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CS 4604: Introduction to Database Management Systems

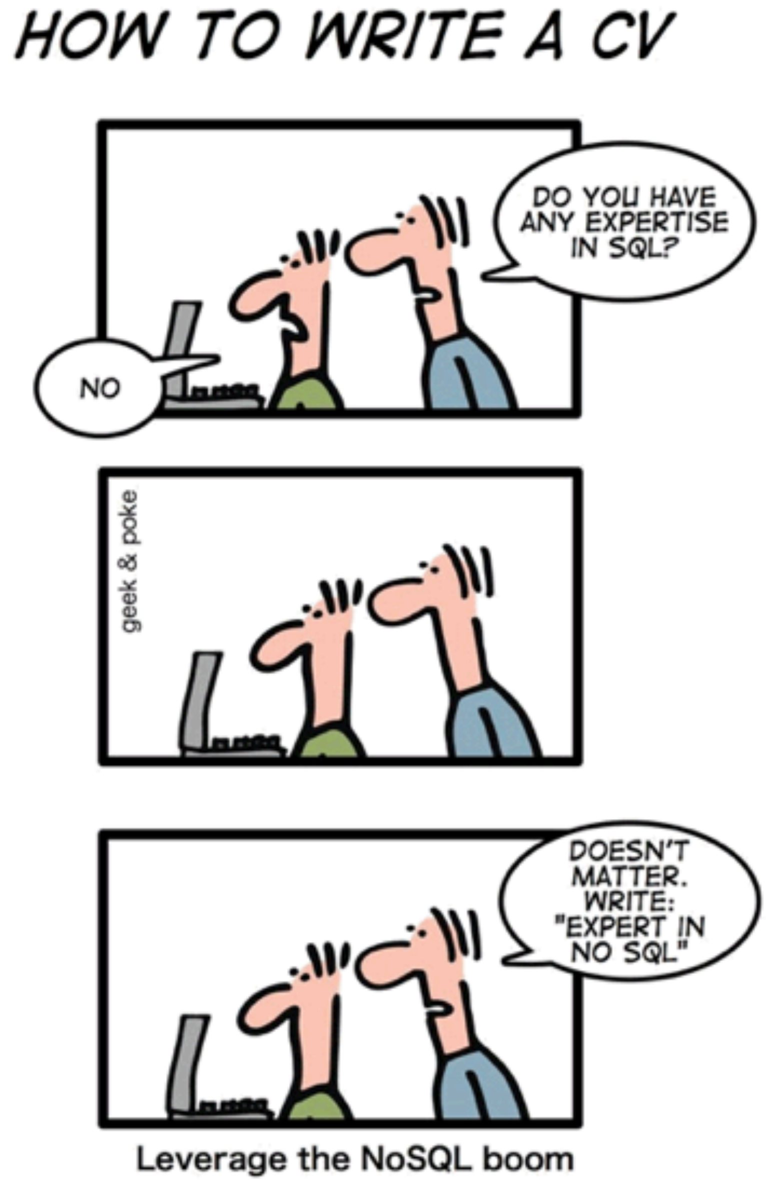
B. Aditya Prakash

Lecture #12: NoSQL and MapReduce

(some slides from Xiao Yu)

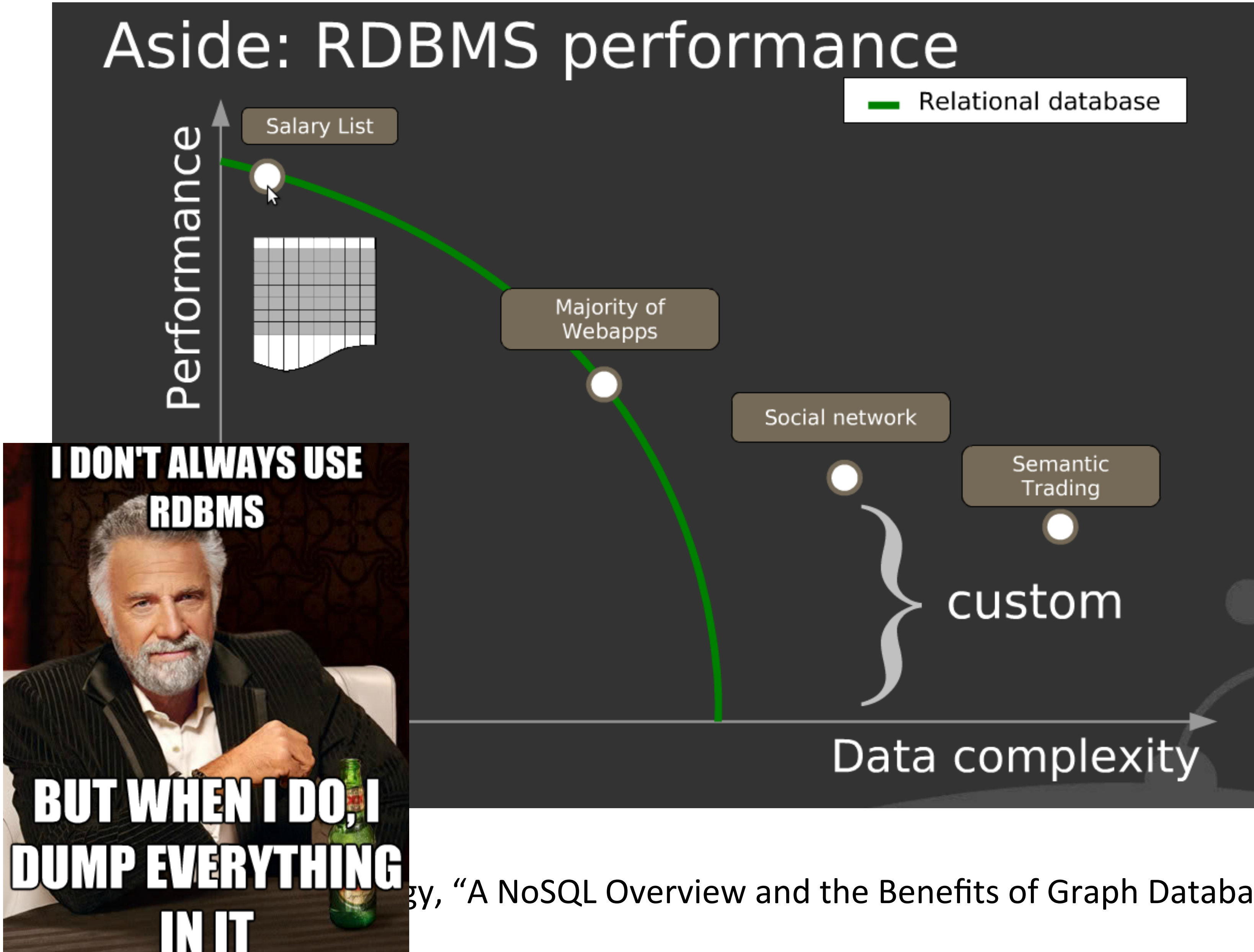
NO SQL

Why No SQL?


HOW TO WRITE A CV
DO YOU HAVE ANY EXPERTISE IN SQL?
NO
geek & poke
DOESN'T MATTER. WRITE: "EXPERT IN NO SQL"
Leverage the NoSQL boom

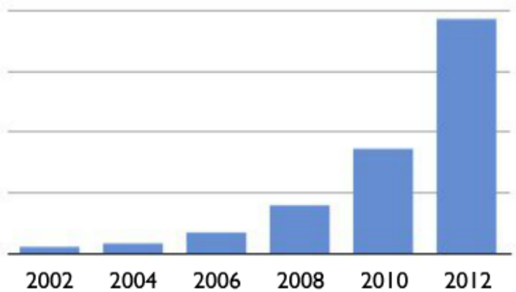
RDBMS

- The predominant choice in storing data
  - Not so true for data miners since we much in txt files.
- First formulated in 1969 by Codd
  - We are using RDBMS everywhere



gy, “A NoSQL Overview and the Benefits of Graph Databases"

When RDBMS met Web 2.0

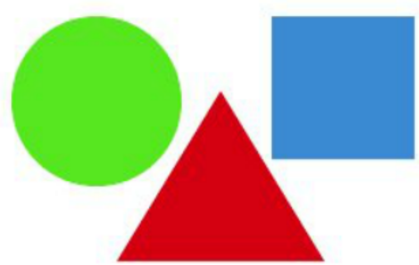


Big data

Connectivity

P2P Knowledge

Concurrency



Diversity

Cloud-Grid

Slide from Lorenzo Alberton, "NoSQL Databases: Why, what and when"

