

THiNK BIG

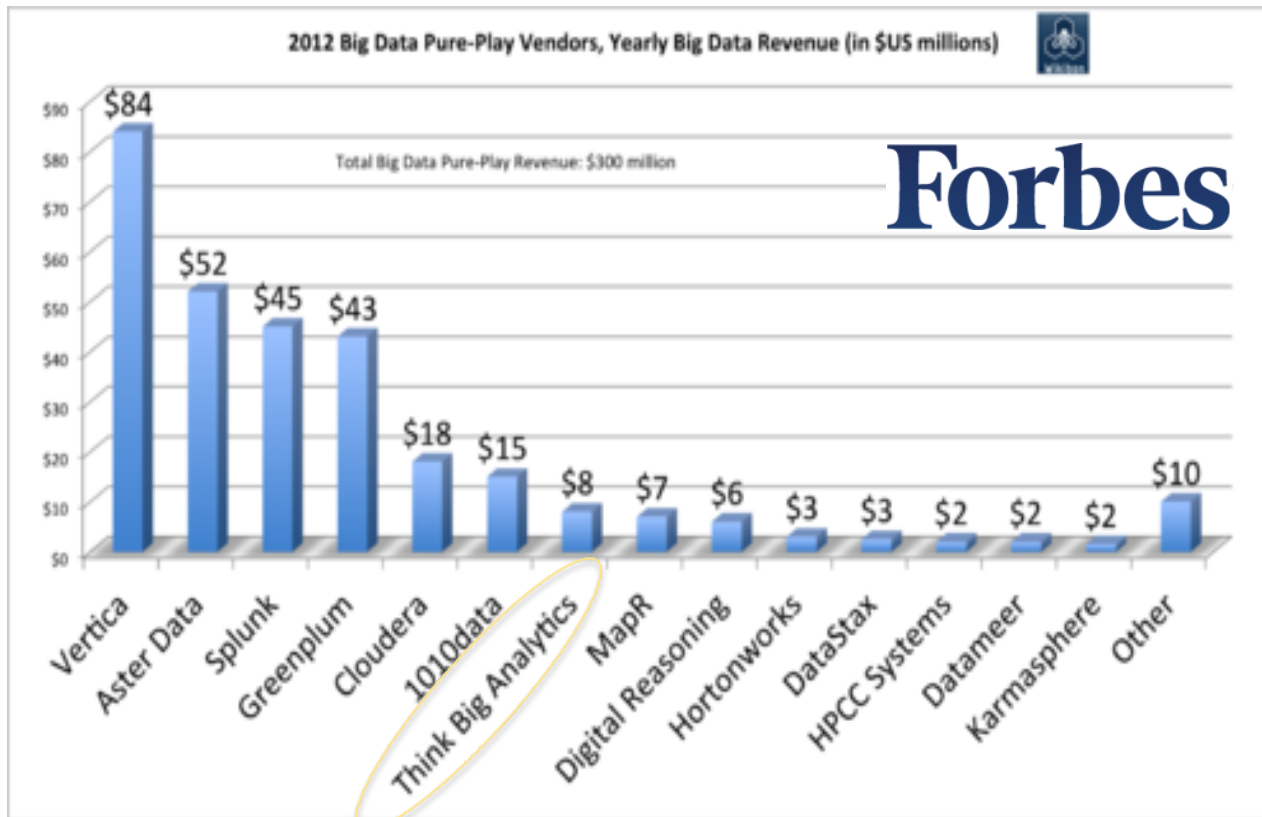
ANALYTICS

Douglas Moore
Principal Consultant, Architect

Big Data / Hadoop / NoSQL Agenda

- Who, Why?
- Data Processing Models
- Integration
- Common Uses
- Futures
- Summary

Big Data: \$50 Billion Market by 2017



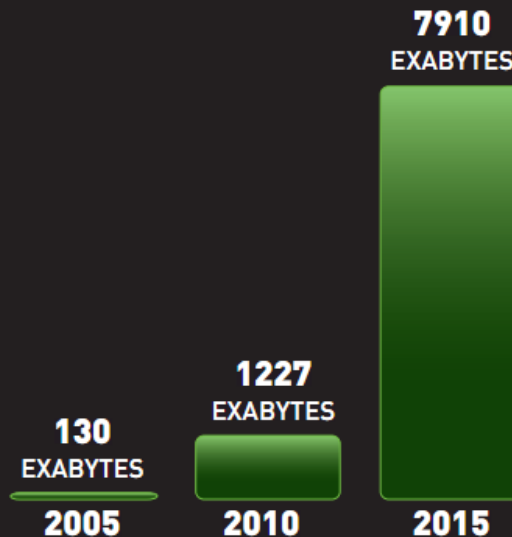
Source: Forbes February 2012

Think Big
Recognized as a
Top Pure-Play Big
Data Vendor

100% Focus on Big Data consulting & Data Science solution services
 Management Background:
 ✓ Cambridge Technology, C-bridge, Oracle, Sun Microsystems, Quantcast, Accenture
 ✓ C-bridge Internet Solutions (CBIS) founder 1996 & executives, IPO 1999

THE
2011
IDC
**DIGITAL
UNIVERSE**
STUDY
sponsored by EMC

A DECADE OF DIGITAL UNIVERSE G R O W T H



So, like our physical universe, the digital universe is something to behold-

1.8 trillion gigabytes

in 500 quadrillion "files"

- and more than doubling every two years. That's nearly as many bits of information in the digital universe as stars in our physical universe.

Source IDC

How Did Hadoop & MapReduce evolve?

Why Hadoop?

