

Aurelius Corporate Solutions

Course- Big Data Hadoop (Basic)

Aurelius Corporate Solutions

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1000+ Unique Technologies Projects Delivered | 500+ Corporate Customers Worldwide | 5000+ Professionals

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Course Topics

✓ Welcome to Big Data World

- Understanding Big Data
- √ Hadoop Architecture

✓ HDFS

- ✓ Deep dive in HDFS Architecture
- ✓ HDFS APTs
- ✓ Introduction to HDP Sandbox
- ✓ HDFS Hands 1 Hour

✓ Introduction to YARN & MR

- √ Hadoop MapReduce framework
- ✓ Programming in Map Reduce

✓ Advance Map Reduce

- ✓ Understanding Counters
- ✓ Differences between MR1 & MR2
- ✓ Introduction to MR API
- ✓ Overview of Map Side Join
- ✓ Overview of Reduce Side Join
- ✓ Map Reduce Hands On 1 hour

Hive

- ✓ Analytics using Hive
- ✓ Understanding HIVE QL

✓ Advanced Hive

- √ Advance Hive
- ✓ Hive Hands On 1 Hour

√ NoSQL & HBase

- ✓ CAP Theorem
- ✓ NoSQL Databases and HBASE
- ✓ HBase Architecture
- ✓ HBase Schema Design
- ✓ Difference between Hive & Hbase
- ✓ Hbase Hands On 1 Hour

✓ Apache Spark

- ✓ Introduction to Spark
- ✓ Why Spark?
- ✓ Spark Stack Overview
- ✓ Overview of RDD, Data Frame & Data Set
- ✓ Spark Actions & Transformation Overview



Topics for Day 1: Covered

- ✓ Team Introduction
- ✓ Introduction to Big Data Why and What?
- ✓ Characteristics of Big Data (4Vs)
- ✓ Overview of Big Data Ecosystem
- ✓ What is Hadoop?
- ✓ History of Hadoop

Tea Break

- ✓ Components of Hadoop
- ✓ Introduction to HDFS
- ✓ HDFS Architecture Name Node / Data Node, Concept of Blocks
- ✓ File Formats in Hadoop
- ✓ HDFS API walk through
- ✓ Anatomy of a File Write and Read

Lunch Break

- ✓ Overview of Lab environment HDP sandbox etc.
- ✓ HDFS Hands on Getting Familiar with HDFS most commonly used commands
- ✓ Introduction to Map Reduce
- ✓ Map Reduce Phases Map, Shuffle-Sort and Reduce
- ✓ Map Reduce Job Submission Flow



Topics for Day 2: Covered

- ✓ Any question from Day 1
- ✓ Understanding Counters
- ✓ Difference Between MR1 & MR2

Tea Break

- ✓ Job Class, GenericOptionsParser, Mapper & Reducer
- ✓ Distributed Cache
- ✓ Custom Input Format
- ✓ Overview of Map Side Join & Reduce Side Join

Lunch Break

- ✓ Map Reduce Hands On
- ✓ Data Integration Choices Sqoop, Flume
- ✓ Introduction to Hive
 - ✓ Hive Architecture
 - ✓ Working with Schema
 - ✓ Introduction to Hive QL
 - ✓ Partitioning & Bucketing



Topics for Today (Day 3)

- ✓ Any question from Day 2
- ✓ NoSQL & HBase
 - ✓ CAP Theorem
 - ✓ NoSQL Databases and HBASE

Tea Break

- ✓ NoSQL & HBase
 - ✓ HBase Architecture
 - ✓ HBase Schema Design
 - ✓ Difference between Hive & Hbase
 - ✓ Hbase Hands On 1 Hour

Lunch Break

- ✓ Apache Spark
 - ✓ Introduction to Spark
 - ✓ Why Spark?
 - ✓ Spark Stack Overview
 - ✓ Overview of RDD, Data Fram
 - ✓ Spark Actions & Transformation Overview



Recap



Create a partitioned table using PARTITIONED BY

```
CREATE EXTERNAL TABLE accounts by state (
    cust id INT,
    fname STRING,
    lname STRING,
    address STRING,
    city STRING,
    state STRING,
    zipcode STRING)
  PARTITIONED BY (state STRING)
  ROW FORMAT DELIMITED
  FIELDS TERMINATED BY ','
  LOCATION '/loudacre/accounts by state';
```

Partition Columns

The partition column is displayed if you DESCRIBE the table

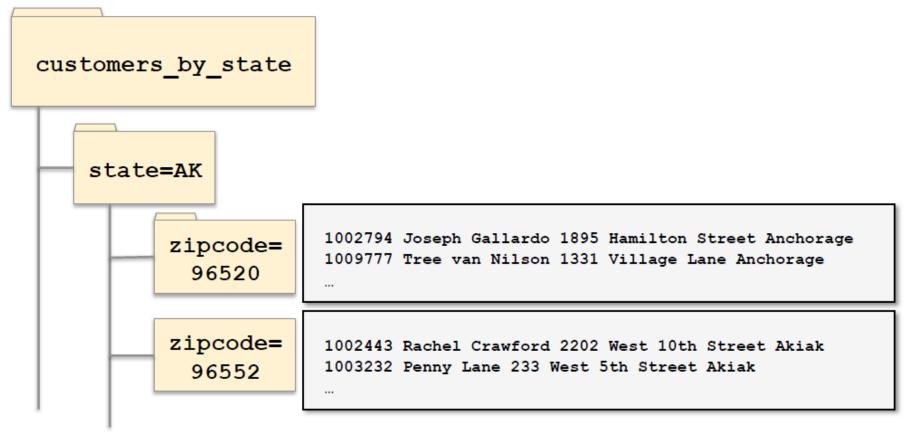
```
DESCRIBE accounts by state;
           | type
                     | comment
  name
  cust id | int
  fname
           | string
             string
  lname
  address | string
  city | string
  zipcode | string
  state
             string
                        A partition column is a "virtual
                        column"; data is not stored in the file
```



Nested Partitions

You can also created nested partitions

... PARTITIONED BY (state STRING, zipcode STRING)



Loading Data Into a Partitioned Table

Dynamic partitioning

- Impala/Hive add new partitions automatically as needed at load time.
- Data is stored into the correct partition (subdirectory) based on column value

Static partitioning

- You define new partitions using ADD PARTITION
- When loading data, you specify which partition to store data in



Dynamic Partitioning

We can create new partitions dynamically from existing data

```
INSERT OVERWRITE TABLE accounts_by_state
    PARTITION(state)
SELECT cust_id, fname, lname, address,
    city, zipcode, state FROM accounts;
```

- Partitions are automatically created based on the value of the last column
 - If the partition does not already exist, it will be created
 - If the partition does exist, it will be overwritten



- In older versions of Hive, dynamic partitioning is not enabled by default
 - Enable it by setting these two properties

```
SET hive.exec.dynamic.partition=true;
SET hive.exec.dynamic.partition.mode=nonstrict;
```

- Note: Hive variables set in Beeline are for the current session only
 - Your system administrator can configure settings permanently



