# Structured Data Processing - Spark SQL

Amir H. Payberah
payberah@kth.se
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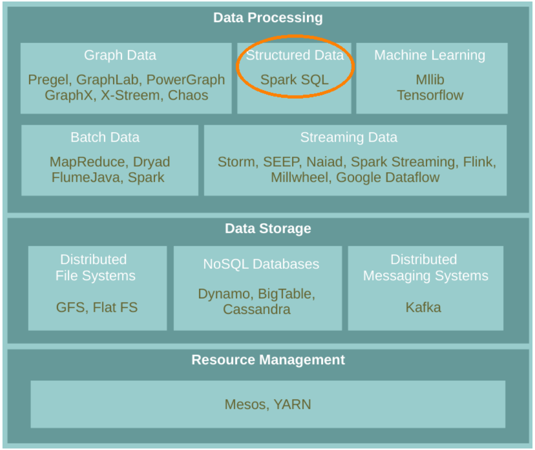
# The Course Web Page

https://id2221kth.github.io

# The Questions-Answers Page

https://tinyurl.com/bdenpwc5

# Where Are We?



Data Processing
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Pregel, GraphLab, PowerGraph
GraphX, X-Streem, Chaos
Structured Data
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NoSQL Databases
Dynamo, BigTable,
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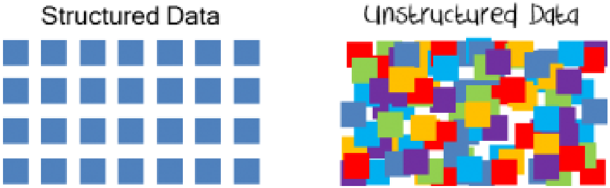
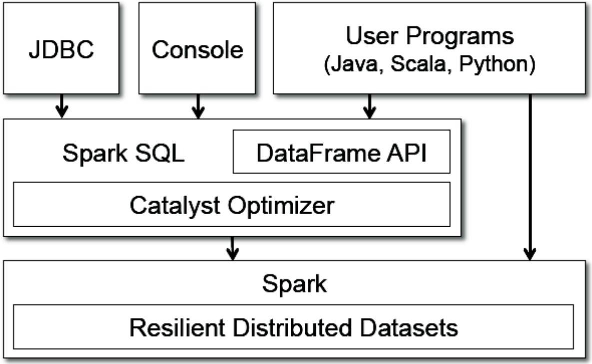
# Motivation



# Spark and Spark SQL



# Structured Data vs. RDD (1/2)

- `case class Account(name: String, balance: Double, risk: Boolean)`
- `RDD[Account]`
- RDDs don't know anything about the schema of the data it's dealing with.

# Structured Data vs. RDD (2/2)

- `case class Account(name: String, balance: Double, risk: Boolean)`
- `RDD[Account]`
- A database/Hive sees it as a columns of named and typed values.

| | | |
|---|---|---|
| name: String | balance: Double | risk: Boolean |
| name: String | balance: Double | risk: Boolean |
| name: String | balance: Double | risk: Boolean |
| name: String | balance: Double | risk: Boolean |

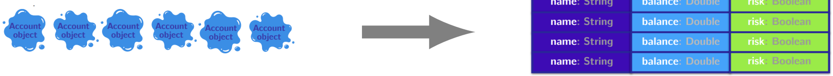
# DataFrames and DataSets

- Spark has two notions of structured collections:
  - DataFrames
  - Datasets
- They are distributed table-like collections with well-defined rows and columns.
- They represent immutable lazily evaluated plans.
- When an action is performed on them, Spark performs the actual transformations and return the result.

# DataFrame

# DataFrame

- Consists of a series of rows and a number of columns.
- Equivalent to a table in a relational database.
- Spark + RDD: functional transformations on partitioned collections of objects.
- SQL + DataFrame: declarative transformations on partitioned collections of tuples.



