

## Tackling The Challenges of Big Data

### Big Data Storage

**Michael Stonebraker**

Professor  
Massachusetts Institute of Technology



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## Tackling The Challenges of Big Data

### Big Data Storage

### Modern Databases

### Introduction

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Massachusetts Institute of Technology



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## History Lesson

- **1970's: relational model invented**
- **1984: DB2 released, RDBMS declared mainstream**
- **Circa 1990: RDBMS takes over**
  - “One-size fits all”
  - I’m the guy with the hammer; everything is a nail
- **2006: ICDE paper**
  - “One-size does not fit all”
  - Co-existence of several solutions
- **2013: One size fits none**



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## Traditional RDBMS Wisdom

- **Dynamic row-level locking**
- **Aries-style write-ahead log**
- **Replication (asynchronous or synchronous)**
  - Update the primary first
  - Then move the log to other sites
  - And roll forward at the secondary(s)



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## Traditional RDBMS Wisdom

- **Data is in disk block formatting (heavily encoded)**
- **With a main memory buffer pool of blocks**
- **Query plans**
  - Optimize CPU, I/O
  - Fundamental operation is read a row
- **Indexing via B-trees**
  - Clustered or unclustered



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## My Thesis

### Current RDBMSs (the elephants)

- All date from the 1980's
- Are legacy systems
- Are currently not good at anything
- Suffer from "The Innovators Dilemma"
- Deserve to be sent to the home for tired software



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## Rest of this Module

- I will explain why one size fits none
- Three main DBMS markets
  - One-third data warehouses
  - One-third OLTP
  - One-third everything-else
- Some conclusions at the end



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**Big Data Storage**

**Modern Databases**

Introduction

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## Tackling The Challenges of Big Data

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Data Warehouses

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## Data Warehouse Marketplace

- Column stores are well along at replacing row stores
- Because they are a factor of 50 – 100 faster



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## Why???

- Most warehouses have a central fact table
  - Who bought what item in what store at what time.
- Surrounded by “dimension” tables
  - Store, time, product, customer, ...
- So-called “star/snowflake schema”
  - Check out anything written by Ralph Kimball for lots of detail



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## Why???

- Typical warehouse query reads 4-5 attributes from a 100 column fact table
  - Row store – reads all 100
  - Column store – reads just the ones you need
- Compression is way easier and more productive in a column store
  - Each block has only one kind of attribute



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## Why???

- **No big record headers in a column store**
  - They don't compress well
- **A column executor is wildly faster than a row executor**
  - Because of "vector processing"
  - See pioneering paper by Martin Kersten on this topic



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## The Participants

- **Native column store vendors**
  - HP/Vertica, SAP/Hana, Paracel (Amazon), SAP/Sybase/IQ
- **Native row store vendors**
  - Microsoft, Oracle, DB2, Netezza
- **In transition**
  - Teradata, Asterdata, Greenplum



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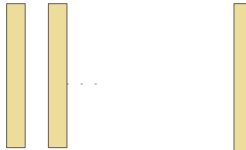
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## Three Slides on Vertica

**Table is decomposed into a collection of materialized views, stored by column and sorted on all attributes left-to-right**



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### Three Slides on Vertica

- A column is stored in 64K "chunklets".  
1st attribute is stored uncompressed,  
remainder are compressed (delta  
compression, lempel-zipf, repeated values,  
huffman, ...)
- Left-most column is usually delta encoded
- Chunklets are decompressed only when  
necessary
- Fundamental operation is "process a  
column"



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### Three Slides on Vertica

- To load fast, there is a main memory  
row-store in front of this column store.
  - Newly loaded tuples go there
  - In bulk, groups of rows are sorted,  
converted to column format and  
compressed
  - And written to new disk segments
  - Segment merge makes these segments  
bigger and bigger
  - Queries go to both places



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### Roughly Speaking

- This architecture also describes Paracel and  
Hana
- It has nothing to do with the traditional  
RDBMS wisdom
- Over time the only successful warehouse  
products will be column stores
- The elephants have an "Innovator's Dilemma"  
problem



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**Big Data Storage**  
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Data Warehouses

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OLTP

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## OLTP Data Bases -- 3 Big Decisions

- Main memory vs disk orientation
- Replication strategy
- Concurrency control strategy



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## Reality Check on OLTP Data Bases

- TP database size grows at the rate transactions increase
- 1 Tbyte is a really big TP data base
- 1 Tbyte of main memory buyable for around \$30K (or less)
  - (say) 64 Gbytes per server in 16 servers
- If your data doesn't fit in main memory now, then wait a couple of years and it will.....



