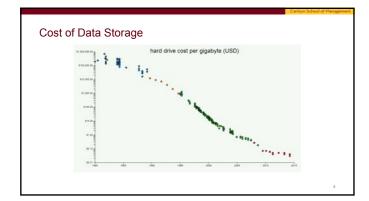
CARLSON SCHOOL		/ AK
	Introduction to Hadoop and Ecosystems	
	MSBA 6320 Prof Liu	
Slides credits: Cloud	dera Academic Partners Program	

Goals

- The goal of this section is to give you a basic understanding of Hadoop's core components (HDFS and MapReduce) and ecosystem
- In this section, you will learn
 - Which factors led to the era of Big Data
 - What Hadoop is and what significant features it provides
 - How does it offer reliable storage for massive amounts of data with HDFS
 - How does it support large scale data processing through MapReduce
 - What are the new capabilities introduced by YARN?
 - How can Hadoop Ecosystem tools boost an analyst's productivity

Topics

- The Motivation For Hadoop
- Hadoop Overview
- HDFS
- MapReduce
- The Hadoop Ecosystem



Traditional storing big data is prohibitively expensive

- How has industry typically dealt with these problem?
 - Perform an ETL (Extract, Transform, Load) on the data to summarize the data, before archiving the result in a data warehouse
 Discarding the details
 - Run queries against the summary data
- · Unfortunately, this process often resulted in lost detail
 - But there could be real nuggets in the lost detail
 - More data == Deeper understanding
 - "There's no data like more data" (Moore 2001)
 - "It's not who has the best algorithms that wins. It's who has the most data"

5

Now we can store data cheaply

- But we're having too much data to process with traditional tools
- Two key problems to address
 - How can we reliably store large amounts of data at a reasonable cost?
 Hardware failures
 - How can we analyze all the data we have stored?
 - Time needed to read the data into memory for analysis
- Hadoop provides reliable distributed storage, and a general framework for parallel processing at low cost.

Topics

- The Motivation For Hadoop
- Hadoop Overview
- HDFS
- MapReduce
- The Hadoop Ecosystem

What Is Apache Hadoop?

- · A system for providing scalable, economical data storage and processing.
- · 'Core' Hadoop consists of two main components
 - Storage: The Hadoop Distributed File System (HDFS)
 - A framework for distributing data across a cluster in ways that are scalable, reliable, available, fast, and economical
 - Processing: MapReduce
 - · A framework for processing data in ways that are scalable, reliable, available, and fast
 - Plus the infrastructure needed to make them work, including
 - · Filesystem and administration utilities
 - · Job scheduling and monitoring

Where Did Hadoop Come From?

- Started with research that originated at Google back in 2003
 - Google's objective was to index the entire World Wide Web
 - Google had reached the limits of scalability of RDBMS technology
 - This research led to a new approach to store and analyze large quantities of data
 Google File Systems (Ghemawat, et al 2003)
 MapReduce: Simplified Data Processing on Large Clusters (Dean and Ghemawat 2004)
- · A developer by the name of Doug Cutting was wrestling with many of the same problems in the implementation of his own open-source search engine, Lucene
 - He started an open-source project based on Google's research and created Hadoop in 2005.
 - Hadoop was named after his son's toy elephant.



- Hadoop is a distributed system
 - A collection of servers running Hadoop software is called a **Cluster**
- Individual servers within a cluster are called **nodes**

 - Typically standard rack-mount servers running Linux Each node both stores and processes data

 Called "data locality"
- · Add more nodes to the cluster to increase scalability
 - Facebook and Yahoo are each running clusters in excess of 4400 nodes

 - Facebook and varioo are each furning deals an electric scalability is linear

 Horizontal scaling simplifies capacity planning as well

 Horizontal scaling: scale by adding more machines to the pool of resources

 Vertical scaling: scale by adding more power CPU/RAM to an existing machine



Powerful Hadoop clusters can be built from cheap commodity hardware, resulting in lowered cost!

