APACHE Spark™

Manipulating Data

in Apache Spark™

databricks

Basic Structured Operations

The explosion of data has opened the gates to a massive diversity of data sources and data types. This has created a high complex challenge for engineering organizations to prepare and process this data for analysis. Apache Spark™ is uniquely suited to handle this challenge with the DataFrame API which is designed to make big data processing even easier for a wider audience.

In Spark, a DataFrame is a distributed collection of data organized into named columns. It is conceptually equivalent to a table in a relational database or a data frame in R/Python, but with richer optimizations under the hood. DataFrames allow engineers to leverage the power of distributed processing through Spark.

This eBook, a curation of content from the Spark: Definitive Guide, dives deep into how Spark makes it easy to manipulate different types whether you're running business logic on your local machine or on a 100-node cluster.

Basic Structured Operations

In <<s2c1---structured-api-overview>>, we introduced the core abstractions of the Structured API. This chapter moves away from the architectural concepts and toward the tactical tools you will use to manipulate DataFrames and the data within them. This chapter focuses exclusively on single DataFrame operations and avoids aggregations, window functions, and joins, are all discussed in depth later in this part of the book.

Definitionally, a DataFrame consists of a series of _records_ (like rows in a table), that are of type ` Row ` , and a number of _columns_ (like columns in a spreadsheet) that represent an computation expression that can performed on each individual record in the Dataset. _Schemas_ define the name as well as the type of data in each column. _Partitioning_ of the DataFrame defines the layout of the DataFrame or Dataset's physical distribution across the cluster. The _partitioning scheme_ defines how that is allocated. You can set this to be based on values in a certain column or nondeterministically.

Let's create a DataFrame with which we can work:

```
// in Scala
val df = spark.read.format("json")
 .load("/data/flight-data/json/2015-summary.json")

# in Python
df = spark.read.format("json").load("/data/flight-data/json/2015-summary.json")
```

We discussed that a DataFame will have columns, and we use a schema to define them. Let's take a look at the schema on our current DataFrame:

```
df.printSchema()
```

Schemas tie everything together, so they're worth belaboring.

Schemas

A schema defines the column names and types of a DataFrame. We can either let a data source define the schema (called __schema-on-read__) or we can define it explicitly ourselves.

NOTE

Deciding whether you need to define a schema prior to reading in your data depends your use case. Often times, for ad hoc analysis, schema-on-read works just fine (although at times it can be a bit slow with plain-text file formats like CSV or JSON). However, this can also lead to precision issues like a *long* type incorrectly set as an integer when reading in a file. When using Spark for production Extract, Transform, and Load (ETL), it is often a good idea to define your schemas manually, especially when working with untyped data sources like csv and json because schema inference can vary depending on the type of data that you read in.

Let's begin with a simple file, which we saw in <<s2c1---structured-api-overview>>, and let the semi-structured nature of line-delimited JSON define the structure. This is https://github.com/databricks/Spark-The-Definitive-Guide/tree/master/data/flight-data[flight data from the United States Bureau of Transportation statistics]:

```
// in Scala
spark.read.format("json").load("/data/flight-data/json/2015-summary.json").schema
```

Scala returns the following:

```
org.apache.spark.sql.types.StructType = ...
StructType(StructField(DEST_COUNTRY_NAME,StringType,true),
StructField(ORIGIN_COUNTRY_NAME,StringType,true),
StructField(count,LongType,true))

# in Python
spark.read.format("json").load("/data/flight-data/json/2015-summary.json").schema
```

Python returns the following:

```
StructType(List(StructField(DEST_COUNTRY_NAME,StringType,true),
StructField(ORIGIN_COUNTRY_NAME,StringType,true),
StructField(count,LongType,true)))
```

A schema is a `StructType` made up of a number of fields, `StructFields`, that have a name, type, a boolean flag which specifies whether that column can contain missing or `null` values, and, finally, users can optionally specify associated metadata with that column. The metadata is a way of storing information about this column (Spark uses this in its machine learning library).

Schemas can contain other `StructType` (Spark's complex types). We will see this in <<s2c3---working-with-different-types-of-data>> when we discuss working with complex types. The example that follows shows how to create and enforce a specific schema on a DataFrame. If the types in the data (at runtime) do not match the schema, Spark will throw an error:

```
// in Scala
import org.apache.spark.sql.types.{StructField, StructType, StringType, LongType}
import org.apache.spark.sql.types.Metadata

val myManualSchema = StructType(Array(
  StructField("DEST_COUNTRY_NAME", StringType, true),
  StructField("ORIGIN_COUNTRY_NAME", StringType, true),
  StructField("count", LongType, false,
    Metadata.fromJson("{\"hello\":\"world\"}"))
))

val df = spark.read.format("json").schema(myManualSchema)
  .load("/data/flight-data/json/2015-summary.json")
```

Here's how to do the same in Python:

```
[source,python]
----
# in Python
from pyspark.sql.types import StructField, StructType, StringType, LongType

myManualSchema = StructType([
  StructField("DEST_COUNTRY_NAME", StringType(), True),
  StructField("ORIGIN_COUNTRY_NAME", StringType(), True),
  StructField("count", LongType(), False, metadata={"hello":"world"})
])
df = spark.read.format("json").schema(myManualSchema)\
  .load("/data/flight-data/json/2015-summary.json")
```

As discussed in <<s2c1---structured-api-overview>>, we cannot simply set types via the per-language types because Spark maintains its own type information. Let's now discuss what schemas define: columns.

Columns and Expressions

Columns in Spark are similar to columns in a spreadsheet, R dataframe, or pandas DataFrame. You can select, manipulate, and remove columns from DataFrames and these operations are represented as—__expressions__.

To Spark, columns are logical constructions that simply represent a value computed on a per-record basis by means of an expression. This means that to have a real value for a column, we need to have a row; and to have a row, we need to have a DataFrame. You cannot manipulate an individual column outside the context of a DataFrame; you must use Spark transformations within a DataFrame to modify the contents of a column.

