# SparkSQL and DataFrame

Lecture 5
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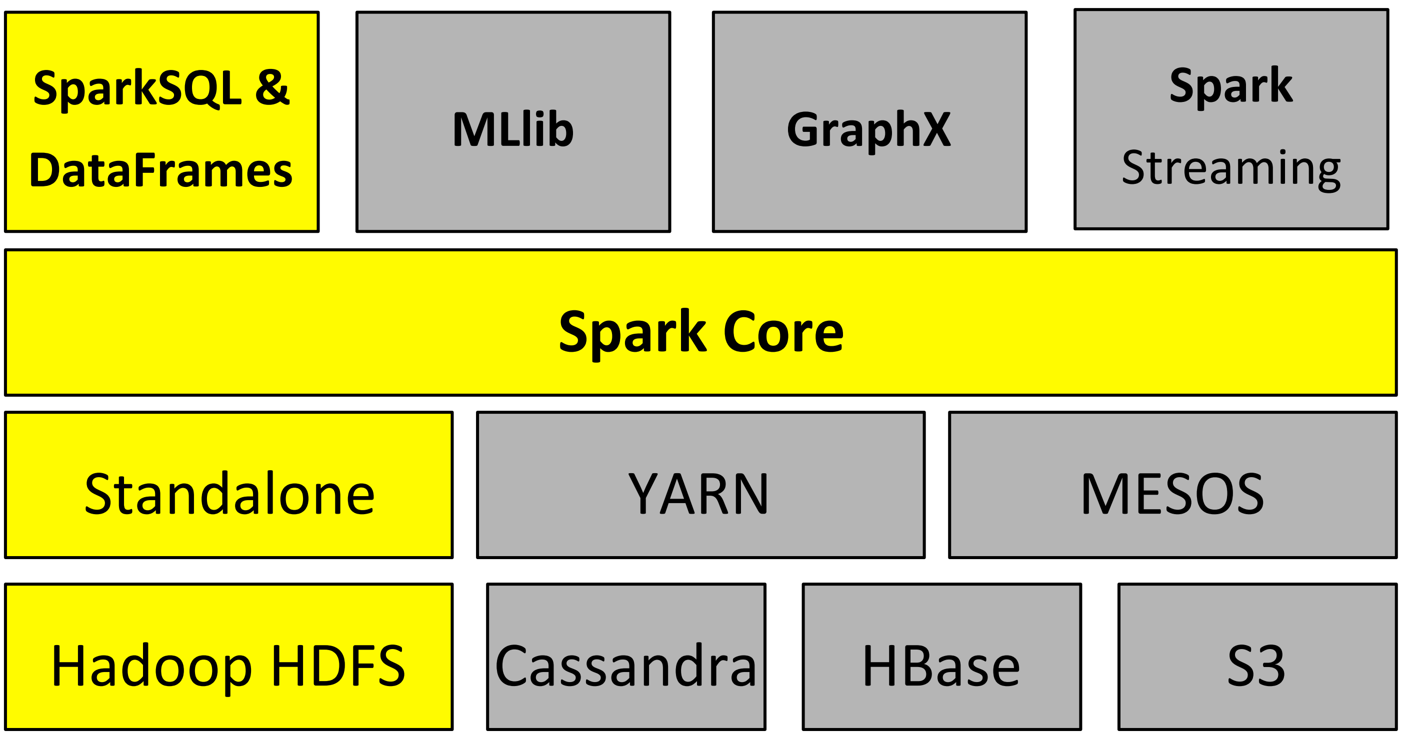
# SparkSQL & DataFrames

- **Special-purpose libraries for a variety of data science tasks**
  - SQL-like query computation by SparkSQL
  - DataFrames: Table




* **Image from https://www.safaribooksonline.com/library/view/data-analytics-with/9781491913734/ch04.html**

# Outline

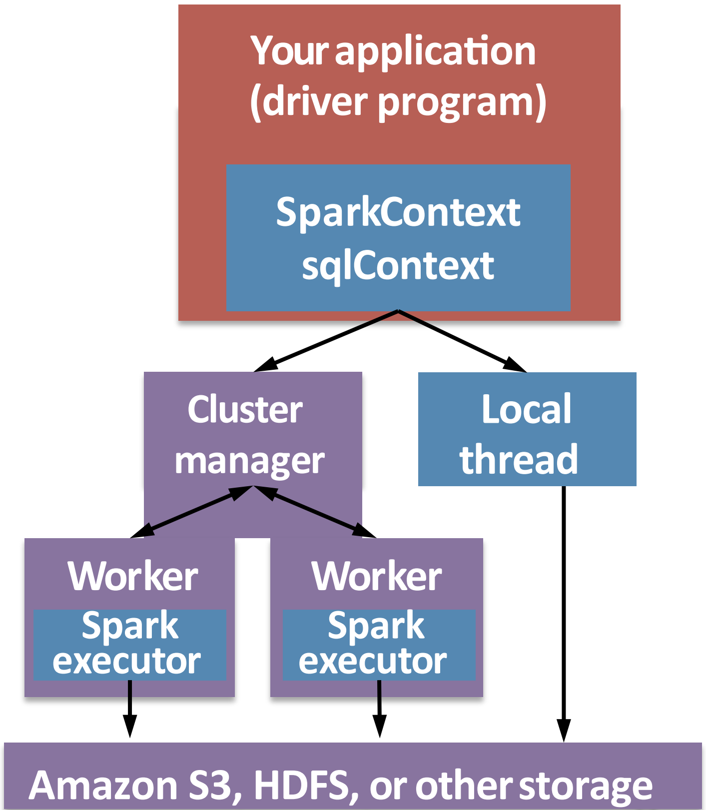
- **DataFrames**
- Spark Transformations and Actions
- Spark Programming Model
- Relational Database and SQL
- SparkSQL

# DataFrames

- **Primary abstraction in Spark**
  - *Immutable* (i.e., read-only) once constructed
  - Track lineage information to efficiently recompute lost data
  - Enable operations on collection of elements in parallel
    - "Here's an operation, run it on all of the data"

- **You can construct DataFrames**
  - by *parallelizing* existing Python collections (lists)
  - by *transforming* an existing Spark or pandas DFs
  - from *files* in HDFS or any other storage system

# Spark Driver and Workers




- **A Spark program is two programs:**
  - A driver program and a workers program
- **Worker programs run on cluster nodes or in local threads**
- **DataFrames are distributed across workers**

# Spark and SQL Contexts

- **A Spark program first creates a `SparkContext` object**
  - `SparkContext` tells Spark how and where to access a cluster
  - pySpark shell automatically creates `SparkContext`
  - iPython and programs must create a new `SparkContext`
- **The program next creates a `sqlContext` object**
- **Use `sqlContext` to create DataFrames**

**In the labs, we create the SparkContext and sqlContext for you**

# DataFrames

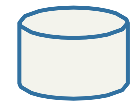
- Each row of a DataFrame is a Row object
- The fields in a Row can be accessed like attributes

```
>>> row = Row(name="Alice", age=11)
>>> row
Row(age=11, name='Alice')
>>> row['name'], row['age']
('Alice', 11)
>>> row.name, row.age
('Alice', 11)
```

# DataFrames

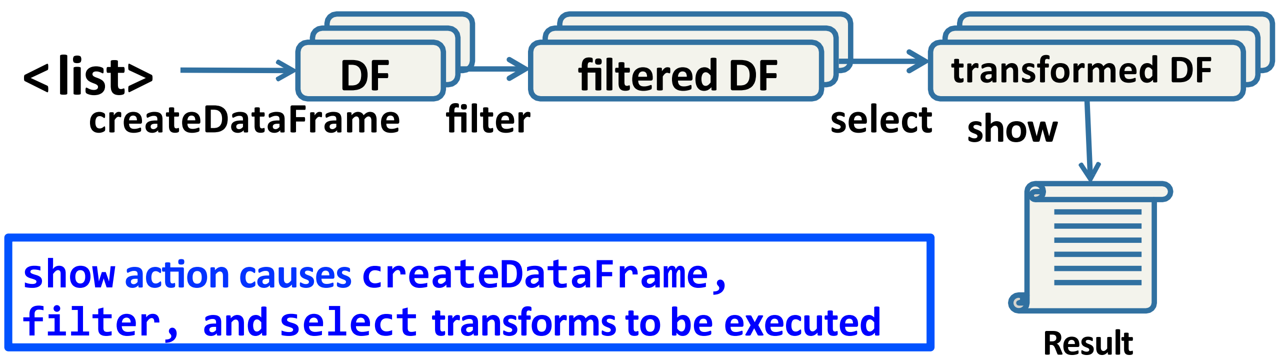
- **Similarities to RDD**
  - Two types of operations: *transformations* and *actions*
  - Transformations are lazy (*not computed immediately*)
  - Transformed DF is executed when action runs on it
  - Persist (cache) DFs in memory or disk

# Working with DataFrames

- Create a DataFrame from a data source:  <list>

- Apply *transformations* to a DataFrame: select, filter, ...