Fault Tolerance

- Paradox: adding nodes increases chances that any one of them will
- Solution: build redundancy into the system and handle it automatically.
 Files loaded into HDFS are replicated across nodes in the cluster.
- If a node fails, its data is re-replicated using one of the other copies
- Data processing jobs are broken into individual tasks
- Each task takes a small amount of data as input
 Thousands of tasks (or more) often run in parallel
 If a node fails during processing, its tasks are rescheduled elsewhere

 Routine failures are handled automatically without any loss of data
 Developers/Users do not need to worry about hardware failures

Review Question

Advantages of a Hadoop system



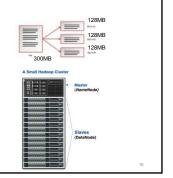
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Carlon School of Management	1
Topics	
The Motivation For Hadoop	
Hadoop Overview	
HDFS MapReduce	
The Hadoop Ecosystem	
13	
Carlon 50ood of Management	1
HDFS: Hadoop Distributed File System	
Provides inexpensive and reliable storage for massive amounts of	
data — Optimized for a relatively small number of large files	
Each file likely to exceed 100 MB, multi-gigabyte files are common	
 Store file in hierarchical directory structure e.g., /sales/reports/asia.txt 	
Cannot modify files once written Need to make changes? remove and recreate	
Use Hadoop specific utilities to access HDFS	
14	<u> </u>
Carlson School of Management.	1
HDFS and Unix File System*	
In some ways, HDFS is similar to a UNIX filesystem	
 Hierarchical, with UNIX/style paths (e.g. /sales/reports/asia.txt) UNIX/style file ownership and permissions 	
There are also some major deviations from UNIX	
No concept of a current directory Cannot modify files once written	
You can delete them and recreate them, but you can't modify them Must use Hadoop specific utilities or custom code to access HDFS	
must use Hadoop specific diffilies of custofff code to access HDFS	

HDFS Architecture (1 Of 3)

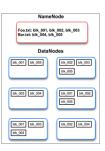
- Blocks: HDFS files are broken into blocks, a smallest unit for read and write. HDFS uses128 MB blocks by default (Windows default block size is 4
 - Each block is replicated multiple times and stored in different nodes of the cluster
- An HDFS cluster has a master/slave architecture
- HDFS NameNode (one or two)
 - Manages namespace (file to block mappings) and metadata (block to machine mappings).
 Monitors dataNodes

- HDFS DataNodes (many)
 Reads and writes the actual data



HDFS Architecture (2 Of 3)

- Example:
 - The NameNode holds metadata for the two files
 - Foo.txt (300MB) and Bar.txt (200MB)
 - · Assume HDFS is configured for 128MB blocks
 - The DataNodes hold the actual blocks
 - · Each block is 128MB in size
 - · Each block is replicated three times on the cluster
 - Block reports are periodically sent to the NameNode



HDFS Architecture (3 Of 3)

- · Optimal for handling millions of large files, rather than billions of small files, because:
 - In pursuit of responsiveness, the NameNode stores all of its file/block information in memory
 - A rule of thumb is each block/directory/file takes about 150 bytes
 - A name node can handle millions of objects, but not billions
 - Too many files will cause the NameNode to run out of memory
 - Too many blocks (if the blocks are small) will also cause the NameNode to run out of memory
 - A Java Virtual Machine (JVM) is required to process a block; if you have too many blocks, you will need many JVMs at the same time, and you will begin to see the limits of HDFS scalability.

Copying Local Data To And From HDFS • Remember that HDFS is separated from your local filesystem - Use hadoop fs -put to copy local files to HDFS - Use hadoop fs -get to copy HDFS files to local files * hadoop fs -put sales.txt /reports * hadoop fs -put sales.txt /reports * hadoop fs -get /reports/sales.txt * hadoop fs -get /reports/sales.txt

Review Question

• HDFS Design



Topics

- The Motivation For Hadoop
- Hadoop Overview
- HDFS
- MapReduce
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Introd	lucina	Map	Reduce

- Now that we have described how Hadoop stores data, lets turn our attention to how it processes data
- We typically process data in Hadoop using MapReduce
- MapReduce is not a language, it's a programming model MapReduce consists of two functions: map and reduce
- Before MapReduce, coordinating the processes in a large-scale distributed computation is a challenge.
 - MapReduce spare the programmer from having to think about failure, since the implementation detects failed tasks and reschedules replacements on machines that are healthy.
 - MapReduce follows shared-nothing architecture, meaning that tasks have no dependence on one other. MapReduce programmers need not worry about order in which tasks run. By contrast, other distributed computing models often require programmers to explicitly manage their own checkpointing and recovery.