Online Industry: 2005-2008

Today: All Industries

Unstructured Data Analytics,
Search & Recommendation for:

- Click Stream
- Log files
- Text
- Voice
- Pictures
- Video
- Docs
- Sensor Logs



New Data Sources, Innovative
Use Cases, Data Science &
Predictive Analytics

+

Compute Processing \$ & Time

ex. 26 Days → 2 min

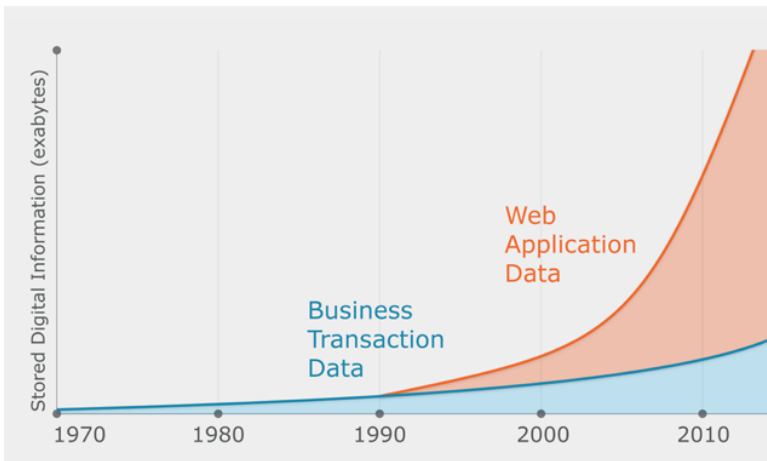
ex. 42 Hours → 40 min

ex. 18 Hours → 16 min

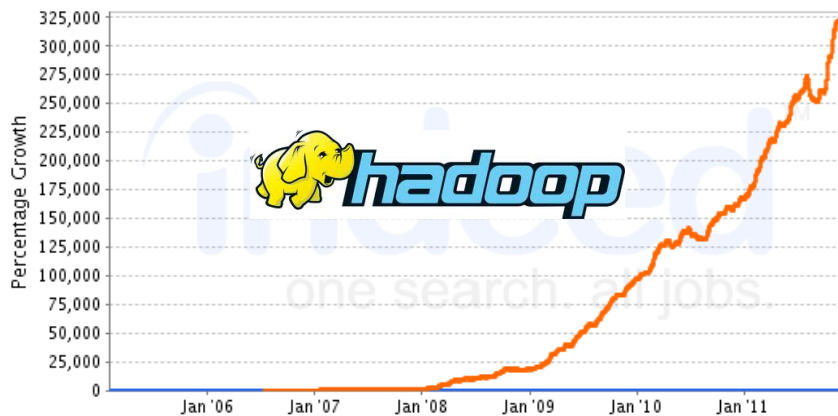
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Business Innovation Velocity

Big Data Growth Indicators



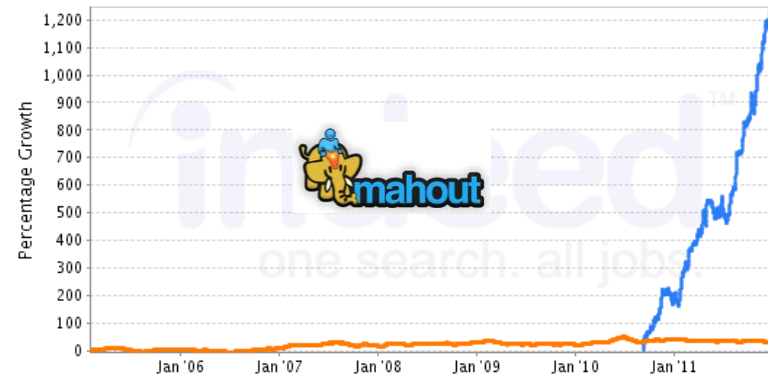
Job Trends from Indeed.com
— hadoop — oracle



Copyright Think Big Analytics

Job Trends from Indeed.com

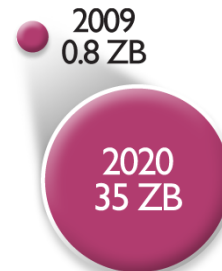
— SAS — mahout



Indeed.com searches millions of jobs from thousands of job sites. This job trends graph shows relative growth for jobs we find matching your search terms.

Find [SAS jobs](#), [Mahout jobs](#)

Digital Universe Growth



Growth Projections

Population ↗
Mobile Phone ↗
Machine Data ↗

Source: IDC Digital Universe Study, sponsored by EMC, May 2010

5/14/12

Real Companies:

- Enterprises 2008-2012 embracing Big Data
- Risk, Fraud, Acquisition, Products, Revenue Up-lift
- Creating Hadoop Big Data capabilities

VISA	2009	<ul style="list-style-type: none"> 360° View of Customer Analytics as a service to LOBs Digital User Profiling and Segmentation Digital User Lifecycle Management Back End processing and analysis
Bank of America	2009	<ul style="list-style-type: none"> Cross-Enterprise Risk for all LOBs Massive Data analysis and processing
PayPal	2010	<ul style="list-style-type: none"> Acquires Where for Mobile wallet and mobile advertising GPS Location Data Services Hyper-Local Analytics for Consumers and Merchants
ZIONS BANK	2011	

Beyond unstructured

- Massive structured data
- Very large compute resources
- Unstructured data

Rapid Innovation:

- Data-driven: massive data not sample data
- Data-driven portfolio and product

Financial Services Big Data Use Case	Digital Adv
Big Data Warehouse for Batch Analysis & Compute	●
Simple Segmentation	●
PII Structured Data Integration	●
Offline Data Integration	●
Scoring	●
Campaign Performance	●
Online Data / GEO & Social	●
Optimization	●
Recommendation Engine	●
Adv. Segmentation & Clone-a-like	●
X Channel Attribution	●
Unstructured Data at Scale	●
Dynamic Content	●
Dynamic Pricing	●
Customer Lifetime Modeling	●
Streaming Ingestion Analytics	●
ML / Predictive Analytics w/ Actions	●
Fraud Monitoring	●
ML / Predictive Analytics w/ Actions	●

Venture capital sees big returns in big data

Recommend 50 people recommend this. Be the first of your friends.
 By Sarah McBride
 SAN FRANCISCO | Fri Feb 17, 2012 3:03pm EST



Obama's big data plans: Lots of cash and lots of open data

Venture Capital Dispatch

An inside look from VentureWire at high-tech start-ups and their investors.
 November 8, 2011, 8:00 AM
 Accel Makes Big Commitment To Big Data With \$100M Fund

Pure Play Vendors



Large-Scale Vendors



Why Hadoop + Big Data is changing the game?