- Apply *actions* to a DataFrame: collect, count, ...



# Creating DataFrames

- **Create DataFrames from Python collections (lists)**

```
>>> data = [('Alice', 1), ('Bob', 2)]

>>> data

[('Alice', 1), ('Bob', 2)]

>>> df = sqlContext.createDataFrame(data)
[Row(_1=u'Alice', _2=1), Row(_1=u'Bob', _2=2)]
>>> sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
```

No computation occurs with `sqlContext.createDataFrame()`

- Spark only records how to create the DataFrame

# pandas: Python Data Analysis Library

- **Open source data analysis and modeling library**
  - An alternative to using R
- **pandas DataFrame: a table with named columns**
  - The most commonly used pandas object
  - Represented as a Python Dict (column_name → Series)
  - Each pandas Series object represents a column
- **1-D labeled array capable of holding any data type**
  - R has a similar data frame type

# Creating DataFrames

- **Easy to create pySpark DataFrames from pandas (and R) DataFrames**

```
# Create a Spark DataFrame from Pandas
>>> spark_df = sqlContext.createDataFrame(pandas_df)
```

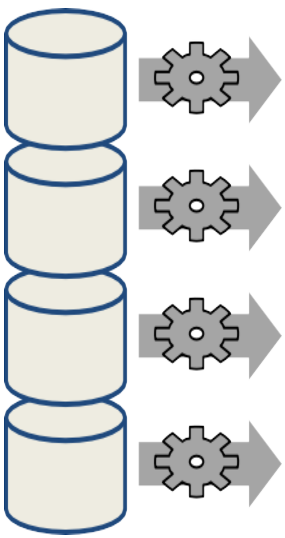
# Creating DataFrames

- **From HDFS, text files, JSON files, Apache Parquet, Hypertable, Amazon S3, Apache Hbase, SequenceFiles, any other Hadoop `InputFormat`, and directory or glob wildcard: `/data/201404*`**

```
>>> df = sqlContext.read.text("README.txt")
>>> df.collect()
[Row(value=u'hello'), Row(value=u'this')]
```

# Creating a DataFrame from a File

```
distFile = sqlContext.read.text ("...")
```



**Loads text file and returns a DataFrame with a single string column named "value"**

**Each line in text file is a row**

***Lazy evaluation*** **means no execution happens now**

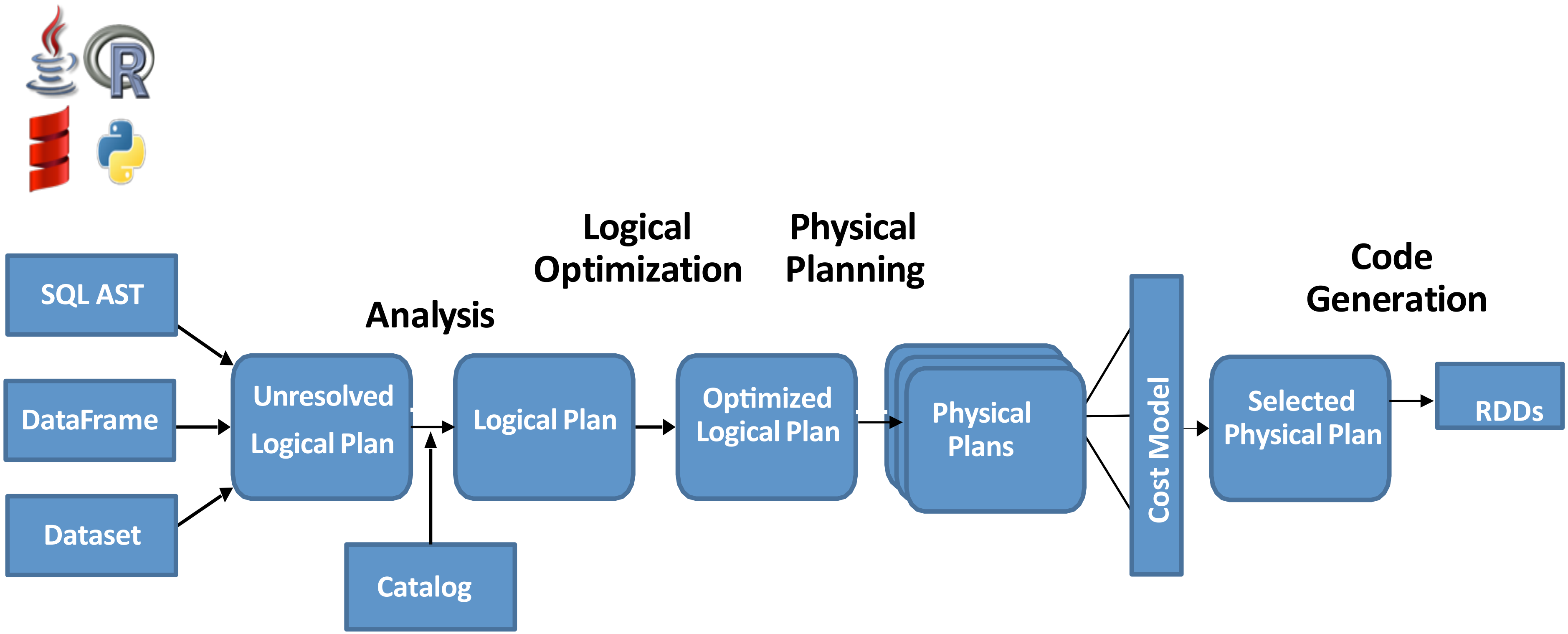
# Outline

- DataFrames
- **Spark Transformations and Actions**
- Spark Programming Model
- Relational Database and SQL
- SparkSQL

# Spark Transformations

- **Create new `DataFrame` from an existing one**
- **Use *lazy evaluation***
  - Results not computed right away – Spark remembers set of transformations applied to base `DataFrame`
  - Spark uses *Catalyst* to optimize the required calculations
  - Spark recovers from failures and slow workers
- ***Think of this as a recipe for creating result***

# Catalyst: Shared Optimization & Execution




- DataFrames, Datasets, and Spark SQL share the same optimization/execution pipeline

# Column Transformations

**The apply method creates a `DataFrame` from one column:**

```
>>> ageCol = people.age
```

# Column Transformations

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**You can select one or more columns from a `DataFrame`:**

```
>>> df.select('*')
```

- `*` selects all the columns

# Column Transformations

**The apply method creates a `DataFrame` from one column:**

```
>>> ageCol = people.age
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**You can select one or more columns from a `DataFrame`:**

```
>>> df.select('*')
```

* selects all the columns

```
>>> df.select('name', 'age')
```

* selects the name and age columns

# Column Transformations

**The apply method creates a `DataFrame` from one column:**

```
>>> ageCol = people.age
```

**You can select one or more columns from a `DataFrame`:**

```
>>> df.select('*')
```

* selects all the columns

```
>>> df.select('name', 'age')
```

* selects the name and age columns

```
>>> df.select(df.name,
              (df.age + 10).alias('age'))
```

* selects the name and age columns,
increments the values in the age column by 10,
and renames (alias) the age + 10 column as age

# More Column Transformations

The drop method returns a new `DataFrame` that drops the specified column:

```
>>> df.drop(df.age)
[Row(name=u'Alice'), Row(name=u'Bob')]
```

# Review: Python `lambda` Functions

- **Small anonymous functions (not bound to a name)**
  - Example: `lambda a, b: a + b`
    - returns the sum of its two arguments
- **Can use lambda functions wherever function objects are required**
- **Restricted to a single expression**

# User Defined Function Transformations

- Transform a DataFrame using a User Defined Function

```
>>> from pyspark.sql.types import IntegerType
>>> slen = udf(lambda s: len(s), IntegerType())
>>> df.select(slen(df.name).alias('slen'))
```

* Creates a DataFrame of [Row(slen=5), Row(slen=3)]

- UDF takes named or lambda function and the return type of the function

# Other Useful Transformations

| Transformation | Description |
|---|---|
| filter(*func*) | returns a new DataFrame formed by selecting those rows of the source on which *func* returns true |
| where(*func*) | where is an alias for filter |
| distinct() | return a new DataFrame that contains the distinct rows of the source DataFrame |
| orderBy(*cols, ***kw*) | returns a new DataFrame sorted by the specified *column(s)* and in the sort order specified by *kw* |
| sort(**cols*, ***kw*) | Like orderBy, sort returns a new DataFrame sorted by the specified *column(s)* and in the sort order specified by *kw* |
| explode(*col*) | returns a new row for each element in the given array or map |

**func is a Python named function or lambda function**

# Using Transformations (1)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
```

# Using Transformations (1)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]

>>> from pyspark.sql.types import IntegerType
>>> doubled = udf(lambda s: s * 2, IntegerType())
>>> df2 = df.select(df.name, doubled(df.age).alias('age'))
[Row(name=u'Alice', age=2), Row(name=u'Bob', age=4)]
```

*** selects the name and age columns, applies the UDF to age column and aliases resulting column to age**

# Using Transformations (1)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]

>>> from pyspark.sql.types import IntegerType
>>> doubled = udf(lambda s: s * 2, IntegerType())
>>> df2 = df.select(df.name, doubled(df.age).alias('age'))
[Row(name=u'Alice', age=2), Row(name=u'Bob', age=4)]
```

* selects the name and age columns, applies the UDF to age column and aliases resulting column to age

```
>>> df3 = df2.filter(df2.age > 3)
[Row(name=u'Bob', age=4)]
```

* only keeps rows with age column greater than 3

# Using Transformations (2)

```
>>> data2 = [('Alice', 1), ('Bob', 2), ('Bob', 2)]
>>> df = sqlContext.createDataFrame(data2, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2),
   Row(name=u'Bob', age=2)]
>>> df2 = df.distinct()
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
```

* only keeps rows that are distinct

# Using Transformations (2)

```
>>> data2 = [('Alice', 1), ('Bob', 2), ('Bob', 2)]
>>> df = sqlContext.createDataFrame(data2, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2),
   Row(name=u'Bob', age=2)]
>>> df2 = df.distinct()
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
```

* only keeps rows that are distinct

```
>>> df3 = df2.sort("age", ascending=False)
[Row(name=u'Bob', age=2),
Row(name=u'Alice', age=1)]
```

* sort ascending on the age column

# Using Transformations (III)

```
>>> data3 = [Row(a=1, intlist=[1,2,3])]
>>> df4 = sqlContext.createDataFrame(data3)
[Row(a=1, intlist=[1,2,3])]
>>> df4.select(explode(df4.intlist).alias("anInt"))
[Row(anInt=1), Row(anInt=2), Row(anInt=3)]
```

*** turn each element of the `intlist` column into a `Row`, alias the resulting column to `anInt`, and select only that column**

# GroupedData Transformations

- `groupBy(*cols)` groups the `DataFrame` using the specified columns, so we can run aggregation on them

| GroupedData Function | Description |
|---|---|
| `agg(*exprs)` | Compute aggregates (avg, max, min, sum, or count) and returns the result as a `DataFrame` |
| `count()` | counts the number of records for each group |
| `avg(*args)` | computes average values for numeric columns for each group |

# Using GroupedData (1)

```
>>> data = [('Alice',1,6), ('Bob',2,8), ('Alice',3,9), ('Bob',4,7)]
>>> df = sqlContext.createDataFrame(data, ['name', 'age', 'grade'])
>>> df1 = df.groupBy(df.name)
>>> df1.agg({"*": "count"}).collect()
[Row(name=u'Alice', count(1)=2), Row(name=u'Bob', count(1)=2)]
```

# Using GroupedData (1)

```
>>> data = [('Alice',1,6), ('Bob',2,8), ('Alice',3,9), ('Bob',4,7)]
>>> df = sqlContext.createDataFrame(data, ['name', 'age', 'grade'])
>>> df1 = df.groupBy(df.name)
>>> df1.agg({"*": "count"}).collect()
[Row(name=u'Alice', count(1)=2), Row(name=u'Bob', count(1)=2)]

>>> df.groupBy(df.name).count()
[Row(name=u'Alice', count=2), Row(name=u'Bob', count=2)]
```

# Using GroupedData (2)

```
>>> data = [('Alice',1,6), ('Bob',2,8), ('Alice',3,9), ('Bob',4,7)]
>>> df = sqlContext.createDataFrame(data, ['name', 'age', 'grade'])
>>> df.groupBy().avg().collect()
[Row(avg(age)=2.5, avg(grade)=7.5)]
```

# Using GroupedData (2)

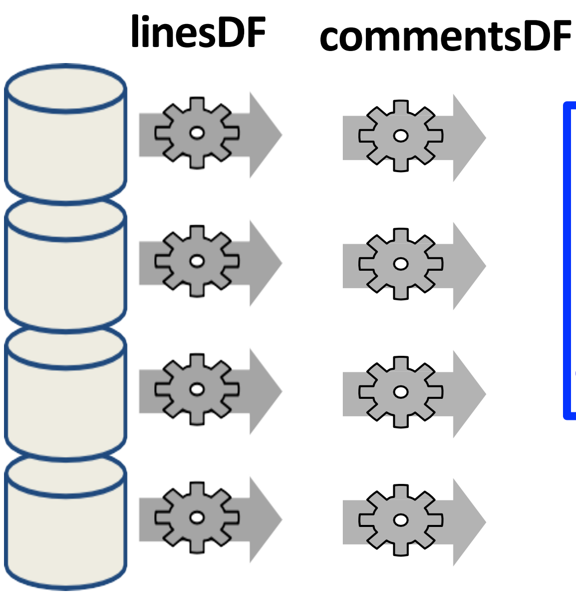
```
>>> data = [('Alice',1,6), ('Bob',2,8), ('Alice',3,9), ('Bob',4,7)]
>>> df = sqlContext.createDataFrame(data, ['name', 'age', 'grade'])
>>> df.groupBy().avg().collect()
[Row(avg(age)=2.5, avg(grade)=7.5)]

>>> df.groupBy('name').avg('age', 'grade').collect()
[Row(name=u'Alice', avg(age)=2.0, avg(grade)=7.5),
    Row(name=u'Bob', avg(age)=3.0, avg(grade)=7.5)]
```

# Transforming a DataFrame

```
linesDF = sqlContext.read.text('...')

commentsDF = linesDF.filter(isComment)
```




Lazy evaluation means nothing executes – Spark saves recipe for transforming source

# Spark Actions

- Cause Spark to execute recipe to transform source
- Mechanism for getting results out of Spark

# Some Useful Actions

| Action | Description |
|---|---|
| `show(n, truncate)` | prints the first *n* rows of the `DataFrame` |
| `take(n)` | returns the first *n* rows as a list of `Row` |
| `collect()` | return all the records as a list of `Row`<br>WARNING: make sure will fit in driver program |
| `count()`* | returns the number of rows in this `DataFrame` |
| `describe(*cols)` | Exploratory Data Analysis function that computes statistics (count, mean, stddev, min, max) for numeric columns – if no columns are given, this function computes statistics for all numerical columns |

