

Principles of Software Construction: Objects, Design, and Concurrency

Distributed System Design, Part 2. MapReduce

Spring 2014

Charlie Garrod Christian Kästner



Administrivia

- Homework 5c due tonight
- Homework 6 coming tomorrow



Road map from last time...

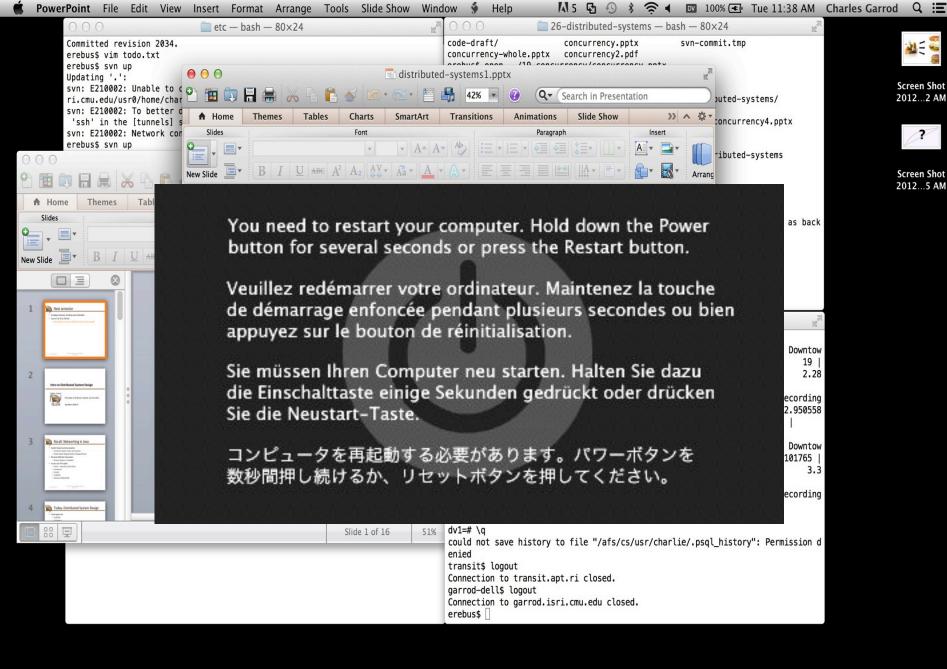
- Application-level communication protocols
- Frameworks for simple distributed computation
 - Remote Procedure Call (RPC)
 - Java Remote Method Invocation (RMI)
- Common patterns of distributed system design
- Complex computational frameworks
 - e.g., distributed map-reduce



Today: Distributed system design, part 2

- Introduction to distributed systems
 - Motivation: reliability and scalability
 - Replication for reliability
 - Partitioning for scalability
- MapReduce: A robust, scalable framework for distributed computation...
 - ...on replicated, partitioned data



