Principles of Software Construction: Objects, Design, and Concurrency

Distributed System Design, Part 2

Fall 2014

Charlie Garrod Jonathan Aldrich

School of Computer Science
institute for SOFTWARE RESEARCH

Administrivia

- Homework 5b due tonight
  - Finish by tomorrow (14 Nov) 10 a.m. if you want to be considered as a "Best Framework" for Homework 5c
- 15-413: Software Engineering Practicum
- Homework 3 arena winners in class next week…

Key concepts from Tuesday

Networking in Java

- The java.net.InetAddress:

```
static InetAddress getByName(String host);
static InetAddress getByAddress(byte[] b);
static InetAddress getLocalHost();
```

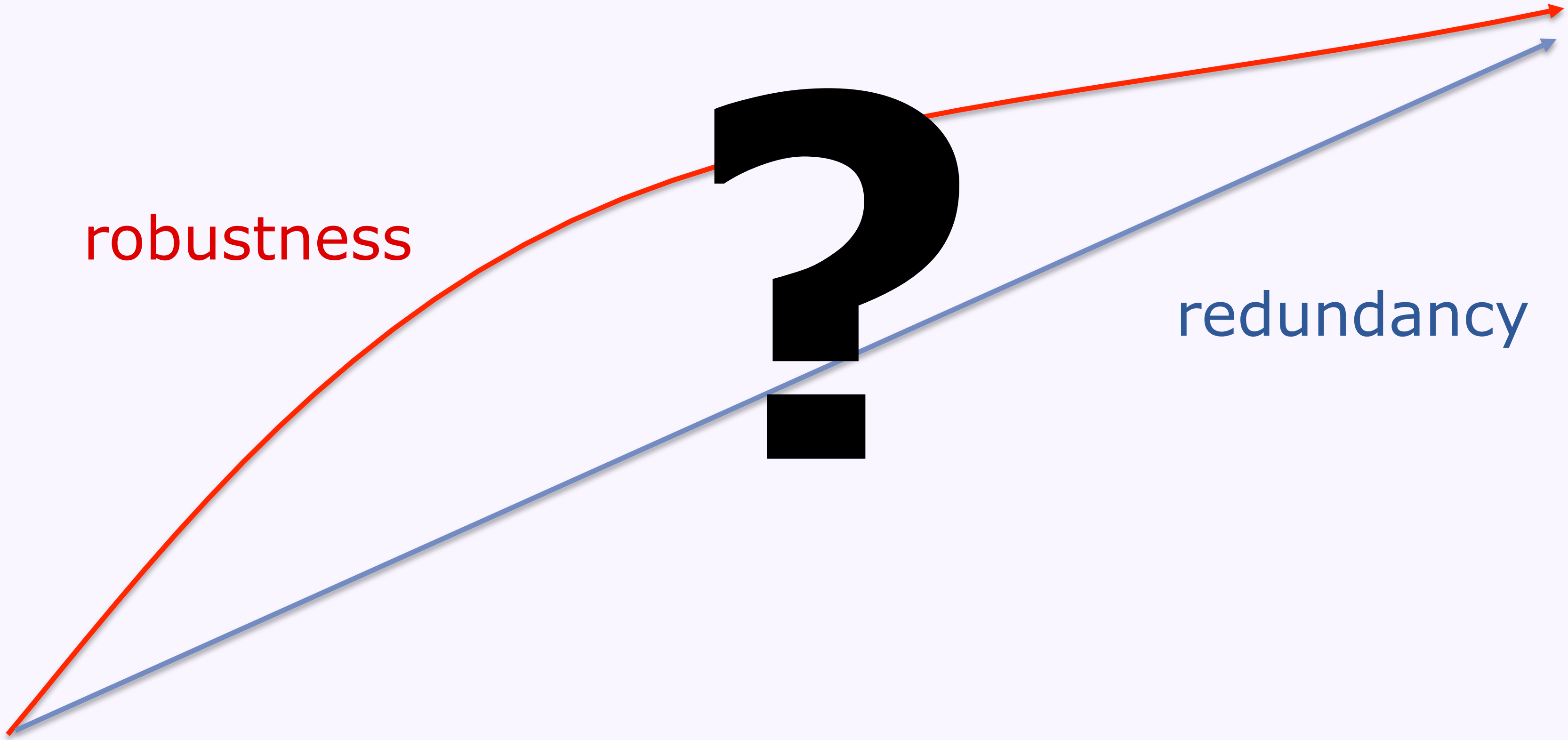
- The java.net.Socket:

```
Socket(InetAddress addr, int port);
boolean      isConnected();
boolean      isClosed();
void         close();
InputStream  getInputStream();
OutputStream getOutputStream();
```

- The java.net.ServerSocket:

```
ServerSocket(int port);
Socket       accept();
void         close();
…
```

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

Today: Distributed system design

- Introduction to distributed systems, continued
  - Motivation: reliability and scalability
  - Failure models
  - Techniques for:
    - Reliability (availability)
    - Scalability
    - Consistency
- MapReduce: A robust, scalable framework for distributed computation…
  - …on replicated, partitioned data

Types of failure behaviors

- Fail-stop
- Other halting failures
- Communication failures
  - Send/receive omissions
  - Network partitions
  - Message corruption
- Data corruption
- Performance failures
  - High packet loss rate
  - Low throughput
  - High latency
- Byzantine failures

