Module 5: Apache Spark

Learning objectives

- List the main bottlenecks of MapReduce
- Explain how Apache Spark solves them

Force your pipeline into Map and Reduce steps

Other workflows? i.e. join, filter, map-reduce-map

Read from disk for each MapReduce job

Iterative algorithms? i.e. machine learning

Only native JAVA programming interface

Other languages? Interactivity?

Solution?

- New framework: same features of MapReduce and more
- Capable of reusing Hadoop ecosystem, e.g. HDFS, YARN...
- Born at UC Berkeley

Solutions by Spark

Other workflows? i.e. join, filter, map-reduce-map

~20 highly efficient distributed operations, any combination of them

Solutions by Spark

Iterative algorithms? i.e. machine learning

in-memory caching of data, specified by the user

Solutions by Spark

Interactivity? Other languages?

Native Python, Scala (, R) interface. Interactive shells.

100TB Sorting competition

	Hadoop MR	Spark	Spark
	Record	Record	1 PB
Data Size	102.5 TB	100 TB	1000 TB
Elapsed Time	72 mins	23 mins	234 mins
# Nodes	2100	206	190
# Cores	50400 physical	6592 virtualized	6080 virtualized
Cluster disk	3150 GB/s (est.)	618 GB/s	570 GB/s
throughput			
Sort Benchmark	Yes	Yes	No
Daytona Rules			
Network	dedicated data	virtualized (EC2)	virtualized (EC2)
	center, 10Gbps	10Gbps network	10Gbps network
Sort rate	1.42 TB/min	4.27 TB/min	4.27 TB/min
Sort rate/node	0.67 GB/min	20.7 GB/min	22.5 GB/min

Architecture of Spark

Worker Node

Spark
Executor
Java Virtual
Machine



Python



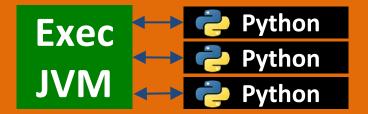
Python

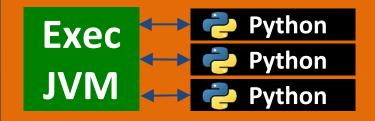


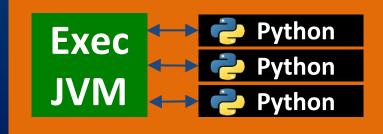
Python



Worker Nodes

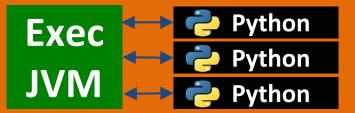


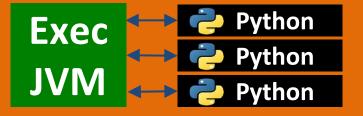


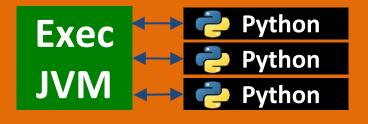


Cluster Manager YARN/Standalone Provision/Restart Workers

Worker Nodes

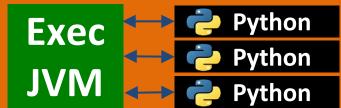


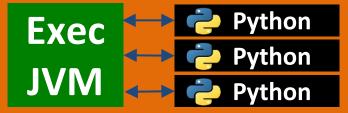


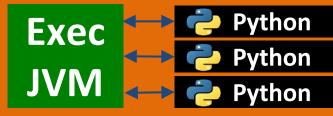


Driver Program Spark Spark Cluster Context **Context** Manager

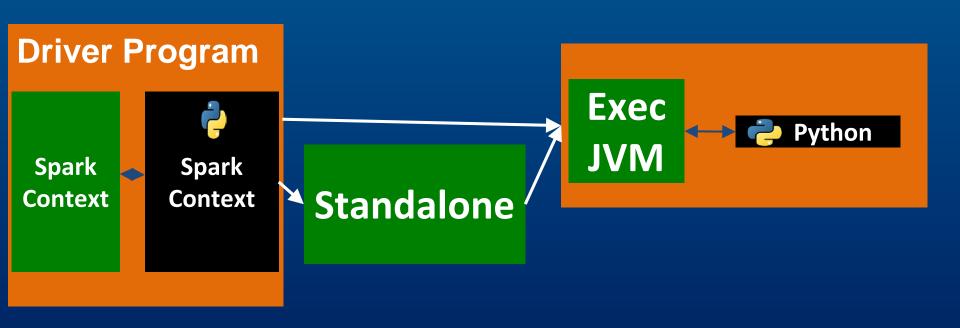
Worker Nodes







on Cloudera VM



EC2 nodes on Amazon EMR **Python** Exec **Python** Master node JVM **Driver Program** Python Exec **Python Spark Spark YARN Context** Context **Python Exec Python**

Resilient Distributed Datasets

Resilient Distributed Dataset

Dataset

Data storage created from: HDFS, S3, HBase, JSON, text, Local hierarchy of folders

Or created transforming another RDD

Resilient Distributed Dataset

Distributed

Distributed across the cluster of machines

Divided in partitions, atomic chunks of data

Resilient Distributed Dataset

Resilient

Recover from errors, e.g. node failure, slow processes

Track history of each partition, re-run

RDD in PySpark

From the PySpark console:

integer_RDD = sc.parallelize(range(10), 3)

Check partitions

Gather all data on the driver:

integer_RDD.collect()

Out: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]

Check partitions

Maintain splitting in partitions:

```
integer_RDD.glom().collect()
```

Out: [[0, 1, 2], [3, 4, 5], [6, 7, 8, 9]]

Read text into Spark

from local filesystem:

```
text_RDD =
```

sc.textFile("file:///home/cloudera/testfile1")

from HDFS:

text_RDD =

sc.textFile("/user/cloudera/input/testfile1")

text_RDD.take(1) #outputs the first line

Wordcount in Spark: map

```
def split_words(line):
    return line.split()

def create_pair(word):
    return (word, 1)
```

pairs_RDD=text_RDD.flatMap(split_words).map(create_pair)

```
pairs_RDD.collect()
Out[]: [(u'A', 1),
(u'long', 1),
(u'time', 1),
(u'ago', 1),
(u'in', 1),
(u'a', 1),
(u'galaxy', 1),
(u'far', 1),
(u'far', 1),
(u'away', 1)]
```

Wordcount in Spark: reduce

```
def sum_counts(a, b):
    return a + b

wordcounts_RDD = pairs_RDD.reduceByKey(sum_counts)

wordcounts_RDD.collect()
```

Out[]: [(u'A', 1), (u'ago', 1), (u'far', 2), (u'away', 1), (u'in', 1), (u'long', 1), (u'a', 1), (u'time', 1), (u'galaxy', 1)]

Transformations

Transformations

- RDD are immutable
- Never modify RDD in place
- Transform RDD to another RDD
- Lazy

Create RDD

from local filesystem:

text_RDD =

sc.textFile("file:///home/cloudera/testfile1")

