Search Engine Architecture

1. Introduction

Noted slides adapted from Lin et al. Big Data Infrastructure, UMD Spring 2015 with cosmetic changes.

What is this course about?

- Information retrieval on big data
- Broad survey of system architectures that enable big data applications
- In-depth focus on key insights behind each
  - Without getting too bogged down

IR is Everywhere

- Web search (Google, Bing, …)
- Finance (Bloomberg)
- Advertising (AdSense, …)
- Fraud detection
- Medical diagnostics
- What are the major architectural problems?

Big Data Storage

- KV – S3, Cassandra, Riak, Redis
- Document – MongoDB, CouchDB, Elasticsearch
- Column – VoltDB, Vertica
- Graph – Neo4j, OrientDB
- Wide Column – BigTable, HBase

Big Data Processing

- MapReduce – Hadoop, Hive, Pig
- DAG – Storm, Dryad, Spark
- Vertex-centric – Pregel, GraphLab

Course Administrivia

Prerequisites

- CSCI-GA 1170 Fundamental Algorithms
- CSCI-GA 2110 Programming Languages
- CSCI-GA 2250 Operating Systems
- Working knowledge of Python
- Ability to Google solutions to problems as they come up

Details

- Lectures Wed 5:10-7pm
- Office hours after class
- Mailing list
  - See assignment 1 for the link if you're not sure
- Grading
  - 10% Class Participation
  - 50% Assignments
  - 40% Final project

Details

- Readings
  - All available online – see course website
  - *Introduction to Information Retrieval* by Manning et al.
  - *Data-Intensive Text-Processing with MapReduce* by Lin et al.
  - Relevant academic articles

Assignments

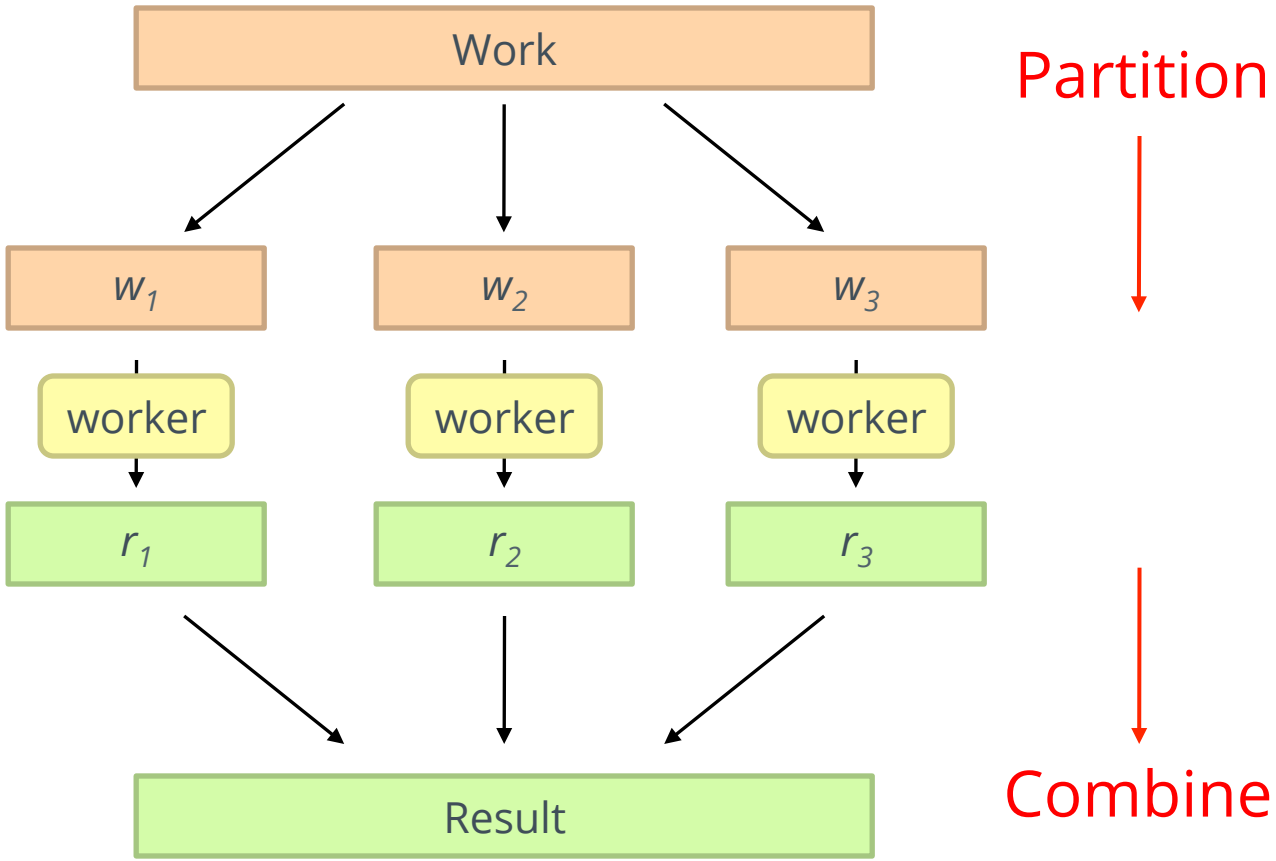
- Designed to introduce you to the material in a structured way
- Feel free to work together, but everything submitted must be prepared (typed) individually
- Late policy
  - Up to 24 hours late: 0.75 multiplier
  - 24 to 48 hours late: 0.5 multiplier
  - And so on

Assignments

- In the history of CS, these topics are extremely new
- New things tend to break
  - Bugs, missing/wrong documentation, incompatible versions
- Be patient
  - We will inevitably encounter problems
- Be flexible
  - We will find workarounds
- Be constructive
  - Tell me how I can improve everyone's experience


Tackling Big Data
Source: Google via Introduction to MapReduce Lin 2013

Divide and Conquer



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Parallelization Challenges

- How do we assign work units to workers?
- What if we have more work units than workers?
- What if workers need to share partial results?
- How do we aggregate partial results?
- How do we know all the workers have finished?
- What if workers die?

What's the common theme of all of these problems?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Common Theme?