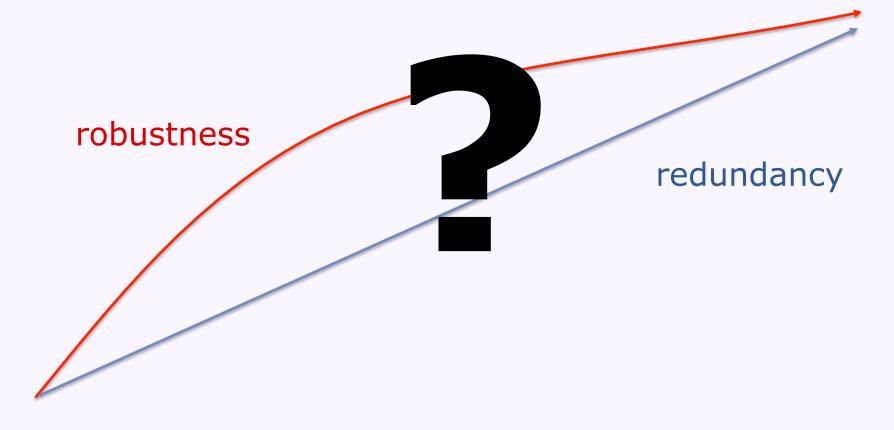


Screen Shot 2012...2 AM



Screen Shot 2012...5 AM

Aside: The robustness vs. redundancy curve

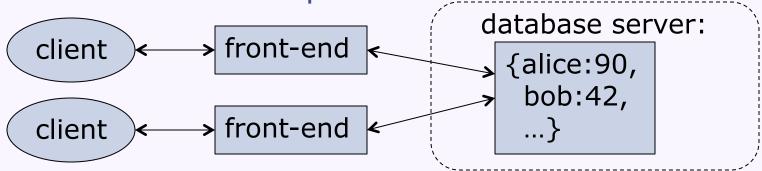


Metrics of success

- Reliability
 - Often in terms of availability: fraction of time system is working
 - 99.999% available is "5 nines of availability"
- Scalability
 - Ability to handle workload growth

A case study: Passive primary-backup replication

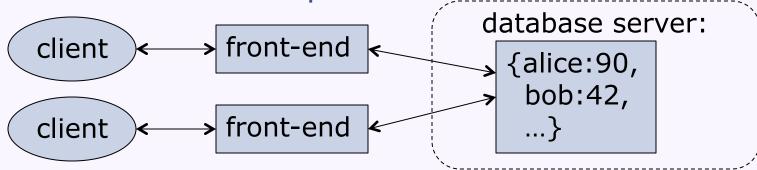
Architecture before replication:



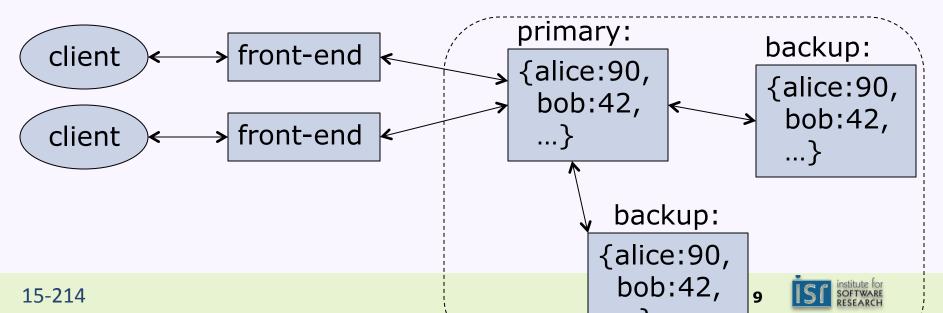
Problem: Database server might fail

A case study: Passive primary-backup replication

Architecture before replication:

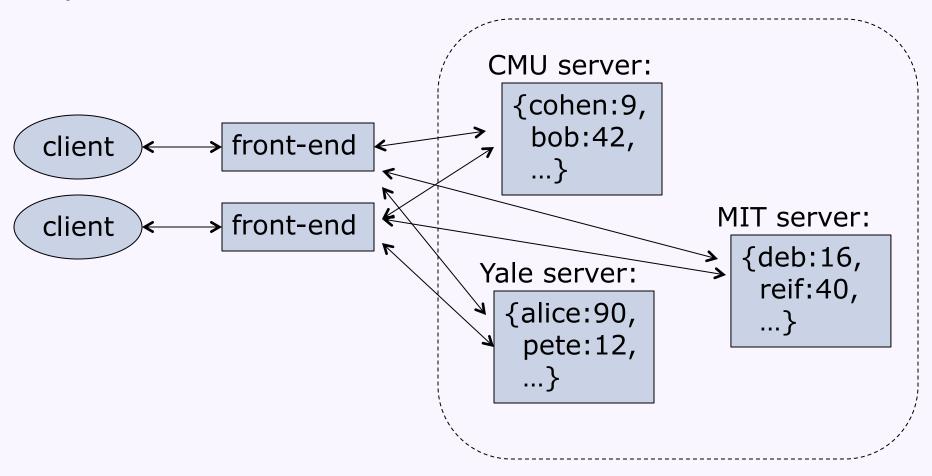


- Problem: Database server might fail
- Solution: Replicate data onto multiple servers



