Big Data: Exam Review

Juliana Freire

General Notes

- May 12!!!
- Questions will be similar to the questions in the quiz
  - Include multiple choice and open-ended questions
- You will not have to write Python or Java code, but you will have to demonstrate your understanding of algorithms, design patterns, and their trade-offs.

Introduction to Databases

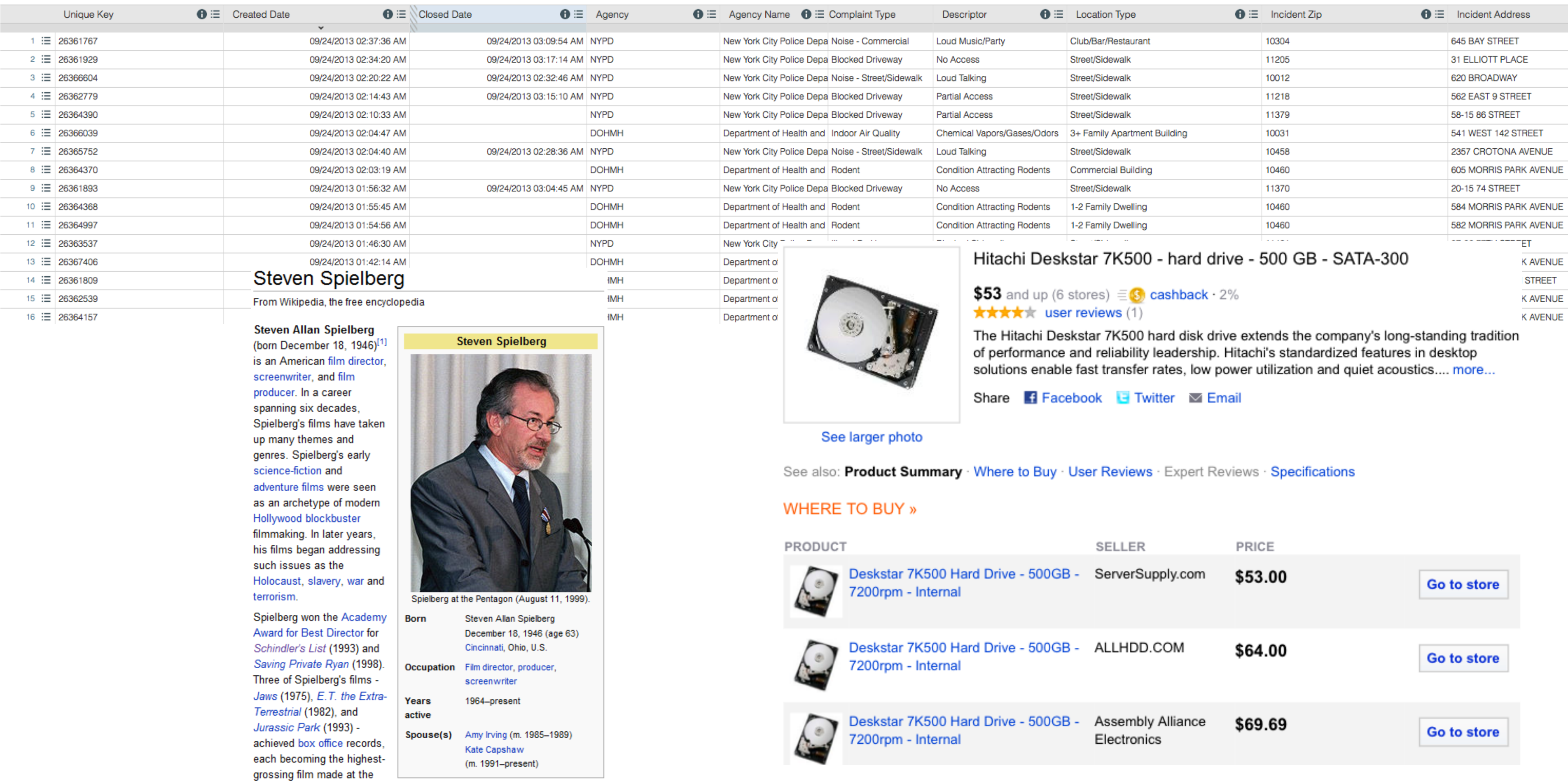
- Introduction to Relational Databases
- Representing structured data with the Relational Model
- Accessing and querying data using SQL

Why study databases?

- Databases used to be *specialized applications,* now they are a *central component* in computing environments
- Knowledge of database concepts is *essential* for computer scientists and for anyone who needs to *manipulate* data

Why study databases?

- Data is often structured



	Unique Key	Created Date	Closed Date	Agency	Agency Name	Complaint Type	Descriptor	Location Type	Incident Zip	Incident Address
1	26361767	09/24/2013 02:37:36 AM	09/24/2013 03:09:54 AM	NYPD	New York City Police Depa	Noise - Commercial	Loud Music/Party	Club/Bar/Restaurant	10304	645 BAY STREET
2	26361929	09/24/2013 02:34:20 AM	09/24/2013 03:17:14 AM	NYPD	New York City Police Depa	Blocked Driveway	No Access	Street/Sidewalk	11205	31 ELLIOTT PLACE
3	26366604	09/24/2013 02:20:22 AM	09/24/2013 02:32:46 AM	NYPD	New York City Police Depa	Noise - Street/Sidewalk	Loud Talking	Street/Sidewalk	10012	620 BROADWAY
4	26362779	09/24/2013 02:14:43 AM	09/24/2013 03:15:10 AM	NYPD	New York City Police Depa	Blocked Driveway	Partial Access	Street/Sidewalk	11218	562 EAST 9 STREET
5	26364390	09/24/2013 02:10:33 AM		NYPD	New York City Police Depa	Blocked Driveway	Partial Access	Street/Sidewalk	11379	58-15 86 STREET
6	26366039	09/24/2013 02:04:47 AM		DOHMH	Department of Health and	Indoor Air Quality	Chemical Vapors/Gases/Odors	3+ Family Apartment Building	10031	541 WEST 142 STREET
7	26365752	09/24/2013 02:04:40 AM	09/24/2013 02:28:36 AM	NYPD	New York City Police Depa	Noise - Street/Sidewalk	Loud Talking	Street/Sidewalk	10458	2357 CROTONA AVENUE
8	26364370	09/24/2013 02:03:19 AM		DOHMH	Department of Health and	Rodent	Condition Attracting Rodents	Commercial Building	10460	605 MORRIS PARK AVENUE
9	26361893	09/24/2013 01:56:32 AM	09/24/2013 03:04:45 AM	NYPD	New York City Police Depa	Blocked Driveway	No Access	Street/Sidewalk	11370	20-15 74 STREET
10	26364368	09/24/2013 01:55:45 AM		DOHMH	Department of Health and	Rodent	Condition Attracting Rodents	1-2 Family Dwelling	10460	584 MORRIS PARK AVENUE
11	26364997	09/24/2013 01:54:56 AM		DOHMH	Department of Health and	Rodent	Condition Attracting Rodents	1-2 Family Dwelling	10460	582 MORRIS PARK AVENUE
12	26363537	09/24/2013 01:46:30 AM		NYPD	New York City					
13	26367406	09/24/2013 01:42:14 AM		DOHMH	Department of					AVENUE
14	26361809			MH	Department of					STREET
15	26362539			MH	Department of					AVENUE
16	26364157			MH	Department of					AVENUE

Steven Spielberg

From Wikipedia, the free encyclopedia

Steven Allan Spielberg (born December 18, 1946)[1] is an American film director, screenwriter, and film producer. In a career spanning six decades, Spielberg's films have taken up many themes and genres. Spielberg's early science-fiction and adventure films were seen as an archetype of modern Hollywood blockbuster filmmaking. In later years, his films began addressing such issues as the Holocaust, slavery, war and terrorism.