Map function

- The map function always runs first
 - Each mapper takes <key, value> pairs as input, one pair at a time
 - Many mappers run in parallel to each other, each assigned to a chunk of the input data.
 For each input pair, a mapper emits a list of output pairs.
 - - (key, value) > list(key, value)
 E.g. "fox jumps over" --> ("fox",1),("jumps",1),("over",1)
 "fox jumps over" --> ("FoX JUMPS OVER")
 - Typically used to "break down"

 - Filter, transform, or parse data,
 e.g. Parse the stock symbol, price and time from a data feed
 Break a sentence into words

 - The output from the map function (eventually) becomes the input to the reduce function

Reduce function

- The reduce function takes a list of values for every key, and transforms the data on the (aggregation) The reduce function takes a list of values for every key, and transforms the data logic provided in the reduce function

 I thakes a *key, value-list-pair as input, and emits a list of *key, value-pairs as output

 (*key, List of values for the key) --> List(*key, Value)

 E.g. (*jumps*,(1,1,2,1,1)) --> (*jumps*,6)

 Each job may have multiple reducers, each responsible for a specific key range.

 Typically used to aggregate data from the map function

 e.g. Compute the average hourly price of the stock

 A reduce step is optional

 * You can up something realled a *man-point on the stock of the stock of

- You can run something called a "map-only" job
- Between map and reduce, there is typically a hidden phase known as the "Shuffle and Sort" which organizes map outputs for delivery to the reducer.

A MapReduce Example The following slides will e

- The following slides will explain an entire MapReduce job
 - Input: a text document (a list of sentences)
 - Output: word counts

SQL DW SQL SQL SSIS SSRS SQL SSAS SSRS DW BI SQL



BI, 1 DW, 2 SQL, 5 SSAS, 1 SSIS, 1 SSRS, 2

05

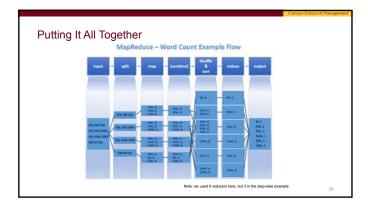
A MapReduce Example - Split and Map

- Hadoop splits a job into many individual map tasks
 - The number of map tasks is determined by the amount of input data
 - Each map task receives a portion of the overall job input to process in parallel
 - In this case, there are 4 mappers, each processing one chunk (in practice, each chunk includes multiple records)

| SQL DW SQL | (SQL, 1) (SQL,

A ManDaduca Evample Chuffle & Cart				
A MapReduce Example – Shuffle & Sort				
Map outputs are shuffled and sorted by key				
Sometimes a combiner is run to before shuffle and sort to reduce the amount of data transferred across the network				
 There may not be a combiner for certain aggregate operations E.g. there are combiners for sum and max. but there is no combiner for average. 				
 Shuffle and sort is implicit and carried out by the MapReduce framework. 				
 It results are feed into reducers (we have three in this case) 				
(SQL, 1) (OW, 1) (SQL, 1) (OW, 1)				
(SQL, 1) (SS15, 1) (SS15, 1) (SS85, 1) (SS85, 1) (SQL, 2) (SQL, 1) (SQL, 1)				
(SQL, 1) (SSAS, 1) (SSAS, 1) (SSAS, 1) (SSAS, 1) (SSAS, 1)				
(89, 1) (1, 1) (
Compliner Shuffle and sort				

A MapReduce Example – Reduce • Reducer input comes from the shuffle and sort process - All value for the same key is collected and feed into a reducer - The reducers aggregates the values and emit a key value pair - Each reducer output file is written to a job specific directory in HDFS ((at. 2) ((bu, 1) (bu, 1) ((bu, 1) ((bu, 1) (bu, 1) ((bu, 1) ((bu, 1) (bu, 1) ((bu, 1) (bu, 1)



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Ron	efits		/lan	₽۵	duce
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- · Simplicity (via fault tolerance)
 - Particularly when compared with other distributed programming models
- · Flexibility
 - Offers more analytic capabilities and works with more data types than platforms like SQL (key, value pairs can accommodate different kinds of structured and unstructured data)
- Scalability
 - Because it works with

 - Small quantities of data at a time
 Running in parallel across a cluster
 - Sharing nothing among the participating nodes

Review Question

The role of MapReduce



The Benefits of MapReduce



Hadoop 2.0

- · So far we have focused original ideas of Hadoop
 - It has batch processing in mind
 - It supports only MapReduce applications, which has too high a latency for interactive and streaming applications.
- Since then, many improvements have been made to the Hadoop, including
 - YARN (Yet Another Resource Negotiator)
 - The ability to run non MapReduce applications (e.g. support Spark)
 - Beyond batch processing: the ability to support interactive and streaming applications.