Creating Partitions from Existing Partition Directories in HDFS

- Partition directories in HDFS can be created and populated outside Hive or Impala
 - For example, by a Spark or MapReduce application
- In Hive, use the MSCK REPAIR TABLE command to create (or recreate)
 partitions for an existing table

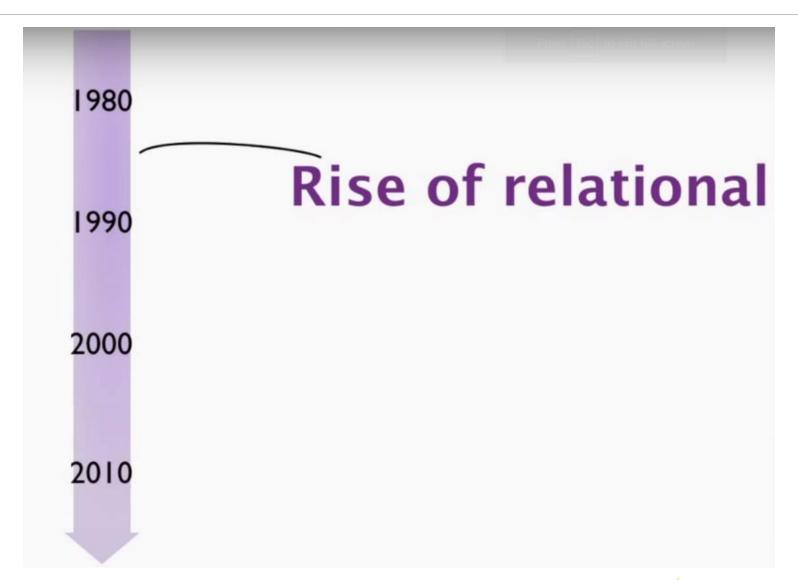


MSCK REPAIR TABLE call_logs;



