An Innovative Approach to Parallel Processing Data

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The Context: Big-data

- Man on the moon with 32KB (1969); my laptop had 2GB RAM (2009)
- Google collects 270PB data in a month (2007), 20PB a day (2008) …
- 2010 census data is a huge gold mine of information
- Data mining huge amounts of data collected in a wide range of domains from astronomy to healthcare has become essential for planning and performance.
- We are in a knowledge economy.
  - Data is an important asset to any organization
  - Discovery of knowledge; Enabling discovery; annotation of data
- We are looking at newer
  - programming models, and
  - Supporting algorithms and data structures
- National Science Foundation refers to it as "data-intensive computing" and industry calls it "big-data" and "cloud computing"

More context

- Rear Admiral Grace Hopper: “In pioneer days they used oxen for heavy pulling, and when one ox couldn't budge a log, they didn't try to grow a larger ox. We shouldn't be trying for bigger computers, but for more systems of computers.”

---From the Wit and Wisdom of Grace Hopper (1906-1992), http://www.cs.yale.edu/homes/tap/Files/hopper-wit.html

Introduction : Ch.1 (Lin and Dyer's text)

- Text processing: web-scale corpora (singular corpus)
- Simple word count, cross reference, n-grams, …
- A simpler technique on more data beat a more sophisticated technique on less data.
- Google researchers call this: "unreasonable effectiveness of data"

--Alon Halevy, Peter Norvig, and Fernando Pereira. The unreasonable effectiveness of data. Communications of the ACM, 24(2):8:12, 2009.

MapReduce

What is MapReduce?

- MapReduce is a programming model Google has used successfully in processing its "big-data" sets (~ 20 peta bytes per day in 2008)
  - Users specify the computation in terms of a *map* and a *reduce* function,
  - Underlying runtime system automatically parallelizes the computation across large-scale clusters of machines, and
  - Underlying system also handles machine failures, efficient communications, and performance issues.

-- Reference: Dean, J. and Ghemawat, S. 2008. **MapReduce: simplified data processing on large clusters.** *Communication of ACM* 51, 1 (Jan. 2008), 107-113.

Big idea behind MR

- **Scale-out** and not scale-up: Large number of commodity servers as opposed large number of high end specialized servers
  - Economies of scale, ware-house scale computing
  - MR is designed to work with clusters of commodity servers
  - Research issues: Read Barroso and Holzle's work
- **Failures are norm** or common:
  - With typical reliability, MTBF of 1000 days (about 3 years), if you have a cluster of 1000, probability of at least 1 server failure at any time is nearly 100%

Big idea (contd.)

- **Moving "processing" to the data**: not literally, data and processing are co-located versus sending data around as in HPC
- **Process data sequentially vs random access**: analytics on large sequential bulk data as opposed to search for one item in a large indexed table
- **Hide system details from the user application**: user application does not have to get involved in which machine does what. Infrastructure can do it.
- **Seamless scalability**: Can add machines / server power without changing the algorithms: this is in-order to process larger data set

Issues to be addressed

- How to break large problem into smaller problems? Decomposition for parallel processing
- How to assign tasks to workers distributed around the cluster?
- How do the workers get the data?
- How to synchronize among the workers?
- How to share partial results among workers?
- How to do all these in the presence of errors and hardware failures?
- MR is supported by a distributed file system that addresses many of these aspects.

MapReduce Basics

- Fundamental concept:
- Key-value pairs form the basic structure of MapReduce <key, value>
- Key can be anything from a simple data types (int, float, etc) to file names to custom types.
- Examples:
  - <docid, docitself>
  - <yourName, yourLifeHistory>
  - <graphNode, nodeCharacteristicsComplexData>
  - <yourId, yourFollowers>
  - <word, itsNumofOccurrences>
  - <planetName, planetInfo>
  - <geneNum, <{pathway, geneExp, proteins}>
  - <Student, stuDetails>

From CS Foundations to MapReduce (Example#1)

Consider a large data collection:

{web, weed, green, sun, moon, land, part, web, green,...}

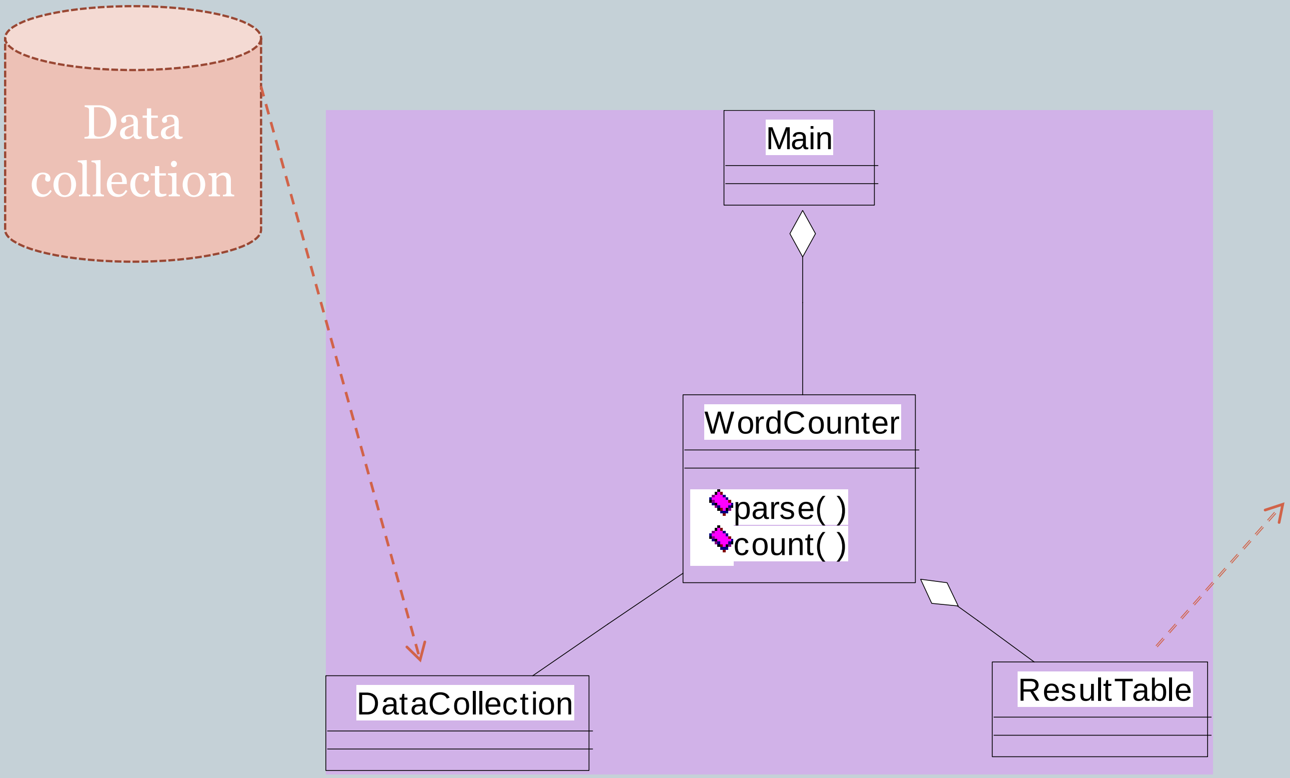
Problem: Count the occurrences of the different words in the collection.

Lets design a solution for this problem;

- We will start from scratch
- We will add and relax constraints
- We will do incremental design, improving the solution for performance and scalability