Common assumptions about failures

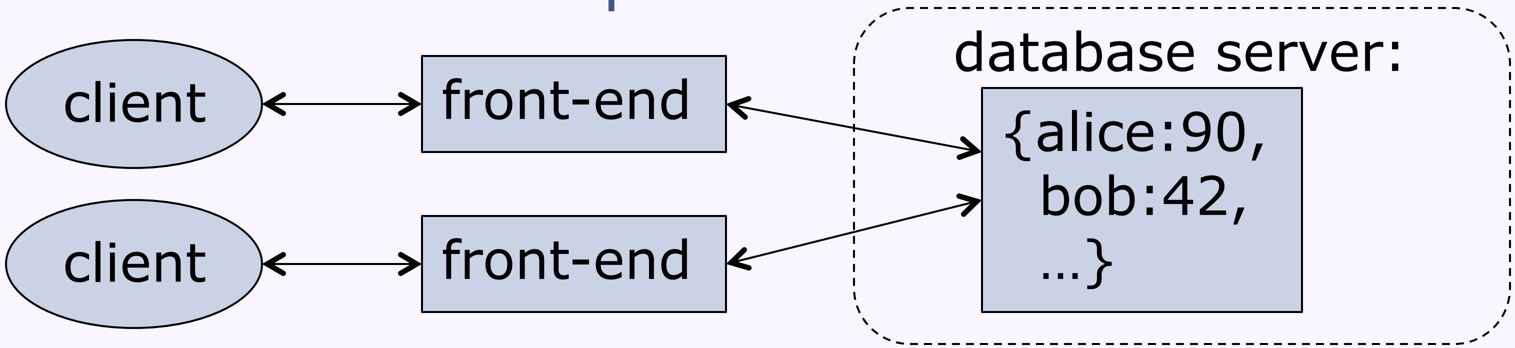
- Behavior of others is fail-stop (ugh)
- Network is reliable (ugh)
- Network is semi-reliable but asynchronous
- Network is lossy but messages are not corrupt
- Network failures are transitive
- Failures are independent
- Local data is not corrupt
- Failures are reliably detectable
- Failures are unreliably detectable

Some distributed system design goals

- The end-to-end principle
  - When possible, implement functionality at the ends (rather than the middle) of a distributed system
- The robustness principle
  - Be strict in what you send, but be liberal in what you accept from others
    - Protocols
    - Failure behaviors
- Benefit from incremental changes
- Be redundant
  - Data replication
  - Checks for correctness

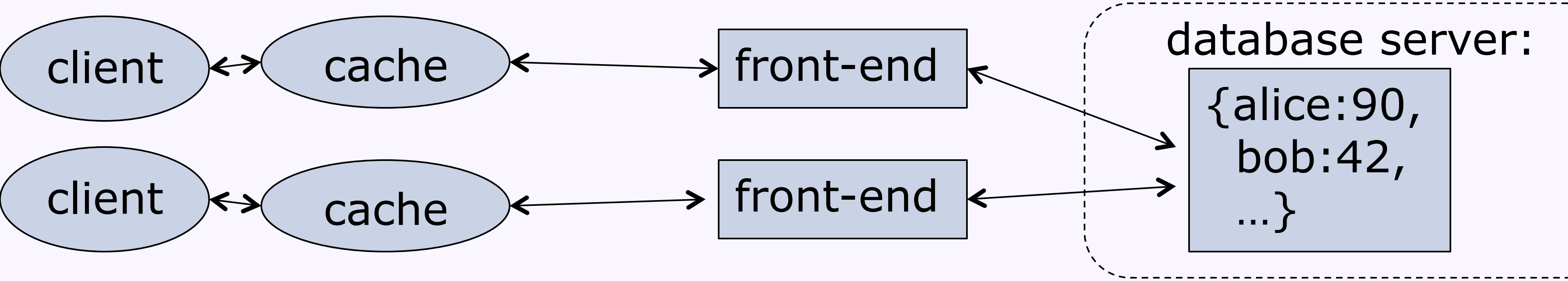
Replication for scalability: Client-side caching

- Architecture before replication:



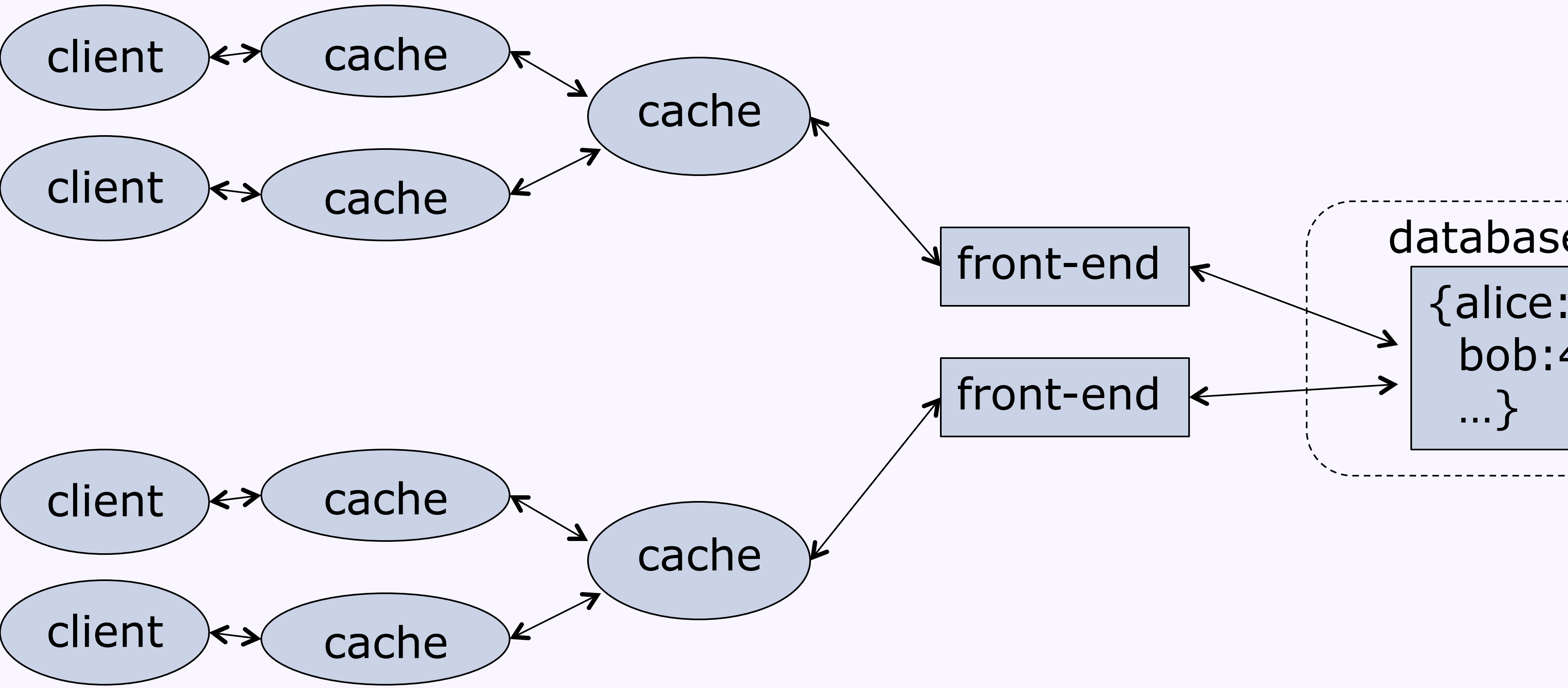
  - Problem: Server throughput is too low