Spielberg won the Academy Award for Best Director for *Schindler's List* (1993) and *Saving Private Ryan* (1998). Three of Spielberg's films - *Jaws* (1975), *E.T. the Extra-Terrestrial* (1982), and *Jurassic Park* (1993) - achieved box office records, each becoming the highest-grossing film made at the

Steven Spielberg

Spielberg at the Pentagon (August 11, 1999).

Born	Steven Allan Spielberg December 18, 1946 (age 63) Cincinnati, Ohio, U.S.
Occupation	Film director, producer, screenwriter
Years active	1964–present
Spouse(s)	Amy Irving (m. 1985–1989) Kate Capshaw (m. 1991–present)

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Deskstar 7K500 Hard Drive - 500GB - 7200rpm - Internal	Assembly Alliance Electronics	$69.69	Go to store

Why study databases?

- Data is often structured
- We can exploit this regular structure
  - To retrieve data in useful ways (that is, we can use a *query* language)
  - To store data efficiently

Why study Databases?

- *Understand concepts and apply to different problems and different areas, e.g., Big Data*
- Because DBMS software is highly successful as a commercial technology (Oracle, DB2, MS SQL Server…)
- Because DB research is highly active and **very** interesting!
  - Lots of opportunities to have practical impact

Database Systems: The Basics

What's in a DBMS?

	Data model	*Query language*	*Transactions and crash recovery*
	Logical DB design Relational Model XML data model	SQL, QBE, views XPath, XQuery	Transactions
"above the water" / *"below the water"*	Map data to files Clustering Indexes	Query optimization Query evaluation	Locking Concurrency control Recovery Logs

Designing a database: The Conceptual Model

- What are the *entities* and *relationships* among these entities in the application?
- What information about these entities and relationships should we store in the database?
- What are the *integrity constraints* or *business rules* that hold?
- Different applications have different needs, and different perspectives – even to model the *same* object

  billing department: patient(id, name, insurance, address)
  visit(patientId, procedure, date, charge)

  inpatient: patient(id,name,age,address)
  alergies(id,alergies)
  prescription(patientId,date,medicine)

Designing a database: The Conceptual Design

- What are the *entities* and *relationships* among these entities in the enterprise?
- What information about these entities and relationships should we store in the database?
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- Dif ifferent perspectives – even to model the *same* object

Requires a good understanding of the *semantics* of the application

billing department: patient(id, name, insurance, address)
visit(patientId, procedure, date, charge)

inpatient: patient(id,name,age,address)
alergies(id,alergies)
prescription(patientId,date,medicine)

Relational Data Model

- ER used for conceptual design is then mapped into the relational model
- The *relational model of data* is the most widely used model today
  - Main concept: *relation*, basically a table with rows and columns
  - Every relation has a *schema*, which describes the columns, or fields
- A *schema* is a description of a particular collection of data, using a given data model

Patient(patientId:int, patientName:str, age: int)

Takes(patientId:int,prescId:inte,prescDate:date)

Prescription(prescId:int, presName:str)

Relational Model: Terminology

Attributes

Constraints

age >=18
and age <=45

tuples

Patient-id	*Patient-name*	*Patient-age*
192-83-7465	Johnson	23
019-28-3746	Smith	78
192-83-7465	Johnson	5
321-12-3123	Jones	14
019-28-3746	Smith	55

schema

Patient(patientId:int, patientName:str, age: int)

Pitfalls in Relational Database Design

- Find a “good” collection of relation schemas
- Bad design may lead to
  - Repetition of information → inconsistencies!
    - E.g., keeping people and addresses in a single file
  - Inability to represent certain information
    - E.g., a doctor that is both a cardiologist and a pediatrician
- Design Goals:
  - Avoid redundant data
  - Ensure that relationships among attributes are represented
  - Ensure constraints are properly modeled: updates check for violation of database integrity constraints

Query Languages

- *Query languages:* Allow *manipulation* and *retrieval* of data from a database
- Queries are posed wrt data model
  - Operations over objects defined in data model
- Relational model supports simple, powerful QLs:
  - Strong formal foundation based on logic
  - Allows for optimization
- Query Languages **!=** programming languages
  - QLs support easy, efficient access to large data sets
  - QLs not expected to be "Turing complete"
  - QLs not intended to be used for complex calculations

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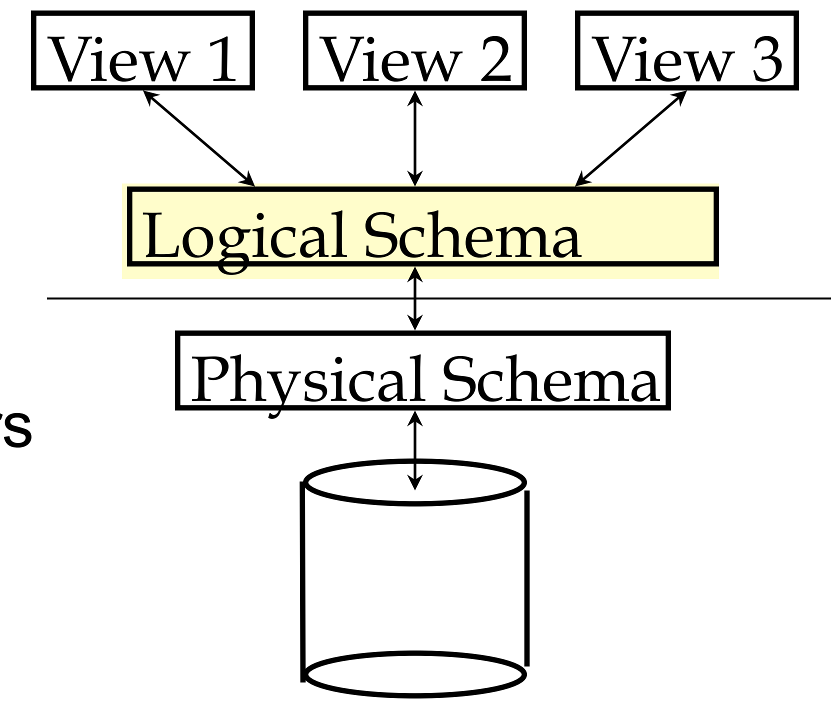
a language that can compute anything that can be computed

Levels of Abstraction

- Many *views*, single *conceptual (logical) schema* and *physical schema*
  - Views describe how users see the data
  - Logical schema defines logical structure
  - Physical schema describes the files and indexes used



Key to good performance

Data Independence

- Applications insulated from how data is structured and stored
- *Logical data independence*: Protection from changes in *logical* structure of data
  - Changes in the logical schema do not affect users as long as their views are still available
- *Physical data independence:* Protection from changes in *physical* structure of data
  - Changes in the physical layout of the data or in the indexes used do not affect the logical relations

One of the most important benefits of using a DBMS!