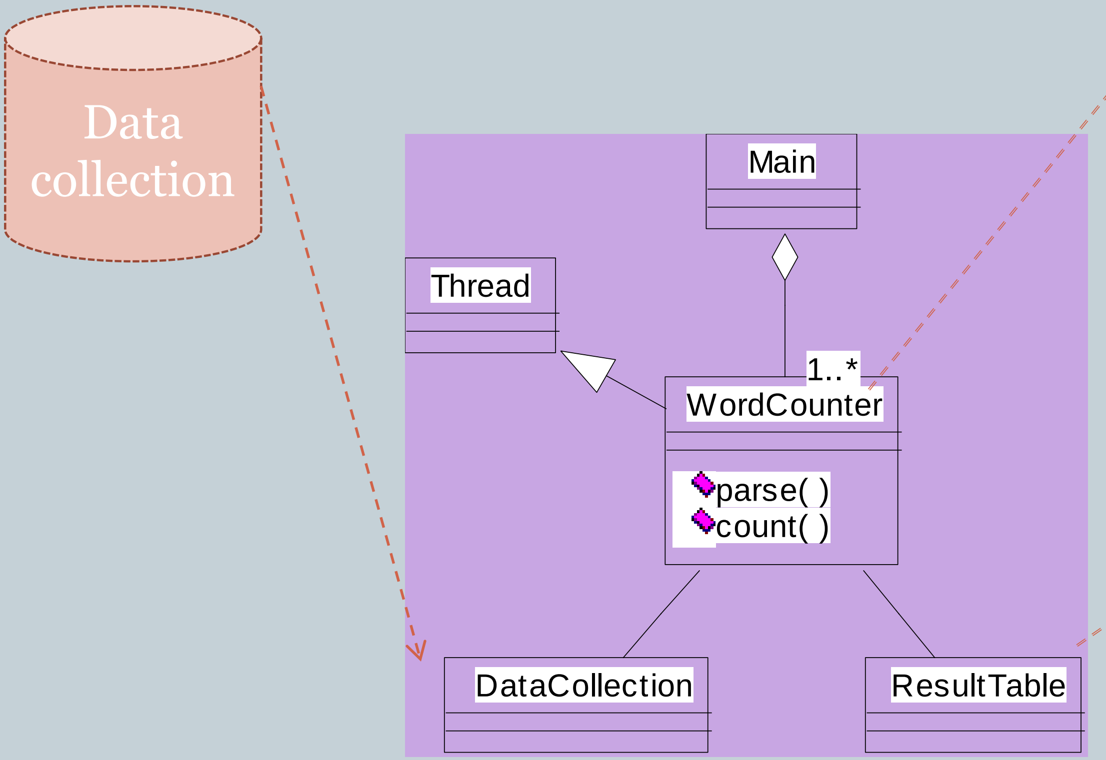
Word Counter and Result Table

{web, weed, green, sun, moon, land, part, web, green,…}



web	**2**
weed	**1**
green	**2**
sun	**1**
moon	**1**
land	**1**
part	**1**

Multiple Instances of Word Counter

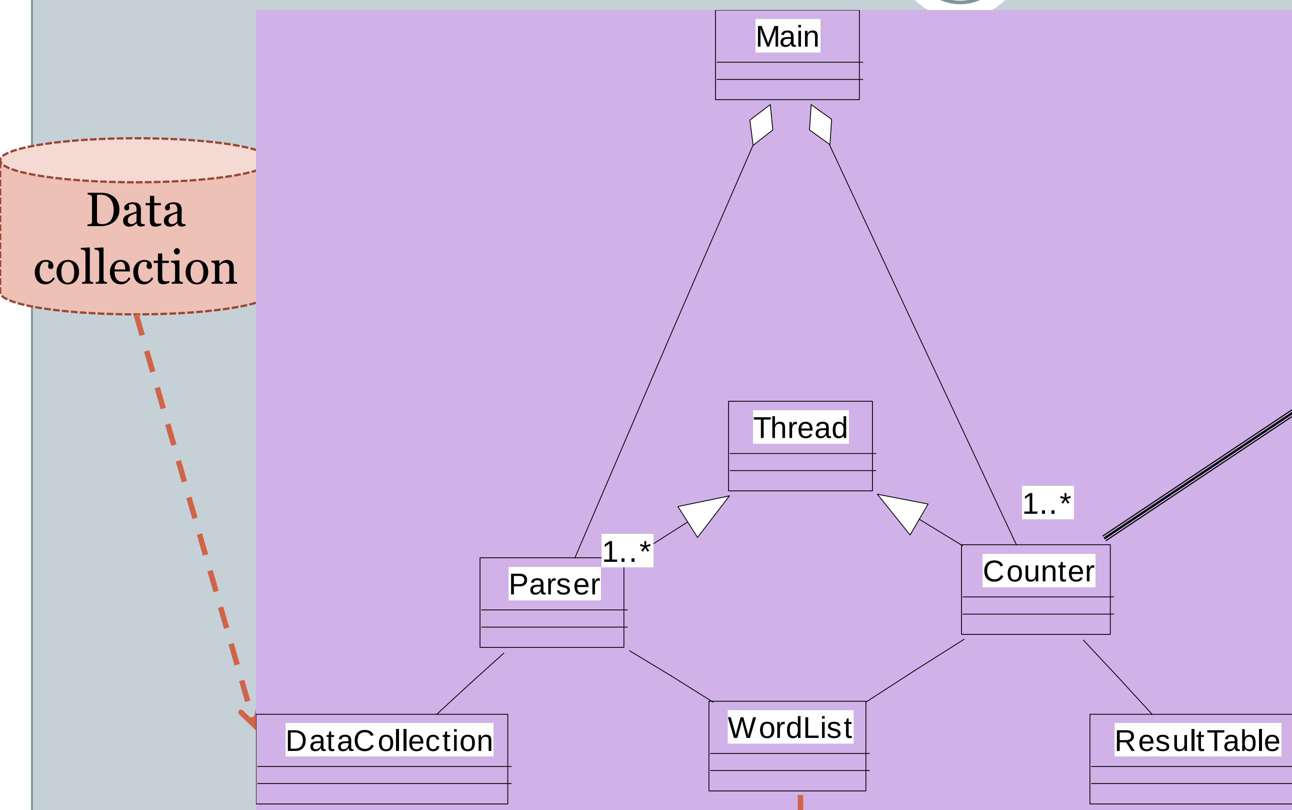


web	2
weed	1
green	2
sun	1
moon	1
land	1
part	1

Observe:
Multi-thread
Lock on shared data

Improve Word Counter for Performance

No need for lock

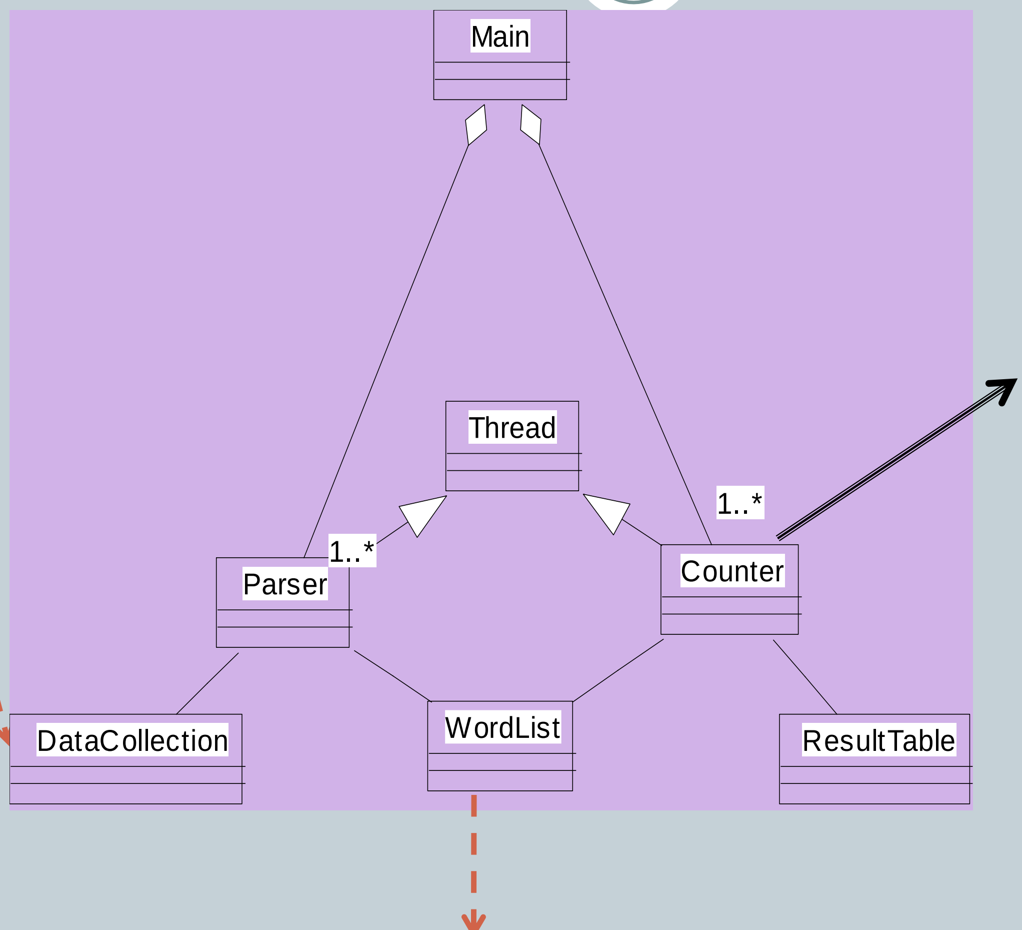


web	2
weed	1
green	2
sun	1
moon	1
land	1
part	1

Separate counters

KEY	web	weed	green	sun	moon	land	part	web	green	…….
VALUE										

Peta-scale Data



web	2
weed	1
green	2
sun	1
moon	1
land	1
part	1

KEY	web	weed	green	sun	moon	land	part	web	green	…….
VALUE										

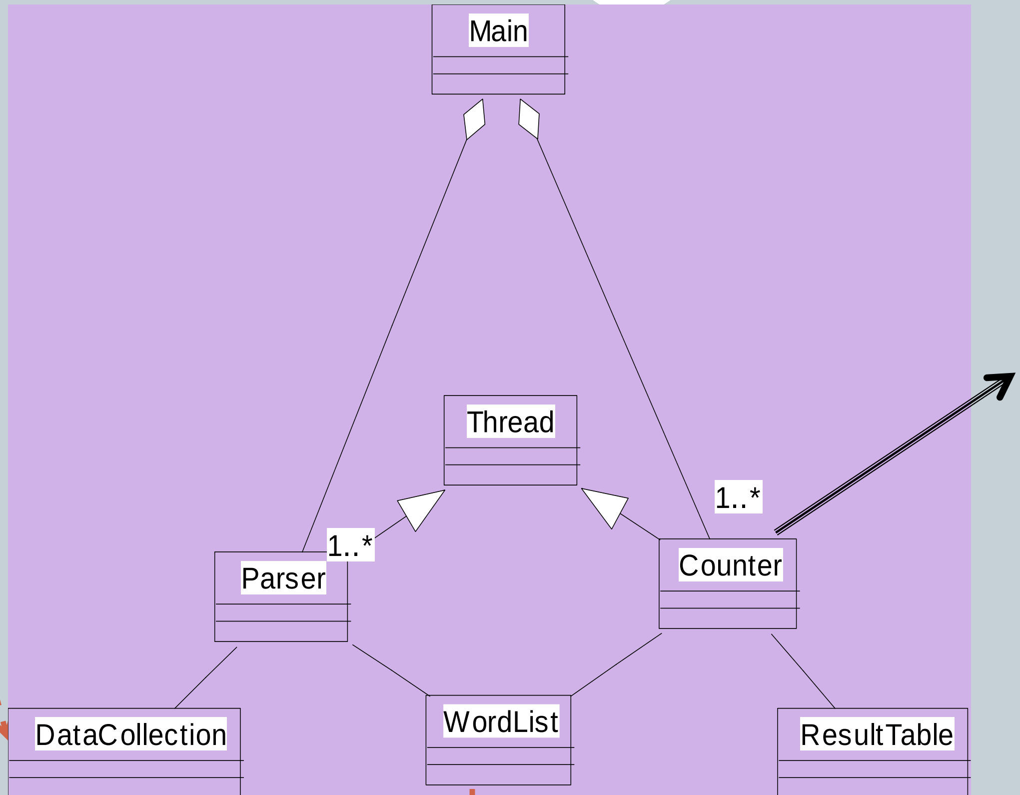
Addressing the Scale Issue

- Single machine cannot serve all the data: you need a distributed special (file) system
- Large number of commodity hardware disks: say, 1000 disks 1TB each
  - Issue: With Mean time between failures (MTBF) or failure rate of 1/1000, then at least 1 of the above 1000 disks would be down at a given time.
  - Thus failure is norm and not an exception.
  - File system has to be fault-tolerant: replication, checksum
  - Data transfer bandwidth is critical (location of data)

- Critical aspects: fault tolerance + replication + load balancing, monitoring
- Exploit parallelism afforded by splitting parsing and counting
- Provision and locate computing at data locations

