Higher Order Functions

Herman van Hövell @westerflyer

2018-10-03, London Spark Summit EU 2018

databricks

About Me

- Software Engineer @Databricks Amsterdam office
- Apache Spark Committer and PMC member
- In a previous life Data Engineer & Data Analyst.

Complex Data

Complex data types in Spark SQL

- Struct. For example: struct(a: Int, b: String)
- Array. For example: array(a: Int)
- Map. For example: map(key: String, value: Int)

This provides primitives to build tree-based data models

- High expressiveness. Often alleviates the need for ‘flat-earth’ multi-table designs.
- More natural, reality like data models

Complex Data - Tweet JSON


```
{
  "created_at": "Wed Oct 03 11:41:57 +0000 2018",
  "id_str": "994633657141813248",
  "text": "Looky nested data #spark #sseu",
  "display_text_range": [0, 140],
  "user": {
    "id_str": "12343453",
    "screen_name": "Westerflyer"
  },
  "extended_tweet": {
    "full_text": "Looky nested data #spark #sseu",
    "display_text_range": [0, 249],
    "entities": {
      "hashtags": [{
        "text": "spark",
        "indices": [211, 225]
      }, {
        "text": "sseu",
        "indices": [239, 249]
      }]
    }
  }
}
```


```
root
 |-- created_at: string (nullable = true)
 |-- id_str: string (nullable = true)
 |-- text: string (nullable = true)
 |-- user: struct (nullable = true)
 |    |-- id_str: string (nullable = true)
 |    |-- screen_name: string (nullable = true)
 |-- display_text_range: array (nullable = true)
 |    |-- element: long (containsNull = true)
 |-- extended_tweet: struct (nullable = true)
 |    |-- full_text: string (nullable = true)
 |    |-- display_text_range: array (nullable = true)
 |    |    |-- element: long (containsNull = true)
 |    |-- entities: struct (nullable = true)
 |    |    |-- hashtags: array (nullable = true)
 |    |    |    |-- element: struct (containsNull = true)
 |    |    |    |    |-- indices: array (nullable = true)
 |    |    |    |    |    |-- element: long (containsNull = true)
 |    |    |    |    |-- text: string (nullable = true)
```


adapted from: https://developer.twitter.com/en/docs/tweets/data-dictionary/overview/intro-to-tweet-json.html

Manipulating Complex Data

Structs are easy :)

Maps/Arrays not so much...

- Easy to read single values/retrieve keys
- Hard to transform or to summarize

Transforming an Array

Let's say we want to add `1` to every element of the `vals` field of every row in an input table.

Id	Vals
1	[1, 2, 3]
2	[4, 5, 6]

→

Id	Vals
1	[2, 3, 4]
2	[5, 6, 7]

How would we do this?

Transforming an Array

Option 1 - Explode and Collect

```
select    id,
          collect_list(val + 1) as vals
from     (select id,
                 explode(vals) as val
         from   input_tbl) x
group by id
```

Transforming an Array

Option 1 - Explode and Collect - Explode

```
select    id,
          collect_list(val + 1) as vals
from     (select id,
                 explode(vals) as val
         from   input_tbl) x
group by id
```

1. Explode

Transforming an Array

Option 1 - Explode and Collect - Explode

Id	Vals
1	[1, 2, 3]
2	[4, 5, 6]

Id	Val
1	1
1	2
1	3
2	4
2	5
2	6

Transforming an Array

Option 1 - Explode and Collect - Collect

```
select    id,
          collect_list(val + 1) as vals      2. Collect
from     (select id,
                explode(vals) as val         1. Explode
         from   input_tbl) x
group by id
```

Transforming an Array

Option 1 - Explode and Collect - Collect

Id	Val
1	1 + 1
1	2 + 1
1	3 + 1
2	4 + 1
2	5 + 1
2	6 + 1

Id	Vals
1	[2, 3, 4]
2	[5, 6, 7]

Transforming an Array

Option 1 - Explode and Collect - Complexity

```
== Physical Plan ==
ObjectHashAggregate(keys=[id], functions=[collect_list(val + 1)])
+- Exchange hashpartitioning(id, 200)
   +- ObjectHashAggregate(keys=[id], functions=[collect_list(val + 1)])
      +- Generate explode(vals), [id], false, [val]
         +- FileScan parquet default.input_tbl
```

