Introduction to Spark II

Galvanize

Introduction to Spark II

OBJECTIVES

- **Explain** the differences between RDDs and DataFrames, and where Spark development is moving
- **Explain** what persisting/caching an RDD means, and situations where this is useful
- **Define** an out of memory error and why it happens
- **Describe** the difference between narrow and wide transformations
- **Discuss** next steps to expanding Spark to new domains

The Evolution of Spark

Spark is **moving from RDDs to DataFrames**

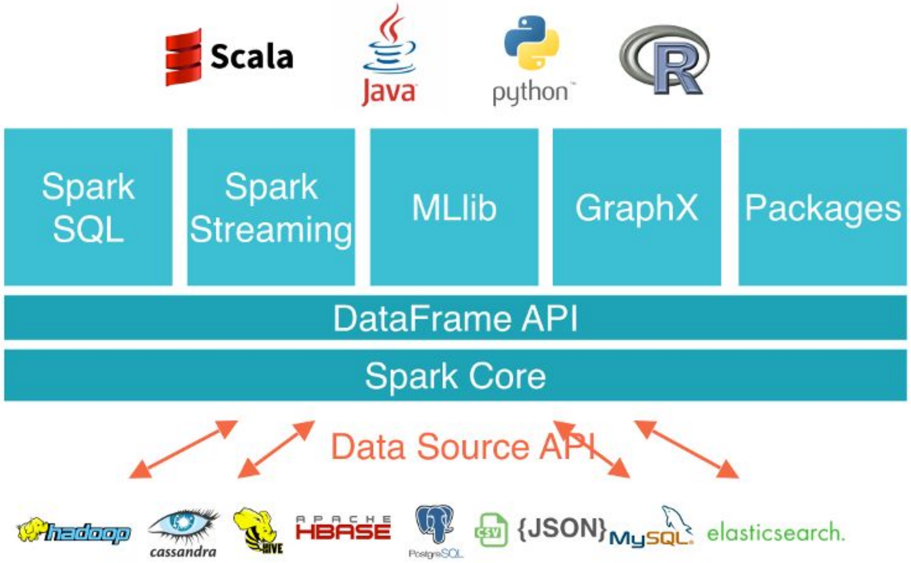
- Since Spark 2.0, the emphasis has shifted
- MLlib (RDD-based) -> ML (DF-based)
- GraphX (RDD-based) -> GraphFrames (DF-based)
- Focus on DataFrames for future proofing

SparkSQL

Introducing **SparkSQL**

- An in-memory database
- Access it using `SparkSession`
- The **primary abstraction is a DataFrame**
- Allows for the execution of SQL commands

```
import pyspark as ps

conf = ps.SparkConf() \
    .setAppName("My App") \
    .setMaster("local[*]")
sc = ps.SparkContext(conf=conf)

spark = ps.sql.SparkSession(sc)
```



What is a DataFrame?

DataFrames are...

- Immutable collections of data (like RDDs)
- Distributed across nodes in a cluster
- **Organized into named columns**
    - not schema-less rows, like RDDs
    - Schema = Table Names + Column Names + Column Types
- Think of them like **an RDD with a schema**

Why are they useful?

- They make large data processing easier
- Allow developers to formalize the structure of the data
- Performance parity
    - Unlike RDDs, which are slower on Python than Scala or Java

```
+--------------------+-----+
|                 col|count|
+--------------------+-----+
|         iHeartAwards|27299|
|          BestFanArmy|19892|
|         BestFans2017|12534|
|         OneDBestFans|10829|
|         GagaBestFans| 9164|
|YOU_NEVER_WALK_ALONE| 8229|
|                  BTS| 7566|
|        CamilaBestFans| 7224|
|             Lovatics| 6491|
|     HappyBirthdayHarry| 5391|
|              NOW2016| 5345|
|     BlackHistoryMonth| 5042|
|        RTした人全員フォローする| 4855|
|     ALDUB81stWeeksary| 4567|
|       ALDUBLoveMonth| 4513|
|        BestMusicVideo| 4435|
|     PBBPADALUCKMAYMAY| 4060|
|            ツインテールの日| 4029|
|           사설토토사이트추천| 3933|
|          gameinsight| 3796|
+--------------------+-----+
```