Apply a transformation: map

map: apply function to each element of RDD

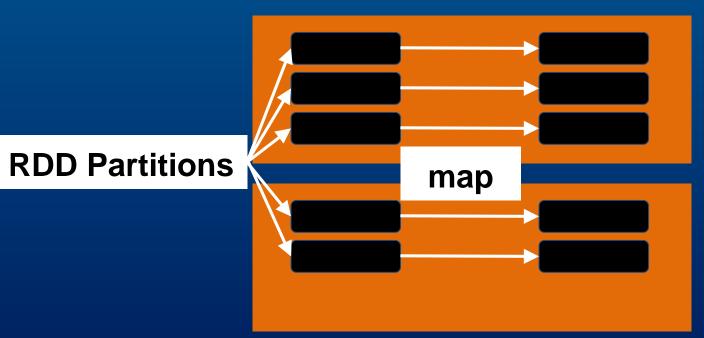
```
def lower(line):
```

return line.lower()

lower_text_RDD = text_RDD.map(lower)

map

map: apply function to each element of RDD



Other transformations

- flatMap(func) map then flatten output
- filter(func) keep only elements where func is true
- sample(withReplacement, fraction, seed) get a random data fraction
- coalesce(numPartitions) merge partitions to reduce them to numPartitions

flatMap

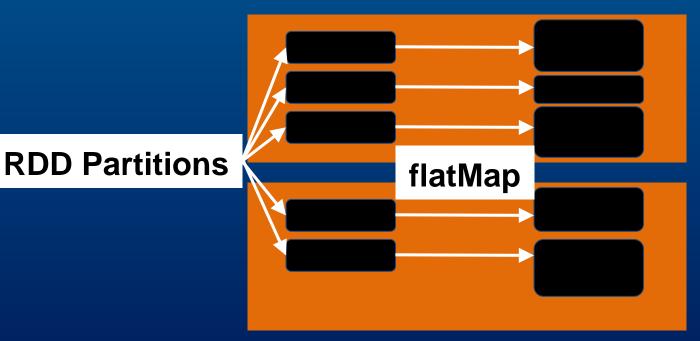
def split_words(line):
 return line.split()

words_RDD =
text_RDD.flatMap(split_words)
words_RDD.collect()

```
[u'A',
u'long',
u'time',
u'ago',
u'in',
u'a'.
u'galaxy',
u'far',
u'far',
u'away']
```

flatMap

flatMap: map then flatten output



filter

```
def starts_with_a(word):
    return word.lower().startswith("a")
words_RDD.filter(starts_with_a).collect()
Out[]: [u'A', u'ago', u'a', u'away']
```

filter

filter: keep only elements where func is true **RDD Partitions** filter

coalesce

```
sc.parallelize(range(10), 4).glom().collect()
```

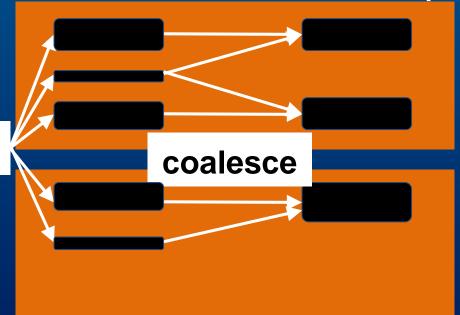
```
Out[]: [[0, 1], [2, 3], [4, 5], [6, 7, 8, 9]]
```

sc.parallelize(range(10), 4).coalesce(2).glom().collect()

Out[]: [[0, 1, 2, 3], [4, 5, 6, 7, 8, 9]]

coalesce

coalesce: reduce the number of partitions



RDD Partitions

Wide Transformations

Transformations of (K,V) pairs

```
def create_pair(word):
    return (word, 1)
```

pairs_RDD=text_RDD.flatMap(split_words).map(create_pair)

```
pairs_RDD.collect()
```

```
Out[]: [(u'A', 1),
(u'long', 1),
(u'time', 1),
(u'ago', 1),
(u'in', 1),
(u'a', 1),
(u'galaxy', 1),
(u'far', 1),
(u'far', 1),
(u'away', 1)]
```

groupByKey

```
groupByKey: (K, V) pairs => (K, iterable of all V)
(A, 1)
(B, 8)
                        (A, [1, 2, 5])
                        (B, [8])
(A, 2)
(A, 5)
```

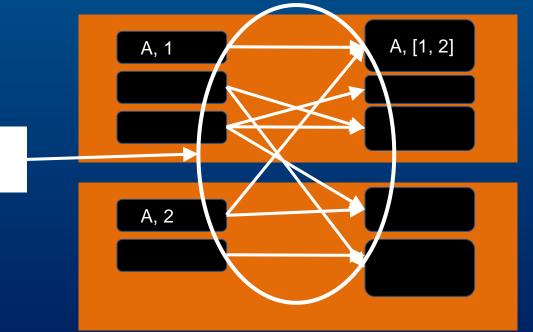
```
pairs_RDD.groupByKey().collect()
```

```
Out[]: [(u'A', <pyspark.resultiterable.ResultIterable at XXX>),
(u'ago', <pyspark.resultiterable.ResultIterable at XXX>),
(u'far', <pyspark.resultiterable.ResultIterable at XXX>),
(u'away', <pyspark.resultiterable.ResultIterable at XXX>),
(u'in', <pyspark.resultiterable.ResultIterable at XXX>),
(u'long', <pyspark.resultiterable.ResultIterable at XXX>),
(u'a', <pyspark.resultiterable.ResultIterable at XXX>),<
<MORE output>
```

```
for k,v in pairs RDD.groupByKey().collect():
     print "Key:", k, ",Values:", list(v)
Out[]: Key: A , Values: [1]
Key: ago , Values: [1]
Key: far , Values: [1, 1]
Key: away , Values: [1]
Key: in , Values: [1]
Key: long , Values: [1]
Key: a , Values: [1]
<MORE output>
```

groupByKey

groupByKey: (K, V) pairs => (K, iterable of all V)



shuffle

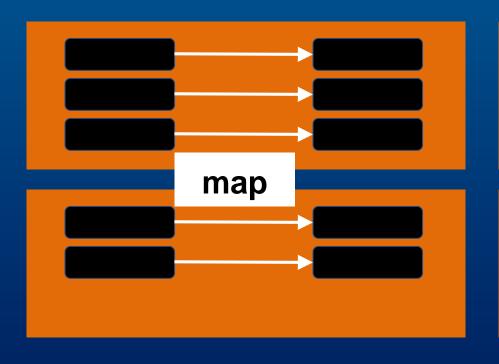
groupbyKey

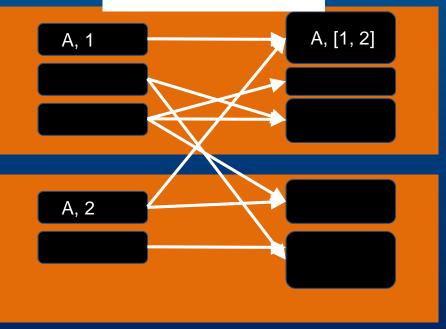
Narrow

VS

Wide

groupbyKey





Wide transformations

- groupByKey : (K, V) pairs => (K, iterable of all V)
- reduceByKey(func): (K, V) pairs => (K, result of reduction by func on all V)
- repartition(numPartitions): similar to coalesce, shuffles all data to increase or decrease number of partitions to numPartitions

Shuffle

Shuffle

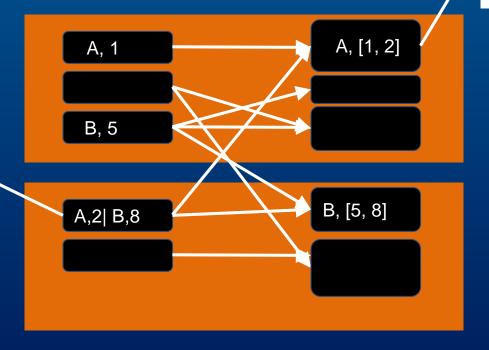
Global redistribution of data

High impact on performance

Shuffle

requests data over the network

writes to disk



Know shuffle, avoid it

Which operations cause it?

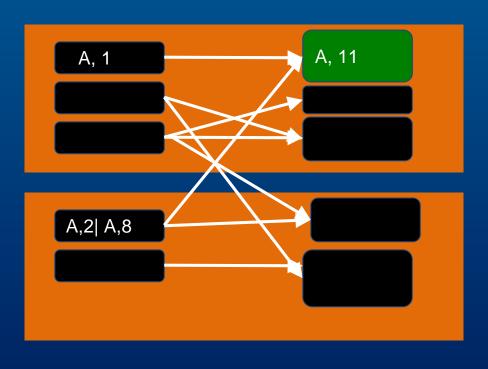
Is it necessary?

Really need groupByKey?