- **Previously impossible to do this analysis**
- **Analysis conducted at fraction of the cost**
- **Analysis conducted in less time**
- **Greater flexibility for future unknowns**

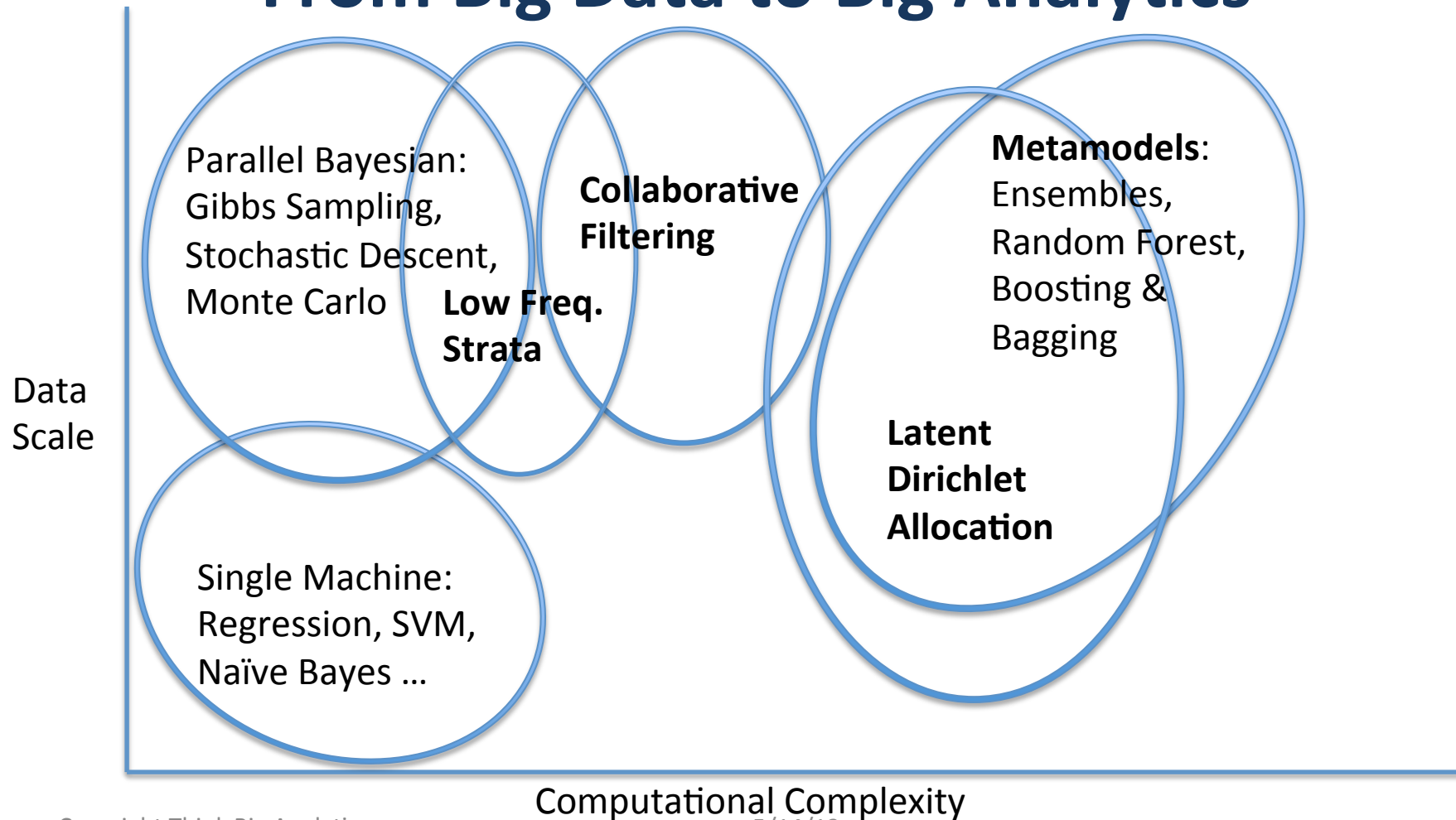
Big Analytics: Starting Simple

- Data-intensive cloud computing lets you work with massive data sets that vary
- Typical Process
 - Exploratory modeling: find patterns in **PBs** of data
 - Baseline modeling: simple models (e.g., Bayesian) iterated quickly
 - Live testing: frequent scoring with Champion/Challenger
 - Refinement: more sophisticated Machine Learning, features, etc.

Simple algorithms and lots of data trump complex models.