DataFrame Speed Comparison I

DataFrames are **fast**

- Imposing a schema allows for optimization
- **Catalyst Optimizer** is at the heart of Spark SQL
    - Eases the addition of new optimizations
- **Project Tungsten** improves memory/CPU use

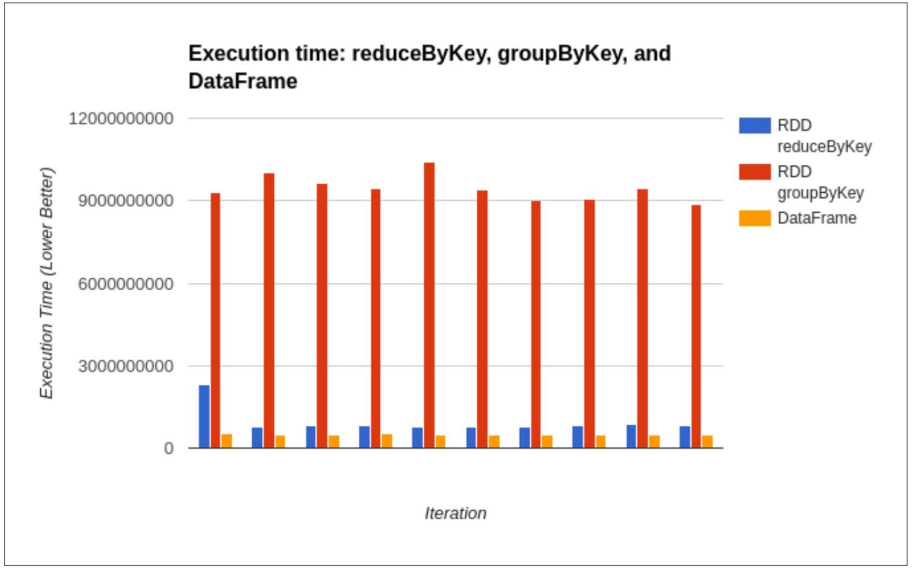


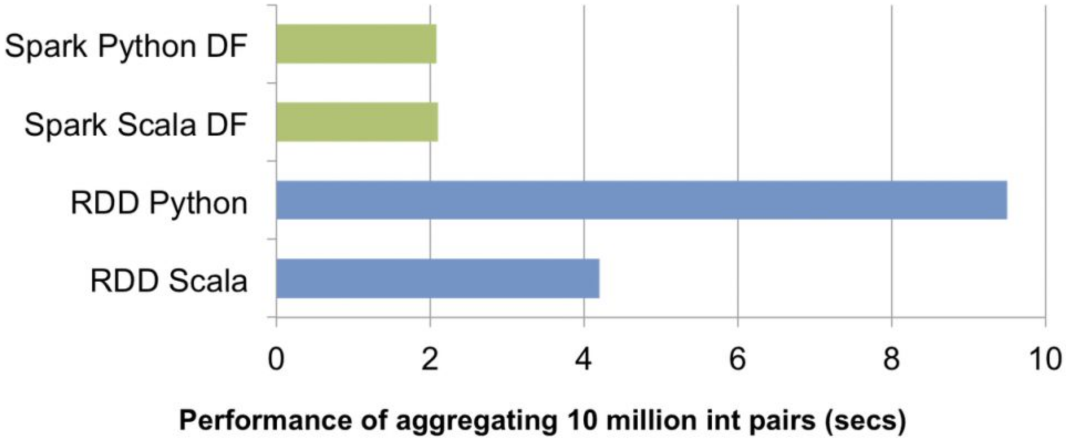
Figure 3-1. Relative performance for RDD versus DataFrames based on SimplePerfTest computing aggregate average fuzziness of pandas

Source: *High Performance Spark*

DataFrame Speed Comparison II

RDDs/Python are **slow**

- There’s an overhead between Python and the JVM
- RDDs (especially older versions) suffered from this
- Python is built to be slow (single threaded, not type safe)



Source: [Databricks]