NoSQL





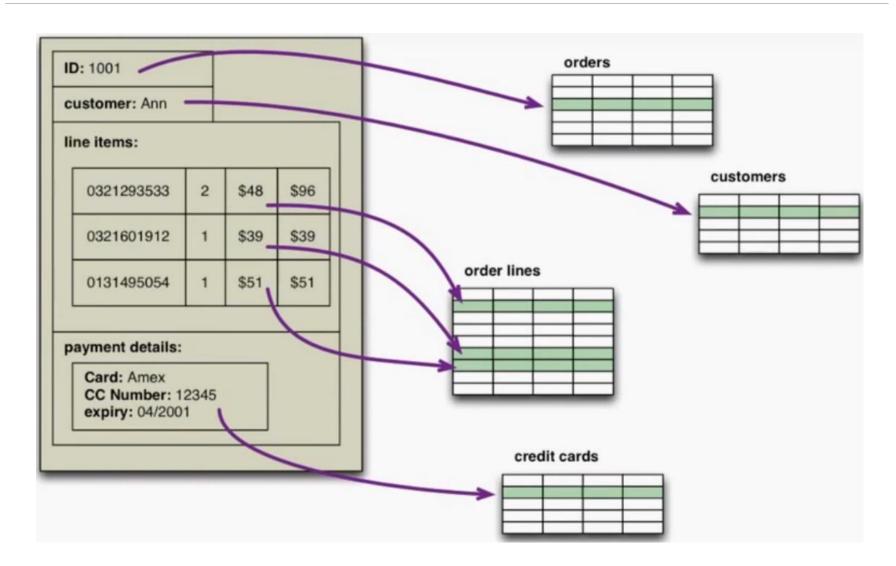


Persistence Integration

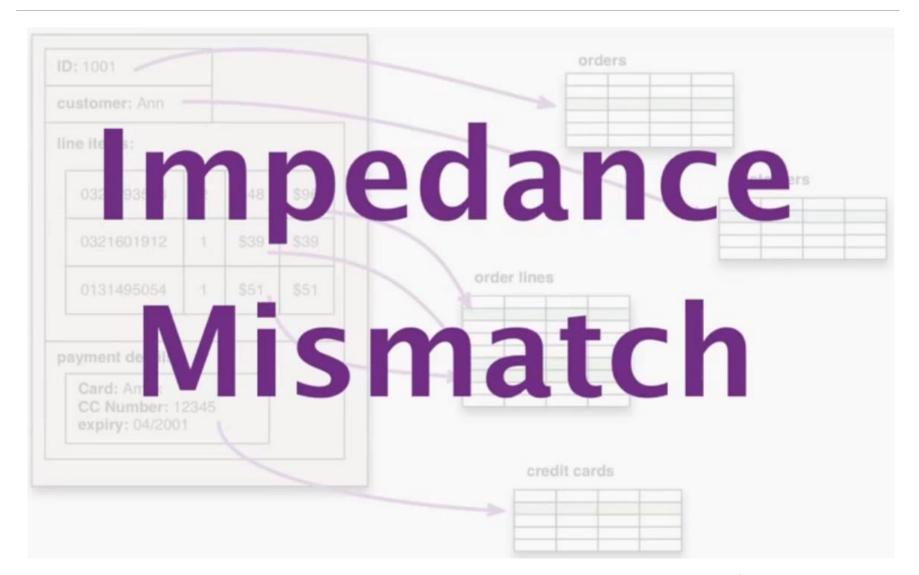
SQL Transactions

Reporting

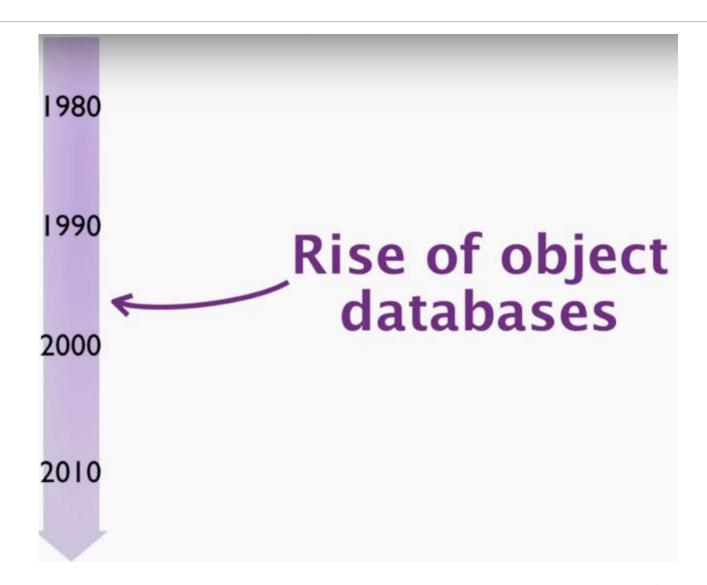




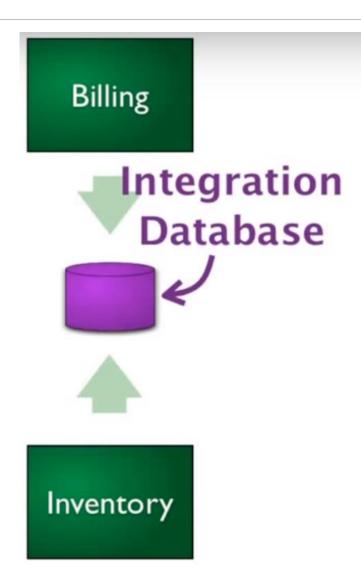




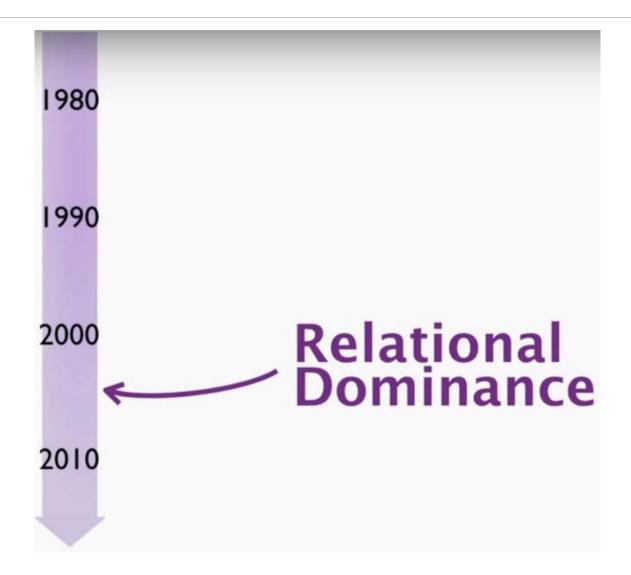








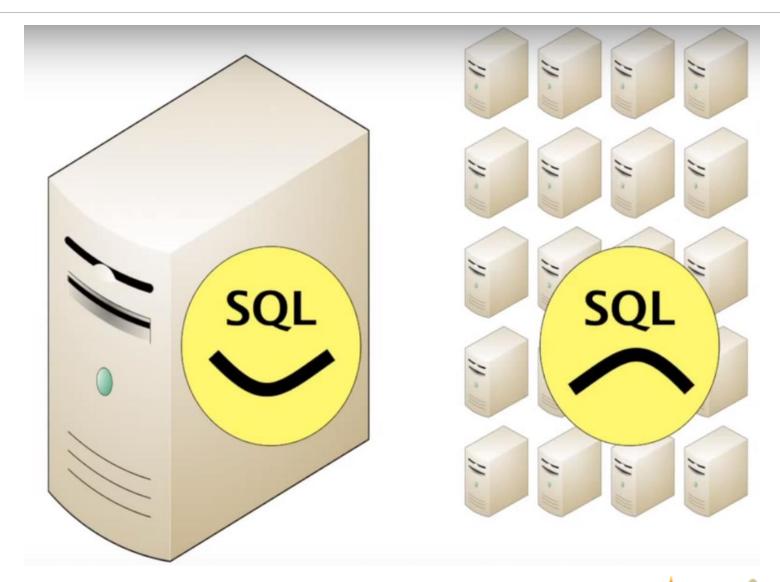


















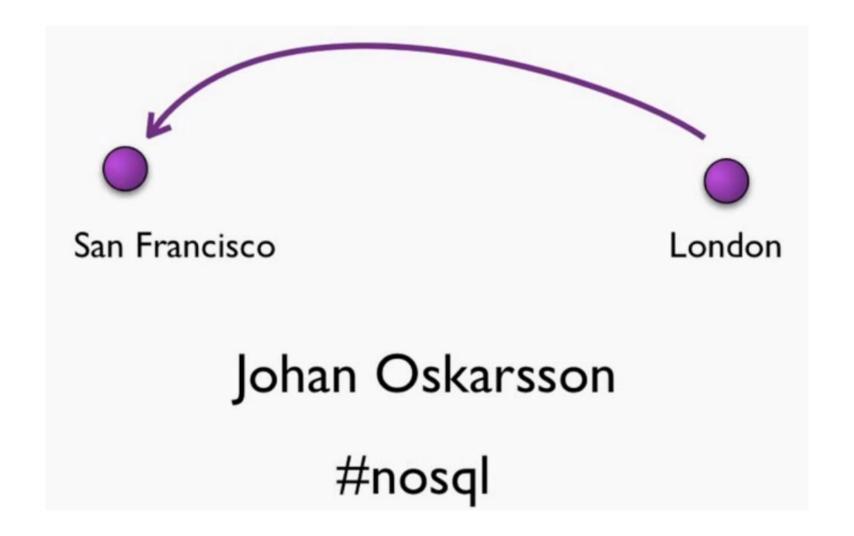
Bigtable





Dynamo

















Dynomite



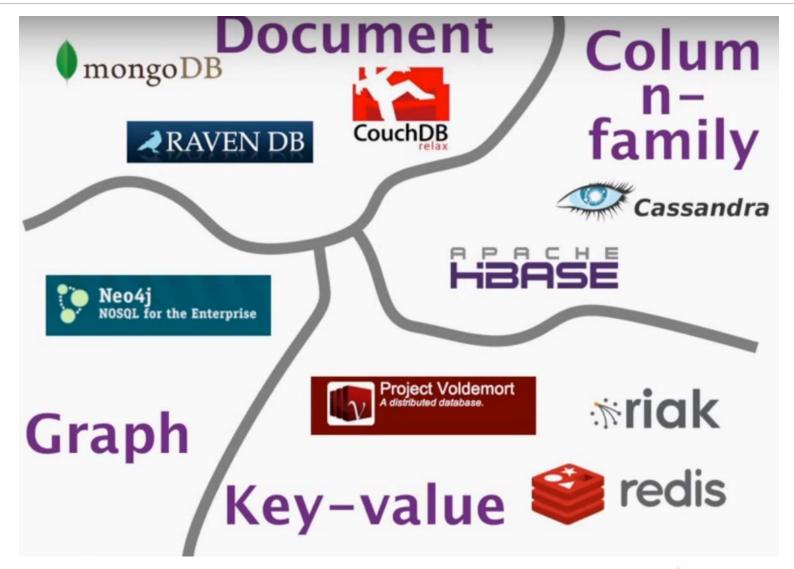


Characteristics of NoSQL

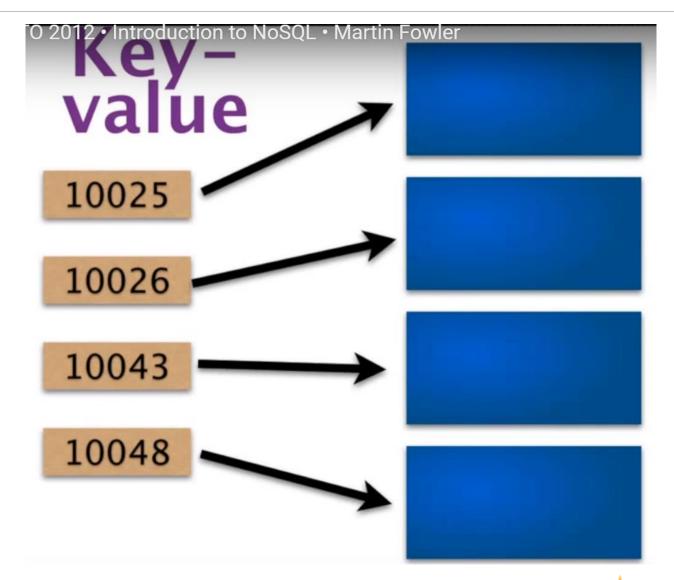
non-relational open-source cluster-friendly 21st Century Web