- Parallelization problems arise from:
  - Communication between workers (e.g., to exchange state)
  - Access to shared resources (e.g., data)
- Thus, we need a synchronization mechanism

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

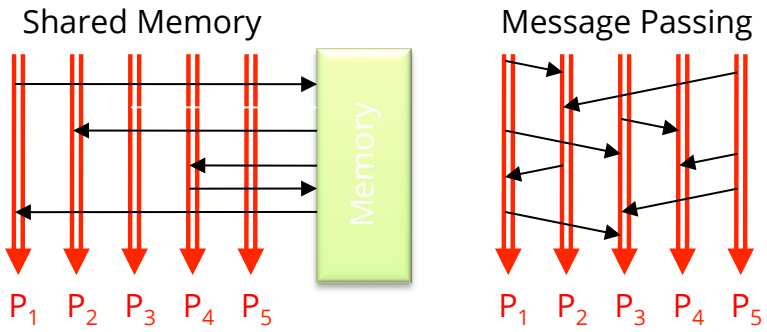
Managing Multiple Workers

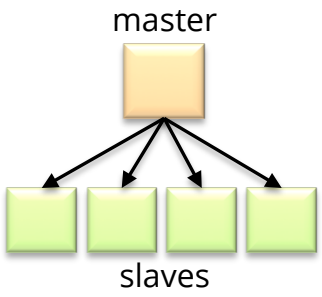
- Difficult because
  - We don't know the order in which workers run
  - We don't know when workers interrupt each other
  - We don't know when workers need to communicate partial results
  - We don't know the order in which workers access shared data
- Thus, we need:
  - Semaphores (lock, unlock)
  - Conditional variables (wait, notify, broadcast)
  - Barriers
- Still, lots of problems:
  - Deadlock, livelock, race conditions...
  - Dining philosophers, sleeping barbers, cigarette smokers...
- Moral of the story: be careful!

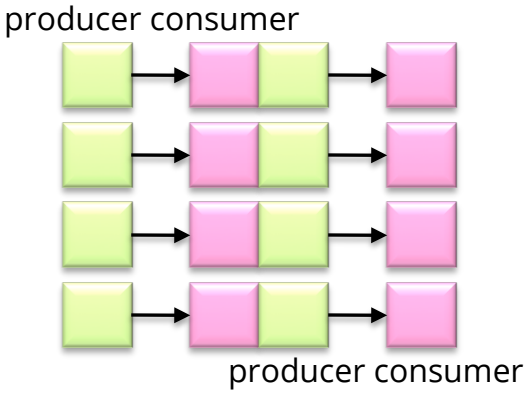
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

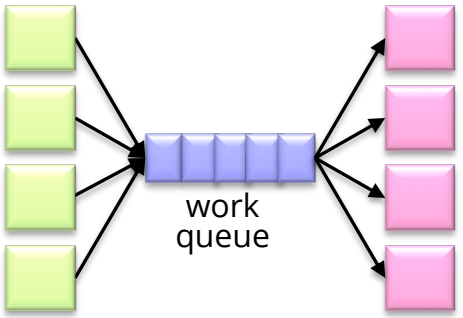
Traditional Tools

- Programming models
  - Shared memory (pthreads)
  - Message passing (MPI)
- Design Patterns
  - Master-slaves
  - Producer-consumer flows
  - Shared work queues