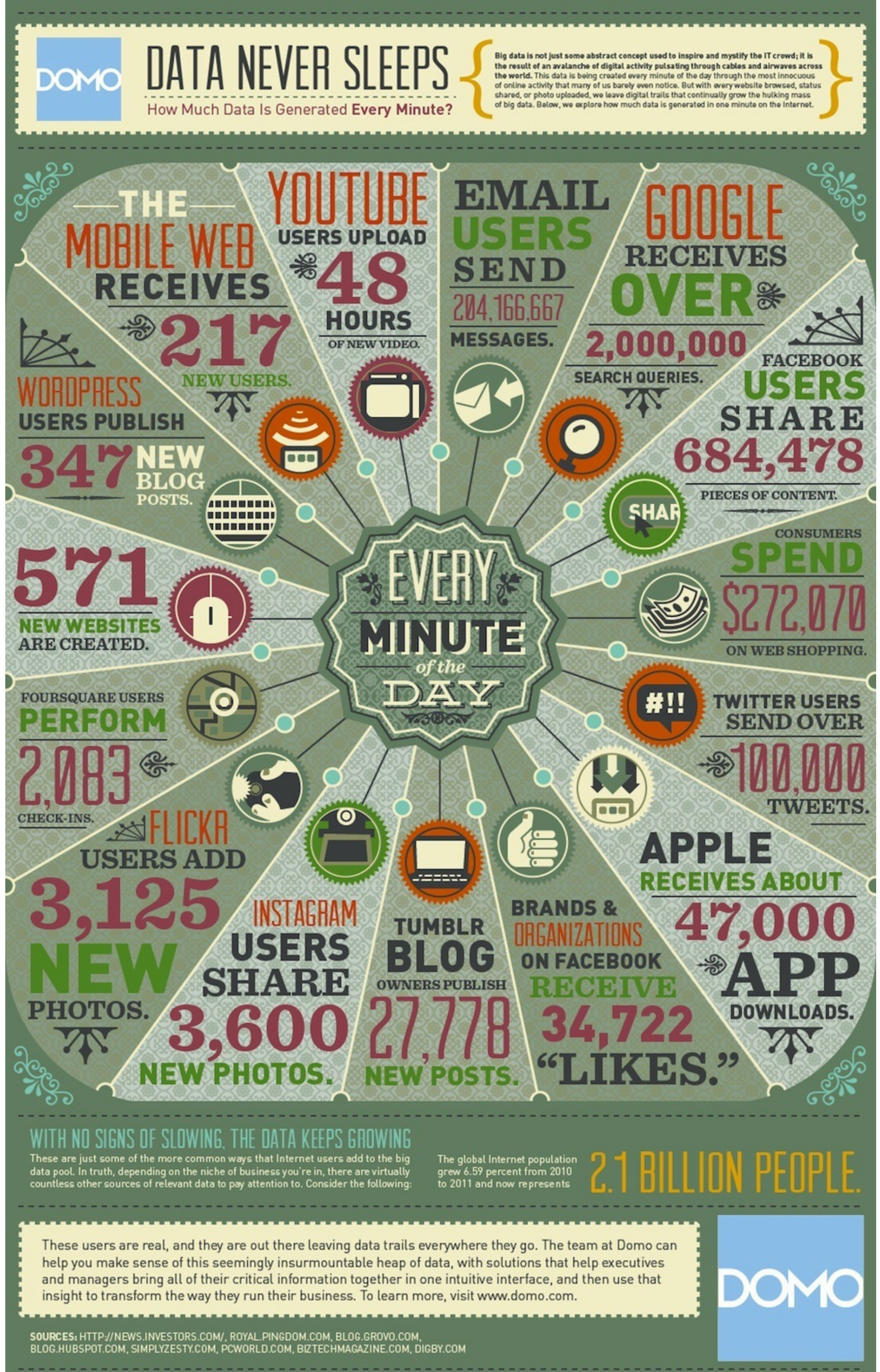
What to do if data is really large?

- Peta-bytes (exabytes, zettabytes …..)

- Google processed 24 PB of data per day (2009)
- FB adds 0.5 PB per day

BIG

data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DATA NEVER SLEEPS
How Much Data Is Generated Every Minute?
Big data is not just some abstract concept used to inspire and mystify the IT crowd; it is the result of an avalanche of digital activity pulsating through cables and airwaves across the world. This data is being created every minute of the day through the most innocuous of online activity that many of us barely even notice. But with every website browsed, status shared, or photo uploaded, we leave digital trails that continually grow the hulking mass of big data. Below, we explore how much data is generated in one minute on the Internet.
THE MOBILE WEB RECEIVES 217 NEW USERS.
YOUTUBE USERS UPLOAD 48 HOURS OF NEW VIDEO.
EMAIL USERS SEND 204,166,667 MESSAGES.
GOOGLE RECEIVES OVER 2,000,000 SEARCH QUERIES.
FACEBOOK USERS SHARE 684,478 PIECES OF CONTENT.
WORDPRESS USERS PUBLISH 347 NEW BLOG POSTS.
571 NEW WEBSITES ARE CREATED.
CONSUMERS SPEND $272,070 ON WEB SHOPPING.
EVERY MINUTE of the DAY
FOURSQUARE USERS PERFORM 2,083 CHECK-INS.
TWITTER USERS SEND OVER 100,000 TWEETS.
FLICKR USERS ADD 3,125 NEW PHOTOS.
APPLE RECEIVES ABOUT 47,000 APP DOWNLOADS.
INSTAGRAM USERS SHARE 3,600 NEW PHOTOS.
TUMBLR BLOG OWNERS PUBLISH 27,778 NEW POSTS.
BRANDS & ORGANIZATIONS ON FACEBOOK RECEIVE 34,722 "LIKES."
WITH NO SIGNS OF SLOWING, THE DATA KEEPS GROWING
These are just some of the more common ways that Internet users add to the big data pool. In truth, depending on the niche of business you're in, there are virtually countless other sources of relevant data to pay attention to. Consider the following:
The global Internet population grew 6.59 percent from 2010 to 2011 and now represents 2.1 BILLION PEOPLE.
These users are real, and they are out there leaving data trails everywhere they go. The team at Domo can help you make sense of this seemingly insurmountable heap of data, with solutions that help executives and managers bring all of their critical information together in one intuitive interface, and then use that insight to transform the way they run their business. To learn more, visit www.domo.com.
SOURCES: HTTP://NEWS.INVESTORS.COM/, ROYAL.PINGDOM.COM, BLOG.GROVO.COM, BLOG.HUBSPOT.COM, SIMPLYZESTY.COM, PCWORLD.COM, BIZTECHMAGAZINE.COM, DIGBY.COM
DOMO

What's Wrong with Relational DB?

- Nothing is wrong. You just need to use the right tool.
- Relational is hard to scale.
  - Easy to scale reads
  - Hard to scale writes

What's NoSQL?

- The misleading term "NoSQL" is short for "Not Only SQL".
- non-relational, schema-free, non-(quite)-ACID
  – More on ACID transactions later in class
- horizontally scalable, distributed, easy replication support
- simple API

Four (emerging) NoSQL Categories

- Key-value (K-V) stores
  - Based on Distributed Hash Tables/ Amazon's Dynamo paper *
  - Data model: (global) collection of K-V pairs
  - Example: Voldemort
- Column Families
  - BigTable clones **
  - Data model: big table, column families
  - Example: HBase, Cassandra, Hypertable

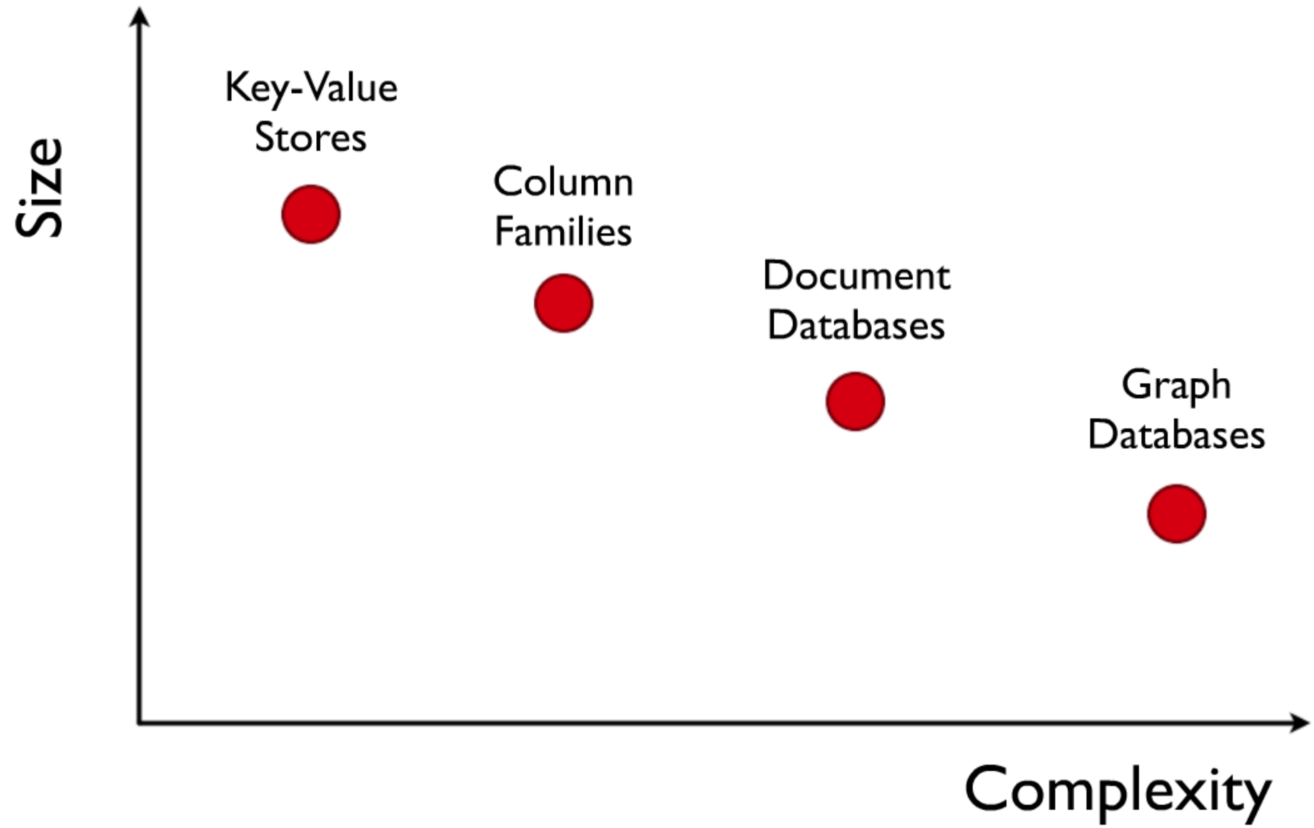
*G DeCandia et al, Dynamo: Amazon's Highly Available Key-value Store, SOSP 07