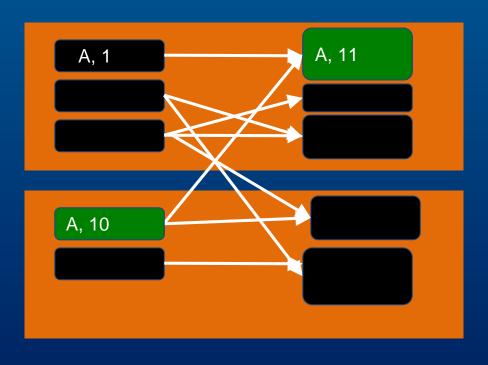
groupByKey: (K, V) pairs => (K, iterable of all V)

if you plan to call reduce later in the pipeline, use reduceByKey instead.

groupByKey + reduce

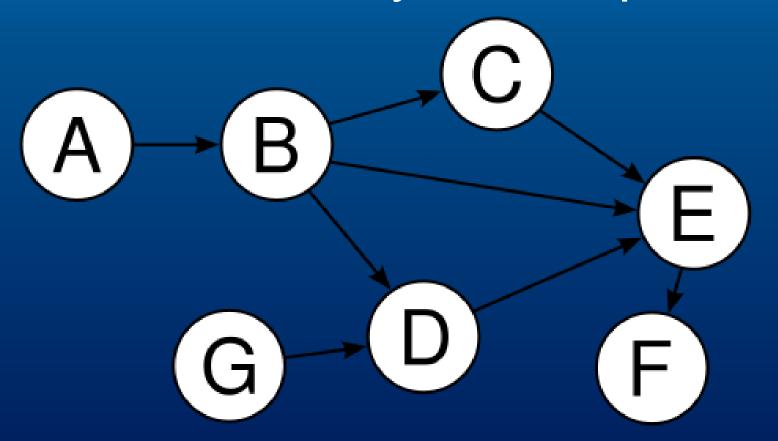


reduceByKey



Directed Acyclic Graph Scheduler

Directed Acyclic Graphs



Directed Acyclic Graphs

Track dependencies!
(also known as lineage or provenance)

DAG in Spark

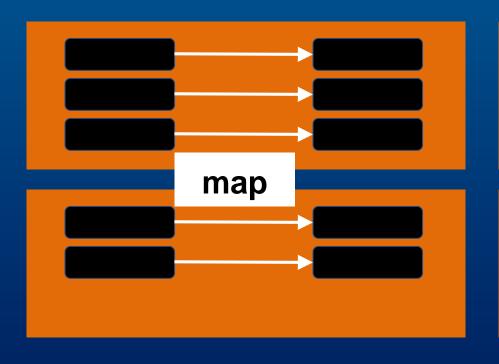
- nodes are RDDs
- arrows are Transformations

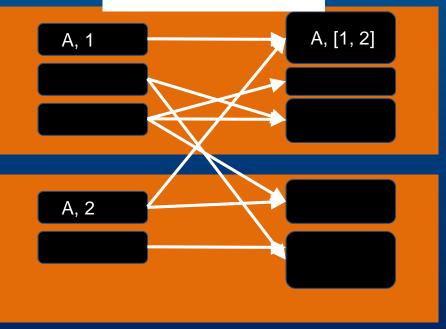
Narrow

VS

Wide

groupbyKey



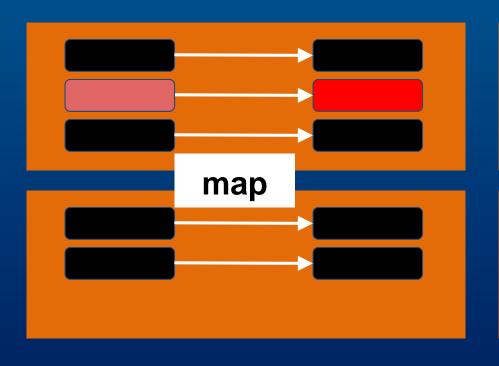


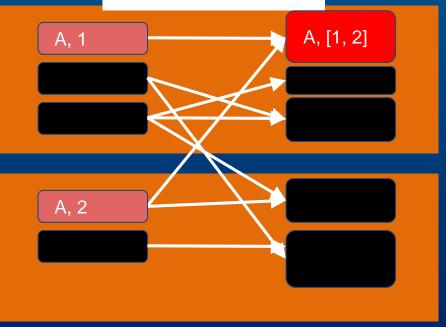
Narrow

VS

Wide

groupbyKey





Transformations of (K,V) pairs

```
def create_pair(word):
    return (word, 1)
```

pairs_RDD=text_RDD.flatMap(split_words).map(create_pair)

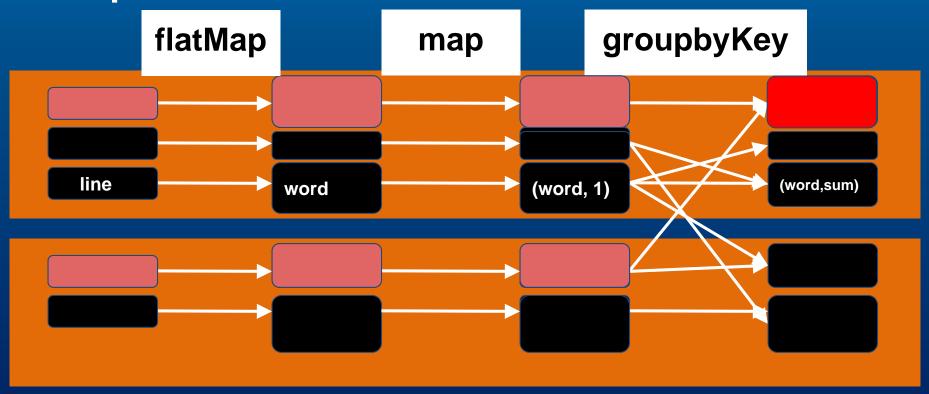
```
for k,v in pairs_RDD.groupByKey().collect():
     print "Key:", k, ", Values:", list(v)
Out[]: Key: A , Values: [1]
Key: ago , Values: [1]
Key: far , Values: [1, 1]
Key: away , Values: [1]
Key: in , Values: [1]
```

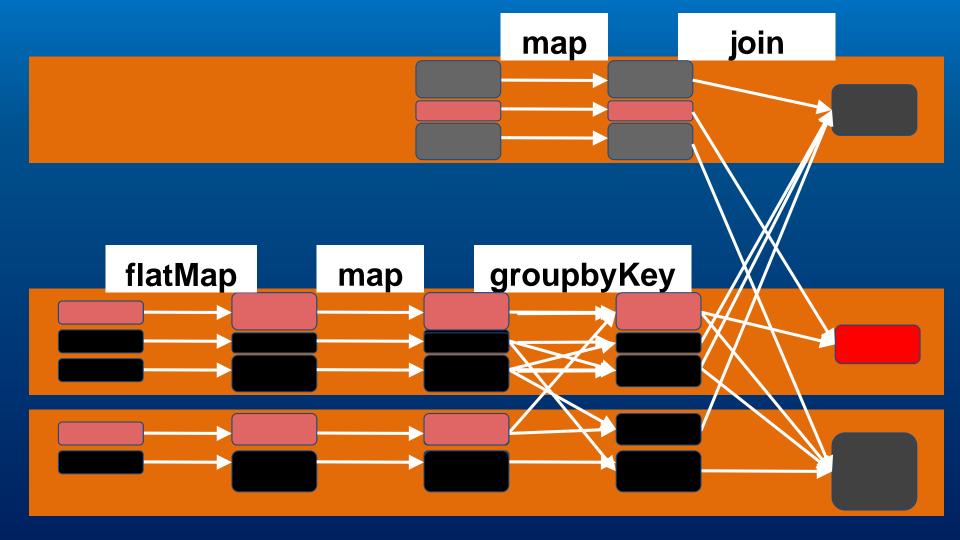
Key: long , Values: [1]