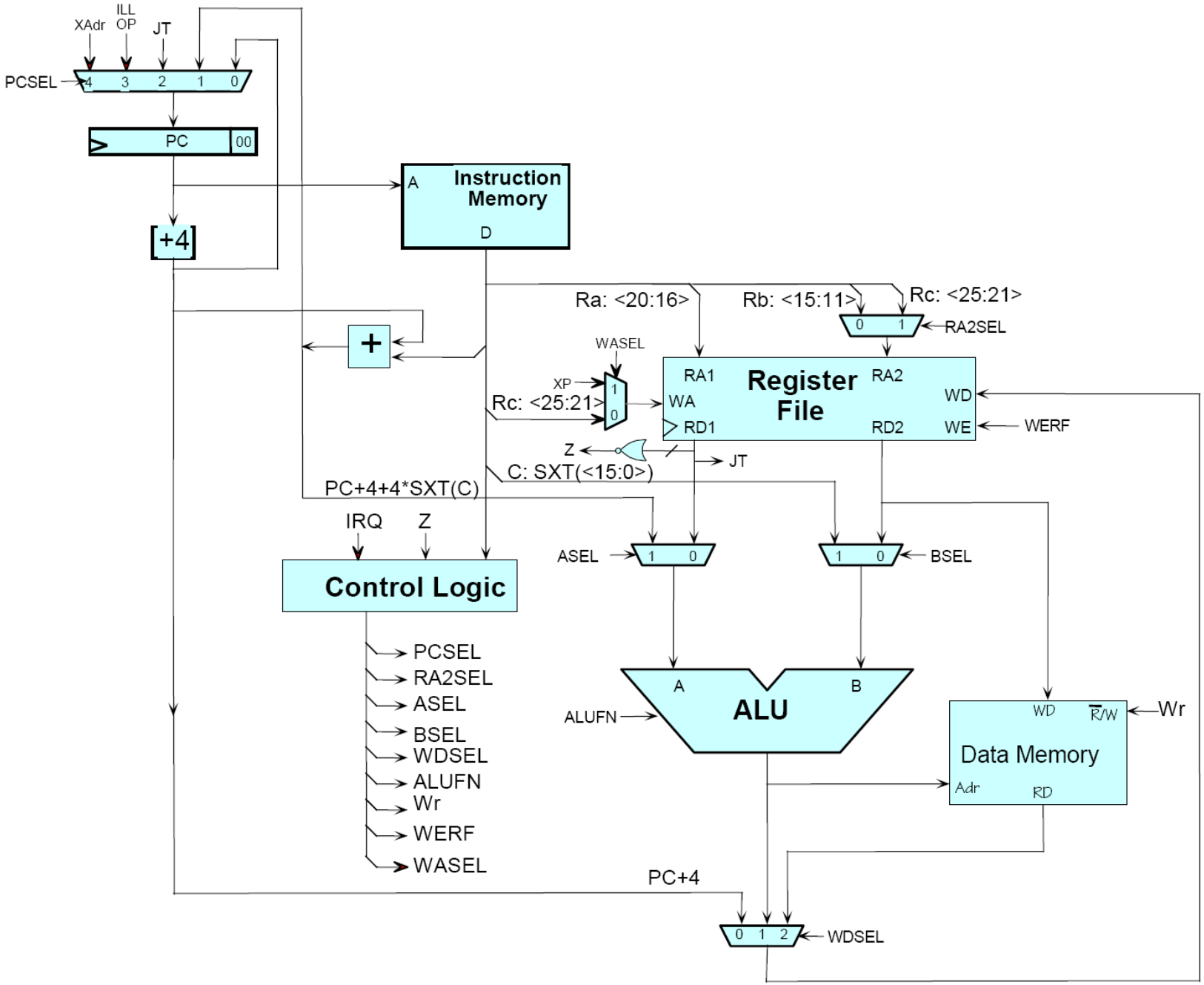


Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Concurrency Realities

- Concurrency is difficult to reason about
- Concurrency is even more difficult to reason about
  - At the scale of datacenters and across datacenters
  - In the presence of failures
  - In terms of multiple interacting services
- Not to mention debugging…
- The reality:
  - Lots of one-off solutions, custom code
  - Write you own dedicated library, then program with it
  - Burden on the programmer to explicitly manage everything

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.



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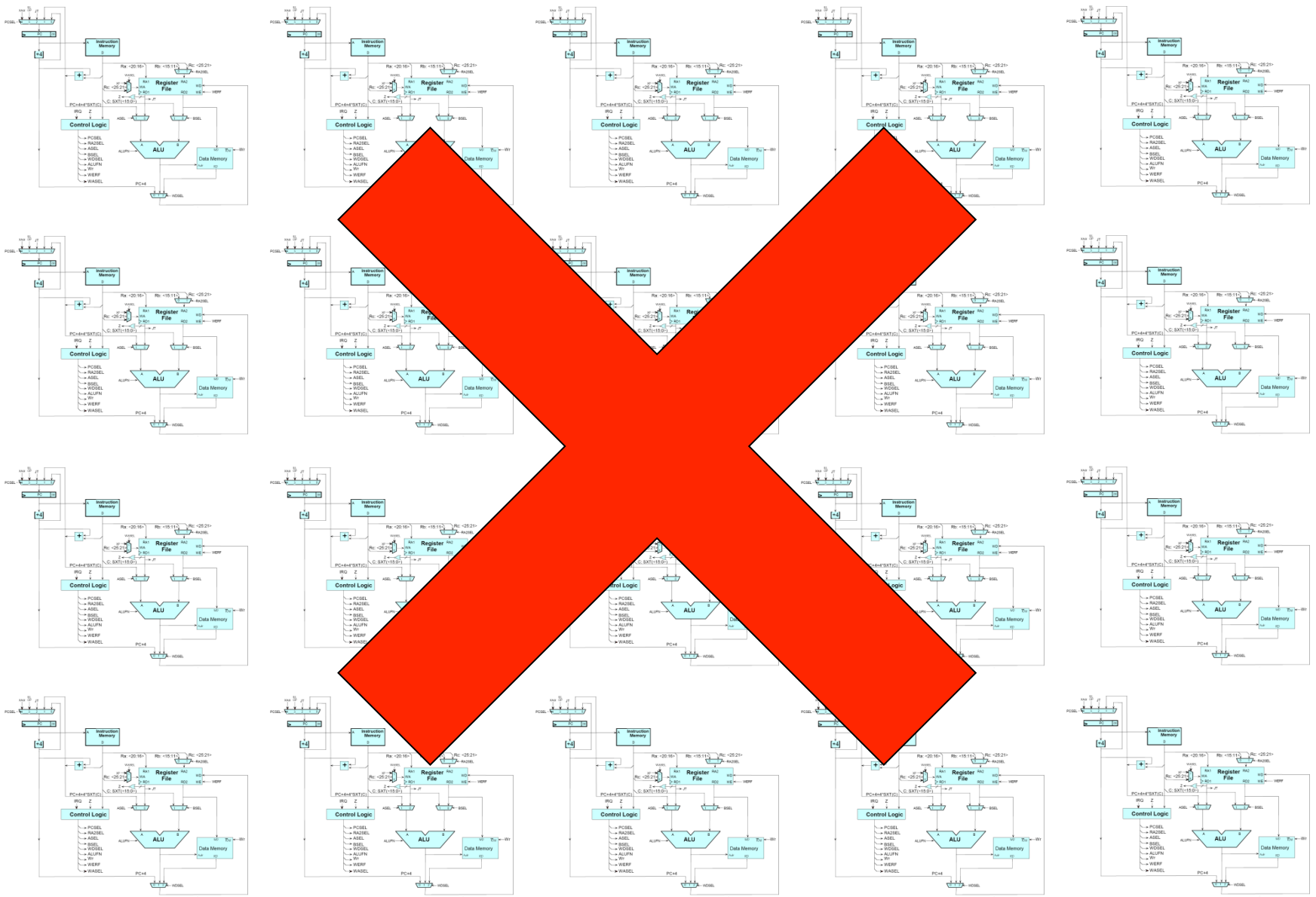


Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

What's the point?

- It's all about the right level of abstraction
  - Moving beyond the von Neumann architecture
  - We need better programming models
- Hide system-level details from the developers
  - No more race conditions, lock contention, etc.
- Separating the *what* from *how*
  - Developer specifies the computation that needs to be performed
  - Execution framework ("runtime") handles actual execution

The datacenter *is* the computer!

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Source: Lin et al. Data-Intensive Computing with MapReduce, UMD Spring 2013.

Big Ideas

Big Ideas

- Scale out, not up
  - Limits of SMP and large shared-memory machines
- Move processing to the data
  - Cluster have limited bandwidth
- Process data sequentially, avoid random access
  - Seeks are expensive, disk throughput is reasonable
- Seamless scalability
  - From the mythical man-month to the tradable machine-hour

Source: Lin et al. Data-Intensive Computing with MapReduce, UMD Spring 2013.

