Lecture 21—High-Performance Languages; MapReduce/Hadoop

ECE 459: Programming for Performance

March 25, 2014

Part I

High-Performance Languages

Introduction

DARPA began a supercomputing challenge in 2002.

Purpose:

create multi petaflop systems (floating point operations).

Three notable programming language proposals:

- X10 (IBM) [looks like Java]
- Chapel (Cray) [looks like Fortran/math]
- Fortress (Sun/Oracle)

Machine Model

We've used multicore machines and will talk about clusters (MPI, MapReduce).

These languages are targeted somewhere in the middle:

- thousands of cores and massive memory bandwidth;
- Partitioned Global Address Space (PGAS) memory model:
  - each process has a view of the global memory
  - memory is distributed across the nodes, but processors know what global memory is local.

Parallelism

These languages require you to specify the parallelism structure:

- Fortress evaluates loops and arguments in parallel by default;
- Others use an explicit construct, e.g. `forall`, `async`.

In terms of addressing the PGAS memory:

- Fortress divides memory into locations, which belong to regions (in a hierarchy; the closer, the better for communication).
- Similarly, places (X11) and locales (Chapel).

These languages make it easier to control the locality of data structures and to have distributed (fast) data.

X10 Example

```
import x10.io.Console;
import x10.util.Random;

class MontyPi {
  public static def main(args:Array[String](1)) {
    val N = Int.parse(args(0));
    val result=GlobalRef[Cell[Double]](new Cell[Double](0));
    finish for (p in Place.places()) at (p) async {
      val r = new Random();
      var myResult:Double = 0;
      for (1..(N/Place.MAX_PLACES)) {
        val x = r.nextDouble();
        val y = r.nextDouble();
        if (x*x + y*y <= 1) myResult++;
      }
      val ans = myResult;
      at (result) atomic result()() += ans;
    }
    val pi = 4*(result()())/N;
  }
}
```

X10 Example: explained

This shows a distributed computation.

Could replace `for (p in Place.places())` by
`for (1..P)` (where P is a number) for a parallel solution.
(Also, remove `GlobalRef`).

`async`: creates a new child activity,
    which executes the statements.
`finish`: waits for all child `asyncs` to finish.
`at`: performs the statement at the place specified;
    here, the processor holding the result increments its value.