- Solution: Cache responses at (or near) the client
  - Cache can respond to repeated read requests



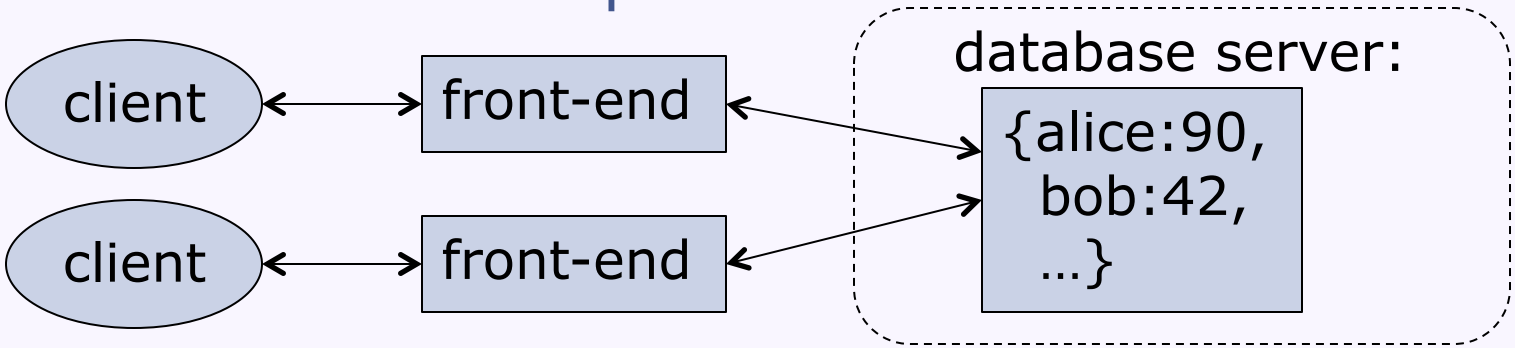
Replication for scalability: Client-side caching

- Hierarchical client-side caches:

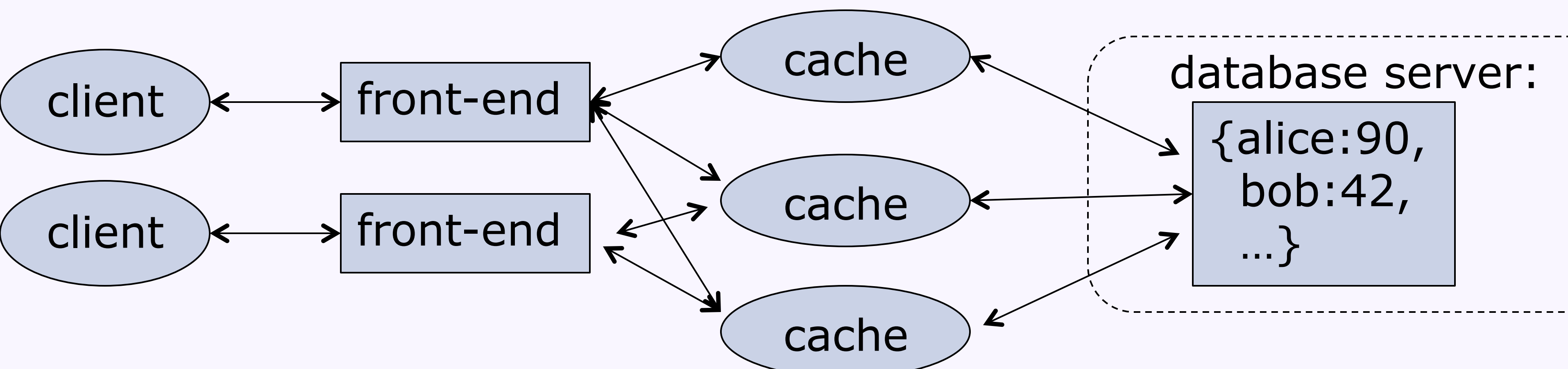


Replication for scalability: Server-side caching

- Architecture before replication:



  - Problem: Database server throughput is too low
- Solution: Cache responses on multiple servers
  - Cache can respond to repeated read requests