Columns

There are a lot of different ways to construct and refer to columns but the two simplest ways are by using the *col* or *column* functions. To use either of these functions, you pass in a column name:

```
// in Scala
import org.apache.spark.sql.functions.{col, column}
col("someColumnName")
column("someColumnName")

# in Python
from pyspark.sql.functions import col, column
col("someColumnName")
column("someColumnName")
```

We will stick to using *col* throughout this book. As mentioned, this column might or might not exist in our DataFrames. Columns are not _resolved_ until we compare the column names with those we are maintaining in the __catalog__. Column and table resolution happens in the _analyzer_ phase, as discussed in <<s2c1---structured-api-overview>>.

NOTE

We just mentioned two different ways of referring to columns. Scala has some unique language features that allow for more shorthand ways of referring to columns. The following bits of syntactic sugar perform the exact same thing, namely creating a column, but provide no performance improvement:

```
// in Scala
$"myColumn"
'myColumn
```

The `$` allows us to designate a string as a special string that should refer to an expression. The tick mark (`'`) is a special thing called a _symbol_; this is Scala-specific construct of referring to some identifier. They both perform the same thing and are shorthand ways of referring to columns by name. You'll likely see all os the aforementioned references when you read different people's Spark code. We leave it to you to use whatever is most comfortable and maintainable for you and those with whom you work.

Explicit Column References

If you need to refer to a specific DataFrame's column, you can use the *col* method on the specific DataFrame. This can be useful when you are performing a join and need to refer to a specific column in one DataFrame that might share a name with another column in the joined DataFrame. We will see this in <<s2c5---joins>>. As an added benefit, Spark does not need to resolve this column itself (during the _analyzer_ phase) because we did that for Spark.

```
df.col("count")
```

Expressions

We mentioned earlier that columns are expressions, so what is an expression? An _expression_ is a set of transformations on one or more values in a record in a DataFrame. Think of it like a function that takes as input one or more column names, resolves them, and then potentially applies more expressions to create a single value for each record in the dataset. Importantly, this "single value" can actually be a complex type like a *Map* or *Array*. We'll see more of the complex types in <<s2c3---working-with-different-types-of-data>>.

In the simplest case, an expression, created via the *expr* function, is just a DataFrame column reference. In the simplest case, *expr("someCol")* is equivalent to *col("someCol")*.

Columns as Expressions

Columns provide a subset of expression functionality. If you use *col()* and want to perform transformations on that column, you must perform those on that column reference. When using an expression, the *expr* function can actually parse transformations and column references from a string and can subsequently be passed into further transformations. Let's look at some examples.

expr("someCol - 5") is the same transformation as performing *col("someCol") - 5*, or even *expr("someCol") - 5*. That's because Spark compiles these to a logical tree specifying the order of operations. This might be a bit confusing at first, but remember a couple of key points.

- Columns are just expressions.
- Columns and transformations of those columns compile to the same logical plan as parsed expressions.

Let’s ground this with an example:

```
(((col(“someCol”) + 5) * 200) - 6) < col(“otherCol”)
```

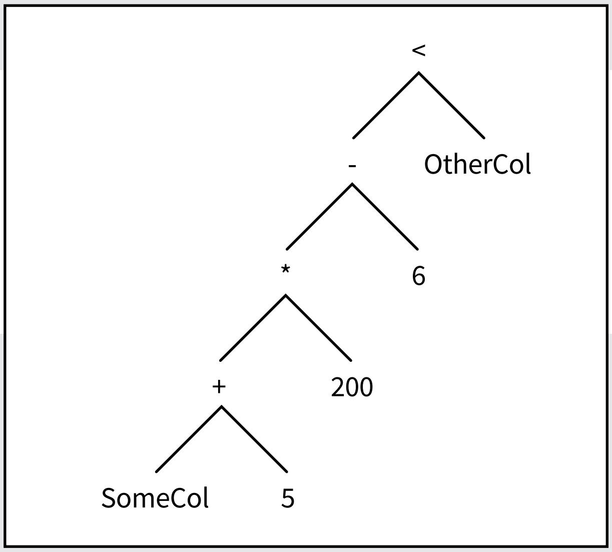


Figure 5-1. A logical tree

<<fig0501>> shows an overview of that logical tree.

This might look familiar because it’s a directed acyclic graph. This graph is represented equivalently by the following code:

```
// in Scala
import org.apache.spark.sql.functions.expr
expr(“(((someCol + 5) * 200) - 6) < otherCol”)

# in Python
from pyspark.sql.functions import expr
expr(“(((someCol + 5) * 200) - 6) < otherCol”)
```

This is an extremely important point to reinforce. Notice how the previous expression is actually valid SQL code, as well, just like you might put in a `SELECT` statement? That’s because this SQL expression and the previous DataFrame code compile to the same underlying logical tree prior to execution. This means that you can write your expressions as DataFrame code or as SQL expressions and get the exact same performance characteristics. This is discussed in <<s2c1---structured-api-overview>>.

Accessing a DataFrame’s Columns

Sometimes, you’ll need to see a DataFrame’s columns, you can do this by using something like `printSchema`; however, if you want to programmatically access columns, you can use the `columns` method to see all columns listed:

```
spark.read.format(“json”).load(“/data/flight-data/json/2015-summary.json”)
  .columns
```

Records and Rows

In Spark, each row in a DataFrame is a single record. Spark represents this record as an object of type *Row*. Spark manipulates Row objects using column expressions in order to produce usable values. Row objects internally represent arrays of bytes. The byte array interface is never shown to users because we only use column expressions to manipulate them.

You'll notice commands that return individual rows to the driver will always return one or more `Row` types when we are working with DataFrames.