“above the water”

“below the water”

Data model	*Query language*	*Transactions and crash recovery*
Logical DB design Relational Model XML data model	SQL, QBE, views XPath, XQuery	Transactions
Map data to files Clustering Indexes	Query optimization Query evaluation	Locking Concurrency control Recovery Logs

Let’s dive now…

Storage and Indexing

- The *DB administrator* designs the physical structures
- Nowadays, database systems can do (some of) this automatically: autoadmin, index advisors
- File structures: sequential, hashing, clustering, single or multiple disks, etc.
- Example – Bank accounts
  - Good for:

    List all accounts in the Downtown branch
  - What about:

    List all accounts with balance = 350

A-217	Brighton	750	
A-101	Downtown	500	
A-110	Downtown	600	
A-215	Mianus	700	
A-102	Perryridge	400	
A-201	Perryridge	900	
A-218	Perryridge	700	
A-222	Redwood	700	
A-305	Round Hill	350	

Storage and Indexing

- Indexes:
  - Select attributes to index
  - Select the type of index
- Storage manager is a module that provides the interface between the low-level data stored in the database and the application programs and queries submitted to the system:
  - interaction with the file manager
  - efficient storing, retrieving and updating of data

Query Optimization and Evaluation

- DBMS must provide efficient access to data
  - In an emergency, can't wait 10 minutes to find patient allergies
- Declarative queries are translated into imperative query plans
  - Declarative queries → logical data model
  - Imperative plans → physical structure
- Relational optimizers aim to find the best imperative plans (i.e., shortest execution time)
  - In practice they avoid the worst plans…

Example: Query Optimization

select number
from accounts
where balance = 350

$$\Pi_{\text{number}}$$
$$|$$
$$\sigma_{\text{balance=350}} \quad \text{, use index(balance)}$$
$$|$$
$$\text{accounts}$$

Different Data Models

- **Relational**
- **Semi-structured/XML**
- Object-oriented
- Object-relational
- Hierarchical
- Network
- …

Will be covered in this course

XML: A First Step Towards Convergence

- XML = *Extensible Markup Language*.
- XML is syntactically related to HTML
- Goal is different:
  - HTML describes document structure
  - XML transmits textual data
- XML *solves* the data exchange problem
  - No need to write specialized wrappers.
  - The schema of an XML document serves as a contract
- XML *does not solve* the problem of efficient access
  - DB research is doing that!
  - Storage techniques, mechanisms for maintaining data integrity and consistency,…

IMDB Example : Data

```xml
<?xml version="1.0" standalone="yes"?>
<imdb>
 <show year="1993"> <!-- Example Movie -->
  <title>Fugitive, The</title>
  <review>
   <suntimes>
    <reviewer>Roger Ebert</reviewer> gives <rating>two thumbs
    up</rating>! A fun action movie, Harrison Ford at his best.
   </suntimes>
  </review>
  <review>
   <nyt>The standard Hollywood summer movie strikes back.</nyt>
  </review>
  <box_office>183,752,965</box_office>
 </show>
 <show year="1994"> <!-- Example Television Show -->
  <title>X Files, The</title>
  <seasons>4</seasons>
 </show>
</imdb>
```

XML Document = Tagged elements + Attributes + Text

XML vs. HTML?

IMDB Example : Schema

```
<element name="show">
 <complexType>
  <sequence>
    <element name="title" type="xs:string"/>
    <sequence minoccurs="0" maxoccurs="unbounded">
      <element name="review" mixed="true"/>
    </sequence>
    <choice>
      <element name="box_office" type="xs:integer"/>
      <element name="seasons" type="xs:integer"/>
    </choice>
  </sequence>
  <attribute name="year" type="xs:integer" use="optional"/>
 </complexType>
</element>
```

Key Concepts in Databases

- Data Model: general conceptual way of structuring data
  - Relational: attributes, tuples, relations, SQL
  - XML: attributes nodes, trees, characters, XPATH/XQuery
- Schema: structure of a particular database under a certain data model
  - Relational: Definition of a set of relations + constraints
  - XML: Grammar for the structure of a document + constraints
- Instance: actual data conforming to a schema
  - Relational: Set of tables (instances of relations)
  - XML: Ordered tree

Relational Model versus XML: Fundamental Differences

- Relations: Schema must be fixed in advance
  XML: Does not require predefined, fixed schema
- Relations: Rigid flat table structure
  XML: Flexible hierarchical structure (defined by regular expressions)
- Relations: simple structure, simple query language
  XML:complex structure, more complex query language

Relational Model versus XML: Additional Differences

- Relations: Ordering of data not relevant (tuple ordering or attribute ordering)
  XML: Ordering forced by document format, may or may not be relevant
- Relations: Transmission and sharing can be problematic
  XML: Designed for easy representation and exchange
- Relations: "Native" data model for all current widely-used commercial DBMSs
  XML: "Add-on," often implemented on top of relations

Formal Relational Query Languages

- Two mathematical Query Languages form the basis for "real" relational languages (e.g., SQL), and for implementation:
  - *Relational Algebra*: More operational, very useful for representing execution plans.
  - *Relational Calculus*: Lets users describe what they want, rather than how to compute it. (Non-operational, *declarative*.)

Basics of Relational Algebra

- Algebra of arithmetic: operands are variables and constants, and operators are the usual arithmetic operators
  - E.g., (x+y)*2 or ((x+7)/(y-3)) + x

- Relational algebra: operands are variables that stand for relations and relations (sets of tuples), and operators are designed to do the most common things we need to do with relations in databases, e.g., *union, intersection, selection, projection, Cartesian product, etc*
  - E.g., $(\pi_{c\text{-}owner}\text{Checking-account}) \cap (\pi_{s\text{-}owner}\text{Savings-account})$

- The result is an algebra that can be used as a *query language* for relations.

Why SQL?

- SQL is a high-level language
  - Say "what to do" rather than "how to do it"
  - Avoid a lot of data-manipulation details needed in procedural languages like C++ or Java
- Database management system figures out "best" way to execute query
  - Called "query optimization"

What is SQL?

- Data manipulation: ad-hoc queries and updates

```
SELECT    *
FROM      Account
WHERE     Type = "checking ";
```

- Data de   ews

```
CREATE TABLE Account
    (Number       integer  NOT NULL,
     Owner        character,
     Balance      currency,
     Type         character,
    PRIMARY KEY (Number));
```