Peta-scale Data

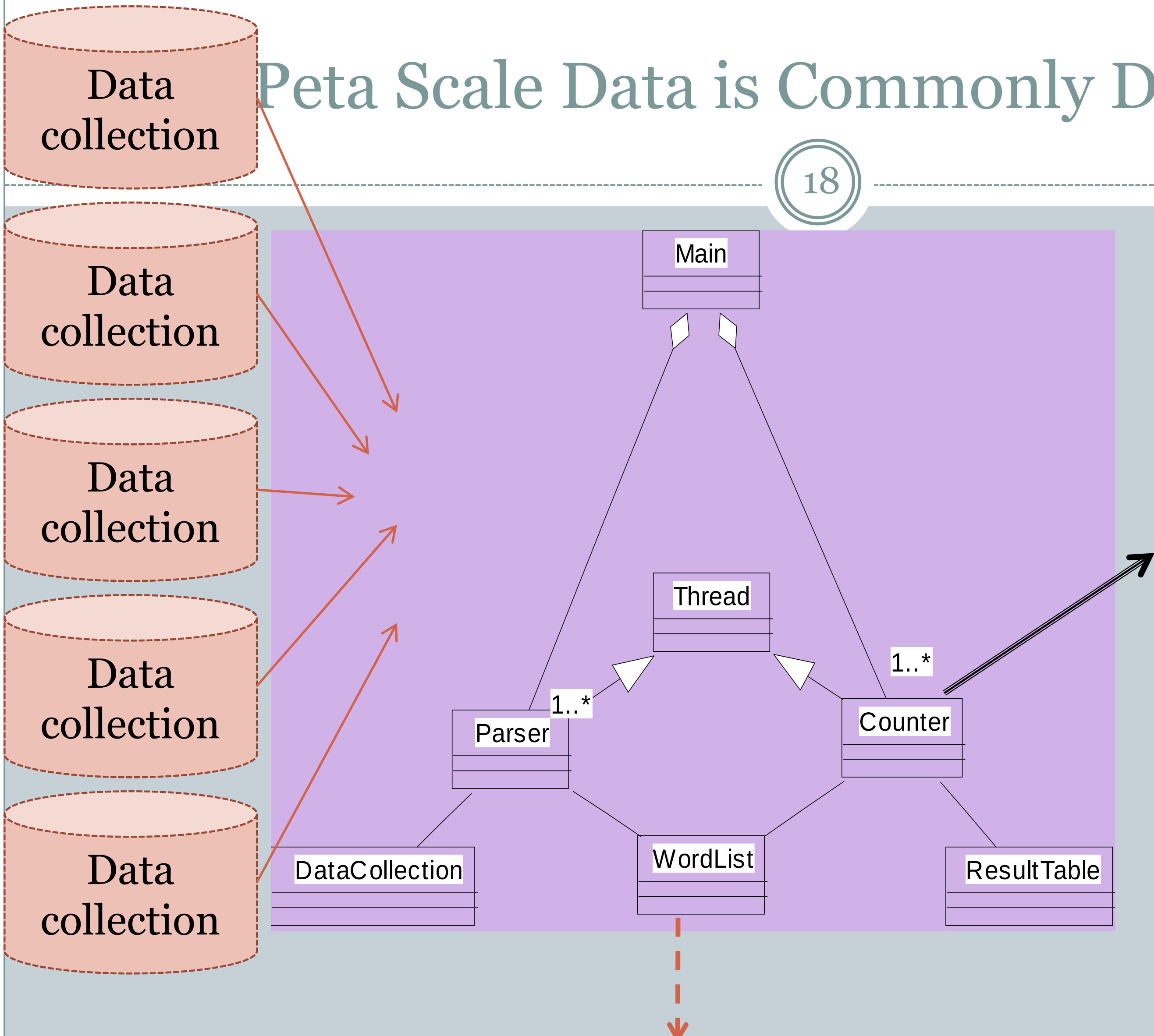
Data collection



web	2
weed	1
green	2
sun	1
moon	1
land	1
part	1

KEY	web	weed	green	sun	moon	land	part	web	green	…….
VALUE										

Peta Scale Data is Commonly Distributed

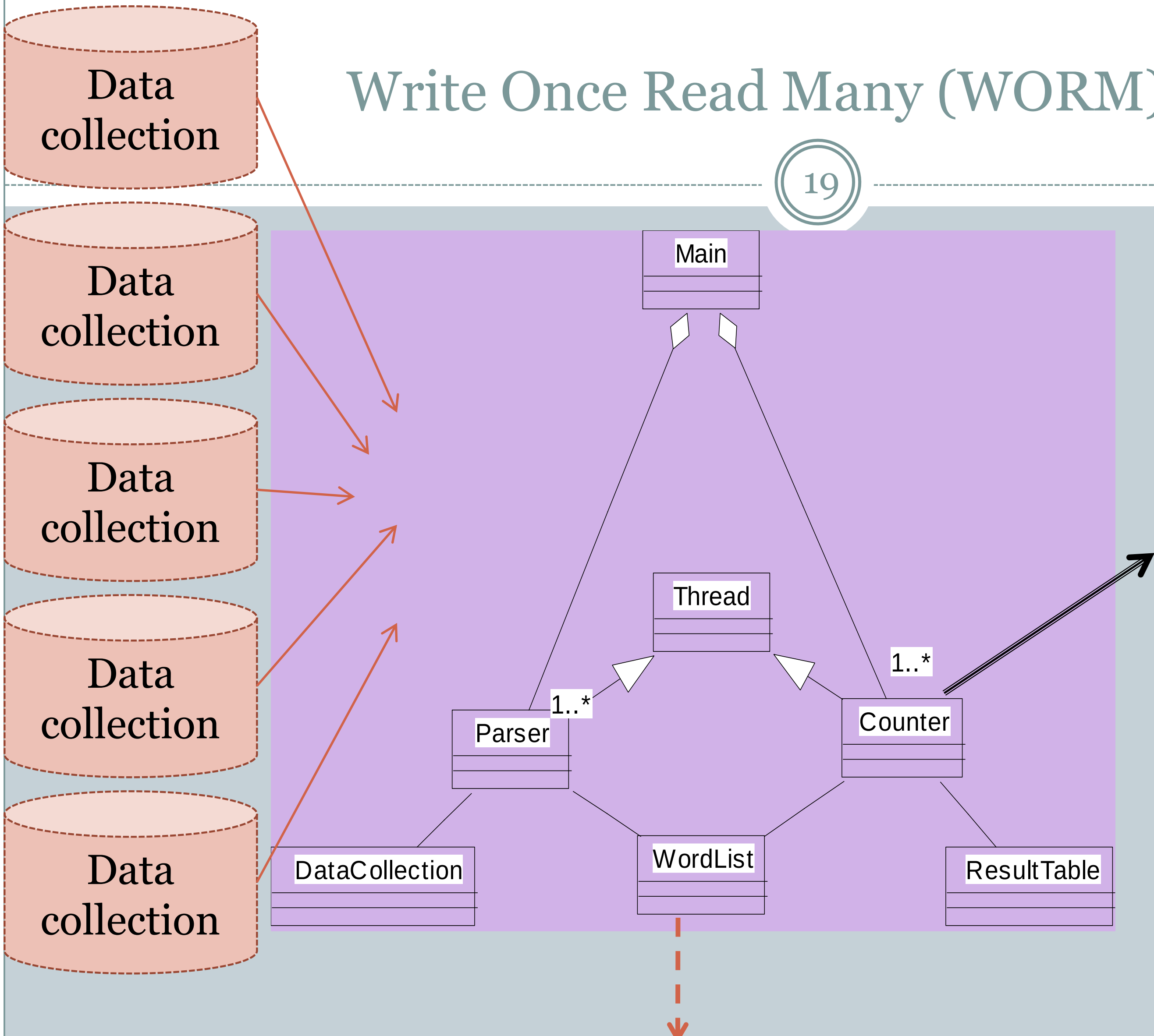


web	2
weed	1
green	2
sun	1
moon	1
land	1
part	1

Issue: managing the large scale data

KEY	web	weed	green	sun	moon	land	part	web	green	…….
VALUE										