Cache invalidation

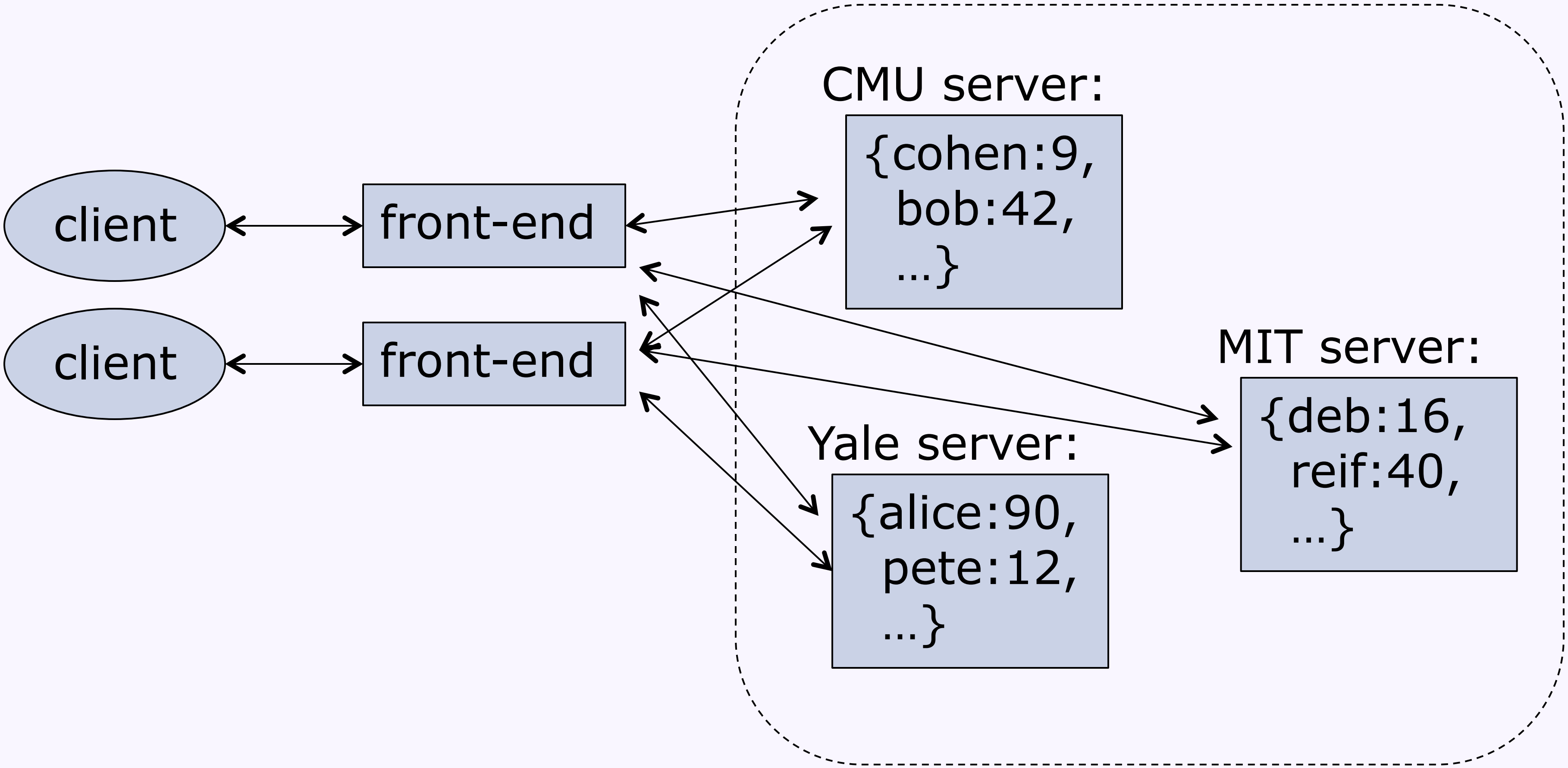
- Time-based invalidation (a.k.a. expiration)
  - Read-any, write-one
  - Old cache entries automatically discarded
  - No expiration date needed for read-only data
- Update-based invalidation
  - Read-any, write-all
  - DB server broadcasts invalidation message to all caches when the DB is updated

Cache replacement policies

- Problem: caches have finite size
- Common* replacement policies
  - Optimal (Belady's) policy
    - Discard item not needed for longest time in future
  - Least Recently Used (LRU)
    - Track time of previous access, discard item accessed least recently
  - Least Frequently Used (LFU)
    - Count # times item is accessed, discard item accessed least frequently
  - Random
    - Discard a random item from the cache

