CH 9 Data Sources

Note - **tab key** activates databricks server autocomplete
I really hate the evernote update

Core Data Sources:

- CSV
- JSON
- Parquet
- ORC
- JDBC/ODBC connections
- Plain-text files

(some) Community-Defined Sources:

- Cassandra
- HBase
- MongoDB
- AWS Redshift
- XML

The core structure for reading data is as follows:

```
DataFrameReader.format(...).option("key", "value").schema(...).load()
```

format is optional because by default Spark will use the **Parque**t format
option allows you to set key-value configurations to parameterize how you will read data
schema is optional if the data source provides a schema or if you intend to use schema inference.
there are required options for each format

Apache Parquet:
Apache Parquet is a free and open-source column-oriented data storage format of the Apache Hadoop ecosystem, similar to columnar-storage file formats in Hadoop - RCFile and ORC, compatible most data processing frameworks in the Hadoop environment.

DataFrameReader - we access this through the *SparkSession* via the *read* attribute:

```
spark.read
```

specify several values:

- The format
- The schema
- The read mode

- A series of option

```
spark.read.format("csv")
.option("mode", "FAILFAST")
.option("inferSchema", "true")
.option("path", "path/to/file(s)")
.schema(someSchema)
.load()
```

*possible to build a map obj and pass in your configurations

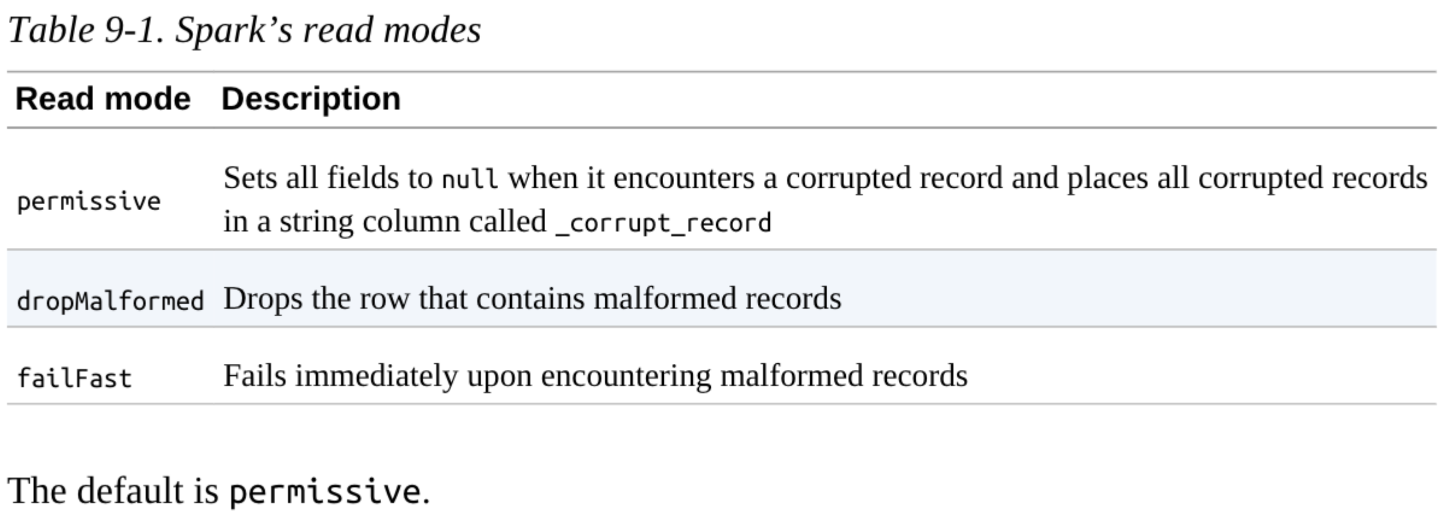


Table 9-1. Spark's read modes

Read mode	Description
`permissive`	Sets all fields to `null` when it encounters a corrupted record and places all corrupted records in a string column called `_corrupt_record`
`dropMalformed`	Drops the row that contains malformed records
`failFast`	Fails immediately upon encountering malformed records

The default is `permissive`.