** F Chang et al, Bigtable: A Distributed Storage System for Structured Data, OSDI 06

Four (emerging) NoSQL Categories

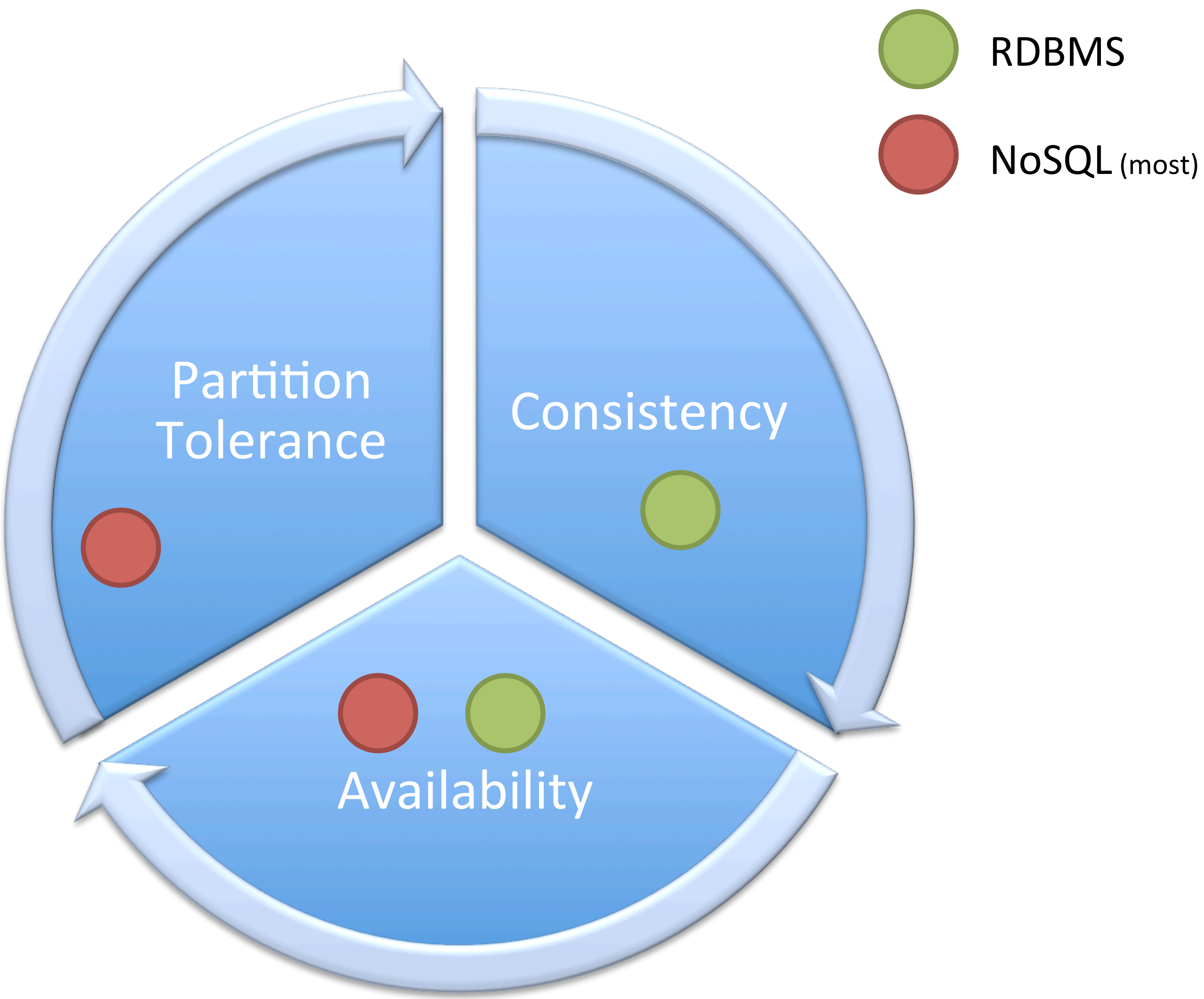
- Document databases
  – Inspired by Lotus Notes
  – Data model: collections of K-V Collections
  – Example: CouchDB, MongoDB
- Graph databases
  – Inspired by Euler & graph theory
  – Data model: nodes, relations, K-V on both
  – Example: AllegroGraph, VertexDB, Neo4j

Focus of Different Data Models



Slide from neo technology, “A NoSQL Overview and the Benefits of Graph Databases"

C-A-P "theorem"


RDBMS
NoSQL (most)
Partition Tolerance
Consistency
Availability

When to use NoSQL?

- Bigness
- Massive write performance
  - Twitter generates 7TB / per day (2010)
- Fast key-value access
- Flexible schema or data types
- Schema migration
- Write availability
  - Writes need to succeed no matter what (CAP, partitioning)
- Easier maintainability, administration and operations
- No single point of failure
- Generally available parallel computing
- Programmer ease of use
- Use the right data model for the right problem
- Avoid hitting the wall
- Distributed systems support
- Tunable CAP tradeoffs

from http://highscalability.com/

Key-Value Stores

id	hair_color	age	height
1923	Red	18	6’0”
3371	Blue	34	NA
…	…	…	…

Table in relational db

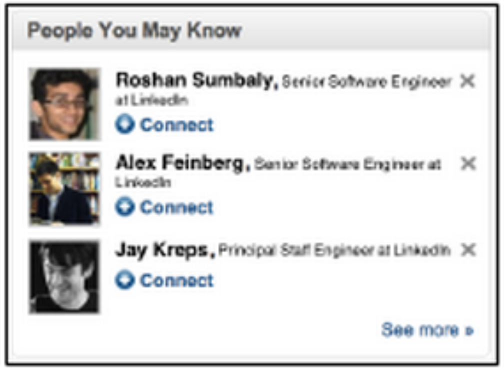
user1923_color	Red
user1923_age	18
user3371_color	Blue
user4344_color	Brackish
user1923_height	6' 0"
user3371_age	34

Store/Domain in Key-Value db

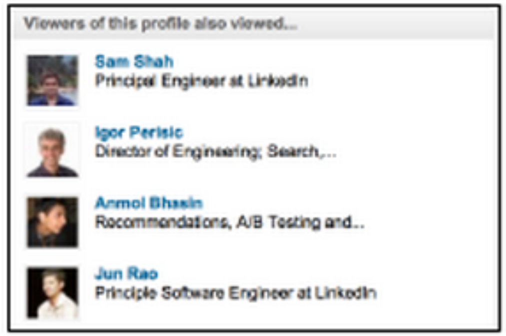
Find users whose age is above 18?
Find all attributes of user 1923?
Find users whose hair color is Red and age is 19?
(Join operation) Calculate average age of all grad students?