* **`count` for `DataFrames` is an action, while for `GroupedData` it is a transformation**

# Getting Data Out of DataFrames (1)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
>>> df.collect()
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
```

# Getting Data Out of DataFrames (1)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
>>> df.collect()
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]

>>> df.show()
+-----+---+
| name|age|
+-----+---+
|Alice|  1|
|  Bob|  2|
+-----+---+
```

# Getting Data Out of DataFrames (1)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
>>> df.collect()
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]

>>> df.show()
+-----+---+
| name|age|
+-----+---+
|Alice|  1|
|  Bob|  2|
+-----+---+


>>> df.count()
2
```

# Getting Data Out of DataFrames (2)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
>>> df.take(1)
[Row(name=u'Alice', age=1)]
```

# Getting Data Out of DataFrames (2)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
>>> df.take(1)
[Row(name=u'Alice', age=1)]

>>> df.describe()
+-------+------------------+
|summary|               age|
+-------+------------------+
|  count|                 2|
|   mean|               1.5|
| stddev|0.7071067811865476|
|    min|                 1|
|    max|                 2|
+-------+------------------+
```

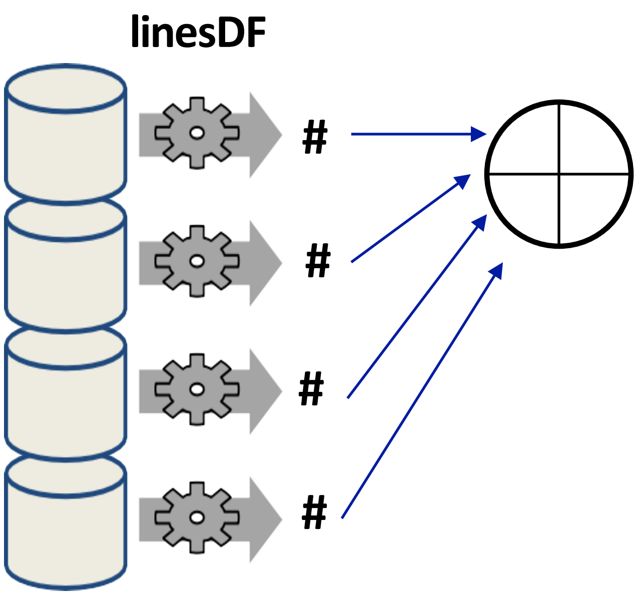
# Outline

- DataFrames
- Spark Transformations and Actions
- **Spark Programming Model**
- Relational Database and SQL
- SparkSQL

# Spark Programming Model

```
linesDF = sqlContext.read.text('...')

print linesDF.count()
```

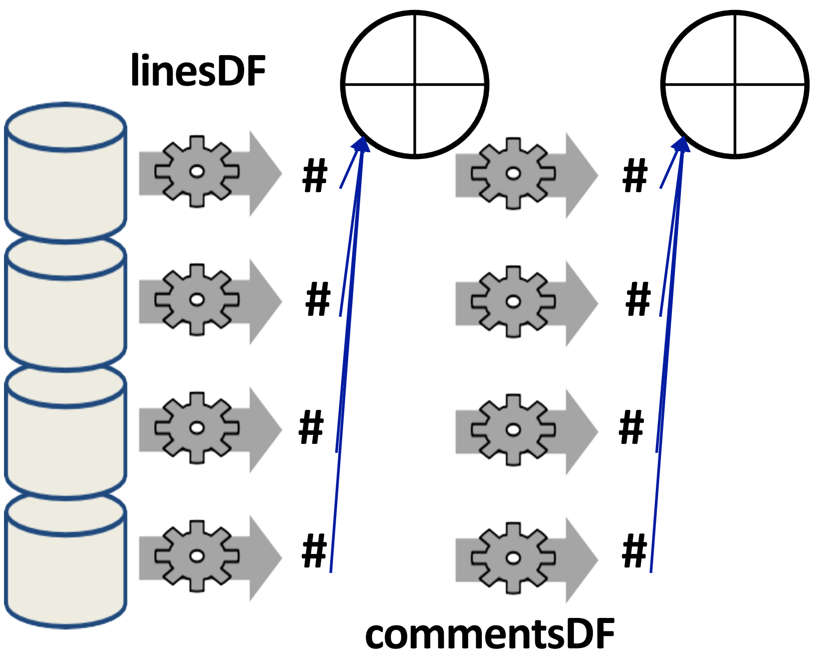



`count()` causes Spark to:

- read data
- sum within partitions
- combine sums in driver

# Spark Programming Model

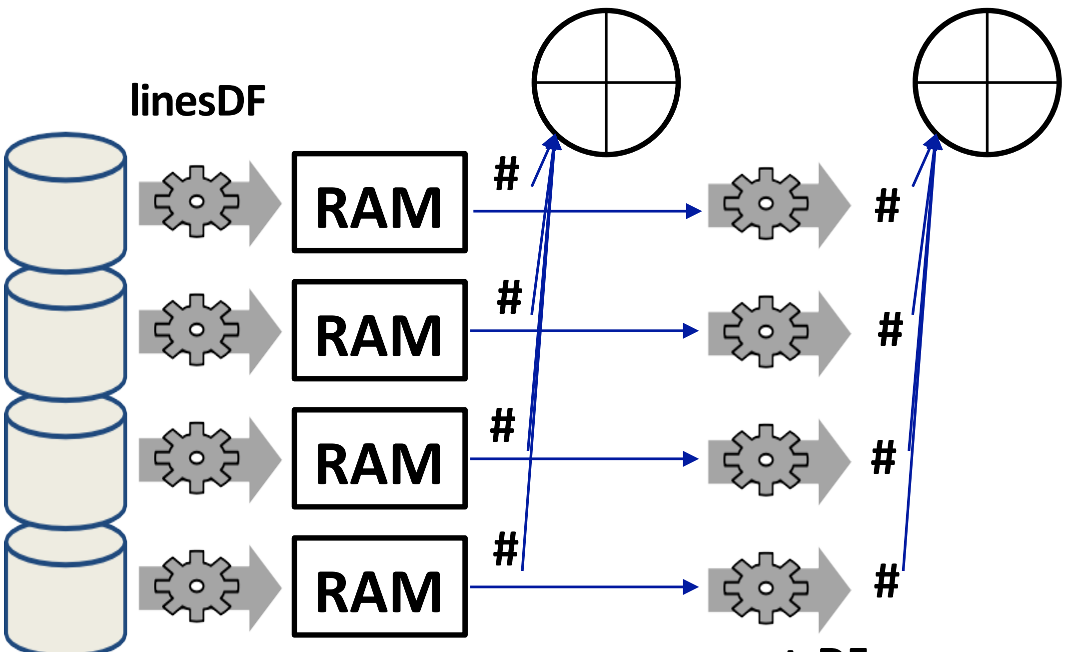
```
linesDF = sqlContext.read.text('...')
commentsDF = linesDF.filter(isComment)
print linesDF.count(), commentsDF.count()
```




**Spark recomputes linesDF:**
- read data (again)
- sum within partitions
- combine sums in driver

# Spark Programming Model