Partitioning for scalability

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



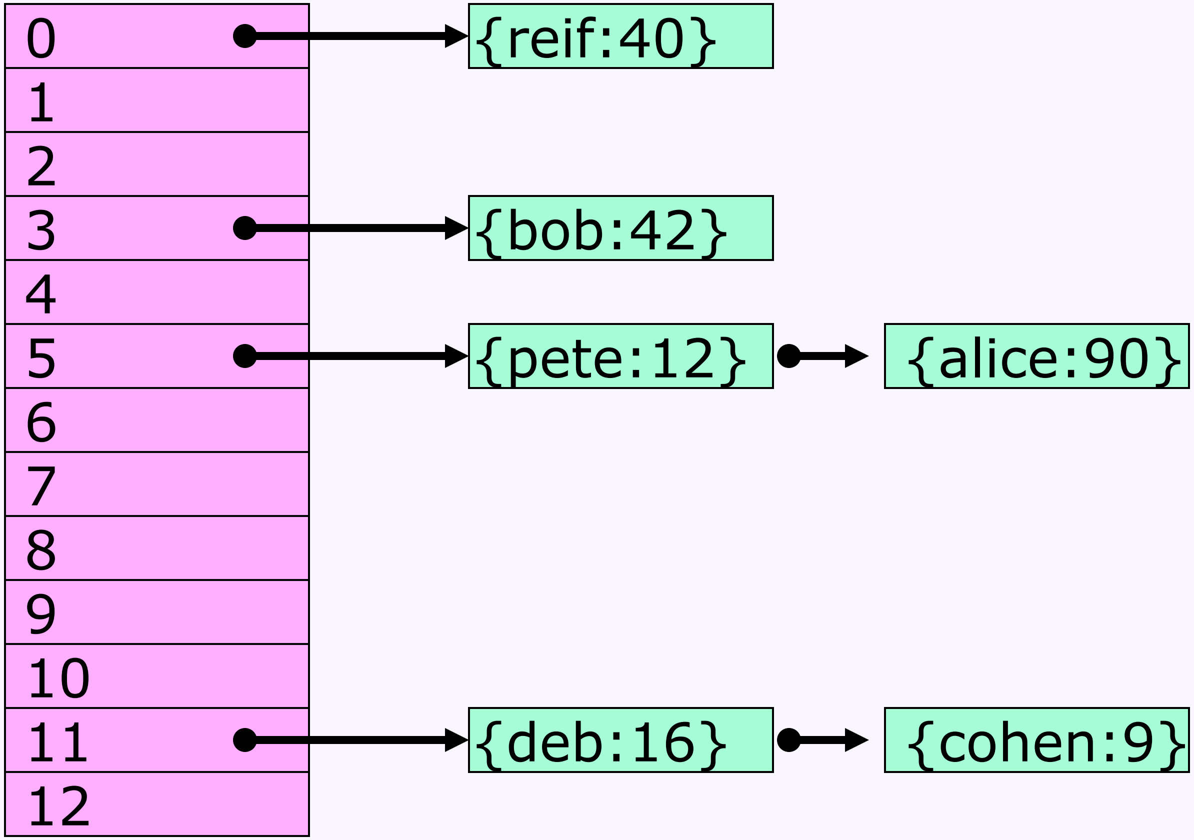
Horizontal partitioning

- a.k.a. "sharding"
- A table of data:

username	school	value
cohen	CMU	9
bob	CMU	42
alice	Yale	90
pete	Yale	12
deb	MIT	16
reif	MIT	40

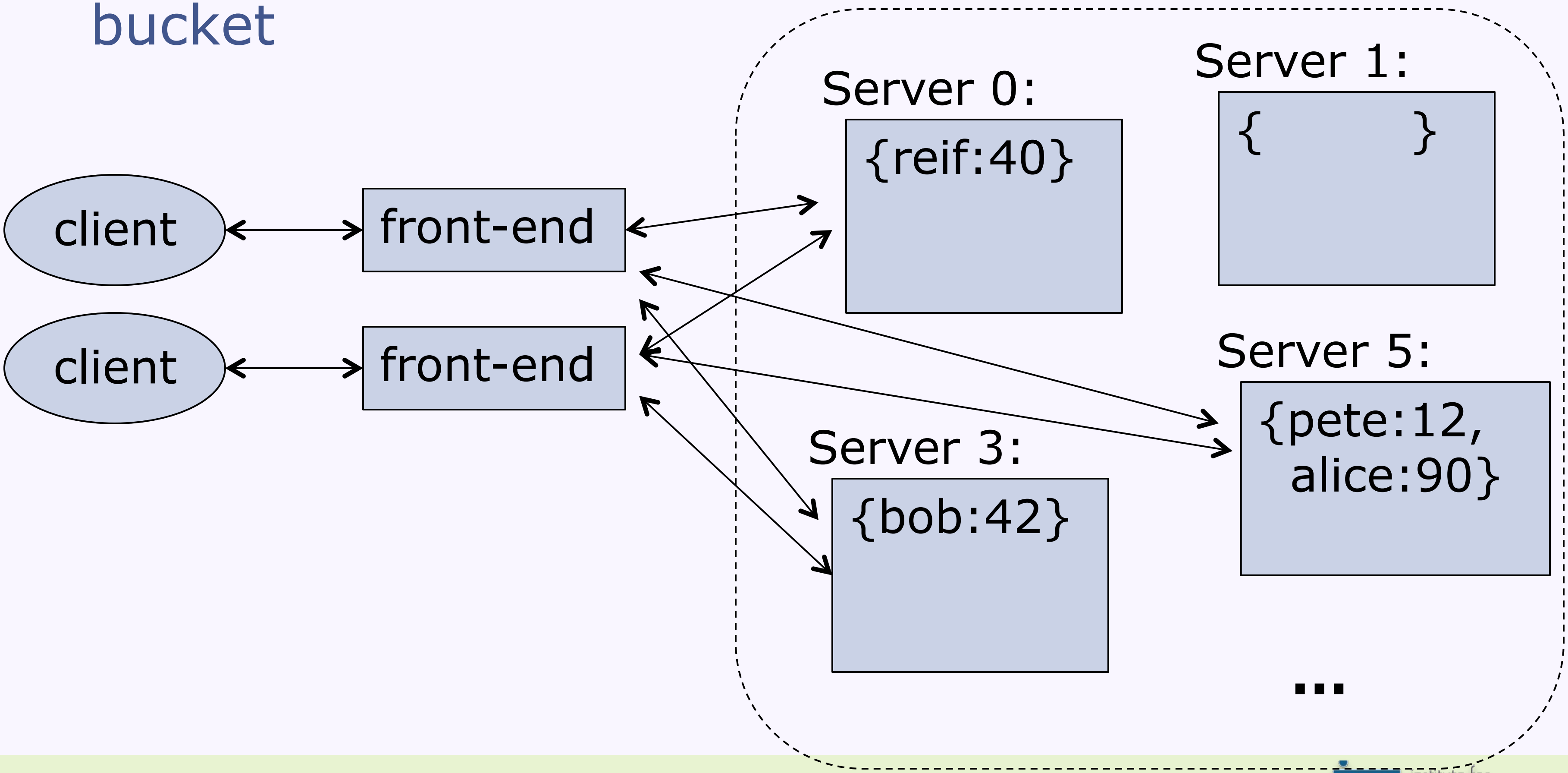
Recall: Basic hash tables

- For `n`-size hash table, put each item `x` in the bucket: `X.hashCode() % n`



Partitioning with a distributed hash table

- Each server stores data for one bucket
- To store or retrieve an item, front-end server hashes the key, contacts the server storing that bucket