Let's see a row by calling *first* on our DataFrame:

```
df.first()
```

> **NOTE**
>
> **We use lowercase "row" and "record" interchangeably in this chapter, with a focus on the latter. A capitalized *Row* refers to the *Row* object.**

Creating Rows

You can create rows by manually instantiating a `Row` object with the values that belong in each column. It's important to note that only DataFrames have schemas. Rows themselves do not have schemas. This means that if you create a `Row` manually, you must specify the values in the same order as the schema of the DataFrame to which they might be appended (we will see this when we discuss creating DataFrames):

```
// in Scala
import org.apache.spark.sql.Row
val myRow = Row("Hello", null, 1, false)

# in Python
from pyspark.sql import Row
myRow = Row("Hello", None, 1, False)
```

Accessing data in rows is equally as easy: you just specify the position that you would like. In Scala or Java, you must either use the helper methods or explicitly coerce the values. However in Python or R, the value will automatically be coerced into the correct type:

```
// in Scala
myRow(0) // type Any
myRow(0).asInstanceOf[String] // String
myRow.getString(0) // String
myRow.getInt(2) // Int
```

```
# in Python
myRow[0]
myRow[2]
```

You can also explicitly return a set of Data in the corresponding Java Virtual Machine (JVM) objects by using the Dataset APIs. This is covered at the end of <<part2>>.

DataFrame Transformations

Now that we briefly defined the core parts of a DataFrame, we will move onto manipulating DataFrames. When working with individual DataFrames there are some fundamental objectives. These break down into several core operations, as depicted in <<fig0502>>.

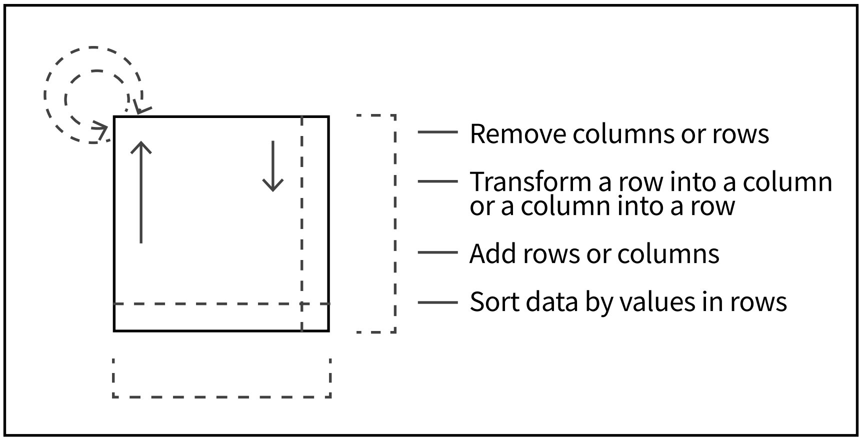


Figure 5-2. Different kinds of transformations

- We can add rows or columns
- We can remove rows or columns
- We can transform a row into a column (or vice versa)
- We can change the order of rows based on the values in columns

Luckily, we can translate all of these into simple transformations, the most common being those that take one column, change it row by row, and then return our results.

Creating DataFrames

As we saw previously, we can create DataFrames from raw data sources. This is covered extensively in <<s2c6---data-sources>>; however, we will use them now to create an example DataFrame (for illustration purposes later in this chapter, we will also register this as a temporary view so that we can query it with SQL and show off basic transformations in SQL, as well):

```
// in Scala
val df = spark.read.format("json")
 .load("/data/flight-data/json/2015-summary.json")
df.createOrReplaceTempView("dfTable")
```

```
# in Python
df = spark.read.format("json").load("/data/flight-data/json/2015-summary.json")
df.createOrReplaceTempView("dfTable")
```

We can also create DataFrames on the fly by taking a set of rows and converting them to a DataFrame.

```
// in Scala
import org.apache.spark.sql.Row
import org.apache.spark.sql.types.{StructField, StructType, StringType, LongType}

val myManualSchema = new StructType(Array(
  new StructField("some", StringType, true),
  new StructField("col", StringType, true),
  new StructField("names", LongType, false)))
val myRows = Seq(Row("Hello", null, 1L))
val myRDD = spark.sparkContext.parallelize(myRows)
val myDf = spark.createDataFrame(myRDD, myManualSchema)
myDf.show()

// in Scala
val myDF = Seq(("Hello", 2, 1L)).toDF("col1", "col2", "col3")

# in Python
from pyspark.sql import Row
from pyspark.sql.types import StructField, StructType, StringType, LongType
myManualSchema = StructType([
  StructField("some", StringType(), True),
  StructField("col", StringType(), True),
  StructField("names", LongType(), False)
])
myRow = Row("Hello", None, 1)
myDf = spark.createDataFrame([myRow], myManualSchema)
myDf.show()
```

NOTE

In Scala, we can also take advantage of Spark's implicits in the console (and if you import them in your JAR code) by running *toDF* on a *Seq* type. This does not play well with *null* types, so it's not necessarily recommended for production use cases.

some	col	names
Hello	null	1

Now that you know how to create DataFrames, let's go over their most useful methods that you're going to be using: the *select* method when you're working with columns or expressions, and the *selectExpr* method when you're working with expressions in strings. Naturally some transformations are not specified as a methods on columns, therefore there exists a group of functions found in the `org.apache.spark.sql.functions` package.

With these three tools, you should be able to solve the vast majority of transformation challenges that you might encourage in DataFrames.

Select and SelectExpr

Select and *SelectExpr* allow you to do the DataFrame equivalent of SQL queries on a table of data:

```
-- in SQL
SELECT * FROM dataFrameTable
SELECT columnName FROM dataFrameTable
SELECT columnName * 10, otherColumn, someOtherCol as c FROM dataFrameTable
```

In the simplest possible terms, you can use them to manipulate columns in your DataFrames. Let's walk through some examples on DataFrames to talk about some of the different ways of approaching this problem. The easiest way is just to use the `select` method and pass in the column names as string with which you would like to work:

```
// in Scala
df.select("DEST_COUNTRY_NAME").show(2)

# in Python
df.select("DEST_COUNTRY_NAME").show(2)

-- in SQL
SELECT DEST_COUNTRY_NAME FROM dfTable LIMIT 2
```

Giving an output of:

DEST_COUNTRY_NAME
United States
United States

You can select multiple columns by using the same style of query, just add more column name strings to your *select* method call:

```
// in Scala
df.select("DEST_COUNTRY_NAME", "ORIGIN_COUNTRY_NAME").show(2)

# in Python
df.select("DEST_COUNTRY_NAME","ORIGIN_COUNTRY_NAME").show(2)

-- in SQL
SELECT DEST_COUNTRY_NAME, ORIGIN_COUNTRY_NAME FROM dfTable LIMIT 2
```