Halevy, Norvig, and Pereira (Google), *IEEE Intelligent Systems*

From Big Data to Big Analytics

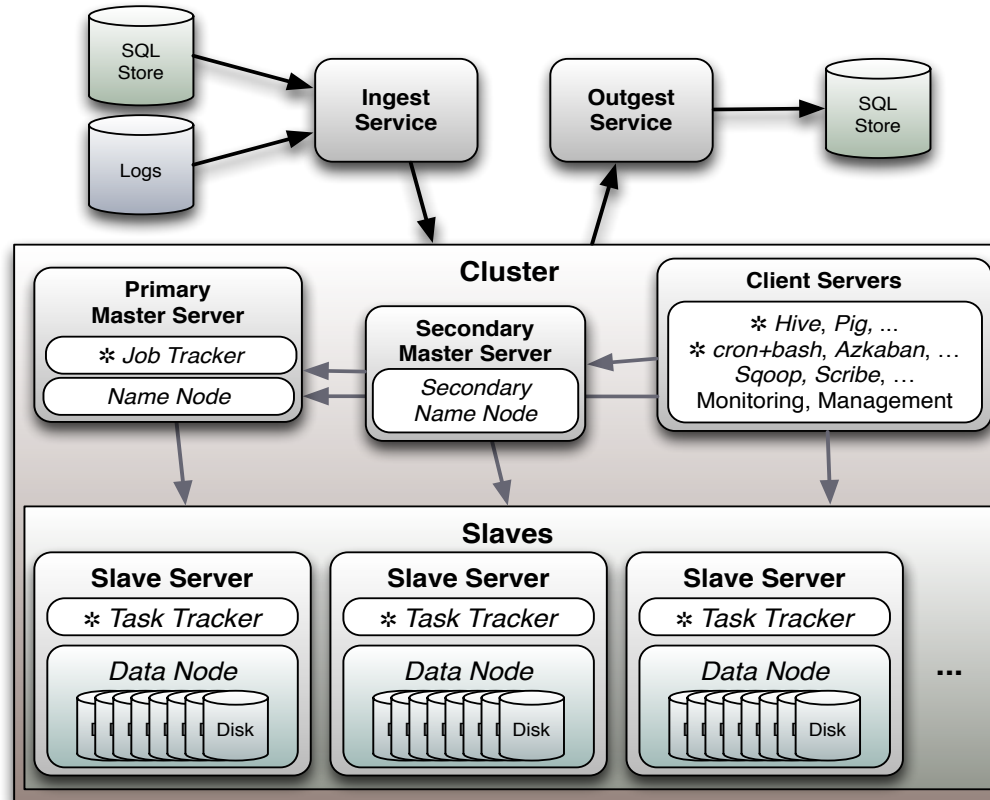


Hadoop Origins

- Open Source Distributed Cluster Software
 - Distributed file system
 - Java-based MapReduce
 - Resource manager
- Started in Nutch project (open source crawler)
- Inspired by Google MapReduce and GFS

Hadoop Components

- Key**
- *italics>: process*
 - * : MR jobs

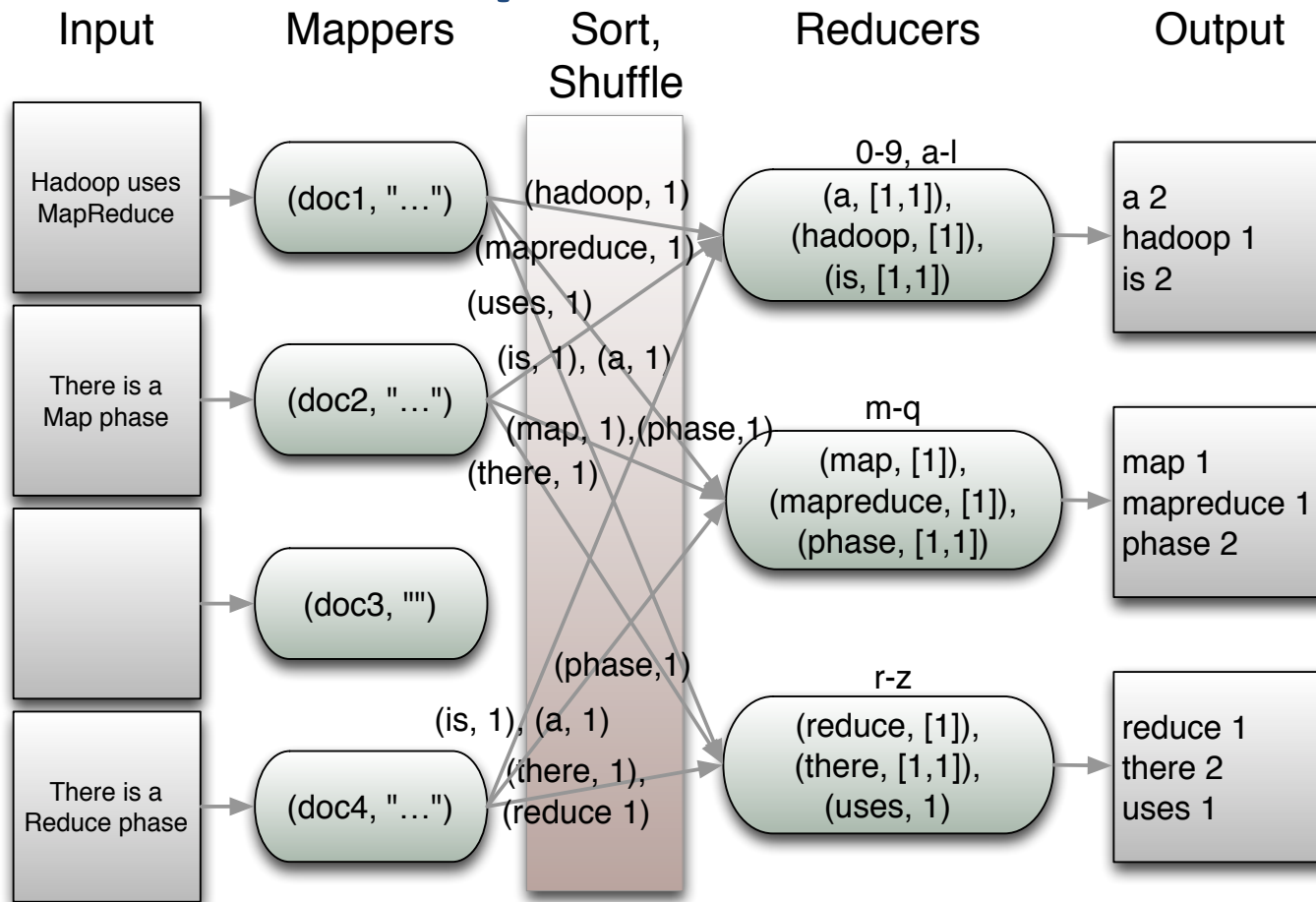


Data Processing Models

MapReduce 100

- Functional programming
 - Filter function $\underline{X}' = \underline{X}$ (if $X_i > 0$)
 - Map function: $\underline{Y} = \sin(\underline{X}')$
 - Reduce function $z = \text{sum}(\underline{Y})$
- Hadoop
 - Spread the data out
 - Send the code to the data
 - Embarrassingly parallel problems work really well
- Many problems can be cast as a Map - Reduce

MapReduce 101



Word Count: Mapper

```
public static class TokenizerMapper
    extends Mapper<Object, Text, Text, IntWritable> {

    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(Object key, Text value, Context context
        ) throws IOException, InterruptedException {
        StringTokenizer itr = new StringTokenizer(value.toString());
        while (itr.hasMoreTokens()) {
            word.set(itr.nextToken());
            context.write(word, one);
        }
    }
}
```


