 22613 "-" "-"
10.0.7.5 - - [04/Apr/2021:03:28:44 +0000] "GET /academics/contact-dcc/ HTTP/1.1" 200 26635 "-" "Mozilla/
9P) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/89.0.4389.102 Mobile Safari/537.36 (compatible; Google
10.0.7.4 - - [04/Apr/2021:03:28:50 +0000] "GET / HTTP/1.1" 301 - "-" "Mozilla/5.0 (Windows NT 10.0; Wind
Chrome/89.0.4389.114 Safari/537.36"
10.0.7.4 - - [04/Apr/2021:03:28:51 +0000] "GET / HTTP/1.1" 200 47769 "-" "Mozilla/5.0 (Windows NT 10.0;
cko) Chrome/89.0.4389.114 Safari/537.36"
10.0.7.4 - - [04/Apr/2021:03:28:51 +0000] "GET /wp-content/plugins/papercite/papercite.css?ver=5.6.2 HT
lla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/89.0.4389.114 Safari
```



# Motivation: Web Crawl & Search

## ► HTML file content

- Build inverted index of words to URLs
- Extract URL and Title
- Extract links, build graph, find PageRank
- Word co-occurrence and clustering

*Remove stop words,  
contractions*



URL	Keywords[]				
u1	We	The	People	Of	India
u2	It	Was	The	Best	Of
u3	Call	Me	Ishmael	Some	Years
u4	Here's	My	Number	Call	me
u5	People	Call	Me	The	Best
u6	Number	Of	People	In	India
u7	Best	Years	Of	My	Life

Keyword	URL List		
People	u1	u5	u6
India	u1	u6	
Best	u2	u5	u7
Call	u3	u4	u5
Ishmael	u3		
Some	u3		
Years	u3	u7	
Here	u4		
Number	u4	u6	
Life	u7		

# Motivation: Web Crawl & Search

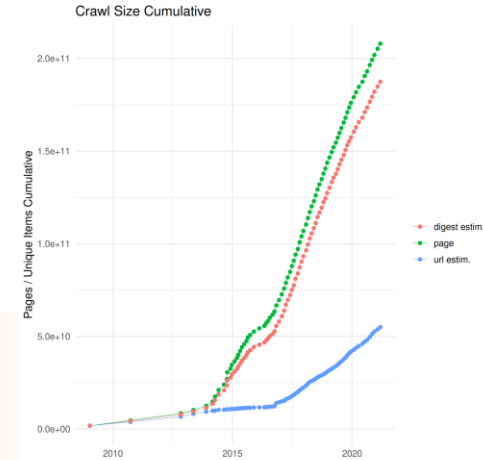
- ▶ HTML file content
  - Build inverted index of words to URLs
  - **Extract URL and Title**
  - Extract links, build graph adjacency list
  - Word co-occurrence and clustering

URL	Title
u1	The Constitution of India
u2	A Tale of Two Cities by Dickens
u3	Project Gutenberg - Moby Dick
u4	Carly Rae Jepsen - Call Me Maybe
u5	Shah Rukh Khan interview
u6	Wikipedia – India's Population
u7	Best Years of My Life Pistol Annies

```
WARC/1.0
WARC-Type: response
WARC-Date: 2014-08-02T09:52:13Z
WARC-Record-ID:
Content-Length: 43428
Content-Type: application/http; msgtype=response
WARC-Warcinfo-ID:
WARC-Concurrent-To:
WARC-IP-Address: 212.58.244.61
WARC-Target-URI: http://news.bbc.co.uk/2/hi/africa/3414345.stm
WARC-Payload-Digest: sha1:M63W6MNGFDWDSLTHF7GWUPCJU4J3J
WARC-Block-Digest: sha1:YHKQUSBOS4CLYFEKQDVGJ457OAPD6IJO
WARC-Truncated: length
```

```
HTTP/1.1 200 OK
Server: Apache
Vary: X-CDN
Cache-Control: max-age=0
Content-Type: text/html
Date: Sat, 02 Aug 2014 09:52:13 GMT
Expires: Sat, 02 Aug 2014 09:52:13 GMT
Connection: close
Set-Cookie: BBC-UID=...; expires=Sun, 02-Aug-15 09:52:13 GMT; path=/; domain=bbc.co.uk;

<!doctype html public "-//W3C//DTD HTML 4.0 Transitional//EN" "http://www.w3.org/TR/REC-html40/loose.dtd">
<html>
<head>
<title>
BBC NEWS | Africa | Namibia braces for Nujoma exit
</title>
...
```



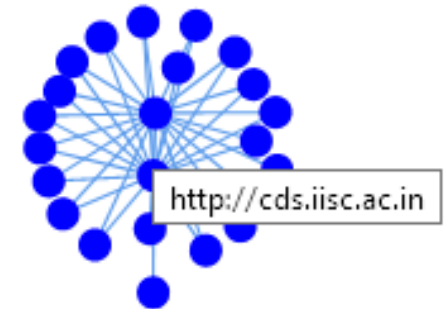


# Motivation: Web Crawl & Search

## ► HTML file content

- Build inverted index of words to URLs
- Extract URL and Title
- Extract links, build graph, find PageRank
- Word co-occurrence and clustering

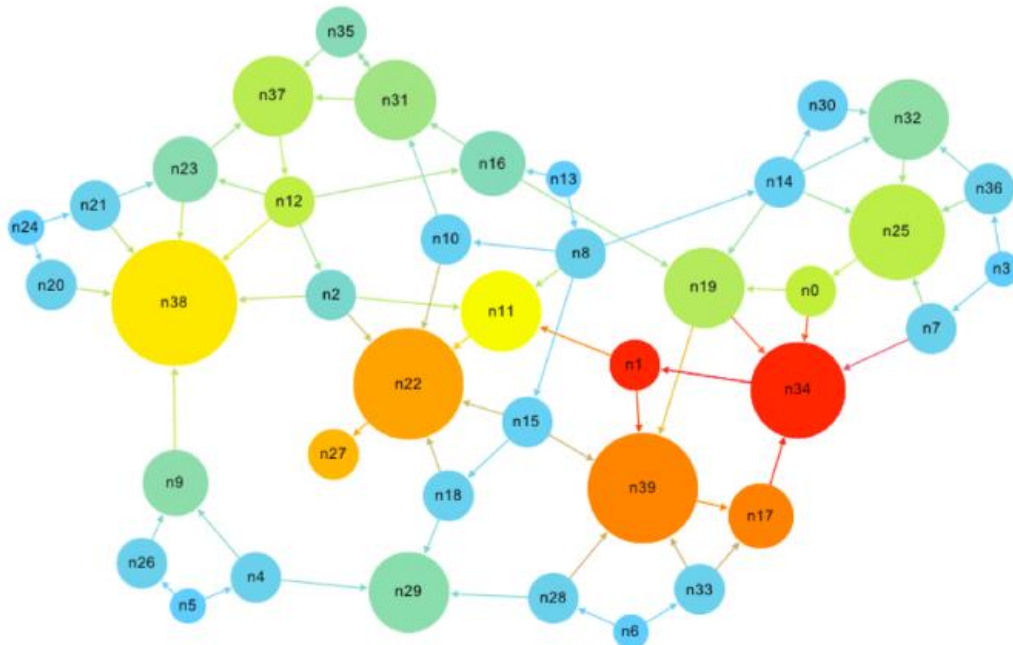
```
<li id="menu-item-307" class="menu-item menu-item-type-post_type menu-item-object-page menu-item-has-children menu-item-307"><a href="https://www.iisc.ac.in/about/student-corner/">Student Corner</a>
<ul class="sub-menu">
<li id="menu-item-310" class="menu-item menu-item-type-custom menu-item-object-custom menu-item-has-children menu-item-310"><a href="/about/student-corner/">General Information</a>
<ul class="sub-menu">
<li id="menu-item-2324" class="menu-item menu-item-type-post_type menu-item-object-page menu-item-2324"><a href="https://www.iisc.ac.in/campus-life/">Campus Life</a></li>
<li id="menu-item-11152" class="menu-item menu-item-type-post_type menu-item-object-page menu-item-11152"><a href="https://www.iisc.ac.in/my-iisc-my-life-a-student-perspective/">My IISc, my life: a student perspective</a></li>
<li id="menu-item-2274" class="menu-item menu-item-type-custom menu-item-object-custom menu-item-2274"><a target="blank" href="http://hostel.iisc.ernet.in/hostel/">Hostels/Mess</a></li>
<li id="menu-item-312" class="menu-item menu-item-type-custom menu-item-object-custom menu-item-312"><a target="blank" href="https://iiscgym.iisc.ac.in/">Gymkhana</a></li>
<li id="menu-item-315" class="menu-item menu-item-type-post_type menu-item-object-page menu-item-315"><a href="https://www.iisc.ac.in/about/student-corner/procedure-for-obtaining-official-transcripts/">Official transcripts</a></li>
<li id="menu-item-3414" class="menu-item menu-item-type-post_type menu-item-object-page menu-item-3414"><a href="https://www.iisc.ac.in/about/campus-facilities/">Campus Facilities</a></li>
<li id="menu-item-317" class="menu-item menu-item-type-custom menu-item-object-custom menu-item-317"><a target="blank" href="/health-centre/">Health Centre</a></li>
<li id="menu-item-11016" class="menu-item menu-item-type-post_type menu-item-object-page menu-item-11016"><a href="https://www.iisc.ac.in/auditoria-and-seminar-halls/">Auditoria and Seminar Halls</a></li>
<li id="menu-item-1170" class="menu-item menu-item-type-post_type menu-item-object-page menu-item-1170"><a href="https://www.iisc.ac.in/icash/">Internal Committee Against Sexual Harassment (ICASH)</a></li>
</ul></li>
```



# Motivation: Web Crawl & Search

## ► HTML file content

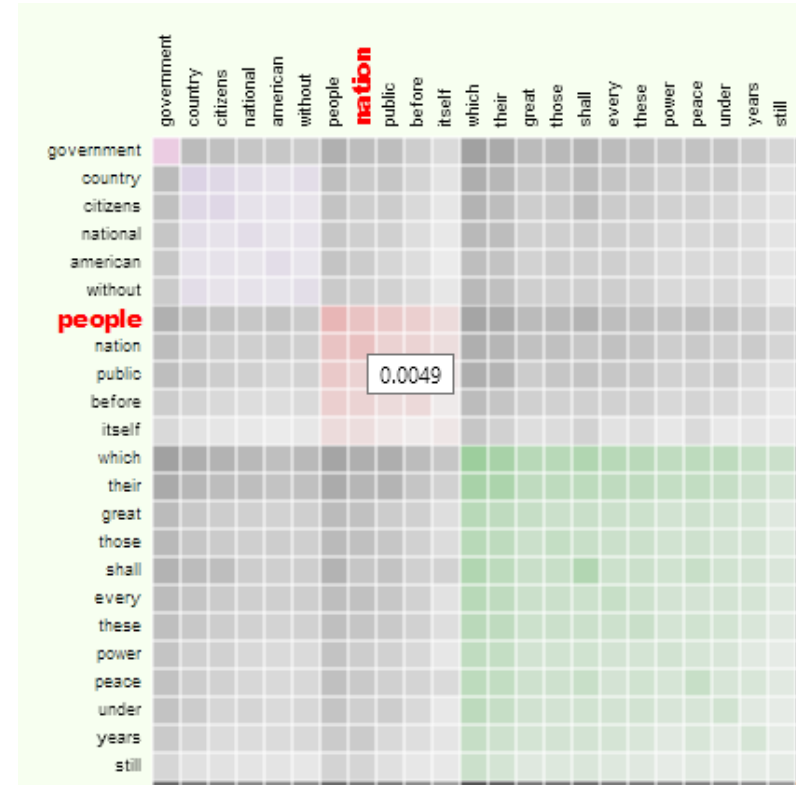
- Build inverted index of words to URLs
- Extract URL and Title
- **Extract links, build graph, find PageRank**
- Word co-occurrence and clustering



URL	PageRank
u1	0.02
u2	0.3
u3	0.08
u4	0.1
u5	0.2
u6	0.25
u7	0.05

# Motivation: Web Crawl & Search

- ▷ HTML file content
  - Build inverted index of words to URLs
  - Extract URL and Title
  - Extract links, build graph, find PageRank
  - **Word co-occurrence and associative rule mining**



# Motivation: Web Crawl & Search

## ▷ Bringing it all together: **Doing a Search**

- **Lookup** of keyword in inverted index, find common URLs for keywords
- **Lookup** PageRank of all matching URLs
- **Sort and Select top  $n$**  PageRank URLs
- **Join** top  $n$  pages with URL and title
- **Return** result to user
- **Suggest** similar searches (co-occurrence)



# Google's MapReduce

*“A simple and powerful interface that enables automatic parallelization and distribution of large-scale computations, combined with an implementation of this interface that achieves high performance on large clusters of commodity PCs.”*

# MapReduce Design Pattern

- ▷ Programming model for distributed applications
  - Clean abstraction for programmers
  - Automatic parallelization & distribution
- ▷ Fault-tolerance
- ▷ Batch data processing system
  - Large inputs sizes
- ▷ Simple data-intensive applications
  - Distributed Grep: Document list → Occurrence of search term
  - URL Access Frequency: URL access list → <URL, freq>
  - Reverse Web-Link Graph: <target,src> → <src, target[]>
  - Term-Vector per Host: <host,word[]> → <host,<word,freq>[]>

# MapReduce: Data-parallel Programming Model

- ▶ Process data using **map** & **reduce** user-defined functions
- ▶  **$\text{map}(k_i, v_i) \rightarrow \text{List}\langle k_m, v_m \rangle$** 
  - *map* is called once on every input item
  - Emits a series of intermediate key/value pairs
- ▶ **shuffle & sort phase**
  - All map output values ( $v_m$ ) with a given key ( $k_m$ ) are *grouped* together, keys *sorted* within a group
  - Happens internally within the framework
- ▶  **$\text{reduce}(k_m, \text{List}\langle v_m \rangle) \rightarrow \text{List}\langle k_r, v_r \rangle$** 
  - *reduce* is called once on *every unique key & all its values*
  - Emits a value that is added to the output

# Histogram using MR

7	2	11	2
2	1	11	4
9	10	6	6
6	3	2	8
0	5	1	10
2	4	8	11
5	0	1	0
<b>M</b>	<b>M</b>	<b>M</b>	<b>M</b>
1,1	0,1	2,1	0,1
0,1	0,1	2,1	1,1
2,1	2,1	1,1	1,1
1,1	0,1	0,1	2,1
0,1	1,1	0,1	2,1
0,1	1,1	2,1	2,1
1,1	0,1	0,1	0,1

## Shuffle

2,1	0,1	0,1	1,1
2,1	0,1	0,1	1,1
2,1	0,1	0,1	1,1
2,1	0,1	0,1	1,1
2,1	0,1	0,1	1,1
2,1	0,1	0,1	1,1
2,1	0,1	0,1	1,1
2,1			1,1
2,1			1,1

<b>R</b>	<b>R</b>	<b>R</b>
2,8	0,12	1,8

Data transfer & shuffle between Map & Reduce (28 items)