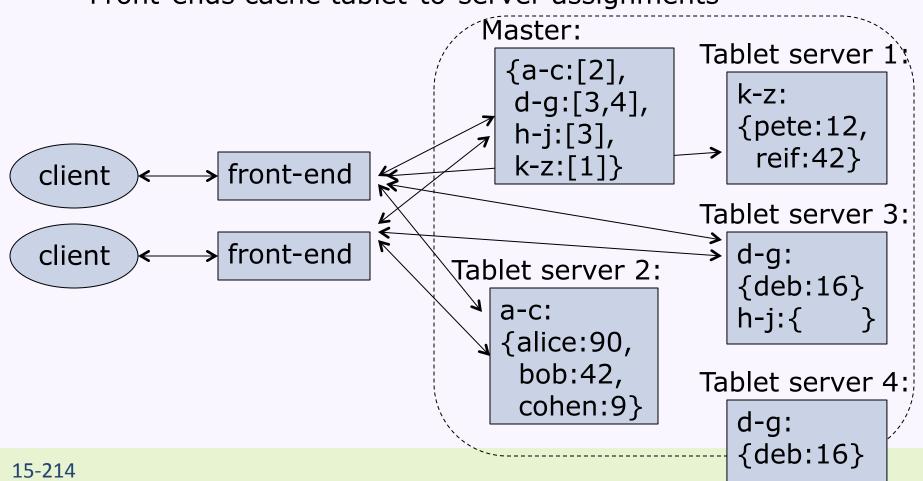
Partitioning for scalability

 Partition data based on some property, put each partition on a different server



Master/tablet-based systems

- Dynamically allocate range-based partitions
 - Master server maintains tablet-to-server assignments
 - Tablet servers store actual data
 - Front-ends cache tablet-to-server assignments



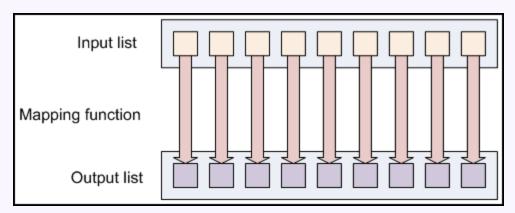
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Map from a functional perspective

- map(f, x[0...n-1])
 - Apply the function f to each element of list x



map/reduce images src: Apache Hadoop tutorials

• E.g., in Python:

```
def square(x): return x*x
map(square, [1, 2, 3, 4]) would return [1, 4, 9, 16]
```

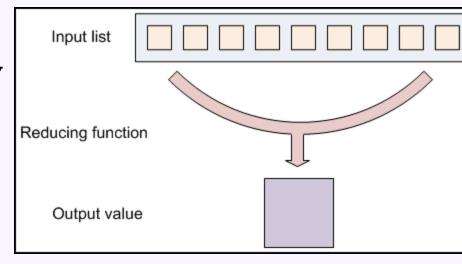
- Parallel map implementation is trivial
 - What is the work? What is the depth?

Reduce from a functional perspective

- reduce(f, x[0...n-1])
 - Repeatedly apply binary function f to pairs of items in x, replacing the pair of items with the result until only one item remains
 - One sequential Python implementation:

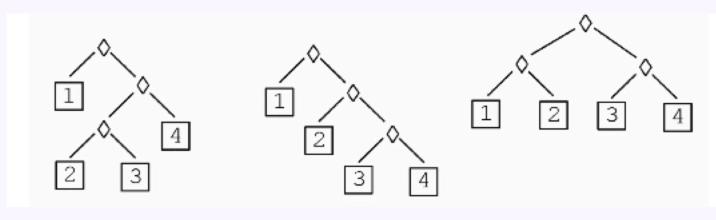
```
def reduce(f, x):
   if len(x) == 1: return x[0]
   return reduce(f, [f(x[0],x[1])] + x[2:])
```

• e.g., in Python:
 def add(x,y): return x+y
 reduce(add, [1,2,3,4])
 would return 10 as
 reduce(add, [1,2,3,4])
 reduce(add, [3,3,4])
 reduce(add, [6,4])
 reduce(add, [10]) -> 10



Reduce with an associative binary function

 If the function f is associative, the order f is applied does not affect the result



$$1 + ((2+3) + 4) \quad 1 + (2 + (3+4)) \quad (1+2) + (3+4)$$

- Parallel reduce implementation is also easy
 - What is the work? What is the depth?

