CS 455: Introduction To Distributed Systems
[Thread Safety & MapReduce]

Are you set on reinventing the wheel?

Shunning libraries and frameworks, are you, despite the peril?
Emerge scathed, from arduous projects, you will

Survived, these have, the scrutiny of a thousand probing eyes
Abrogating your choice, is what this implies

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Frequently asked questions from the previous class survey

- ConcurrentHashMap
  - Does the lock operate over a consecutive space?
  - During resize operations can elements be added/removed?
- Latches:
  - Why not use a counter object, that is guarded by synchronous methods?

Topics covered in this lecture

- Thread safety wrap-up
  - Synchronizers and summary
- Map Reduce

Synchronizers

Semaphores

- Counting semaphores control the **number of activities** that can:
  - Access a certain resource
  - Perform a given action
- Used to implement resource pools or impose bounds on a collection

Semaphores

- Manage a set of virtual **permits**
  - Initial number passed to the constructor
- Activities *acquire* and *release* permits
- If **no permits** are available?
  - `acquire` *blocks* until one is available
- The `release` method returns a permit to the semaphore

Semaphores are useful for implementing resource pools

- Block if the pool is empty
  - Unblock if the pool is non-empty
- Initialize a semaphore to the **pool size**
- `acquire` a permit before trying to fetch a resource from pool
- `release` the permit after putting the resource back in pool
- `acquire` **blocks** until the pool is non-empty

Binary semaphores

- Semaphore with an **initial count of 1**
- Can be used as a *mutex* with non-reentrant locking semantics
  - Whoever holds the sole permit holds the mutex

Using Semaphores to bound a collection

```
public BoundedHashSet<T> {
   private final Set<T> set;
   private final Semaphore sem;
   public BoundedHashSet(int bound) {
     this.set = Collections.synchronizedSet(new HashSet<T>());
     sem = new Semaphore(bound);
   }
   public boolean add(T o) throws InterruptedException {
     sem.acquire();
     boolean wasAdded = false;
     try {
       wasAdded = set.add(o);
       return wasAdded;
     } finally {
         if (!wasAdded) sem.release();
     }
   }
   public boolean remove(Object o) {
     boolean wasRemoved = set.remove(o);
     if (wasRemoved) sem.release();
     return wasRemoved;
  }
}
```


Barriers

- Barriers are similar to latches in that they **block a group of threads** till an event has occurred
- All threads must come together at **barrier point** *at the same time* to proceed
  - Latches wait for *events*, barriers ***wait for other threads***

Barriers and dinner …

- Family rendezvous protocol
- Everyone meet at Panera @ 6:00 pm;
  - Once you get there, stay there … till everyone shows up
  - Then we'll figure out what we do next

Barriers

- Often used in simulations where work to calculate one step can be done in parallel
  - But all work associated with a given step must complete before advancing to the next step
- All threads complete step k, before moving on to step $k+1$

CyclicBarrier

- Allows a fixed number of parties to *rendezvous* at a fixed point
- Useful in **parallel iterative algorithms**
  - Break problem into fixed number of independent subproblems
- Creation of a `CyclicBarrier`
  - ```
    Runnable  cyclicBarrierAction = ... ;
    CyclicBarrier cyclicBarrier =
                      new CyclicBarrier(2,  cyclicbarrierAction);
    ```


Using Cylic Barriers