```
int bucketWidth = 4 // input
```

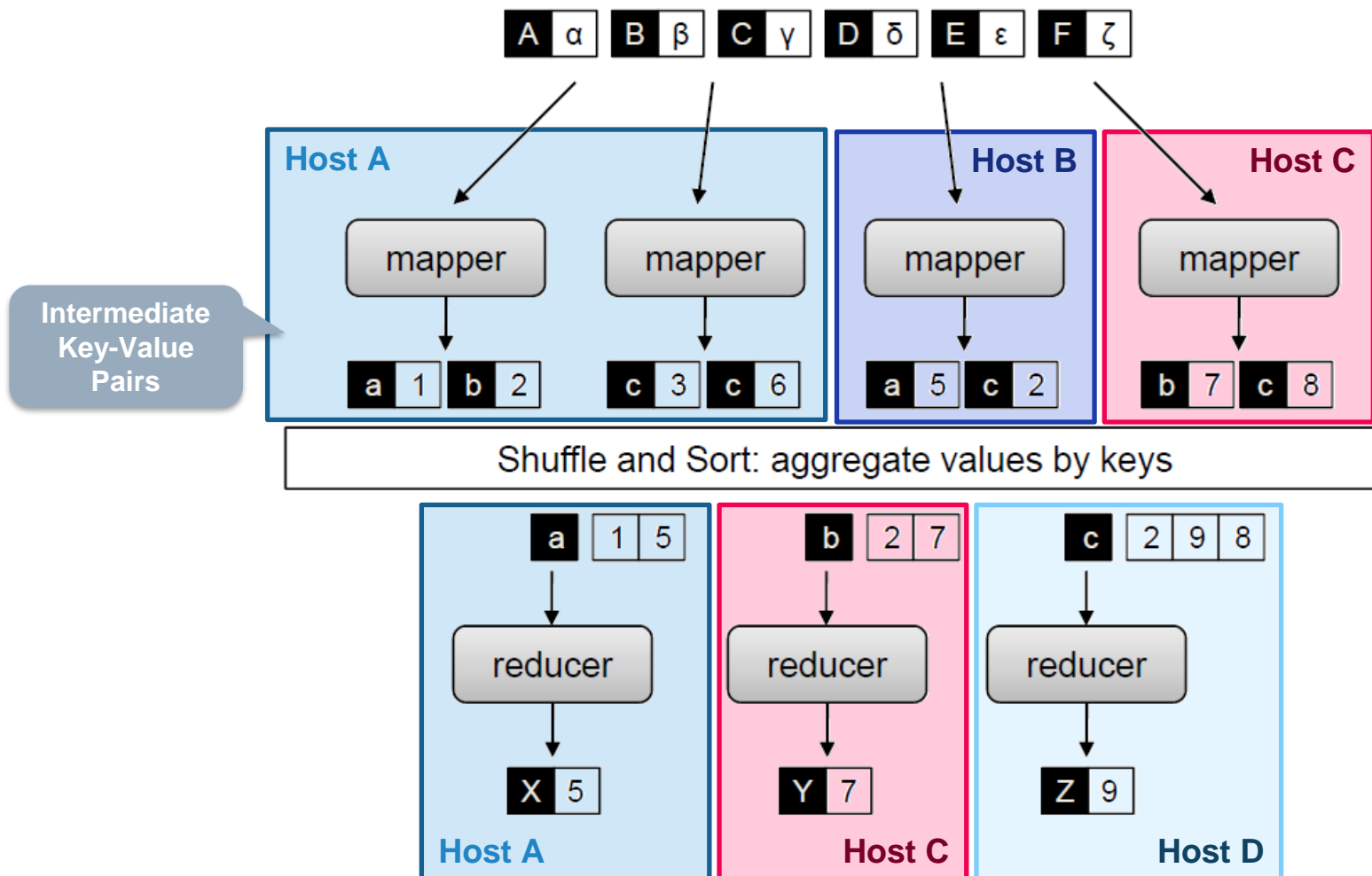
```
Map(k, v) {
    emit(floor(v/bucketWidth), 1)
    // <bucketID, 1>
}
```