Word Count: Reducer

```
public static class IntSumReducer
    extends Reducer<Text,IntWritable,Text,IntWritable> {
    private IntWritable result = new IntWritable();

    public void reduce(Text key, Iterable<IntWritable> values,
        Context context
        ) throws IOException, InterruptedException
    {
        int sum = 0;
        for (IntWritable val : values) {
            sum += val.get();
        }
        result.set(sum);
        context.write(key, result);
    }
}
```

MapReduce Wiring

```
public static void main(String[] args) throws Exception {
    Configuration conf = new Configuration();
    String[] otherArgs = new GenericOptionsParser(conf, args).
        getRemainingArgs();
    if (otherArgs.length != 2) {
        System.err.println("Usage: wordcount <in> <out>");
        System.exit(2);
    }
    Job job = new Job(conf, "word count");
    job.setJarByClass(WordCount.class);
    job.setMapperClass(TokenizerMapper.class);
    job.setCombinerClass(IntSumReducer.class);
    job.setReducerClass(IntSumReducer.class);
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    FileInputFormat.addInputPath(job, new Path(otherArgs[0]));
    FileOutputFormat.setOutputPath(job, new Path(otherArgs[1]));
    System.exit(job.waitForCompletion(true) ? 0 : 1);
}
```



Hive Overview

- A *SQL*-based tool for *data warehousing* using Hadoop clusters.
- Lowers the *barrier* for Hadoop *adoption* for existing SQL apps and users..
 - Translates SQL to MapReduce
 - Provides an *optimizer*
- Extensible data types & UDFs
- The first popular *meta-data service* for Hadoop



Word Count in Hive

```
CREATE TABLE docs (line STRING);

LOAD DATA INPATH 'docs' OVERWRITE INTO
TABLE docs;

CREATE TABLE word_counts AS
SELECT word, count(1) as count from
  (SELECT explode(split(line, '\\s'))
   AS word FROM docs) w
GROUP BY word
ORDER BY count DESC, word;
```



Pig Overview

- *Pig Latin* is a higher-level map/reduce language
- A simple data flow language designed for productivity ... not Turing complete (yet!)
- Built-in support for joins, filters, etc.
- Provides an *optimizer*
 - translates into Hadoop map reduce job steps
- Allows user-defined functions
- With *HCatalog* will share metadata with Hive



Sample Pig Script

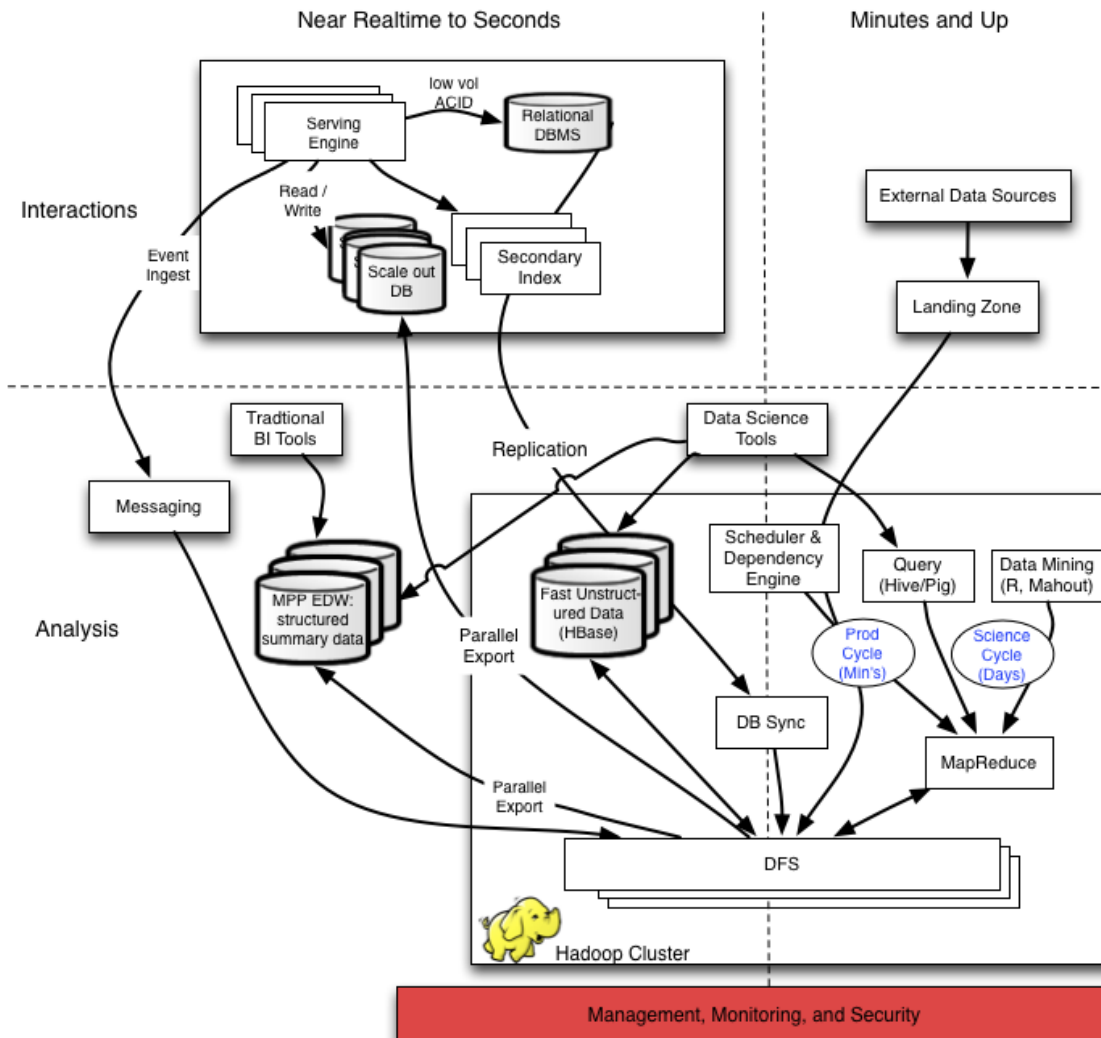
```
lines = LOAD 'docs/*' USING TextLoader();  
  
words = FOREACH lines GENERATE FLATTEN(TOKENIZE($0));  
  
groups = GROUP words BY $0;  
  
counts = FOREACH groups GENERATE $0, COUNT($1);  
  
sorted = ORDER counts BY $1 desc, $0;  
  
STORE sorted INTO 'output/wc' USING PigStorage('\t');
```



MapReduce Frameworks

- Cascading
 - Java-based optimizer & relational operators
- Crunch
 - Abstract collections and optimizer
- Streaming, Pipes
 - Non-Java integration (Perl, Python, Ruby, C/C++,...)
- Tap
 - Simplify time series processing, use of diverse tools and data formats

Integration



Source: Think Big Analytics

Reference Architecture

- Additive data processing power for flexibility.
- Big Data Strategy is integrated with HBase, relational, existing BI and data warehouse technology.
- Provides capability to create data science discipline using full set data.
- Analysis capability on “all” internal data with capability to add external data at will.