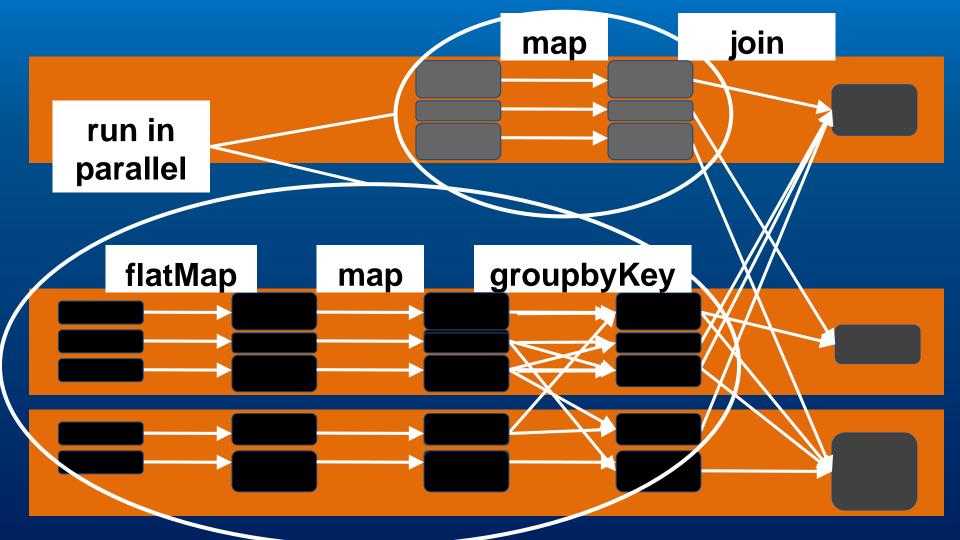
Key: a , Values: [1]

<MORE output>

Spark DAG of transformations



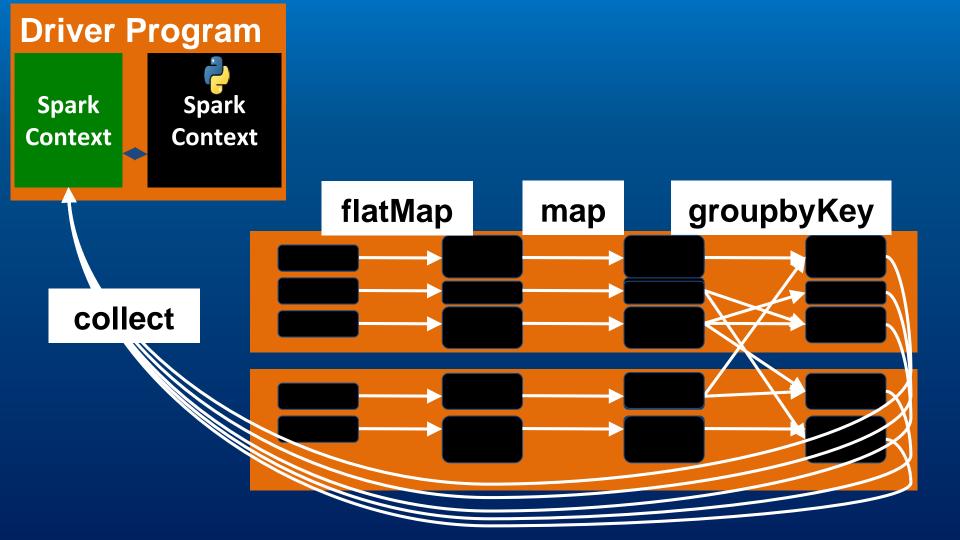




Actions

What is an action

- Final stage of workflow
- Triggers execution of the DAG
- Returns results to the Driver or writes to HDFS



Actions

- collect() copy all elements to the driver
- take(n) copy first n elements
- reduce(func) aggregate elements with func (takes 2 elements, returns 1)
- saveAsTextFile(filename) save to local file or HDFS

Caching

Caching

- By default each job re-processes from HDFS
- Mark RDD with .cache()
- Lazy

When?

- Generally not the input data
- Do validation and cleaning
- Cache for iterative algorithm

How?

- Memory (most common)
- Disk (rare)
- Both (for heavy calculations)

Speedup

- Easily 10x or even 100x depending on application
- Caching is gradual
- Fault tolerant

Wordcount with caching

from HDFS:

text_RDD =

sc.textFile("/user/cloudera/input/testfile1")

```
return line.split()
def create_pair(word):
  return (word, 1)
pairs_RDD=text_RDD.flatMap(split_words).map(create_pair)
pairs_RDD.cache()
```

def split_words(line):

```
def sum_counts(a, b):
  return a + b
wordcounts_RDD = pairs_RDD.reduceByKey(sum_counts)
First job:
wordcounts_RDD.collect()
Second job:
pairs_RDD.take(1)
```

Broadcast variables

Broadcast variables

- Large variable used in all nodes
- Transfer just once per Executor
- Efficient peer-to-peer transfer

Broadcast variable example

For example large configuration dictionary or lookup table:

```
config = sc.broadcast({"order":3, "filter":True})
```

config.value

Accumulators

Accumulator

- Common pattern of accumulating to a variable across the cluster
- Write-only on nodes

Accumulator example

```
accum = sc.accumulator(0)
def test_accum(x):
  accum_add(x)
sc.parallelize([1, 2, 3, 4]).foreach(test_accum)
accum.value
Out[]: 10
```

Big Data Analytics in Apache Spark

Big Data Analytics with Spark

- Spark Dataframes to work with tabular data
- Data cleaning, summary, statistics
- Spark Dataframes with SQL and Hive

Open PySpark

PYSPARK_DRIVER_PYTHON=ipython pyspark

Introduction to Spark Dataframes

Types of RDD: text

```
from local filesystem:
text_RDD =
sc.textFile("file:///home/cloudera/testfile1")
```

text_RDD.collect()

Out[]: [u'A long time ago in a galaxy far far away']

Types of RDD: key-value pairs

```
def split_words(line):
  return line.split()
def create_pair(word):
  return (word, 1)
pairs_RDD=text_RDD.flatMap(split_words)
).map(create_pair)
```

```
pairs_RDD.collect()
Out[]: [(u'A', 1),
(u'long', 1),
(u'time', 1),
(u'ago', 1),
(u'in', 1),
(u'a', 1),
(u'galaxy', 1),
(u'far', 1),
(u'far', 1),
(u'away', 1)]
```

Tabular dataset

Most real-world datasets have records (rows)

each with multiple values (columns)

Tweets

user	text	datetime	favorites	retweets
andreazonca	"spark is cool"	"2015-10-1 9:04"	5	3

Reviews

business	text	datetime	starts	user
Pan Bon	"great pizza!"	"2015-10-1 9:04"	5	andreazonca

Logs

http_code	ip	datetime	user_agent
200	127.0.0.1	"2015-10-1 9:04"	Firefox

Tabular datasets

```
students = sc.parallelize([
[100, "Alice", 8.5, "Computer Science"],
[101, "Bob", 7.1, "Engineering"],
[102, "Carl", 6.2, "Engineering"]
])
```

Mean of a column

```
def extract_grade(row):
    return row[2]
```

students.map(extract_grade).mean()

Out[]: 17.26666

```
def extract_degree_grade(row):
  return (row[3], row[2])
degree_grade_RDD =
students.map(extract_degree_grade)
degree_grade_RDD.collect()
```

Intermediate RDD:

degree_grade_RDD.collect()

Out[]:

[('Computer Science', 8.5),

('Engineering', 7.09999999999999),

('Engineering', 6.2000000000000000)]

Reduce by key to get the final result:

degree_grade_RDD.reduceByKey(max).collect()

Out[]:

[('Engineering', 7.099999999999999),

('Computer Science', 8.5)]

Introducing Spark Dataframes

User friendly interface

Under-the-hood optimization for table-like datasets

```
students_df = sqlCtx.createDataFrame(students,
   ["id", "name", "grade", "degree"])
students df.printSchema()
root
|-- id: long (nullable = true)
-- name: string (nullable = true)
-- grade: double (nullable = true)
-- degree: string (nullable = true)
```

sqlCtx.createDataFrame?