Giving an output of:

DEST_COUNTRY_NAME	ORIGIN_COUNTRY_NAME
United States	Romania
United States	Croatia

As covered in the section <<columns-and-expressions>>, you can refer to columns in a number of different ways; all you need to keep in mind is that you can use them interchangeably:

```
// in Scala
import org.apache.spark.sql.functions.{expr, col, column}
df.select(
  df.col("DEST_COUNTRY_NAME"),
  col("DEST_COUNTRY_NAME"),
  column("DEST_COUNTRY_NAME"),
  'DEST_COUNTRY_NAME,
  $"DEST_COUNTRY_NAME",
  expr("DEST_COUNTRY_NAME"))
 .show(2)

# in Python
from pyspark.sql.functions import expr, col, column
df.select(
  expr("DEST_COUNTRY_NAME"),
  col("DEST_COUNTRY_NAME"),
  column("DEST_COUNTRY_NAME"))\
 .show(2)
```

One common error is attempting to mix *Column* objects and strings. For example, the following code will result in a compiler error:

```
df.select(col("DEST_COUNTRY_NAME"), "DEST_COUNTRY_NAME")
```

As we've seen thus far, *expr* is the most flexible reference that we can use. It can refer to a plain column or a string manipulation of a column. To illustrate, let's change the column name, and then change it back by using the *AS* keyword and then the *alias* method on the column:

```
// in Scala
df.select(expr("DEST_COUNTRY_NAME AS destination")).show(2)

# in Python
df.select(expr("DEST_COUNTRY_NAME AS destination")).show(2)

-- in SQL
SELECT DEST_COUNTRY_NAME as destination FROM dfTable LIMIT 2
```

This changes the column name to "destination." You can further manipulate the result of your expression as another expression:

```
// in Scala
df.select(expr("DEST_COUNTRY_NAME as destination").alias("DEST_COUNTRY_NAME"))
  .show(2)

# in Python
df.select(expr("DEST_COUNTRY_NAME as destination").alias("DEST_COUNTRY_NAME"))\
  .show(2)
```

The preceding operation changes the column name back to its original name.

Because `select` followed by a series of `expr` is such a common pattern, Spark has a shorthand for doing this efficiently: `selectExpr`. This is probably the most convenient interface for everyday use:

```
// in Scala
df.selectExpr("DEST_COUNTRY_NAME as newColumnName", "DEST_COUNTRY_NAME").show(2)

# in Python
df.selectExpr("DEST_COUNTRY_NAME as newColumnName", "DEST_COUNTRY_NAME").show(2)
```

This opens up the true power of Spark. We can treat `selectExpr` as a simple way to build up complex expressions that create new DataFrames. In fact, we can add any valid non-aggregating SQL statement, and as long as the columns resolve, it will be valid! Here's a simple example that adds a new column `withinCountry` to our DataFrame that specifies whether the destination and origin are the same:

```
// in Scala
df.selectExpr(
   "*", // include all original columns
   "(DEST_COUNTRY_NAME = ORIGIN_COUNTRY_NAME) as withinCountry")
 .show(2)

# in Python
df.selectExpr(
 "*", # all original columns
 "(DEST_COUNTRY_NAME = ORIGIN_COUNTRY_NAME) as withinCountry")\
 .show(2)

-- in SQL
SELECT *, (DEST_COUNTRY_NAME = ORIGIN_COUNTRY_NAME) as withinCountry
FROM dfTable
LIMIT 2
```

Giving an output of:

DEST_COUNTRY_NAME	ORIGIN_COUNTRY_NAME	count	withinCountry
United States	Romania	15	false
United States	Croatia	1	false

With select expression, we can also specify aggregations over the entire DataFrame by taking advantage of the functions that we have. These look just like what we have been showing so far:

```
// in Scala
df.selectExpr("avg(count)", "count(distinct(DEST_COUNTRY_NAME))").show(2)

# in Python
df.selectExpr("avg(count)", "count(distinct(DEST_COUNTRY_NAME))").show(2)

-- in SQL
SELECT avg(count), count(distinct(DEST_COUNTRY_NAME)) FROM dfTable LIMIT 2
```

Giving an output of:

avg(count)	count(DISTINCT DEST_COUNTRY_NAME)
1770.765625	132

Converting to Spark Types (Literals)

Sometimes, we need to pass explicit values into Spark that aren't a new column but are just a value. This might be a constant value or something we'll need to compare to later on. The way we do this is through _literals_. This is basically a translation from a given programming language's literal value to one that Spark understands. Literals are expressions and you can use them in the same way:

```
// in Scala
import org.apache.spark.sql.functions.lit
df.select(expr("*"), lit(1).as("One")).show(2)

# in Python
from pyspark.sql.functions import lit
df.select(expr("*"),lit(1).alias("One")).show(2)

In SQL, literals are just the specific value:

-- in SQL
SELECT *, 1 as One FROM dfTable LIMIT 2
```

Giving an output of:

DEST_COUNTRY_NAME	ORIGIN_COUNTRY_NAME	count	One
United States	Romania	15	1
United States	Croatia	1	1

This will come up when you might need to check whether a value is greater than some constant or other programmatically created variable.