Creating DataFrames

```
# read JSON
df = spark.read.json('data/sales.json')

# prints the schema
df.printSchema()

# some functions are still valid
print("line count: {}".format(df.count()))

# show the table in a oh-so-nice format
df.show()
```

Creating and Querying DataFrames

```python
# read CSV
df_sales = spark.read.csv('data/sales.csv',
                          header=True,        # use headers or not
                          quote='"',          # char for quotes
                          sep=",",            # char for separation
                          inferSchema=True)   # do we infer schema or
                          not ?

# Now create an SQL table and issue SQL queries against it without
# using the sqlContext but through the SparkSession object.
# Creates a temporary view of the DataFrame
df_sales.createOrReplaceTempView("sales")

result = spark.sql('''
    SELECT state, AVG(amount) as avg_amount
    FROM sales
    GROUP BY state
    ''')
result.show()
```

```python
# import the many data types
from pyspark.sql.types import *

# create a schema of your own
schema = StructType( [
    StructField('id',IntegerType(),True),
    StructField('date',StringType(),True),
    StructField('store',IntegerType(),True),
    StructField('state',StringType(),True),
    StructField('product',IntegerType(),True),
    StructField('amount',FloatType(),True) ] )

# feed that into a DataFrame
df = spark.createDataFrame(rdd_sales,schema)

# show the result
df.show()

# print the schema
df.printSchema()
```

Caching/Persisting DFs and RDDs

Use the **`.cache()` method** to cache

- This keeps a copy of your data at that point in time
- When an action is called Spark figures out the answer and then throws away all the data
- For multiple passes across your data (e.g. iterative algorithms), cache your results

Use the **`.persist()` method** to cache to disk

Level	**Meaning**
MEMORY_ONLY	Same as cache()
MEMORY_AND_DISK	Cache in memory then overflow to disk
MEMORY_AND_DISK_SER	Like above; in cache keep objects serialized instead of live
DISK_ONLY	Cache to disk not to memory