schema-less







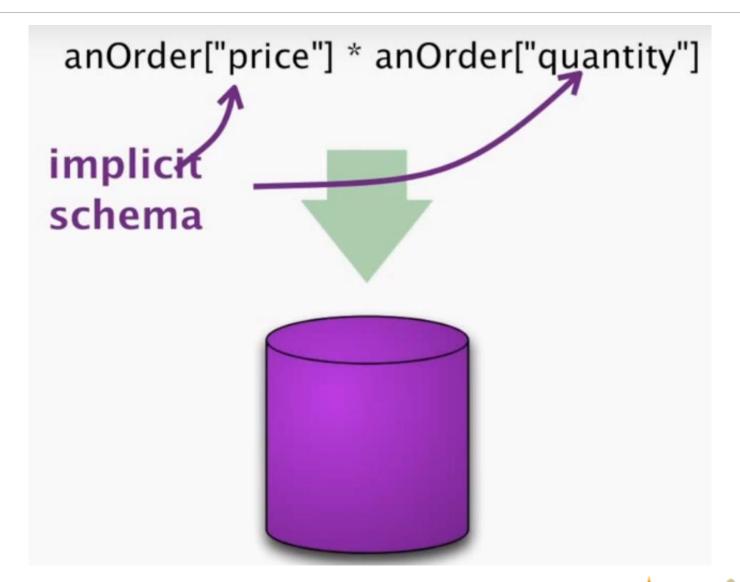




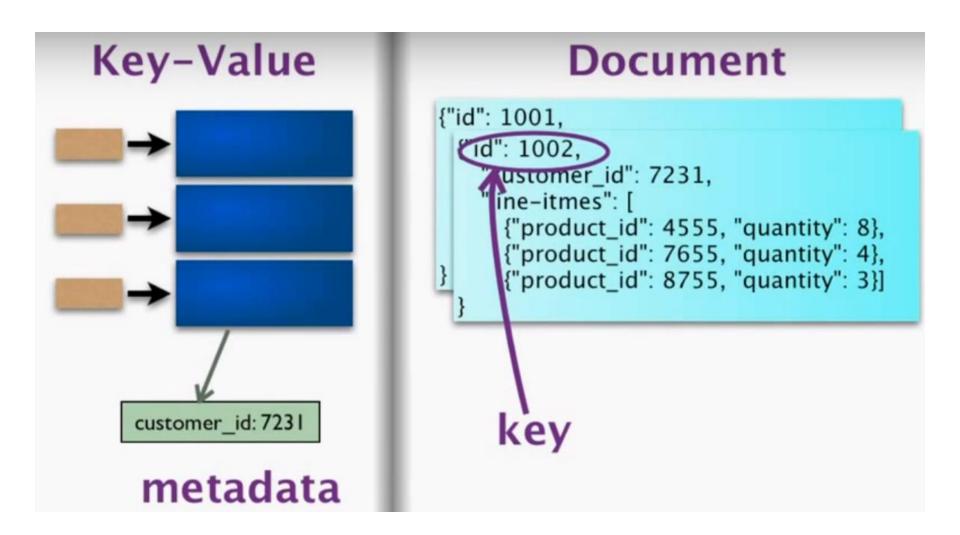
Document

```
{"id": 1001,
"customer_id": 7231,
"line-itmes":
{"product_id": 4555, "quantity": 8},
{"product_id": 7655, "quantity": 4}, {"product_id": 8755,
{"id": 1002,
"customer_id": 9831,
"line-itmes": [
{"product_id": 4555, "quantity": 3},
{"product_id": 155, "quantity": 4}],
"discount-code
```