Adding Columns

There's also a more formal way of adding a new column to a DataFrame, and that's by using the `withColumn` method on our DataFrame. For example, let's add a column that just adds the number one as a column:

```
// in Scala
df.withColumn("numberOne", lit(1)).show(2)

# in Python
df.withColumn("numberOne", lit(1)).show(2)

-- in SQL
SELECT *, 1 as numberOne FROM dfTable LIMIT 2
```

Giving an output of:

DEST_COUNTRY_NAME	ORIGIN_COUNTRY_NAME	count	numberOne
United States	Romania	15	1
United States	Croatia	1	1

Let's do something a bit more interesting and make it an actual expression. In the next example, we'll set a Boolean flag for when the origin country is the same as the destination country:

```
// in Scala
df.withColumn("withinCountry", expr("ORIGIN_COUNTRY_NAME == DEST_COUNTRY_NAME"))
  .show(2)

# in Python
df.withColumn("withinCountry", expr("ORIGIN_COUNTRY_NAME == DEST_COUNTRY_NAME"))\
  .show(2)
```

Notice that the `withColumn` function takes two arguments: the column name and the expression that will create the value for that given row in the DataFrame. Interestingly, we can also rename a column this way. The SQL syntax is the same as we had previously, so we can omit it in this example:

```
df.withColumn("Destination", expr("DEST_COUNTRY_NAME")).columns
```

Resulting in:

... DEST_COUNTRY_NAME, ORIGIN_COUNTRY_NAME, count, Destination

Renaming Columns

Although we can rename a column in the manner that we just described, another alternative is to use the `withColumnRenamed` method. This will rename the column with the name of the string in the first argument to the string in the second argument:

```
// in Scala
df.withColumnRenamed("DEST_COUNTRY_NAME", "dest").columns

# in Python
df.withColumnRenamed("DEST_COUNTRY_NAME", "dest").columns
```

... dest, ORIGIN_COUNTRY_NAME, count

Reserved Characters and Keywords

One thing that you might come across is reserved characters like spaces or dashes in column names. Handling these means escaping column names appropriately. In Spark, we do this by using backtick (+`+) characters. Let's use `` `withColumn` ``, which you just learned about to create a column with reserved characters. We'll show two examples: in the one that follows, we don't need escape characters; in the second one, we do:

```
// in Scala
import org.apache.spark.sql.functions.expr

val dfWithLongColName = df.withColumn(
  "This Long Column-Name",
  expr("ORIGIN_COUNTRY_NAME"))

# in Python
dfWithLongColName = df.withColumn(
    "This Long Column-Name",
    expr("ORIGIN_COUNTRY_NAME"))
```

We don't need escape characters here because the first argument to `` `withColumn` `` is just a string for the new column name. In the following, however, we need to use backticks because we're referencing a column in an expression:

```
// in Scala
dfWithLongColName.selectExpr(
    "`This Long Column-Name`",
    "`This Long Column-Name` as `new col`")
  .show(2)

# in Python
dfWithLongColName.selectExpr(
    "`This Long Column-Name`",
    "`This Long Column-Name` as `new col`")\
  .show(2)

dfWithLongColName.createOrReplaceTempView("dfTableLong")

-- in SQL
SELECT `This Long Column-Name`, `This Long Column-Name` as `new col`
FROM dfTableLong LIMIT 2
```

We can refer to columns with reserved characters (and not escape them) if we're doing an explicit string to column reference, which is interpreted as a literal instead of an expression. We only need to escape expressions that use reserved characters or keywords. The following two examples both result in the same DataFrame:

```
// in Scala
dfWithLongColName.select(col("This Long Column-Name")).columns

# in Python
dfWithLongColName.select(expr("`This Long Column-Name`")).columns

==== Case Sensitivity

By default Spark is case insensitive; however, you can make Spark case sensitive by setting the configuration:

-- in SQL
set spark.sql.caseSensitive true
```

Removing Columns

Now that we've created this column, let's take a look at how we can remove columns from DataFrames. You likely already noticed that we can do this by using *select*. However there is also a dedicated method called *drop*:

```
df.drop("ORIGIN_COUNTRY_NAME").columns
```

We can drop multiple columns by passing in multiple columns as arguments:

```
dfWithLongColName.drop("ORIGIN_COUNTRY_NAME", "DEST_COUNTRY_NAME")
```

Changing a Column's Type (cast)

Sometimes, we might need to convert from one type to another; for example, if we have a set of *StringType* that should be integers. We can convert columns from one type to another by casting the column from one type to another. For instance, let's convert our *count* column from an integer to a type *Long*.

```
df.withColumn("count2", col("count").cast("long"))
-- in SQL
SELECT *, cast(count as long) AS count2 FROM dfTable
```

Filtering Rows

To filter rows, we create an expression that evaluates to true or false. You then filter out the rows that have expression that is equal to false. The most common way to do this with DataFrames is to create either an expression as a String or build an expression by using a set of column manipulations. There are two methods to perform this operation, you can use *where* or *filter* and they both will perform the same operation and accept the same argument types when used with DataFrames. We will stick to *where* because of its familiarity to SQL; however, *filter* is valid as well.

NOTE

When using the Dataset API from either Scala or Java, *filter* also accepts an arbitrary function that Spark will apply to each record in the Dataset. See <<s2c6---data-sources>> for more information.

The following filters are equivalent, and the results are the same in Scala and Python:

```
df.filter(col("count") < 2).show(2)
df.where("count < 2").show(2)

-- in SQL
SELECT * FROM dfTable WHERE count < 2 LIMIT 2
```

Giving an output of:

DEST_COUNTRY_NAME	ORIGIN_COUNTRY_NAME	count
United States	Croatia	1
United States	Singapore	1

Instinctually, you might want to put multiple filters into the same expression. Although this is possible, it is not always useful, because Spark automatically performs all filtering operations at the same time regardless of the filter ordering. This optimization is called pipelining and is one of the things that makes Spark efficient. This means that if you want to specify multiple AND filters, just chain them sequentially and let Spark handle the rest:

```
// in Scala
df.where(col("count") < 2).where(col("ORIGIN_
COUNTRY_NAME") =!= "Croatia")
  .show(2)
```

```
# in Python
df.where(col("count") < 2).where(col("ORIGIN_
COUNTRY_NAME") != "Croatia")\
  .show(2)
```

```
-- in SQL
SELECT * FROM dfTable WHERE count < 2 AND
ORIGIN_COUNTRY_NAME != "Croatia"
LIMIT 2
```

Giving an output of:

DEST_COUNTRY_NAME	ORIGIN_COUNTRY_NAME	count
United States	Singapore	1
Moldova	United States	1