The core structure for writing data is as follows:

```
DataFrameWriter.format(...).option(...).partitionBy(...).bucketBy(...).sortBy(  ...).save()
```

format - optional because by default,Spark will use the Parquet format.
option - allows us to configure how to write out our given data.
PartitionBy, *bucketBy*, and *sortBy* work only for file-based data sources; you can use them to control the specific layout of files at the destination

Writing Data:
We always need to write out some given data source, we access the DataFrameWriter on a per-DataFrame basis via the write attribute:

```
dataFrame.write
```

we specify three values: **the format, a series of options ,and the save mode**

Table 9-2. Spark's save modes

Save mode	Description
`append`	Appends the output files to the list of files that already exist at that location
`overwrite`	Will completely overwrite any data that already exists there
`errorIfExists`	Throws an error and fails the write if data or files already exist at the specified location
`ignore`	If data or files exist at the location, do nothing with the current DataFrame

The default is `errorIfExists`. This means that if Spark finds data at the location to which you're writing, it will fail the write immediately.

CSV

- large number of options
- no assumptions can be made
- for example, commas inside of columns when the file is also comma-delimited or null values labeled in an unconventional way

Table 9-3. CSV data source options

Read/write	Key	Potential values	Default	Description
Both	`sep`	Any single string character	,	The single character that is used as separator for each field and value.
Both	`header`	`true`, `false`	`false`	A Boolean flag that declares whether the first line in the file(s) are the names of the columns.
Read	`escape`	Any string character	\	The character Spark should use to escape other characters in the file.
Read	`inferSchema`	`true`, `false`	`false`	Specifies whether Spark should infer column types when reading the file.
				Declares whether leading

Read	`ignoreLeadingWhiteSpace`	`true`, `false`	`false`	spaces from values being read should be skipped.
Read	`ignoreTrailingWhiteSpace`	`true`, `false`	`false`	Declares whether trailing spaces from values being read should be skipped.
Both	`nullValue`	Any string character	“”	Declares what character represents a `null` value in the file.
Both	`nanValue`	Any string character	NaN	Declares what character represents a NaN or missing character in the CSV file.
Both	`positiveInf`	Any string or character	Inf	Declares what character(s) represent a positive infinite value.
Both	`negativeInf`	Any string or character	-Inf	Declares what character(s) represent a negative infinite value.
Both	`compression` or `codec`	None, `uncompressed`, `bzip2`, `deflate`, `gzip`, `lz4`, or `snappy`	none	Declares what compression codec Spark should use to read or write the file.
Both	`dateFormat`	Any string or character that conforms to java’s `SimpleDataFormat`.	yyyy-MM-dd	Declares the date format for any columns that are date type.
Both	`timestampFormat`	Any string or character that conforms to java’s `SimpleDataFormat`.	yyyy-MM-dd’T’HH:mm:ss.SSSZZ	Declares the timestamp format for any columns that are timestamp type.
Read	`maxColumns`	Any integer	20480	Declares the maximum number of columns in the file.
				Declares the maximum

Read	`maxCharsPerColumn`	Any integer	1000000	number of characters in a column.
Read	`escapeQuotes`	`true`, `false`	`true`	Declares whether Spark should escape quotes that are found in lines.
Read	`maxMalformedLogPerPartition`	Any integer	10	Sets the maximum number of malformed rows Spark will log for each partition. Malformed records beyond this number will be ignored.
Write	`quoteAll`	`true`, `false`	`false`	Specifies whether all values should be enclosed in quotes, as opposed to just escaping values that have a quote character.
Read	`multiLine`	`true`, `false`	`false`	This option allows you to read multiline CSV files where each logical row in the CSV file might span multiple rows in the file itself.