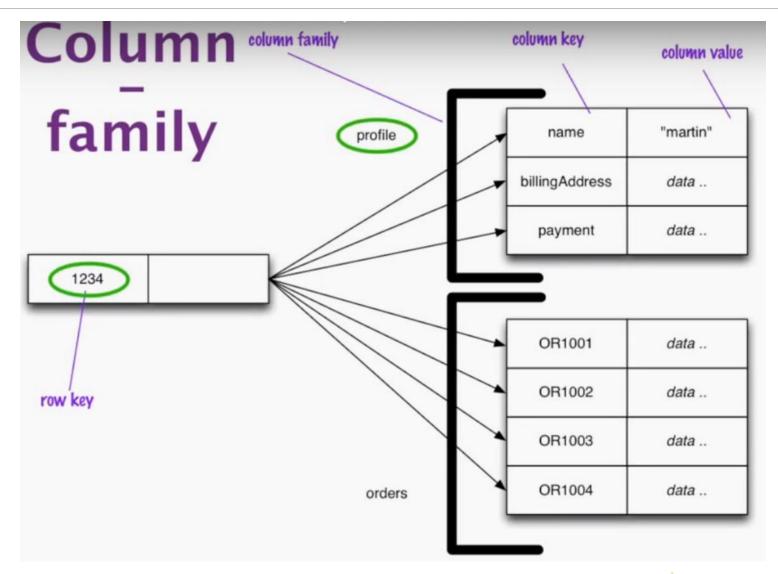




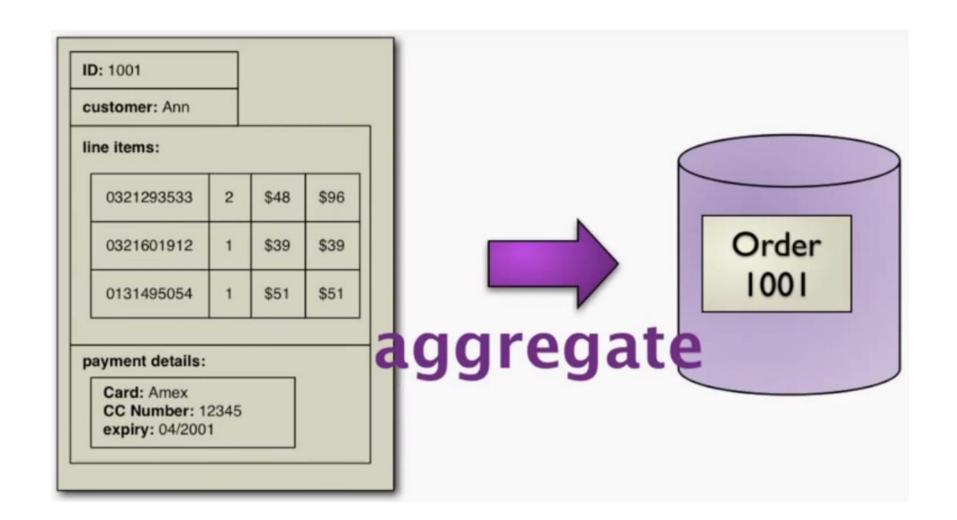




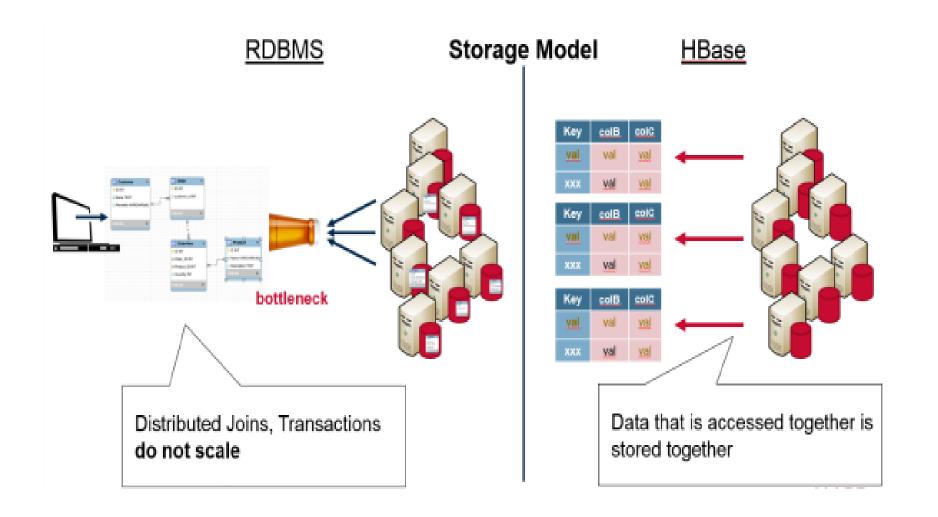












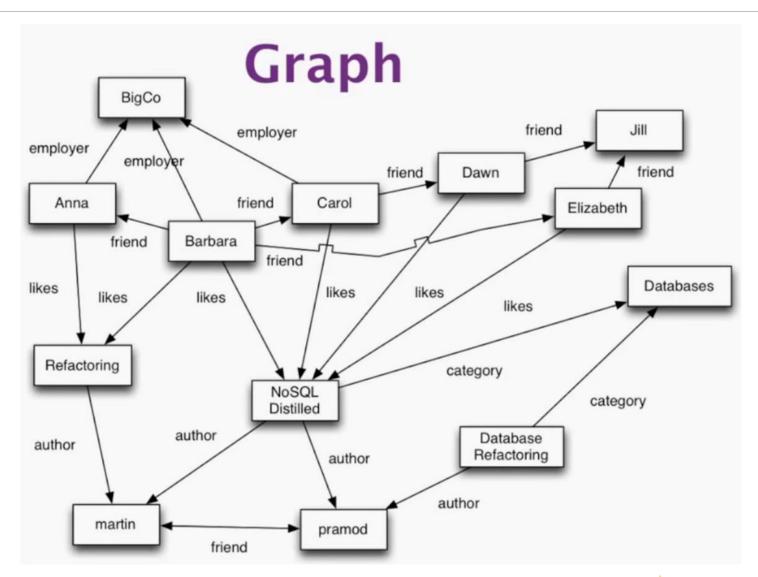


Aggregate-Oriented

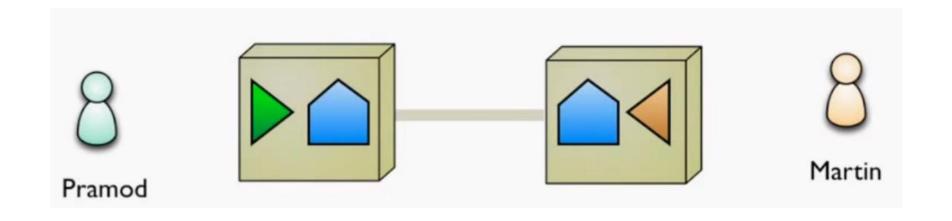
Documen Columnfamily Key-value

Graph

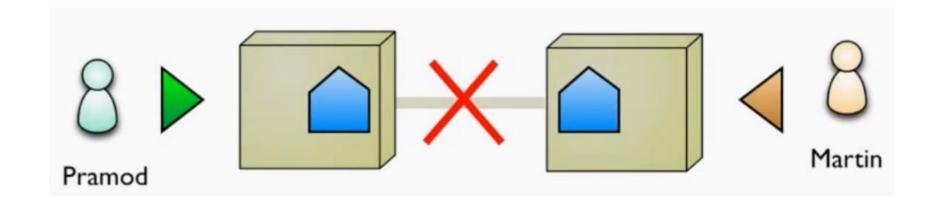




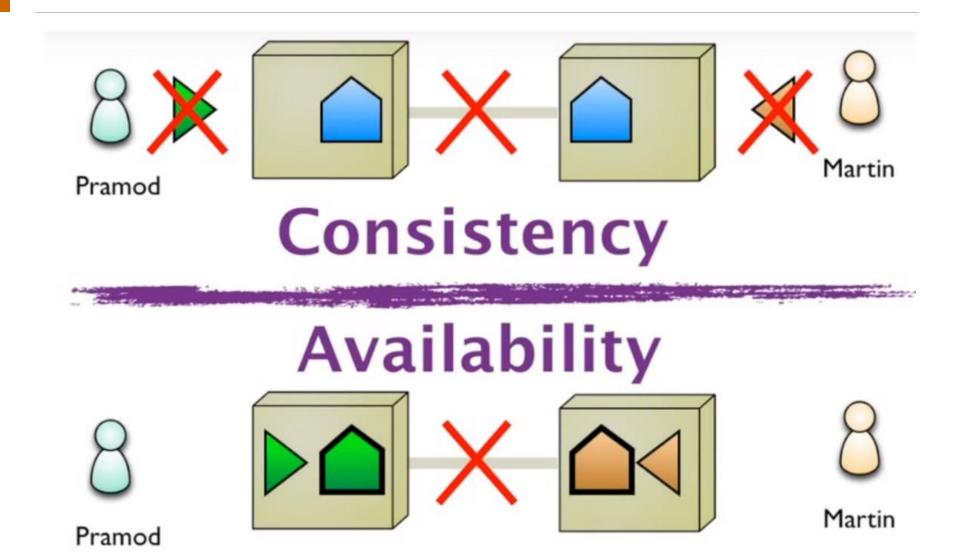




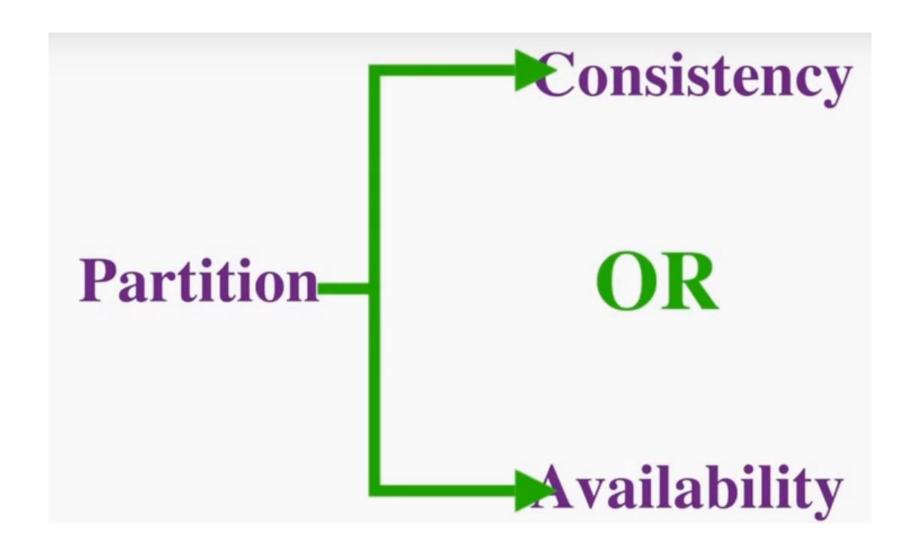














CAP Theorem

Consistency

Availability

PartitionTolerance

Pick any 2



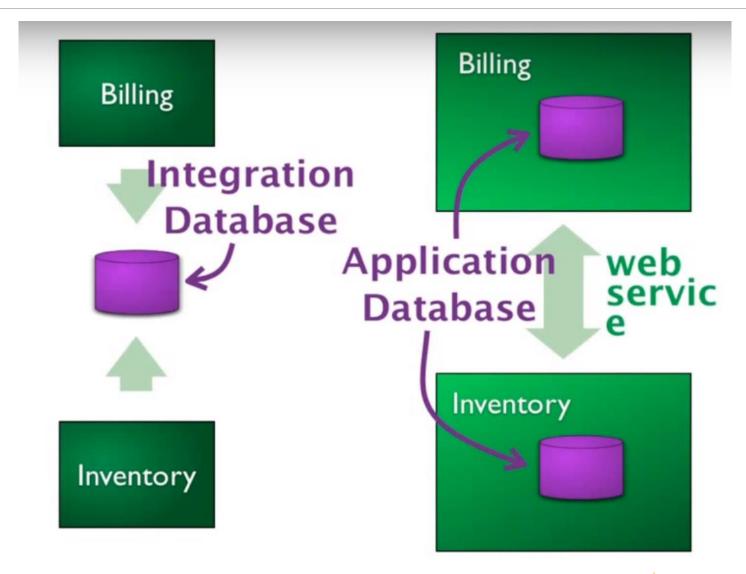
Relaxing Durability

Eventual Consistency

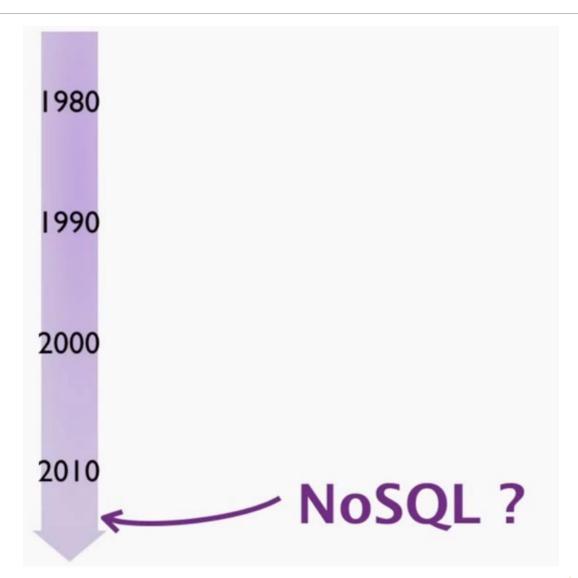
Quorums

Read-Your-Writes Consistency

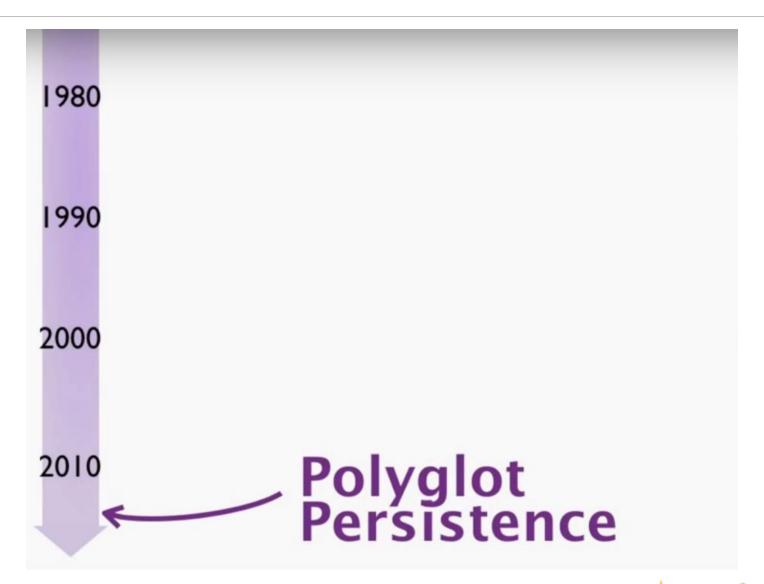


















HBase



Apache Spark



Topics

- What is Apache Spark?
- Using the Spark Shell
- RDDs (Resilient Distributed Datasets)



What is Apache Spark?

 Apache Spark is a fast and general engine for large-scale data processing



- Written in Scala
 - Functional programming language that runs in a JVM
- Spark Shell
 - Interactive for learning or data exploration
 - Python or Scala
- Spark Applications
 - For large scale data processing
 - Python, Scala, or Java



Clip slide

Component Stack

Spark SQL structured data

Spark streaming real-time

Spark Core

Spark Core

Standalone

YARN

MLlib machine learning

Graph X graph processing