Voldemort in LinkedIn

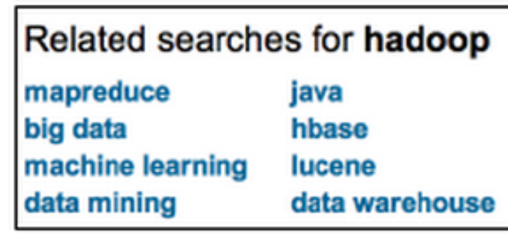
People You May Know



Viewers of this profile also viewed



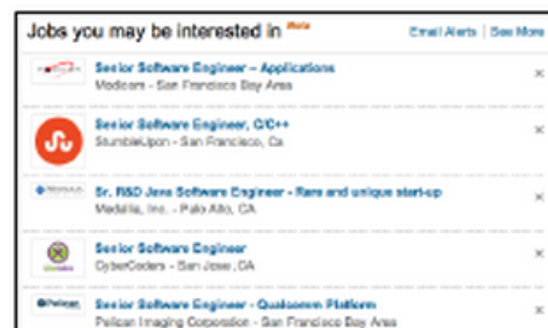
Related Searches



Events you may be interested in

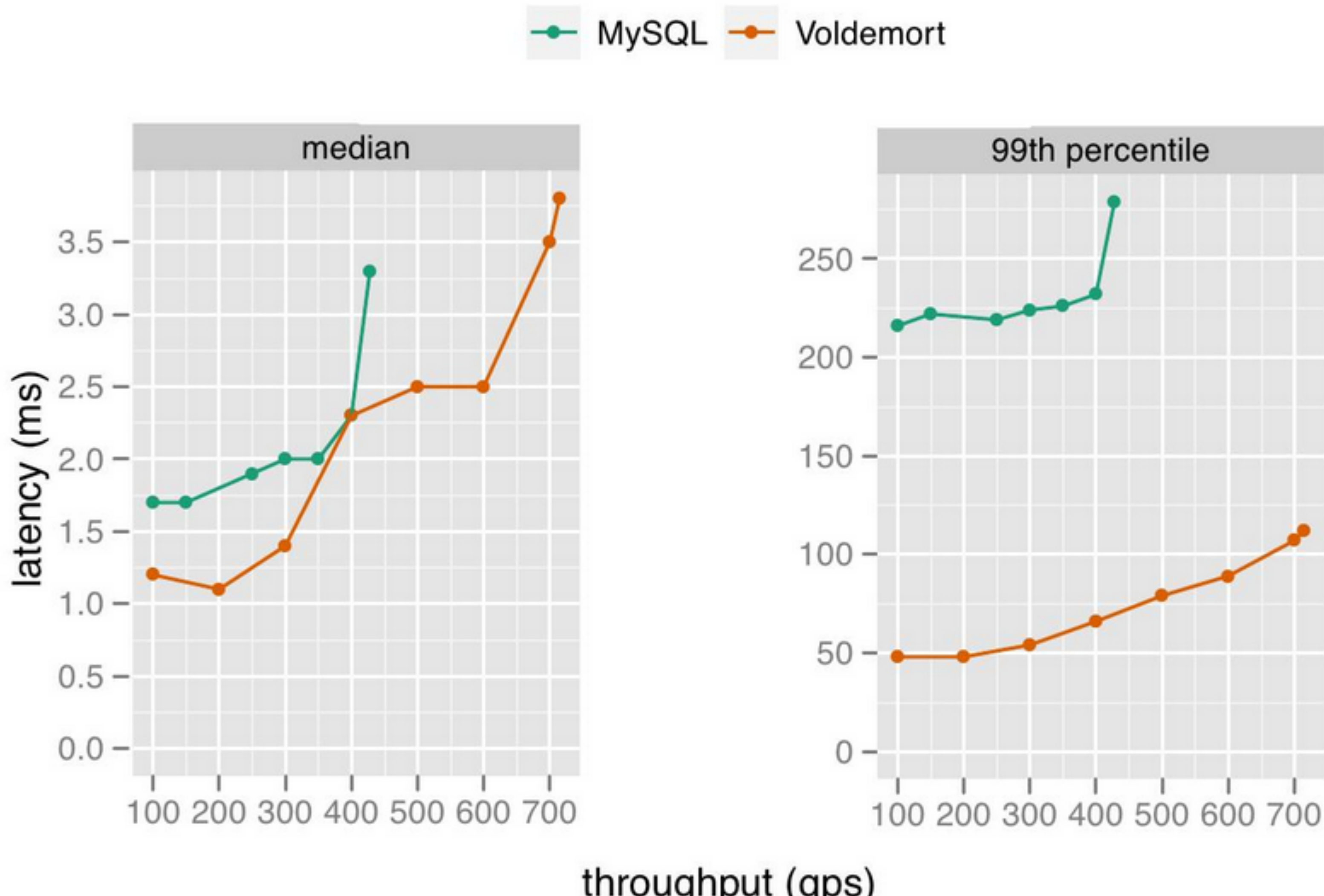
LinkedIn Skills

Jobs you may be interested in



Sid Anand, LinkedIn Data Infrastructure (QCon London 2012)

Voldemort vs MySQL



Sid Anand, LinkedIn Data Infrastructure (QCon London 2012)

Column Families – BigTable like

Sparse, distributed, persistent multi-dimensional sorted map indexed by (*row_key*, *column_key*, *timestamp*)

F Chang, et al, Bigtable: A Distributed Storage System for Structured Data, osdi 06

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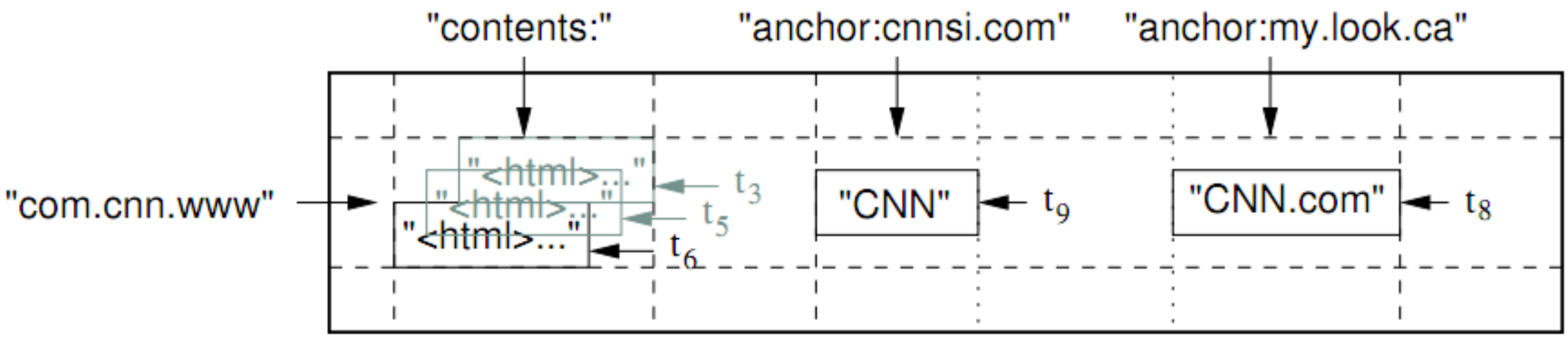
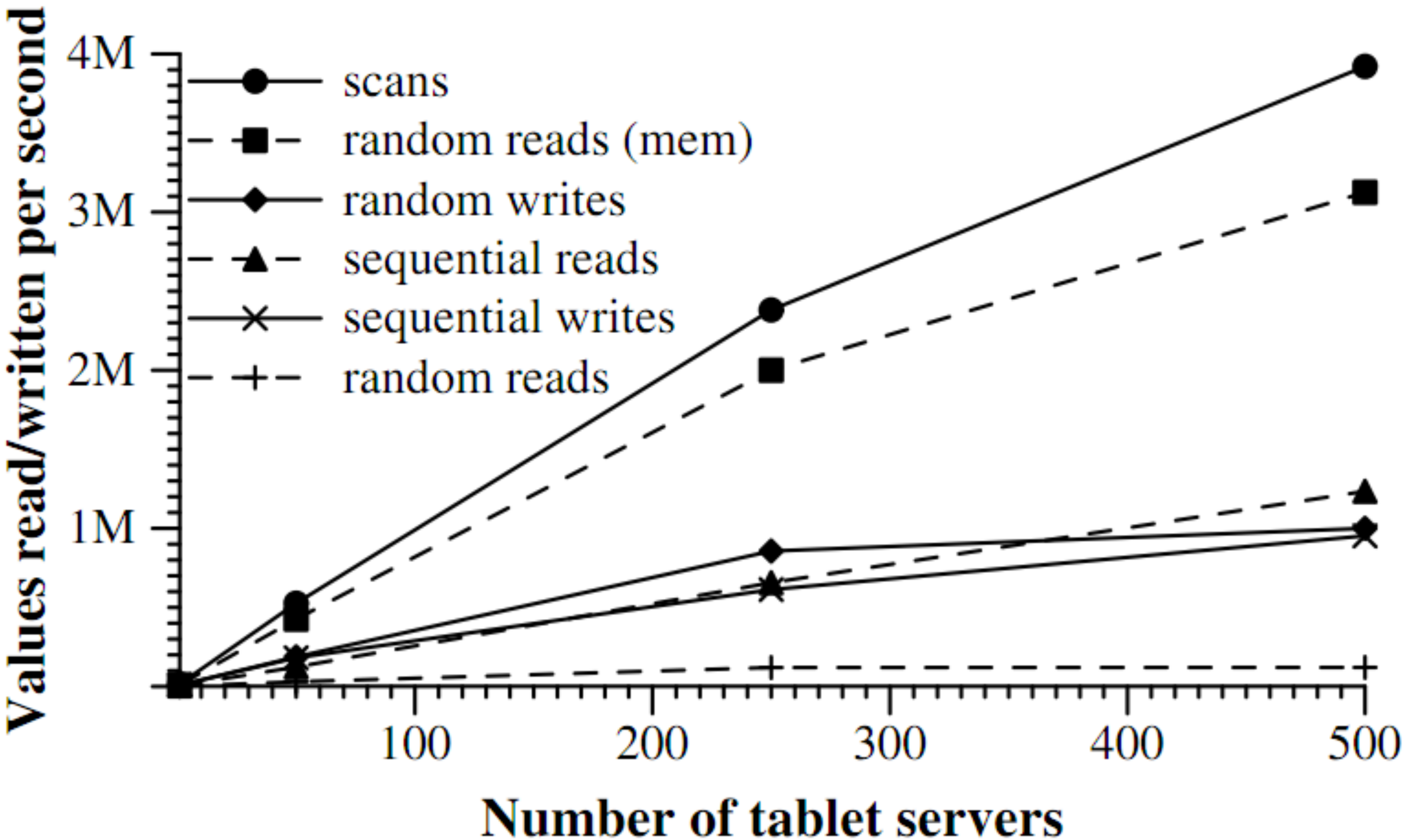
BigTable Data Model



The row name is a reversed URL. The contents column family contains the page contents, and the anchor column family contains the text of any anchors that reference the page.