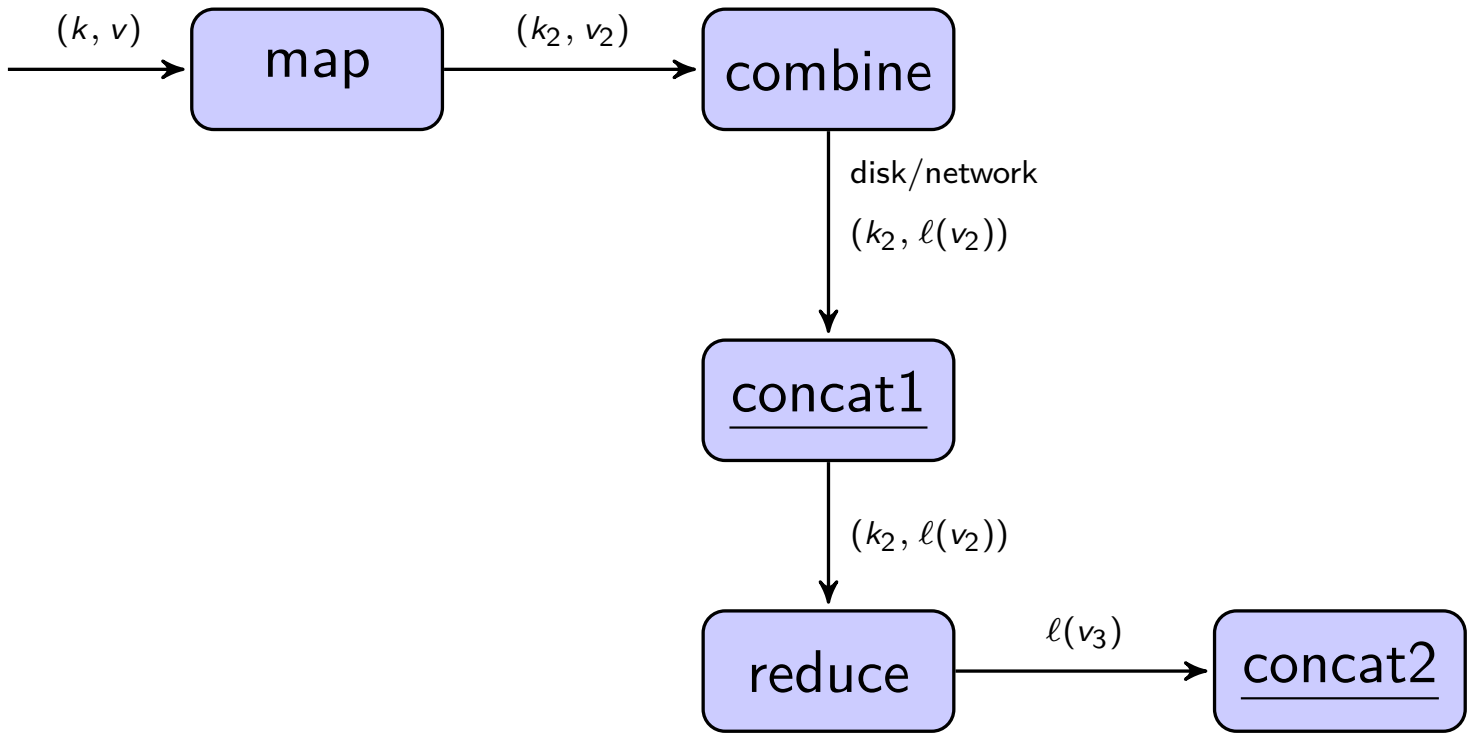
HPC Language Summary

- Three notable supercomputing languages: X10, Chapel, and Fortress (end-of-life).
- Partitioned Global Adress Space memory model: allows distributed memory with explicit locality.
- Parallel programming aspect to the languages are very similar to everything else we've seen in the course.

Part II

MapReduce

MapReduce


(k, v)
map
(k_2, v_2)
combine
disk/network
$(k_2, \ell(v_2))$
concat1
$(k_2, \ell(v_2))$
reduce
$\ell(v_3)$
concat2

Introduction: MapReduce

Framework introduced by Google for large problems.
Consists of two functional operations: map and reduce.

```
>>> map(lambda x: x*x, [1, 2, 3, 4, 5])
[1, 4, 9, 16, 25]
```

- **map**: applies a function to an iterable data-set.

```
>>> reduce(lambda x, y: x+y, [1, 2, 3, 4, 5])
15
```

- **reduce**: applies a function to an iterable data-set cumulatively.
  ((((1+2)+3)+4)+5) in this example.

MapReduce Intuition

In functional languages, functions are "pure" (no side-effects).
Since they are pure, and hence independent,
it's always safe to parallelize them.

Note: functional languages, like Haskell,
have their own parallel frameworks,
which allow easy parallelization.

Many problems can be represented as
a map operation followed by a reduce.

Hadoop

Apache Hadoop is a framework which implements MapReduce.

- Hadoop is the most widely used open source framework, used by Amazon's EC2 (elastic compute cloud).
- Allows work to be distributed across many different nodes (or re-tried if a node goes down).
- Includes HDFS (Hadoop distributed file system): distributes data across nodes and provides failure handling. (You can also use Amazon's S3 storage service).

Map (massive parallelism)

You split the input file into multiple pieces.

The pieces are then processed as (key, value) pairs.

Your **Mapper** function uses these (key, value) pairs and outputs another set of (key, value) pairs.

Reduce (not as parallel)

Collects the input files from the previous map
(which may be on different nodes, needing copying).

Merge-sorts the files,
so that the key-value pairs for a given key are contiguous.

Reads the file sequentially and
splits the values into lists of values with the same key.

Passes this data, consisting of keys and lists of values,
to your **reduce** method (in parallel), & concatenates results.

Combine (optional)

This step may be run right after map and before reduce.

Takes advantage of the fact that elements produced by the map operation are still available in memory.