HAD TO CLEAR OUT FREE TIER FILE STORE:

```
dbutils.fs.rm("/FileStore/tables", True)
```

JSON

In Spark - Referring to *line-delimited* JSON files - **NOT** files that have a large JSON object or array per file

multiLine - set this option to true, to read an entire file as *one json object* and Spark will go through the work of parsing that into a DataFrame

Line-delimited JSON is more stable format

- can append to a file with a new record (rather than having to read in an entire file and then write it out)
- easier to infer from JS formats

Table 9-4. JSON data source options

Read/write	Key	Potential values	Default
Both	`compression` or `codec`	None, `uncompressed`, `bzip2`, `deflate`, `gzip`, `lz4`, or `snappy`	none
Both	`dateFormat`	Any string or character that conforms to Java's `SimpleDataFormat`.	yyyy-MM-dd
Both	`timestampFormat`	Any string or character that conforms to Java's `SimpleDataFormat`.	yyyy-MM-dd'T'HH:mm:ss.SSSZZ
Read	`primitiveAsString`	`true`, `false`	`false`
Read	`allowComments`	`true`, `false`	`false`
Read	`allowUnquotedFieldNames`	`true`, `false`	`false`

Read	`allowSingleQuotes`	`true`, `false`	`true`
Read	`allowNumericLeadingZeros`	`true`, `false`	`false`
Read	`allowBackslashEscapingAnyCharacter`	`true`, `false`	`false`
Read	`columnNameOfCorruptRecord`	Any string	Value of `spark.sql.column&NameOfCorruptRecord`

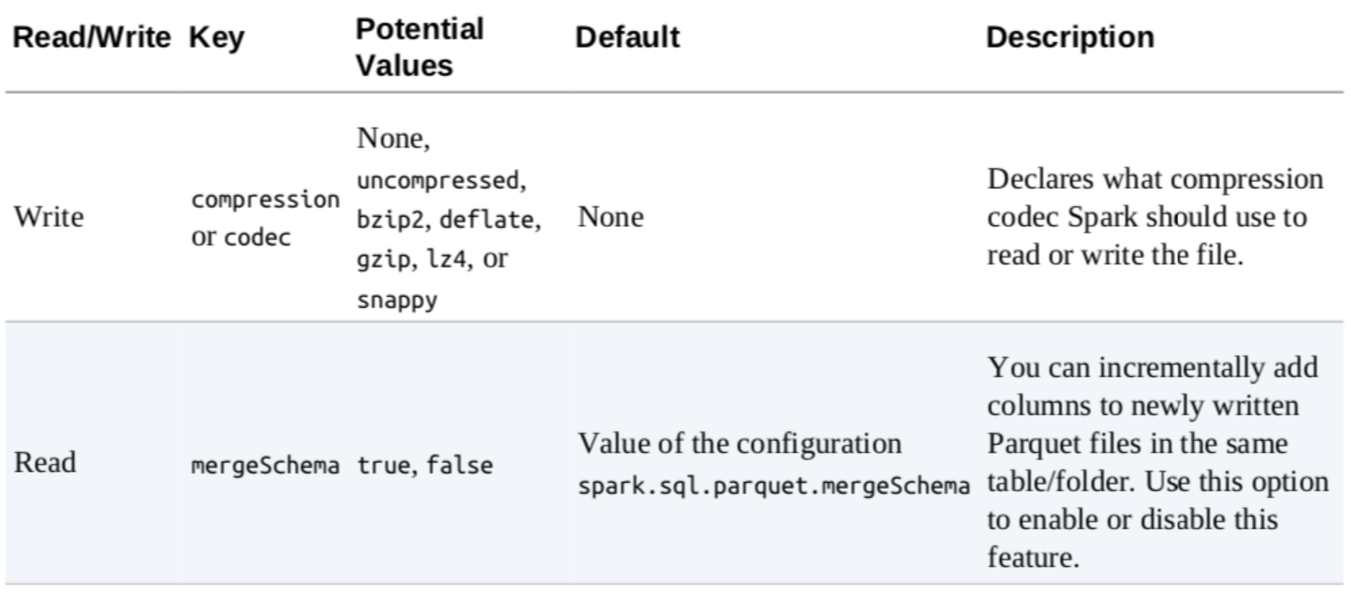
Read	multiLine	true, false	false

Parquet - column-oriented data store has storage optimizations for analytics workloads