BigTable Performance



Document Database - mongoDB

Last Name	First Name	Age
DUMONT	Jean	43
PELLERIN	Franck	29
MATTHIEU	Nicolas	51

Table in relational db

```
{
    "_id": ObjectId("4efa8d2b7d284dad101e4bc9"),
    "Last Name": "DUMONT",
    "First Name": "Jean",
    "Age": 43
},
{
    "_id": ObjectId("4efa8d2b7d284dad101e4bc7"),
    "Last Name": "PELLERIN",
    "First Name": "Franck",
    "Age": 29,
    "Address": "1 chemin des Loges",
    "City": "VERSAILLES"
}
```

Documents in a collection

Initial release 2009

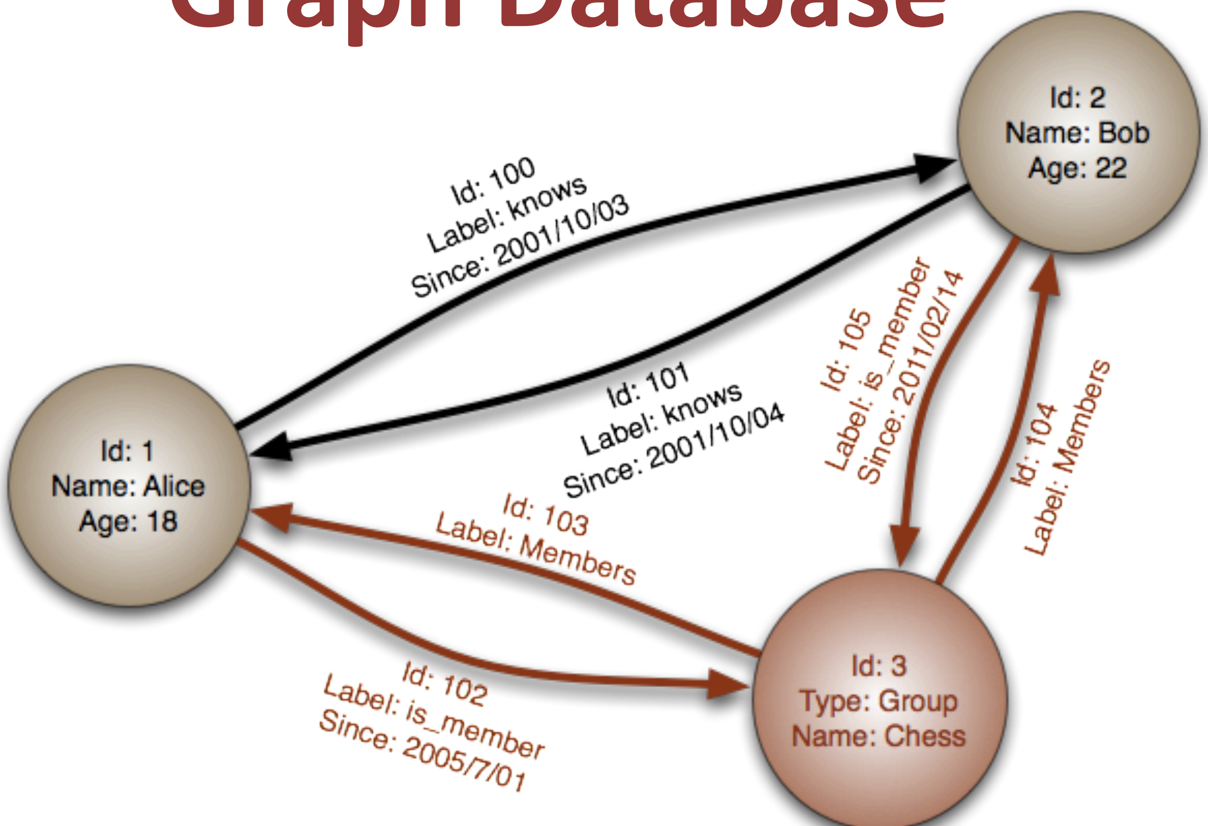
Open source, document db
Json-like document with dynamic schema

mongoDB Product Deployment

the national archives
Pinterest
Springer science+business media
ACTIVESPHERE
淘宝网 Taobao.com
about.me
ATHENA CAPITAL RESEARCH
GLOBAL ADVERTISERS
agentstorm
AdMaster Digital Consulting
bit.ly
The New York Times
sourceforge
github SOCIAL CODING
bump TECHNOLOGIES
Buzzers
Grooveshark
GILT GROUPE
SAP
EA
BuzzFeed
Doodle
foursquare
Disney
Forbes
Eventbrite Events Made Easy
CNN TÜRK .com
craigslist

And much more…

Graph Database



Data Model Abstraction:

- Nodes
- Relations
- Properties

Neo4j - Build a Graph

```
NeoService neo = ... // Get factory


// Create Thomas 'Neo' Anderson
Node mrAnderson = neo.createNode();
mrAnderson.setProperty( "name", "Thomas Anderson" );
mrAnderson.setProperty( "age", 29 );

// Create Morpheus
Node morpheus = neo.createNode();
morpheus.setProperty( "name", "Morpheus" );
morpheus.setProperty( "rank", "Captain" );
morpheus.setProperty( "occupation", "Total bad ass" );

// Create a relationship representing that they know each other
mrAnderson.createRelationshipTo( morpheus, RelTypes.KNOWS );
// ...create Trinity, Cypher, Agent Smith, Architect similarly
```

Slide from neo technology, “A NoSQL Overview and the Benefits of Graph Databases"

A Debatable Performance Evaluation

Conclusion

- Use the right data model for the right problem

THE HADOOP ECOSYSTEM

Prakash 2016

Single vs Cluster

- 4TB HDDs are coming out
- Cluster?
  - How many machines?
  - Handle machine and drive failure
  - Need redundancy, backup..

3% of 100K HDDs fail in <= 3 months

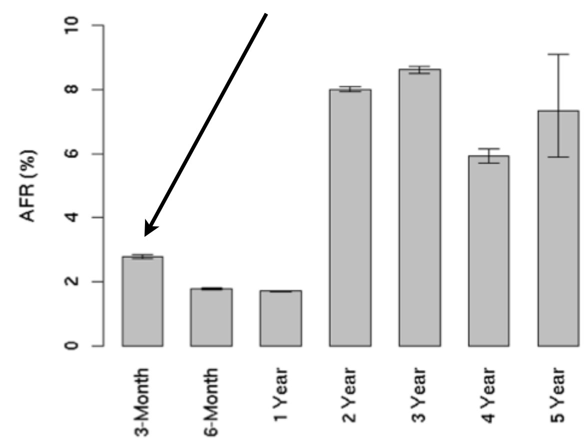


Figure 2: Annualized failure rates broken down by age groups

http://static.googleusercontent.com/external_content/untrusted_dlcp/research.google.com/en/us/archive/disk_failures.pdf

Hadoop

- Open source software
  - Reliable, scalable, distributed computing

- Can handle thousands of machines
- Written in JAVA
- A simple programming model
- HDFS (Hadoop Distributed File System)
  - Fault tolerant (can recover from failures)

Idea and Solution

- **Issue: Copying data over a network takes time**
- **Idea:**
  - Bring computation close to the data
  - Store files multiple times for reliability
- **Map-reduce** addresses these problems
  - Google's computational/data manipulation model
  - Elegant way to work with big data
  - **Storage Infrastructure – File system**
    - Google: GFS. Hadoop: HDFS
  - **Programming model**
    - Map-Reduce

Map-Reduce [Dean and Ghemawat 2004]

- Abstraction for simple computing
  - Hides details of parallelization, fault-tolerance, data-balancing
  - MUST Read!

http://static.googleusercontent.com/media/research.google.com/en/us/archive/mapreduce-osdi04.pdf

Hadoop VS NoSQL

- Hadoop: computing framework
  - Supports data-intensive applications
  - Includes MapReduce, HDFS etc.

    (we will study MR mainly next)

- NoSQL: Not only SQL databases
  - Can be built ON hadoop. E.g. HBase.