Scale out, not up

- Prefer solutions that use many low-end machines instead of few high-end machines
- Typically, more than twice as expensive to double number of cores
- Commodity machines see better economies of scale
- What are reasons to scale up instead? Scale in?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Assume failures will happen

- Example: MTBF of 1,000 years (3 years)
- 1,000 node cluster will experience 1 failure per day
- System architectures must be designed with fault-tolerance in mind
  - Automatically take failed nodes offline
  - Resubmit failed jobs
  - Watch for stragglers

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Good APIs hide system details

- Keeping track of details makes programming hard
- Counterexample: threading
  - Traditional means of parallelization
  - Many hazards: race conditions, deadlock, livelock
  - Difficult to reason about
  - Require higher-level design patterns (e.g. producer-consumer queues) to avoid pitfalls

Aim for ideal scalability

- N machines should handle (nearly) N times the load
- Avoid serial computation (dependencies)
- Avoid shared memory (side effects)
- Example: MapReduce

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Move code to the data

- In recent years, CPUs have become much faster
- Storage has become much faster and more dense
- But network speeds haven't changed much, so network is often the bottleneck for large-scale batch computation
- Solution: rather than fetching data from remote storage and processing it, move the processing code to the nodes that are storing your data

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Avoid random disk access

- Random disk access is slow
- Example:
  - 1 TB database containing 10^{10} 100-byte records
  - Updating 1% of records will take one month on one machine
  - But rewriting entire database will take less than one day
- Solutions:
  - Process data sequentially
  - Don’t go to disk at all

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Our Application: Information Retrieval

Information Retrieval

- “Information retrieval (IR) is the activity of obtaining information resources relevant to an information need from a collection of information resources.”
- Very general because applications vary widely
- Typically:
  1. Index documents according to some model
  2. Use this index to find relevant documents

Documents

- Examples:
  - Web pages, emails, books, patents, images, time series
- Typically semi-structured
  - Some amount of structured metadata
    - E.g. URL domain
    - Easy to index and search
  - Main body is unstructured
    - E.g. web page text
    - Not so easy to index

Grep Is Not Enough

- In natural language there are many ways to express the same notion
- Some matches will be better than others
- Searching over every record isn’t going to scale

Documents vs. Records

- RDBMS records are typically highly structured
- RDBMS systems invariably use B-tree indexes for exact match record lookup
- For many IR applications, record-based data store is not a great fit

IR Concerns

- Relevance
  - Generally, whether the retrieved document meets the user's information need
  - Retrieval models define relevance
  - Ranking algorithms use model to find relevant documents
  - Models typically capture statistical properties of the unstructured content
    - E.g. counting word occurrences vs. parsing sentences

IR Concerns

- Evaluation
  - How do we know if we're doing a good job?
  - Test collections (TREC)
  - Metrics (precision, recall)

IR Concerns

- Meeting Information Needs
  - User interaction
  - Log mining
  - Query expansion, query suggestion
  - Relevance feedback

Search Engine Concerns

- Fast retrieval
- Fast, timely, and comprehensive indexing
- Scaling with users and data
- Application-specific issues (tuning, spam)