- Control: integrity

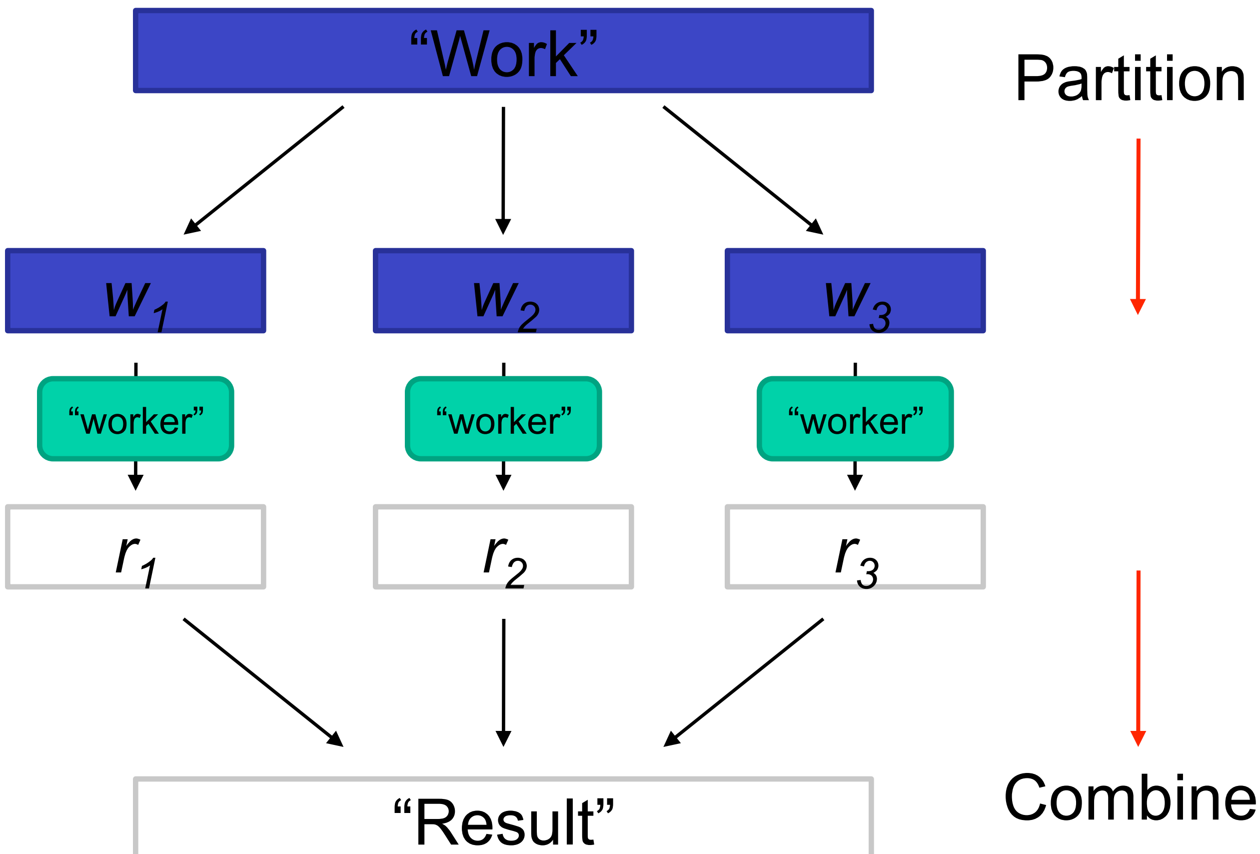
```
CHECK (Owner IS NOT NULL)
```

Relational Algebra vs. SQL

- Relational algebra = query only
- SQL = data manipulation + data definition + control
- SQL data manipulation is similar to, but not exactly the same as relational algebra
  - SQL is based on set and relational operations *with certain modifications and enhancements*
  - We will study the differences
- We coverage the various operations and some details about using SQL

MapReduce

- Large data
- New parallel architectures



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 is the common theme of all of these problems?

Common Theme?

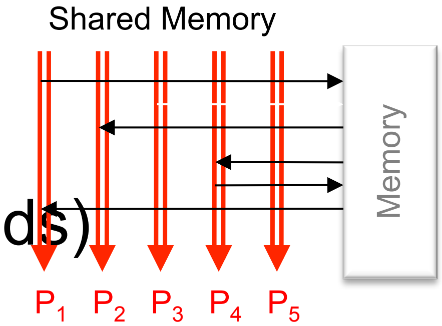
- Parallelization problems arise from:
  - Communication between workers (e.g., to exchange state)
  - Access to shared resources (e.g., data)
- Thus, we need a synchronization mechanism

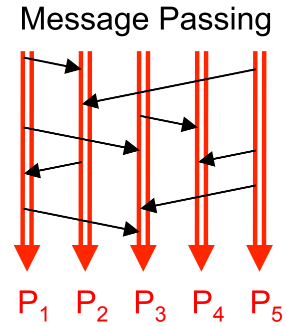
Managing Multiple Workers

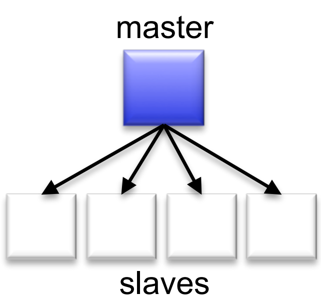
- Difficult because
  - We don’t know the order in which workers run
  - We don’t know when workers interrupt each other
  - We don’t know the order in which workers access shared data
- Thus, we need:
  - Semaphores (lock, unlock)
  - Conditional variables (wait, notify, broadcast)
  - Barriers
- Still,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

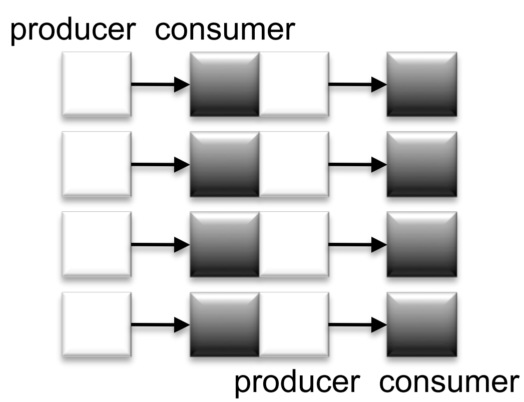
Current Tools

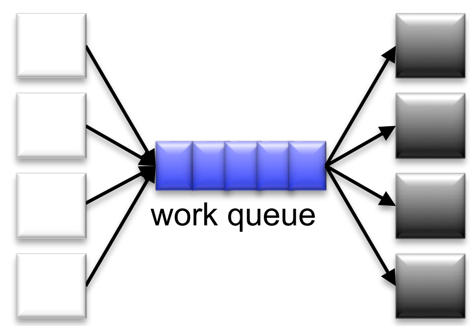
- Programming models
  – Shared memory (pthreads)
  – Message passing (MPI)
- Design Patterns
  – Master-slaves
  – Producer-consumer flows
  – Shared work queues











Where the rubber meets the road

- Concurrency is difficult to reason about
- Concurrency is even more difficult to reason about
  - At the scale of datacenters (even 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

What's the point?

- It's all about the right level of abstraction
  - The von Neumann architecture has served us well, but is no longer appropriate for the multi-core/cluster environment
- 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!

Big Ideas: Scale Out vs. Scale Up

- Scale up: small number of high-end servers
  - Symmetric multi-processing (SMP) machines, large shared memory
  - Not cost-effective – cost of machines does not scale linearly; and no single SMP machine is big enough
- Scale out: Large number of commodity low-end servers is more effective for data-intensive applications
  - 8 128-core machines vs. 128 8-core machines

"low-end server platform is about 4 times more cost efficient than a high-end shared memory platform from the same vendor", Barroso and Hölzle, 2009

Big Ideas: Failures are Common

- Suppose a cluster is built using machines with a *mean-time between failures (MTBF) of 1000 days*
- For a 10,000 server cluster, there are on average 10 failures per day!
- MapReduce implementation cope with failures
  – Automatic task restarts

Big Ideas: Move Processing to Data

- Supercomputers often have processing nodes and storage nodes
  – Computationally expensive tasks
  – High-capacity interconnect to move data around
- Many data-intensive applications are not very processor-demanding
  – Data movement leads to a bottleneck in the network!
  – New idea: move processing to where the data reside
- In MapReduce, processors and storage are co-located
  – Leverage locality

Big Ideas: Avoid Random Access

- Disk seek times are determined by mechanical factors
  - Read heads can only move so fast and platters can only spin so rapidly

Big Ideas: Avoid Random Access

Example:

- 1 TB database containing 10^{10} 100 byte records
- Random access: each update takes ~30ms (seek ,read, write)
  - Updating 1% of the records takes ~35 days
- Sequential access: 100MB/s throughput
  - Reading the whole database and rewriting all the records, takes 5.6 hours

- MapReduce was designed for batch processing --- organize computations into long streaming operations

Typical Large-Data Problem

Map

- Iterate over a large number of records
- Extract something of interest from each
- Shuffle and sort intermediate results
- Aggregate intermediate results
- Generate final output