```
class Solver {
   final int N;     final CyclicBarrier barrier;
   class Worker implements Runnable {
     int myRow;
     Worker(int row) { myRow = row; }
     public void run() {
       while (!done()) {
         processRow(myRow);
         try {
           barrier.await();
          } catch (BrokenBarrierException ex) {
           ...
         }
       }
     }
   }
   public Solver(float[][] matrix) {
     data = matrix;     N = matrix.length;
     barrier = new CyclicBarrier(N, new Runnable() { public void run() {
                                                        mergeRows(...);  } });
     for (int i = 0; i < N; ++i)
       new Thread(new Worker(i)).start(); //DO NOT START THREAD in constructor.
     waitUntilDone();
```

Source: From the Java API

Exchanger

- Another type of barrier
- Two-party barrier
- Parties **exchange data** at the barrier point
- Useful when asymmetric activities are performed
  - Producer-consumer problem
- When 2 threads exchange objects via Exchanger
  - Safe publication of objects to other party

Thread Safety Summary

Thread Safety: Summary [1/4]

- It's all about *mutable*, *shared* **state**
  - The less mutable state there is, the easier it is to ensure thread-safety
- Make fields **`final`** unless they need to be mutable
- **Immutable** objects are automatically thread-safe
- **Encapsulation** makes it practical to manage complexity

Thread Safety: Summary [2/4]

- Guard each mutable variable with a **lock**
- Guard all variables in an invariant with the ***same lock***
- Hold locks for the *duration* of compound actions
```

Thread Safety: Summary [3/4]

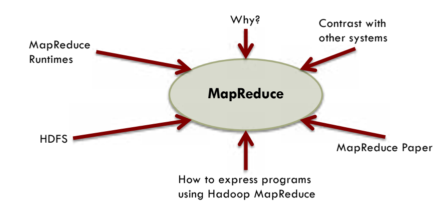
- Program that access mutable variables from multiple threads without synchronization?
  - Broken program
- Include thread-safety in the design process
  - Document if your class is not thread-safe
- Document your synchronization policy

Thread Safety: Summary [4/4]

- Rather than scattering access to shared state throughout your programs and attempting *ad hoc* reasoning about interleaved access
  - Structure program to facilitate reasoning about concurrency
  - Use a set of standard synchronization primitives to control access to shared state

MapReduce

MapReduce: What we will look at



Cloud Computing

The volume of data that we produce has increased dramatically

- IDC (International Data Corporation) estimates
  - 180 EB (10^{18}) in 2006
  - 1.8 ZB (10^{21}) in 2011
    - Roughly a disk drive per person!
  - 40 ZB by 2020

Some of the sources of this deluge

- New York Stock Exchange
  - 1 TB of new trade data every day
- Facebook
  - ~10^{12} photos
- Internet Archive
  - Stores 2 PB of data … growing at 20 TB per month
- LHC produces 15 PB per year

Amount of data generated by machines will outpace what people produce

- Machine logs
- RFID readers
- Sensor networks
- Instruments
- Vehicle GPS traces
- IoT
  - 20-35 billion IoT devices are expected to be online in 2020

Hard disk capacities, seek rates, and transfer times

- 1990
  - 1 GB HDDs with a transfer speed of 4.4 MB/sec
- Now
  - 1 TB hard drives are common
  - But the transfer speed is just 100 MB/sec
    - Writing is even slower!

Data transfers can be improved by using multiple disks

- What if we use 100 disk drives?
  - Each holding 1/100th of the data
- We could have *cumulative transfer* speeds of up to 100 x 100 MB/sec or 10 GB/sec
- But isn't using 1/100th of disk wasteful?
  - Not if you store a 100 different datasets on these disks
  - Provide shared access to the disks

But there's more than just reading and writing from multiple disks in parallel

- **Cope with hardware failures**
  - As the number of components increase, so does the probability of failure
- Analysis tasks need to be able to **combine data**
  - Dataset is dispersed over multiple disks

What MapReduce provides …

- Programming model that **abstracts** the problem from disk reads and writes
- Transform the problem into **computations** over sets of keys and values
- Supports **distributed processing** on large datasets over a cluster of computers

But why not use databases with lots of disks? [1/2]

- Another trend in disk drives
  - Seek time is improving *much slower* than transfer rates
- If data access pattern is dominated by seeks?
  - It takes longer to read or write large portions of the dataset than streaming through it
    - Streaming through dataset operates at transfer speed

But why not use databases with lots of disks? [2/2]

- Updating a small proportion of records in the dataset
  - Traditional B-Tree works well
- For updating a majority of the dataset
  - B-Tree is less efficient than MapReduce which uses Sort/Merge to rebuild the dataset

