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CON3525: Java, Scala and Friends

Touring the Java Bedrock of Big Data

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So, Who Is This Talk For?

Curious about Hadoop

- Have used Hadoop, or want to
- Would like to know more about how the system functions



Curious about Internals

- Not particularly focused on Big Data
- Curious about what Big Data internals might be relevant to your projects



Program Agenda

- A Quick Primer on Hadoop History
- Core Hadoop and Java
- Declarative Big Data Builds on Java
- Scala and Spark Speed Things Up



Quick Refresher: Hadoop History

- Hadoop is
 - A framework for distributed processing of large data sets across clusters of computers using simple programming models.
 - Designed to scale up from single servers to thousands of machines, each offering local computation and storage.
- Created by Cutting and Cafarella @ Yahoo! in 2005
 - Part of the infrastructure for the Nutch search engine project
- 10 years later: synonymous with "Big Data"



"Core Hadoop" Components

Hadoop Common

Programming Model

MapReduce

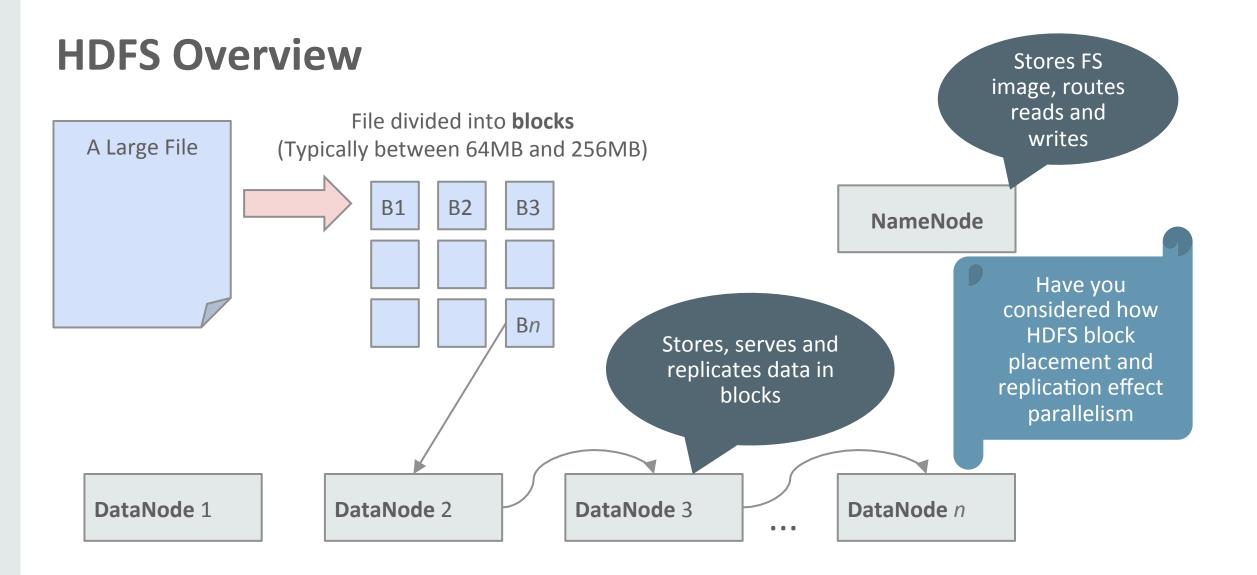
Resource Management

YARN (Yet Another Resource Negotiator)

Distributed Storage

HDFS (Hadoop Distributed File System)







HDFS Overview

- For Java Programmers
 - Not a child of nio.file.FileSystem
 - Expanded approach to a FileSystem class
- Subclasses for
 - -S3
 - FTP
 - Local
 - And more

Can you think of ways to leverage AbstractFilesystem subclasses to access more data?

- For System Users
 - Presents as a Unix filesystem
 - Standard operations
 - |S
 - mkdir
 - chmod/chown
 - Repair functions
 - fsck
 - Safe Mode: when block replication inconsistency is too high



App Master secures containers **MapReduce Overview** and distributes user code Reduce-stage **App Master** containers apply an aggregation function to map output Map-stage Each container is a containers read child process in its records and apply **Reduce** Reduce own JVM a function to each **Container** Container racard **Network Shuffle Map Container Map Container Map Container Map Container**

DataNode 3



DataNode 1

DataNode 2

. . .