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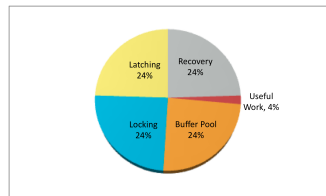
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## Reality Check – Main Memory Performance

- TPC-C CPU cycles
- On the Shore DBMS prototype
- “Elephants” should be similar



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## To Go Fast

- Must focus on overhead
  - Better B-trees affects a small fraction of the path length
- Must get rid of all four pie slices
  - Anything less gives you a marginal win
  - Times10 as an example



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## Single Threading

- **Toast unless you do this**
  - Unless you get rid of queuing (somehow)
  - Or eliminate shared data structures (somehow)
- **H-Store (and VoltDB) statically divide shared memory among the cores**
  - Would be interesting to look at more flexible schemes



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## Main Memory

- **Again, you're toast unless you do this**
- **What happens if my data doesn't fit?**
  - See VLDB '14 paper by Debrabant et. al.



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## Concurrency Control

- **MVCC popular (NuoDB, Hekaton)**
- **Time stamp order popular (H-Store/VoltDB)**
- **Lightweight combinations of time stamp order and dynamic locking (Calvin, Dora)**
- **I don't know anybody who is doing normal dynamic locking**
  - It's too slow!!!!



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## What about Logging?

- **Command logging much faster than data logging**
  - See ICDE '14 paper by Malviya
- **HA is now a requirement**
  - Failover to a replica; rarely recover from a log



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## The Old Way vs The New Way

- **Main memory not disk**
- **Anti-caching not caching**
- **Command logging not data logging**
- **Failover not recovery from a log**
- **MVCC or timestamp order not dynamic locking**
- **Single threaded not multi-threaded**



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## New Way Systems

- **Hekaton (Microsoft)**
- **Hana (SAP)**
- **VoltDB, MemSQL, SQLFire, ...**



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## Summary

- New is a factor of 100 or so faster than old
- If you don't care about performance, then stay with the elephants
- Otherwise, a changeover is in your future



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OLTP

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Everything Else

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## Everything Else

- NoSQL
- Array stores
- GraphDBMSs
- Hadoop



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## NoSQL – 75 or so Vendors

- Give up SQL
  - Completely misguided
  - SQL is compiled (at compile time) into the low level utterances of the NoSQL folks
  - Nobody codes in assembler any more!!!
  - Never bet against the compiler!!



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## NoSQL – 75 or so Vendors

- Give up ACID
  - If you are guaranteed that you won't need it (now or in the future) then you are ok
  - Otherwise, your hair will be on fire



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## NoSQL – 75 or so Vendors

- **Schema later**

- Most support semi-structured data – adding a new “column” is trivial

- Don’t have to think about your data upfront

- \* **Good or bad depending on your point of view**



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## NoSQL – Summary

- **Moving quickly toward SQL**

- Cassandra and MongoDB are moving to (yup) SQL

- **Moving toward ACID**

- Even Jeff Dean (Google) now admits ACID is a good idea

- **NoSQL**

- Used to mean “No SQL”

- Then meant “Not only SQL”

- Moving toward “Not yet SQL” (i.e. convergence)



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## NoSQL – Summary

- **Systems are fine for “low end” applications**

- E.g webby things

- E.g. protection/ authentication data bases

- Etc.



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## Array DBMSs and Complex Analytics

- Machine learning
- Data clustering
- Predictive models
- Recommendation engines
- Regressions
- Estimators

i.e. "Data Mining"



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## Complex Analytics

- By and large, they are defined on arrays
- As collections of linear algebra operations
- They are not in SQL!
- And often

- Are defined on large amounts of data
- And/or in high dimensions



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## Complex Analytics on Array Data – An Accessible Example

- Consider the closing price on all trading days for the last 20 years for two stocks A and B

- What is the covariance between the two time-series?

$$= (1/N) * \sum (A_i - \text{mean}(A)) * (B_i - \text{mean}(B))$$



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## Now Make It Interesting ...