```
// one reduce per bucketID
```

```
Reduce(k, v[]){
    sum=0;
    foreach(n in v[]) sum+=n;
    emit(k, sum)
    // <bucketID, frequency>
}
```

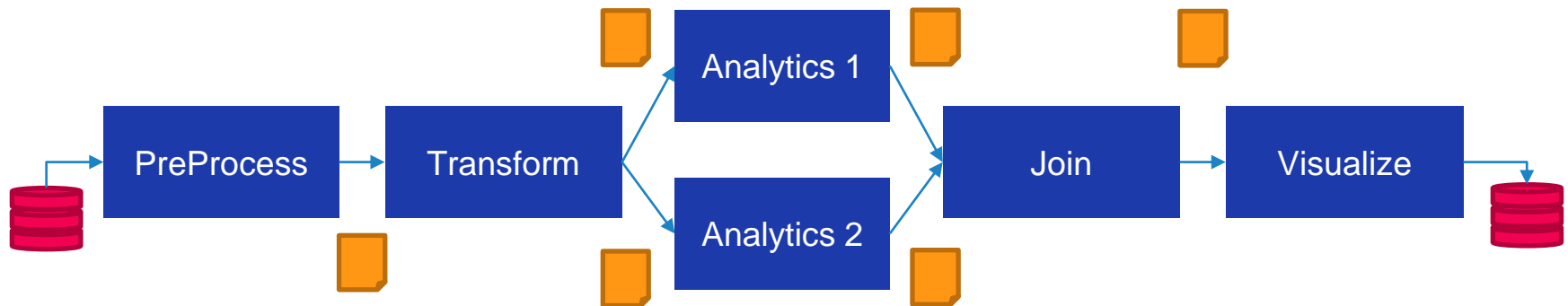


# Map-Shuffle-Sort-Reduce



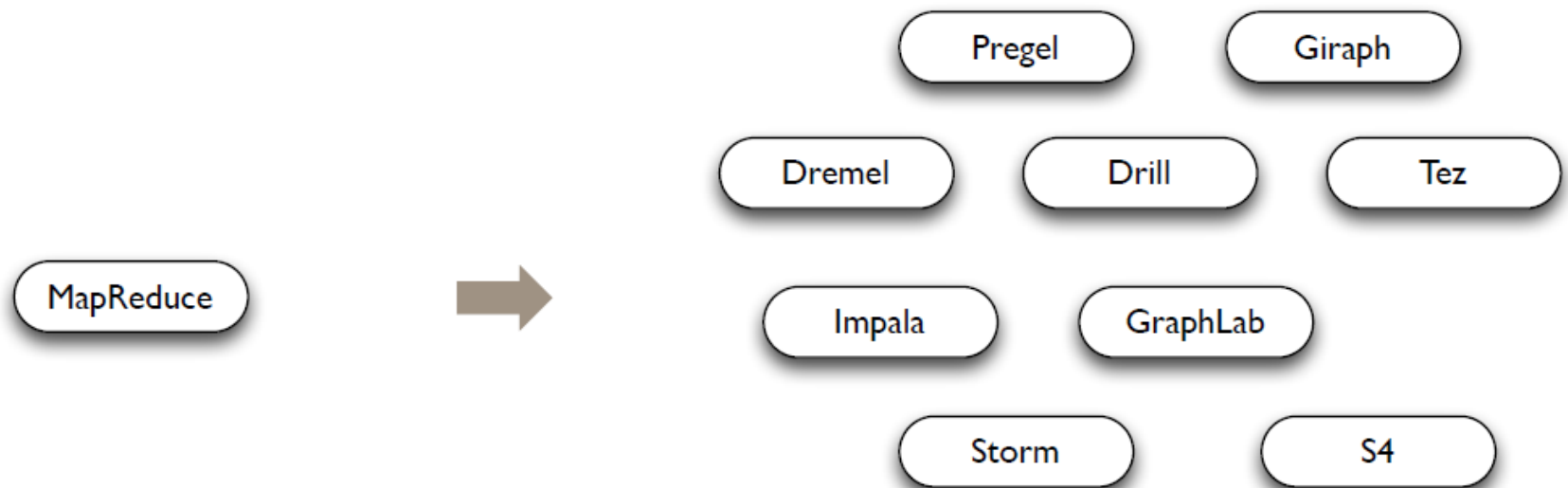
# Limitations of MapReduce

- ▷ Multi-stage computing not simple
  - Many different jobs
- ▷ Complex code for simple transformations
  - Repetitive, not *data centric*



# Limitations of MapReduce

- ▶ Limited support for non-text, Non-static data



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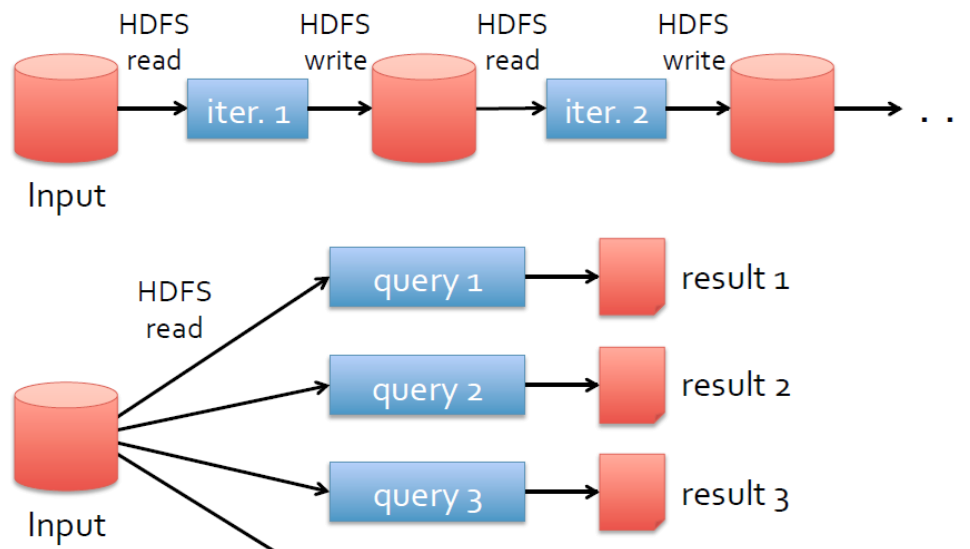
**General Batch Processing**

---

**Specialized Systems:**  
iterative, interactive, streaming, graph, etc.

# Limitations of MapReduce

- ▷ Poor performance for:
  - Complex, multi--stage applications (e.g. iterative machine learning & graph processing)
  - Interactive *ad hoc* queries



# Latency & Bandwidth

- ▷ L1 cache reference
- ▷ L2 cache reference
- ▷ Main memory reference
- ▷ Send 1K bytes over 1 Gbps network
- ▷ Read 4K randomly from SSD\*
- ▷ Read 1MB sequentially from memory
- ▷ Round trip within same datacenter
- ▷ Read 1MB sequentially from SSD\*
- ▷ Send 1MB over 1 Gbps network
- ▷ Disk seek
- ▷ Read 1MB sequentially from disk
- ▷ Send packet CA->NL->CA

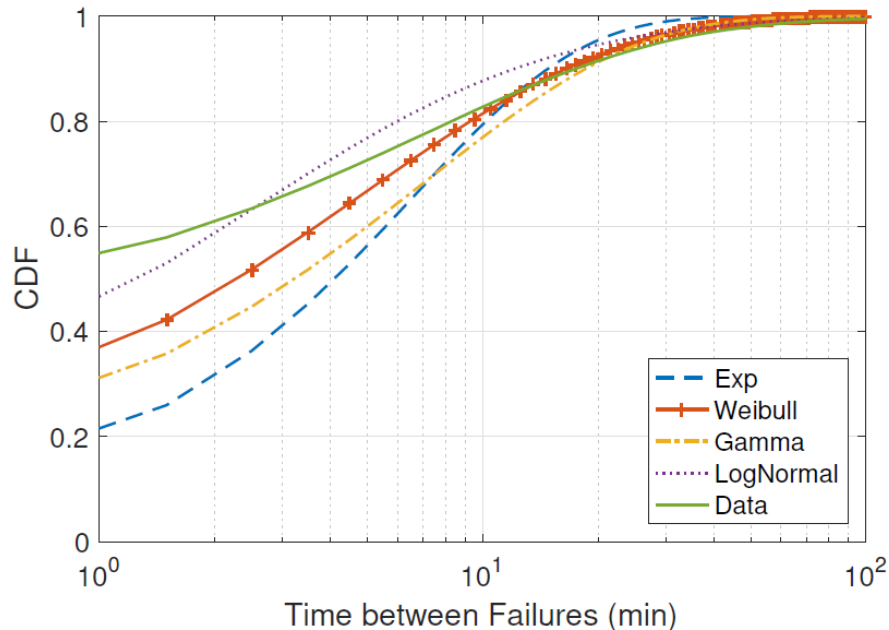
# Latency & Bandwidth

▷ L1 cache reference	0.5	ns			
▷ L2 cache reference	7	ns			
▷ Main memory reference	100	ns			
▷ Send 1K bytes over 1 Gbps network	10,000	ns	10	μs	
▷ Read 4K randomly from SSD*	150,000	ns	150	μs	
▷ Read 1MB sequentially from memory	250,000	ns	250	μs	
▷ Round trip within same datacenter	500,000	ns	500	μs	
▷ Read 1MB sequentially from SSD*	1,000,000	ns	1,000	μs	1 ms
▷ Send 1MB over 1 Gbps network			8,250	μs	8 ms
▷ Disk seek	10,000,000	ns	10,000	μs	10 ms
▷ Read 1MB sequentially from disk	20,000,000	ns	20,000	μs	20 ms
▷ Send packet CA->NL->CA	150,000,000	ns	150,000	μs	150 ms



*Bandwidth of Memory  $\gg$  Network or Disk*

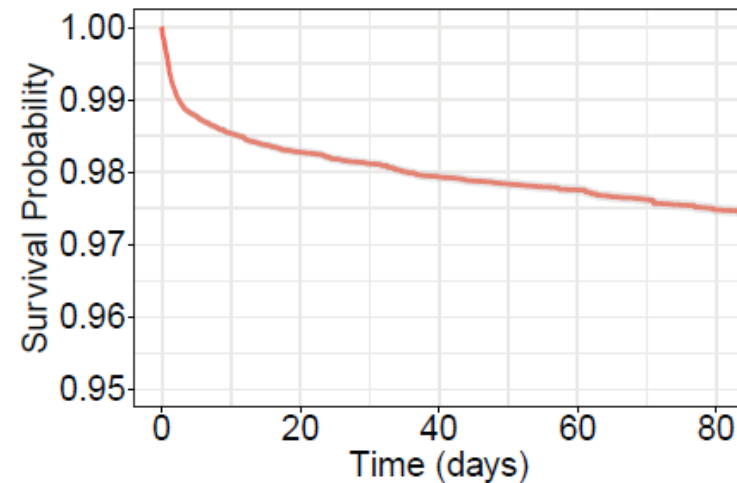
# MTTF in Data Center



*“The MTBF (mean time between failures) across all data centers we investigate (with hundreds of thousands of servers) is only 6.8 minutes, while the MTBF in different data centers varies between 32 minutes and 390 minutes.”*

→ **MTBF with 1000 servers is 680mins**

→ **MTBF with 100 servers is 6800mins (4.7 days)**



**Figure 4: Kaplan Meier survival estimate of datacenter switches, shaded region shows 95% confidence intervals.**

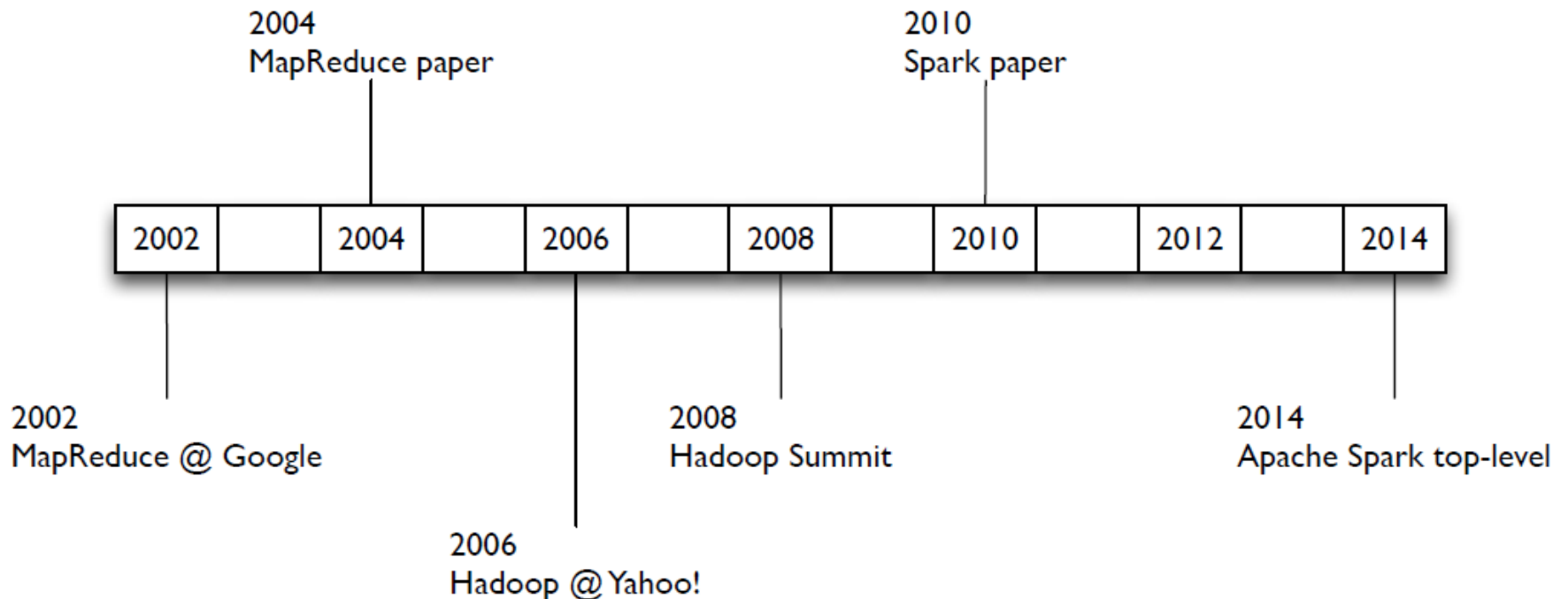




*Failures may be infrequent during the lifetime of an application execution*

# From MapReduce to Spark

- ▷ Google's MapReduce
  - Programming Model
  - Apache Hadoop runtime environment



# Apache Spark

## Learning Spark

Holden Karau, Andy Konwinski, Patrick Wendell & Matei Zaharia,  
O'Reilly, First and Second Editions



- ▷ *Hands-on in the next class*
  - ▷ *Bring your laptops*
- ▷ *Access Google Colab using your IISc*
  - ▷ *Shared URL for Notebook:*  
<https://bit.ly/ds221-spark>

# The Spark Ecosystem

- ▷ Core Spark Engine
  - RDDs, Transformations, Actions, batch processing
- ▷ Higher level abstractions
  - Data frames, SQL-like queries
  - Discretized streams, semi-realtime data
  - Machine learning libraries, **MLlib**
  - Linked data analytics, **GraphX**

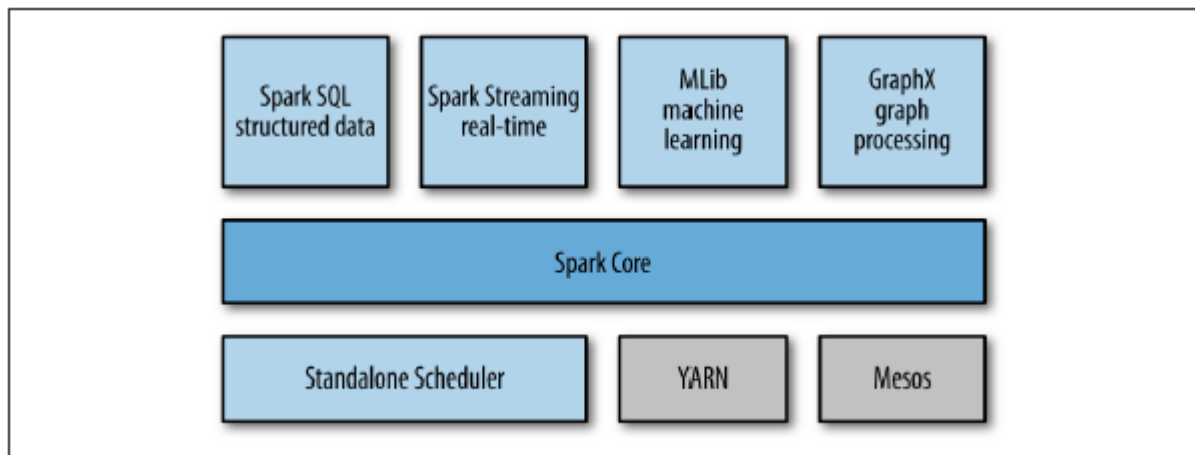
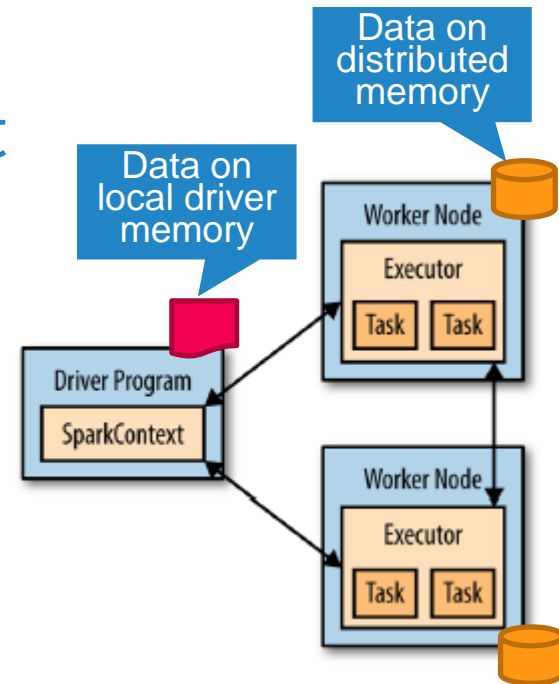


Figure 1-1. The Spark stack

# Spark: A Distributed Execution Engine

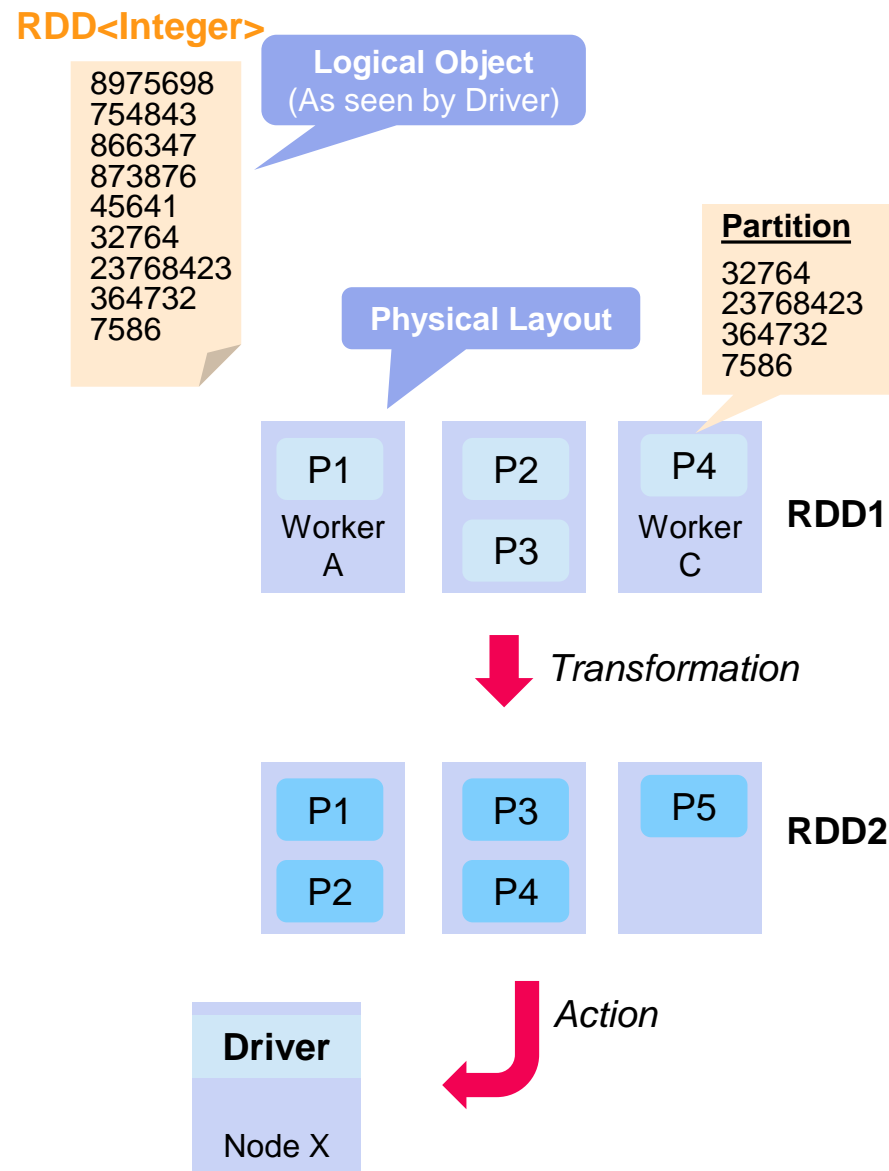
- ▷ **Driver:** User program for application, uses Spark Context, **local variables**
- ▷ **Spark Context:** Gives access to **distributed computing environment**
- ▷ **Worker:** Machines on which actual heavy-lift happens
- ▷ **Executor:** Spark execution environment in a worker, Process, exclusive to an application
- ▷ **Task:** Single operation on data, thread



# Spark RDD

Resilient Distributed Dataset

- ▷ Collection of homogeneous objects
  - Order is not preserved\*
- ▷ **Distributed** on workers
  - 1 or more **Partitions**
- ▷ **Read-only**, immutable
- ▷ Can be **rebuilt**
- ▷ Can be **cached**
- ▷ MR like data-parallel operations
  - **Execute** on workers



# Creating an RDD

- ▷ Create RDD by loading data
  - Can load from HDFS, local vars, filesystem, NoSQL DB, etc.
- ▷ Data is loaded on partitions on different workers
- ▷ RDD Object offers a logical view of the dataset
- ▷ Can perform operations on the object

*Example 3-1. Creating an RDD of strings with `textFile()` in Python*