MLlib machine learning

MLlib machine learning

MLlib machine learning

Graph X graph processing





Spark Shell



Type :help for more information.

scala>

RDD (Resilient Distributed Dataset)

- RDD (Resilient Distributed Dataset)
 - Resilient if data in memory is lost, it can be recreated
 - Distributed processed across the cluster
 - Dataset initial data can come from a file or be created programmatically
- RDDs are the fundamental unit of data in Spark
- Most Spark programming consists of performing operations on RDDs



Creating an RDD

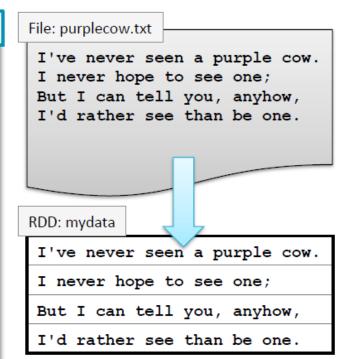
Three ways to create an RDD

- From a file or set of files
- From data in memory
- From another RDD



Example: A File-Based RDD

```
Language: Scala
> val mydata = sc.textFile("purplecow.txt")
15/01/29 06:20:37 INFO storage.MemoryStore:
  Block broadcast 0 stored as values to
  memory (estimated size 151.4 KB, free 296.8
  MB)
> mydata.count()
15/01/29 06:27:37 INFO spark.SparkContext: Job
  finished: take at <stdin>:1, took
  0.160482078 s
```

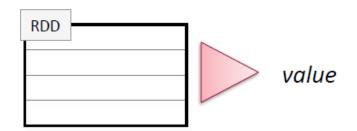




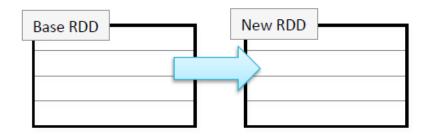
RDD Operations

Two types of RDD operations

Actions – return values



 Transformations – define a new RDD based on the current one(s)



Pop quiz:

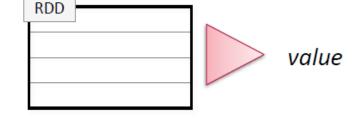
- Which type of operation is count()?