- **columnar compression** - which saves storage space and allows for reading individual columns instead of entire files.
- works exceptionally well with Apache Spark - *is the default file format*
- Recommended to write data out to Parquet for long-term storage - *reading from a Parquet file will always be more efficient than JSON or CSV*
- Parquet supports complex types - if your column is an array (which would fail with a CSV file, for example), map, or struct, you'll still be able to read and write that file without issue.
- Here's how to specify Parquet as the read format:

```
spark.read.format("parquet")\
  .load("/FileStore/tables/2010_summary.csv").show(5)
```

warning - incompatible parquet files due to spark versioning



Read/Write	Key	Potential Values	Default	Description
Write	compression or codec	None, uncompressed, bzip2, deflate, gzip, lz4, or snappy	None	Declares what compression codec Spark should use to read or write the file.
Read	mergeSchema	true, false	Value of the configuration spark.sql.parquet.mergeSchema	You can incrementally add columns to newly written Parquet files in the same table/folder. Use this option to enable or disable this feature.

ORC

- Optimized Row Columnar- *Self-describing, type-aware columnar* file format designed for Hadoop workloads.
- Optimized for large streaming reads, but with integrated support for finding required rows quickly
- Actually has no options for reading in data because Spark understands the file format inherently

- Difference between ORC and Parquet?
    - Parquet is further optimized for use with Spark
    - ORC is further optimized for Hive

SQL

SQL datasources are one of the more powerful connectors because there are a variety of systems to which you can connect (as long as that system speaks SQL):

- MySQL database
- PostgreSQL database
- Oracle database
- SQLite - this example.

authentication and connectivity

- you'll need to determine whether the network of your Spark cluster is connected to the network of your database system
- avoid setting up a database for the purposes of this book - reference sample that runs SQLite.

SQLite

- can work with minimal setup on your local machine
- limitation of not being able to work in a distributed setting
- most used database engine in the entire world
- powerful, fast, and easy to understand
- SQLite database is just a file
- source file included in the official repository for this book - download that file to your local machine, and you will be able to read from it and write to it.
- the primary difference (in terms of use here) is in the properties that you include when you connect to the database - with SQLite, there's no user or password

To read and write from these databases

- include the *Java Database Connectivity (JDBC) driver* for you particular database on the spark classpath
- provide the proper JAR for the driver itself.

For example, to be able to read and write from PostgreSQL, you might run something like this:

```
./bin/spark-shell
\--driver-class-path postgresql-9.4.1207.jar
\--jars postgresql-9.4.1207.jar
```