Create a DataFrame from an RDD of tuple/list, list or pandas.DataFrame.

schema` could be :class:`StructType` or a list of column names.

When `schema` is a list of column names, the type of each column will be inferred from `rdd`.

When `schema` is None, it will try to infer the column name and type from `rdd`, which should be an RDD of :class:`Row`, or namedtuple, or dict.

If referring needed, `samplingRatio` is used to determined how many rows will be used to do referring. The first row will be used if `samplingRatio` is None.

:param data: an RDD of Row/tuple/list/dict, list, or pandas.DataFrame :param schema: a StructType or list of names of columns :param samplingRatio: the sample ratio of rows used for inferring :return: a DataFrame

```
>>> I = [('Alice', 1)]
>>> sqlCtx.createDataFrame(I).collect()
[Row(_1=u'Alice', _2=1)]
>>> sqlCtx.createDataFrame(I, ['name', 'age']).collect()
[Row(name=u'Alice', age=1)]
```

Mean of a column

students_df.agg({"grade": "mean"}).collect()

Find all available operations:

```
students_df.groupBy("degree").max("grade").collect()
Row(degree=u'Computer Science',
MAX(grade#30)=8.5),
Row(degree=u'Engineering',
MAX(grade#30)=7.09999999999)]
```

Pretty print with show

students_df.groupBy("degree").max("grade").show()

degree MAX(grade#30)

Computer Science 8.5

Engineering 7.1

Final remarks on Dataframes

- special kind of RDD
- transformations/actions/DAG work the same way
- automatic optimization to Java bytecode
- Python as fast as Scala/Java

Create Spark Dataframes

Specify a Schema

```
students_df = sqlCtx.createDataFrame(students, ["id", "name", "grade", "degree"]
```

from pyspark.sql.types import *

schema = StructType([

StructField("id", LongType(), True),

StructField("name", StringType(), True),

StructField("grade", DoubleType(), True),

StructField("degree", StringType(), True)])

students_df = sqlCtx.createDataFrame(students, schema)

```
students_df.printSchema()
```

root

- -- id: long (nullable = true)
- -- name: string (nullable = true)
- -- grade: double (nullable = true)
- -- degree: string (nullable = true)

Load a JSON file

```
students_json = [
'{"id":100, "name":"Alice", "grade":8.5,
"degree":"Computer Science"}',
'{"id":101, "name":"Bob", "grade":7.1,
"degree":"Engineering"}']
with open("students.json", "w") as f:
  f.write("\n".join(students_json))
```

Dump JSON file conent

cat students.json

"degree":"Engineering"}

```
{"id":100, "name":"Alice", "grade":8.5, "degree":"Computer
Science"}

{"id":101, "name":"Bob", "grade":7.1,
```

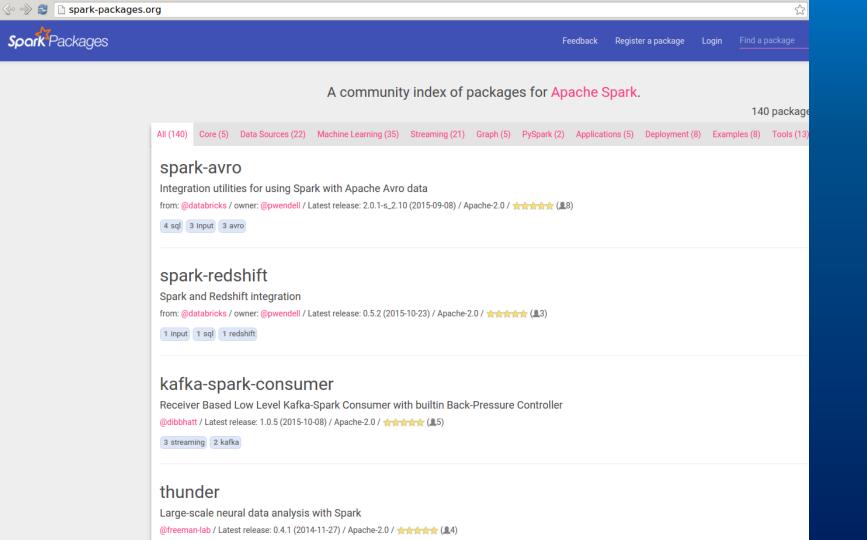
Create Dataframe with jsonFile

sqlCtx.jsonFile("file:///home/cloudera/students.json").show()

```
degree grade id name
Computer Science 8.5 100 Alice
Engineering 7.1 101 Bob
```

Load Dataframe from CSV

- Not included in Spark
- Load from spark-packages.org



Restart PySpark

PYSPARK_DRIVER_PYTHON=ipython pyspark -- packages com.databricks:spark-csv_2.10:1.2.0

Automatically download and include new packages and dependencies

Load sample yelp csv

```
yelp_df = sqlCtx.load(
source="com.databricks.spark.csv",
header = 'true',
inferSchema = 'true',
path =
'file:///usr/lib/hue/apps/search/examples/collections/solr_co
nfigs_yelp_demo/index_data.csv')
```

```
yelp_df.printSchema()
root
   business_id: string (nullable = true)
   cool: integer (nullable = true)
   date: string (nullable = true)
   funny: integer (nullable = true)
   id: string (nullable = true)
   stars: integer (nullable = true)
   text: string (nullable = true)
   type: string (nullable = true)
   useful: integer (nullable = true)
   user id: string (nullable = true)
   name: string (nullable = true)
   full address: string (nullable = true)
   latitude: double (nullable = true)
   longitude: double (nullable = true)
   neighborhoods: string (nullable = true)
   open: string (nullable = true)
   review count: integer (nullable = true)
```

state: string (nullable = true)

yelp_df.count()
Out[]: 1000L

Analytics with Dataframes on a Yelp reviews dataset

Explore the Yelp dataset

```
yelp_df = sqlCtx.load(
source='com.databricks.spark.csv',
header = 'true',
inferSchema = 'true',
path =
'file:///usr/lib/hue/apps/search/examples/collections/solr_co
nfigs_yelp_demo/index_data.csv')
```

Reference a column

```
As attribute:

yelp_df.useful

Out[]: Column<useful>

As key:

yelp_df["useful"]

Out[]: Column<useful>
```

Filtering

```
yelp_df.filter(yelp_df.useful >= 1).count()
yelp_df.filter(yelp_df["useful"] >= 1).count()
yelp_df.filter("useful >= 1").count()
Out[]: 601L
```

select

```
yelp_df["useful"].agg({"useful":"max"}).collect()
Out[]: AttributeError: 'Column' object has no attribute 'agg'
yelp_df.select("useful")
Out[]: DataFrame[useful: int]
yelp_df.select("useful").agg({"useful":"max"}).collect()
Out[]: [Row(MAX(useful#267)=28)]
```

Create a modified DataFrame

Rescale the useful column from 0-28 to 0-100.