IR System: Bird's Eye View

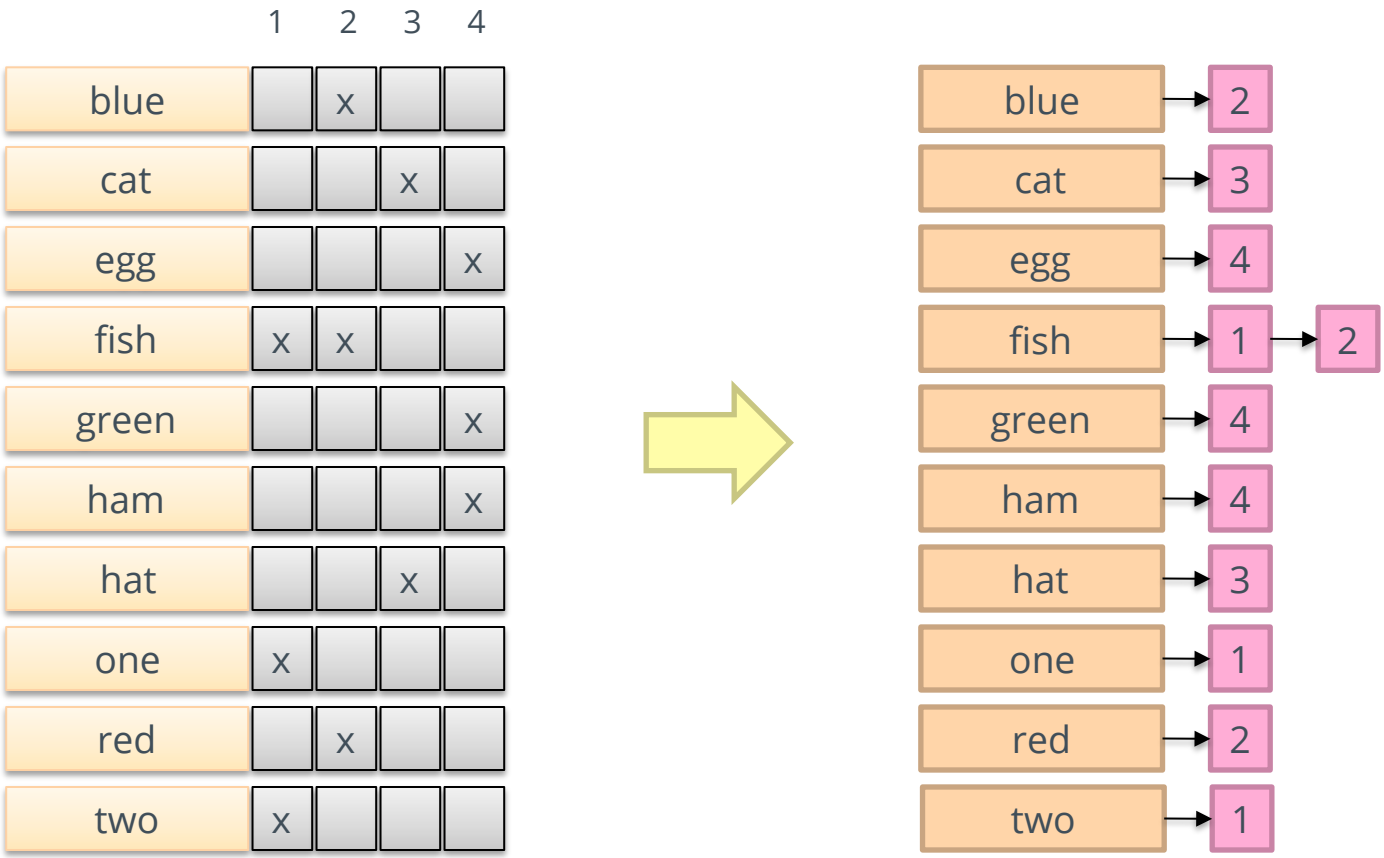
Index

Doc 1 one fish, two fish

Doc 2 red fish, blue fish

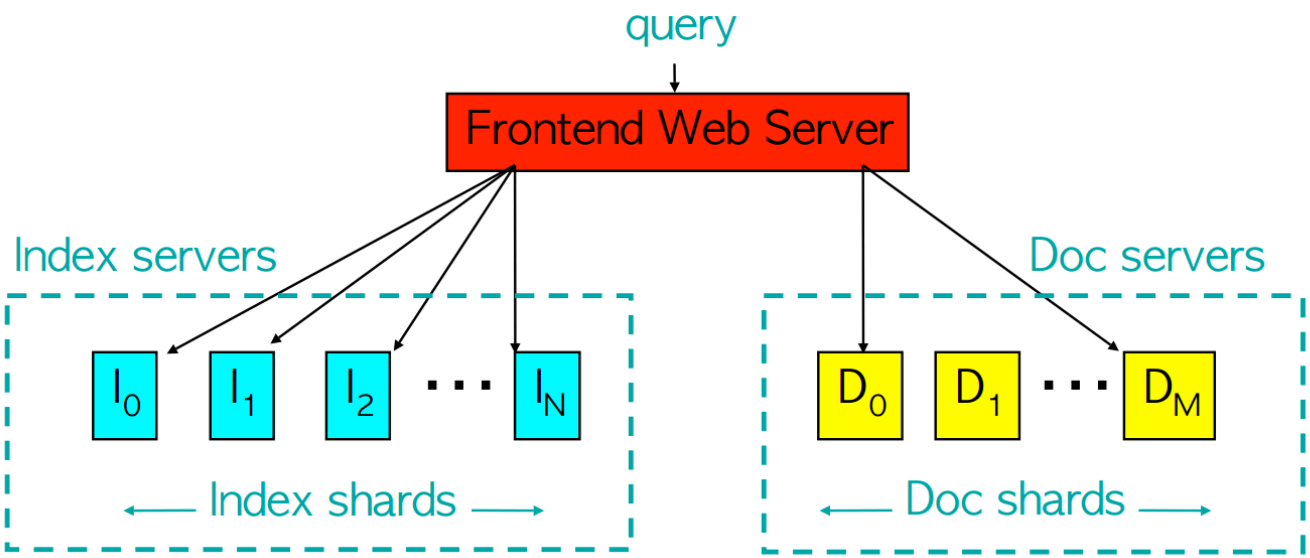
Doc 3 cat in the hat

Doc 4 green eggs and ham



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