Storage Infrastructure

- **Problem:**
  - If nodes fail, how to store data persistently?
- **Answer:**
  - **Distributed File System:**
    - Provides global file namespace
    - Google GFS; Hadoop HDFS;
- **Typical usage pattern**
  - Huge files (100s of GB to TB)
  - Data is rarely updated in place
  - Reads and appends are common

Distributed File System

- Chunk servers
  - File is split into contiguous chunks
  - Typically each chunk is 16-64MB
  - Each chunk replicated (usually 2x or 3x)
  - Try to keep replicas in different racks
- Master node
  - a.k.a. Name Node in Hadoop's HDFS
  - Stores metadata about where files are stored
  - Might be replicated
- Client library for file access
  - Talks to master to find chunk servers
  - Connects directly to chunk servers to access data

Programming Model: MapReduce

Warm-up task:

- We have a huge text document
- Count the number of times each distinct word appears in the file
- **Sample application:**
  – Analyze web server logs to find popular URLs

Task: Word Count

Case 1:

- File too large for memory, but all <word, count> pairs fit in memory

Case 2:

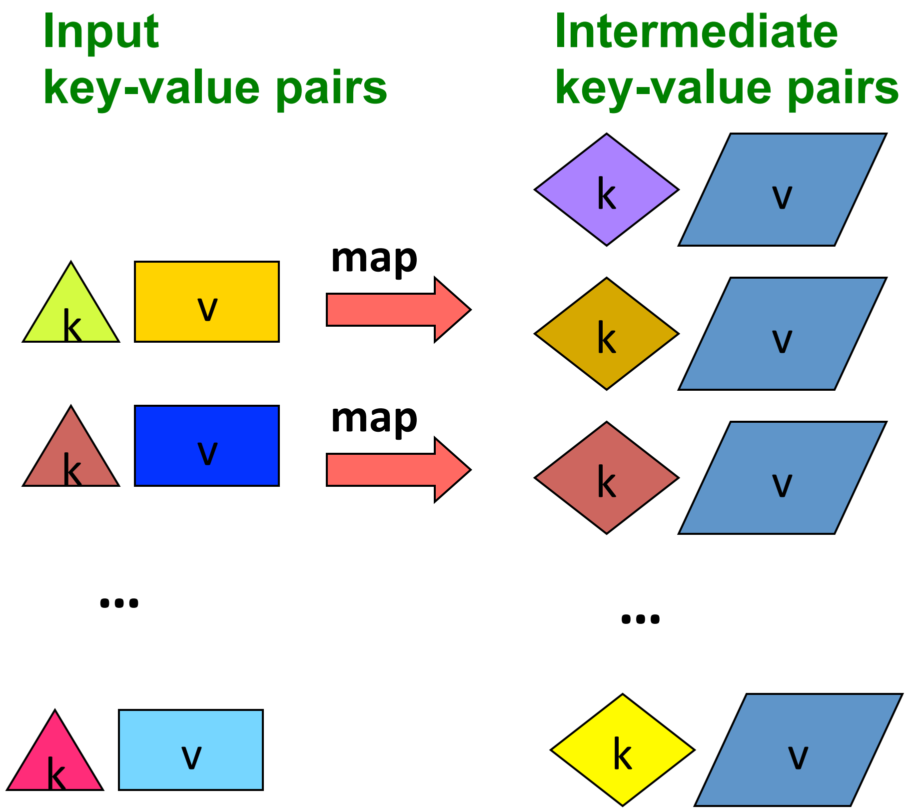
- Count occurrences of words:
  - `words(doc.txt) | sort | uniq -c`
    - where **`words`** takes a file and outputs the words in it, one per a line
- Case 2 captures the essence of **MapReduce**
  - Great thing is that it is naturally parallelizable

MapReduce: Overview

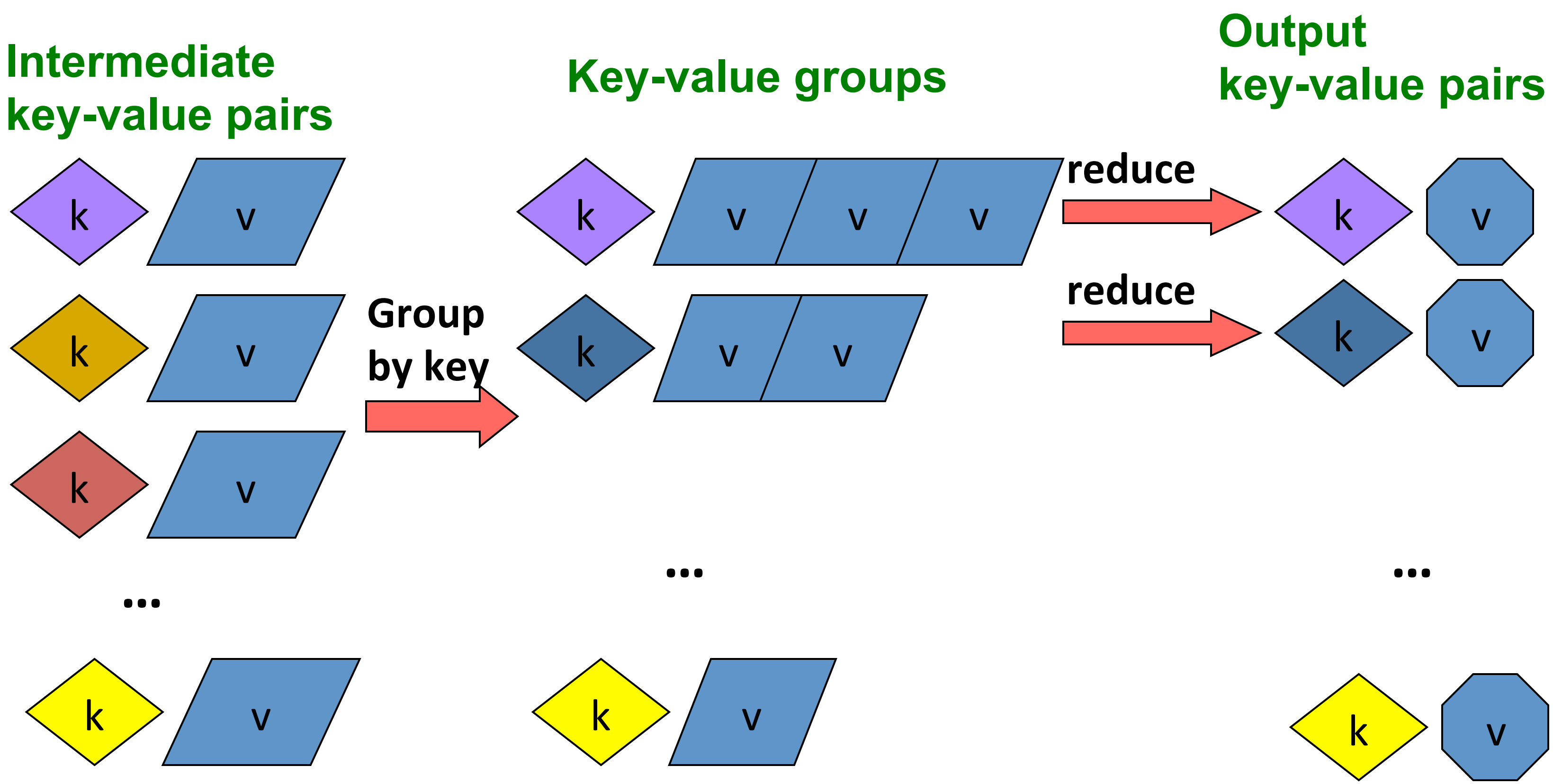
- Sequentially read a lot of data
- **Map:**
  - Extract something you care about
- **Group by key:** Sort and Shuffle
- **Reduce:**
  - Aggregate, summarize, filter or transform
- Write the result

Outline stays the same, **Map** and **Reduce** change to fit the problem

MapReduce: The Map Step



MapReduce: The Reduce Step



More Specifically

- **Input:** a set of key-value pairs
- Programmer specifies two methods:
  - **Map(k, v)** → <k', v'>*
    - Takes a key-value pair and outputs a set of key-value pairs
      - E.g., key is the filename, value is a single line in the file
    - There is one Map call for every *(k,v)* pair
  - **Reduce(k', <v'>*)** → <k', v''>*
    - **All values *v'* with same key *k'* are reduced together and processed in *v'* order**
    - There is one Reduce function call per unique key *k'*

MapReduce: Word Counting

Provided by the programmer

MAP:
Read input and produces a set of key-value pairs

Group by key:
Collect all pairs with same key

Provided by the programmer

Reduce:
Collect all values belonging to the key and output

The crew of the space shuttle Endeavor recently returned to Earth as ambassadors, harbingers of a new era of space exploration. Scientists at NASA are saying that the recent assembly of the Dextre bot is the first step in a long-term space-based man/mache partnership. '"The work we're doing now -- the robotics we're doing -- is what we're going to need ……………………..

Big document

(The, 1)
(crew, 1)
(of, 1)
(the, 1)
(space, 1)
(shuttle, 1)
(Endeavor, 1)
(recently, 1)
….