DataNode n

How Do We Coordinate All These Nodes?

- Dynamic Proxies!
- Define a single interface between server and client
 - @ProtocolInfo(protocolName = "org.apache.hadoop.mapreduce.v2.api.MR(
 protocolVersion = 1)
 - @ProtocolInfo(protocolName = "org.apache.hadoop.hdfs.server.protocol
 protocolVersion = 1)
 - Server sets up with RPC.Builder(setInstance(new Protocolkiass()))
 - Client runs RPC.getProxy(ProtocolKlass.class,...)
- Simple RPC interface which maintains backward wire-compatibility
- Core to: HDFS, Common, YARN, MapReduce Client, etc.

Dynamic Proxies provide a straightforward way to define stable RPC interfaces over time.



What About User Code?

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

```
public void reduce(
      Fext key,
      Iterable Intwritable varalyes,
        Context context) throws IOException,
       InterruptedException
     int sum = 0;
     for (Inttwittable aval values) {
       sum += valiget();
     result.set(sum);
result.set(sum);
     context.write(key, result);
context.write(key, result);
```



What's Up With Those Types?

- Hadoop introduces new types for serialization
- Writables
 - Text, IntWritable, FloatWritable, etc.
- Why? We've had serialization for a long time.
- Answer: Java serialized objects store type
- The other nodes in the job know the type
 - We just need to serialize to transfer the data
- Writables are more compact
 - .get() and .set(val) methods allow us to minimize creation overhead





The Demand for More Languages

- Not everyone is comfortable writing distributed Java code
 - For joining data
 - For multiple passes on intermediate data
- Data Analysts and Engineers demand declarative languages
- Enter Pig and Hive
 - Apache Pig (2007), developed as a dataflow language inside Yahoo!
 - Apache Hive (2009), developed as SQL-on-MapReduce at Facebook



Pig Code and Deployment

```
input_lines = LOAD '/tmp/my-copy-of-all-pages-on-internet'
   AS (line:chararray);

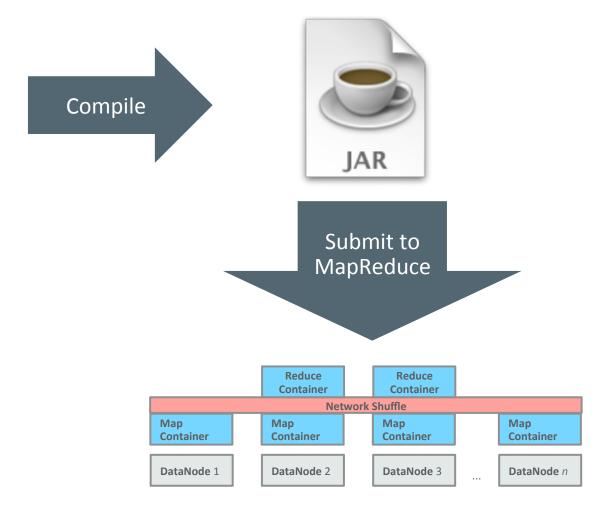
words = FOREACH input_lines GENERATE
   FLATTEN(TOKENIZE(line)) AS word;

filtered_words = FILTER words BY word MATCHES '\\w+';

word_groups = GROUP filtered_words BY word;

word_count = FOREACH word_groups GENERATE
   COUNT(filtered_words) AS count, group AS word;

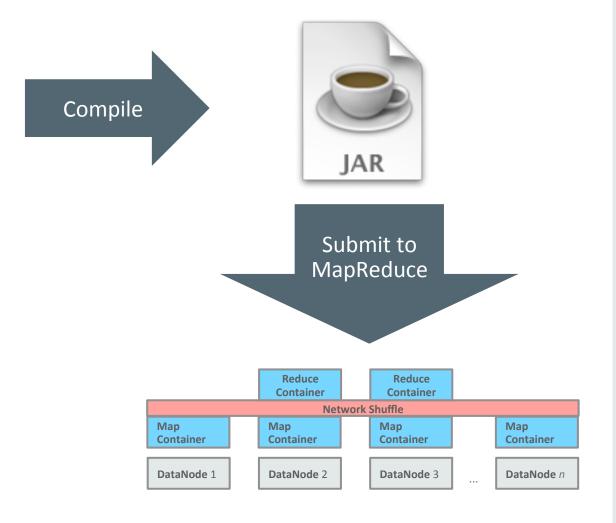
ordered_word_count = ORDER word_count BY count DESC;
   STORE ordered_word_count
   INTO '/tmp/number-of-words-on-internet';
```