Getting Unique Rows

A very common use case is to extract the unique or distinct values in a DataFrame. These values can be in one or more columns. The way we do this is by using the *distinct* method on a DataFrame, which allows us to deduplicate any rows that are in that DataFrame. For instance, let's get the unique origins in our dataset. This, of course, is a transformation that will return a new DataFrame with only unique rows:

```
// in Scala
df.select("ORIGIN_COUNTRY_NAME", "DEST_COUNTRY_NAME").distinct().count()

# in Python
df.select("ORIGIN_COUNTRY_NAME", "DEST_COUNTRY_NAME").distinct().count()

-- in SQL
SELECT COUNT(DISTINCT(ORIGIN_COUNTRY_NAME, DEST_COUNTRY_NAME)) FROM dfTable

256

// in Scala
df.select("ORIGIN_COUNTRY_NAME").distinct().count()

# in Python
df.select("ORIGIN_COUNTRY_NAME").distinct().count()

-- in SQL
SELECT COUNT(DISTINCT ORIGIN_COUNTRY_NAME) FROM dfTable

125
```

Random Samples

Sometimes, you might just want to sample some random records from your DataFrame. You can do this by using the *sample* method on a DataFrame, which makes it possible for you to specify a fraction of rows to extract from a DataFrame and whether you'd like to sample with or without replacement:

```
val seed = 5
val withReplacement = false
val fraction = 0.5
df.sample(withReplacement, fraction, seed).count()
```

```
# in Python
seed = 5
withReplacement = False
fraction = 0.5
df.sample(withReplacement, fraction, seed).count()
```

Giving an output of: 126

Random Splits

Random splits can be helpful when you need to break up your DataFrame, well...randomly, in such a way that you cannot guarantee that all records are in one of the DataFrames from which you're sampling. This is often used with machine learning algorithms to create training, validation, and test sets. In this next example, we'll split our DataFrame into two different DataFrames by setting the weights by which we will split the DataFrame (these are the arguments to the function). Because this method is designed to be arbitrary, we will also specify a seed. It's important to note that if you don't specify a proportion for each DataFrame that adds up to one, they will be normalized so that they do:

```
// in Scala
val dataFrames = df.randomSplit(Array(0.25, 0.75), seed)
dataFrames(0).count() > dataFrames(1).count() // False

# in Python
dataFrames = df.randomSplit([0.25, 0.75], seed)
dataFrames[0].count() > dataFrames[1].count() # False
```

Concatenating and Appending Rows (Union)

As you learned in the previous section, DataFrames are immutable. This means users cannot append to DataFrames because that would be changing it. To append to a DataFrame, you must _union_ the original DataFrame along with the new DataFrame. This just concatenates the two DataFramess. To union two DataFrames, you must be sure that they have the same schema and number of columns; otherwise, the union will fail.

WARNING

Unions are currently performed based on location, not on the schema. This means that columns will not automatically line up the way you think they might.

```
// in Scala
import org.apache.spark.sql.Row
val schema = df.schema
val newRows = Seq(
  Row("New Country", "Other Country", 5L),
  Row("New Country 2", "Other Country 3", 1L)
)
val parallelizedRows = spark.sparkContext.parallelize(newRows)
val newDF = spark.createDataFrame(parallelizedRows, schema)
df.union(newDF)
  .where("count = 1")
  .where($"ORIGIN_COUNTRY_NAME" =!= "United States")
  .show() // get all of them and we'll see our new rows at the end
```

In Scala, you must use the `=!=` operator so that you don't just compare the unevaluated column expression to a string but instead to the evaluated one:

```
# in Python
from pyspark.sql import Row
schema = df.schema
newRows = [
 Row("New Country", "Other Country", 5L),
 Row("New Country 2", "Other Country 3", 1L)
]
parallelizedRows = spark.sparkContext.parallelize(newRows)
newDF = spark.createDataFrame(parallelizedRows, schema)

# in Python
df.union(newDF)\
 .where("count = 1")\
 .where(col("ORIGIN_COUNTRY_NAME") != "United States")\
 .show()
```

Giving the output of:

DEST_COUNTRY_NAME	ORIGIN_COUNTRY_NAME	count
United States	Singapore	1
...	...	...
United States	Namibia	1
New Country 2	Other Country 3	1

As expected, you'll need to use this new DataFrame reference in order to refer to the DataFrame with the newly appended rows. A common way to do this is to make the DataFrame into a view or register it as a table so that you can reference it more dynamically in your code.

Sorting Rows

When we sort the values in a DataFrame, we always want to sort with either the largest or smallest values at the top of a DataFrame. There are two equivalent operations to do this *sort* and *orderBy* that work the exact same way. They accept both column expressions and strings as well as multiple columns. The default is to sort in ascending order:

```
// in Scala
df.sort("count").show(5)
df.orderBy("count", "DEST_COUNTRY_NAME").show(5)
df.orderBy(col("count"), col("DEST_COUNTRY_NAME")).show(5)

# in Python
df.sort("count").show(5)
df.orderBy("count", "DEST_COUNTRY_NAME").show(5)
df.orderBy(col("count"), col("DEST_COUNTRY_NAME")).show(5)
```

To more explicitly specify sort direction, you need to use the *asc* and *desc* functions if operating on a column. These allow you to specify the order in which a given column should be sorted:

```
// in Scala
import org.apache.spark.sql.functions.{desc, asc}
df.orderBy(expr("count desc")).show(2)
df.orderBy(desc("count"), asc("DEST_COUNTRY_NAME")).show(2)

# in Python
from pyspark.sql.functions import desc, asc
df.orderBy(expr("count desc")).show(2)
df.orderBy(col("count").desc(), col("DEST_COUNTRY_NAME").asc()).show(2)

-- in SQL
SELECT * FROM dfTable ORDER BY count DESC, DEST_COUNTRY_NAME ASC LIMIT 2
```

An advanced tip is to use *asc_nulls_first*, *desc_nulls_first*, *asc_nulls_last*, or *desc_nulls_last* to specify where you would like your null values to appear in an ordered DataFrame.