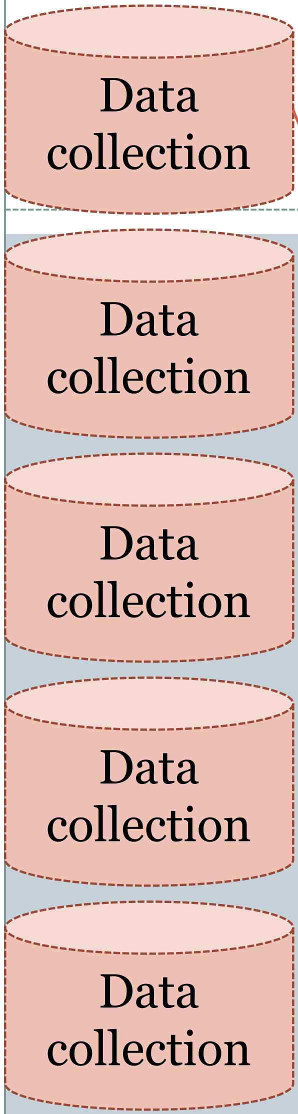
Write Once Read Many (WORM) data

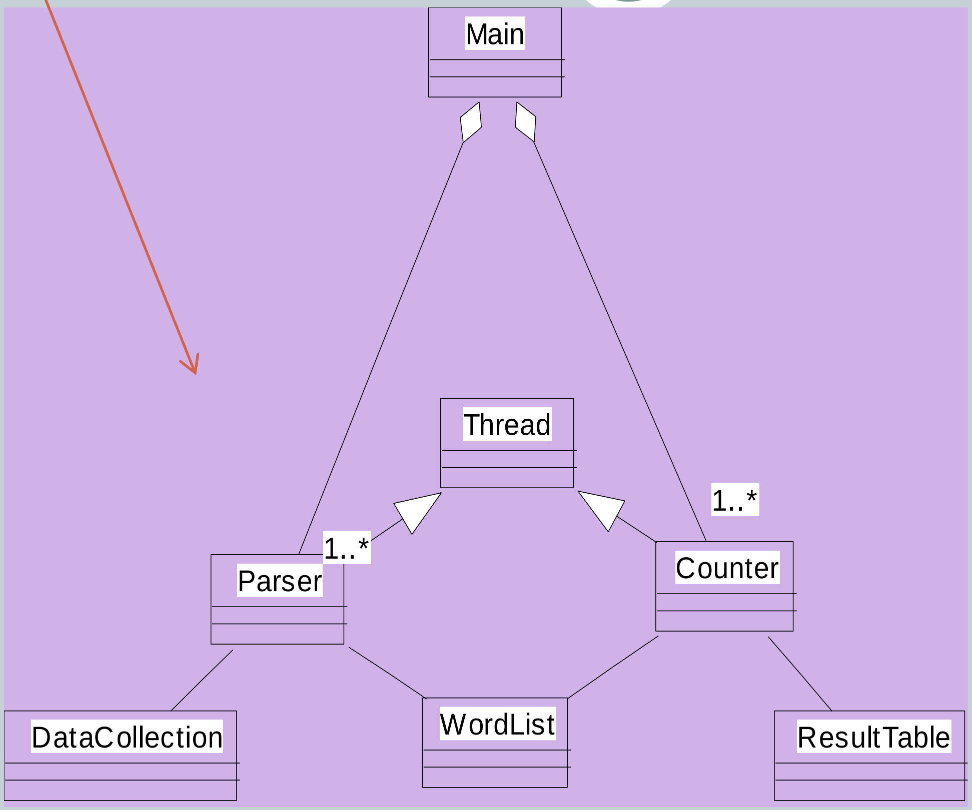


web	2
weed	1
green	2
sun	1
moon	1
land	1
part	1

KEY	web	weed	green	sun	moon	land	part	web	green	…….
VALUE										

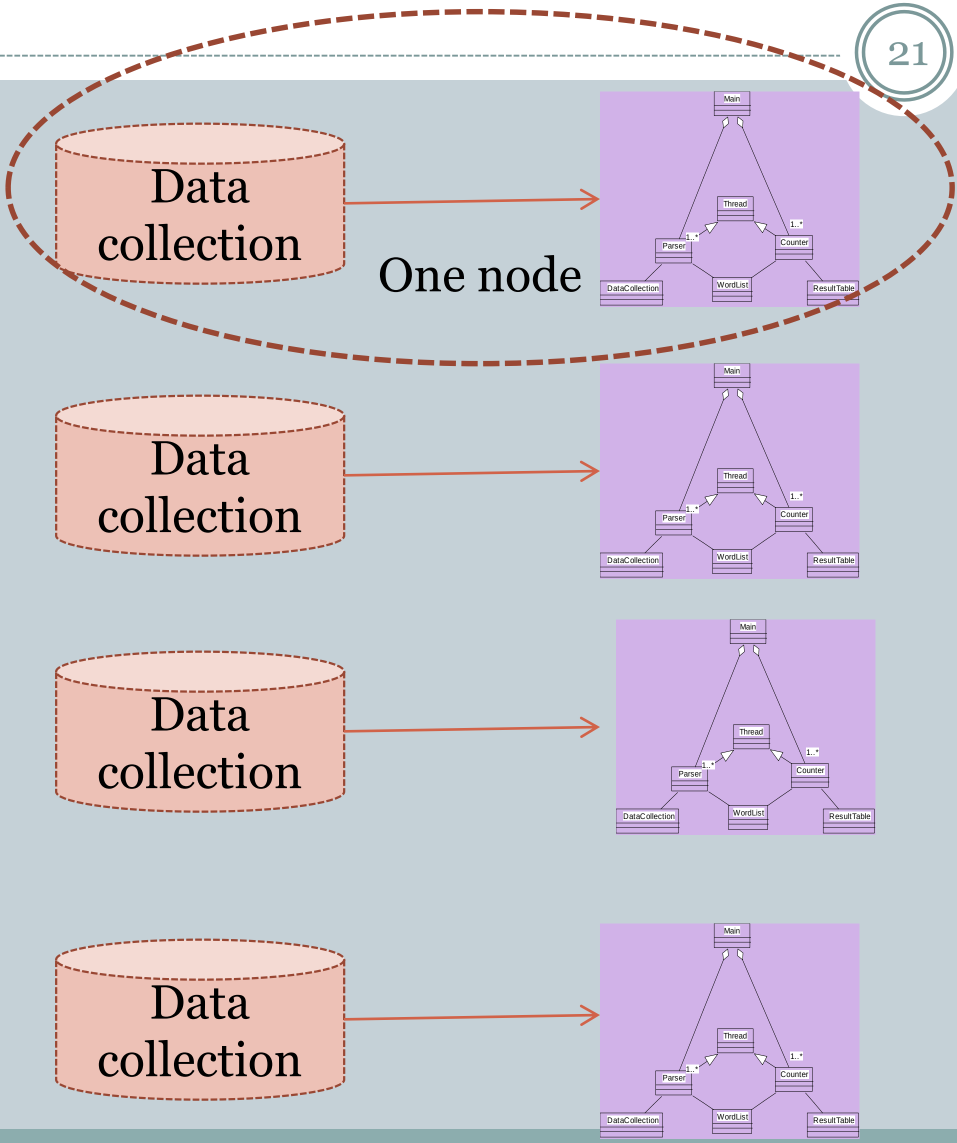
WORM Data is Amenable to Parallelism





1. Data with WORM characteristics : yields to parallel processing;
2. Data without dependencies: yields to out of order processing