Hive Follows Suit, But With SQL

```
SELECT word, COUNT(*)
FROM doc
LATERAL VIEW
   explode(split(text, ' ')) myTable
   as word
GROUP BY word;
```





Hive is Just a SQL-Layer, What's Java Got To Do With It?

- Java types for columns!
 - Maps
 - Arrays
 - Structs (named maps of variable type)
- Built on the back of DataNucleus
 - Hive has to put metadata somewhere
 - Usually MySQL, but sometimes Derby
 - Metadata operations use DataNucleus to communicate with backing store



Is That Good Enough?

Map #1:

Read records from *sales* and *store_locations*

Emit all records as (join_key, record)

Reduce #1:

Read (join_key, record) pairs

If join_key_A == join_key_B, emit record_A+record_B

Checkpoint

Map #2:

Read joined records

Emit all records as (location, sales)

Reduce #2:

Sum all (location, sales) pairs Emit (location, sum(sales)) Forced checkpointing: Must write and re-read

Good for fault-tolerance Bad for performance



Apache Spark Takes Big Data to the Next Level





What Does Spark Offer?

- More generic DAGs
 - Avoid the checkpointing overhead
- In-memory storage for iterative operations
 - Radical speed-up for iterative operations
- Richer abstractions and functions
 - Inherit collection behaviors from Scala
 - Program in Java, Scala, or Python
- REPLs for interactive use
 - Scala, Python

Up to **10**× faster on disk, **100**× in memory

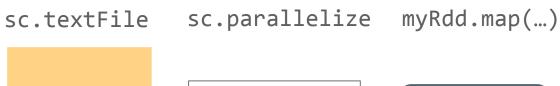
2-5× less code



Core Abstraction: Resilient Distributed Datasets (RDDs)

- RDDs are immutable, distributed collections
 - Doesn't need to exist in physical storage
- Handle to an RDD → How to compute from known-good storage
- Lazy and ephemeral
 - Partitions are materialized on-demand