Create a 2 columns DataFrame

```
yelp_df.select("id", "useful").take(5)
[Row(id=u'fWKvX83p0-ka4JS3dc6E5A', useful=5),
Row(id=u'IjZ33sJrzXqU-0X6U8NwyA', useful=0),
Row(id=u'IESLBzqUCLdSzSqm0eCSxQ', useful=1),
Row(id=u'G-WvGalSbqqaMHINnByodA', useful=2),
Row(id=u'1uJFq2r5QfJG_6ExMRCaGw', useful=0)]
```

Modify column

```
yelp_df.select("id", yelp_df.useful/28*100).show(5)
```

```
((useful / 28) * 100)
id
fWKvX83p0-ka4JS3d... 17.857142857142858
IjZ33sJrzXqU-0X6U... 0.0
IESLBzqUCLdSzSqm0... 3.571428571428571
G-WvGalSbqqaMHlNn... 7.142857142857142
1uJFq2r5QfJG_6ExM... 0.0
```

Cast (truncate) to integer

```
yelp_df.select("id",
(yelp_df.useful/28*100) cast("int") show(5)
                CAST(((useful / 28) * 100)), IntegerType)
id
fWKvX83p0-ka4JS3d... 17
IjZ33sJrzXqU-0X6U... 0
IESLBzqUCLdSzSqm0... 3
G-WvGalSbqqaMHlNn...7
1uJFq2r5QfJG_6ExM... 0
```

Save as new dataframe

```
useful_perc_data = yelp_df.select(
   "id".
   (yelp_df.useful/28*100).cast("int")
useful_perc_data.columns
Out[]: [u'id', u'CAST(((useful / 28) * 100), IntegerType)']
```

alias - rename a column

```
useful_perc_data = yelp_df.select(
    "id",
    (yelp_df.useful/28*100).cast("int").alias("useful_perc")
)
```

useful_perc_data.columns

Out[]: [u'id', u'useful_perc']

alias - rename a column

```
useful_perc_data = yelp_df.select(
    "id",
    (yelp_df.useful/28*100).cast("int").alias("useful_perc")
)
```

useful_perc_data.columns

Out[]: [u'id', u'useful_perc']

alias - rename also id

```
useful_perc_data = yelp_df.select(
   yelp_df["id"].alias("uid"),
   (yelp_df.useful/28*100).cast("int").alias("useful_perc")
)
```

useful_perc_data.columns

Out[]: [u'uid', u'useful_perc']

Ordering by column

Import functions for ascending/descending order:

from pyspark.sql.functions import asc, desc

order by usefulness

```
useful_perc_data = yelp_df.select(
    yelp_df["id"].alias("uid"),
        (yelp_df.useful/28*100).cast("int").alias("useful_perc")
.orderBy(desc("useful_perc"))
```

```
useful_perc_data.show(2)
uid useful_perc
RqwFPp_qPu-1h87pG... 100
YAXPKM-Hck6-mjF74... 82
```

Join inputs

id	useful_perc
9yKzy9PApe	17

id	review_count	state
9yKzy9PApe	6	"CA"

Join results

id	useful_perc	review_count
9yKzy9PApe	17	6

Join

```
useful_perc_data.join(
    velp_df.

yelp_df.id == useful_perc_data.uid,

"inner"
)
```

Join - select

```
useful_perc_data.join(
    yelp_df,
    yelp_df.id == useful_perc_data.uid,
    "inner"
).select(useful_perc_data.uid, "useful_perc", "review_count")
```

Join - select - show

```
useful_perc_data.join(
   yelp_df,
   yelp_df.id == useful_perc_data.uid,
   "inner"
).select(useful_perc_data.uid, "useful_perc",
"review_count").show(5)
```

Output dataset

uid	useful_perc	review_count
WRBYytJAaJI1BTQC	55 71	362
GXj4PNAi095-q9ynP	3	76
1sn0-eY_d1Dhr6Q2u	0	9
MtFe-FuiOmo0vlo16.	0	7
EMYmuTlyeNBy5QB	9P 7	19

Cache in memory

```
useful_perc_data.join(
  yelp_df,
  yelp_df.id == useful_perc_data.uid,
  "inner"
).cache()|select(useful_perc_data.uid, "useful_perc",
"review_count").show(5)
```

Run it again!

Analytics with Dataframes on HTTP server logs

Log analytics

Available in the Cloudera VM at:

```
/usr/lib/hue/apps/search/examples/collections/solr_configs_log_analytics_demo/index_data.csv
```

Log analytics

Check file contents on the terminal:

head

/usr/lib/hue/apps/search/examples/collecti

ons/solr_configs_log_analytics_demo/index

data.csv

Columns

code,protocol,request,app,user_age nt_major,region_code,country_code ,id,city,subapp,latitude,method,client _ip,user_agent_family,bytes,referer, country_name,extension,url,os_maj or,longitude,device_family,record,us er_agent,time,os_family,country_co de3

Start PySpark

Need to load spark-csv for CSV support:

```
PYSPARK_DRIVER_PYTHON=ipython pyspark -- packages com.databricks:spark-csv_2.10:1.X.X
```

(Try to) read logs CSV

```
logs_df = sqlCtx.load(
source="com.databricks.spark.csv",
header = 'true',
inferSchema = 'true',
path =
'file:///usr/lib/hue/apps/search/examples/collections/solr_co
nfigs_log_analytics_demo/index_data.csv')
```

logs_df.count()

Parsing error

ERROR csv.CsvRelation\$: Exception while parsing

line: ",Mozilla/4.0 (compatible; MSIE 7.0;

Windows NT 5.1; Trident/4.0;

Inspect the file with VIM

- 3 ",Mozilla/5.0 (compatible; phpservermon/3.0.1; +http://www.phpservermonitgr.org),2014-05-04T06:35:49Z,Other,SGP^M
 4 200,HTTP/1.1,GET /metastore/table/default/sample_07 HTTP/1.1,metastore,;00,SG,6ddf6e38-7b83-423c-8873-39842cca2dbb,
 - ore/table/default/sample_07,,103.85579999999999,0ther,"demo.gethue.com:80 128.199.234.236 - [04/May/2014:0<mark>6:35:50 .0 (compati</mark>ple; phpservermon/3.0.1; +http://www.phpservermonitor.org)""
- Mozilla/2.0 (compatible; phpservermon/3.0.1; +http://www.phpservermonitor.org),2014-05-04T06:35:50Z,0ther,SGP^M
- 6 200, HTTP/1.1, GET /search/?collection=10000001 HTTP/1.1, search,,00,SG,313bb28e-dd7c-4364-alle-9ffb0db7b303,Singapore

Access Hadoop configuration

Spark relies on Hadoop functionality for reading data.

sc._jsc.hadoopConfiguration()

Set input file delimiter

Spark relies on Hadoop functionality for reading data.

sc._jsc.hadoopConfiguration().set('textinputforma
t.record.delimiter', '\r\n')

Read logs CSV

```
logs_df = sqlCtx.load(
source="com.databricks.spark.csv",
header = 'true', inferSchema = 'true',
path =
'file://usr/lib/hue/apps/search/examples/collections/solr_co
nfigs_log_analytics_demo/index_data.csv')
```

logs_df.count()

Out[]: 9410L

Display of logs DataFrame

```
user agent major region code country code id
code protocol request
                            app
e extension url
                                                         device family record
                              os major longitude
                                                                                          user agent
   HTTP/1.1 GET /metastore/ta... metastore null
                                                          66
                                                                     56
                                                                                  8836e6ce-9a21-449...
           /metastore/table/... null
                                       103.85579999999999 Other
                                                                      demo.gethue.com:8... Mozilla/5.0
200 HTTP/1.1 GET /metastore/ta... metastore null
                                                                                  6ddf6e38-7b83-423...
                                                          \Theta\Theta
                                       103.8557999999999 Other
                                                                      demo.gethue.com:8... Mozilla/5.0
           /metastore/table/... null
   HTTP/1.1 GET /search/?coll... search
                                          nul l
                                                          ΘÐ
                                                                      56
                                                                              313bb28e-dd7c-436...
                                       103.8557999999999 Other
           /search/?collecti... null
                                                                      demo.gethue.com:8... Mozilla/5.0
   HTTP/1.1 GET /search/?coll... search
                                          null
                                                                                 ecb47c61-a9e4-4b5...
                                                          00
           /search/?collecti... null
                                       103.8557999999999 Other
                                                                      demo.gethue.com:8... Mozilla/5.0
   HTTP/1.1 HEAD / HTTP/1.1
                                          null
                                                                      56
                                                                                  affdb6b9-3657-4d1...
                                                          88
                                                                      demo.gethue.com:8... Mozilla/5.0
                               null
                                       103.8557999999999 Other
```

root code: integer (nullable = true) protocol: string (nullable = true) request: string (nullable = true) app: string (nullable = true) user_agent_major: integer (nullable = true) region_code: string (nullable = true) country_code: string (nullable = true) id: string (nullable = true) city: string (nullable = true) subapp: string (nullable = true) latitude: double (nullable = true) method: string (nullable = true) client_ip: string (nullable = true) user_agent_family: string (nullable = true) bytes: integer (nullable = true) referer: string (nullable = true) country_name: string (nullable = true)