# Schema

- Defines the column names and types of a DataFrame.
- Assume `people.json` file as an input:


```
{"name":"Michael", "age":15, "id":12}
{"name":"Andy", "age":30, "id":15}
{"name":"Justin", "age":19, "id":20}
{"name":"Andy", "age":12, "id":15}
{"name":"Jim", "age":19, "id":20}
{"name":"Andy", "age":12, "id":10}
```


```scala
val people = spark.read.format("json").load("people.json")
people.schema

// returns:
StructType(StructField(age,LongType,true),
StructField(id,LongType,true),
StructField(name,StringType,true))
```

# Column (1/2)

- They are like columns in a table.
- `col` returns a reference to a column.
- `expr` performs transformations on a column.
- `columns` returns all columns on a DataFrame

```
val people = spark.read.format("json").load("people.json")

col("age")

exp("age + 5 < 32")

people.columns
// returns: Array[String] = Array(age, id, name)
```

# Column (2/2)

- Different ways to refer to a column.

```
val people = spark.read.format("json").load("people.json")

people.col("name")

col("name")

column("name")

'name

$"name"

expr("name")
```

# Row

- A row is a record of data.
- They are of type `Row`.
- Rows do not have schemas.
  - The order of values should be the same order as the schema of the DataFrame to which they might be appended.
- To access data in rows, you need to specify the position that you would like.

```scala
import org.apache.spark.sql.Row

val myRow = Row("Seif", 65, 0)
```

```scala
myRow(0) // type Any
myRow(0).asInstanceOf[String] // String
myRow.getString(0) // String
myRow.getInt(1) // Int
```

# Creating a DataFrame

- Two ways to create a DataFrame:
  1. From an RDD
  2. From raw data sources

# Creating a DataFrame - From an RDD

- The schema automatically inferred.
- You can use `toDF` to convert an RDD to DataFrame.

```
val tupleRDD = sc.parallelize(Array(("seif", 65, 0), ("amir", 40, 1))
val tupleDF = tupleRDD.toDF("name", "age", "id")
```

- If RDD contains `case` class instances, Spark infers the attributes from it.

```
case class Person(name: String, age: Int, id: Int)
val peopleRDD = sc.parallelize(Array(Person("seif", 65, 0), Person("amir", 40, 1)))
val peopleDF = peopleDF.toDF
```

# Creating a DataFrame - From Data Source

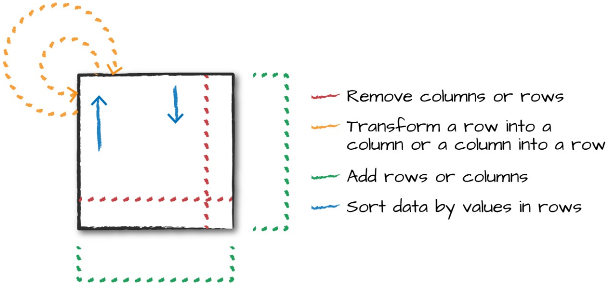
- Data sources supported by Spark.
  - CSV, JSON, Parquet, ORC, JDBC/ODBC connections, Plain-text files
  - Cassandra, HBase, MongoDB, AWS Redshift, XML, etc.

```
val peopleJson = spark.read.format("json").load("people.json")

val peopleCsv = spark.read.format("csv")
  .option("sep", ";")
  .option("inferSchema", "true")
  .option("header", "true")
  .load("people.csv")
```

# DataFrame Transformations (1/5)

- Add and remove rows or columns
- Transform a row into a column (or vice versa)
- Change the order of rows based on the values in columns




[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

# DataFrame Transformations (2/5)

- `select` and `selectExpr` allow to do the DataFrame equivalent of SQL queries on a table of data.

```
// select
people.select("name", "age", "id").show(2)
```

```
// selectExpr
people.selectExpr("*", "(age < 20) as teenager").show()
people.selectExpr("avg(age)", "count(distinct(name))", "sum(id)").show()
```

# DataFrame Transformations (3/5)

- `filter` and `where` both filter rows.
- `distinct` can be used to extract unique rows.

```
people.filter("age < 20").show()

people.where("age < 20").show()

people.select("name").distinct().show()
```

# What is the output?

```
people.selectExpr("avg(age)", "count(distinct(name)) as distinct").show()

+---+---+-------+
|age| id|   name|
+---+---+-------+
| 15| 12|Michael|
| 30| 15|   Andy|
| 19| 20|   Andy|
+---+---+-------+
```

```
Option 1                    Option 2
+--------+--------+         +--------+--------+
|avg(age)|distinct|         |avg(age)|distinct|
+--------+--------+         +--------+--------+
|  21.333|       3|         |  21.333|       2|
+--------+--------+         +--------+--------+
```

# DataFrame Transformations (4/5)

- `withColumn` adds a new column to a DataFrame.
- `withColumnRenamed` renames a column.
- `drop` removes a column.

```
// withColumn
people.withColumn("teenager", expr("age < 20")).show()

// withColumnRenamed
people.withColumnRenamed("name", "username").columns

// drop
people.drop("name").columns
```