Unstructured Data Ingestion

Batch log shipping

- No distributed management and monitoring

Syslog forwarding

- No distributed management and monitoring

Apache Kafka

- Distributed message routing
- Distributed monitoring and management (agents)
- Written in Java

Apache Flume

- Pluggable sources, adapters, sinks
- Distributed monitoring and management (agents)
- Written in Java

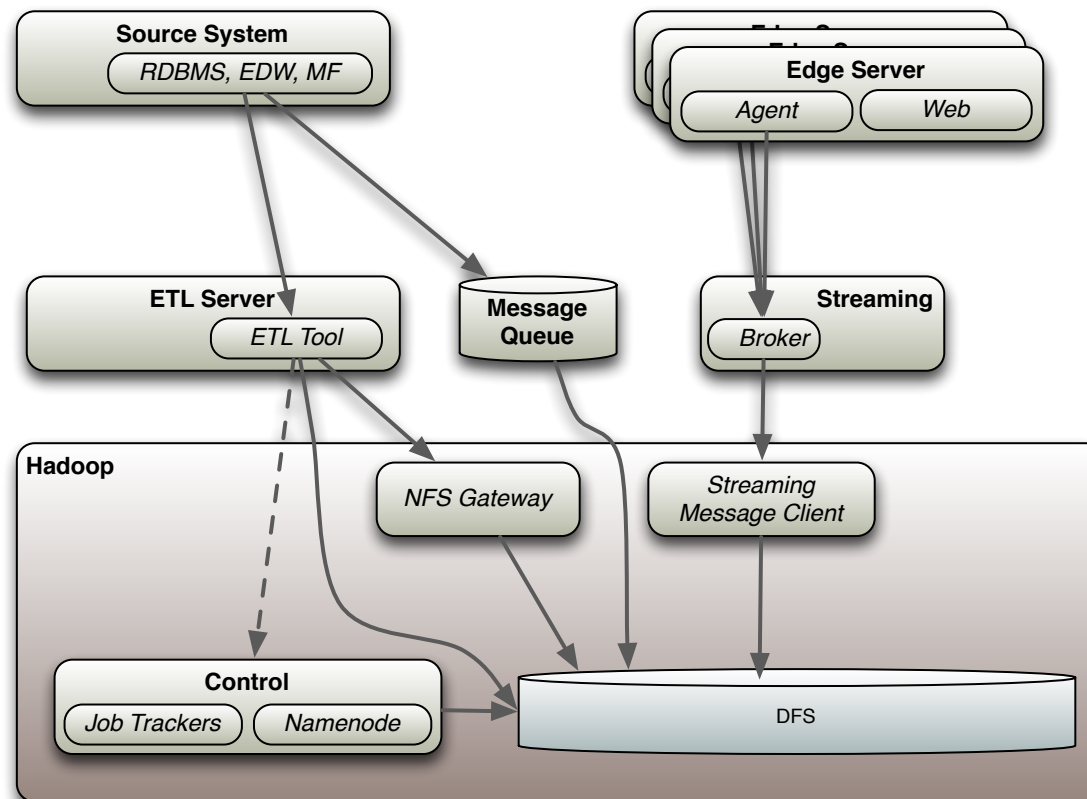
Other streaming frameworks

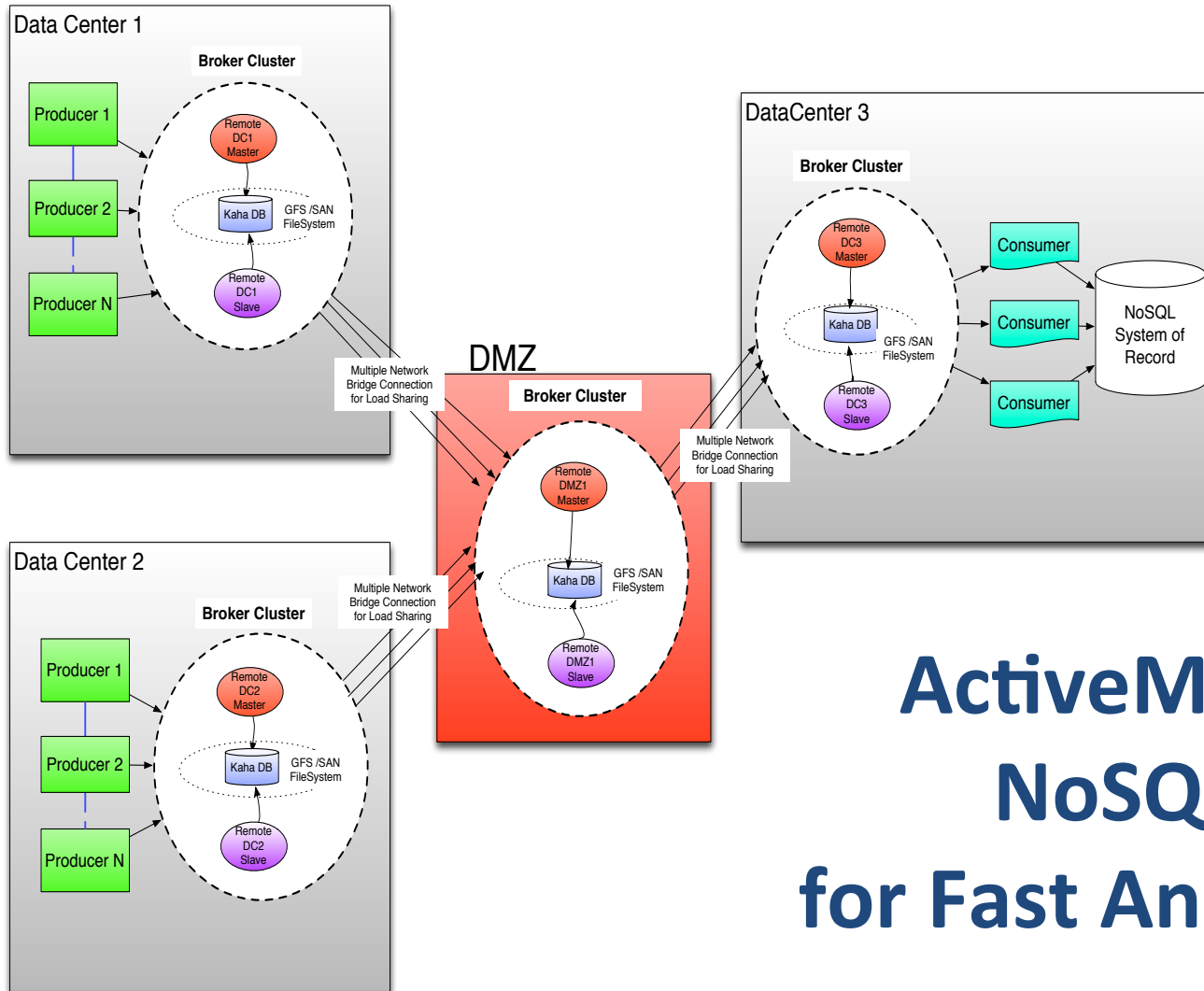
- Scribe, Chukwa, Honu

Message Queues

- ActiveMQ, ZeroMQ

Ingestion Architecture Alternatives





ActiveMQ + NoSQL for Fast Analytics

HBase

- Tables for Hadoop...
inspired by Google's Big Table
- Supports both batch and random access
 - Ad hoc lookup
 - Website serving queries...
- High Consistency
- Maturing rapidly (e.g., reducing latency variance)
- Still a performance tax vs. DFS