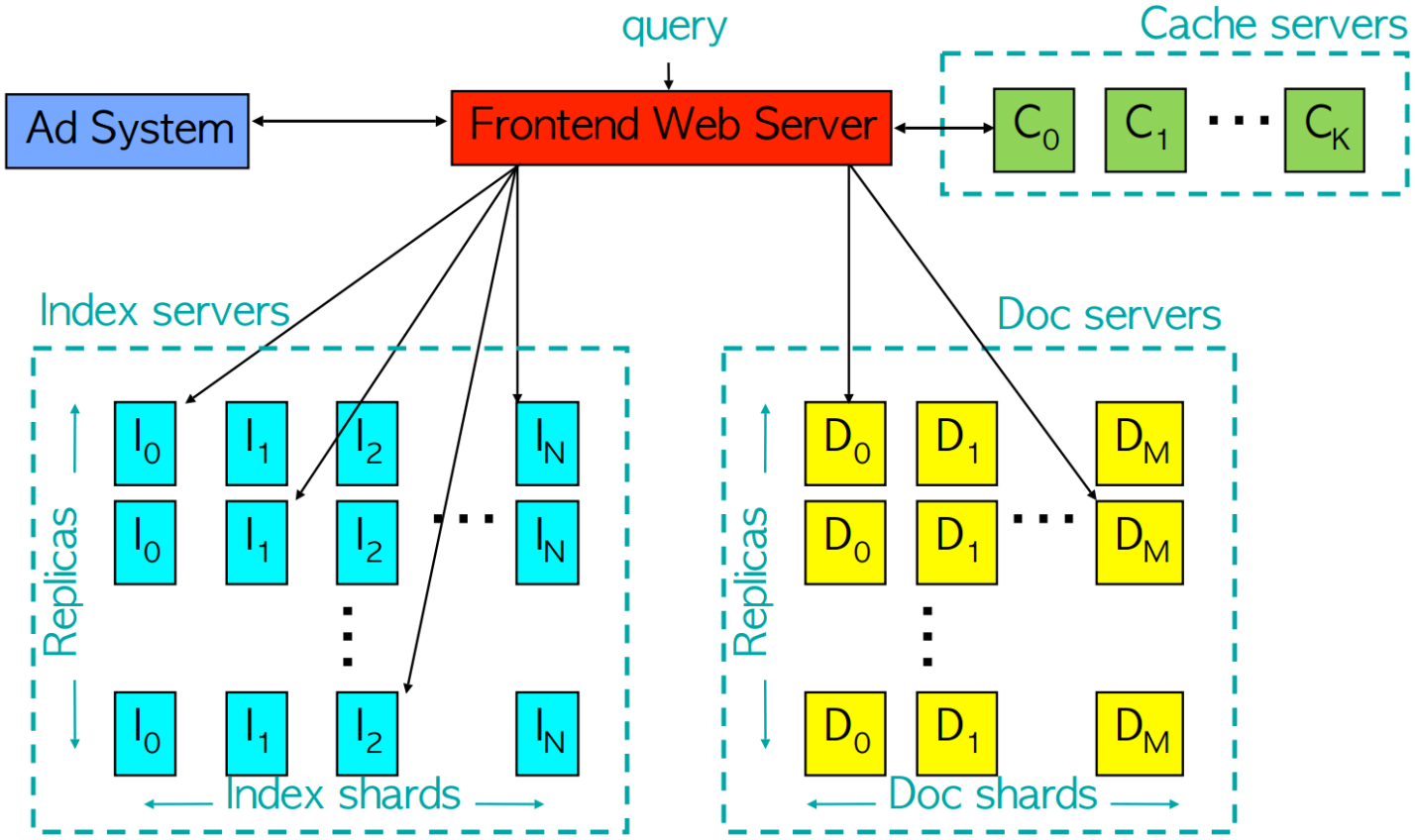
Architecture circa 1999



Google

Source: Jeff Dean WSDM 2009

Architecture



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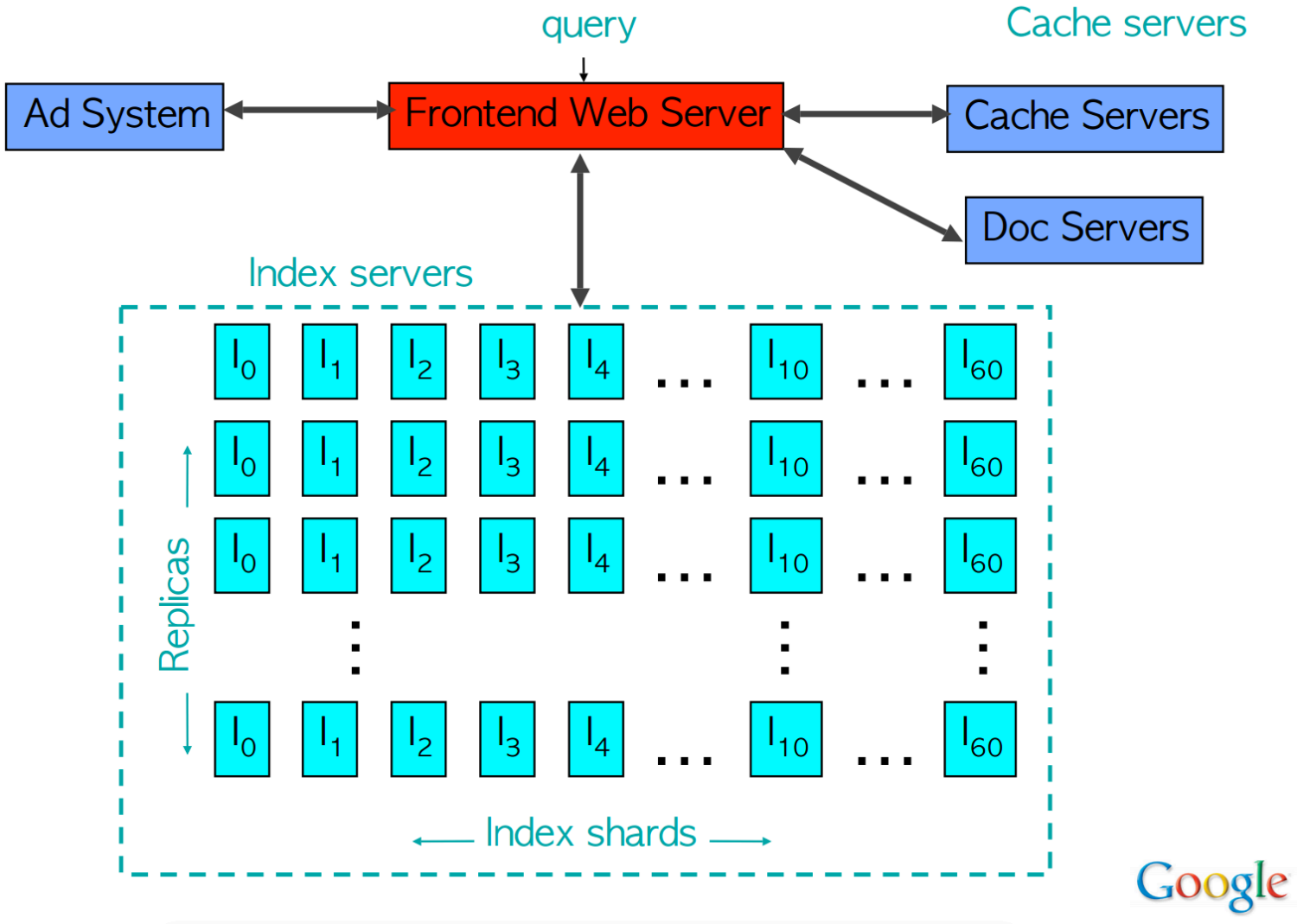
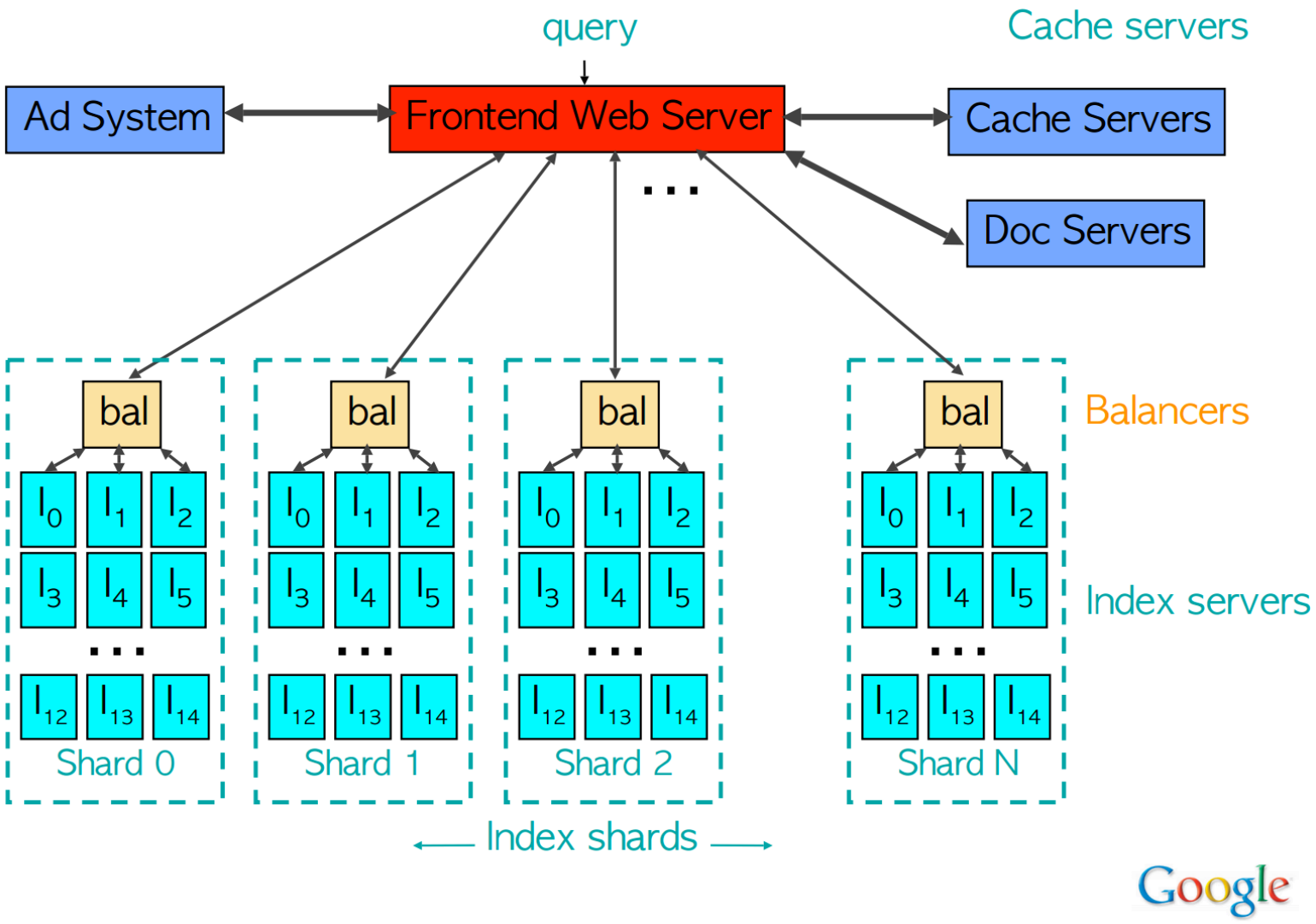
Growth