(key, value)

(crew, 1)
(crew, 1)
(space, 1)
(the, 1)
(the, 1)
(the, 1)
(shuttle, 1)
(recently, 1)
…

(key, value)

(crew, 2)
(space, 1)
(the, 3)
(shuttle, 1)
(recently, 1)
…

(key, value)

Only sequential reads

Word Count Using MapReduce

```
map(key, value):
// key: document name; value: text of the document
   for each word w in value:
    emit(w, 1)


reduce(key, values):
// key: a word; value: an iterator over counts
    result = 0
    for each count v in values:
        result += v
    emit(key, result)
```

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Map-Reduce (MR) as SQL

- select count(*) ← **Reducer**

  from DOCUMENT

  group by word

Mapper

Map-Reduce: Environment

Map-Reduce environment takes care of:

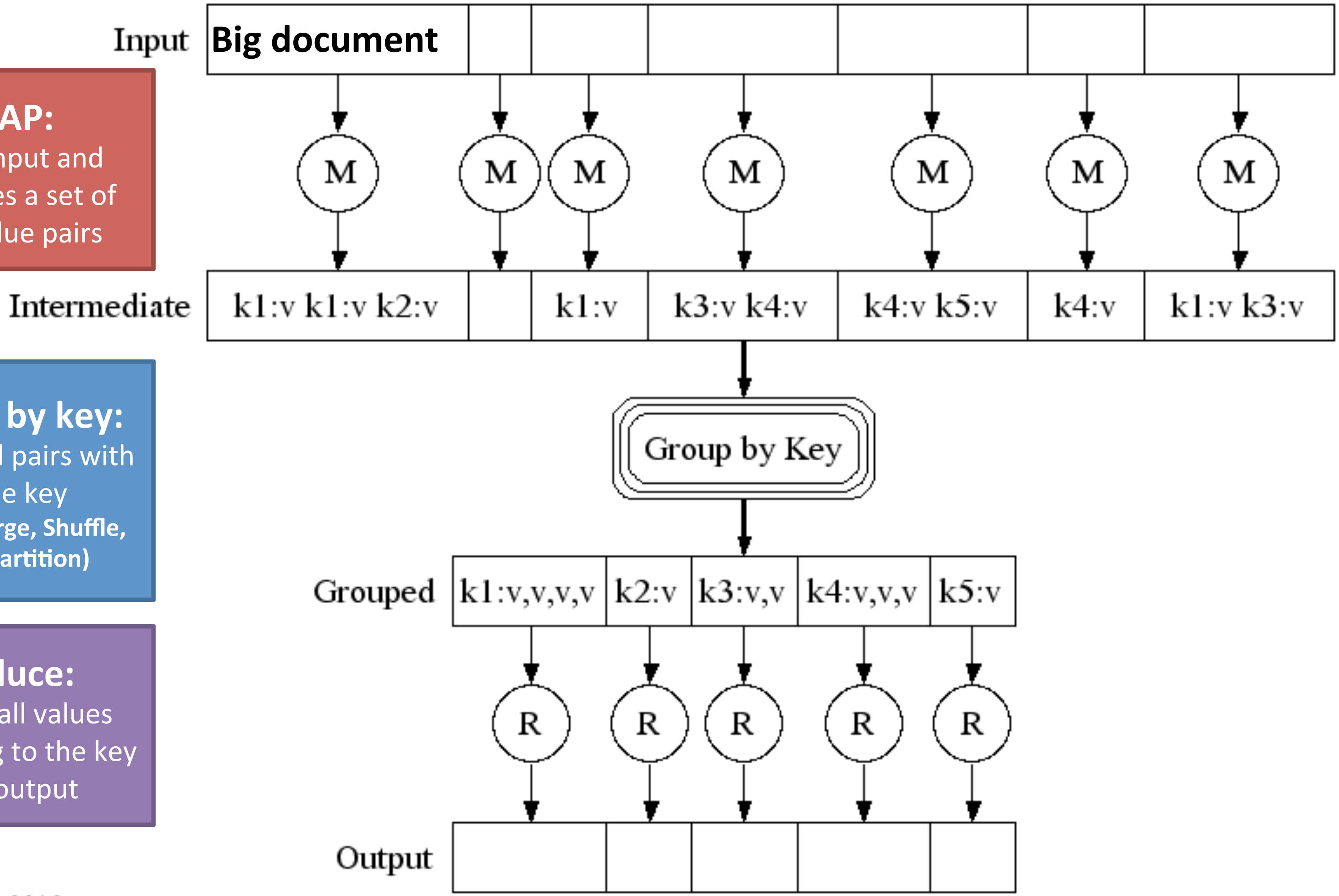
- Partitioning the input data
- Scheduling the program's execution across a set of machines
- Performing the **group by key** step
- Handling machine failures
- Managing required inter-machine communication

Map-Reduce: A diagram

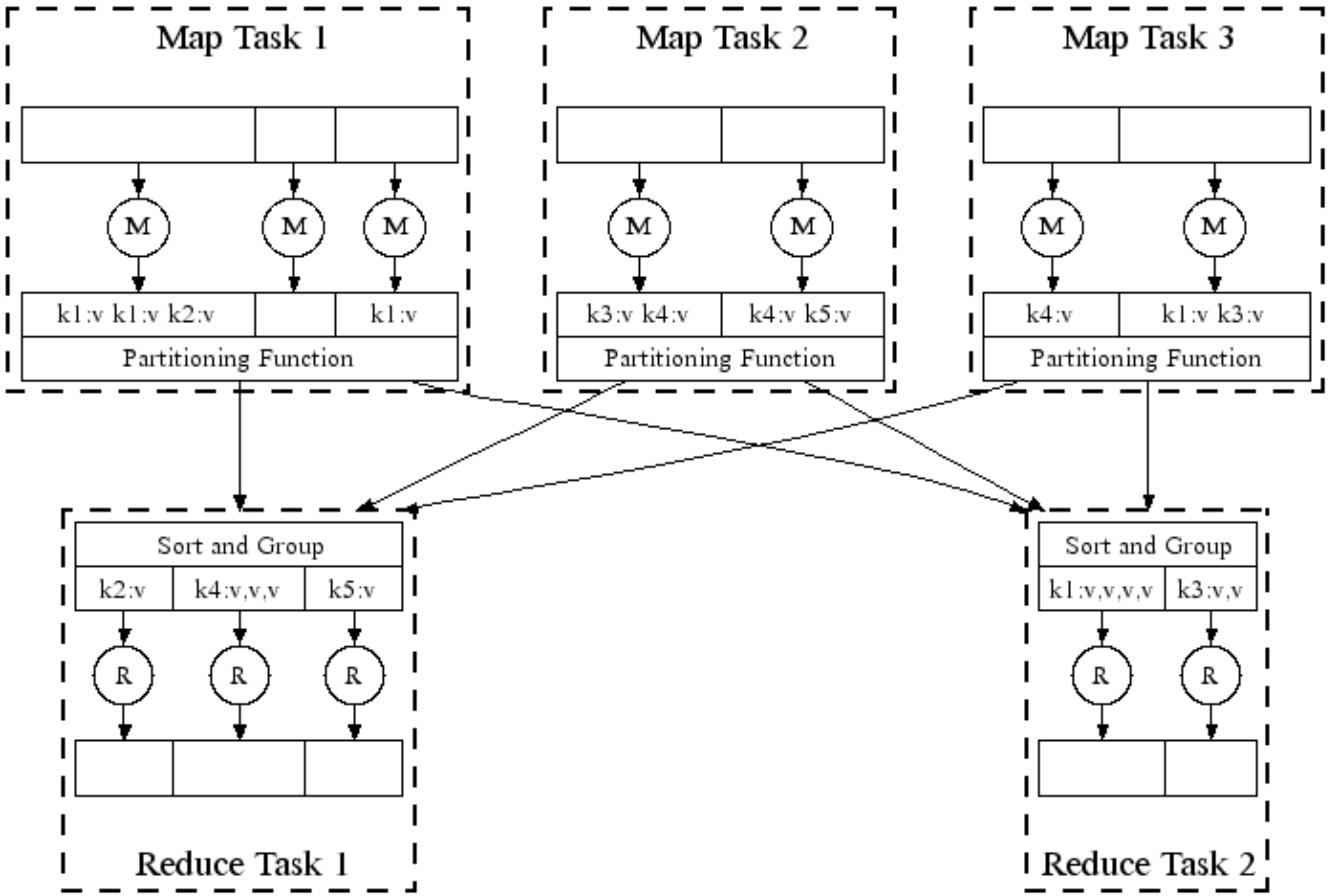
MAP:
Read input and produces a set of key-value pairs

Group by key:
Collect all pairs with same key
(Hash merge, Shuffle, Sort, Partition)

Reduce:
Collect all values belonging to the key and output



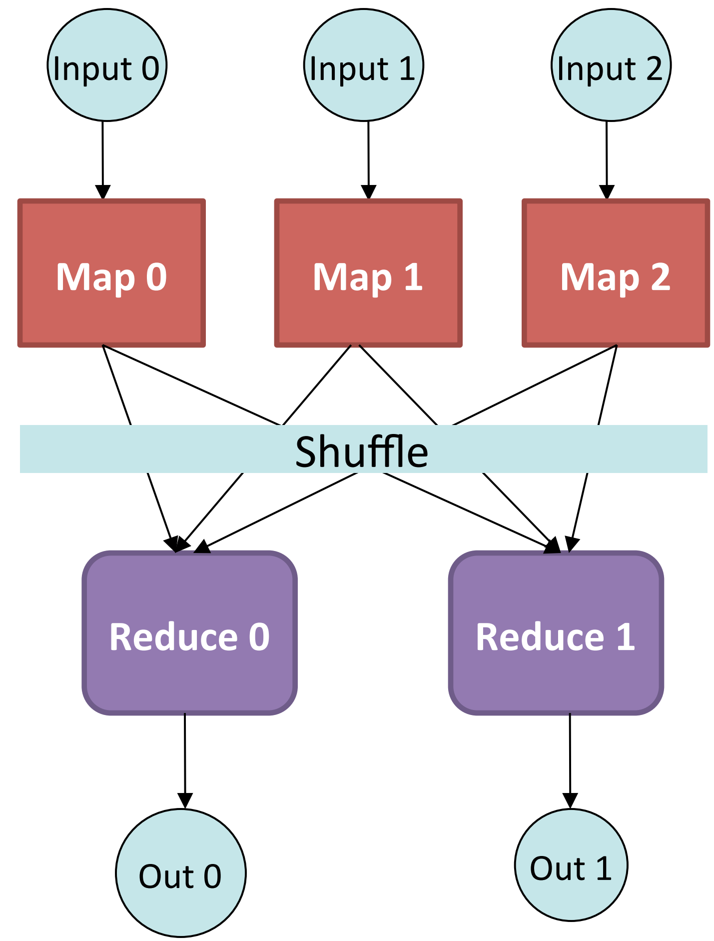
Map-Reduce: In Parallel



All phases are distributed with many tasks doing the work

Map-Reduce

- Programmer specifies:
  - Map and Reduce and input files
- **Workflow:**
  - Read inputs as a set of key-value-pairs
  - **Map** transforms input kv-pairs into a new set of k'v'-pairs
  - Sorts & Shuffles the k'v'-pairs to output nodes
  - All k’v’-pairs with a given k’ are sent to the same **reduce**
  - **Reduce** processes all k'v'-pairs grouped by key into new k''v''-pairs
  - Write the resulting pairs to files
- All phases are distributed with many tasks doing the work