```
>>> lines = sc.textFile("README.md")
```

*Example 3-5. `parallelize()` method in Python*

```
lines = sc.parallelize(["pandas", "i like pandas"])
```



## Operations on an RDD

- ▷ **Transformations:** Creates another RDD, present on distributed workers
- ▷ **Actions:** Returns a value, local to the Driver

*Example 3-2. Calling the filter() transformation*

```
>>> pythonLines = lines.filter(lambda line: "Python" in line)
```

*Example 3-3. Calling the first() action*

```
>>> pythonLines.first()  
u'## Interactive Python Shell'
```

# Language Bindings

- ▷ Users can provide driver code in multiple languages
  - Scala, Java, Python
- ▷ Spark offers equivalent transformations and actions in each language
- ▷ Logic within transformations and actions can also be in these languages
- ▷ Actual Spark execution environment is in Scala
  - Standard data structure mapping
  - Python code is pickled (de/serialize) and shipped remotely

# Passing Functions to Spark Operations

## ▷ Lambda syntax

- **Functions** are *input parameters* to other functions
- Pass short functions concisely, inline

```
pythonLines = lines.filter(lambda line: "Python" in line)
```



```
def hasPython(line):  
    return "Python" in line
```

```
pythonLines = lines.filter(hasPython)
```

# Programming with RDDs

## Learning Spark

Holden Karau, Andy Konwinski, Patrick Wendell & Matei Zaharia,  
O'Reilly, First Edition

## Chapter 3

# Basics of Transformations

- ▷ Returns a new RDD, computed lazily
- ▷ Transforms tend to be **element-wise** operations
  - **Iterate** through each item, apply the operation, e.g. *Filter*
- ▷ **Filter** on *inputRDD* does not affect *inputRDD*
  - Returns a new RDD, *warningsRDD*
- ▷ **Union** operates on two RDDs
  - One of them is an input parameter

```
inputRDD = sc.textFile("log.txt")
errorsRDD = inputRDD.filter(lambda x: "error" in x)
warningsRDD = inputRDD.filter(lambda x: "warning" in x)
badLinesRDD = errorsRDD.union(warningsRDD)
```

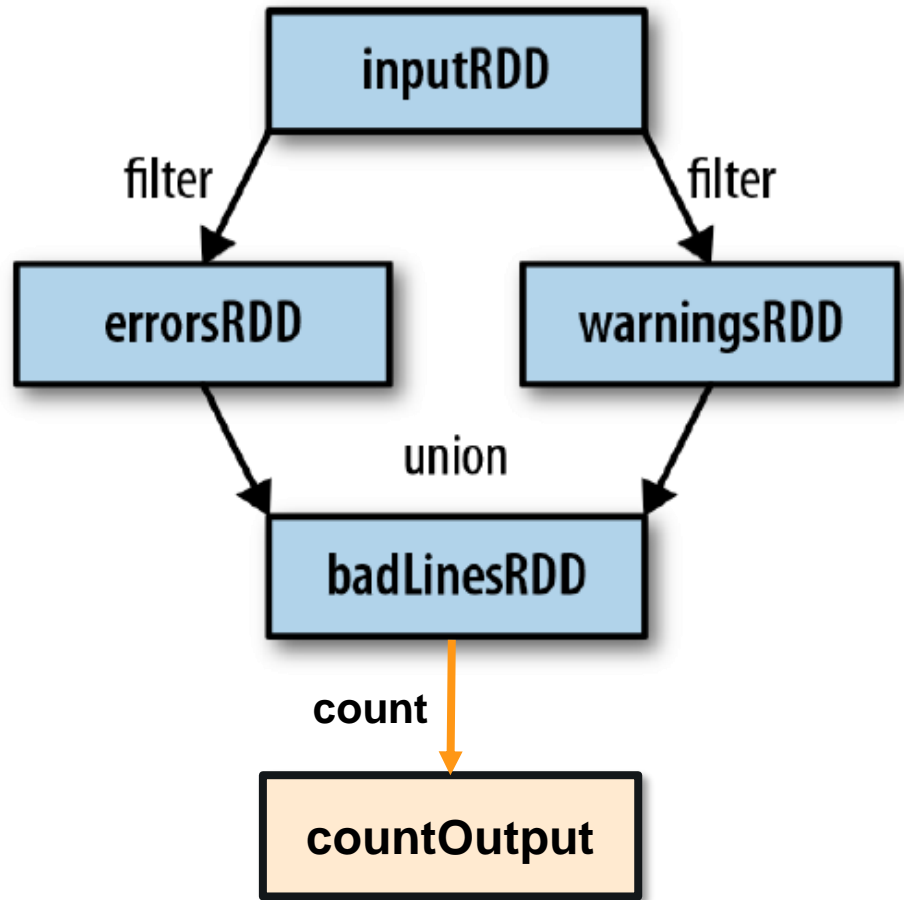
# Basics of Actions

- ▷ *Actually* triggers operations, returns a final result to driver
  - Force any required transformations to be executed
  - Count, Take, Collect
- ▷ Result of action must fit in memory of driver
  - Else, can write RDD to HDFS, `saveAsTextFile`
- ▷ RDDs are computed from scratch when actions are called...See *persist/cache*

```
print "Input had " + badLinesRDD.count() + " concerning lines"
print "Here are 10 examples:"
for line in badLinesRDD.take(10):
    print line
```

# Lineage Graph

- ▷ Keeps track of operations used to derive an RDD
- ▷ Helps *lazily materialize* RDD
- ▷ Helps *recover* RDD or their partitions that are lost



# Lazy Evaluation

- ▷ Transformations are lazily evaluated
  - Calling a transform does NOT immediately execute it
- ▷ **Action triggers** execution of *dependent transformations*
- ▷ E.g., `load().map().count()`
  - **Load** & **Map** do not execute till we see **Count**
- ▷ Allows Spark to reduce the number of passes through the data
  - Materializes RDD only when required
  - Reused RDDs that have been materialized earlier
  - Immutability!



# RDD Persistence

```
val result = input.map(x => x*x)
println(result.count())
println(result.collect().mkString(", "))
```

Double Exec.

- ▶ Dependent RDDs recomputed for each action
- ▶ Need to *persist* RDDs to reuse without recompute
- ▶ Levels of Persistence
  - Memory (Obj. or Ser.)
    - LRU eviction
  - Memory and Disk (O | S)
    - Spill to disk if less memory
  - Disk only
- ▶ Recomputed if node fails or on LRU eviction
- ▶ Can manually *unpersist*

Level	Space used	CPU time	In memory	On disk
MEMORY_ONLY	High	Low	Y	N
MEMORY_ONLY_SER	Low	High	Y	N
MEMORY_AND_DISK	High	Medium	Some	Some
MEMORY_AND_DISK_SER	Low	High	Some	Some
DISK_ONLY	Low	High	N	Y

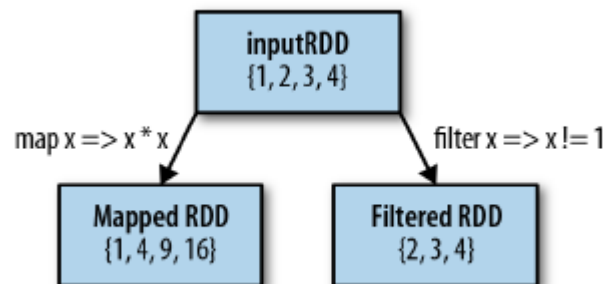
```
val result = input.map(x => x * x)
result.persist(StorageLevel.DISK_ONLY)
```

# Common Transformations

## ▷ Element-wise transformations

### ▷ **Filter**

- Applies conditional logic to each element
- User logic (lambda fn.) returns true/false
  - If true, input element copies to output RDD
  - if false, input element omitted
- RDD output type is same as input



# Common Transformations

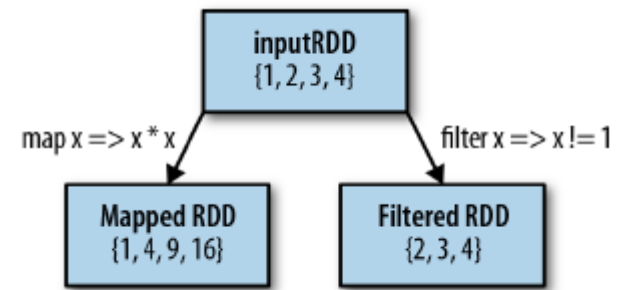
## ▷ Element-wise transformations

### ▷ Map

- Applies user logic to each element
- Logic returns **exactly one output** for each input item
- RDD output type can be different from input

### ▷ Can perform any user operation

- E.g., Parsing a string, fetching a webpage

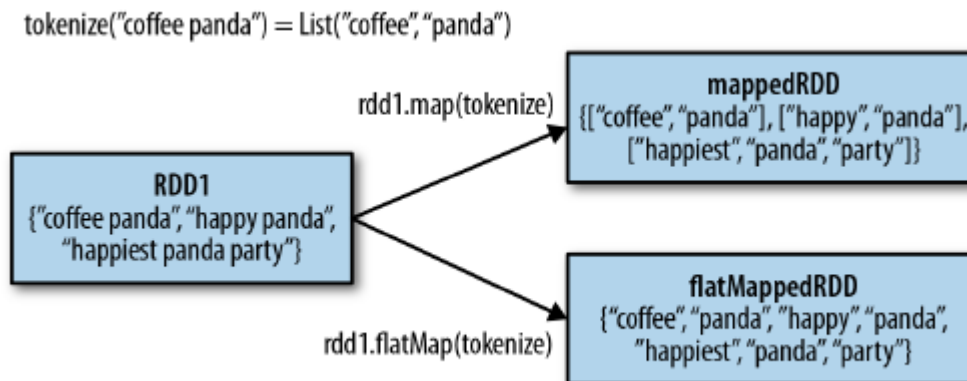


*Example 3-26. Python squaring the values in an RDD*

```
nums = sc.parallelize([1, 2, 3, 4])
squared = nums.map(lambda x: x * x).collect()
for num in squared:
    print "%i " % (num)
```

# Common Transformations

- ▷ Element-wise transformations
- ▷ **FlatMap**
  - Applies user logic to each element
  - Logic returns *zero or more* output items for each input item
  - RDD output type can be different from input



# Common Transformations

- ▷ Element-wise transformations
- ▷ **FlatMap**
  - Applies user logic to each element
  - Logic returns *zero or more* output items for each input item
  - RDD output type can be different from input

*Example 3-29. flatMap() in Python, splitting lines into words*

```
lines = sc.parallelize(["hello world", "hi"])
words = lines.flatMap(lambda line: line.split(" "))
words.first() # returns "hello"
```

## Filter using FlatMap. Using Map?