Reduce

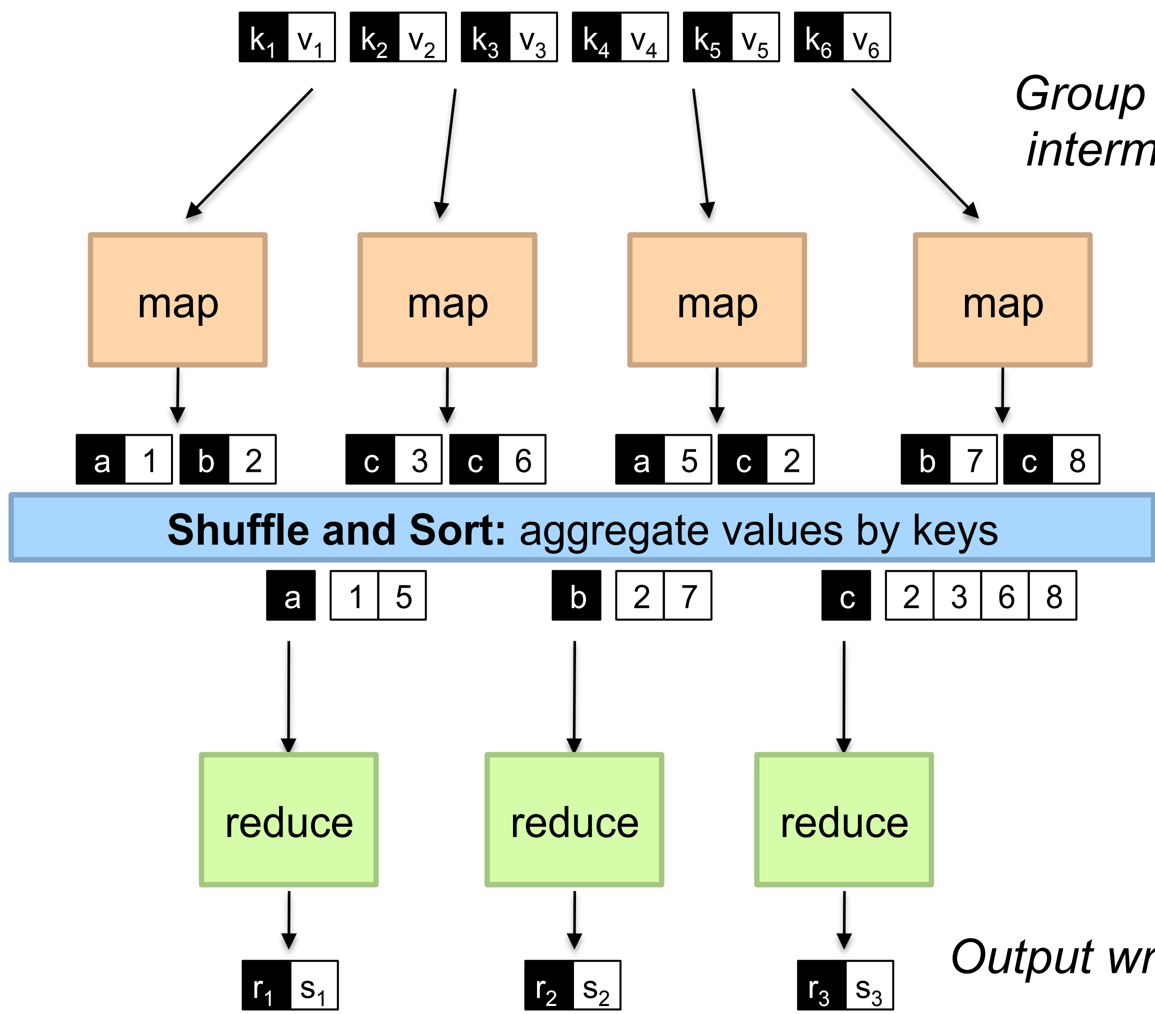
Key idea: provide a functional abstraction for these two operations

(Dean and Ghemawat, OSDI 2004)

Map and Reduce

- The idea of Map, and Reduce is 40+ year old
  - Present in all Functional Programming Languages.
  - See, e.g., APL, Lisp and ML
- Alternate names for Map: Apply-All
- Higher Order Functions
  - take function definitions as arguments, or
  - return a function as output
- Map and Reduce are higher-order functions.

MapReduce



Group by is applied to intermediate keys

Output written to DFS

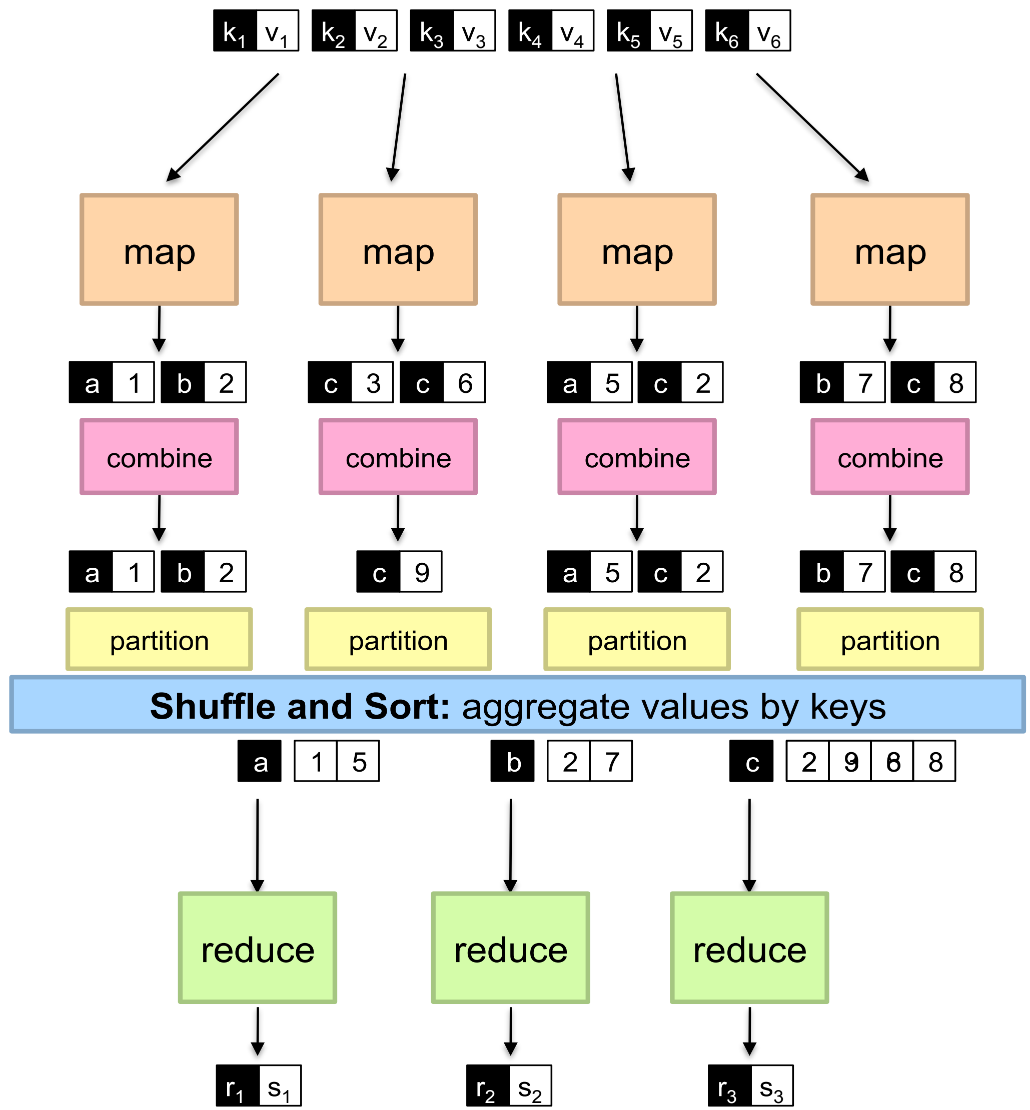
Two more details…

- Barrier between map and reduce phases
  - But we can begin copying intermediate data earlier
- Keys arrive at each reducer in sorted order
  - No enforced ordering *across* reducers

MapReduce “Runtime”

- Handles scheduling
  - Assigns workers to map and reduce tasks
- Handles “data distribution”
  - Moves processes to data
- Handles synchronization
  - Gathers, sorts, and shuffles intermediate data
- Handles errors and faults
  - Detects worker failures and restarts
- Everything happens on top of a *distributed FS* (later)