Divide and Conquer: Provision Computing at Data Location



For our example,
#1: Schedule parallel parse tasks
#2: Schedule parallel count tasks

This is a particular solution;
Lets generalize it:

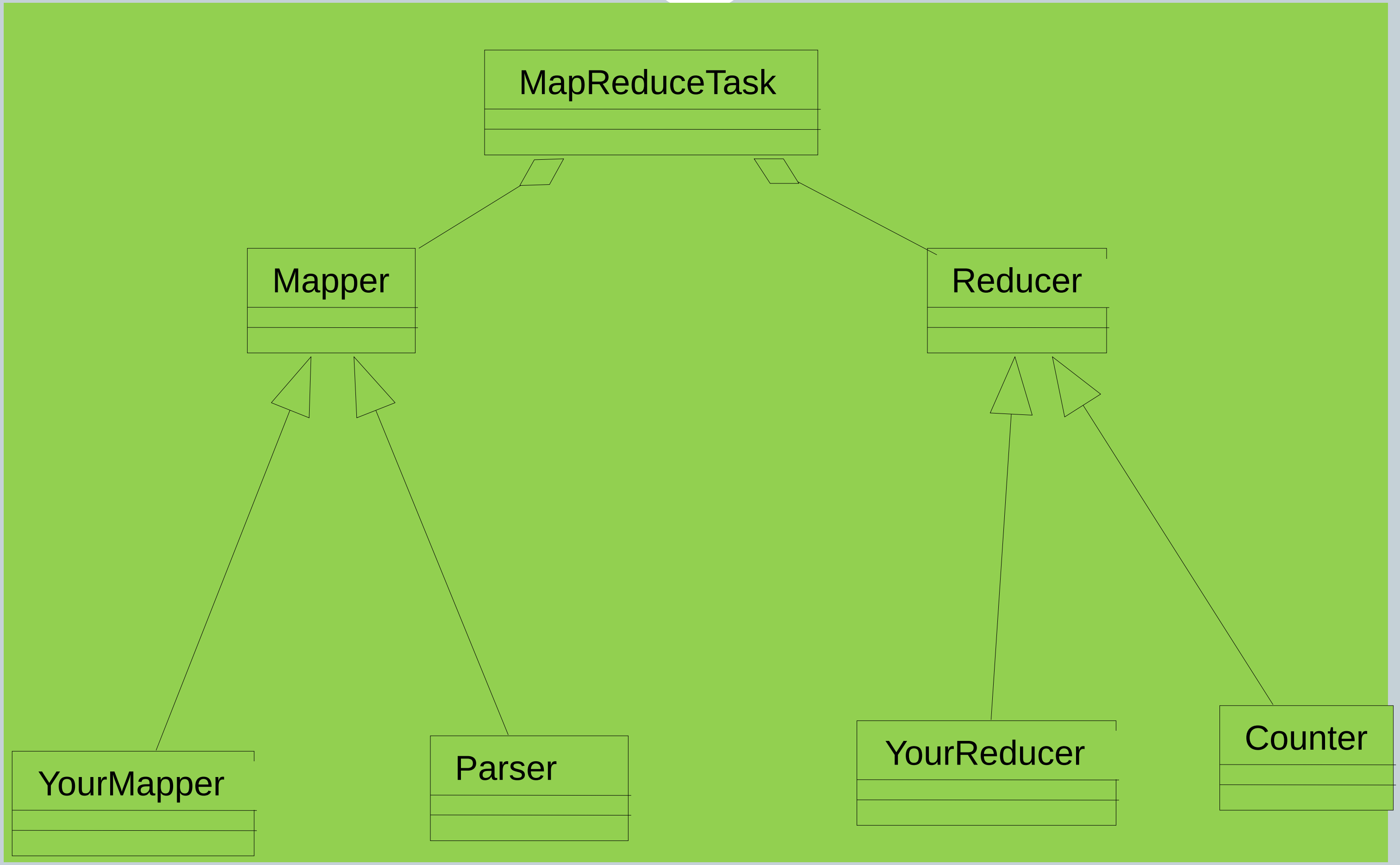
Our parse is a mapping operation:
MAP: input → <key, value> pairs

Our count is a reduce operation:
REDUCE: <key, value> pairs reduced

Map/Reduce originated from Lisp
But have different meaning here

Runtime adds distribution + fault tolerance + replication + monitoring + load balancing to your base application!