How to Make an RDD

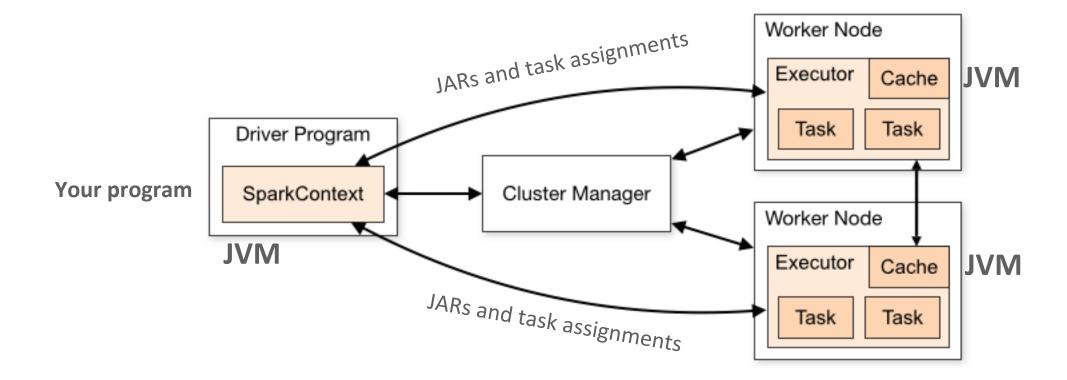








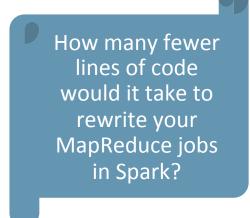
Spark Cluster Architecture





Scala Makes RDDs Expressive

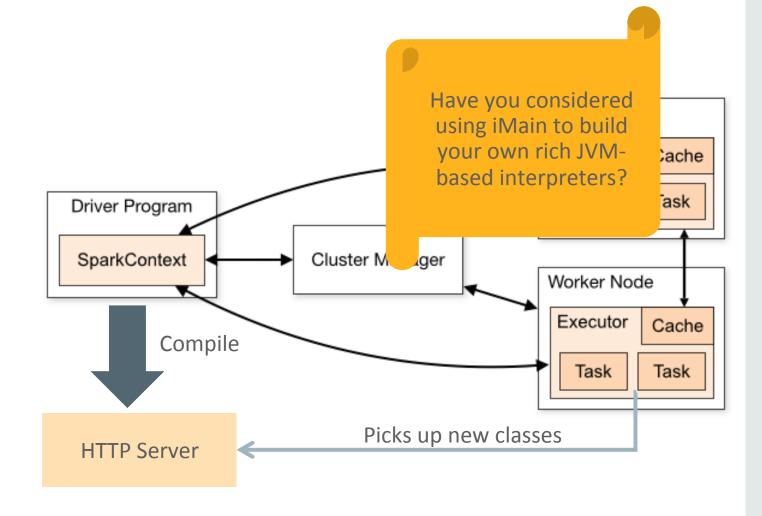
- RDDs support most of the operations of Scala collections
 - Specifically Traversable and Iterable
- Map, Reduce, and...
 - flatMap, filter, groupBy
 - count, max, min
 - fold, reduce, take, collect
- Why?
- Scala closures are serializable!
- 2. We can efficiently send closures to a distributed set of workers





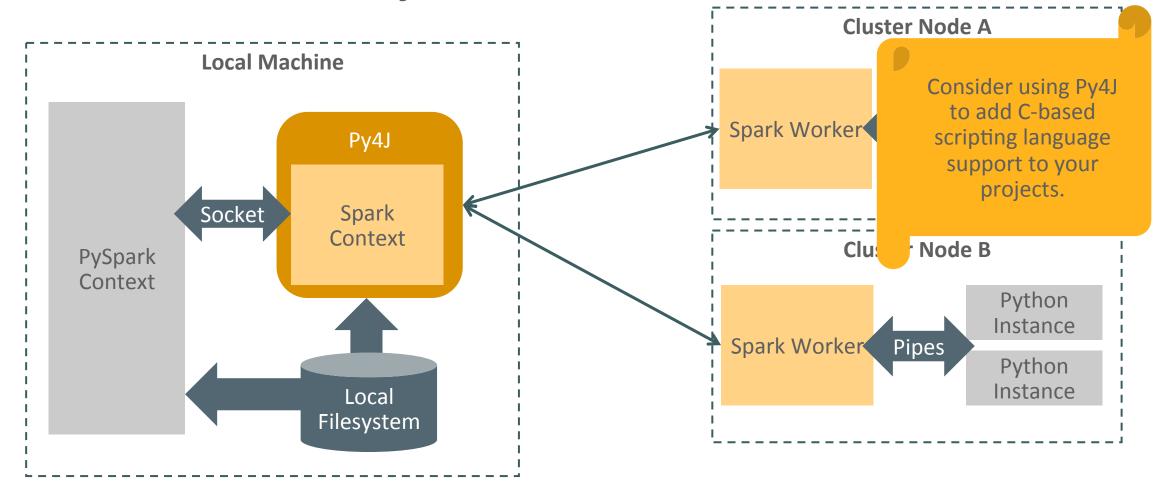
How Does it Become Interactive?

- Have you ever looked at scala.tools.nsc.interpreter?
- The **IMain** class \rightarrow
 - The Scala interpreter
- Provides compile methods!
 - Compile code on the fly
 - Generate a class file
- Compile REPL definitions
 - Let executors pick them up





But What About Python?





Where does it go from here?

- Right now
 - Streaming With Spark
 - Massively Scalable Message Transport with Kafka
 - Interactive Data Science with Zeppelin
- On the horizon
 - Twill: Simpler distributed systems
 - Kylin: OLAP for Big Data
 - DeepLearning4J: Scalable Deep Learning on GPUs or Spark



Integrated Cloud Applications & Platform Services