MapReduce: The Complete Picture



MapReduce

- Programmers specify two functions:

  map (k, v) → <k', v'>*

  reduce (k', v') → <k', v'>*

  – All values with the same key are reduced together
- Mappers and reducers can specify arbitrary computations
  – Be careful with access to external resources!
- The execution framework handles everything else…
- Not quite…usually, programmers also specify:

  partition (k', number of partitions) → partition for k'

  – Often a simple hash of the key, e.g., hash(k') mod n

  – Divides up key space for parallel reduce operations

  combine (k', v') → <k', v'>*

  – Mini-reducers that run in memory after the map phase

  – Used as an optimization to reduce network traffic

Distributed File System

- Don't move data to workers… move workers to the data!
  - Store data on the local disks of nodes in the cluster
  - Start up the workers on the node that has the data local
- Why?
  - Not enough RAM to hold all the data in memory
  - Disk access is slow, but disk throughput is reasonable
- A distributed file system is the answer
  - GFS (Google File System) for Google's MapReduce
  - HDFS (Hadoop Distributed File System) for Hadoop

GFS: Design Decisions

- Files stored as chunks
  - Fixed size (e.g., 64MB)
- Reliability through replication
  - Each chunk replicated across 3+ chunkservers
- Single master to coordinate access, keep metadata
  - Simple centralized management
- No data caching
  - Little benefit due to large datasets, streaming reads
- Simplify the API
  - Push some of the issues onto the client (e.g., data layout)

HDFS = GFS clone (same basic ideas)

Designing Algorithms for MapReduce

- Need to adapt to a restricted model of computation
- Goals
  - Scalability: adding machines will make the algo run faster
  - Efficiency: resources will not be wasted
- The translation some algorithms into MapReduce isn't always obvious
- But there are useful design patterns that can help
- We covered patterns and examples to illustrate how they can be applied

Tools for Synchronization

- Cleverly-constructed data structures
  – Bring partial results together
- Sort order of intermediate keys
  – Control order in which reducers process keys
- Partitioner
  – Control which reducer processes which keys
- Preserving state in mappers and reducers
  – Capture dependencies across multiple keys and values

Strategy: Local Aggregation

- Use combiners
- Do aggregation inside mappers
- In-mapper combining
  - Fold the functionality of the combiner into the mapper by preserving state across multiple map calls
- Advantages
  - Explicit control aggregation
  - Speed
- Disadvantages
  - Explicit memory management required
  - Potential for order-dependent bugs

Limiting Memory Usage

- To limit memory usage when using the in-mapper combining technique, block input key-value pairs and flush in-memory data structures periodically
  - E.g., counter variable that keeps track of the number of input key-value pairs that have been processed
- Memory usage threshold needs to be determined empirically: with too large a value, the mapper may run out of memory, but with too small a value, opportunities for local aggregation may be lost
- Note: Hadoop physical memory is split between multiple tasks that may be running on a node concurrently – difficult to coordinate resource consumption

Combiner Design

- Combiners and reducers share same method signature
  – Sometimes, reducers can serve as combiners

When is this the case?

  – Often, not…works only when reducer is commutative and associative
- Remember: combiner are optional optimizations
  – Should not affect algorithm correctness
  – May be run 0, 1, or multiple times
- Example: find average of all integers associated with the same key

MapReduce: Large Counting Problems

- Term co-occurrence matrix for a text collection = specific instance of a large counting problem
  – A large event space (number of terms)
  – A large number of observations (the collection itself)
  – Goal: keep track of interesting statistics about the events
- Basic approach
  – Mappers generate partial counts
  – Reducers aggregate partial counts

How do we aggregate partial counts efficiently?

First Try: "Pairs"

- Each mapper takes a sentence:
  - Generate all co-occurring term pairs
  - For all pairs, emit (a, b) → count
- Reducers sum up counts associated with these pairs
- Advantages
  - Easy to implement, easy to understand
- Disadvantages
  - Lots of pairs to sort and shuffle around (upper bound?)
  - Not many opportunities for combiners to work

Another Try: "Stripes"

- Idea: group together pairs into an associative array

(a, b) → 1
(a, c) → 2
(a, d) → 5
(a, e) → 3
(a, f) → 2

a → { b: 1, c: 2, d: 5, e: 3, f: 2 }

- Each mapper takes a sentence:
  - Generate all co-occurring term pairs
  - For each term, emit a → { b: $count_b$, c: $count_c$, d: $count_d$ … }
- Reducers perform element-wise sum of associative arrays

a → { b: 1, d: 5, e: 3 }
\+ a → { b: 1, c: 2, d: 2, f: 2 }
a → { b: 2, c: 2, d: 7, e: 3, f: 2 }

Key: cleverly-constructed data structure brings together partial results

“Stripes” Analysis

- Advantages
  - Far less sorting and shuffling of key-value pairs
  - Can make better use of combiners
- Disadvantages
  - More difficult to implement
  - Underlying object more heavyweight
  - Fundamental limitation in terms of size of event space

“Order Inversion”

- Common design pattern
  - Computing relative frequencies requires marginal counts
  - But marginal cannot be computed until you see all counts
  - Buffering is a bad idea!
  - Trick: getting the marginal counts to arrive at the reducer before the joint counts
- Optimizations
  - Apply in-memory combining pattern to accumulate marginal counts
  - Should we apply combiners?

The Debate Starts…

MapReduce: A major step backwards – The Database Column

homes.cs.washington.edu/~billhowe/mapreduce_a_major_step_backwards.html

impac Introducing...antsmanship Pottermore: ...J.K. Rowling Childrens Books Ricardo's wireless NYC PS Gifted Andy Beckett...rdian.co.uk

This is Google's cache of http://databasecolumn.vertica.com/2008/01/mapreduce_a_major_step_back.html. It is a snapshot of the page as it appeared on Sep 27, 2009 00:24:13 GMT. The current page could have changed in the meantime. Learn more

These search terms are highlighted: **search** These terms only appear in links pointing to this page: **hl en&safe off&q** Text-only version

The Database Column
A multi-author blog on database technology and innovation.

MapReduce: A major step backwards

By David DeWitt on January 17, 2008 4:20 PM | Permalink | Comments (44) | TrackBacks (1)
[Note: Although the system attributes this post to a single author, it was written by David J. DeWitt and Michael Stonebraker]

On January 8, a Database Column reader asked for our views on new distributed database research efforts, and we'll begin here with our views on MapReduce. This is a good time to discuss it, since the recent trade press has been filled with news of the revolution of so-called "cloud computing." This paradigm entails harnessing large numbers of (low-end) processors working in parallel to solve a computing problem. In effect, this suggests constructing a data center by lining up a large number of "jelly beans" rather than utilizing a much smaller number of high-end servers.

For example, IBM and Google have announced plans to make a 1,000 processor cluster available to a few select universities to teach students how to program such clusters using a software tool called MapReduce [1]. Berkeley has gone so far as to plan on teaching their freshman how to program using the MapReduce framework.