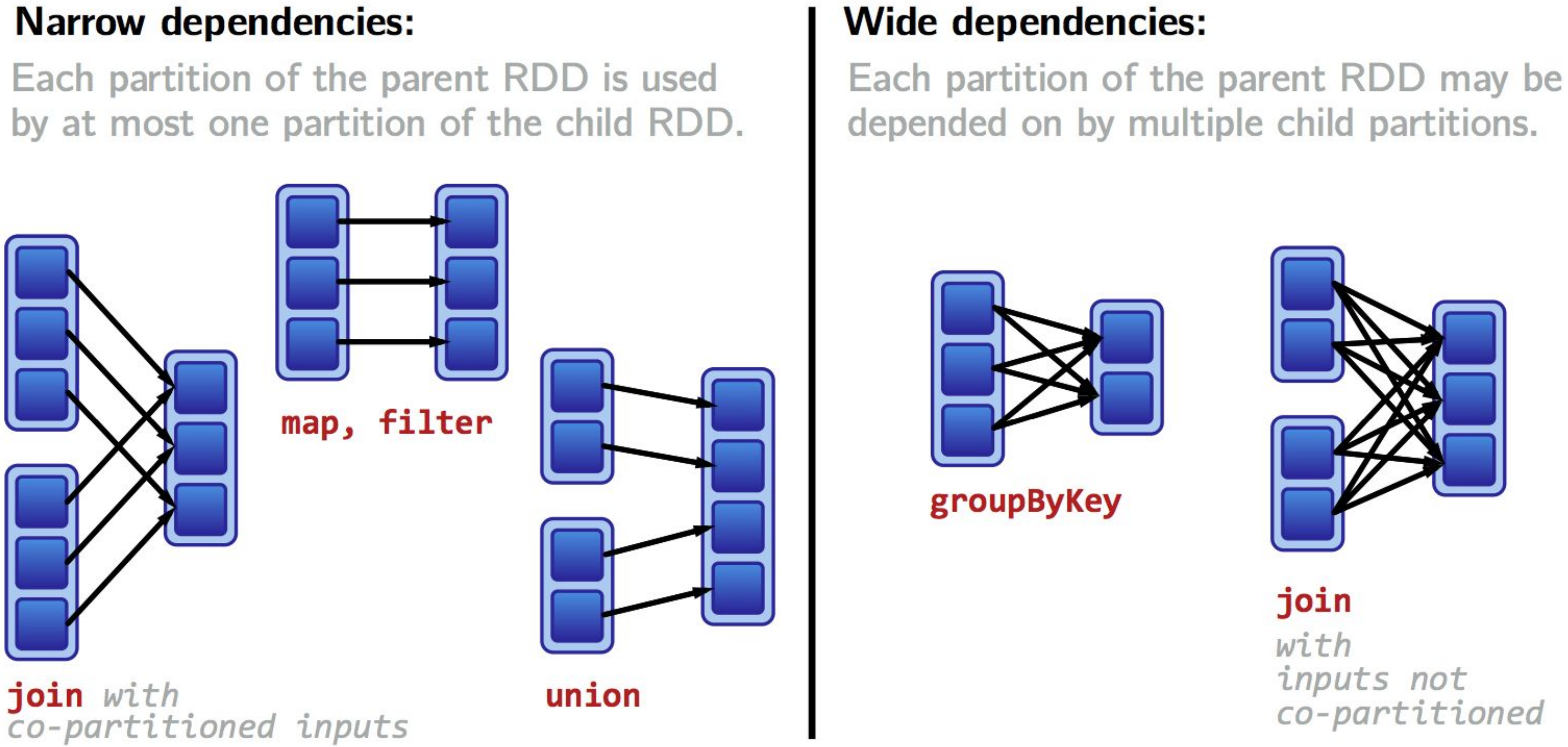
```
import random
num_count = 500*1000
num_list = [random.random() for i in range(num_count
rdd1 = sc.parallelize(num_list)
rdd2 = rdd1.sortBy(lambda num: num)

%time rdd2.count()
%time rdd2.count()
%time rdd2.count()
%time rdd2.count()
%time rdd2.count()
```

```
CPU times: user 8.34 ms, sys: 1.25 ms, total: 9.59 m
Wall time: 1.25 s
CPU times: user 9.04 ms, sys: 1.79 ms, total: 10.8 m
Wall time: 515 ms
CPU times: user 8.93 ms, sys: 1.5 ms, total: 10.4 ms
Wall time: 608 ms
CPU times: user 6.48 ms, sys: 1.37 ms, total: 7.85 m
Wall time: 616 ms
CPU times: user 7.06 ms, sys: 1.54 ms, total: 8.6 ms
Wall time: 563 ms

500000
```

```
rdd2.cache()
%time rdd2.count()
%time rdd2.count()
%time rdd2.count()
%time rdd2.count()
%time rdd2.count()
```

```
CPU times: user 5.13 ms, sys: 1.1 ms, total: 6.23 ms
Wall time: 581 ms
CPU times: user 6.12 ms, sys: 1.5 ms, total: 7.62 ms
Wall time: 79.8 ms
CPU times: user 5.34 ms, sys: 1.63 ms, total: 6.97 m
Wall time: 110 ms
CPU times: user 8.43 ms, sys: 2.13 ms, total: 10.6 m
Wall time: 135 ms
CPU times: user 5.51 ms, sys: 1.28 ms, total: 6.79 m
Wall time: 97.1 ms

500000
```

Narrow vs Wide Dependencies I

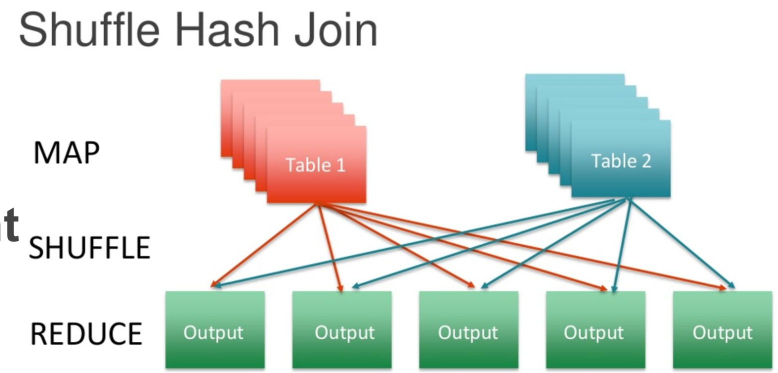


Source: https://github.com/rohitvg/scala-spark-4/wiki/Wide-vs-Narrow-Dependencies