Source: Jeff Dean WSDM 2009

In-Memory Index



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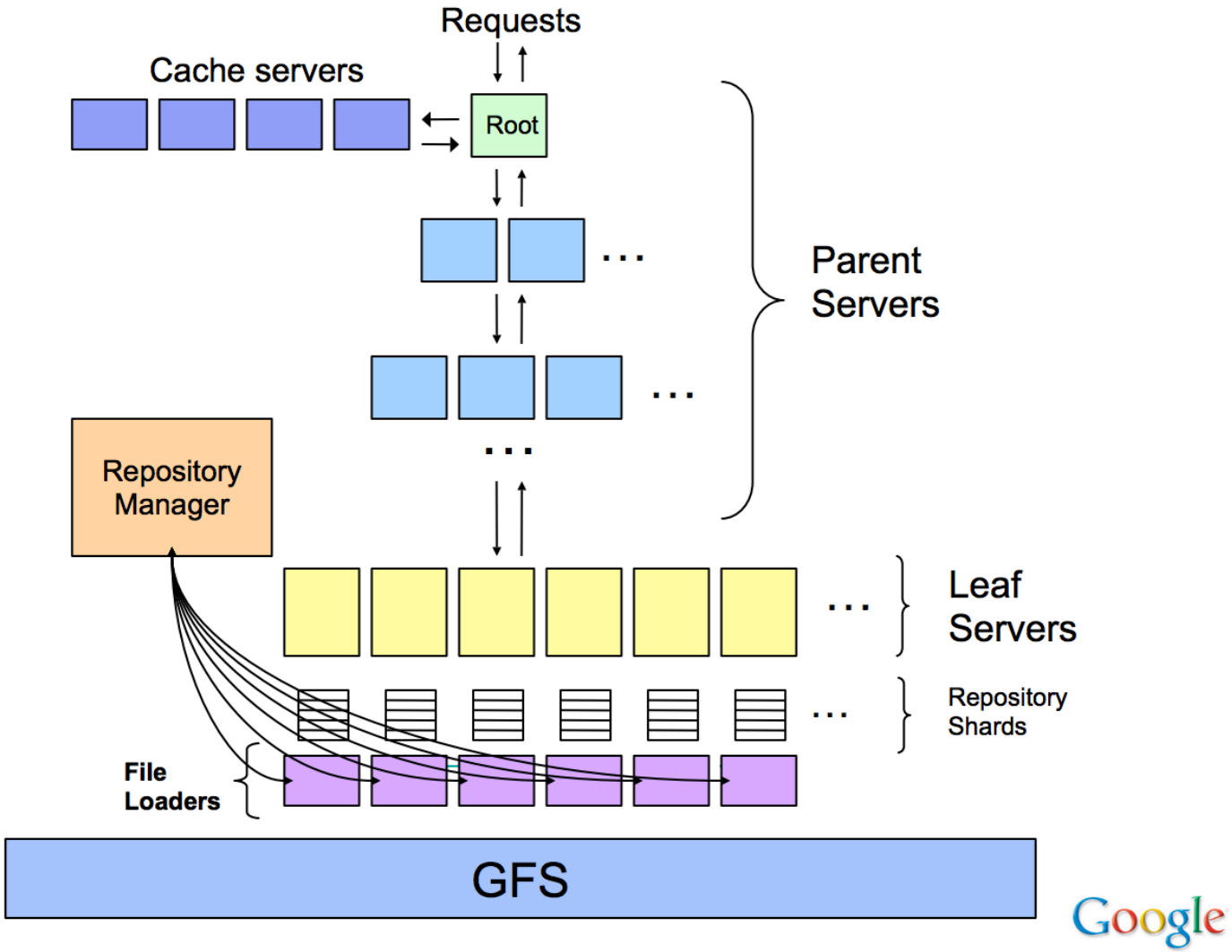
Source: Jeff Dean WSDM 2009