Consistent hashing

- Goal: Benefit from incremental changes
  - Resizing the hash table (i.e., adding or removing a server) should not require moving many objects
- E.g., Interpret the range of hash codes as a ring
  - Each bucket stores data for a range of the ring
    - Assign each bucket an ID in the range of hash codes
    - To store item `x` don't compute `x.hashCode() % n`. Instead, place `x` in bucket with the same ID as or next higher ID than `x.hashCode()`

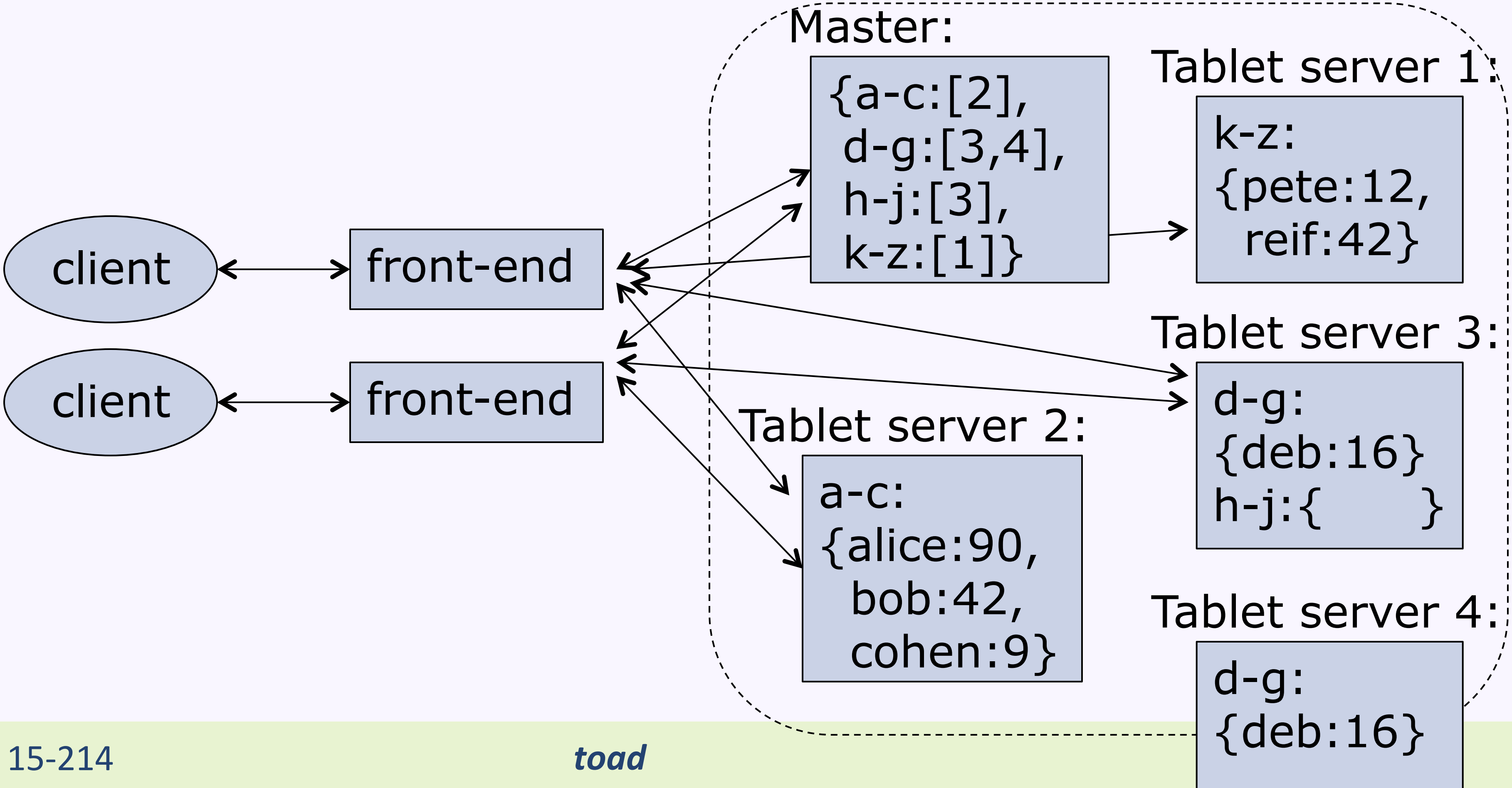
Problems with hash-based partitioning

- Front-ends need to determine server for each bucket
  - Each front-end stores look-up table?
  - Master server storing look-up table?
  - Routing-based approaches?
- Places related content on different servers
  - Consider *range* queries:

```
SELECT * FROM users WHERE lastname STARTSWITH 'G'
```