```
linesDF =   sqlContext.read.text('...')
linesDF.cache() # save, don't recompute!
commentsDF =   linesDF.filter(isComment)
print linesDF.count(),commentsDF.count()
```

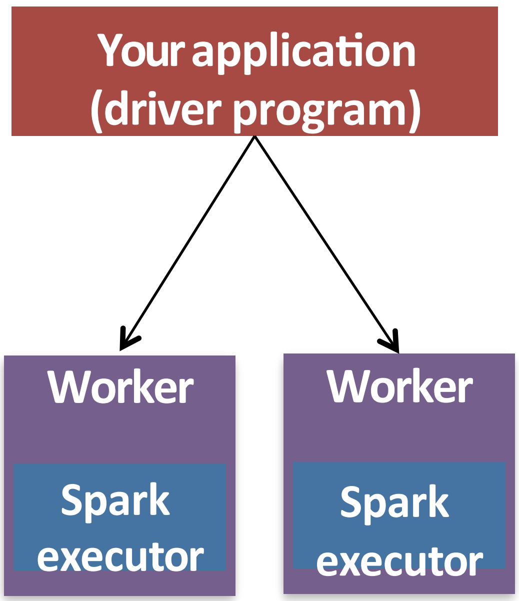


# Spark Program Lifecycle

- Create DataFrames from external data or createDataFrame from a collection in driver program
- Lazily transform them into new DataFrames
- `cache()` some DataFrames for reuse
- Perform actions to execute parallel computation and produce results

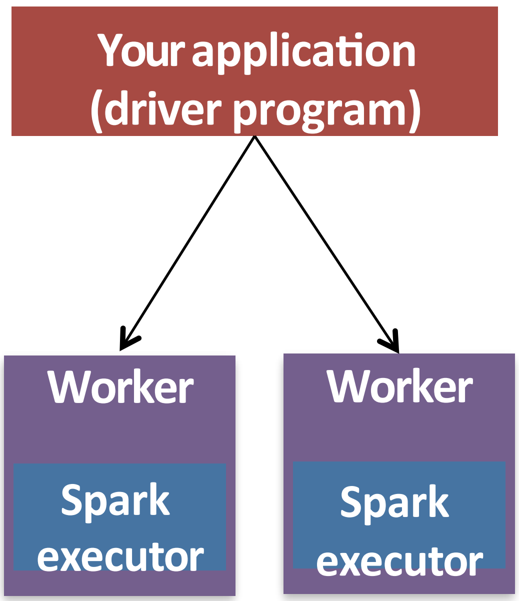
# Local or Distributed?

- **Where does code run?**
  - Locally, in the driver
  - Distributed at the executors
  - Both at the driver and the executors
- **Very important question:**
  - Executors run in parallel
  - Executors have much more memory



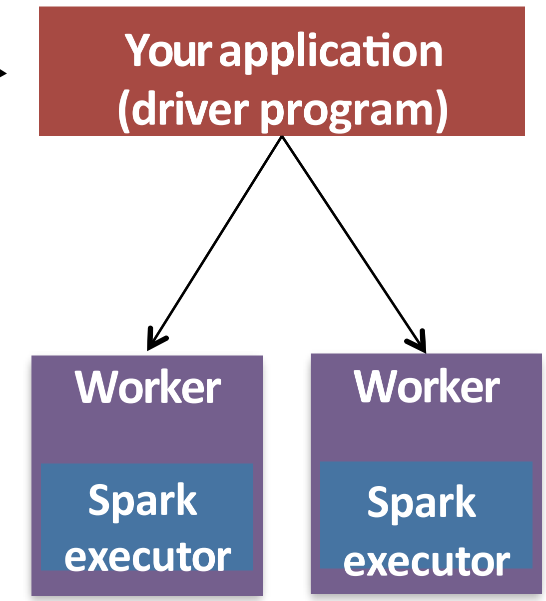
# Where Code Runs

- **Most Python code runs in driver**
  - Except for code passed to transformations
- **Transformations run at executors**
- **Actions run at executors and driver**



# Examples

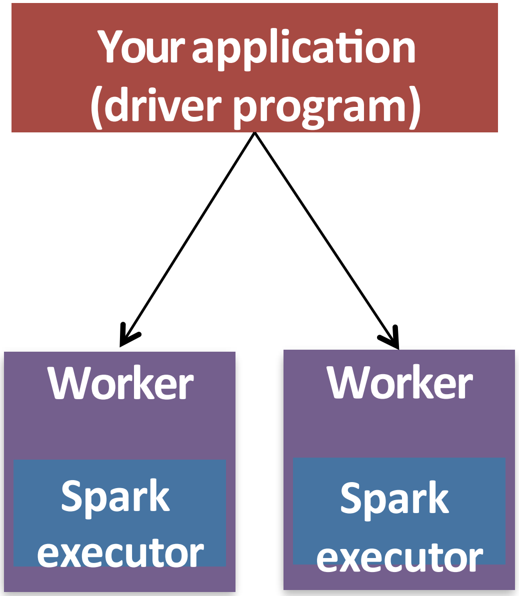
```
>>> a = a + 1
```



# Examples

```
>>> a = a + 1

>>> linesDF.filter(isComment)
```

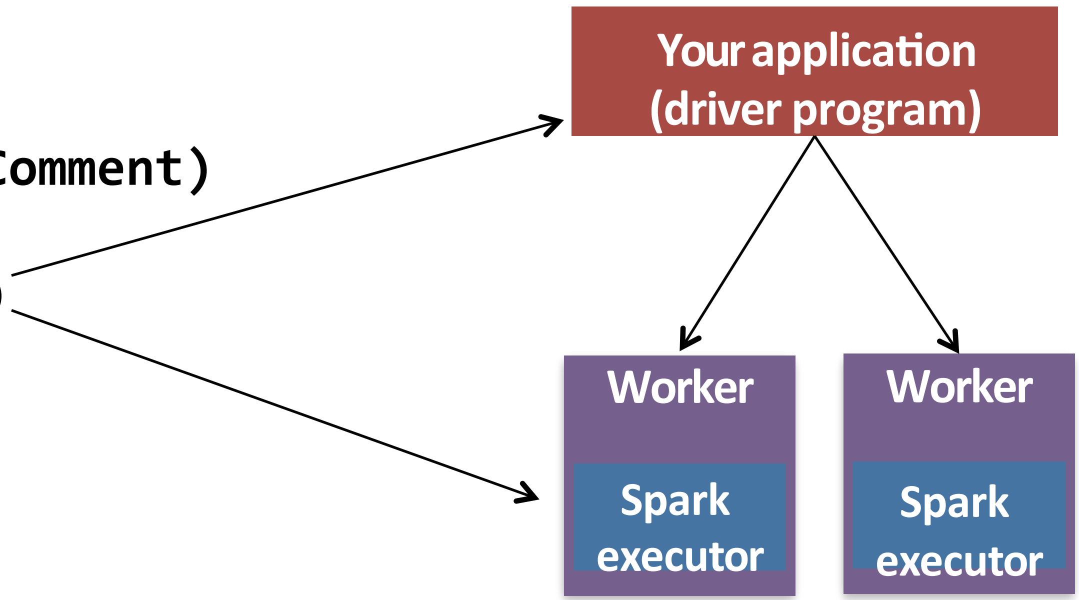


# Examples

```
>>> a = a + 1

>>> linesDF.filter(isComment)

>>> commentsDF.count()
```



# How Not to Write Code

- Let's say you want to combine two DataFrames: aDF, bDF
- You remember that `df.collect()` returns a list of Row, and in Python you can combine two lists with +
- A naïve implementation would be:

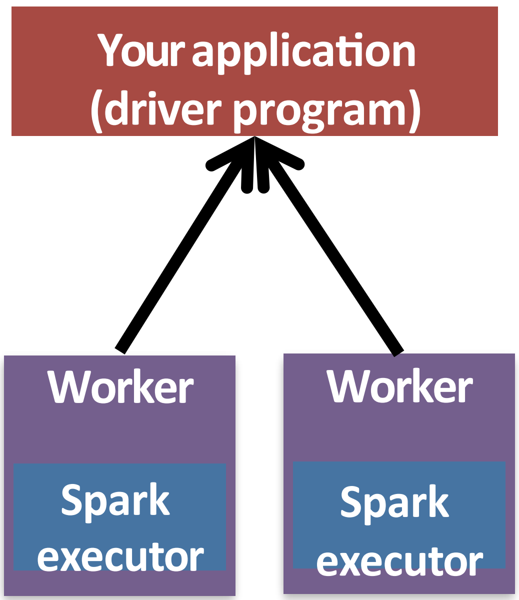
```
>>> a = aDF.collect()
>>> b = bDF.collect()
>>> cDF = sqlContext.createDataFrame(a + b)
```

- Where does this code run?

# How Not to Write Code