Data Flow

- **Input and final output are stored on a distributed file system (FS):**
  – Scheduler tries to schedule map tasks "close" to physical storage location of input data
- **Intermediate results are stored on local FS of Map and Reduce workers**
- **Output is often input to another MapReduce task**

Coordination: Master

- Master node takes care of coordination:
  - **Task status:** (idle, in-progress, completed)
  - **Idle tasks** get scheduled as workers become available
  - When a map task completes, it sends the master the location and sizes of its *R* intermediate files, one for each reducer
  - Master pushes this info to reducers
- Master pings workers periodically to detect failures

Dealing with Failures

- **Map worker failure**
  - Map tasks completed or in-progress at worker are reset to idle
  - Reduce workers are notified when task is rescheduled on another worker
- **Reduce worker failure**
  - Only in-progress tasks are reset to idle
  - Reduce task is restarted
- **Master failure**
  - MapReduce task is aborted and client is notified

PROBLEMS SUITED FOR MAP-REDUCE

Example: Host size

- **Suppose we have a large web corpus**
- Look at the metadata file
  - Lines of the form: (URL, size, date, …)
- **For each host, find the total number of bytes**
  - That is, the sum of the page sizes for all URLs from that particular host

- Other examples:
  - Link analysis and graph processing
  - Machine Learning algorithms

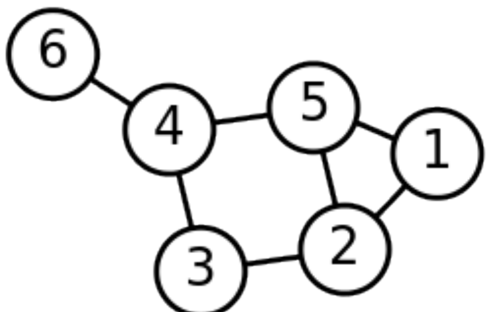
Example: Language Model

- **Statistical machine translation:**
  - Need to count number of times every 5-word sequence occurs in a large corpus of documents

- **Very easy with MapReduce:**
  - **Map:**
    - Extract (5-word sequence, count) from document
  - **Reduce:**
    - Combine the counts

Degree of graph Example

- Find degree of every node in a graph



Example: In a friendship graph, what is the number of friends of every person:

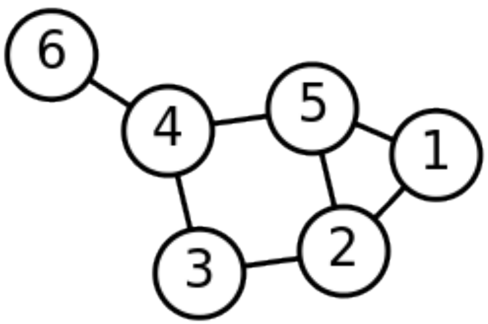
Node 6 = 1   Node 2 = 3

Node 4 = 3   Node 1 = 2

Node 3 = 2   Node 5 = 3

Degree of each node in a graph

- Suppose you have the edge list



===

```
6  4
4  6
4  3
3  4
4  5
5  4
...
```

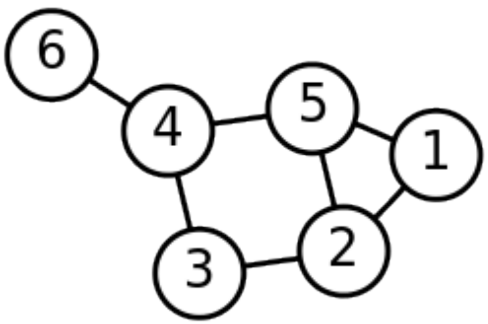
== a table!

Schema?

Edges(from, to)

Degree of each node in a graph

- Suppose you have the edge list



===

6	4
4	6
4	3
3	4
4	5
5	4
...	

== a table!

Schema?

Edges(from, to)

SQL for degree list?

SELECT from, count(*)
FROM Edges
GROUP BY from

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Degree of each node in a graph

- So in SQL:

```
SELECT from, count(*)
FROM Edges
GROUP BY from
```

- MapReduce?

Mapper:

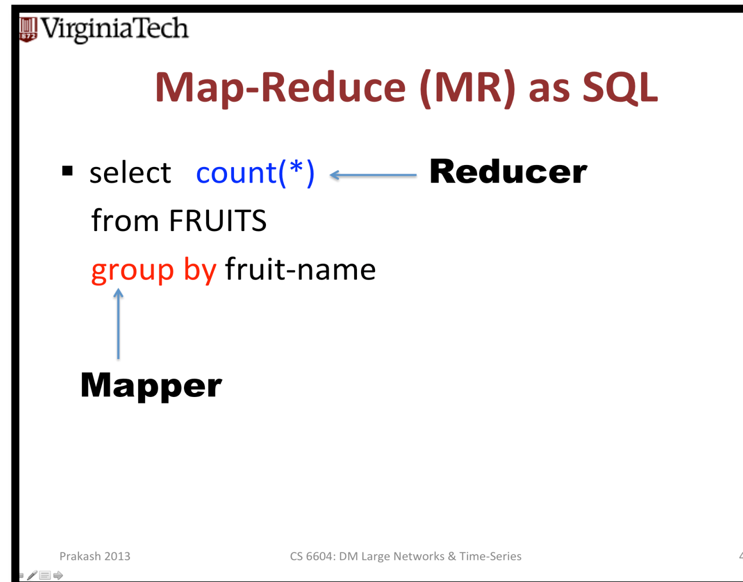
emit (from, 1)

Reducer:

emit (from, count())

6	4
4	6
4	3
3	4
4	5
5	4
. . .	

Remember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Map-Reduce (MR) as SQL

- select count(*) ← **Reducer**

  from FRUITS

  group by fruit-name

Mapper

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I.E. essentially equivalent to the 'word-count' example ☺

In HW5

- You will have to find the degree *distribution* of a network.

Conclusions

- Hadoop is a distributed data-intensive computing framework
- MapReduce
  - Simple programming paradigm
  - Surprisingly powerful (may not be suitable for all tasks though)
- Hadoop has specialized FileSystem, Master-Slave Architecture to scale-up

NoSQL and Hadoop

- Hot area with several new problems
  - Good for academic research
  - Good for industry

= Fun AND Profit ☺

POINTERS AND FURTHER READING

Implementations

- Google
  - Not available outside Google
- Hadoop
  - An open-source implementation in Java
  - Uses HDFS for stable storage
  - Download: http://lucene.apache.org/hadoop/
- Aster Data
  - Cluster-optimized SQL Database that also implements MapReduce

Cloud Computing

- Ability to rent computing by the hour
  – Additional services e.g., persistent storage
- Amazon's "Elastic Compute Cloud" (EC2)
- Aster Data and Hadoop can both be run on EC2

Reading

- Jeffrey Dean and Sanjay Ghemawat: MapReduce: Simplified Data Processing on Large Clusters
  - http://labs.google.com/papers/mapreduce.html

- Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung: The Google File System
  - http://labs.google.com/papers/gfs.html

Resources

- Hadoop Wiki
  - Introduction
    - http://wiki.apache.org/lucene-hadoop/
  - Getting Started
    - http://wiki.apache.org/lucene-hadoop/GettingStartedWithHadoop
  - Map/Reduce Overview
    - http://wiki.apache.org/lucene-hadoop/HadoopMapReduce
    - http://wiki.apache.org/lucene-hadoop/HadoopMapRedClasses
  - Eclipse Environment
    - http://wiki.apache.org/lucene-hadoop/EclipseEnvironment
- Javadoc
  - http://lucene.apache.org/hadoop/docs/api/

Resources

- Releases from Apache download mirrors
  - http://www.apache.org/dyn/closer.cgi/lucene/hadoop/
- Nightly builds of source
  - http://people.apache.org/dist/lucene/hadoop/nightly/
- Source code from subversion
  - http://lucene.apache.org/hadoop/version_control.html

Further Reading

- Programming model inspired by functional language primitives
- Partitioning/shuffling similar to many large-scale sorting systems
  - NOW-Sort ['97]
- Re-execution for fault tolerance
  - BAD-FS ['04] and TACC ['97]
- Locality optimization has parallels with Active Disks/Diamond work
  - Active Disks ['01], Diamond ['04]
- Backup tasks similar to Eager Scheduling in Charlotte system
  - Charlotte ['96]
- Dynamic load balancing solves similar problem as River's distributed queues
  - River ['99]