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Distributed MapReduce

 The distributed MapReduce idea is similar to (but not the same as!):

```
reduce(f2, map(f1, x))
```

- Key idea: a "data-centric" architecture
 - Send function £1 directly to the data
 - Execute it concurrently
 - Then merge results with reduce
 - Also concurrently
- Programmer can focus on the data processing rather than the challenges of distributed systems

MapReduce with key/value pairs (Google style)

Master

- Assign tasks to workers
- Ping workers to test for failures

Map workers

- Map for each key/value pair
- Emit intermediate key/value pairs

the shuffle:

Node 1

Mapping process

Reducing process

Reducing process

Reduce workers

- Sort data by intermediate key and aggregate by key
- Reduce for each key

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MapReduce with key/value pairs (Google style)

- E.g., for each word on the Web, count the number of times that word occurs
 - For Map: key1 is a document name, value is the contents of that document
 - For Reduce: key2 is a word, values is a list of the number of counts of that word

```
Map: (\text{key1, v1}) \rightarrow (\text{key2, v2})^* Reduce: (\text{key2, v2*}) \rightarrow (\text{key3, v3})^* MapReduce: (\text{key1, v1})^* \rightarrow (\text{key3, v3})^*
```

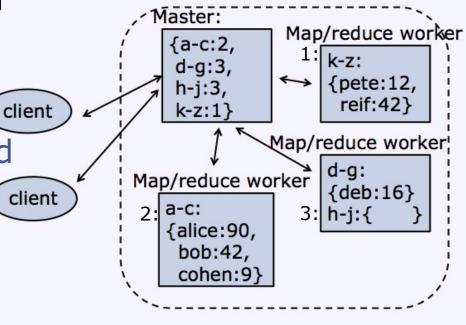
MapReduce: (docName, docText)* → (word, wordCount)*

MapReduce architectural details

- Usually integrated with a distributed storage system
 - Map worker executes function on its share of the data
- Map output usually written to worker's local disk

 Shuffle: reduce worker often pulls intermediate data from map worker's local disk

 Reduce output usually written back to distributed storage system



Handling server failures with MapReduce

Map worker failure:

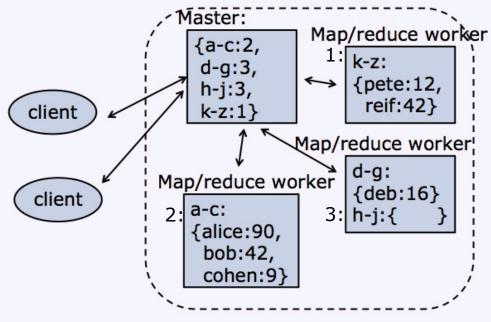
 Re-map using replica of the storage system data

Reduce worker failure:

 New reduce worker can pull intermediate data from map worker's local disk, re-reduce

Master failure:

- Options:
 - Restart system using new master
 - Replicate master
 - ...



The beauty of MapReduce

- Low communication costs (usually)
 - The shuffle (between map and reduce) is expensive
- MapReduce can be iterated
 - Input to MapReduce: key/value pairs in the distributed storage system
 - Output from MapReduce: key/value pairs in the distributed storage system



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Another MapReduce example

- E.g., for person in a social network graph, output the number of mutual friends they have
 - For Map: key1 is a person, value is the list of her friends
 - For Reduce: key2 is ???, values is a list of ???

```
f1(String key1, String value): f2(String key2, Iterator values):
```

MapReduce: (person, friends)* \rightarrow (pair of people, count of mutual friends)*

Another MapReduce example

- E.g., for person in a social network graph, output the number of mutual friends they have
 - For Map: key1 is a person, value is the list of her friends
 - For Reduce: key2 is a pair of people, values is a list of 1s, for each mutual friend that pair has

```
f1(String key1, String value):
  for each pair of friends
      in value:
    EmitIntermediate(pair, 1);
```

```
f2(String key2, Iterator values):
  int result = 0;
  for each v in values:
    result += v;
  Emit(key2, result);
```

MapReduce: (person, friends)* \rightarrow (pair of people, count of mutual friends)*

And another MapReduce example

- E.g., for each page on the Web, create a list of the pages that link to it
 - For Map: key1 is a document name, value is the contents of that document
 - For Reduce: key2 is ???, values is a list of ???

```
f1(String key1, String value): f2(String key2, Iterator values):
```

MapReduce: $(docName, docText)^* \rightarrow (docName, list of incoming links)^*$

Thursday

• More distributed systems...

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