RDD Operations: Actions

Some common actions

- count() return the number of elements
- take (n) return an array of the first n
 elements



- collect() return an array of all elements
- saveAsTextFile (file) save to text file(s)

```
Language: Python
> mydata =
    sc.textFile("purplecow.txt")

> mydata.count()
4

> for line in mydata.take(2):
    print line
I've never seen a purple cow.
I never hope to see one;
```

```
language: Scala
> val mydata =
    sc.textFile("purplecow.txt")

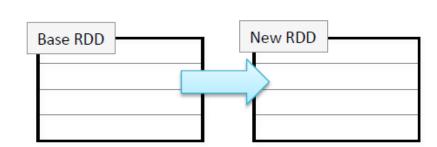
> mydata.count()
4

> for (line <- mydata.take(2))
    println(line)
I've never seen a purple cow.
I never hope to see one;</pre>
```



RDD Operations: Transformations

- Transformations create a new RDD from an existing one
- RDDs are immutable
 - Data in an RDD is never changed
 - Transform in sequence to modify the data as needed



Some common transformations

- -map (function) creates a new RDD by performing a function on each record in the base RDD
- filter (function) creates a new RDD by including or excluding each record in the base RDD according to a boolean function



Example: map and filter Transformations

Language: Python I've never seen a purple cow. Language: Scala I never hope to see one; But I can tell you, anyhow, I'd rather see than be one. map(line => line.toUpperCase) map(lambda line: line.upper()) I'VE NEVER SEEN A PURPLE COW. I NEVER HOPE TO SEE ONE; BUT I CAN TELL YOU, ANYHOW, I'D RATHER SEE THAN BE ONE. filter(lambda line: line.startswith('I')) filter(line => line.startsWith('I')) I'VE NEVER SEEN A PURPLE COW. I NEVER HOPE TO SEE ONE; I'D RATHER SEE THAN BE ONE.



Lazy Execution

 Data in RDDs is not processed until an action is performed

```
But I can tell you, anyhow,
                                                              I'd rather see than be one.
                                                            RDD: mydata
                                        Language: Scala
                                                              I've never seen a purple cow.
> val mydata = sc.textFile("purplecow.txt")
                                                              I never hope to see one;
> val mydata uc = mydata.map(line =>
                                                              But I can tell you, anyhow,
   line.toUpperCase())
                                                              I'd rather see than be one.
> val mydata filt = mydata uc.filter(line
                                                            RDD: mydata uc
   => line.startsWith("I"))
                                                              I'VE NEVER SEEN A PURPLE COW.
> mydata filt.count()
                                                              I NEVER HOPE TO SEE ONE;
                                                              BUT I CAN TELL YOU, ANYHOW,
                                                              I'D RATHER SEE THAN BE ONE.
                                                            RDD: mydata filt
                                                              I'VE NEVER SEEN A PURPLE COW.
                                                              I NEVER HOPE TO SEE ONE;
                                                              I'D RATHER SEE THAN BE ONE.
```

File: purplecow.txt

I've never seen a purple cow.

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I never hope to see one;

Chaining Transformations (Python)

Same example in Python

```
> mydata = sc.textFile("purplecow.txt")
> mydata_uc = mydata.map(lambda s: s.upper())
> mydata_filt = mydata_uc.filter(lambda s: s.startswith('I'))
> mydata_filt.count()
3
```

is exactly equivalent to

```
> sc.textFile("purplecow.txt").map(lambda line: line.upper()) \
    .filter(lambda line: line.startswith('I')).count()
3
```

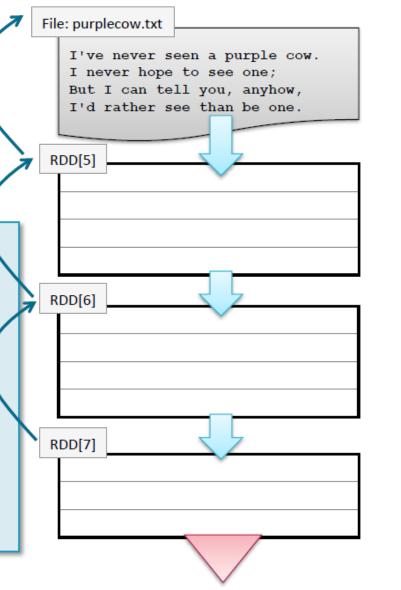


RDD Lineage and toDebugString (Scala)

- Spark maintains each RDD's lineage
 the previous RDDs on which it depends
- Use toDebugString to view the lineage of an RDD

```
> val mydata_filt =
    sc.textFile("purplecow.txt").
    map(line => line.toUpperCase()).
    filter(line => line.startsWith("I"))
> mydata_filt.toDebugString

(2) FilteredRDD[7] at filter ...
    | MappedRDD[6] at map ...
    | purplecow.txt MappedRDD[5] ...
    | purplecow.txt HadoopRDD[4] ...
```



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Example: flatMap and distinct

```
> sc.textFile(file) \
          .flatMap(lambda line: line.split()) \ Language: Python
          .distinct()
       > sc.textFile(file).
                                                       Language: Scala
           flatMap(line => line.split(' ')).
           distinct()
                                   I've
                                                    I've
                                   never
                                                    never
I've never seen a purple cow.
                                   seen
                                                    seen
I never hope to see one;
                                                    a
But I can tell you, anyhow,
                                   purple
                                                    purple
I'd rather see than be one.
                                   COW
                                                    COW
                                   Ι
                                                    hope
                                   never
                                   hope
                                                    to
                                   to
```

```
[root@sandbox-hdp ~]# date
Sat Mar 17 18:06:14 UTC 2018
[root@sandbox-hdp ~]# pyspark
SPARK MAJOR VERSION is set to 2, using Spark2
Python 2.6.6 (r266:84292, Aug 18 2016, 15:13:37)
[GCC 4.4.7 20120313 (Red Hat 4.4.7-17)] on linux2
Type "help", "copyright", "credits" or "license" for more information.
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
18/03/17 18:06:22 WARN Utils: Service 'SparkUI' could not bind on port 4040. Attempting port 4041.
/usr/hdp/current/spark2-client/python/pyspark/context.py:205: UserWarning: Support for Python 2.6 is deprecated as of Spark 2.0.0
warnings.warn("Support for Python 2.6 is deprecated as of Spark 2.0.0")
Welcome to
Using Python version 2.6.6 (r266:84292, Aug 18 2016 15:13:37)
SparkSession available as 'spark'.
>>> counts = sc.textFile("/user/root/input.txt").flatMap(lambda line: line.split()).map(lambda word: (word,1)).reduceByKey(lambda v1,v2
: v1+v2)
>>> counts.take(5)
[(u'world', 1), (u'hello', 2), (u'again', 1)]
>>> quit()
[root@sandbox-hdp ~] # hdfs dfs -cat /user/root/input.txt
hello world
hello again
[root@sandbox-hdp ~]#
```



DataFrames and SparkSQL

In this chapter you will learn

- What Spark SQL is
- What features the DataFrame API provides
- How to create a SQLContext
- How to load existing data into a DataFrame
- How to query data in a DataFrame



What is Spark SQL?