# What is the output?

```
people.withColumn("teenager", expr("age < 20")).show()

+---+---+-------+
|age| id|   name|
+---+---+-------+
| 15| 12|Michael|
| 30| 15|   Andy|
| 19| 20| Justin|
+---+---+-------+
```

```
Option 1
+---+---+-------+--------+
|age| id|   name|teenager|
+---+---+-------+--------+
| 15| 12|Michael|    true|
| 30| 15|   Andy|   false|
| 19| 20| Justin|    true|
+---+---+-------+--------+
```

```
Option 2
+---+---+-------+--------+
|age| id|   name|teenager|
+---+---+-------+--------+
| 15| 12|Michael|    true|
| 19| 20| Justin|    true|
+---+---+-------+--------+
```

# DataFrame Transformations (5/5)

- You can use udf to define new column-based functions.

```
import org.apache.spark.sql.functions.{col, udf}

val df = spark.createDataFrame(Seq((0, "hello"), (1, "world"))).toDF("id", "text")

val upper: String => String = _.toUpperCase
val upperUDF = spark.udf.register("upper", upper)

df.withColumn("upper", upperUDF(col("text"))).show
```

# DataFrame Actions

- Like RDDs, DataFrames also have their own set of actions.
- `collect`: returns an array that contains all of rows in this DataFrame.
- `count`: returns the number of rows in this DataFrame.
- `first` and `head`: returns the first row of the DataFrame.
- `show`: displays the top 20 rows of the DataFrame in a tabular form.
- `take`: returns the first n rows of the DataFrame.

# Aggregation

# Aggregation

- In an aggregation you specify
  - A key or grouping
  - An aggregation function
- The given function must produce one result for each group.

# Grouping Types

- Summarizing a complete DataFrame
- Group by
- Windowing

# Grouping Types

- Summarizing a complete DataFrame
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# Summarizing a Complete DataFrame Functions (1/2)

- count returns the total number of values.
- countDistinct returns the number of unique groups.
- first and last return the first and last value of a DataFrame.

```
val people = spark.read.format("json").load("people.json")

people.select(count("age")).show()

people.select(countDistinct("name")).show()

people.select(first("name"), last("age")).show()
```

# Summarizing a Complete DataFrame Functions (2/2)

- min and max extract the minimum and maximum values from a DataFrame.
- sum adds all the values in a column.
- avg calculates the average.

```
val people = spark.read.format("json").load("people.json")

people.select(min("name"), max("age"), max("id")).show()

people.select(sum("age")).show()

people.select(avg("age")).show()
```

# Grouping Types

- Summarizing a complete DataFrame
- Group by
- Windowing

# Group By (1/3)

- Perform aggregations on groups in the data.
- Typically on categorical data.
- We do this grouping in two phases:
  1. Specify the column(s) on which we would like to group.
  2. Specify the aggregation(s).

# Group By (2/3)

- Grouping with expressions
  - Rather than passing that function as an expression into a `select` statement, we specify it as within agg.

```
val people = spark.read.format("json").load("people.json")

people.groupBy("name").agg(count("age").alias("ageagg")).show()
```

# Group By (3/3)

- Grouping with Maps
  - Specify transformations as a series of Maps
  - The key is the column, and the value is the aggregation function (as a string).

```
val people = spark.read.format("json").load("people.json")

people.groupBy("name").agg("age" -> "count", "age" -> "avg", "id" -> "max").show()
```

# What is the output?

```
people.groupBy("name").agg("age" -> "count", "age" -> "avg", "id" -> "max").show()

+---+---+-------+
|age| id|   name|
+---+---+-------+
| 15| 12|Michael|
| 30| 15|   Andy|
| 19| 20|   Andy|
+---+---+-------+
```

```
Option 1
+-------+----------+--------+-------+
|   name|count(age)|avg(age)|max(id)|
+-------+----------+--------+-------+
|Michael|         1|    15.0|     12|
|   Andy|         2|    24.5|     20|
+-------+----------+--------+-------+
```

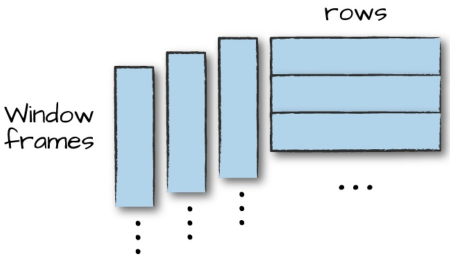
```
Option 2
+-------+----------+--------+-------+
|   name|count(age)|avg(age)|max(id)|
+-------+----------+--------+-------+
|Michael|         1|   21.33|     20|
|   Andy|         2|   21.33|     20|
+-------+----------+--------+-------+
```

# Grouping Types

- Summarizing a complete DataFrame
- Group by
- Windowing

# Windowing (1/2)

- Computing some aggregation on a specific window of data.
- The window determines which rows will be passed in to this function.
- You define them by using a reference to the current data.
- A group of rows is called a frame.