```
>>> a = aDF.collect()
>>> b = bDF.collect()
```

* all distributed data for a and b is sent to driver

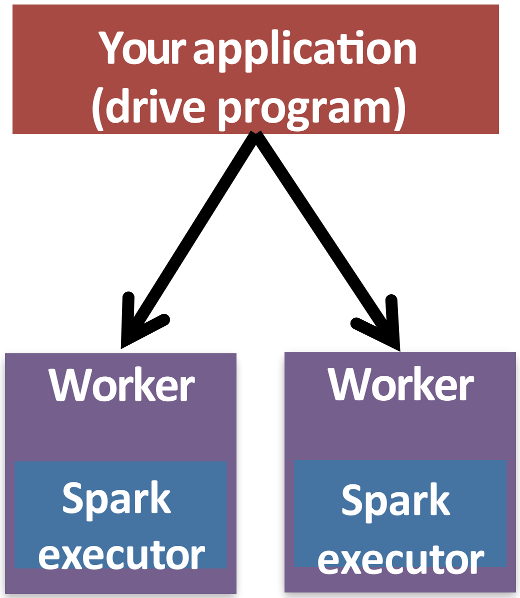



- **What if a and/or b is very large?**
  - Driver could run out of memory: Out Of Memory error (OOM)
  - Also, takes a long time to send the data to the driver

# How Not to Write Code

```
>>> cDF = sqlContext.createDataFrame(a + b)
```

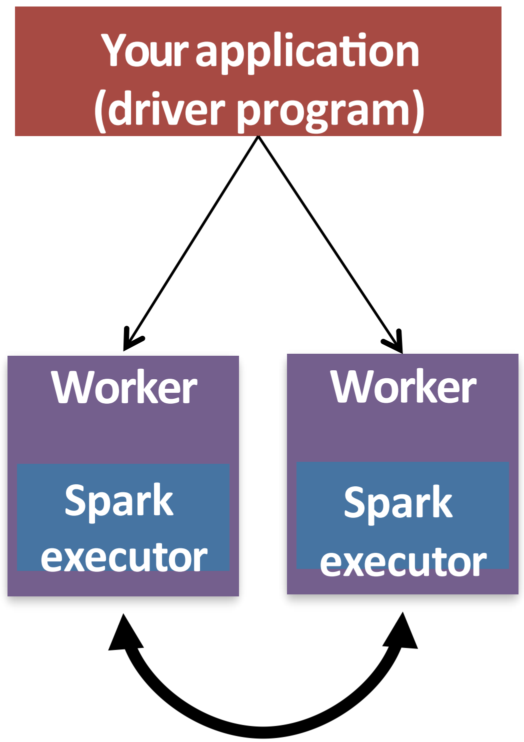
* all data for cDF is sent to the executors




- **What if the list a + b is very large?**
  - Driver could run out of memory: Out Of Memory error (OOM)
  - Also, takes a long time to send the data to executors

# How Not to Write Code: The Best Way

```
>>> cDF = aDF.unionAll(bDF)
```




- **Use the DataFrame reference API**
  - `unionAll()`
    "Return a new `DataFrame` containing union of rows in this frame and another frame"
- **Runs completely at executors:**
  - Very scalable and efficient

# Some Programming Best Practices

- **Use Spark Transformations and Actions wherever possible**
  - Search `DataFrame` reference API
- **Never use `collect()` in production, instead use `take(n)`**
- **`cache()` DataFrames that you reuse a lot**

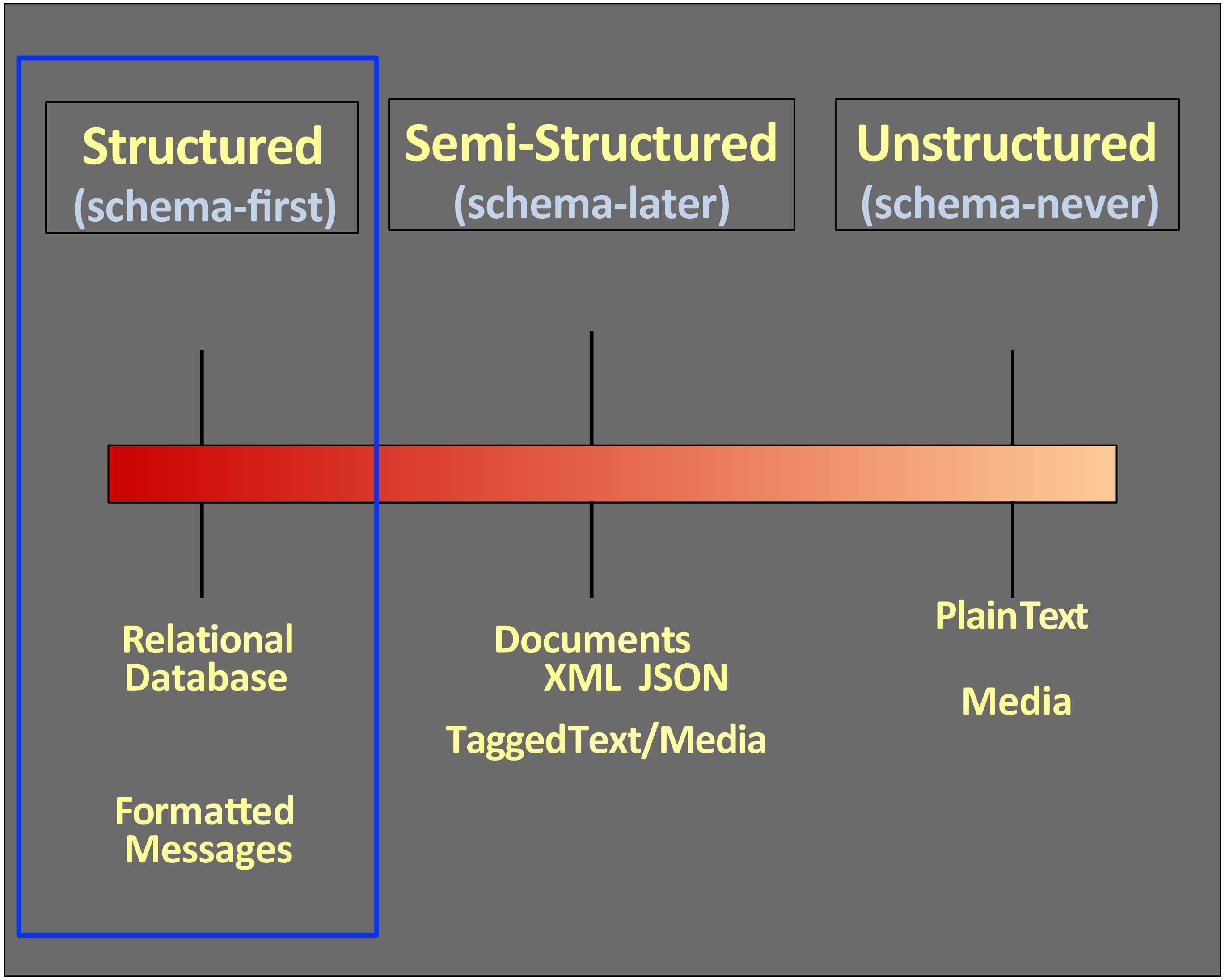
# Outline

- DataFrames
- Spark Transformations and Actions
- Spark Programming Model
- **Relational Database and SQL**
- **SparkSQL**

# Key Data Management Concepts

- A data model is a collection of concepts for describing data
- A schema is a description of a particular collection of data, using a given data model
- A relational data model is the most used data model
  - Relation, a table with rows and columns
  - Every relation has a schema defining fields in columns

# The Structure Spectrum




Next topic

# Relational Database: Definitions

- ***Relational database:*** **a set of *relations***
- **Two parts to a *Relation*:**
  - *Schema*: specifies name of relation, plus each column's name and type