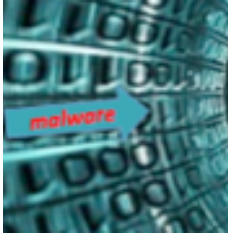



Streaming Big Data

- Responding to incoming events at scale
- SQL-style
 - SQLStream, InfoSphere Streams
- MapReduce-style emerging
 - Kafka, S4, Storm, FlumeBase ...

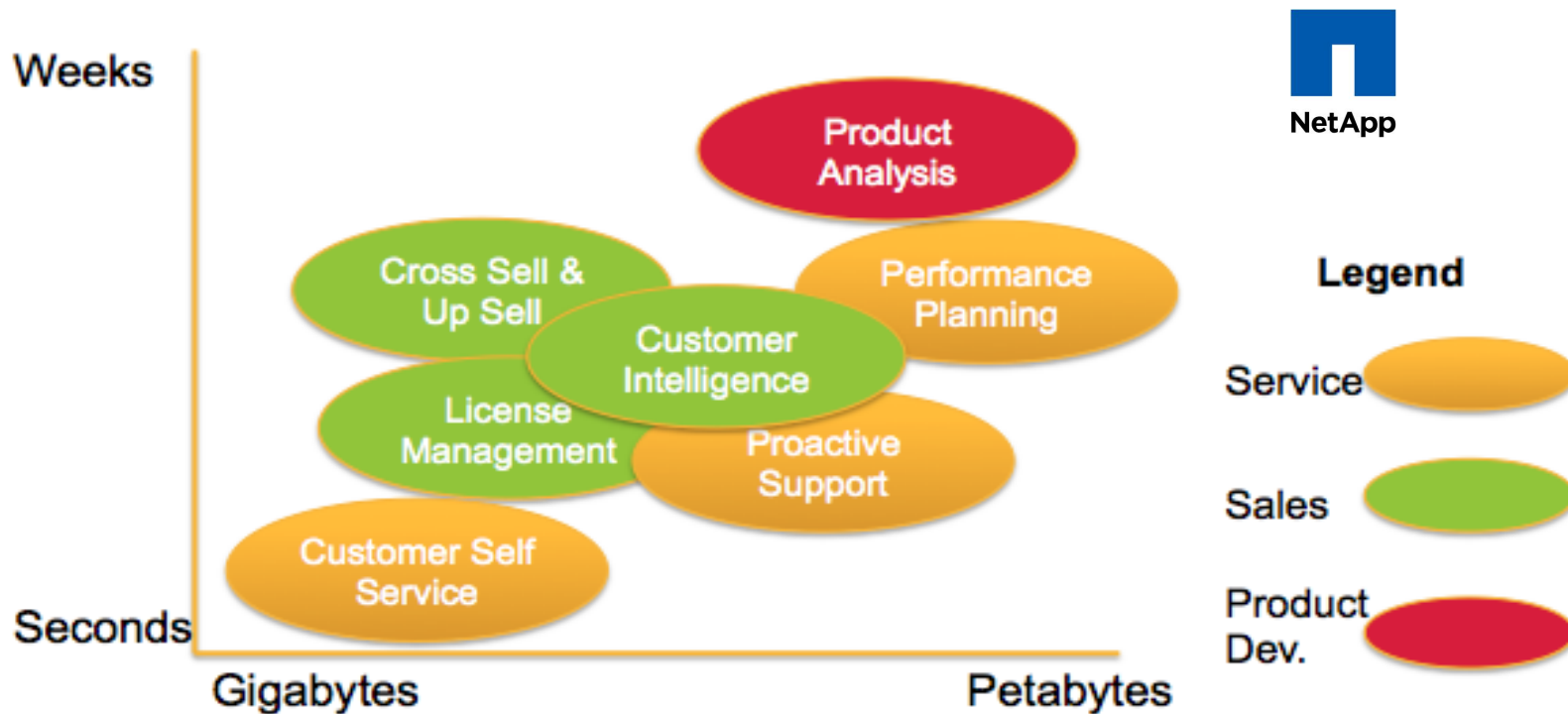
Common Uses

Common Workloads

- Batch processing
 - ETL
 - Model training
 - Model scoring
- Fast analytics
 - Search
 - Lookup

	IT Log & Security Forensics & Analytics	Find New Signal Predict Events React in real time	100% Capture Data Governance Shared Services
	Automated Device Data Analytics	Failure Analysis Proactive Fixes Product Planning	Cross Sell/Upsell Customer Analytics Monetize Data
	Advertising Analytics	Attribution Customer Value Segmentation	Insights Optimization Social Media
	Big Data Warehouse Analytics	Hadoop + MPP + EDW Cost Reduction Flexibility	Ad Hoc Insight Predictive Analytics

Automated Device Support Case Study



Why Big Data Warehouse?