For optimization purposes, it's sometimes advisable to sort within each partition before another set of transformations. You can do this by using the *sortWithinPartitions* method:

```
// in Scala
spark.read.format("json").load("/data/flight-data/json/*-summary.json")
 .sortWithinPartitions("count")
```

```
# in Python
spark.read.format("json").load("/data/flight-data/json/*-summary.json")\
 .sortWithinPartitions("count")
```

We will discuss this more when we look at tuning and optimization in <<part3>>.

Limit

Oftentimes, you might want to restrict what you extract from a DataFrame; for example, you might want just the top ten of some DataFrame. You can do this by using the *limit* method:

```
// in Scala
df.limit(5).show()

# in Python
df.limit(5).show()

-- in SQL
SELECT * FROM dfTable LIMIT 6
```

```
// in Scala
df.orderBy(expr("count desc")).limit(6).show()

# in Python
df.orderBy(expr("count desc")).limit(6).show()

-- in SQL
SELECT * FROM dfTable ORDER BY count desc LIMIT 6
```

Repartition and Coalesce

Another important optimization opportunity is to partition the data according to some frequently filtered columns, which control the physical layout of data across the cluster including the partitioning scheme and the number of partitions.

Repartition will incur a full shuffle of the data, regardless of whether one is necessary. This means that you should typically only repartition when the future number of partitions is greater than your current number of partitions or when you are looking to partition by a set of columns:

```
// in Scala
df.rdd.getNumPartitions // 1

# in Python
df.rdd.getNumPartitions() # 1
```

```
// in Scala
df.repartition(5)

# in Python
df.repartition(5)
```

If you know that you're going to be filtering by a certain column often, it can be worth repartitioning based on that column:

```
// in Scala
df.repartition(col("DEST_COUNTRY_NAME"))
```

```
# in Python
df.repartition(col("DEST_COUNTRY_NAME"))
```

You can optionally specify the number of partitions you would like, too:

```
// in Scala
df.repartition(col("DEST_COUNTRY_NAME"))
```

```
# in Python
df.repartition(col("DEST_COUNTRY_NAME"))
```

Coalesce, on the other hand, will not incur a full shuffle and will try to combine partitions. This operation will shuffle your data into five partitions based on the destination country name, and then coalesce them (without a full shuffle):

```
// in Scala
df.repartition(5, col("DEST_COUNTRY_NAME")).coalesce(2)
```

```
# in Python
df.repartition(5, col("DEST_COUNTRY_NAME")).coalesce(2)
```

Collecting Rows to the Driver

As we covered in the previous chapters, Spark maintains the state of the cluster in the driver. There are times when you'll want to collect some of your data to the driver in order to manipulate it on your local machine.

Thus far, we did not explicitly define this operation. However, we used several different methods for doing so that are effectively all the same. *collect* gets all data from the entire DataFrame, *take* selects the first _N_ rows, and *show* prints out a number of rows nicely.

```
// in Scala
val collectDF = df.limit(10)
collectDF.take(5) // take works with an Integer count
collectDF.show() // this prints it out nicely
collectDF.show(5, false)
collectDF.collect()
```

```
# in Python
collectDF = df.limit(10)
collectDF.take(5) # take works with an Integer count
collectDF.show() # this prints it out nicely
collectDF.show(5, False)
collectDF.collect()
```

There's an additional way of collecting rows to the driver in order to iterate over the entire dataset. The method *toLocalIterator* collects partitions to the driver as an iterator. This method allows you to iterate over the entire dataset partition-by-partition in a serial manner:

```
collectDF.toLocalIterator()
```

WARNING

Any collection of data to the driver can be a very expensive operation! If you have a large dataset and call *collect*, you can crash the driver. If you use *toLocalIterator* and have very large partitions, you can easily crash the driver node and lose the state of your application. This is also expensive because we can operate on a one-by-one basis, instead of doing so in parallel.