```
Students(sid: string, name: string, email: string,
         age: integer, gpa: real)
```

  - *Instance*: the actual data at a given time
    - # rows = *cardinality*
    - # fields = *degree*

# What is a Database?

- **A large organized collection of data**
  - Transactions used to modify data

- **Models real world, e.g., enterprise**
  - Entities
    - e.g., teams, games
  - Relationships
    - e.g., A plays against B in The World Cup

# Large Databases

- **US Internal Revenue Service: 150Terabytes**
- **Australian Bureau of Stats: 250 Terabytes**
- **AT&T call records: 312 Terabytes**
- **eBay database: 1.4 Petabytes**
- **Yahoo click data: 2 Petabytes**
- ***What matters for these databases?***

# Large Databases

- US Internal Revenue Service: 150 Terabytes
- Australian Bureau of Stats: 250 Terabytes
- AT&T call records: 312 Terabytes
- eBay database: 1.4 Petabytes
- Yahoo click data: 2 Petabytes
- *What matters for these databases?*

Accuracy, Consistency, Durability, Rich queries

Fast, Rich queries

Accuracy, Consistency, Durability

Availability
Timeliness

# Example: Instance of Students

Attribute names

`Students(sid:string, name:string, login:string, age:integer, gpa:real)`

Table name

| sid | name | login | age | gpa |
|---|---|---|---|---|
| [illegible]66 | Jones | jones@eecs | 18 | 3.4 |
| 53688 | Smith | smith@statistics | 18 | 3.2 |
| 53650 | Smith | smith@math | 19 | 3.8 |

Tuples or rows

- **Cardinality = 3 (rows)**
- **Degree = 5 (columns)**
- **All rows (tuples) are distinct.**

# SQL – A language for Relational DBs

- **SQL = Structured Query Language**
- **Supported by Spark DataFrames (SparkSQL)**
- **Some of the functionality SQL provides:**
  - Create, modify, delete relations
  - Add, modify, remove tuples
  - ***Specify queries to find tuples matching criteria***

# Queries in SQL

- Single-table queries are straightforward
- To find all 18 year old students, we can write:

```
SELECT *
  FROM Students S
 WHERE S.age=18
```

- To find just names and logins:

```
SELECT S.name, S.login
  FROM Students S
 WHERE S.age=18
```

# Querying Multiple Relations

- Can specify a *join* over two tables as follows:

```
SELECT S.name, E.cid
 FROM Students S, Enrolled E
 WHERE S.sid=E.sid
```

**Enrolled**

**E**

| E.sid | E.cid | E.grade |
|---|---|---|
| 53831 | Physics203 | A |
| 53650 | Topology112 | A |
| 53341 | History105 | B |

**Students**

**S**

| S.sid | S.name | S.login | S.age | S.gpa |
|---|---|---|---|---|
| 53341 | Jones | jones@cs | 18 | 3.4 |
| 53831 | Smith | smith@ee | 18 | 3.2 |

- First, combine the two tables, S and E

# Querying Multiple Relations

- **Cross Join: Cartesian product of two tables (E x S)**

**Enrolled**

**E**

| E.sid | E.cid | E.grade |
|---|---|---|
| 53831 | Physics203 | A |
| 53650 | Topology112 | A |
| 53341 | History105 | B |

**Students**

**S**

| S.sid | S.name | S.login | S.age | S.gpa |
|---|---|---|---|---|
| 53341 | Jones | jones@cs | 18 | 3.4 |
| 53831 | Smith | smith@ee | 18 | 3.2 |

# Querying Multiple Relations

- **Cross Join: Cartesian product of two tables (E x S) (cont'd)**

**Enrolled**

**E**

| E.sid | E.cid | E.grade |
|---|---|---|
| 53831 | Physics203 | A |
| 53650 | Topology112 | A |
| 53341 | History105 | B |

**Students**

**S**

| S.sid | S.name | S.login | S.age | S.gpa |
|---|---|---|---|---|
| 53341 | Jones | jones@cs | 18 | 3.4 |
| 53831 | Smith | smith@ee | 18 | 3.2 |

| E.sid | E.cid | E.grade | S.sid | S.name | S.login | S.age | S.gpa |
|---|---|---|---|---|---|---|---|
| 53831 | Physics203 | A | 53341 | Jones | jones@cs | 18 | 3.4 |
| 53650 | Topology112 | A | 53341 | Jones | jones@cs | 18 | 3.4 |
| 53341 | History105 | B | 53341 | Jones | jones@cs | 18 | 3.4 |
| 53831 | Physics203 | A | 53831 | Smith | smith@ee | 18 | 3.2 |
| 53650 | Topology112 | A | 53831 | Smith | smith@ee | 18 | 3.2 |
| 53341 | History105 | B | 53831 | Smith | smith@ee | 18 | 3.2 |

# Querying Multiple Relations

- **Where clause: Choose matching rows using Where clause:**

```
SELECT S.name, E.cid
 FROM Students S, Enrolled E
 WHERE S.sid=E.sid
```

| E.sid | E.cid | E.grade | S.sid | S.name | S.login | S.age | S.gpa |
|---|---|---|---|---|---|---|---|
| 53831 | Physics203 | A | 53341 | Jones | jones@cs | 18 | 3.4 |
| 53650 | Topology112 | A | 53341 | Jones | jones@cs | 18 | 3.4 |
| 53341 | History105 | B | 53341 | Jones | jones@cs | 18 | 3.4 |
| 53831 | Physics203 | A | 53831 | Smith | smith@ee | 18 | 3.2 |
| 53650 | Topology112 | A | 53831 | Smith | smith@ee | 18 | 3.2 |
| 53341 | History105 | B | 53831 | Smith | smith@ee | 18 | 3.2 |

# Querying Multiple Relations

- **Select clause: Filter columns using Select clause:**

```
SELECT S.name, E.cid
 FROM Students S, Enrolled E
 WHERE S.sid=E.sid
```

| E.sid | E.cid | E.grade | S.sid | S.name | S.login | S.age | S.gpa |
|---|---|---|---|---|---|---|---|
| 53831 | Physics203 | A | 53341 | Jones | jones@cs | 18 | 3.4 |
| 53650 | Topology112 | A | 53341 | Jones | jones@cs | 18 | 3.4 |
| 53341 | History105 | B | 53341 | Jones | jones@cs | 18 | 3.4 |
| 53831 | Physics203 | A | 53831 | Smith | smith@ee | 18 | 3.2 |
| 53650 | Topology112 | A | 53831 | Smith | smith@ee | 18 | 3.2 |
| 53341 | History105 | B | 53831 | Smith | smith@ee | 18 | 3.2 |

# Querying Multiple Relations

- **Results**

```
SELECT S.name, E.cid
 FROM Students S, Enrolled E
 WHERE S.sid=E.sid
```

**Enrolled**

**E**

| E.sid | E.cid | E.grade |
|---|---|---|
| 53831 | Physics203 | A |
| 53650 | Topology112 | A |
| 53341 | History105 | B |

**Students**

**S**

| S.sid | S.name | S.login | S.age | S.gpa |
|---|---|---|---|---|
| 53341 | Jones | jones@cs | 18 | 3.4 |
| 53831 | Smith | smith@ee | 18 | 3.2 |

**Result =**

| S.name | E.cid |
|---|---|
| Jones | History105 |
| Smith | Physics203 |

# Explicit SQL Joins

```
SELECT S.name, E.classid
 FROM Students S INNER JOIN  Enrolled  E ON S.sid=E.sid
```

**S**

| S.name | S.sid |
|---|---|
| Jones | 11111 |
| Smith | 22222 |
| Brown | 33333 |

**E**

| E.sid | E.classid |
|---|---|
| 11111 | History105 |
| 11111 | DataScience194 |
| 22222 | French150 |
| 44444 | English10 |

**Result**

| S.name | E.classid |
|---|---|
| Jones | History105 |
| Jones | DataScience194 |
| Smith | French150 |

# Equivalent SQL Join Notations

- Explicit Join notation (preferred):

```
SELECT S.name, E.classid
 FROM Students S INNER JOIN Enrolled E ON S.sid=E.sid
```

```
SELECT S.name, E.classid
 FROM Students S JOIN Enrolled E ON S.sid=E.sid
```

- Implicit join notation (deprecated):