As both educators and researchers, we are amazed at the hype that the MapReduce proponents have spread about how it represents a paradigm shift in the development of scalable, data-intensive applications. MapReduce may be a good idea for writing certain types of general-purpose computations, but to the database community, it is:

1. A giant step backward in the programming paradigm for large-scale data intensive applications
2. A sub-optimal implementation, in that it uses brute force instead of indexing
3. Not novel at all -- it represents a specific implementation of well known techniques developed nearly 25 years ago
4. Missing most of the features that are routinely included in current DBMS
5. Incompatible with all of the tools DBMS users have come to depend on

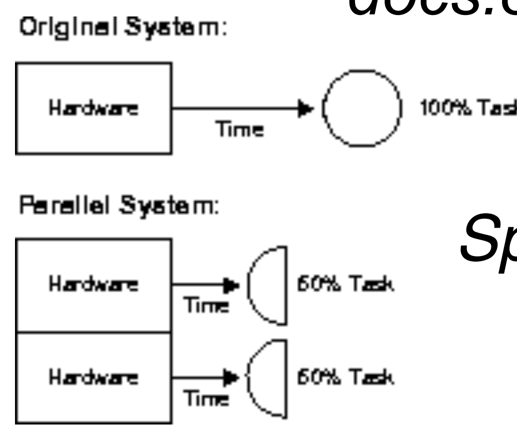
The Debate Continues…

- A comparison of approaches to large-scale data analysis. Pavlo et al., SIGMOD 2009
  - *Parallel DBMS beats MapReduce by a lot!*
  - Many were outraged by the comparison
- MapReduce: A Flexible Data Processing Tool. Dean and Ghemawat, CACM 2010
  - Pointed out inconsistencies and mistakes in the comparison
- MapReduce and Parallel DBMSs: Friends or Foes? Stonebraker et al., CACM 2010
  - Toned down claims…

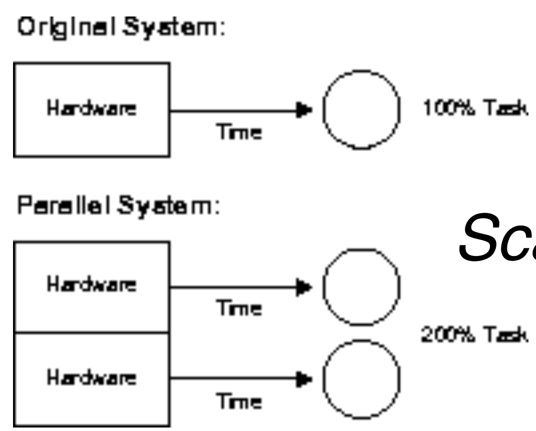
Parallel DBMSs

- Old and mature technology --- late 80's: Gamma, Grace
- Aim to improve performance by executing operations in parallel
- Benefit: easy and cheap to scale
  - Add more nodes, get higher speed
  - Reduce the time to run queries
  - Higher transaction rates
  - Ability to process more data
- Challenge: minimize overheads and efficiently deal with contention

docs.oracle.c



Speedup



Scaleup

Partitioning a Relation across Disks

- If a relation contains only a few tuples which will fit into a single disk block, then assign the relation to a single disk
- Large relations are preferably partitioned across all the available disks
- The distribution of tuples to disks may be **skewed** — that is, some disks have many tuples, while others may have fewer tuples
- Ideal: partitioning should be balanced

Horizontal Data Partitioning

- Relation R split into P chunks R_0, ..., R_{P-1}, stored at the P nodes
- *Round robin:* tuple T_i to chunk (i mod P)
- *Hash based partitioning on attribute A*:
  – Tuple t to chunk h(t.A) mod P
- *Range based partitioning on attribute A*:
  – Tuple t to chunk i if v_{i-1} <t.A< v_i
  – E.g., with a partitioning vector [5,11], a tuple with partitioning attribute value of 2 will go to disk 0, a tuple with value 8 will go to disk 1, while a tuple with value 20 will go to disk 2.

Partitioning in Oracle:

http://docs.oracle.com/cd/B10501_01/server.920/a96524/c12parti.htm

Partitioning in DB2:

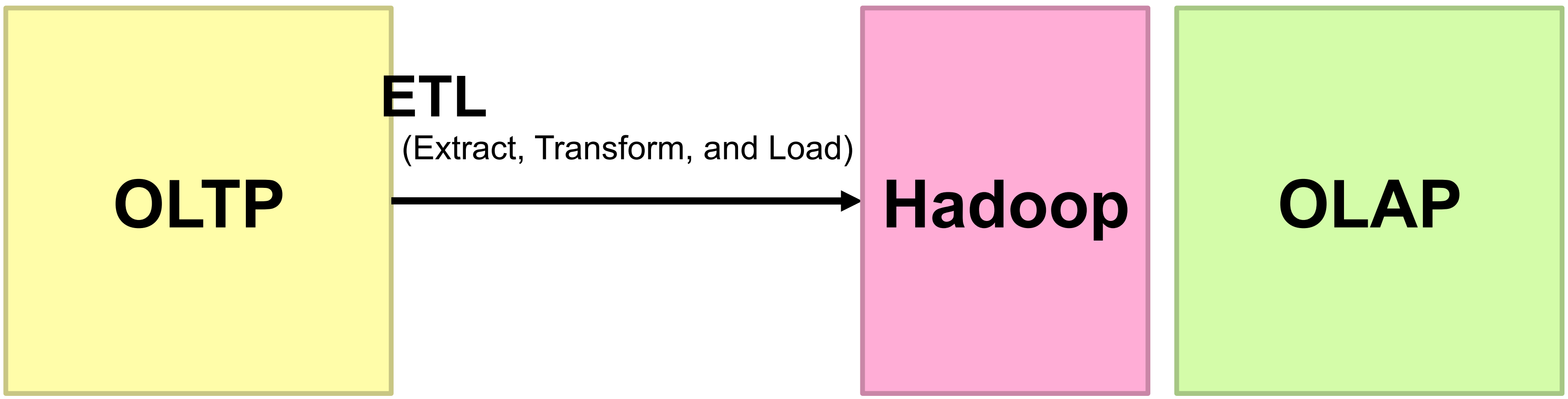
http://www.ibm.com/developerworks/data/library/techarticle/dm-0605ahuja2/

Range Partitioning in DBMSs

```
CREATE TABLE sales_range
(salesman_id  NUMBER(5),
salesman_name VARCHAR2(30),
sales_amount  NUMBER(10),
sales_date    DATE)
PARTITION BY RANGE(sales_date)
(
PARTITION sales_jan2000 VALUES LESS THAN(TO_DATE('02/01/2000','DD/MM/YYYY')),
PARTITION sales_feb2000 VALUES LESS THAN(TO_DATE('03/01/2000','DD/MM/YYYY')),
PARTITION sales_mar2000 VALUES LESS THAN(TO_DATE('04/01/2000','DD/MM/YYYY')),
PARTITION sales_apr2000 VALUES LESS THAN(TO_DATE('05/01/2000','DD/MM/YYYY'))
);
```

```
CREATE TABLE sales_hash
(salesman_id  NUMBER(5),
salesman_name VARCHAR2(30),
sales_amount NUMBER(10),
week_no      NUMBER(2))
PARTITION BY HASH(salesman_id)
PARTITIONS 4
STORE IN (data1, data2, data3, data4);
```

OLTP/OLAP/Hadoop Architecture



Why does this make sense?

Projection in MapReduce

- Easy
  - Map over tuples, emit new tuples with appropriate attributes
  - No reducers, unless for regrouping or resorting tuples
  - Alternatively: perform in reducer, after some other processing

- Basically limited by HDFS streaming speeds
  - Speed of encoding/decoding tuples becomes important
  - Semistructured data? No problem!