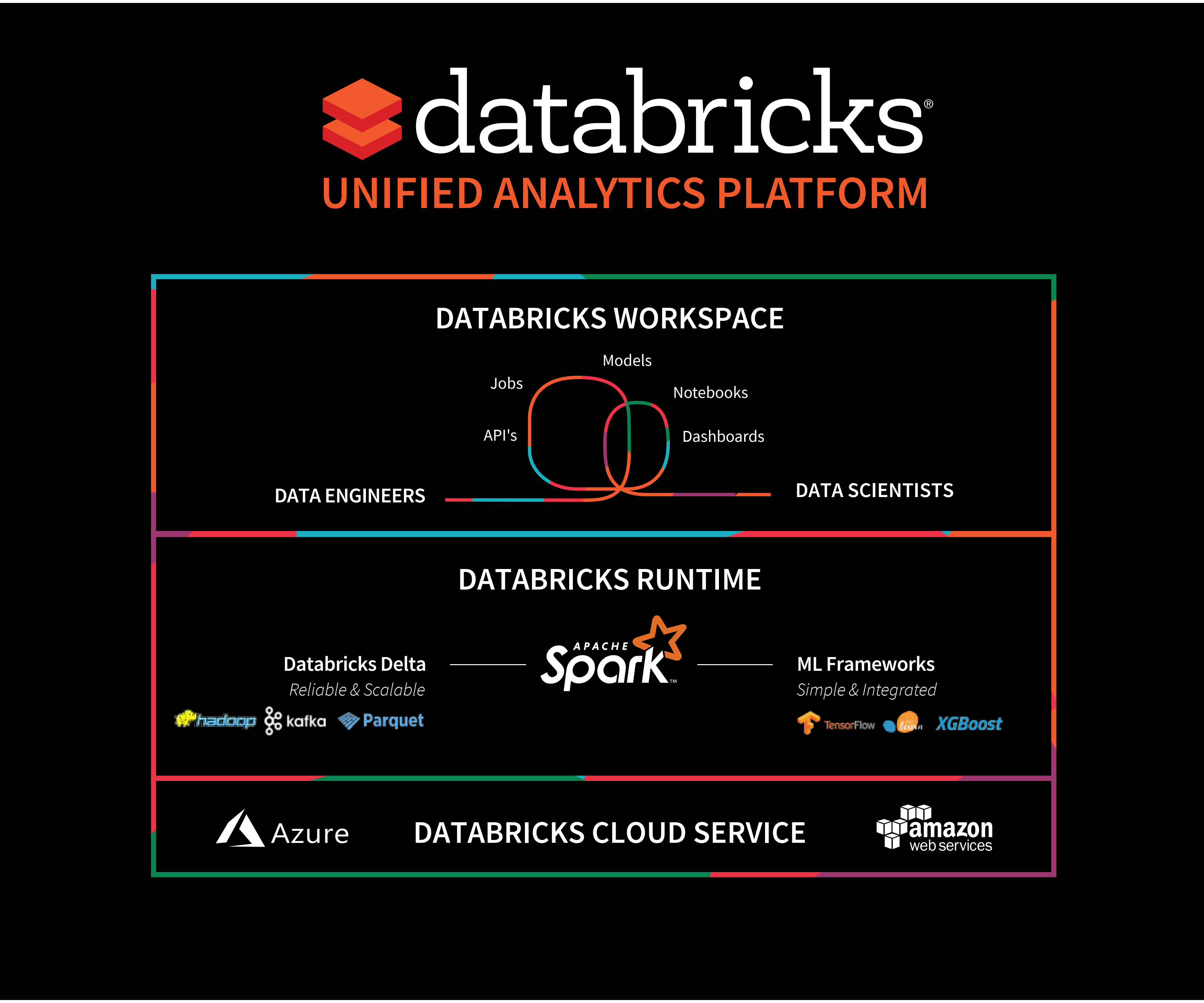
Conclusion

This chapter covered basic operations on DataFrames. You learned the simple concepts and tools that you will need to be successful with Spark DataFrames. <<s2c3---working-with-different-types-of-data>> covers in much greater detail all of the different ways in which you can manipulate the data in those DataFrames.

Accelerating Innovation by Unifying Data and AI

The early foundations to simplify big data and AI have been laid by Apache Spark, the first unified analytics engine, which combines big data processing with machine learning. Spark supports a wide range of analytics — data loading, SQL queries, machine learning and streaming computation with a consistent set of APIs

Spark has also become the de-facto analytics engine in the enterprises today due to its speed, ease of use, and sophisticated analytics.



The Databricks Unified Analytics Platform - Powered by Apache Spark

AI has enormous promise, introducing the potential to drive disruptive innovations affecting most enterprises on the planet. However, despite the allure of AI, most enterprises are struggling to succeed with AI as data and AI teams are siloed in disjointed systems and different organizations. This organizational separation creates friction and slows projects down, becoming an impediment to the highly iterative nature of AI projects.

The Databricks Unified Analytics Platform, from the original creators of Apache Spark, enables organizations to accelerate innovation by unifying data and AI technologies. Designed for the data engineers and data scientists, Databricks streamlines collaboration across the AI lifecycle, speeding up the process to prepare data for best-in-class AI applications, allowing to continuously train and deploy cutting-edge AI models on big data faster while keeping data safe and secure and reducing infrastructure complexity.

Unify Data and AI Teams

With a unified approach to data and AI, data engineering and data science teams can collaborate using Databricks' collaborative workspace. With Databricks' interactive workspace, teams can build data pipelines, train and productionize machine learning models, and share insights to the business all from the same environment.

Thanks to its flexible and extensible platform, teams have full flexibility to handle all analytic processes — from data engineers focusing on data preparation and ETL, to data scientists building and training machine learning models at scale — in a common, unified framework, leveraging familiar tools, languages, and skills, via interactive notebooks or APIs.

Technology is nothing without people to make it great, and Databricks ensures a team can become heroes, by providing a common interface and tooling for all stakeholders, regardless of skill set, to collaborate with one another. This eliminates data silos and allows teams to collaborate across the AI lifecycle, from experimentation to production, which in turn benefits their organization and increases innovation.

Build Reliable and Performant Data Pipelines

For data engineers, it's critical to process data no matter the scale as quickly as possible. The Databricks Unified Analytics Platform, makes it simpler to ingest and transform various and large data sets, speeding up the process to explore and prepare massive data sets essentials for best-in-class AI applications.

Through various optimizations for large-scale data processing in the cloud, we've made Spark faster and more performant. Recent benchmarks clock Databricks at a rate of 50x faster than Apache Spark on AWS. It also allows for reliable management of changing data, providing businesses with cost efficiency and scalable real-time analysis.

Build Cutting-Edge AI Models at Massive Scale

With Databricks, data science teams can leverage the Unified Analytics Platform to easily train, evaluate, and deploy more effective AI models to production. Easily connect with prepared data sets to perform data exploration, analysis, and transformations using SQL, R, or Python. And interactively explore data with collaborative notebooks that allow data scientists to take machine learning models from experimentation-to-production at scale. And with prepackaged AI frameworks such as TensorFlow, Horovod, Keras, XGBoost, PyTorch, SciKit-Learn, MLlib, GraphX, and sparklyr, data science teams can easily provision AI-ready Databricks clusters and notebooks in seconds on its cloud native service.

Finally, the Databricks Unified Analytics Platform significantly simplifies parallelization and distributed model training on CPU and GPU across cloud platforms via built-in optimization features and libraries (Horovod Estimator). It also natively decouples compute and storage, reducing the need to move data over and allowing significantly faster analysis on massive amount of data at lower cost.

Reliable, Scalable, and Secure Management Cloud Service

The proliferation of siloed-data types and point solutions for data management (data lakes, data warehouse, and streaming) is increasing costs and operational complexity. Further complicating matters are the inherent limitations of on-premises infrastructure which are difficult and costly to scale to meet the real-time needs of the business; as well as stringent security and compliance requirements.

Databricks' highly elastic cloud service is designed to reduce operational complexity while ensuring reliability and cost efficiency at scale. Businesses can now reap the benefits of a fully managed service and remove the complexity of big data and machine learning, while keeping data safe and secure, with a unified security model featuring fine-grained controls, data encryption, identity management, rigorous auditing, and support for compliance standards.