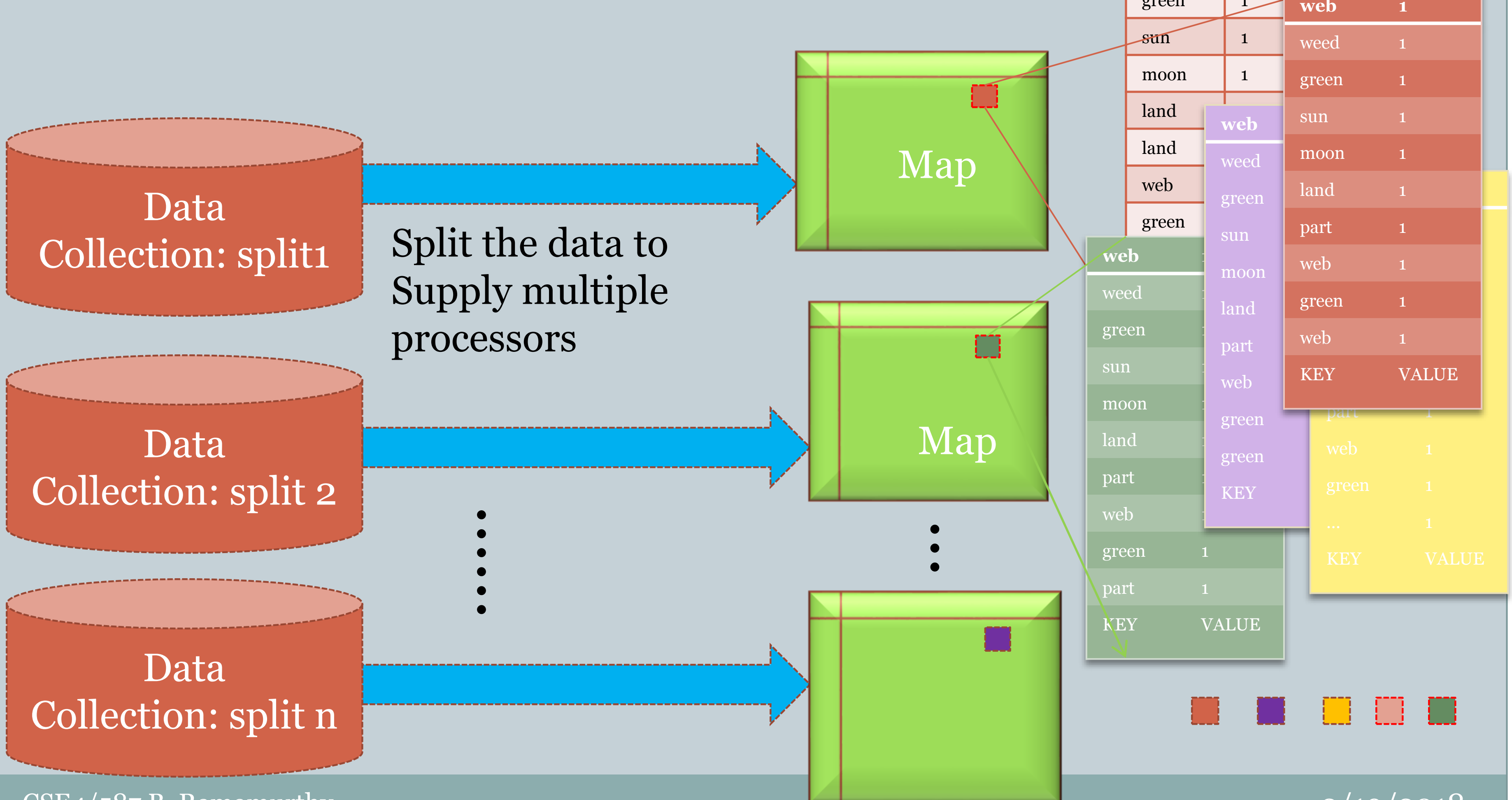
Mapper and Reducer



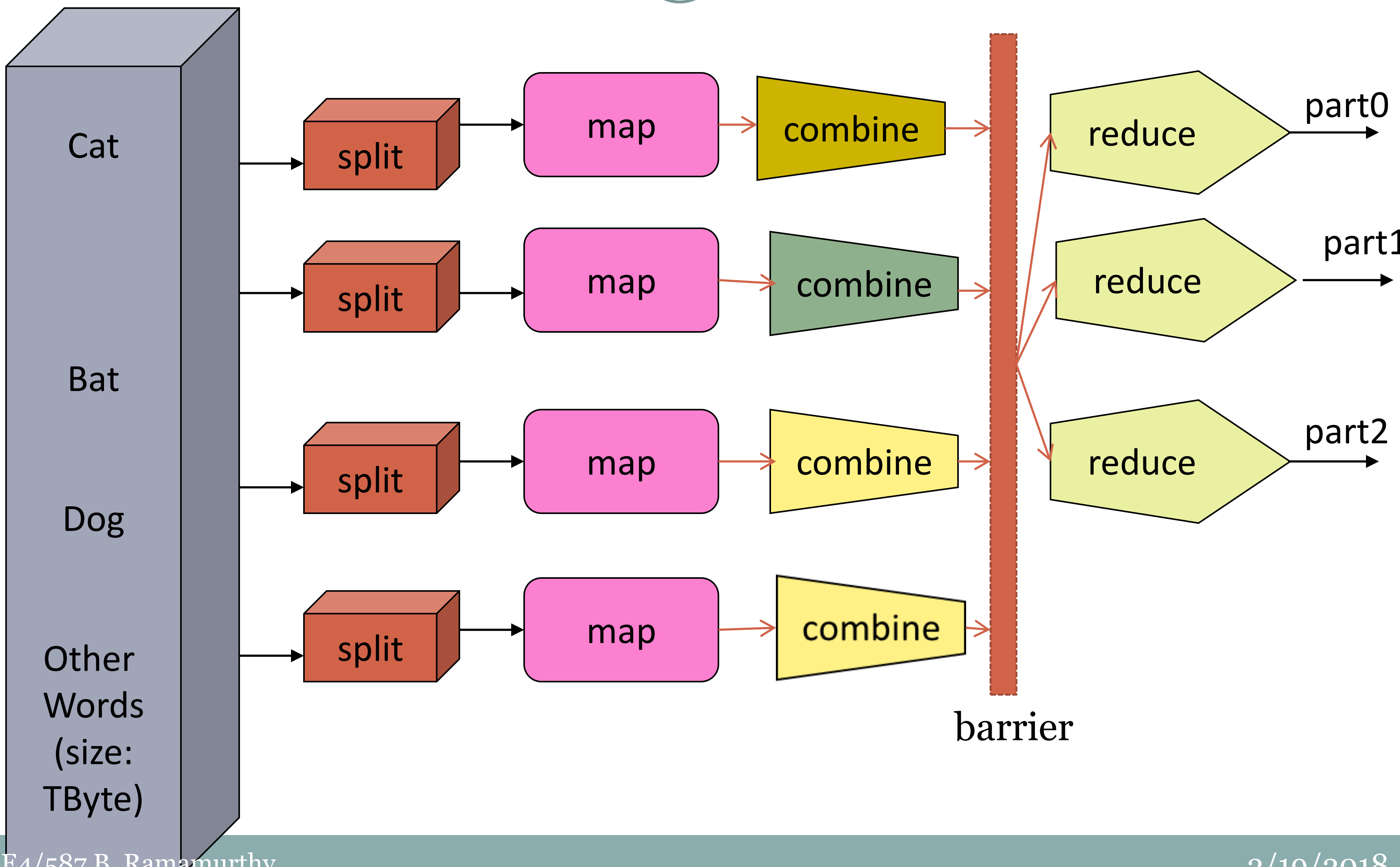
Remember: MapReduce is simplified processing for larger data sets

Map Operation

MAP: Input data ➔ <key, value> pair



MapReduce Example #2



MapReduce Design

- You focus on Map function, Reduce function and other related functions like combiner etc.
- Mapper and Reducer are designed as classes and the function defined as a method.
- Configure the MR "Job" for location of these functions, location of input and output (paths within the local server), scale or size of the cluster in terms of #maps, # reduce etc., run the job.
- Thus a complete MapReduce job consists of code for the mapper, reducer, combiner, and partitioner, along with job configuration parameters. The **execution framework** handles everything else.
- The way we configure has been evolving with versions of hadoop.

The code


```
class Mapper
    method Map(docid a; doc d)
    for all term t in doc d do
        Emit(term t; count 1)

class Reducer
    method Reduce(term t; counts [c1; c2; : : :])
     sum =  0
    for all count c in counts [c1; c2; : : :] do
        sum = sum + c
    Emit(term t; count sum)
```

Text Word Count Problem

This is a cat
Cat sits on a roof

The roof is a tin roof
There is a tin can on the roof

Cat kicks the can
It rolls on the roof and falls on the next roof

The cat rolls too
It sits on the can

Problem: Count the word frequency. Include all the words. We will worry about stop words and stemming later.

MapReduce Example: Mapper

This is a cat
Cat sits on a roof
<this 1> <is 1> <a 1> <cat 1> <cat 1> <sits 1> <on 1><a 1> <roof 1>

The roof is a tin roof
There is a tin can on the roof
<the 1> <roof 1> <is 1> <a 1> <tin 1 ><roof 1> <there 1> <is 1> <a 1> <tin 1><can 1> <on 1><the 1> <roof 1>

Cat kicks the can
It rolls on the roof and falls on the next roof
<cat 1> <kicks 1> <the 1><can 1> <it 1> <rolls 1> <on 1> <the 1> <roof 1> <and 1> <falls 1><on 1> <the 1> <next 1> <roof 1>

The cat rolls too
It sits on the can
<the 1> <cat 1> <rolls 1> <too 1> <it 1> <sits 1> <on 1> <the 1> <can 1>

MapReduce Example: Shuffle to the Reducer

Output of Mappers:

<this 1> <is 1> <a 1> <cat 1> <cat 1> <sits 1> <on 1><a 1> <roof 1>

<the 1> <roof 1> <is 1> <a 1> <tin 1 ><roof 1> <there 1> <is 1> <a 1> <tin 1><can 1> <on 1><the 1> <roof 1>

<cat 1> <kicks 1> <the 1><can 1> <it 1> <rolls 1> <on 1> <the 1> <roof 1> <and 1> <falls 1><on 1> <the 1> <next 1> <roof 1>

<the 1> <cat 1> <rolls 1> <too 1> <it 1> <sits 1> <on 1> <the 1> <can 1>

Input to the reducer: delivered sorted... By key

..

<can <1, 1>>

<cat <1,1,1,1>>

...

<roof <1,1,1,1,1,1>>

.....

Reduce (sum in this case) the counts: comes out sorted!!!

..

<can 2>

<cat 4>

..

<roof 6>

More on MR

- All Mappers work in parallel.
- Barriers enforce all mappers completion before Reducers start.
- Mappers and Reducers typically execute on the same machine
- You can configure job to have other combinations besides Mapper/Reducer: ex: identify mappers/reducers for realizing “sort” (that happens to be a Benchmark)
- Mappers and reducers can have side effects; this allows for sharing information between iterations.

MapReduce Characteristics

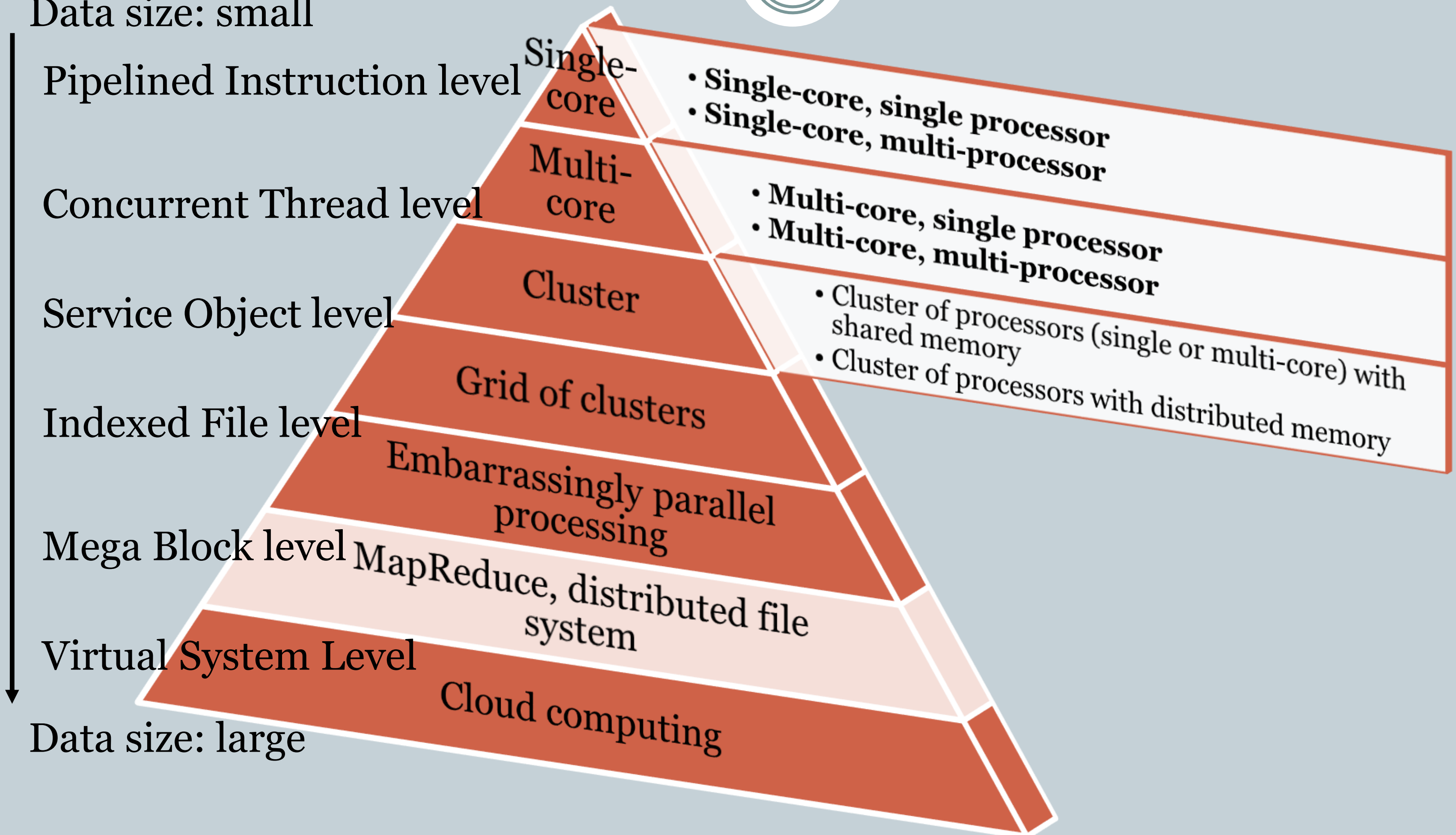
- Very large scale data: peta, exa bytes
- Write once and read many data: allows for parallelism without mutexes
- Map and Reduce are the main operations: simple code
- There are other supporting operations such as combine and partition: we will look at those later.
- Operations are provisioned near the data.
- Commodity hardware and storage.
- Runtime takes care of splitting and moving data for operations.
- Special distributed file system: Hadoop Distributed File System and Hadoop Runtime.