Circa 2004



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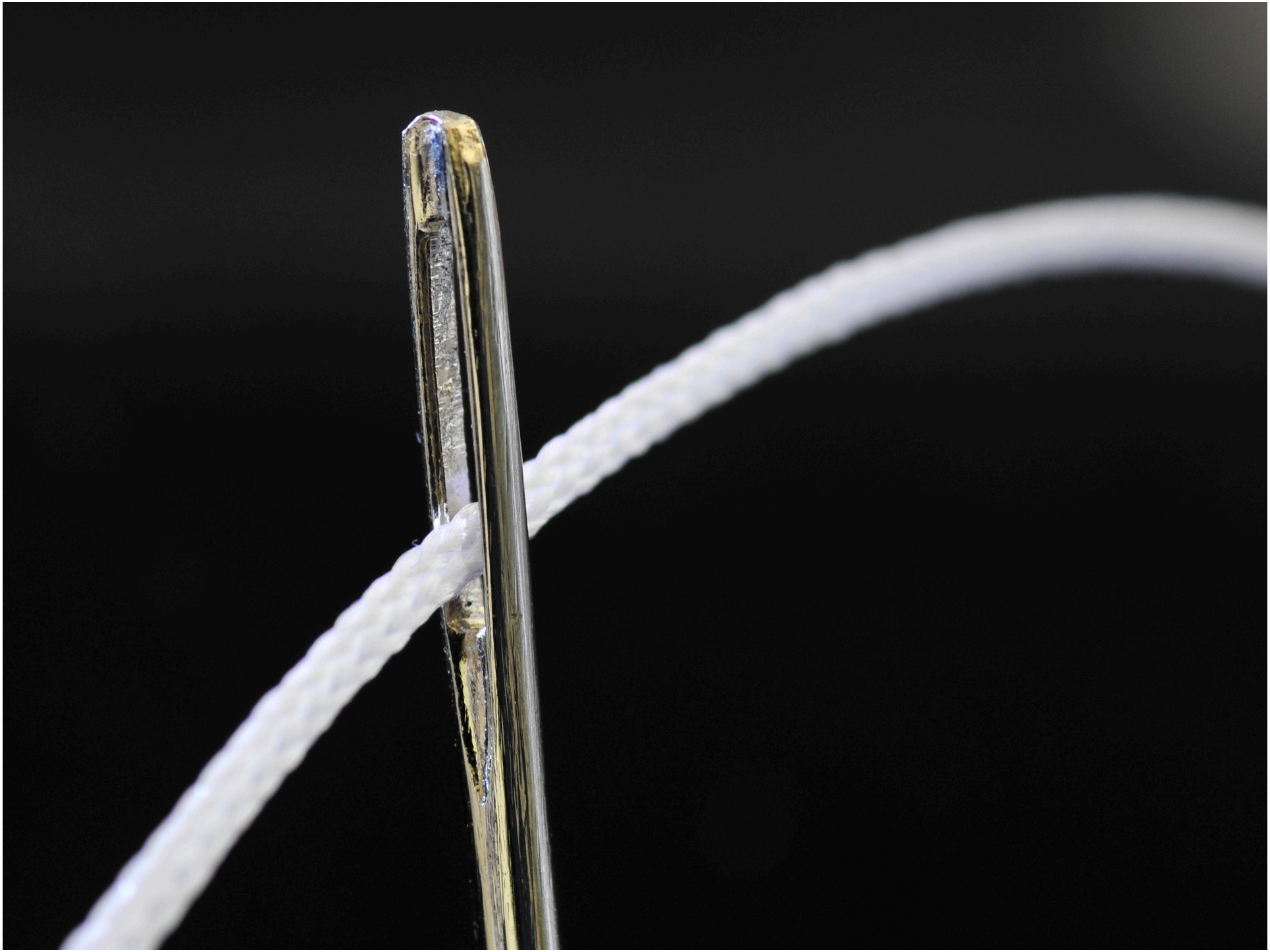

Single-Threaded Asynchronous Execution

The Problem

- User makes a request to a server
- We need to spend a little time coming up with a response
- In the meantime, we still need to be able to accept new connections!
- What are some solutions to this problem?

Traditional Solutions

- Prefork processes
- Spawn a worker thread
- Disadvantages:
  - Thread and process overhead
  - Reasoning about multithreaded code
- Let’s talk about an alternative …

Blocking vs. Non-blocking Sockets

- Blocking sockets: API calls will block until action (send, recv, connect, accept) has finished
- Non-blocking sockets: these calls will return immediately without doing anything
- In Python, use socket.setblocking(0) to make a socket non-blocking

Event Loop

- Single thread, single process
- Uses non-blocking I/O to wait for data to come back
  - Allows us to service new connections while we wait
- All non-I/O activity within the process will still block

Tornado

- Event loop-based web framework
- Started at FriendFeed
- Bought by Facebook
- Lots in common with Twisted
- Includes C10k web server

select vs. poll vs. epoll

- select – system call that allows a program to monitor multiple file descriptors (sockets)
- Builds a bitmap of all fds, turns on bits for fds of interest
- Each call is O(highest file descriptor)

select vs. poll vs. epoll

- poll – requires registering file descriptors of interest
- Each call is O(number of registered file descriptors)

select vs. poll vs. epoll

- epoll – better event notification
- Same API as poll
- Each call is O(number of active file descriptors)

Web Server Example

```
import tornado.ioloop
import tornado.web

class MainHandler(tornado.web.RequestHandler):
    def get(self):
        self.write("Hello, world")

if __name__ == "__main__":
    application = tornado.web.Application([
        (r"/", MainHandler),
    ])
    application.listen(8888)
    tornado.ioloop.IOLoop.instance().start()
```

Source: “Structure of a Tornado web application.” Tornado User’s Guide.

Tornado Coroutines

```
class AsyncHandler(RequestHandler):
    @asynchronous
    def get(self):
        http_client = AsyncHTTPClient()
        http_client.fetch("http://example.com",
                          callback=self.on_fetch)

    def on_fetch(self, response):
        do_something_with_response(response)
        self.render("template.html")
```

Source: “tornado.gen – Simplify asynchronous code.” Tornado User’s Guide.

Tornado Coroutines

```
class GenAsyncHandler(RequestHandler):
    @gen.coroutine
    def get(self):
        http_client = AsyncHTTPClient()
        response = yield http_client.fetch("http://example.com")
        do_something_with_response(response)
        self.render("template.html")
```

Source: “tornado.gen – Simplify asynchronous code.” Tornado User’s Guide.

Until next time...

- Assignment 1 has been posted
  - Due next week
- My email: doherty@cs.nyu.edu
- Questions?