- **Do this for all pairs of 15000 stocks**
  - The data is the following 15000 x 4000 matrix

Stock	$t_1$	$t_2$	$t_3$	$t_4$	$t_5$	$t_6$	$t_7$	...	$t_{4000}$
$S_1$									
$S_2$									
...									
$S_{15000}$									



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## Array Answer

- **Ignoring the  $(1/N)$  and subtracting off the means ....**

$$\text{Stock} * \text{StockT}$$



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## System Requirements

- **Complex analytics**
  - Covariance is just the start
  - Defined on arrays!!
- **Data management**
  - Leave out outliers
  - Just on securities with a market cap over \$10B
- **Scalability to many cores, many nodes and out-of-memory data**



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## Array DBMSs -- e.g. SciDB

- **Array SQL**
  - For joins filters,...
- **Built in functions**
  - For SVD, Co-variance, eigenvalues,...
- **User-defined extensions**
  - If you don't see what you need



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## Array DBMSs -- Summary

- **Will get tractions**
  - When the world moves to complex analytics
- **Don't look at all like the traditional wisdom**



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## Graph DBMSs

- **Focus on things like Facebook/twitter graphs**
- **OLTP focus (Neo4J)**
- **Analytics focus (shortest path, minimum cut set, ...)**
- **Can you beat**
  - RDBMS simulations
  - Array simulations
- **Jury is still out**



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Hadoop

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## What is Hadoop?

- **Open source version of Google's Map-Reduce**
- **Two operations**
  - Map (basically filter, transform)
  - Reduce (basically rollup)
- **Very good for “embarrassingly parallel” operations**
  - E.g. document search



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## The Hadoop Stack

- **Hive (or Pig) at the top**
  - Think SQL
- **Hadoop (Map-Reduce) in the middle**
- **HDFS (a file system) at the bottom**
- **Runs across any number of nodes**
  - Scalable!



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## Possible Uses for Hadoop Stack

- **Embarrassingly parallel computations**
- **SQL aggregates (e.g. warehouse-style queries)**
  - Factor of 100 worse than a warehouse DBMS
- **Complex analytics**
  - Factor of 100 worse than an array DBMS
- **Scientific codes (e.g. computational fluid dynamics)**
  - Factor of 100 worse than MPI-based systems



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## Hadoop Usage at Facebook

- **95+% Hive**
  - For which Hadoop layer is a disaster



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## What is Happening Now?

- **Cloudera, Hortonworks and Facebook are ALL doing the same thing**
  - Defining and building an execution engine that processes Hive without using Hadoop layer
- **Effectively moving to compete in the warehouse market**
  - All warehouse vendors have Hive interfaces



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## Most Likely Future

- **There is a small market for embarrassingly parallel Hadoop framework**
- **There is a much bigger market for a Hive-SQL framework**
  - Execution engines will look like data warehouse products
- **HDFS may or may not survive**
  - It is also horribly inefficient



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## Big Data Storage

## Modern Databases

### Summary

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## Thoughts While Shaving

- **Warehouses will be a column store market**
  - If you are not running one now, you will have to switch
  - Ask your vendor what his column store plans are
- **OLTP will be a main memory market**
  - If you are not running one now, you will have to switch
  - Ask your vendor what his main memory plans are



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## Thoughts While Shaving

- **Array DBMSs and Graph DBMS may get traction**
  - You should (at the very least) understand what they are good for
- **NoSQL**
  - Is popular for low-end applications
  - Especially document management, web stuff and places where you want schema-later
  - ACID-less



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## Thoughts While Shaving

- **The Hadoop stack will morph into something completely different**
  - Hold onto your seat belt!!
  - At the very least -- see if you are contemplating embarrassingly parallel applications – if not, you are in deep doo-doo
- **Current elephant products will only survive long-term in low performance applications**



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## The Curse -- May You Live in Interesting Times

- **Lots of new DBMS ideas and products!!!**
- **BI folks will keep more and more stuff**
  - Warehouses will get bigger and bigger
- **Sea change from simple analytics to complex analytics expected**
- **The “internet of things” is a force to be dealt with**
  - i.e. everything on the planet of material significance will be sensor-tagged -- generating yet more data deluge



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## The Curse -- May You Live in Interesting Times

**Hire a really really good chief data officer to help you sort out the future**



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**Big Data Storage**  
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Summary

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