What is Spark SQL?

- Spark module for structured data processing
- Replaces Shark (a prior Spark module, now deprecated)
- Built on top of core Spark

What does Spark SQL provide?

- The DataFrame API a library for working with data as tables
 - Defines DataFrames containing Rows and Columns
 - DataFrames are the focus of this chapter!
- Catalyst Optimizer an extensible optimization framework
- A SQL Engine and command line interface



SQL Context

The main Spark SQL entry point is a SQL Context object

- Requires a SparkContext
- The SQL Context in Spark SQL is similar to Spark Context in core Spark

There are two implementations

- SQLContext
 - basic implementation

HiveContext

- Reads and writes Hive/HCatalog tables directly
- Supports full HiveQL language
- Requires the Spark application be linked with Hive libraries
- Recommended starting with Spark 1.5



Creating a SQL Context

SQLContext is created based on the SparkContext

from pyspark.sql import SQLContext
sqlCtx = SQLContext(sc)

Language: Scala

Language: Python

import org.apache.spark.sql.SQLContext
val sqlCtx = new SQLContext(sc)
import sqlCtx._



DataFrames

DataFrames are the main abstraction in Spark SQL

- Analogous to RDDs in core Spark
- A distributed collection of data organized into named columns
- Built on a base RDD containing Row objects

DataFrames can be created

- From an existing structured data source (Parquet file, JSON file, etc.)
- From an existing RDD
- By performing an operation or query on another DataFrame
- By programmatically defining a schema



Example: Creating a DataFrame from a JSON File

```
from pyspark.sql import SQLContext
sqlCtx = SQLContext(sc)
peopleDF = sqlCtx.jsonFile("people.json")

Language: Python

to sqlCtx = sqlCtx.jsonFile("people.json")

Language: Scala

val sqlCtx = new SQLContext(sc)
import sqlCtx.
val peopleDF = sqlCtx.jsonFile("people.json")
```

```
file: people.json

{"name":"Alice", "pcode":"94304"}

{"name":"Brayden", "age":30, "pcode":"94304"}

{"name":"Carla", "age":19, "pcode":"10036"}

{"name":"Diana", "age":46}

{"name":"Étienne", "pcode":"94104"}
```

age	name	pcode
null	Alice	94304
30	Brayden	94304
19	Carla	10036
46	Diana	null
null	Étienne	94104



Creating a DataFrame from a Data Source

- Methods on the SQLContext object
- Convenience functions
 - jsonFile(filename)
 - -parquetFile(filename)
- Generic base function: load
 - -load(filename, source) load filename of type source (default Parquet)
 - load (source, options...) load from a source of type source using options
 - Convenience functions are implemented by calling load
 - -jsonFile("people.json") = load("people.json",
 "json")



Generic Load Function Example: JDBC

Example: Loading from a MySQL database

```
val accountsDF = sqlCtx.load("jdbc",
    Map("url"-> "jdbc:mysql://dbhost/dbname?user=...&password=...",
    "dbtable" -> "accounts"))
```

```
accountsDF = sqlCtx.load(source="jdbc", \
  url="jdbc:mysql://dbhost/dbname?user=...&password=...", \
  dbtable="accounts")
```

Warning: Avoid direct access to databases in production environments, which may overload the DB or be interpreted as service attacks

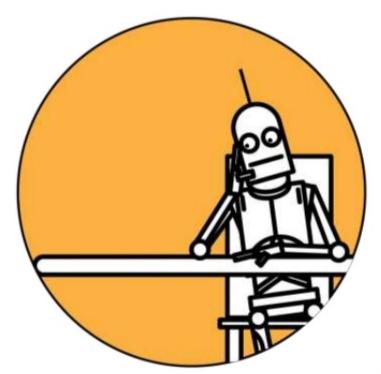
Use Sqoop to import instead



Clip slide

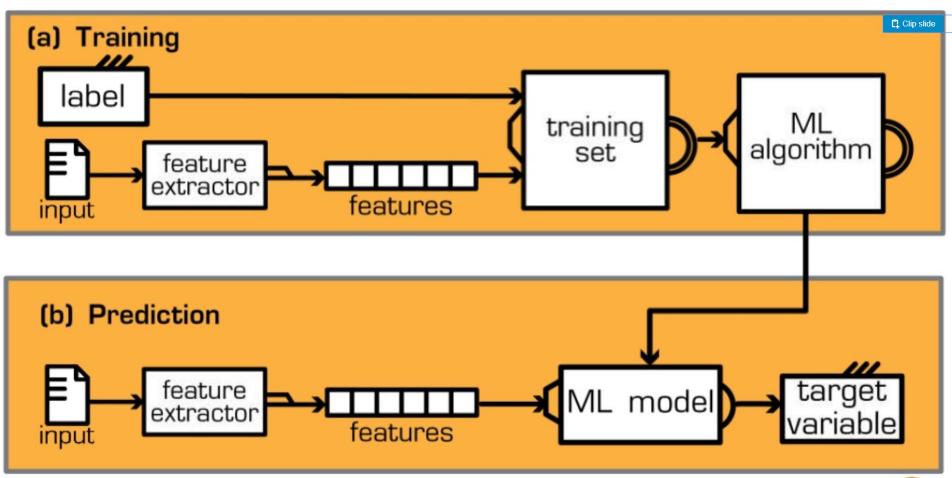
Machine Learning

is the study of computer algorithms that improve automatically through experience









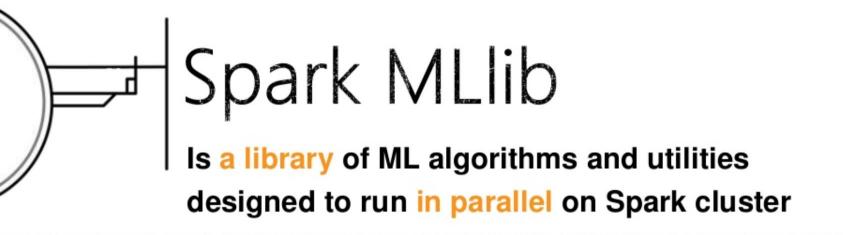
http://www.slideshare.net/liweiyang5/spark-mllib-training-material

(17)



javascript:void(0)







Clip slide

spark.mllib Features

- Utilities: linear algebra, statistics, etc.
- Features extraction, features transforming, etc.
- Regression
- Classification
- Clustering
- Collaborative filtering, e.g. alternating least squares
- Dimensionality reduction
- And many more

http://spark.apache.org/docs/latest/mllib-guide.html