-- extension: string (nullable = true)

Count by HTTP code

Count the log events by HTTP code (i.e. how many 200 OK, 404 Not found...)

logs_df.groupBy("code").count().show()

code count

500 2

301 71

302 1943

502 6

304 117

400 1

200 7235

401 10

404 11

from pyspark.sql.functions import asc, desc

logs_df.groupBy("code").count().orderBy(desc("count")).show()

code count

200 7235

302 1943

304 117

301 71

408 14

404 11

Compute average

logs_df.groupBy("code").avg("bytes").show()

code AVG(bytes#47)

500 4684.5

301 424.61971830985914

302 415.6510550694802

502 581.0

304 185.26495726495727

400 0.0

Mean, Min, Max by code

Compute in a single operation Mean, Min and Max by HTTP code

```
import pyspark.sql.functions as F
logs_df.groupBy("code").agg(
             logs_df.code,
             F.avg(logs_df.bytes),
             F.min(logs_df.bytes),
             F.max(logs_df.bytes)
).show()
```

Mean, Min, Max by code

code	AVG(bytes#47)	MIN(bytes#47)	MAX(bytes#47)
500	4684.5	422	8947
301	424.61971830985914	331	499
302	415.6510550694802	304	1034
502	581.0	581	581
304	185.26495726495727	157	204
400	0.0	0	0
200	41750.03759502419	0	9045352
401	12472.8	8318	28895
404	17872.454545454544	7197	23822
408	440.57142857142856	0	514

Completed DataFrames

- Completed analytics with DataFrames
- Next we'll focus on interoperability with SQL query language and Hive

Spark SQL

DataFrames and Databases

DataFrame & Database table: conceptually equivalent.

Spark makes them interoperable

DataFrames & SQL

- Query existing Spark DataFrames (however created) with SQL
 - -Same functionality, different interface
 - –Legacy SQL

Read data and persistency

- Load data from Hive / other databases
- Save tables to Hive

Explore the Yelp dataset

```
yelp_df = sqlCtx.load(
source='com.databricks.spark.csv',
header = 'true',
inferSchema = 'true',
path =
'file:///usr/lib/hue/apps/search/examples/collections/solr_co
nfigs_yelp_demo/index_data.csv')
```

Register as a SQL table

- DataFrame already has Schema
- Create a temporary table with: yelp_df.registerTempTable("yelp")

Run SQL statements

```
filtered_yelp = sqlCtx.sql("SELECT * FROM yelp WHERE useful >= 1")
filtered_yelp
```

Out[]: DataFrame[business_id: string, cool: int, date: string, funny: int, id: string, stars: int, text: string, type: string, useful: int, user_id: string, name: string, full_address: string, latitude: double, longitude: double, neighborhoods: string, open: string, review_count: int, state: string]

Filtering

filtered_yelp.count()

Out[]: 601L

yelp_df.filter(yelp_df.useful >= 1).count()

Out[]: 601L

aggregation

```
sqlCtx.sql("SELECT MAX(useful) AS max_useful FROM
yelp").collect()
Out[]: [Row(max_useful)=28)]
yelp_df.agg({"useful":"max"}).collect()
Out[]: [Row(MAX(useful#267)=28)]
```

Join - select - show

```
useful_perc_data.join(
    yelp_df,
    yelp_df.id == useful_perc_data.uid,
    "inner"
).select(useful_perc_data.uid, "useful_perc", "review_count")
```

Register as SQL table

useful_perc_data.registerTempTable("useful_perc_data")

join

```
sqlCtx.sql(
"""SELECT useful_perc_data.uid, useful_perc,
review_count
FROM useful_perc_data
INNER JOIN yelp
ON useful_perc_data.uid=yelp.id"""
```

Performance

- Either DataFrame calls or SQL
- Same under-the-hood optimizer (Catalyst)
- Creates DAG
- Parallel execution
- Creates bytecode

Spark and Hive

Spark and Hive

- copied hive-site.xml to Spark conf/
- Spark read / write to Hive

Hive table to DataFrame

- sqlCtx.sql has access to Hive tables
- Load data uploaded during the Hive class
- Result is a DataFrame

```
customers_df = sqlCtx.sql("SELECT * FROM customers")
customers_df.show()
```

Printout of customers_df

customer_			customer_email	customer_password				customer_zipcode
1	Richard	Hernandez	$XXXXXXXX\overline{X}$	XXXXXXXXX	6303 Heather Plaza	Brownsville	TX	78521
2	Mary	Barrett	XXXXXXXX	XXXXXXXX	9526 Noble Embers		CO	80126
3	Ann	Smith	XXXXXXXX	XXXXXXXX	3422 Blue Pioneer	Caguas	PR	00725
4	Mary	Jones	XXXXXXXX	XXXXXXXX	8324 Little Common	San Marcos	CA	92069
5	Robert	Hudson	XXXXXXXX	XXXXXXXX	10 Crystal River	Caguas	PR	00725
6	Mary	Smith	XXXXXXXX	XXXXXXXX	3151 Sleepy Quail	Passaic	NJ	07055
7	Melissa	Wilcox	XXXXXXXX	XXXXXXXX	9453 High Concession	Caguas	PR	00725
8	Megan	Smith	XXXXXXXX	XXXXXXXX	3047 Foggy Forest	Lawrence	MA	01841
9	Mary	Perez	XXXXXXXX	XXXXXXXX	3616 Quaking Street	Caguas	PR	00725
10	Melissa	Smith	XXXXXXXX	XXXXXXXX	8598 Harvest Beac	Stafford	VA	22554
11	Mary	Huffman	XXXXXXXX	XXXXXXXX	3169 Stony Woods	Caguas	PR	00725
12	Christopher	Smith	XXXXXXXX	XXXXXXXX	5594 Jagged Ember	San Antonio	TX	78227
13	Mary	Baldwin	XXXXXXXX	XXXXXXXX	7922 Iron Oak Gar	Caguas	PR	00725
14	Katherine	Smith	XXXXXXXX	XXXXXXXX	5666 Hazy Pony Sq	Pico Rivera	CA	90660
15	Jane	Luna	XXXXXXXX	XXXXXXXX	673 Burning Glen	Fontana	CA	92336
16	Tiffany	Smith	XXXXXXXX	XXXXXXXX	6651 Iron Port	Caguas	PR	00725
17	Mary	Robinson	XXXXXXXX	XXXXXXXX	1325 Noble Pike	Taylor	MI	48180
18	Robert	Smith	XXXXXXXX	XXXXXXXX	2734 Hazy Butterf	Martinez	CA	94553
19	Stephanie	Mitchell	XXXXXXXX	XXXXXXXX	3543 Red Treasure	Caguas	PR	00725
20	Mary	Fllic	XXXXXXXXX	XXXXXXXXX	4703 Old Route	West New York	NI	07003

```
customers_df.printSchema()
root
```

- -- customer_id: integer (nullable = true)
- -- customer_fname: string (nullable = true)
- -- customer_Iname: string (nullable = true)
- -- customer_email: string (nullable = true)
- -- customer_password: string (nullable = true)
- -- customer_street: string (nullable = true)
- -- customer_city: string (nullable = true)
- -- customer_state: string (nullable = true)
- -- customer_zipcode: string (nullable = true)

Run unmodified SQL queries

```
sqlCtx.sql("""select c.category_name,
count(order_item_quantity) as count from order_items oi
inner join products p on oi.order_item_product_id =
p.product_id inner join categories c on c.category_id =
p.product_category_id group by c.category_name
order by count desc
limit 10"""
).show()
```