[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

# Windowing (2/2)

- Unlike grouping, here each row can fall into one or more frames.

```
import org.apache.spark.sql.expressions.Window
import org.apache.spark.sql.functions.col

val people = spark.read.format("json").load("people.json")

val windowSpec = Window.rowsBetween(-1, 1)
val avgAge = avg(col("age")).over(windowSpec)
people.select(col("name"), col("age"), avgAge.alias("avg_age")).show
```

# What is the output?

```
val windowSpec = Window.rowsBetween(-1, 1)
val avgAge = avg(col("age")).over(windowSpec)
people.select(col("name"), col("age"), avgAge.alias("avg_age")).show()

+---+---+-------+
|age| id|   name|
+---+---+-------+
| 15| 12|Michael|
| 30| 15|   Andy|
| 19| 20|   Andy|
+---+---+-------+
Option 1                          Option 2
+-------+---+--------+            +-------+---+--------+
|   name|age| avg_age|            |   name|age| avg_age|
+-------+---+--------+            +-------+---+--------+
|Michael| 15|    22.5|            |Michael| 15|     7.5|
|   Andy| 30|   21.33|            |   Andy| 30|    22.5|
|   Andy| 19|    24.5|            |   Andy| 19|   21.33|
+-------+---+--------+            +-------+---+--------+
```

# Joins

# Joins

- Joins are relational constructs you use to combine relations together.
- Different join types: inner join, outer join, left outer join, right outer join, left semi join, left anti join, cross join

| Employee ID | First Name | Department ID |
|---|---|---|
| 1 | John | 10 |
| 2 | Daniel | 20 |
| 3 | Anne | 10 |
| 4 | George | 20 |
| 5 | Tim | 10 |

| Department ID | Department Name |
|---|---|
| 10 | Sales |
| 20 | HR |

| First Name | Department Name |
|---|---|
| John | Sales |
| Daniel | HR |
| Anne | Sales |
| George | HR |
| Tim | Sales |

# Joins Example

```
val person = Seq((0, "Seif", 0), (1, "Amir", 1), (2, "Sarunas", 1))
                .toDF("id", "name", "group_id")

val group = Seq((0, "SICS/KTH"), (1, "KTH"), (2, "SICS"))
               .toDF("id", "department")
```

# Joins Example - Inner

```
val joinExpression = person.col("group_id") === group.col("id")

var joinType = "inner"

person.join(group, joinExpression, joinType).show()
```

```
+---+-------+--------+---+----------+
| id|   name|group_id| id|department|
+---+-------+--------+---+----------+
|  0|   Seif|       0|  0|  SICS/KTH|
|  1|   Amir|       1|  1|       KTH|
|  2|Sarunas|       1|  1|       KTH|
+---+-------+--------+---+----------+
```

# Joins Example - Outer

```
val joinExpression = person.col("group_id") === group.col("id")

var joinType = "outer"

person.join(group, joinExpression, joinType).show()
```

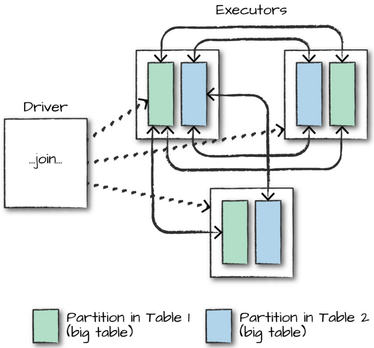
```
+----+-------+--------+---+----------+
|  id|   name|group_id| id|department|
+----+-------+--------+---+----------+
|   1|   Amir|       1|  1|       KTH|
|   2|Sarunas|       1|  1|       KTH|
|null|   null|    null|  2|      SICS|
|   0|   Seif|       0|  0|  SICS/KTH|
+----+-------+--------+---+----------+
```

# Joins Communication Strategies

- Two different communication ways during joins:
  - Shuffle join: big table to big table
  - Broadcast join: big table to small table