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

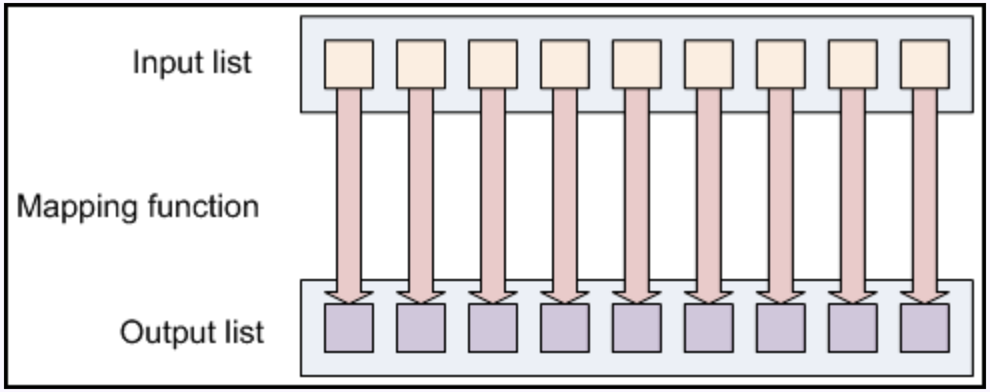


Today: Distributed system design

- Introduction to distributed systems, continued
  - Motivation: reliability and scalability
  - Failure models
  - Techniques for:
    - Reliability (availability)
    - Scalability
    - Consistency
- MapReduce: A robust, scalable framework for distributed computation…
  - …on replicated, partitioned data

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:

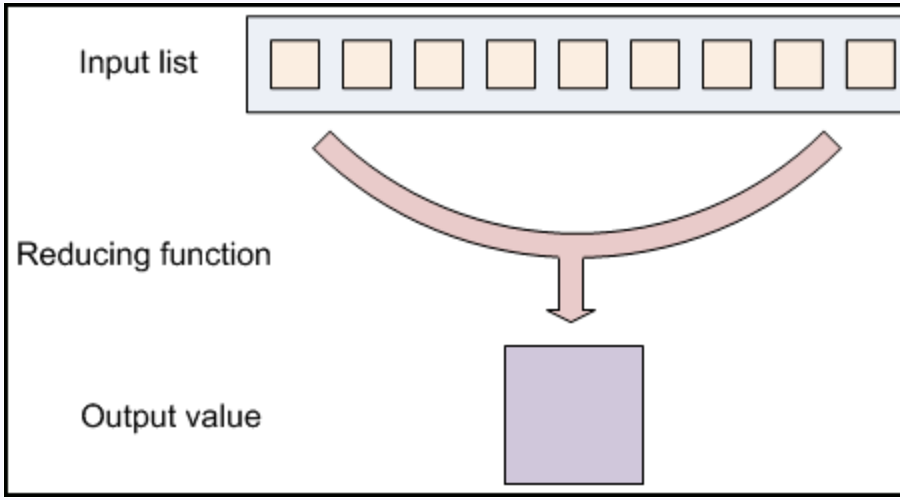
```
def reduce(f, x):
  if len(x) == 1: return x[0]
  return reduce(f, [f(x[0],x[1])] + x[2:])
```

  - e.g., in Python:

```
def add(x,y): return x+y
reduce(add, [1,2,3,4])
```

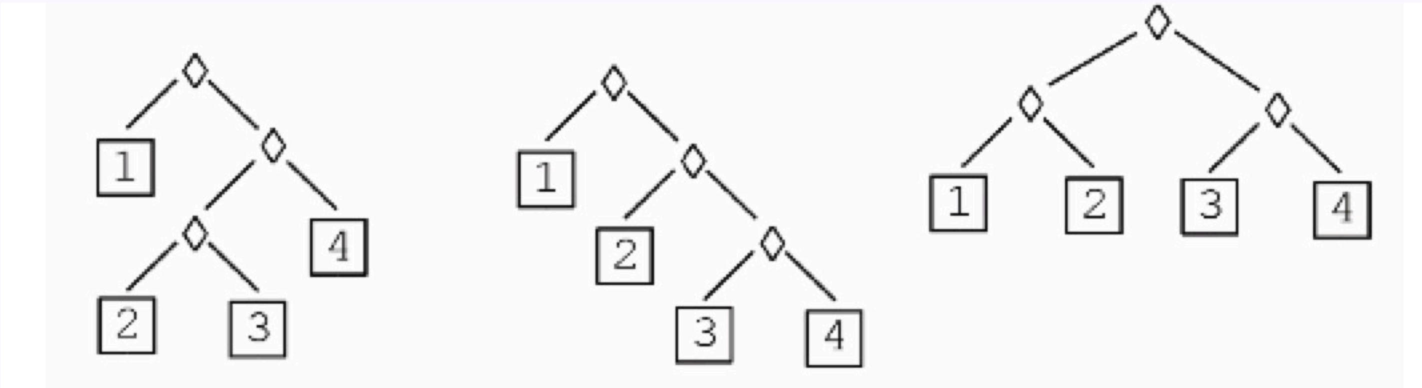
would return 10 as

```
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)   1 + (2 + (3+4))   (1+2) + (3+4)

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

Distributed MapReduce

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

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

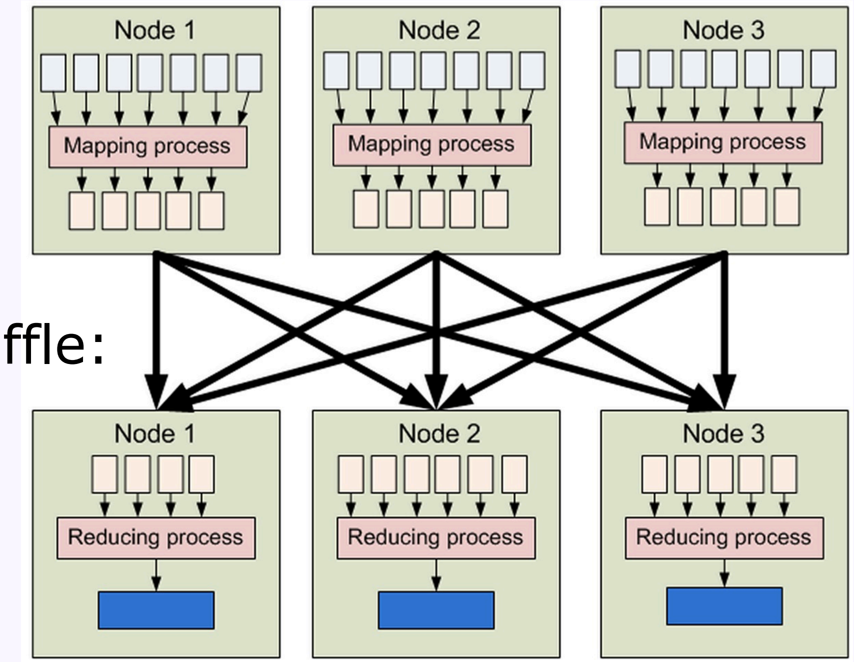
- Key idea: a "data-centric" architecture
  - Send function `f1` directly to the data
    - Execute it concurrently
  - Then merge results with reduce
    - Also concurrently

- 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:



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

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