```
RDD2=RDD1.filter( item : foo(item) {item > 10})
```

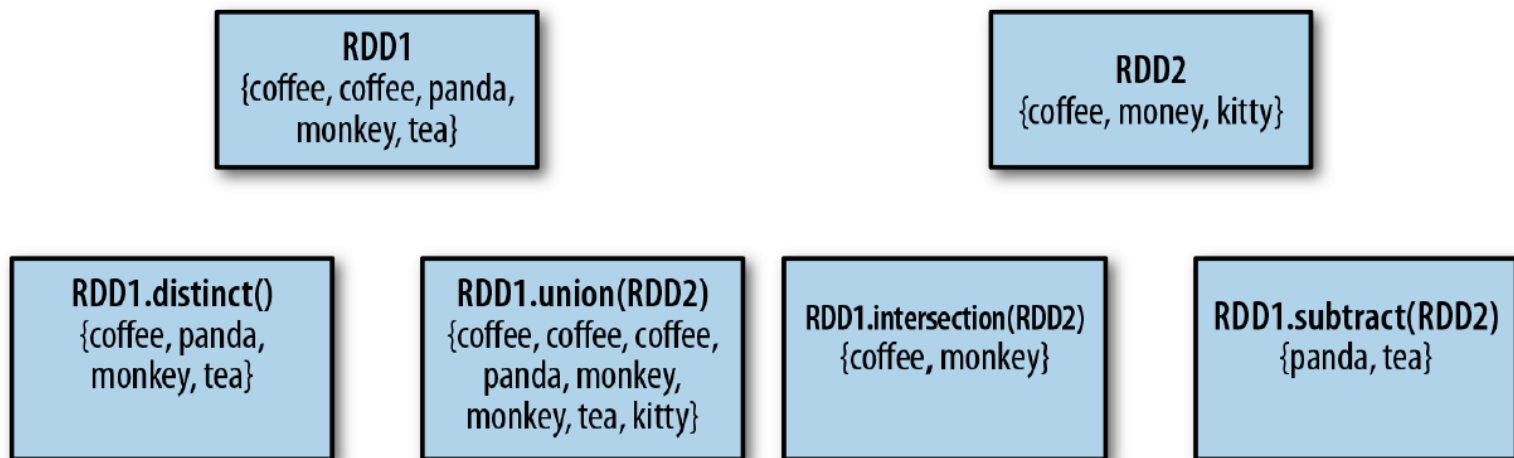
```
RDD2= RDD1.flatMap(item : if(foo(item)) then  
return item)
```

```
RDD2= RDD1.map(item : if(foo(item)) then return  
item)
```

```
[null, item, item, null...]
```

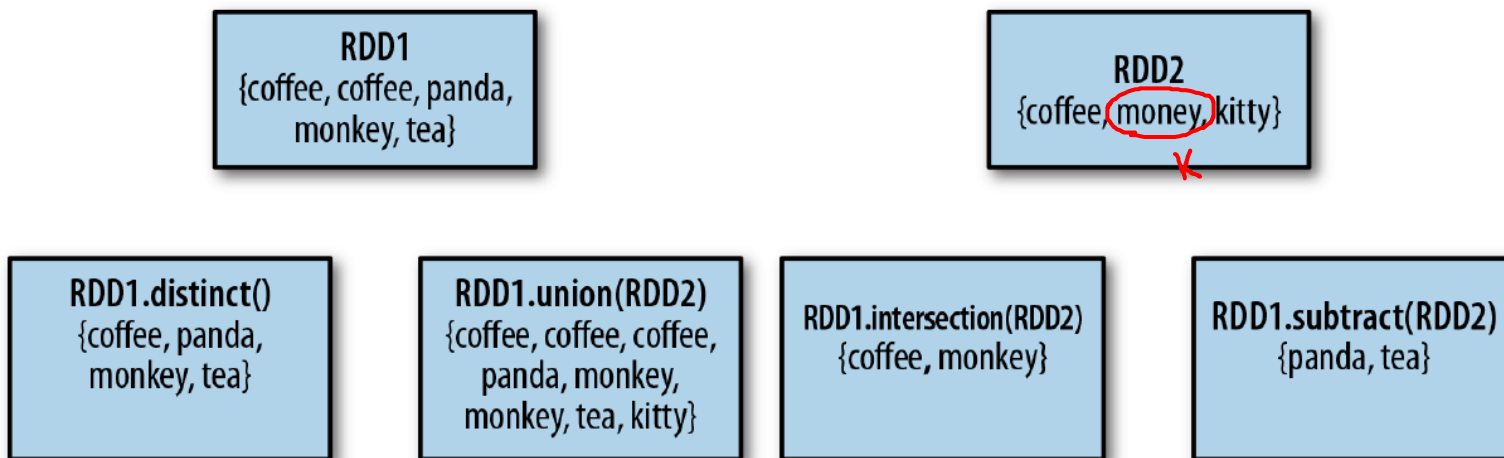
# Common Transformations

- ▷ Pseudo set operations
- ▷ **Distinct**
  - Copy only unique items into output RDD
- ▷ **Union**
  - Concatenate items in two RDDs into output RDD
  - Duplicates are NOT removed



# Common Transformations

- ▷ Pseudo set operations
- ▷ **Intersection**
  - Find common items in two RDDs, and copy into output RDD. Duplicates are removed.
- ▷ **Subtraction**
  - Copy items from first RDD into output RDD, except those present in second RDD



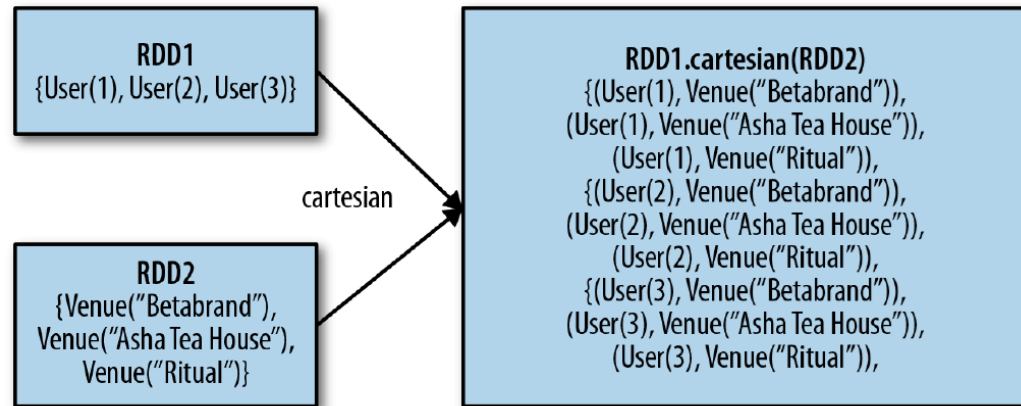


# Common Transformations

## ▷ Pseudo set operations

## ▷ Cartesian Product

- All-to-all combination of inputs from 2 RDDs in the output RDD



## ▷ Sample(withReplace, fraction, seed)

- Copies a sampled subset of items into output RDD
- Same fraction sampled from each partition
- Output count may not exactly be (fraction\*input count)
- Seed guarantees same samples \*IF\* RDD content was not changed, e.g., due to lazy (re)evaluation

# Common Actions

- ▷ **collect**
  - Returns the entire RDD to driver
- ▷ **take(n)**
  - Return  $n$  items to driver from fewest partitions
  - May not be evenly sampled, not ordered
- ▷ **takeOrdered(num, order?)**
  - Return  $n$  items using ascending (or given) ordering
  - If RDD is sorted, will return smallest  $n$  sorted items
- ▷ **takeSample(withReplace, num, seed)**
  - Return  $n$  items, sampled evenly from all partitions
  - Assumes each partition has uniform distribution
- ▷ **top(n)**
  - For sorted RDD, return largest  $n$  items.
  - *Opposite order of default ordering in TakeOrdered*

# Example

P1	P2	P3
1	3	4
7	2	1
5	1	6
6		2
		5

- ▷ **count()**
  - $4+3+5=12$
- ▷ **take(8)**
  - **3,2,1,4,1,6,2,5**
  - Returns items from fewest partitions
- ▷ **takeOrdered(4)**
  - **1,1,1,2**
  - Returns  $n$  items in ascending order
- ▷ **top(4)**
  - **7,6,6,5**
  - Returns  $n$  items in descending order
- ▷ **takeSample(6, replace=false)**
  - **1,5,3,1,6,5**
  - Uniformly samples items from each partitions, without picking same item twice
- ▷ **takeSample(6, replace=true)**
  - **1,5,2,2,6,5**
  - Uniformly samples items from each partitions, allowing same item to be picked twice

```
# Convert our RDD of strings to numeric data so we can compute stats and  
# remove the outliers.
```

```
distanceNumerics = distances.map(lambda string: float(string))  
stats = distanceNumerics.stats()  
mean = stats.mean()
```

*Table 6-2. Summary statistics available from StatsCounter*

Method	Meaning
count()	Number of elements in the RDD
mean()	Average of the elements
sum()	Total
max()	Maximum value
min()	Minimum value
variance()	Variance of the elements
sampleVariance()	Variance of the elements, computed for a sample
stdev()	Standard deviation
sampleStdev()	Sample standard deviation

## Numeric RDD

- ▶ Common statistics for RDDs having numeric types
- ▶ Single **stats()** action to populate all stats
- ▶ Individual functions (actions) also available

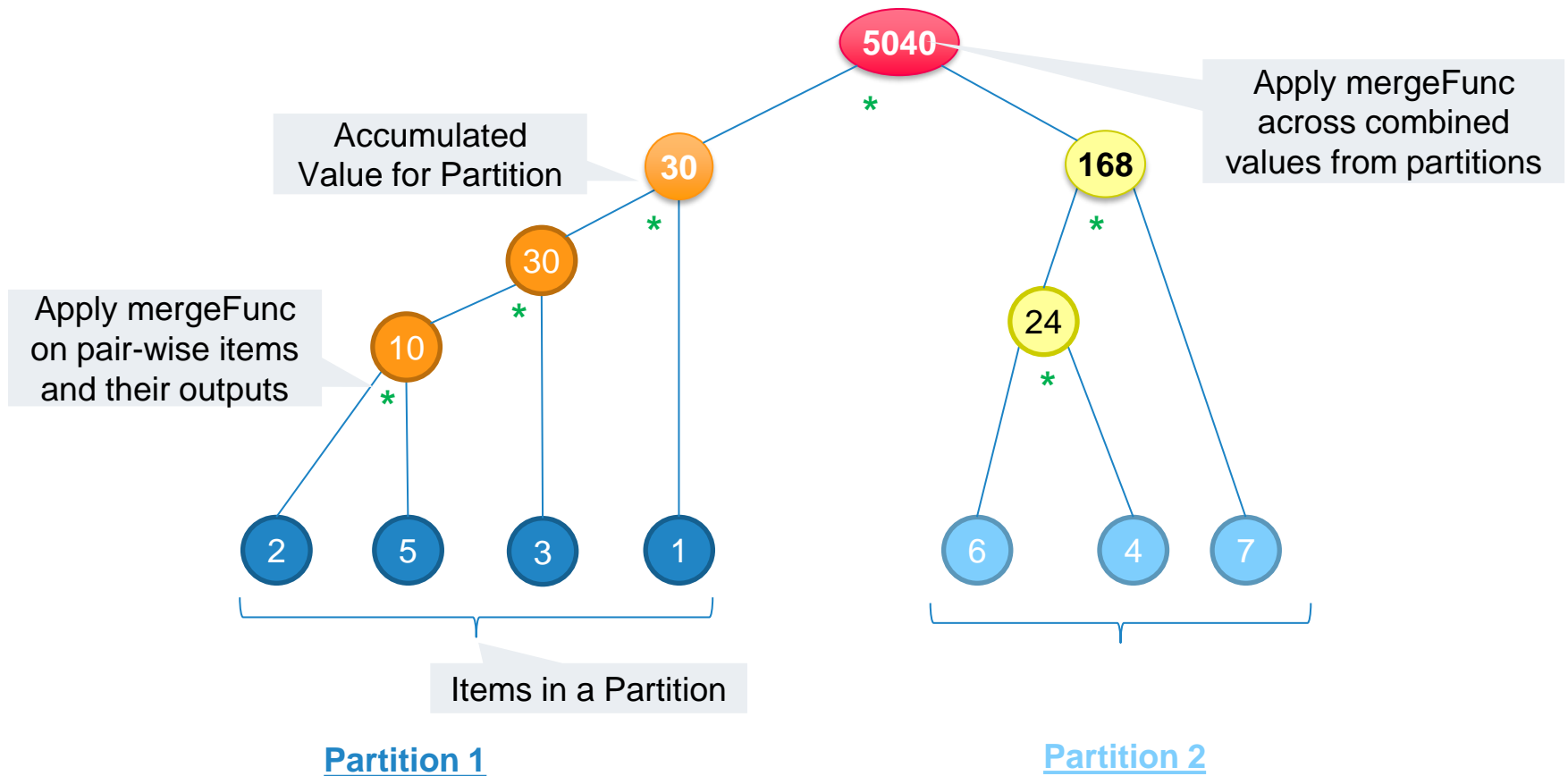
# Common Actions