# Shuffle Join

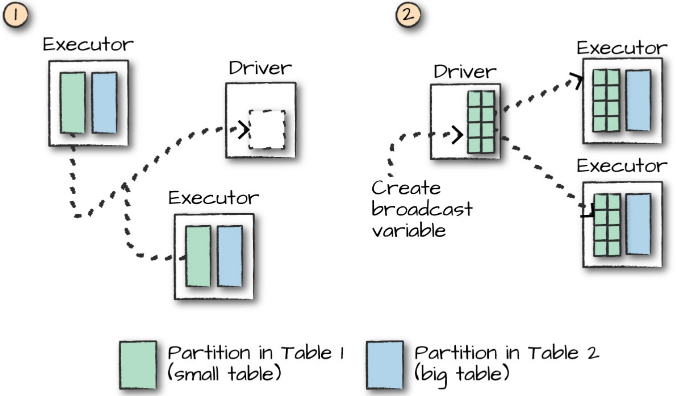
- Every node talks to every other node.
- They share data according to which node has a certain key or set of keys.




[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

# Broadcast Join

- When the table is small enough to fit into the memory of a single worker node.




[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

# SQL

# SQL

- You can run SQL queries on views/tables via the method `sql` on the `SparkSession` object.

```
spark.sql("SELECT * from people_view").show()
```

```
+---+---+-------+
|age| id|   name|
+---+---+-------+
| 15| 12|Michael|
| 30| 15|   Andy|
| 19| 20| Justin|
| 12| 15|   Andy|
| 19| 20|    Jim|
| 12| 10|   Andy|
+---+---+-------+
```

# Temporary View

- `createOrReplaceTempView` creates (or replaces) a lazily evaluated view.
- You can use it like a table in Spark SQL.

```
people.createOrReplaceTempView("people_view")

val teenagersDF = spark.sql("SELECT name, age FROM people_view WHERE age BETWEEN 13 AND 19")
```

# DataSet

# Untyped API with DataFrame

- DataFrames elements are `Rows`, which are generic untyped JVM objects.
- Scala compiler cannot type check Spark SQL schemas in DataFrames.
- The following code compiles, but you get a runtime exception.
  - `id_num` is not in the DataFrame columns `[name, age, id]`

```
// people columns: ("name", "age", "id")
val people = spark.read.format("json").load("people.json")

people.filter("id_num < 20") // runtime exception
```

# Why DataSet?

- Assume the following example

```
case class Person(name: String, age: BigInt, id: BigInt)
val peopleRDD = sc.parallelize(Array(Person("seif", 65, 0), Person("amir", 40, 1)))
val peopleDF = peopleRDD.toDF
```

- Now, let's use `collect` to bring back it to the master.

```
val collectedPeople = peopleDF.collect()
// collectedPeople: Array[org.apache.spark.sql.Row]
```

- What is in `Row`?

# Why DataSet?

- To be able to work with the collected values, we should cast the Rows.
  - How many columns?
  - What types?

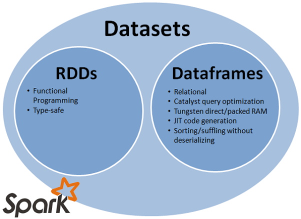
```
// Person(name: Sting, age: BigInt, id: BigInt)

val collectedList = collectedPeople.map {
  row => (row(0).asInstanceOf[String], row(1).asInstanceOf[Int], row(2).asInstanceOf[Int])
}
```

- But, what if we cast the types wrong?
- Wouldn't it be nice if we could have both Spark SQL optimizations and typesafety?

# DataSet

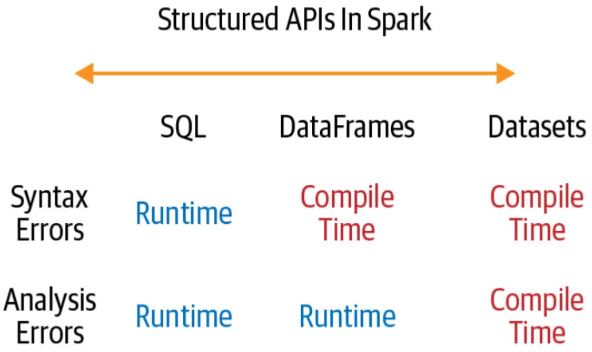
- Datasets can be thought of as typed distributed collections of data.
- Dataset API unifies the DataFrame and RDD APIs.
- You can consider a `DataFrame` as an alias for `Dataset[Row]`, where a `Row` is a generic untyped JVM object.

```
type DataFrame = Dataset[Row]
```




