### **Extreme** Computing

# Distributed Data-Parallel Programming



THE UNIVERSITY of EDINBURGH

Amir Shaikhha, Fall 2023

### Part 1

### **Programming Models/Languages**

# THE INTERNET IN 2023 every minute



https://ediscoverytoday.com/2023/04/20/2023-internet-minute-infographic-by-ediscovery-today-and-ltmg-ediscovery-trends/

## Mainstream Languages for Data Scientists







Mainstream Languages for Data Scientists (cont.)

Pros

- ✓ Rapid Development
- ✓ Large community
- Cons
- What to do with large datasets?



# Is there any language without this issue?



# Why Scala is related to BigData?

### **How Technologies Are Connected**



#### MACHINE LEARNING, ARTIFICIAL INTELLIGENCE, AND DATA (MAD) LANDSCAPE 2021

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mattturck.com/data2021

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# Mainstream Big Data models

How to store, manage and process Big Data by harnessing large clusters of commodity nodes

 MapReduce family: simpler, more constrained

APACHE



 Dataflow family: enables more complex processing & data, optimization opportunities



### The Hadoop Ecosystem



### Spark Software Stack



### **PROGRAMMING MODELS**

### The vision...

### Sample function: convert all text to upper case

Splits may be stored at diff. nodes



convertUpper()

### The vision (2) More complicated: the word-count problem

- Huge file  $\rightarrow$  extract frequencies of words
- Example

Logic will get you from A to B. Imagination will take you everywhere.



### Extracted frequencies:

Einstein once said...

• <Logic,1>, <will,2>, <get,1>, <you,2>, ...

### The vision (3) Sample application: the word-count example



### MapReduce programming model

- Data model: everything is a <key,value> pair
- Programming model two core functions
  - Map(key,value): Invoked for every split of the input data. Value corresponds to the split.
  - Reduce(key,list(values)): Invoked for every unique key emitted by Map. List(values) corresponds to all values emitted from ALL mappers for this key.
- These are second-order functions
  - Map(key,value, MapperClassName)
  - Reduce(key,list(values), ReducerClassName)
- $\rightarrow$  parallelism and deployment handled by the system

### MapReduce programming model (2)

- The word-count problem
  - Input: Text file, broken in splits
  - Output: Frequency of each word observed in the file
  - Map(key,value): value: a split of the text file
     for each word in value
     emit pair <word,+1>
  - Reduce(key,list(values)): Key: word, values: list of (+1's)

```
count=0
```

```
for each value in list(values)
```

```
count+=value
```

```
emit pair<key,count>
```

### MapReduce – under the hood



### Dataflow programming model

- MapReduce simple but weak for some reqs.
  - Cannot define complex processes
  - Everything file-based, no distributed memory
  - Procedural  $\rightarrow$  difficult to optimize
- Dataflow
  - Processing expressed as a DAG, tree, graph with cycles, ...
  - Vertices: processing tasks
  - Edges: Communication
    - DAG: Spark, Dryad
    - Tree: Dremel
    - Directed graph with cycles: Pregel



Spark DAG example

### Dataflow programming model (2)

Describing the processing tasks

### - Declarative languages, e.g., Dremel

SELECT DocId AS Id, COUNT(Name.Language.Code) WITHIN Name AS Cnt FROM t WHERE REGEXP(Name.Url, '^http');

### - Functional programming, e.g., Spark

val wordCounts = textFile.flatMap(line => line.split(" ")).

map(word => (word, 1)).

reduceByKey((a, b) = a + b)

wordCounts.collect()

### Domain-specific languages, e.g., Pregel

for graph processing

```
class PageRankVertex
: public Vertex<double, void, double> {
    public: virtual void Compute(MessageIterator* msgs) {
        const int64 n = GetOutEdgeIterator().size();
        SendMessageToAllNeighbors(GetValue() / n);
    }
};
```

## Why Spark? (1)



### Similar API ③

# Which programming language is this?

Integer totalAgeReduce =
roster.stream()

- .map(Person::getAge)
- .reduce( 0, (a, b) -> a + b);

Map<String, List<String>> a = words
 .stream().collect(
 Collectors.groupingBy(w ->
 sortChars(w)));

# PLs that have a functional collection interface like Scala

C++, C#, F#, Clojure, Haskell, Java8, JavaScript, Perl, PHP, Python, Ruby, Scheme, Smalltalk, Standard ML, OCAML,

See

https://en.wikipedia.org/wiki/Map\_(higher-order\_function)

### Fault Tolerance

- Essential for scaling out
- The main reason behind the success of MapReduce in Google
- Requires writing intermediate data to disk

## Fault Tolerance in Spark

- Data
  - Immutable
  - In-memory
- Operations = Functional transformations
- Fault tolerance = Replay operations

# Why Spark? (2)

- Compared to Hadoop MapReduce, improves efficiency through:
  - General execution graphs
  - In-memory storage

Up to 10 × faster on disk, 100 × in memory



Logistic regression in Hadoop and Spark http://spark.apache.org/

# Why Spark? (3)



# Why Spark? (4)



### Learn Scala

### **Scala School!**

From ø to Distributed Service

#### Other Languages:

한국어 Русский 简体中文

### About

Scala school started as a series of lectures at Twitter to prepare experienced engineers to be productive Scala programmers. Scala is a relatively new language, but draws on many familiar concepts. Thus, these lectures assumed the audience knew the concepts and showed how to use them in Scala. We found this an effective way of getting new engineers up to speed quickly. This is the written material that accompanied those lectures. We have found that these are useful in their own right.

#### Lessons

#### **Basics**

Values, functions, classes, methods, inheritance, trycatch-finally. Expression-oriented programming

#### **Basics continued**

Case classes, objects, packages, apply, update,

Functions are Objects (uniform access principle), pattern matching.

#### Collections

Lists, Maps, functional combinators (map, foreach, filter, zip, folds)

#### Pattern matching & functional composition

More functions! PartialFunctions, more Pattern Matching

#### Type & polymorphism basics

Rasic Types and type polymorphism type inference

### https://twitter.github.io/scala\_school/

### **QUESTIONS?**