YARN

- YARN (Yet Another Resource Negotiator) is a new component added in Hadoop 2.0
 - In Hadoop 1.0, MapReduce does both distributed computing and resource management (via jobtracker)
 - jouruscker)

 Limits availability, scalability, resource utilization, and running non-MapReduce applications. If the job tracker fails, all jobs must restart.

 YARN takes over the resource management (CPU, memory etc) and job scheduling, allows multiple kinds of processing to run on a single Hadoop cluster (e.g. batch processing, interactive application, streaming)



Hadoop 2.0 Architecture

- Separate MapReduce into a YARN layer and MR (for batch processing)
- Support non-MapReduce applications, e.g. streaming and interactive applications (e.g. Impala, Spark, Storm, HBase, Giraph etc)
- Improved nameNode availability



Read more: http://saphanatutorial.com/hadoop-1-0-vs-hadoop-2-0/

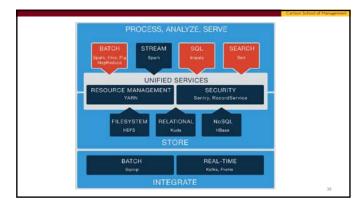
Review Qustion

• Hadoop 2.0 improvements

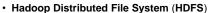


Topics

- The Motivation For Hadoop
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Data Storage





HBASE

- HDFS is the storage layer for Hadoop
 Provides inexpensive reliable storage for massive amounts of data on commodity hardware
- Data is distributed when stored
- · Apache HBase
 - A NoSQL distributed database built on HDFS
 - Scales to support very large amounts of data
 High throughout

 - A table can have many thousands of columns & billions of rows
 No high-level query language, API access only.

Apache Kudu



- Distributed columnar (key-value) storage for structured data
- Allows random access and updating data (unlike HDFS)
- Supports **SQL**-based analytics
- · Works directly on native file system; is not built on HDFS
- Integrates with Spark, MapReduce, and Apache Impala
- Created at Cloudera, donated to Apache Software Foundation

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Data Integration Tools (1)

- HDFS
 - Direct file transfer



- · Apache Sqoop
 - High speed import for HDFS from RDBMS (and vice versa)
 - Supports many RDBMS:
 - E.g. Oracle, Teradata, MySQL, MongoDB, Netezza



Data Integration Tools (2) • Apache Kafka — A high throughput, scalable messaging system — Distributed, reliable publish-subscribe system • Apache Kafka Apache Kafka • Apache Flume — Distributed service for ingesting streaming data — Ideally suited for event data from multiple systems

Batch Processing Tools (1 of 4)

- Hadoop MapReduce is the original Hadoop framework
 - Primarily Java based
 - Was the core Hadoop processing engine
 - Has mature fault tolerance built into the framework
 - But quickly losing ground to Spark and other engines

ap(String name, String contents):
 for each word w in contents:
 if (IsCapitalized(w)):
 uppercase->Increment();
 EmitIntermediate(w, "1");



Batch Processing Tools (2 of 4)

- Apache Pig builds on Hadoop to offer high-level data processing
 - An alternative to write low-level MapReduce code
 - Useful for ETL (extract, transformation, and loading)
 - Used by developers and analysts
- Pig Interpreter
 - Turns Pig Latin scripts into MapReduce (or Spark) Jobs
 - Submits those jobs to a Hadoop cluster

people = LOAD '/user/training/oustomers' AS (oust_id, name);
orders = LOAD '/user/training/orders' AB (orst_id, cust_id, cust);
groups = GEOD' orders ET cust_id;
tatals = TORRACH groups GENERACH group, SOM(orders.cost) AS t;
result = JOHE totals ET group, people ET cust_id;



Batch Processing Tools (3 of 4)

- Apache Hive is the data warehouse application for Hadoop.
 - Uses a SQL-like language called HiveQL
 - Useful for managing and querying large tables in Hadoop
 - Translate SQL to MapReduce jobs

SELECT zipcode, SUM(cost) AS total FROM customers JOIN orders ON customers.cust_id = orders.cust_id WHERE zipcode LIRE '63' GODER BY total DESC;



Batch Processing Tools (4 of 4)

- Spark: Spark is a fast large-scale in-memory processing engine
- Interface with YARN clusters and HDFS, and many other storage options
- Highly popular, is overtaking Hadoop
- Has core spark and four components
 SQL, Streaming, Mllib, GraphX



 Spark SQL – for SQL operations; not a SQL engine but flexible for SQL based data munging.