Table 9-6. JDBC data source options

Property Name	Meaning
`url`	The JDBC URL to which to connect. The source-specific connection properties can be specified in the URL; for example, *jdbc:postgresql://localhost/test?user=fred&password=secret*.
`dbtable`	The JDBC table to read. Note that anything that is valid in a FROM clause of a SQL query can be used. For example, instead of a full table you could also use a subquery in parentheses.
`driver`	The class name of the JDBC driver to use to connect to this URL.
`partitionColumn`, `lowerBound`, `upperBound`	If any one of these options is specified, then all others must be set as well. In addition, `numPartitions` must be specified. These properties describe how to partition the table when reading in parallel from multiple workers. `partitionColumn` must be a numeric column from the table in question. Notice that `lowerBound` and `upperBound` are used only to decide the partition stride, not for filtering the rows in the table. Thus, all rows in the table will be partitioned and returned. This option applies only to reading.
`numPartitions`	The maximum number of partitions that can be used for parallelism in table reading and writing. This also determines the maximum number of concurrent JDBC connections. If the number of partitions to write exceeds this limit, we decrease it to this limit by calling `coalesce(numPartitions)` before writing.
`fetchsize`	The JDBC fetch size, which determines how many rows to fetch per round trip. This can help performance on JDBC drivers, which default to low fetch size (e.g., Oracle with 10 rows). This option applies only to reading.
`batchsize`	The JDBC batch size, which determines how many rows to insert per round trip. This can help performance on JDBC drivers. This option applies only to writing. The default is 1000.
`isolationLevel`	The transaction isolation level, which applies to current connection. It can be one of `NONE`, `READ_COMMITTED`, `READ_UNCOMMITTED`, `REPEATABLE_READ`, or `SERIALIZABLE`, corresponding to standard transaction isolation levels defined by JDBC's `Connection` object. The default is `READ_UNCOMMITTED`. This option applies only to writing. For more information, refer to the documentation in java.sql.Connection.
`truncate`	This is a JDBC writer-related option. When `SaveMode.Overwrite` is enabled, Spark truncates an existing table instead of dropping and re-creating it. This can be more efficient, and it prevents the table metadata (e.g., indices) from being removed. However, it will not work in some cases, such as when the new data has a different schema. The default is `false`. This option applies only to writing.
`createTableOptions`	This is a JDBC writer-related option. If specified, this option allows setting of database-specific table and partition options when creating a table (e.g., CREATE TABLE t (*name string*) ENGINE=InnoDB). This option applies only to writing.

	TABLE t (name string) ENGINE=InnoDB). This option applies only to writing.
`createTableColumnTypes`	The database column data types to use instead of the defaults, when creating the table. Data type information should be specified in the same format as CREATE TABLE columns syntax (e.g., “name CHAR(64), comments VARCHAR(1024)”). The specified types should be valid Spark SQL data types. This option applies only to writing.

Skipping straight to Spark SQL because SQLContext wont run without JDBC driver set up, which requires a token, which isn't available on my practice account???

plain-text files

- Each line in the file becomes a record in theDataFrame
- Apache log files -> more structured format, parse some plain text for natural-language processing
- Text files make a great argument for the Dataset API due to its ability to take advantage of the flexibility of *native types*

Reading text files is straightforward: you simply specify the type to be **textFile**. With textFile, partitioned directory names are ignored. To read and write text files according to partitions, you should use text, which respects partitioning on reading and writing.

When you write a text file, **specify only one string column**; otherwise, the write will fail:

```
csvFile.select("DEST_COUNTRY_NAME").write.text("/tmp/simple-text-file.txt")
```

Partitioning when performing your write

- columns will manifest as directories in the folder to which you’re writing out to, instead of columns

Can control specific data layout via **bucketing** and **partitioning**:

Certain file formats are fundamentally **splittable**.

- This can improve speed because it makes it possible for Spark to avoid reading an entire file
- Access only the parts of the file necessary to satisfy your query.
- If you use Hadoop Distributed FileSystem (HDFS), splitting a file can provide further optimization if that file spans multiple blocks.
- **Compression** - Not all compression schemes are splittable. **Parquet with gzip compression** is recommended storage

Reading in Parallel

- Multiple executors cannot read from the same file at the same time
- can *read* different files at the same time
- When you read from a folder with multiple files in it, each one of those files will become a partition in

your DataFrame
- will be read by available executors in parallel
- remaining queue up behind the others

Writing in Parallel
- The number of files or data written is dependent on the number of partitions the DataFrame has
- By default, one file is written per partition of the data
- When we specify a “file,” it’s actually a number of files within a folder, with the name of the specified file, with one file per each partition that is written

the following code

```
csvFile.repartition(5).write.format("csv").save("/tmp/multiple.csv")
```

will end up with five files inside of that folder -

```
ls /tmp/multiple.csv
```