Challenges

- Cost to store unstructured data
- Poor response time to changing BI needs
- Data Warehouse access for departments

Goals

- Integrate unstructured data with data warehouse
- Predictive analytics based on data science
- Comprehensive access to cluster for all users

Hadoop's Role

- Support semi-structured and unstructured data
- Large scale storage
 - Transaction-level detail (e.g., clickstreams)
 - Archival
 - Integrated data: multiple warehouses, new data sources, ...
- Powerful processing capacity
 - Perform large scale analyses/studies
 - Drill to detail in large fact tables
 - Query without structure: agility to analyze data without preprocessing
 - Transformation to build dimensional models, aggregates, and summaries
- Build predictive models

Data Agility

Classic Warehouse

- ETL
- Pre-parse all data
- Normalize up front
- Feed data marts
- New ideas need IT projects

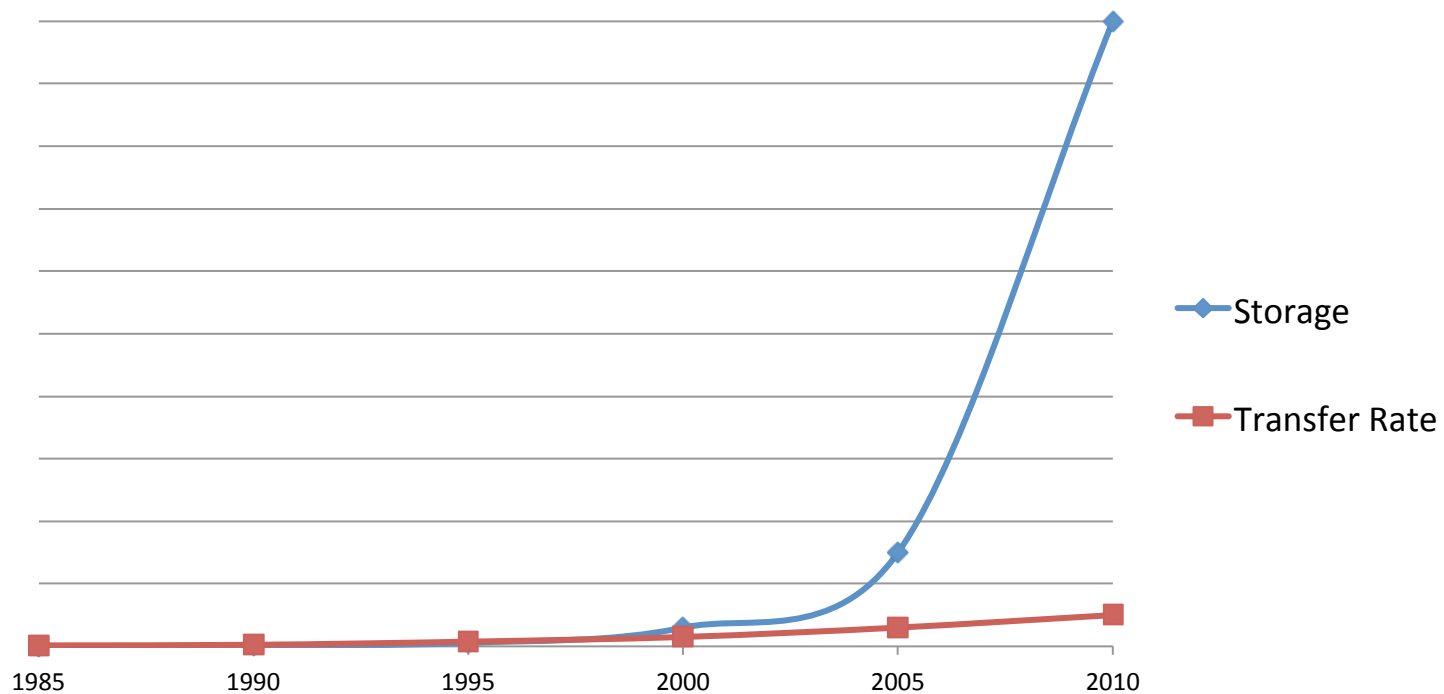
Big Data Warehouse

- Store raw data
- Parse only when proven
- Approximate parse on demand
- Capacity for analysis on demand
- Prove ideas *before* projects to optimize

Futures

Computing Trends

- The growth of storage density has well outpaced the growth of data transfer rates



Computing Trends, cont'd.

- In 1990, you could read all the data from a typical drive in about 5 minutes
- Today, it would take over 2 hours
- And, seek times have improved even more slowly than data transfer rates (SSDs improve this)
- Network speeds in the data center have improved at a comparable speed (60%/yr.)
- So clusters of commodity servers allow throughput
- Clusters of servers allow RAM density

Trends in Big Data for 2012

- Hadoop 0.23 (2.0?)
 - Explosion in New Application Models (e.g. MPI)
- HBase Prominence
- Data Science
 - Practices, Tools,
 - Technologies
- Integration
 - External Tools

Commodity Hardware in 2016?

- 512 GB of RAM
- 64 cores
- 15 TB spinning disks
- 1 TB SSDs for caching
- 100 Gigabit (InfiniBand?)

Summary

- Massive data volumes
 - Processing, Computation
- Ingestion is critical
 - High Volume
 - Reliable, Durable, HA, DR
 - Variety of sources
- All critical to delivering analytics
 - Low latency

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ANALYTICS

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We're hiring...