```
sum = rdd.reduce(lambda x, y: x + y)
```

```
prod = rdd.reduce(lambda x, y : x * y)
```

## ▷ **reduce(mergeFunc)**

- Combines items in an RDD using an aggregation function
  - *mergeFunc* output type same as input type
  - *mergeFunc* must be Commutative and Associative
  - *mergeFunc* also applied on outputs from each partitions

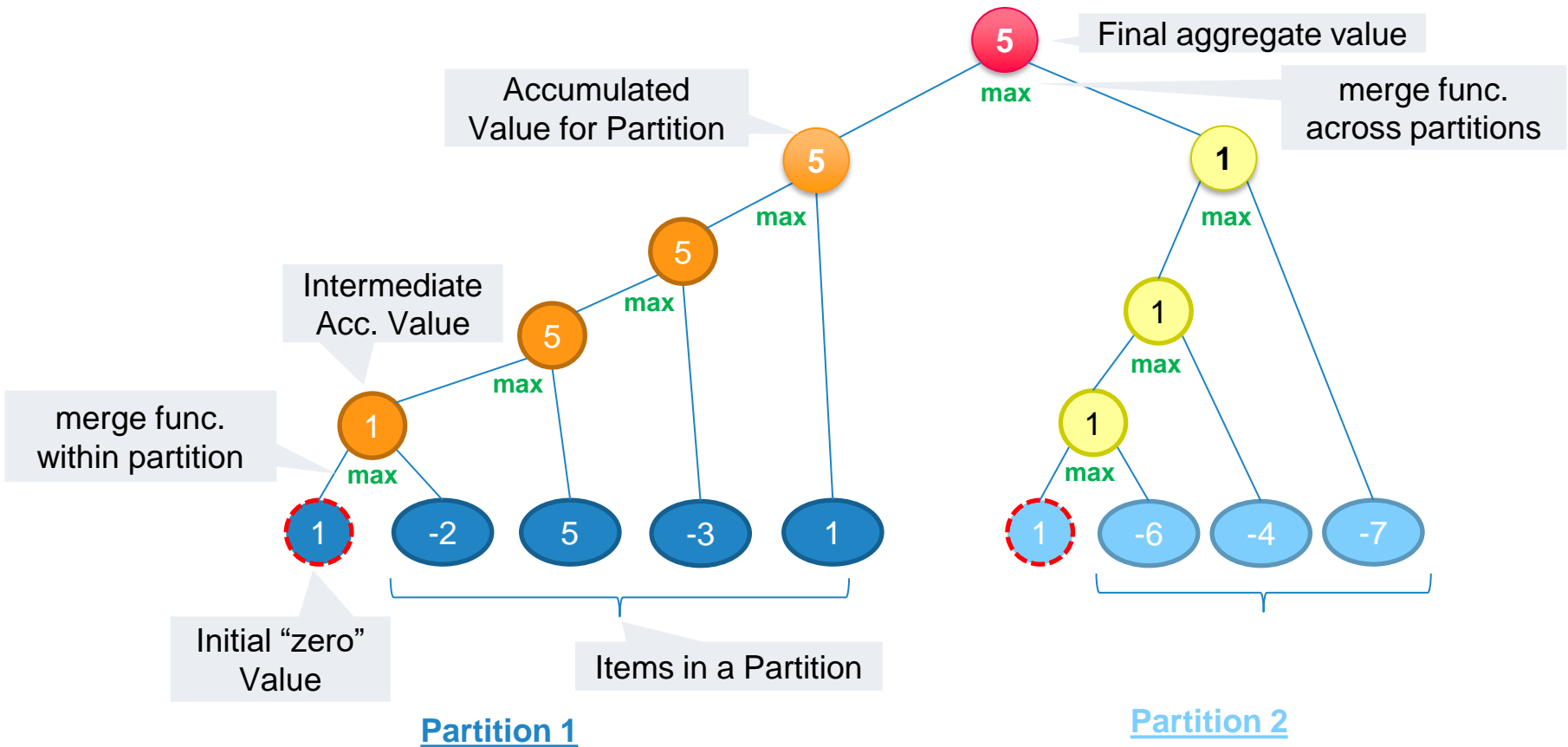


# Common Actions

```
prod = rdd.fold(1, lambda x, y : x * y)
mx = rdd.fold(1, lambda x, y : max(x,y))
```

## ▷ **fold**(zeroVal, mergeFunc)

- Similar to reduce, but takes a *zeroValue* as initial accumulator per partition
  - Can have side-effects per (empty) partition!
- Can be used as a threshold, e.g. avoid divide by zero



# Common Actions

- ▷ **aggregate**(zeroVal, mergeFunc, combineFunc)
  - acc=zeroVal, acc=mergeFunc(acc, value),  
acc=combineFunc(acc1, acc2)
  - Combines items in RDD but can have different intermediate and output type from the input
  - Same as fold if *mergeFunc* and *combineFunc* are same

```
sum = nums.aggregate(0,  
                    lambda x, y : x + y,  
                    lambda x, y : x + y)
```

```
strs = sc.parallelize(['ababab', 'ab', 'abcd'])  
strs.aggregate(0, lambda acc, v : acc+len(v), lambda a1, a2: a1+a2)
```

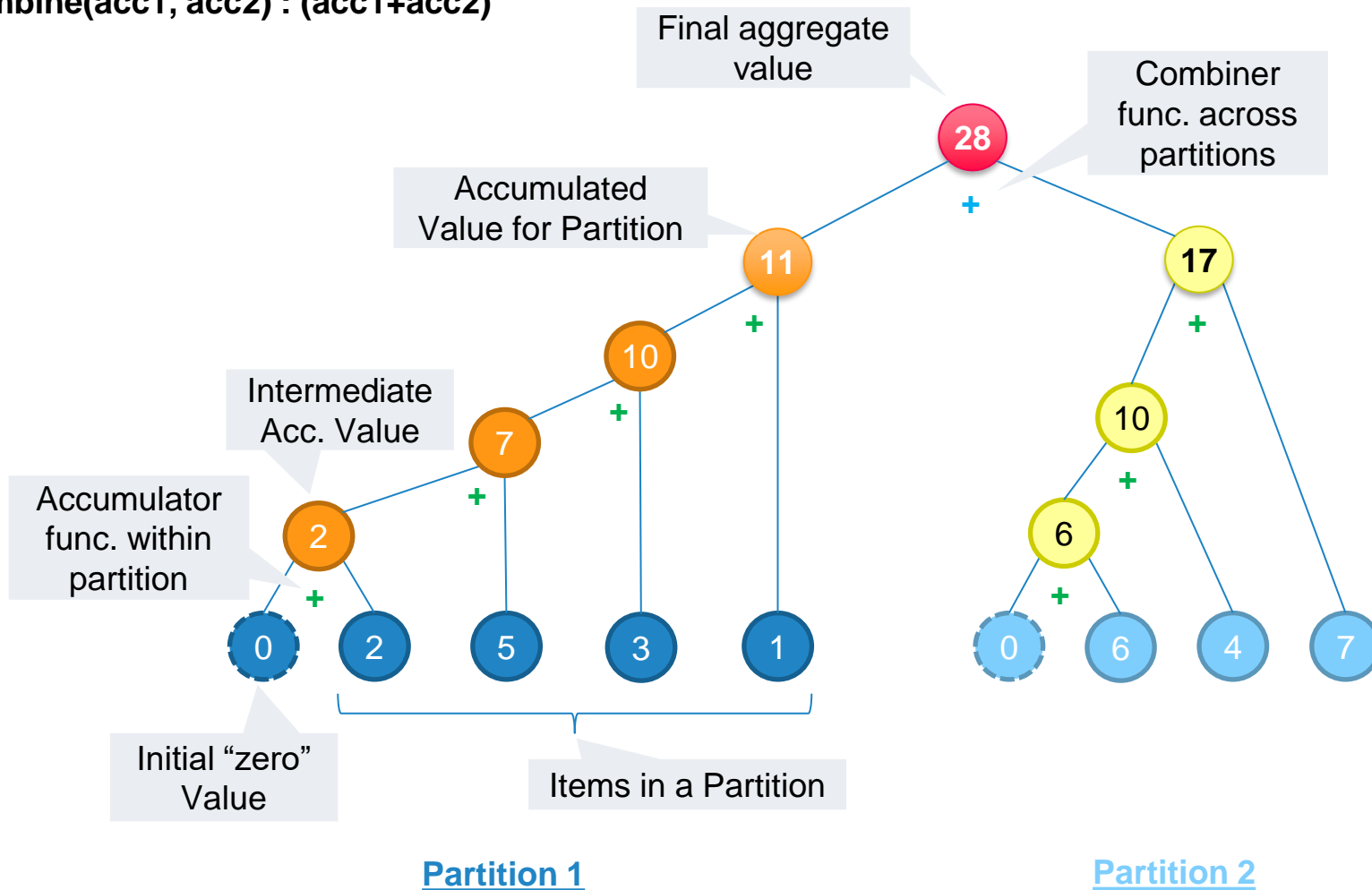
```
sumCount = nums.aggregate((0, 0),  
                        lambda acc, val : (acc[0] + val, acc[1] + 1)  
                        lambda acc1, acc2 : (acc1[0] + acc2[0], acc1[1] + acc2[1])  
                        )  
return sumCount[0] / float(sumCount[1])
```

# Aggregate: Incremental Evaluation within and across Partitions

**zeroVal:** *default for data type*

**merge(acc, val) :** (acc+val)

**combine(acc1, acc2) :** (acc1+acc2)



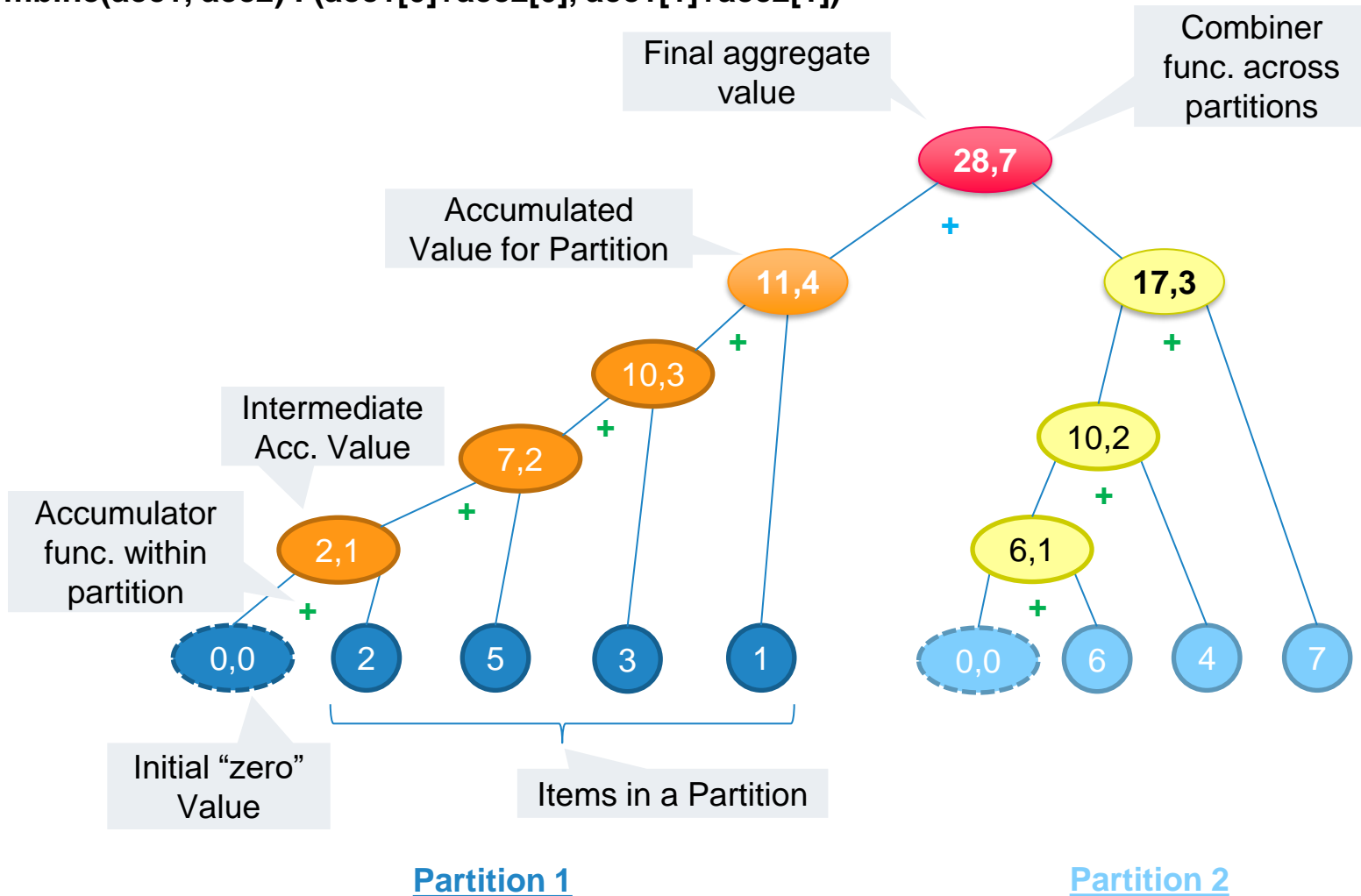


# Aggregate: Incremental Evaluation within and across Partitions

**zeroVal: (0,0)**

**merge(acc, val) : (acc[0]+val, acc[1]+1)**

**combine(acc1, acc2) : (acc1[0]+acc2[0], acc1[1]+acc2[1])**



# Common Actions

- ▷ **forEach(fn)**
  - Iterates through each item and applied function
  - Function needs to persist it. Not returned to driver.
- ▷ **count**
  - Returns the number of items in collection
- ▷ **countByValue**
  - Returns frequency of unique values, {val, count}

# Working with Key/Value Pairs

## Learning Spark

Holden Karau, Andy Konwinski, Patrick Wendell & Matei Zaharia,  
O'Reilly, First Edition

## Chapter 4

## <Key, Value> RDDs (or) Pair RDD

- ▷ Has a key and associated value
  - Key is not distinct. Single value for each key.
- ▷ Used to perform aggregate operations
  - Pair RDD exposes additional transformation and actions
  - Derives from base RDD. All base operations supported.
- ▷ Use ETL to get your data into Pair RDD type
  - Enables join, reduce by key, data parallel operations by key

# Creating Pair RDD

- ▶ Create by applying a *map* transform on an RDD
  - Return a Pair of (key, value) or a Tuple2 object

Python