```
f1(String key1, String value):
  for each word w in value:
    EmitIntermediate(w, 1);
```

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

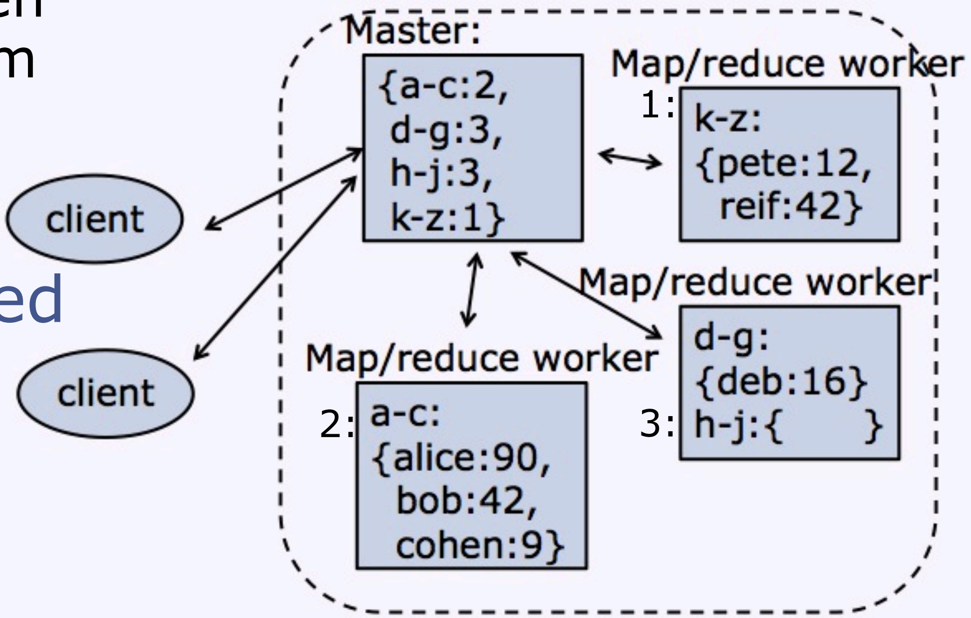
Map: (key1, v1) → (key2, v2)* Reduce: (key2, v2*) → (key3, v3)*

MapReduce: (key1, v1)* → (key3, v3)*

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

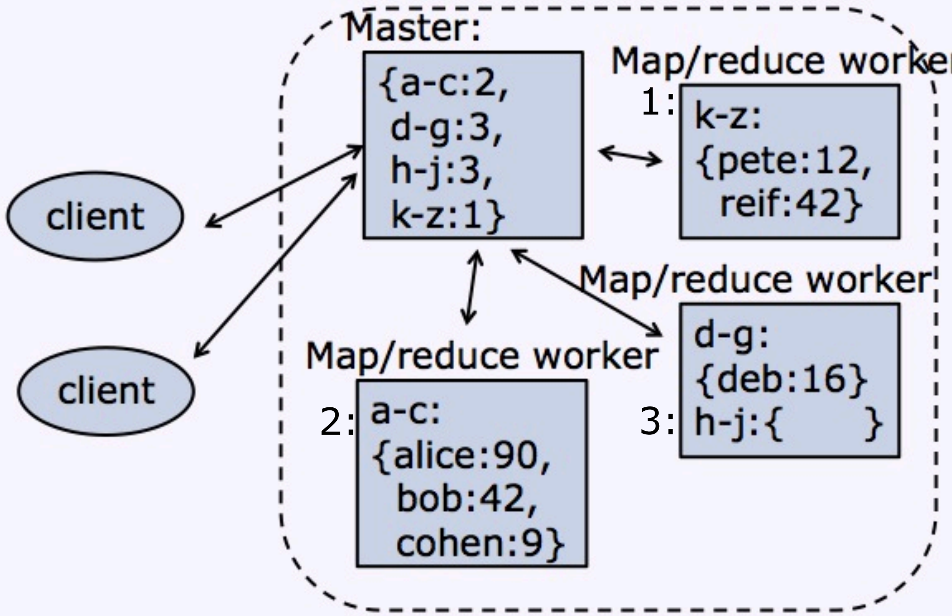
MapReduce architectural details

- 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

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)* → (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)* → (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)* → (docName, list of incoming links)*

Coming next…

- More distributed systems
  - MapReduce