```
SELECT S.name, E.cid
 FROM Students S, Enrolled E  WHERE
 S.sid=E.sid
```

# SQL Types of Joins

```
SELECT S.name, E.classid
 FROM Students S INNER JOIN  Enrolled  E ON S.sid=E.sid
```

**S**

| S.name | S.sid |
|---|---|
| Jones | 11111 |
| Smith | 22222 |
| Brown | 33333 |

**E**

| E.sid | E.classid |
|---|---|
| 11111 | History105 |
| 11111 | DataScience194 |
| 22222 | French150 |
| 44444 | English10 |

**Result**

| S.name | E.classid |
|---|---|
| Jones | History105 |
| Jones | DataScience194 |
| Smith | French150 |

**Unmatched keys**

**The type of join controls how unmatched keys are handled**

# SQL Joins: Left Outer Join

```
SELECT S.name, E.classid
 FROM Students S LEFT OUTER  JOIN  Enrolled  E  ON  S.sid=E.sid
```

**S**

| S.name | S.sid |
|---|---|
| Jones | 11111 |
| Smith | 22222 |
| Brown | 33333 |

**E**

| E.sid | E.classid |
|---|---|
| 11111 | History105 |
| 11111 | DataScience194 |
| 22222 | French150 |
| 44444 | English10 |

**Result**

| S.name | E.classid |
|---|---|
| Jones | History105 |
| Jones | DataScience194 |
| Smith | French150 |
| Brown | <NULL> |

**Unmatched keys**

# SQL Joins: Right Outer Join

```
SELECT S.name, E.classid
 FROM Students S LEFT OUTER  JOIN Enrolled  E ON S.sid=E.sid
```

**S**

| S.name | S.sid |
|---|---|
| Jones | 11111 |
| Smith | 22222 |
| Brown | 33333 |

**E**

| E.sid | E.classid |
|---|---|
| 11111 | History105 |
| 11111 | DataScience194 |
| 22222 | French150 |
| 44444 | English10 |

**Result**

| S.name | E.classid |
|---|---|
| Jones | History105 |
| Jones | DataScience194 |
| Smith | French150 |
| <NULL> | English10 |

**Unmatched keys**

# Running an SQL query on Spark

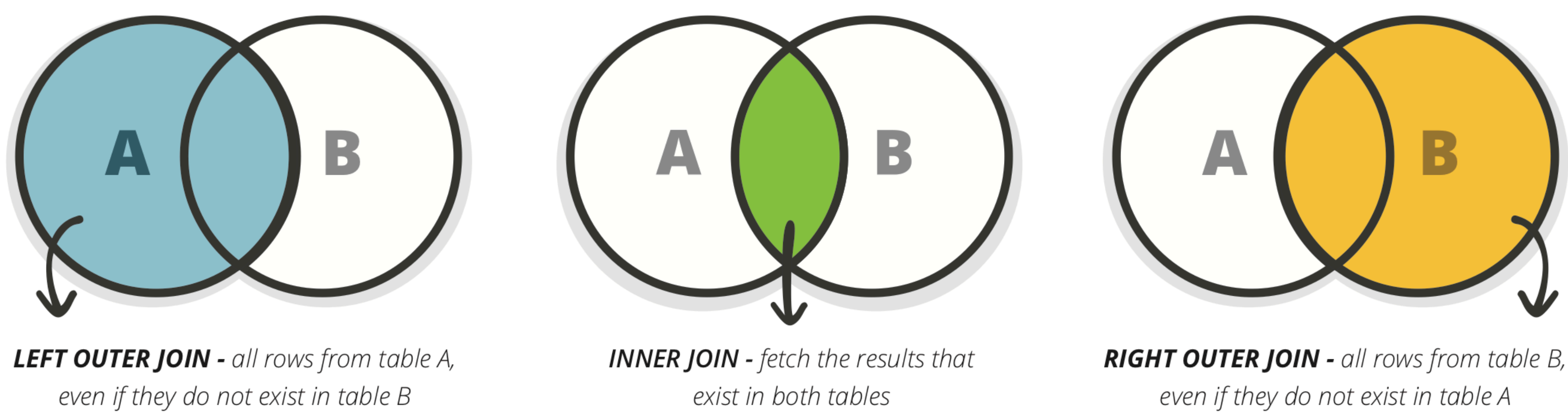
- **`SparkSession.sql(`*`sqlQuery`*`)`**
  - Returns a DataFrame representing the result of the given query.

```
>>> df.createOrReplaceTempView("table1")
>>> df2 = spark.sql("SELECT field1 AS f1, field2 as f2 from table1")
>>> df2.collect()
[Row(f1=1, f2=u'row1'), Row(f1=2, f2=u'row2'), Row(f1=3, f2=u'row3')]
```

- **`createOrReplaceTempView(`*`name`*`)`**
  - Creates or replaces a local temporary view with this DataFrame
  - The lifetime of this temporary table is tied to the `SparkSession` that was used to create this `DataFrame`.

# Spark Joins

- SparkSQL and Spark DataFrames support joins
- `join(other, on, how)`:
  - other – right side of the join
  - on –join column name, list of column (names), or join expression
  - how – inner, outer, left_outer, right_outer, ...




**Source:** https://zeroturnaround.com/rebellabs/sql-cheat-sheet/

# Spark Join Examples (1)

- Inner Join – `X.join(Y, cols)`
  - Return DF of rows with matching cols in both X and Y

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
>>> df2 = sqlContext.createDataFrame(data2,['name', 'height'])
[Row(name=u'Chris', height=80), Row(name=u'Bob', height=85)]

>>> df.join(df2, 'name')
[Row(name=u'Bob', age=2, height=85)]
```

# Spark Join Examples (2)

- **Inner Join – `X.join(Y, cols)`**
  - Return DF of rows with matching cols in both X and Y

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
>>> df2 = sqlContext.createDataFrame(data2,['name', 'height'])
[Row(name=u'Chris', height=80), Row(name=u'Bob', height=85)]

>>> df.join(df2, 'name').select(df.name, df2.height)
[Row(name=u'Bob', height=85)]
```

# Spark Join Examples (3)

- **Outer Join – `X.join(Y, cols,'outer')`**
  - Return DF of rows with matching cols in either X and Y

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
>>> df2 = sqlContext.createDataFrame(data2,['name', 'height'])
[Row(name=u'Chris', height=80), Row(name=u'Bob', height=85)]

>>> df.join(df2, 'name', 'outer')
[Row(name=u'Chris', age=None, height=80),
Row(name=u'Alice', age=1, height=None),
Row(name=u'Bob', age=2, height=85)]
```

# Spark Join Examples (4)

- **Outer Join – `X.join(Y, cols,'outer')`**
  - Return DF of rows with matching cols in either X and Y

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
>>> df2 = sqlContext.createDataFrame(data2,['name', 'height'])
[Row(name=u'Chris', height=80), Row(name=u'Bob', height=85)]

>>> df.join(df2, 'name', 'outer').select('name', 'height')
[Row(name=u'Chris', height=80),
 Row(name=u'Alice', height=None),
 Row(name=u'Bob', height=85)]
```

# Spark Join Examples (5)

- **Left Outer Join – `X.join(Y, cols, 'left_outer')`**
  - Return DF of rows with matching cols in X

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
>>> df2 = sqlContext.createDataFrame(data2,['name', 'height'])
[Row(name=u'Chris', height=80), Row(name=u'Bob', height=85)]

>>> df.join(df2, 'name', 'left_outer')
[Row(name=u'Alice', age=1, height=None),
Row(name=u'Bob', age=2, height=85)]
```

# Spark Join Examples (6)

- **Right Outer Join – `X.join(Y, cols, 'right_outer')`**
  - Return DF of rows with matching cols in Y

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
>>> df2 = sqlContext.createDataFrame(data2,['name', 'height'])
[Row(name=u'Chris', height=80), Row(name=u'Bob', height=85)]

>>> df.join(df2, 'name', 'right_outer')
[Row(name=u'Chris', age=None, height=80),
Row(name=u'Bob', age=2, height=85)]
```