```
pairs = lines.map(lambda x: (x.split(" ")[0], x))
```

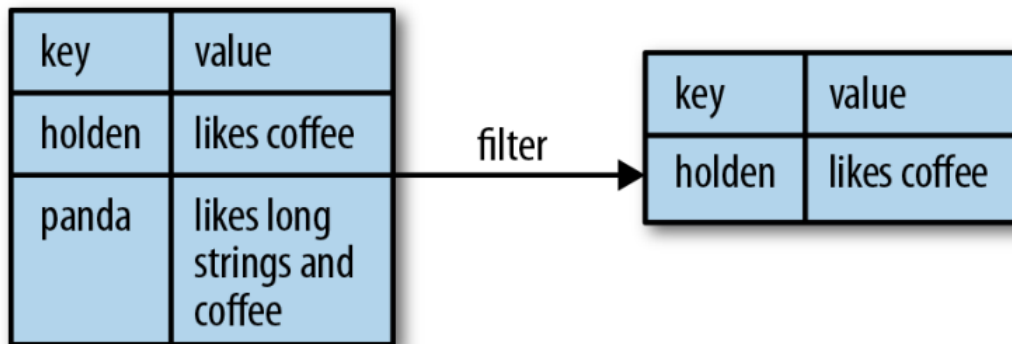
Java

```
PairFunction<String, String, String> keyData =  
    new PairFunction<String, String, String>() {  
        public Tuple2<String, String> call(String x) {  
            return new Tuple2(x.split(" ")[0], x);  
        }  
    };  
JavaPairRDD<String, String> pairs = lines.mapToPair(keyData);
```

# Transformations on Pair RDDs

- ▷ All operations of regular RDDs
  - Each item is a (Key,Value) pair
  - Special *MapValues* transform to operate only on vals

```
result = pairs.filter(lambda keyValue: len(keyValue[1]) < 20)
```



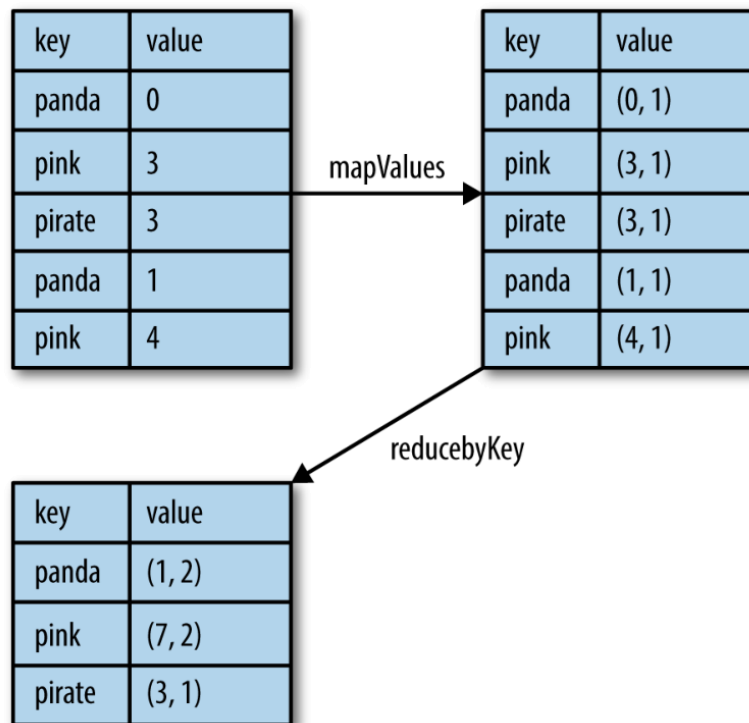
- ▷ Transformations on single Pair RDDs
  - *Aggregation, Grouping, Sorting*
- ▷ Transformations on two Pair RDDs: *Join*

# Aggregation Transforms on a Pair RDD

## ▷ **reduceByKey(mergeFunc)**

- Combines the values, after grouping by key
- Automatically triggers map-side *combiner*

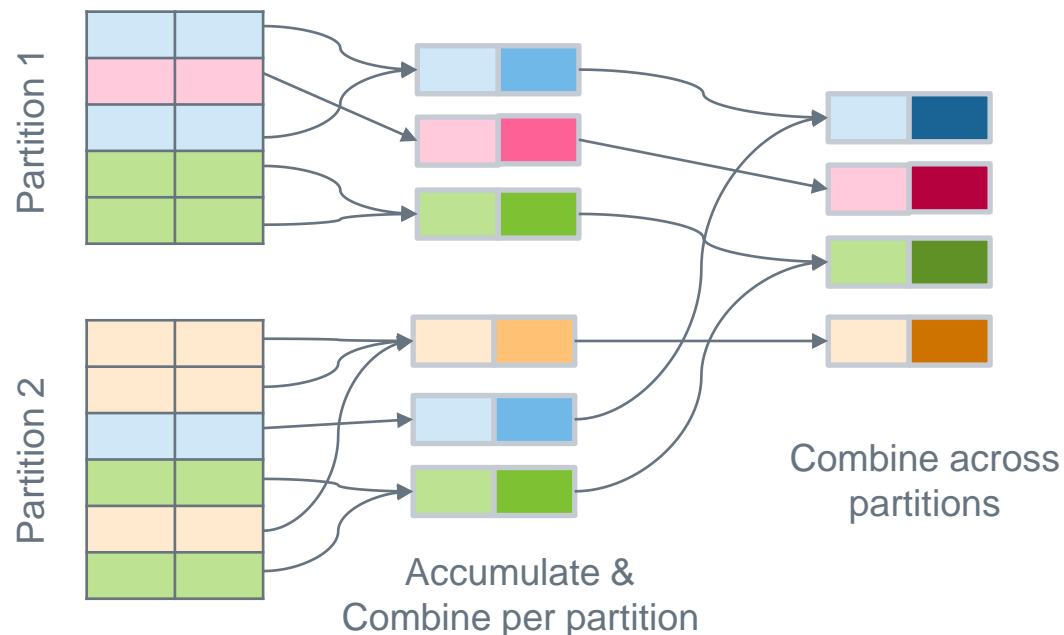
```
rdd.mapValues(lambda x: (x, 1)).reduceByKey(lambda x, y: (x[0] + y[0], x[1] + y[1]))
```



Finding the  
Average per  
Key

# Aggregation Transforms on a Pair RDD

- ▷ **combineByKey** (*createCombiner*, *mergeValueFunc*, *mergeCombinersFunc*, *partitioner*)
  - Iterates through each (K,V) pair, on each partition
  - Accumulates values per key per partition
  - Combines accumulated values per key, across partitions





# Aggregation Transforms on a Pair RDD

- ▷ **combineByKey** (*createCombiner*, *mergeValue*, *mergeCombiners*, *partitioner*)
  - *createCombiner*: Function called the first time a key is seen on each partition. Initializes the *accumulator* value for that key.
  - *mergeValue*: Function called for each subsequent value for a key on a partition. Merges value with current accumulator's value.
  - *mergeCombiners*: Function used to combine accumulator values for the same key from multiple partitions
- **reduceByKey** is just combineByKey with default functions. *createCombiner* initialized to same type as *value*. Input fn is used both as *mergeValue* and *mergeCombiner*

# Per Key Average using combineByKey

Create Combiner,  
Once per key per  
partition

Merge Value, Once  
per value for a key in  
a partition

```
sumCount = nums.combineByKey((lambda x: (x,1)),  
                             (lambda x, y: (x[0] + y, x[1] + 1)),  
                             (lambda x, y: (x[0] + y[0], x[1] + y[1])))  
sumCount.map(lambda key, xy: (key, xy[0]/xy[1])).collectAsMap()
```

Accumulator

Sum

Count

Value

Merge Accumulators for a  
key, Across partitions

- ▷ Each value is a (sum, count)
- ▷ Combiner initializes sum to first value x, sets count to 1
- ▷ Accumulator sums the values, increments the count for each value for a key
- ▷ Merge accumulators across partitions by adding their sums and their counts

# Per Key Average using combineByKey

```
def createCombiner(value):  
  (value, 1)
```

```
def mergeValue(acc, value):  
  (acc[0] + value, acc[1] + 1)
```

```
def mergeCombiners(acc1, acc2):  
  (acc1[0] + acc2[0], acc1[1] + acc2[1])
```

*User provided functions*

Partition 1

coffee	1
coffee	2
panda	3

Partition 1 trace:

(coffee, 1) -> new key

accumulators[coffee] = createCombiner(1)

(coffee, 2) -> existing key

accumulators[coffee] = mergeValue(accumulators[coffee], 2)

(panda, 3) -> new key

accumulators[panda] = createCombiner(3)

Partition 2 trace:

(coffee, 9) -> new key

accumulators[coffee] = createCombiner(9)

Merge Partitions:

```
mergeCombiners(partition1.accumulators[coffee],  
                partition2.accumulators[coffee])
```

*Execution within  
combineByKey*

# Grouping Transforms on a Pair RDD

## ▷ **groupByKey**

- Groups all values for each key, {Key, Iterator<Value>}
- Returns an iterator over values for each key
- User can perform *map*, etc. to operate over values

## ▷ **pair\_rdd1.cogroup(pair\_rdd2)**

- Combines values for two RDDs having the same key
- Returns <key, (iter1, iter2)>
- If key is missing in an RDD, its iterator is empty
- Can also work on more than 2 RDDs
- $\{(a, 2), (c, 4), (c, 6)\} \# \{(c, 9), (b, 7)\} = \{(a, ([2], [])), (b, [], [7]), (c, ([4, 6], [9]))\}$

## ▷ **subtract(pair\_rdd2)**

- Removes entries from RDD1 where the same key is also present in RDD2
- $\{(1, 2), (3, 4), (3, 6)\} - \{(3, 9)\} = \{(1, 2)\}$

# Stratified Sampling

- ▷ **sampleByKey**(*withReplace*, *keyFractions*, *seed*)
  - *keyFractions* is a map of  $\langle k, f_k \rangle$
  - Sample approximately  $\lceil f_k \times n_k \rceil$  items, where  $f_k$  is the fraction of values for key  $k$ , and  $n_k$  is the number of key-value pairs for key  $k$
  - Return  $n$  items where  $n \approx \sum_k \lceil f_k \times n_k \rceil$ , sampled evenly from all partitions

# Join Transforms on two Pair RDDs

## ▷ Join

- Performs inner join
- Only keys in both RDDs are joined and returned
- Cross product of values for same key from both RDDs
  - $\{(1, 2), (3, 4), (3, 6)\} \bowtie \{(3, 9)\} = \{(3, (4, 9)), (3, (6, 9))\}$

## ▷ Left Outer Join

- Returns an entry for all keys in first RDD
  - $\{(1, 2), (3, 4), (3, 6)\} \bowtie \{(3, 9)\} = \{(1, (2, \text{None})), (3, (4, 9)), (3, (6, 9))\}$

## ▷ Right Outer Join

- Returns an entry for all keys in other RDD
  - $\{(1, 2), (3, 4), (3, 6)\} \bowtie \{(3, 9)\} = \{(3, (4, 9)), (3, (6, 9))\}$

# Sorting Transforms on a Pair RDD

- ▷ Sorting useful just before returning result
  - Collect, Save
- ▷ **sortByKey**: Sorting done by key for Pair RDD
  - Default is ascending. Values are NOT considered.
- ▷ Key function can be used to transform key to apply its default comparator
  - E.g., treat *number* key as a *string* key

```
rdd.sortByKey(ascending=True, numPartitions=None, keyfunc = lambda x: str(x))
```

■  $\{(1,2), (3,6), (3,5), (2, 4)\} \rightarrow \{(1,2), (2,4), (3,6), (3,5)\}$

# Actions on a Pair RDD

- ▷ All normal RDD actions can be done
- ▷ In addition, some special actions
  - **countByKey**: Returns a count for each key as (key,count)
  - **collectAsMap**: Returns the RDD as a native Dictionary or Map object
  - **lookup(key)**: Returns all the value(s) for a specific key



# Summary

- ▷ Load data from diverse sources to form RDDs
- ▷ Different types of data transformations and actions using Spark
  - Helps to process large datasets, across 10s of machines **at scale**
- ▷ Put together data analytics pipelines, ETL pipelines
  - Operate on structured and semi-structured data
  - Data preparation and analytics
  - Complex workflows

# Using Spark RDD for Web Crawl & Search

# ETL for Web Crawl & Search

- ▶ Crawl the web and store files into HDFS
  - Append each URL+HTML file as a “record” in HDFS
- ▶ Load RDD with URL as key as HTML content as value
- ▶ Parse the HTML file and extract <title>
  - <url>,<title>  
`titleRdd = HTMLRdd.mapValue(html :parseOutTitle(html))`

URL	Title
u1	The Constitution of India
u2	A Tale of Two Cities by Dickens
u3	Project Gutenberg - Moby Dick
u4	Carly Rae Jepsen - Call Me Maybe
u5	Shah Rukh Khan interview
u6	Wikipedia – India's Population
u7	Best Years of My Life Pistol Annies

# ETL for Web Crawl & Search

- ▷ Parse the HTML file and extract <a href> URL links
  - <url>, List<url>[ ]  
`links = HTMLRdd.mapValue(html : parseOutLinks(html))`
- ▷ Run PageRank on the Adjacency List
  - <url>, PageRank
  - *How?*

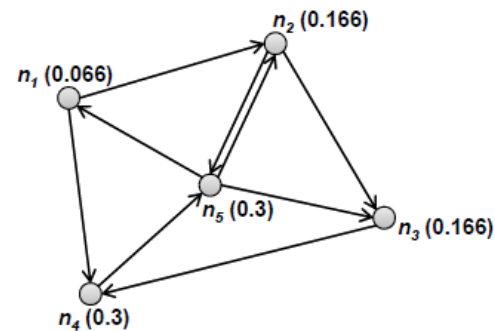
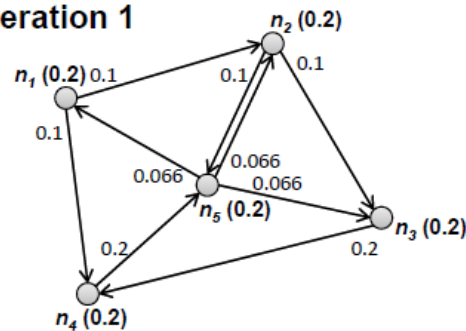
URL	PageRank
u1	0.02
u2	0.3
u3	0.08
u4	0.1
u5	0.2
u6	0.25
u7	0.05

# PageRank

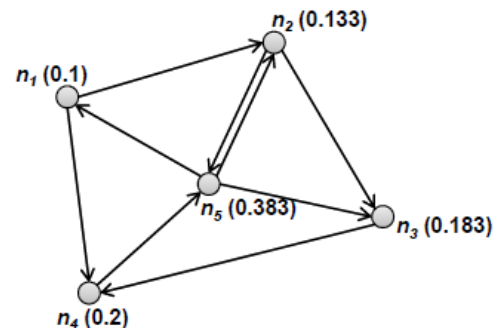
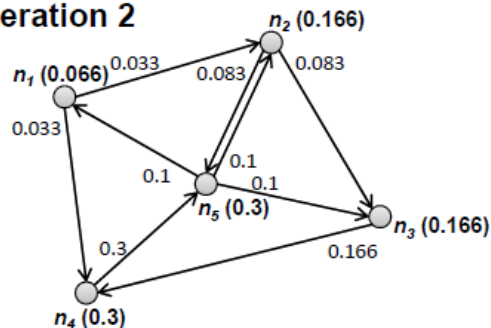
$$P(n) = \alpha \left( \frac{1}{|G|} \right) + (1 - \alpha) \sum_{m \in L(n)} \frac{P(m)}{C(m)}$$

- ▷ Vertex Centrality metric. Importance of a vertex.
- ▷ Calculated iteratively
- ▷ Rank of vertex (**n**) depends on rank of neighbors (**L(n)**), normalized by # of out edges for neighbors (**C(m)**)

Iteration 1



Iteration 2



# PageRank using Spark

links

Src	Sink[ ]

**contribs(0) =**  
*links.join(ranks).flatMap()*

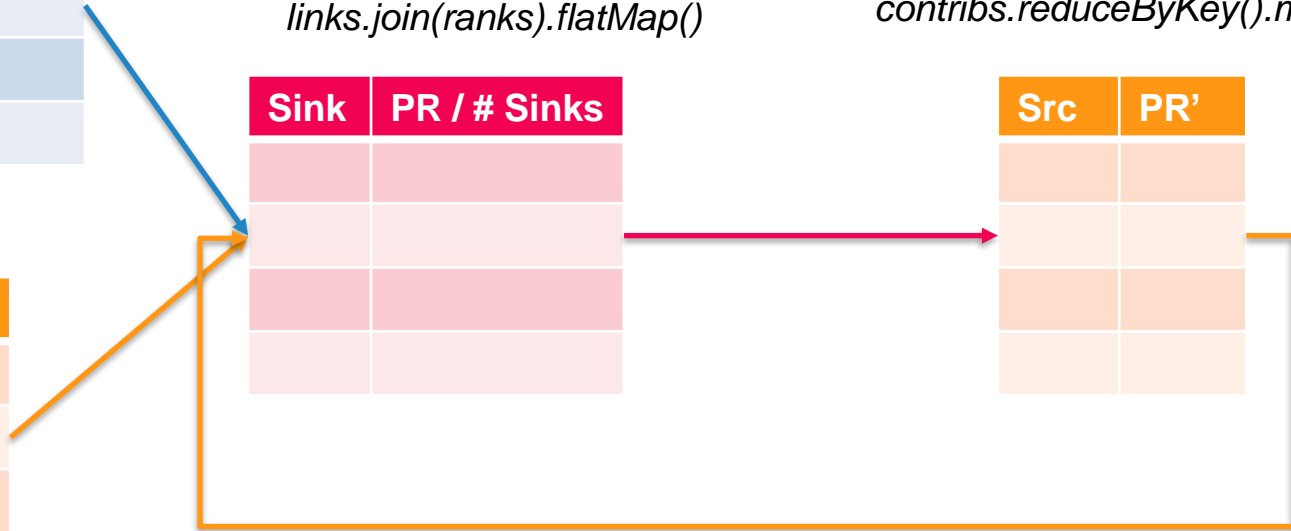
**ranks(1) =**  
*contribs.reduceByKey().mapValues()*

ranks(0)

Src	PR

Sink	PR / # Sinks

Src	PR'



# PageRank using Spark

```
def computeContribs(sink_urls, src_rank):
    for sink_url in sink_urls:
        yield (sink_url, src_rank / len(sink_urls))
-----
# Loads all URLs with other URL(s) link
# and initialize ranks of them to 1.0
ranks = links.map(Lambda (src, sinks): (src, 1.0))

# Calculates and updates URL ranks continuously using PageRank algorithm.
for iteration in range(30):
    # Calculates URL contributions to the rank of other URLs.
    contribs = links.join(ranks).flatMap(Lambda src_sinks_rank:
        computeContribs(src_sinks_rank[1][0], src_sinks_rank[1][1]))

    # Re-calculates URL ranks based on neighbor contributions.
    ranks = contribs.reduceByKey(add).mapValues(Lambda rank: rank*0.85 + 0.15)

# Collects all URL ranks and dump them to console.
for (link, rank) in ranks.collect():
    print("%s has rank: %s." % (link, rank))
```

# ETL for Web Crawl & Search

- ▷ Parse the HTML file and extract list of words

- <url>, <words>

```
HTMLKeyRdd = HTMLRdd.flatMap((url, html) :  
    (url, html.parseOutKeyWords()))
```

- ▷ Remove stop words, etc. Identify keywords

- <url>, <words>

- <keyword>, <url>

```
HTMLOkKeyRdd = HTMLKeyRdd.filter((url, keys)  
    : keys NOT IN STOP_LIST)
```



# ETL for Web Crawl & Search

Keyword	URL List		
People	u1	u5	u6
India	u1	u6	
Best	u2	u5	u7
Call	u3	u4	u5
Ishmael	u3		
Some	u3		
Years	u3	u7	
Here	u4		
Number	u4	u6	
Life	u7		

## ▷ Build inverted index from keywords

- <keyword>, List<url>[ ]

```
keyUrlRdd = HTMLOkKeyRdd.map((url, okKeys) :  
(okKeys, url))
```

```
keysUrlRdd = keyUrlRdd.groupByKey()
```

# ETL for Web Crawl & Search

## ► Bringing it all together: **Doing a Search**

- **Lookup** of keyword in inverted index, find common URLs for keywords

```
for (item in searchPhrase.split())  
    urls[item] = keysUrlRdd.lookup(item)  
matchUrls = urls.intersection()
```

- **Lookup** PageRank of all matching URLs

- **Sort and Select top  $n$**  PageRank URLs

```
bestMatches = ranks.filter(url in matchUrls)  
                .map((url, rank) : (rank, url))  
                .sortByKey().takeOrdered(10)
```

Keyword	URL List			
People	u1	u5	u6	
India	u1	u6		
Best	u2	u5	u7	
Call	u3	u4	u5	
Ishmael	u3			
Some	u3			
Years	u3	u7		
Here	u4			
Number	u4	u6		
Life	u7			

Filter, Intersection

URL	PageRank
u1	0.02
u2	0.3
u3	0.08
u4	0.1
u5	0.2
u6	0.25
u7	0.05

Join, Sort, Select  $n$

URL	Title
u1	The Constitution of India
u2	A Tale of Two Cities by Dickens
u3	Project Gutenberg - Moby Dick
u4	Carly Rae Jepsen - Call Me Maybe
u5	Shah Rukh Khan interview
u6	Wikipedia – India's Population
u7	Best Years of My Life Pistol Annies

Join, Return  $n$

Keywords

# ETL for Web Crawl & Search

- ▷ Bringing it all together: **Doing a Search**
  - Join top n pages with URL and title  
**`titleRdd.filter(url in bestMatches)`**
  - Return result to user
  - Suggest similar searches (co-occurrence)
    - *How?*