Classes of problems "mapreducable"

- Benchmark for comparing: Jim Gray's challenge on data-intensive computing. Ex: "Sort"
- Google uses it (we think) for wordcount, adwords, pagerank, indexing data.
- Simple algorithms such as grep, text-indexing, reverse indexing
- Bayesian classification: data mining domain
- Facebook uses it for various operations: demographics
- Financial services use it for analytics
- Astronomy: Gaussian analysis for locating extra-terrestrial objects.
- Expected to play a critical role in semantic web and web3.0

Scope of MapReduce

Data size: small



Data size: large

Lets Review Map/Reducer

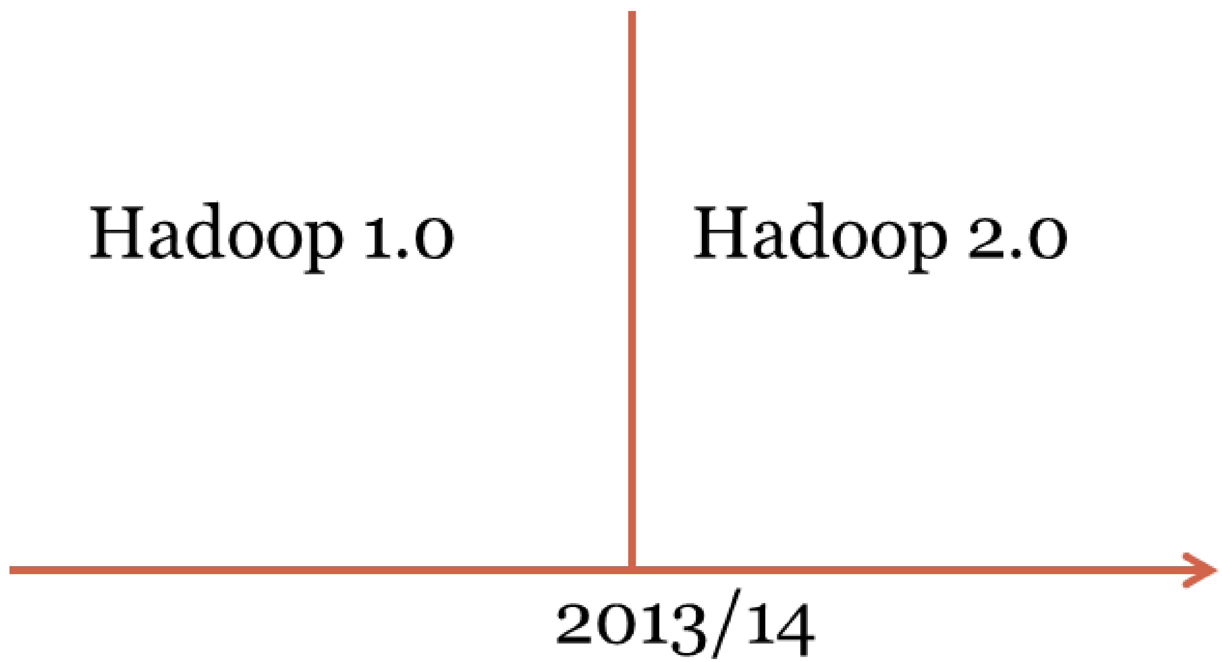
- Map function maps one <key,value> space to another. One to many: "expand" or "divide"
- Reduce does that too. But many to one: "merge"
- There can be multiple "maps" in a single machine…
- Each mapper(map) runs parallel with and independent of the other (think of a bee hive)
- All the outputs from mappers are collected and the "key space" is partitioned among the reducers. (what do you need to partition?)
- Now the reducers take over. One reduce/per key (by default)
- Reduce operation can be anything.. Does not have to be just counting…(operation [list of items]) – You can do magic with this concept.

Hadoop

What is Hadoop?

- At Google MapReduce operation are run on a special file system called Google File System (GFS) that is highly optimized for this purpose.
- GFS is not open source.
- Doug Cutting and Yahoo! reverse engineered the GFS and called it Hadoop Distributed File System (HDFS).
- The software framework that supports HDFS, MapReduce and other related entities is called the project Hadoop or simply Hadoop.
- This is open source and distributed by Apache.