Most popular categories

category name	count
Cleats	24551
Men's Footwear	22246
Women's Apparel	21035
Indoor/Outdoor Games	19298
Fishing	17325
Water Sports	15540
Camping & Hiking	13729
Cardio Equipment	12487
Shop By Sport	10984
Electronics	3156

Run unmodified SQL queries

```
sqlCtx.sql("""select p.product_id, p.product_name, r.revenue
from products p inner join
(select oi.order item product id, sum(cast(oi.order item subtotal as float)) as
revenue from order_items oi inner join orders o on oi.order_item_order_id =
o.order id
where o.order status <> 'CANCELED'
and o.order_status <> 'SUSPECTED_FRAUD'
group by order_item_product_id) r
on p.product_id = r.order_item_product_id
order by r.revenue desc limit 10"""
).show()
```

Top 10 products by revenue

```
product id product name
                                revenue
1004
           Field & Stream Sp... 6637668.282318115
365
           Perfect Fitness P... 4233794.3682899475
957
           Diamondback Women... 3946837.004547119
191
           Nike Men's Free 5... 3507549.2067337036
502
           Nike Men's Dri-FI... 3011600.0
1073
           Pelican Sunstream... 2967851.6815185547
1014
           O'Brien Men's Neo... 2765543.314743042
403
           Nike Men's CJ Eli... 2763977.4868011475
627
           Under Armour Girl... 1214896.220287323
565
           adidas Youth Germ... 63490.0
```

Save DataFrames to Hive

registerTempTable only gives temporary SQL-like access to DataFrames

Store permanently to Hive with:

yelp_df.saveAsTable("yelp_reviews")

Check persistency

- Restart PySpark
- Run: sqlCtx.sql("SELECT * FROM yelp").show()
- Fails with "Table not found"

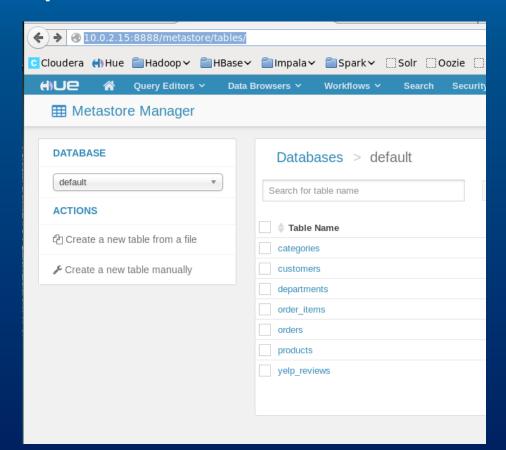
Check persistency

- Restart PySpark
- Run: sqlCtx.sql("SELECT * FROM yelp_reviews").show()
- Restores from Hive

Loaded Yelp DataFrame

business_id		date		funny	id	stars	text	type	useful	user_id	name	full_address	latitude	longitude	neighbor
hoods open review_o															
9yKzy9PApeiPPOUJE		2011-0	01-26	Θ	fWKvX83p0-ka4JS3d	4	My wife took me h	business	5	rLtl8ZkDX5vH5nAx9	Morning Glory Cafe	6106 S 32nd St Ph	33.3907928467	-112.012504578	[1]
True 116		AZ													
ZRJwVLyzEJq1VAihD	. 0	2011-0	07-27	Θ	IjZ33sJrzXqU-0X6U	4	I have no idea wh	business	0	0a2KyEL0d3Yb1V6ai	Spinato's Pizzeria	4848 E Chandler B	33.305606842	-111.978759766	[]
True 102		AZ													
6oRAC4uyJCsJl1X0W	. 0	2012-0	06-14	Θ	IESLBzqUCLdSzSqm0	4	love the gyro pla	business	1	<pre>0hT2KtfLiobPvh6cD</pre>	Haji-Baba	1513 E Apache Bl	33.4143447876	-111.913032532	[]
True 265		AZ													
1QQZuf4zZ0yFCvXc		2010-0	05-27	Θ	G-WvGaISbqqaMHlNn	4	Rosie, Dakota, an	business	2	uZetl9T0NcR0G0yFf	Chaparral Dog Park	5401 N Hayden Rd	33.5229454041	-111.90788269	[]
True 88		AZ													
6ozycU1RpktNG2-1B	. 0	2012-0	01-05	Θ	luJFq2r5QfJG 6ExM	4	General Manager S	business	0	vYmM4KTsC8ZfQBg-j	Discount Tire	1357 S Power Road	33.3910255432	-111.68447876	[]
True 5		AZ													
-yxfBYGB6SEqszmxJ	. 4	2007-	12-13	1	m2CKSsepBCoRYWxiR	3	Quiessence is, si	business	3	sqYN3lNgvPbPCTRsM	Quiessence Restau	6106 S 32nd St Ph	33.3907928467	-112.012504578	[]
True 109		AZ													
zp713qNhx8d9KCJJn	. 7	2010-0	02-12	4	riFQ3vxNpP4rWLk C	4	Drop what you're	business	7	wFweIWhv2fREZV dY	La Condesa Gourme	1919 N 16th St Ph	33.4691314697	-112.04750824	[]
True 307		AZ													
hW0Ne HTHEAgGF1rA	. 0	2012-0	07-12	Θ	JL7GXJ9u4YMx7Rzs0	3	Luckily, I didn't	business	1	lieuYcKS7zeAv Ul5	Phoenix Sky Harbo	3400 E Sky Harbor	33.4347496033	-112.006439209	[]
True 862		AZ													
wNUea3IXZWD63bb0Q	. 0	2012-0	08-17	Θ	XtnfnYmnJYi71yIuG	3	Definitely come f	business	0	Vh DlizgGhSqQh4qf	Stingray Sushi	2574 E Camelback	33.5096054077	-112.025741577	[]
True 163		AZ			,					=					
nMHhuYan8e3c0No3P	. 0	2010-0	08-11	Θ	jJAIXA46pUlswYyRC	4	Nobuo shows his u	business	1	sUNkXq8-KFtCMODV6	Nobuo At Teeter H	622 E Adams St Ph	33.4495391846	-112.065666199	[]
True 189		AZ			· · · · · · · · · · · · · · · · · · ·										
AsSCvθq BWqIe3mX2	1	2010-0	06-16	1	E11jzpKz9Kw5K7fuA	4	The oldish man wh	business	3	-OMIS6yWkYjVldNhC	Cookiez On Mill	514 S Mill Ave St	33.4248809814	-111.940200806	П
False 74		AZ													
e9nN4XxidHi4qtKCO	. 1	2011-	10-21	Θ	3rPt0LxF7ramEUrzn	4	Wonderful Vietnam	business	1	ClrHp3dmepNea7Xio	Lee's Sandwiches	1901 W Warner Rd	33.3347129822	-111.874786377	[1
True 192		AZ													
h53YuCiIDfEFSJCQp		2010-0	01-11	Θ	cGnKNX3I9rthE0-TH	4	They have a limit	business	2	UPtysDF6cUDUxq2KY	Jason's Deli	1065 E Baseline R	33.3796195984	-111.809425354	[1]
True 36		AZ					and the same of								
WGNIYMeXPyoWav1AP			12-23	Θ	FvEEw1 OsrYdvwLV5	4	Good tattoo shop	business	2	Xm8HXE1JHascXe5BK	The Lady Luck Tat	961 E Guadalupe R	33.3637619019	-111.9272995	[1]
True 25		AZ					seed tattee snopiiii	545211655		, monstered and severe server a	ine cas, caen identi	Joi L Jadatarapa III.I.	33.303.013013		
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Conclusion

- Analytics with DataFrames, filtering, aggregation, joins, grouping
- How to add new packages to Spark and modify Hadoop configuration
- Operate on DataFrames with SQL
- Persist DataFrames as Hive tables