Every so many elements, you can use your combine operation to take (key, value) outputs of the map and create new (key, value) inputs of the same types.

WordCount Example

Say we want to count the number of occurrences of words in some files.

Consider, for example, the following files:

```
Hello World Bye World
```

```
Hello Hadoop Goodbye Hadoop
```

We want the following output:

```
(Bye, 1)
(Goodbye, 1)
(Hadoop, 2)
(Hello, 2)
(World, 2)
```

WordCount: Example Operations

Mapper

- Split the input file into strings, representing words.
- For each word, output the following (key, value) pair: **(word, 1)**

Reduce

- Sum all values for each word (key) and output: **(word, sum)**

Combine

- We could do the reduce step for in-memory values while doing map.

  Note: here, the output of map and input/output of reduce are the same, but they don't have to be.

WordCount: Running the Example (File 1)

```
Hello World Bye World
```

After map:

```
(Hello, 1)
(World, 1)
(Bye, 1)
(World, 1)
```

After combine:

```
(Hello, 1)
(Bye, 1)
(World, 2)
```

WordCount: Running the Example (File 2)

```
Hello Hadoop Goodbye Hadoop
```

After map:

```
(Hello, 1)
(Hadoop, 1)
(Goodbye, 1)
(Hadoop, 1)
```

After combine:

```
(Hello, 1)
(Goodbye, 1)
(Hadoop, 2)
```

WordCount: Running the Example (Reduce)

After concatenation, sorting, and creating lists of values:

```
(Bye, [1])
(Goodbye, [1])
(Hadoop, [2])
(Hello, [1, 1])
(World, [2])
```

After the reduce, we get what we want:

```
(Bye, 1)
(Goodbye, 1)
(Hadoop, 2)
(Hello, 2)
(World, 2)
```

WordCount Example: C++ Code (1)

Credit: `http://wiki.apache.org/hadoop/C++WordCount`.

- APIs for Java/Python also exist.

```
#include "hadoop/Pipes.hh"
#include "hadoop/TemplateFactory.hh"
#include "hadoop/StringUtils.hh"

class WordCountMap: public HadoopPipes::Mapper {
public:
  WordCountMap(HadoopPipes::TaskContext& context){}
  void map(HadoopPipes::MapContext& context) {
    std::vector<std::string> words =
      HadoopUtils::splitString(context.getInputValue()," ");
    for(unsigned int i=0; i < words.size(); ++i) {
      context.emit(words[i], "1");
    }
  }
};
```

WordCount Example C++ Code (2)

```
class WordCountReduce: public HadoopPipes::Reducer {
public:
  WordCountReduce(HadoopPipes::TaskContext& context){}
  void reduce(HadoopPipes::ReduceContext& context) {
    int sum = 0;
    while (context.nextValue()) {
      sum += HadoopUtils::toInt(context.getInputValue());
    }
    context.emit(context.getInputKey(),
                 HadoopUtils::toString(sum));
  }
};

int main(int argc, char *argv[]) {
  return HadoopPipes::runTask(
    HadoopPipes::TemplateFactory<WordCountMap,
                                 WordCountReduce>());
}
```

Other Examples

- Distributed Grep.
- Count of URL Access Frequency.
- Reverse Web-Link Graph.
- Term-Vector per Host.
- 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.
  - **Output:** all of the output pairs from reducing form a simple inverted index.

Other Notes

Hive builds on top of Hadoop and allows you to use an SQL-like language to query outputs on HDFS; or you can provide custom mappers/reducers to get more information.

The cloud is a great way to start a new project: you can add or remove nodes easily as your problem changes size. (Hadoop or MPI are good examples).

References:

`http://wiki.apache.org/hadoop/`

`https://hadoop.apache.org/docs/r1.2.1/mapred_tutorial.html`

(There used to be a Google MapReduce tutorial but it no longer seems to be on the Internet.)

Summary

MapReduce is an excellent framework
for dealing with massive data-sets.

Hadoop is a common implementation you can use
(on most cloud computing services, even!)

You just need 2 functions (optionally 3):
mapper, reducer and combiner.

Just remember:
output of the mapper/combiner is input to the reducer.