Hadoop

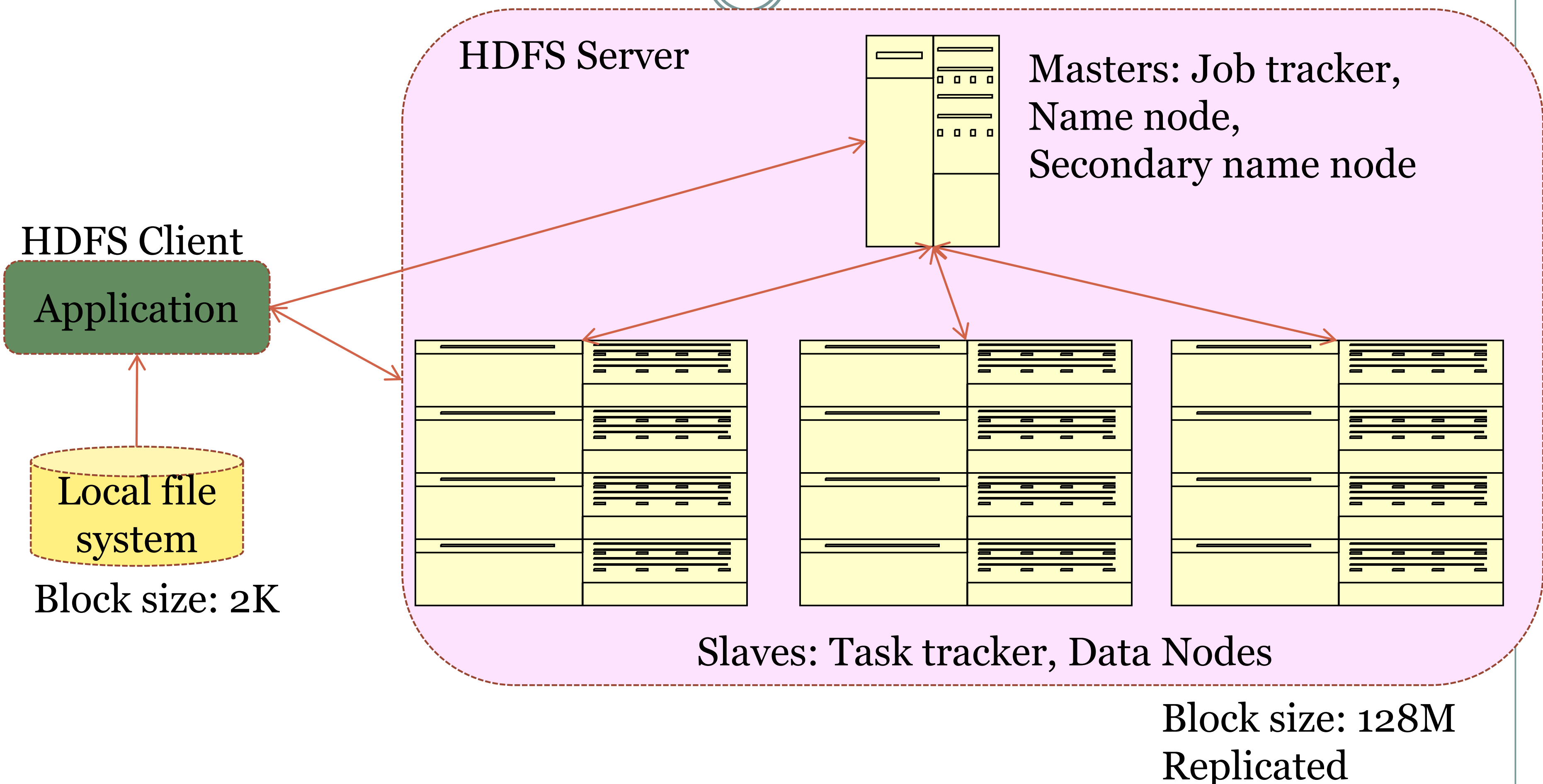


What has changed? Hmm…

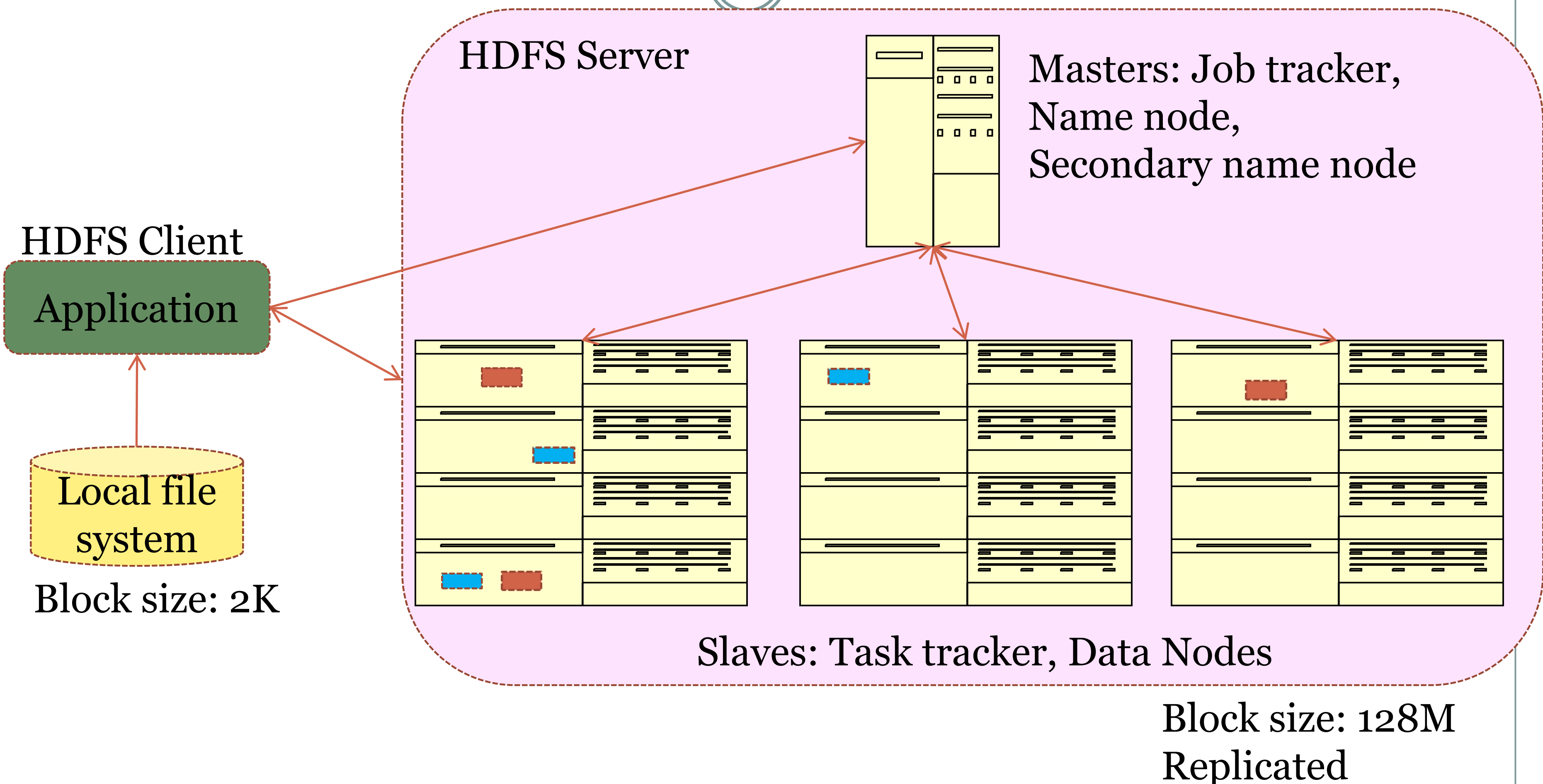
Basic Features: HDFS

- Highly fault-tolerant
- High throughput
- Suitable for applications with large data sets
- Streaming access to file system data
- Can be built out of commodity hardware
- HDFS core principles are the same in both major releases of Hadoop.

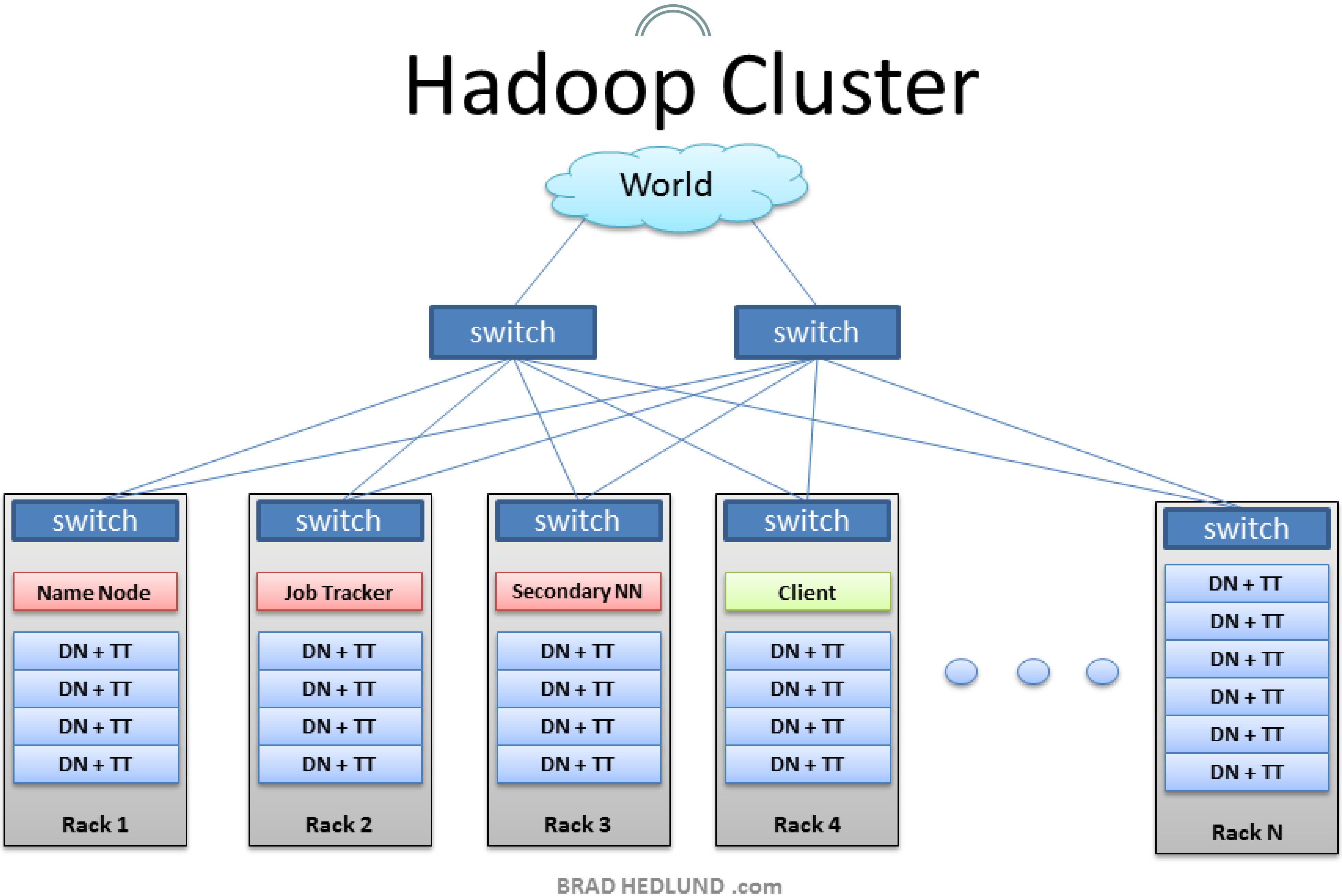
Hadoop Distributed File System



Hadoop Distributed File System



From Brad Hedlund: a very nice picture



Hadoop (contd.)

- What are : Job tracker, Name node, Secondary name node, data node, task tracker…?
- What are their roles?
- Before we discuss those: lets look a demo of mapreduce on Hadoop MapReduce