MapReduce should be seen as being complementary to databases

- MapReduce is good for problems that access the **entire dataset**
  - Particularly *ad hoc* analysis
  - Write once, read many times
- RDBMS is good for point queries or updates
  - Dataset **has been indexed** for low-latency retrieval and update times
  - Read and write many times

Grid Computing/HPC systems

- Distribute work across a cluster of machines that access a **shared file system**
- Works well for predominantly compute-intensive jobs
  - Problem when access to large data volumes is needed
    - Network bandwidth is a bottleneck and compute nodes become idle

MapReduce tries to collocate data with the compute node

- **Data Locality**
  - Data access is fast since it is local
  - Conserves network bandwidth
- Implementations go to great lengths to conserve it
  - Model network topology

MPI (Message Passing Interface) gives great control to the programmer

- MPI requires **explicit handling** of the mechanics of *data flow*
  - In MapReduce, the mechanics of data flow is implicit
- MapReduce spares programmers from having to think about failures
  - Detect failures and schedule replacements on healthy machines
  - Done with a **shared-nothing architecture**
  - MPI programs have to deal with checkpointing and recovery
    - More control but difficult to write

Volunteer computing

- SETI@home
- Volunteers donate cycles not bandwidth
- MapReduce
  - Runs jobs lasting minutes or hours on trusted, dedicated machines with high-bandwidth interconnects
- Volunteer computing
  - Perpetual computations on untrusted machines
    - Highly variable connection speeds and no data locality

MapReduce

Materials Based On
Jeffrey Dean and Sanjay Ghemawat: *MapReduce: Simplified Data Processing on Large Clusters.* OSDI 2004: 137-150

Source of raw data at Google

- **Crawled** data
- **Log** of the web requests

Several computations work on this raw data to compute derived data

- Inverted indices
- Representation of the graph structure of web documents
- Pages crawled per host
- Most frequent queries in a day …

Most computations are conceptually straightforward

- But data is large
- Computations must be **scalable**
  - Distributed across thousands of machines
  - To complete in a reasonable amount of time

Complexity of managing distributed computations can …

- Obscure **simplicity** of original computation
- Contributing factors:
  - How to ***parallelize*** the computation
  - Distribute the ***data***
  - Handle ***failures***

MapReduce was developed to cope with this complexity

- Express simple computations
- Hide messy details of:
  1. Parallelization
  2. Data distribution
  3. Fault tolerance
  4. Load balancing

MapReduce

- Programming model
- Associated implementation for
  - Processing & Generating large data sets

Programming model

- Computation takes a set of **input** *key/value* pairs
- Produces a set of **output** *key/value* pairs
- Express the computation as two functions:
  - Map
  - Reduce

Map

- Takes an input pair
- Produces a set of intermediate key/value pairs

Mappers

- If map operations are **independent** of each other they can be performed in parallel
  - **Shared nothing**
- This is usually the case

MapReduce library

- **Groups** all intermediate values with the same intermediate key
- **Passes** them to the Reduce function

Reduce function

- Accepts intermediate *key* I and
  - Set of *values* for that *key*
- **Merge** these *values* together to get
  - Smaller set of *value*

Counting number occurrences of each word in a large collection of documents

```
map (String key, String value)
    //key: document name
    //value: document contents

  for each word w in value
     EmitIntermediate(w, "1")
```


Counting number occurrences of each word in a large collection of documents

```
reduce (String key, Iterator values)
     //key: a word
    //value: a list of counts

    int result = 0;
    for each v in values
       result += ParseInt(v);
    Emit(AsString(result));
```

Sums together all counts emitted for a particular word

The contents of this slide set are based on the following references

- Hadoop: The Definitive Guide by Tom White. Early Release. 3rd Edition. O'Reilly. [Chapter 1]
- Jeffrey Dean, Sanjay Ghemawat: *MapReduce: Simplified Data Processing on Large Clusters*. OSDI 2004: 137-150
- Jeffrey Dean, Sanjay Ghemawat: MapReduce: simplified data processing on large clusters. Commun. ACM 51(1): 107-113 (2008)