/tmp/multiple.csv/part-00000-767df509-ec97-4740-8e15-4e173d365a8b.csv
/tmp/multiple.csv/part-00001-767df509-ec97-4740-8e15-4e173d365a8b.csv
/tmp/multiple.csv/part-00002-767df509-ec97-4740-8e15-4e173d365a8b.csv
/tmp/multiple.csv/part-00003-767df509-ec97-4740-8e15-4e173d365a8b.csv
/tmp/multiple.csv/part-00004-767df509-ec97-4740-8e15-4e173d365a8b.csv

Partitioning is a tool that allows you to control what data is stored (and where) as you write it
- When you write a file to a partitioned directory (or table), you basically encode a column as a folder
- Gives ability to *Skip lots of data when you go to read it in later*,
- read in only the data relevant to your problem instead of having to scan the complete dataset
- lowest-hanging optimization that you can use when you have a table that is frequently filtered before manipulating
- **dat**e is particularly common for a partition because we want to look at only the previous week’s data (instead of scanning the entire list of records).

Python -

```
csvFile.limit(10).write.mode("overwrite").partitionBy("DEST_COUNTRY_NAME")\
.save("/tmp/partitioned-files.parquet")
```

Upon writing, you get a list of folders in your Parquet “file”:

```
$ ls /tmp/partitioned-files.parquet
```

DEST_COUNTRY_NAME=Costa Rica/
DEST_COUNTRY_NAME=Egypt/
DEST_COUNTRY_NAME=Equatorial Guinea/
DEST_COUNTRY_NAME=Senegal/
DEST_COUNTRY_NAME=United States/

Each of these will contain Parquet files that contain that data where the previous predicate was true:

```
$ ls /tmp/partitioned-files.parquet
```

/DEST_COUNTRY_NAME=Senegal/part-00000-tid.....parquet

Bucketing is another file organization approach

- can control the data that is specifically written to each file
- can help avoid shuffles later when you go to read the data
- data with the same bucket ID will all be grouped together into one physical partition
- data is prepartitioned according to how you expect to use that data later on
- avoid expensive shuffles when joining or aggregating
- Rather than partitioning on a specific column (could write out many directories)
- will create a certain number of files and organize our data into those “buckets”

```
valnumberBuckets=10
valcolumnToBucketBy="count"
csvFile.write.format("parquet").mode("overwrite").bucketBy(numberBuckets,columnToBucketBy).saveAsTab
le("bucketedFiles")
```

```
$ ls /user/hive/warehouse/bucketedfiles/
```

part-00000-tid-1020575097626332666-8....parquet
part-00000-tid-1020575097626332666-8....parquet
part-00000-tid-1020575097626332666-8....parquet

Although Spark can work with all of these types, *not every single type works well with every data file format*. For instance, CSV files do not support complex types, whereas Parquet and ORC do.

Managing file sizes is an important factor not so much for writing data, but reading it later on

- When writing small files - there’s a significant metadata overhead that you incur managing all of those files
- Spark especially does not do well with small files, although many filesystems (like HDFS) don’t handle

lots of small files well, either.

- Referred to as the **“small file problem”**
- The opposite is also true: you don’t want files that are too large either, because it becomes inefficient to have to read entire blocks of data when you need only a few rows
- Spark 2.2 introduced a new method for controlling file sizes in a more automatic way.
    - can take advantage of another tool in order to limit output file sizes so that you can target an optimum file size
    - can use **themaxRecordsPerFile** option and specify a number of your choosing.
    - allows you to better control file sizes by controlling the number of records that are written to each file
    - For example, if you set an option for a writer as

```
df.write.option("maxRecordsPerFile", 5000)
```

Spark will ensure that files will contain at most 5,000 records