[http://why-not-learn-something.blogspot.com/2016/07/apache-spark-rdd-vs-dataframe-vs-dataset.html]

# Structured APIs in Spark




[J.S. Damji et al., Learning Spark - Lightning-Fast Data Analytics]

# Creating DataSets

- To convert a sequence or an RDD to a Dataset, we can use `toDS()`.
- You can call `as[SomeCaseClass]` to convert the DataFrame to a Dataset.

```
case class Person(name: String, age: BigInt, id: BigInt)
val personSeq = Seq(Person("Max", 33, 0), Person("Adam", 32, 1))
```

```
val ds1 = sc.parallelize(personSeq).toDS
```

```
val ds2 = spark.read.format("json").load("people.json").as[Person]
```

# DataSet Transformations

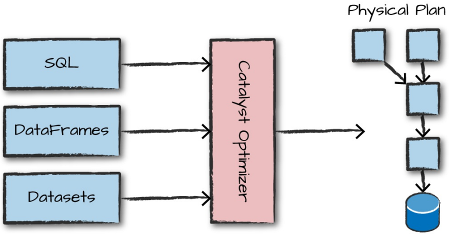
- Transformations on Datasets are the same as those that we had on DataFrames.
- Datasets allow us to specify more complex and strongly typed transformations.

```
case class Person(name: String, age: BigInt, id: BigInt)

val people = spark.read.format("json").load("people.json").as[Person]

people.filter(x => x.age < 40).show()

people.map(x => (x.name, x.age + 5, x.id)).show()
```

# Structured Data Execution

# Structured Data Execution Steps

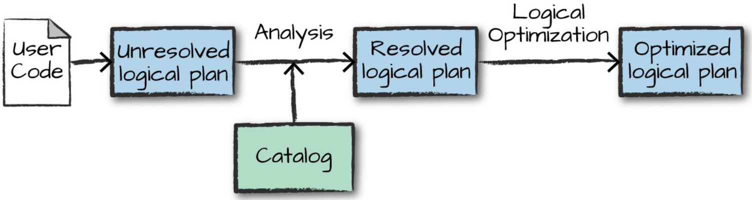
- 1. Write DataFrame/Dataset/SQL Code.
- 2. If valid code, Spark converts this to a logical plan.
- 3. Spark transforms this logical plan to a Physical Plan
  - Checking for optimizations along the way.
- 4. Spark then executes this physical plan (RDD manipulations) on the cluster.




[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

# Logical Planning (1/2)

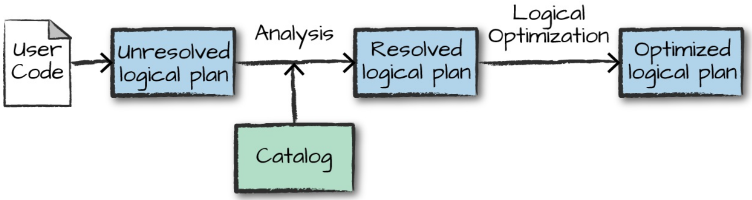
- The logical plan represents a set of abstract transformations.
- This plan is unresolved.
  - The code might be valid, the tables/columns that it refers to might not exist.
- Spark uses the catalog, a repository of all table and DataFrame information, to resolve columns and tables in the analyzer.




[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

# Logical Planning (2/2)

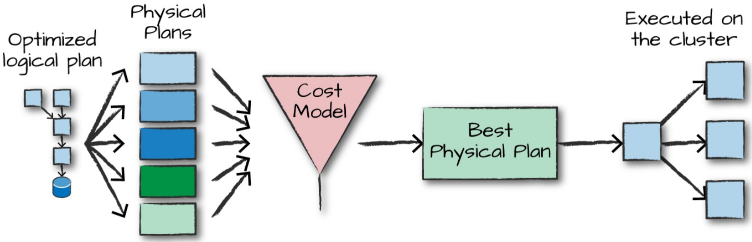
- The analyzer might reject the unresolved logical plan.
- If the analyzer can resolve it, the result is passed through the Catalyst optimizer.
- It converts the user's set of expressions into the most optimized version.




[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

# Physical Planning

- The physical plan specifies how the logical plan will execute on the cluster.
- Physical planning results in a series of RDDs and transformations.




[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

# Execution

- Upon selecting a physical plan, Spark runs all of this code over RDDs.
- Spark performs further optimizations at runtime.
- Finally the result is returned to the user.

# Summary

# Summary

- RDD vs. DataFrame vs. DataSet
- Logical and physical plans

# References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Questions?