Interactive Query Tools (1 of 2)

- Apache Impala is a high-performance, interactive SQL engine
 - Very low latency measured in milliseconds
 - Run on Hadoop clusters
 - Supports a dialect of SQL (Impala SQL)

SELECT zipcode, SUM(cost) AS total
FROM customers
JOIN orders
ON customers.cust_id = orders.cust_id
MHERE zipcode LIEE '63'
GROUP BY zipcode
GROUP SY zipcode



Interactive Query Tools (2 of 2)

- Apache Drill is a high performance SQL engine that can query a variety of structured, semi-structured data formats
 - Uses Standard ANSI SQL
 - Query semi-structured data formats and sources, e.g. HDFS, HBase, JSON, MongoDB, Amazon S3.
 - High performance, scalable.

SELECT * FROM dfs.root.'/web/logs';

SELECT country, count(*)
FROM mongodb.web.users
GROUP BY country;

SELECT timestamp
FROM s3.root.'clicks.json'
WHERE user_id = 'jdoe';



Machine Learning

- Apache Mahout is a machine learning (ML) software for Hadoop
 - It provides a host of pre-made ML algorithms
 - Recently undergone big changes to provide a R-like programming environment
- Apache Spark MLlib: a Machine Learning component of spark
- H2O: in-memory, distributed, fast, and scalable machine learning platform; can be used from R, Python, Scala.
- H2O/Sparkling Water: Combine H2O with Spark







Streaming

- Apache Storm is a distributed and faulttolerance real-time computation platform
 - Horizontal scalability
 - Guaranteed data processing
 - Fault-tolerance
 - High-performance
- Spark Streaming: the streaming component of Apache Spark





Other Hadoop Ecosystem Tools

Other Hadoop Ecosystem Tools

• Apache Sentry: Provides fine-grained access control for varous Hadoop ecosystem components.



 Apache Zookeeper: a distributed hierarchical key-value store for providing a distributed configuration service, synchronization service, and naming registry for large distributed systems.

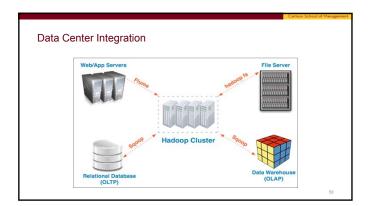


 Apache Ooozie: A workflow engine that ensures jobs are submitted in the correct sequence.



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The Hadoop Ecosystem		
Data ingestion/integration:		
Storage: Grans HEASE		
Batch processing: 🚜 🗽 spork		
Interactive Processing: Impala, Drill 💡 🏠		
Machine Learning: 🗞 🎎 📆 H₂O		
Streaming processing: Storm Sport Sport		



Hadoop & Data Lake

- A Data Lake approach
 - The traditional Data Mart /Data Warehouse is a "store of bottled water"
- The data lake is a "large body of water in a more nature state" (James Dixon, CTO of Pentaho)

 Contents of the data lake stream in from a source to fill the lake, and various uses can examine, dive in, or take samples.

 Hadoop is an ideal platform for building a data lake
- - It provides for storing a mixture of structured and unstructured data, side by side.

 It could be used to store far more detail about the transaction than you would in an ordinary RDBMS (due to costs limitations)

Source: date science central Read mone: Hester, L. 2016. "Maximizing Data Value with a Data Lake," Data

Bibliography The following offer more information on topics discussed in this section Hadoop: The Definitive Guide, 4th Edition (U of M Students have free access) The following offer more information on topics discussed in this section Hadoop: The Definitive Guide, 4th Edition (U of M Students have free access) The following offer more information on topics discussed in this section of the following discussed in this section of the following discussed in this section of the following discussed in	Count Should Managed	
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