Narrow vs Wide Dependencies II

A **ShuffleHashJoin is the Spark default**

- Wide dependencies
- Maps data in two DFs -> shuffles based on field in join condition -> reduces to join two datasets
- Best when evenly distributed data across cluster
- **Joins are expensive**



A **BroadcastHashJoin can be more performant**

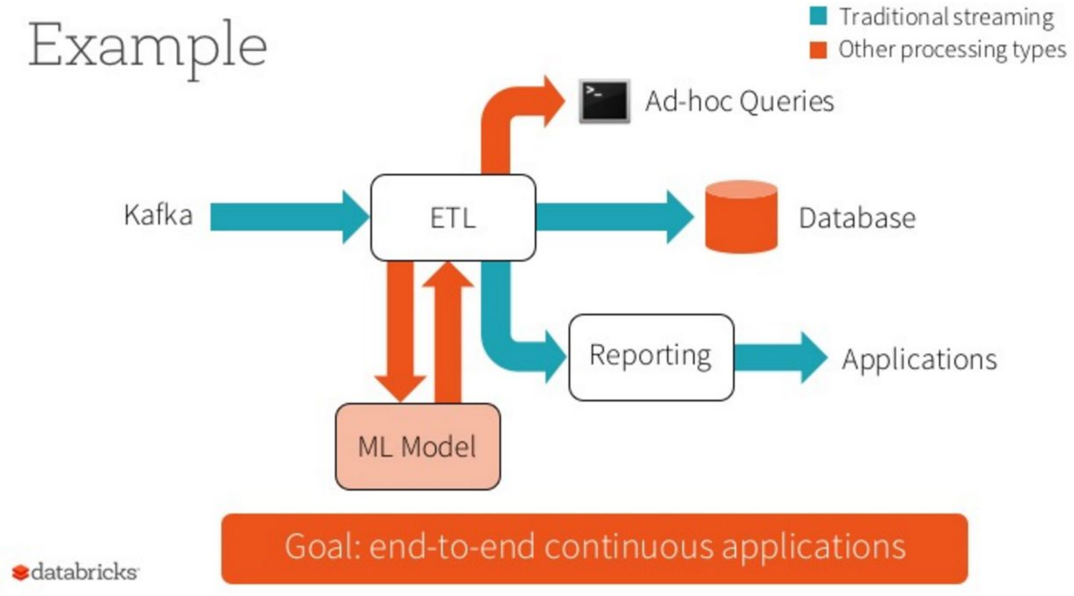
- Narrow dependencies
- Broadcasts a small DF to each of the larger partitions
- Use when the smaller DF is small enough to fit on a single machine
- Minimizes data transfer

Source: Databricks

The Spark Ecosystem II

Spark can be the **center of your data product**

- Extract Transform Load (ETL)
- Ad-hoc queries (OLAP)
- Transactions (OLTP)
- Stream processing
- Check out the SMACK stack



Source: [Databricks]

Extending your knowledge of Spark

Possible **future avenues** for understanding Spark

- Probabilistic data structures
- Difference in local and distributed ML algorithms
- Look into the SMACK stack
- Learn Scala to maximize your use of Spark
  - Allows for Datasets API
  - Python can't use Datasets because it's not type safe
- Contribute to Spark core, or community projects

Resources

- Spark Documents: Best stop for the most up to date (and versioned) information
- JF's Walkthroughs: Galvanize instructor who made some helpful walkthroughs
- *Learning PySpark*: An up-to-date intro to the python API to Spark. Good treatment of machine learning
- *Learning Spark*: A good introduction to Spark written on Spark 1.X. Parts of it are still relevant for a high level overview, but most of it is outdated
- *High Performance Spark*: More recent publication by the author of *Learning Spark*
- Databrick's explanation of key terms

Questions?