- And other relational operations…

Join Algorithms in MapReduce

- Reduce-side join
- Map-side join
- In-memory join

Reduce-Side Join

- Basic idea: group by join key
  - Map over both sets of tuples
  - Emit tuple as value with **join key as the intermediate key**
  - Execution framework brings together tuples sharing the same key
  - Perform actual join in reducer
  - Similar to a "sort-merge join" in database terminology
- Two variants
  - 1-to-1 joins
  - 1-to-many and many-to-many joins

Map-Side Join: Parallel Scans

- If datasets are sorted by join key, join can be accomplished by a scan over both datasets
- How can we accomplish this in parallel?
  - Partition and sort both datasets in the same manner
- In MapReduce:
  - Map over one dataset, read from other corresponding partition
  - No reducers necessary (unless to repartition or resort)
- Consistently partitioned datasets: realistic to expect?
  - Depends on the workflow
  - For ad hoc data analysis, reduce-side are more general, although less efficient

In-Memory Join

- Basic idea: load one dataset into memory, stream over other dataset
  - Works if R << S and R fits into memory
  - Called a “hash join” in database terminology
- MapReduce implementation
  - Distribute R to all nodes
  - Map over S, each mapper loads R in memory, hashed by join key
  - For every tuple in S, look up join key in R
  - No reducers, unless for regrouping or resorting tuples

Need for High-Level Languages

- Hadoop is great for large-data processing!
  – But writing Java programs for everything is verbose and slow
  – Not everyone wants to (or can) write Java code
- Solution: develop higher-level data processing languages
  – Hive: HQL is like SQL
  – Pig: Pig Latin is a bit like Perl

Hive and Pig

- Hive: data warehousing application in Hadoo
  - Query language is HQL, variant of SQL
  - Tables stored on HDFS as flat files
  - Developed by Facebook, now open source
- Pig: large-scale data processing system
  - Scripts are written in Pig Latin, a dataflow language
  - Developed by Yahoo!, now open source
  - Roughly 1/3 of all Yahoo! internal jobs

- Common idea:
  - Provide higher-level language to facilitate large-data processing
  - Higher-level language “compiles down” to Hadoop jobs

Association Rule Discovery

Supermarket shelf management:

•**Goal:** Identify items that are bought together by sufficiently many customers – the *frequent itemsets*

–Items that co-occur more frequently than would be expected were the item bought independently

–Bread + milk is not surprising…

–Hot dogs + mustard is not surprising either, but supermarkets can do clever marketing: hot dogs on sale and

TID	*Items*
1	**Bread, Coke, Milk**
2	**Beer, Bread**
3	**Beer, Coke, Diaper, Milk**
4	**Beer, Bread, Diaper, Milk**
5	**Coke, Diaper, Milk**

The Market-Basket Model

- A large set of *items*, e.g., things sold in a supermarket
  – $I = \{i_1, i_2, \ldots, i_m\}$
- A large set of *baskets/ transactions*, e.g., the things one customer buys on one day
  – t a set of items, and $t \subseteq I$.
- Transaction Database T: a set of transactions $T = \{t_1, t_2, \ldots, t_n\}$.

TID	*Items*
1	**Bread, Coke, Milk**
2	**Beer, Bread**
3	**Beer, Coke, Diaper, Milk**
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5	**Coke, Diaper, Milk**

Frequent Itemsets

- Simplest question: find sets of items that appear "frequently" in the baskets.
- *Support* for itemset *I* = the number of baskets containing all items in *I*.
  - Often expressed as a fraction of the total number of baskets
- Given a *support threshold* *s*, sets of items that appear in at least *s* baskets are called *frequent itemsets*.

Support of {Beer, Bread} = 2

TID	*Items*
1	**Bread, Coke, Milk**
2	**Beer, Bread**
3	**Beer, Coke, Diaper, Milk**
4	**Beer, Bread, Diaper, Milk**
5	**Coke, Diaper, Milk**

Association Rules

- If-then rules about the contents of baskets.
- $\{i_1, i_2,\ldots,i_k\} \rightarrow j$ means: "if a basket contains all of $i_1,\ldots,i_k$ then it is *likely* to contain j."
- *Confidence* of this association rule is the probability of j given $i_1,\ldots,i_k$.

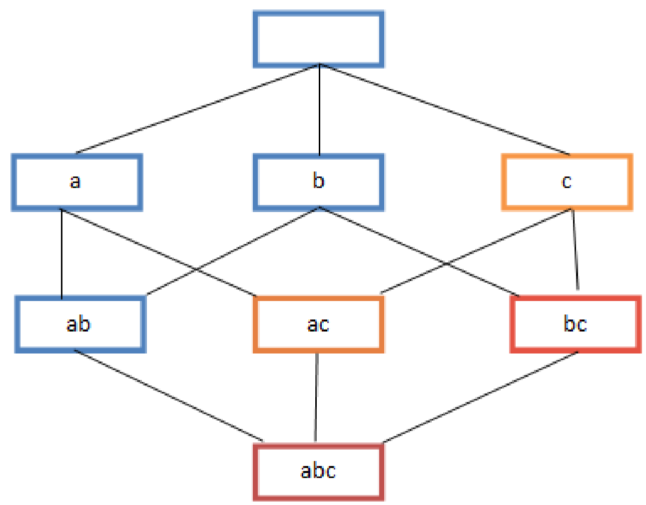
$$\mathrm{conf}(I \rightarrow j) = \frac{\mathrm{support}(I \cup j)}{\mathrm{support}(I)}$$

Details of Main-Memory Counting

- Two approaches:
  1. Count all pairs, using a triangular matrix.
  2. Keep a table of triples [*i*, *j*, *c*] = "the count of the pair of items {*i*, *j* } is *c*."
- (1) requires only 4 bytes/pair.
  - Note: always assume integers are 4 bytes.
- (2) requires 12 bytes, but only for those pairs with count > 0.

A-Priori Algorithm – (1)

- A two-pass approach called *a-priori* limits the need for main memory.
- Key idea: *monotonicity* : if a set of items appears at least *s* times, so does every subset.
- Contrapositive for pairs: if item *i* does not appear in *s* baskets, then
can appear in *s* baskets.



Association Rules: Not enough memory

- Counting for candidates C2 requires a lot of memory -- $O(n^2)$
- Can we do better?
- *PCY*: In pass 1, there is a lot of memory left, leverage that to help with pass 2
  - Maintain a hash table with as many buckets as fit in memory
  - Keep count for each bucket into which pairs of items are hashed
    - Just the count, not the pairs!
- *Multistage* improves PCY

Other Algorithms

- Random
- SON – for mapreduce

Three Essential Techniques for Similar Documents

1. When the sets are so large or so many that they cannot fit in main memory.
2. Or, when there are so many sets that comparing all pairs of sets takes too much time.
3. Or both.

Three Essential Techniques for Similar Documents

1. *Shingling* : convert documents, emails, etc., to sets.
2. *Minhashing* : convert large sets to short signatures, while preserving similarity.
3. *Locality-sensitive hashing* : focus on pairs of signatures likely to be similar.

Also covered similarity metrics

Some Graph Problems

- Finding shortest paths
  - Routing Internet traffic and UPS trucks
- Finding minimum spanning trees
  - Telco laying down fiber
- Finding Max Flow
  - Airline scheduling
- Identify “special” nodes and communities
  - Breaking up terrorist cells, spread of avian flu
- Bipartite matching
  - Monster.com, Match.com
- And of course... PageRank

How to scale?

Graphs and MapReduce

- Graph algorithms typically involve:
  - Performing computations at each node: based on node features, edge features, and local link structure
  - Propagating computations: “traversing” the graph
- Generic recipe:
  - Represent graphs as adjacency lists
  - Perform local computations in mapper
  - Pass along partial results via outlinks, keyed by destination node
  - Perform aggregation in reducer on inlinks to a node
  - Iterate until convergence: controlled by external “driver”
  - Don’t forget to pass the graph structure between iterations

Efficient Graph Algorithms

- Runtime dominated by copying intermediate data across the network
- Sparse vs. dense graphs
  – MapReduce algorithms are often impractical for dense graphs
- Optimization is possible through the use of in-mapper combiners
  – E.g., in parallel BFS, compute the min in mapper
  – Only useful if nodes pointed to by multiple nodes are processed by the same map task
  – Maximize opportunities for local aggregation
    - Simple tricks: sorting the dataset in specific ways

Alternatives to MapReduce

- MapReduce is not suitable for applications that re-use a working data set across multiple parallel operations
- A number of alternative approaches have been proposed:
  - Twister
  - Spark
  - Pregel
  - Haloop