Transforming an Array

Option 1 - Explode and Collect - Complexity

```
== Physical Plan ==
ObjectHashAggregate(keys=[id], functions=[collect_list(val + 1)])
+- Exchange hashpartitioning(id, 200)
   +- ObjectHashAggregate(keys=[id], functions=[collect_list(val + 1)])
      +- Generate explode(vals), [id], false, [val]
         +- FileScan parquet default.input_tbl
```

- Shuffles the data around, which is very expensive
- collect_list does not respect pre-existing ordering

Transforming an Array

Option 1 - Explode and Collect - Pitfalls

Keys need to be unique

Id	Vals
1	[1, 2, 3]
1	[4, 5, 6]

Id	Vals
1	[5, 6, 7, 2, 3, 4]

Values need to have data

Id	Vals
1	null
2	[4, 5, 6]

Id	Vals
2	[5, 6, 7]

Transforming an Array

Option 2 - Scala UDF

```
def addOne(values: Seq[Int]): Seq[Int] = {
  values.map(value => value + 1)
}
```

Transforming an Array

Option 2 - Scala UDF

```
def addOne(values: Seq[Int]): Seq[Int] = {
  values.map(value => value + 1)
}
val plusOneInt = spark.udf.register("plusOneInt", addOne(_:Seq[Int]):Seq[Int])
```

Transforming an Array

Option 2 - Scala UDF

```
def addOne(values: Seq[Int]): Seq[Int] = {
  values.map(value => value + 1)
}
val plusOneInt = spark.udf.register("plusOneInt",  addOne(_:Seq[Int]):Seq[Int])

val newDf = spark.table("input_tbl").select($"id", plusOneInt($"vals"))
```

Transforming an Array

Option 2 - Scala UDF

Pros

- Is faster than Explode & Collect
- Does not suffer from correctness pitfalls

Cons

- Is relatively slow, we need to do a lot serialization
- You need to register UDFs per type
- Does not work for SQL
- Clunky

When are you going to talk about Higher Order Functions?

Higher Order Functions

Let’s take another look at Option 2 - Scala UDF

```
def addOne(values: Seq[Int]): Seq[Int] = {
  values.map(value => value + 1)
}
val plusOneInt = spark.udf.register("plusOneInt",
addOne(_:Seq[Int]):Seq[Int])

val newDf = spark.table("input_tbl").select($"id", plusOneInt($"vals"))
```

Higher Order Functions

Let’s take another look at Option 2 - Scala UDF

```
def addOne(values: Seq[Int]): Seq[Int] = {
  values.map(value => value + 1)
}
val plusOneInt = spark.udf.register("plusOneInt",
addOne(_:Seq[Int]):Seq[Int])

val newDf = spark.table("input_tbl").select($"id", plusOneInt($"vals"))
```

Higher Order Function

Higher Order Functions

Let's take another look at Option 2 - Scala UDF

```
def addOne(values: Seq[Int]): Seq[Int] = {
  values.map(value => value + 1)
}
val plusOneInt = spark.udf.register("plusOneInt",
addOne(_:Seq[Int]):Seq[Int])

val newDf = spark.table("input_tbl").select($"id", plusOneInt($"vals"))
```

Anonymous 'Lambda' Function

Higher Order Function

Can we do the same for Spark SQL?

Higher Order Functions in Spark SQL

```
select  id, transform(vals, val -> val + 1) as vals
from    input_tbl
```

- Spark SQL native code: fast & no serialization needed
- Works for SQL

Higher Order Functions in Spark SQL

```
select  id, transform(vals, val -> val + 1) as vals
from    input_tbl
```

Higher Order Function

`transform` is the Higher Order Function. It takes an input array and an expression, it applies this expression to each element in the array

Higher Order Functions in Spark SQL

```
select  id, transform(vals, val -> val + 1) as vals
from    input_tbl
```

Anonymous 'Lambda' Function

`val -> val + 1` is the lambda function. It is the operation that is applied to each value in the array. This function is divided into two components separated by a `->` symbol:

1. The Argument list.
2. The expression used to calculate the new value.

Higher Order Functions in Spark SQL

Nesting

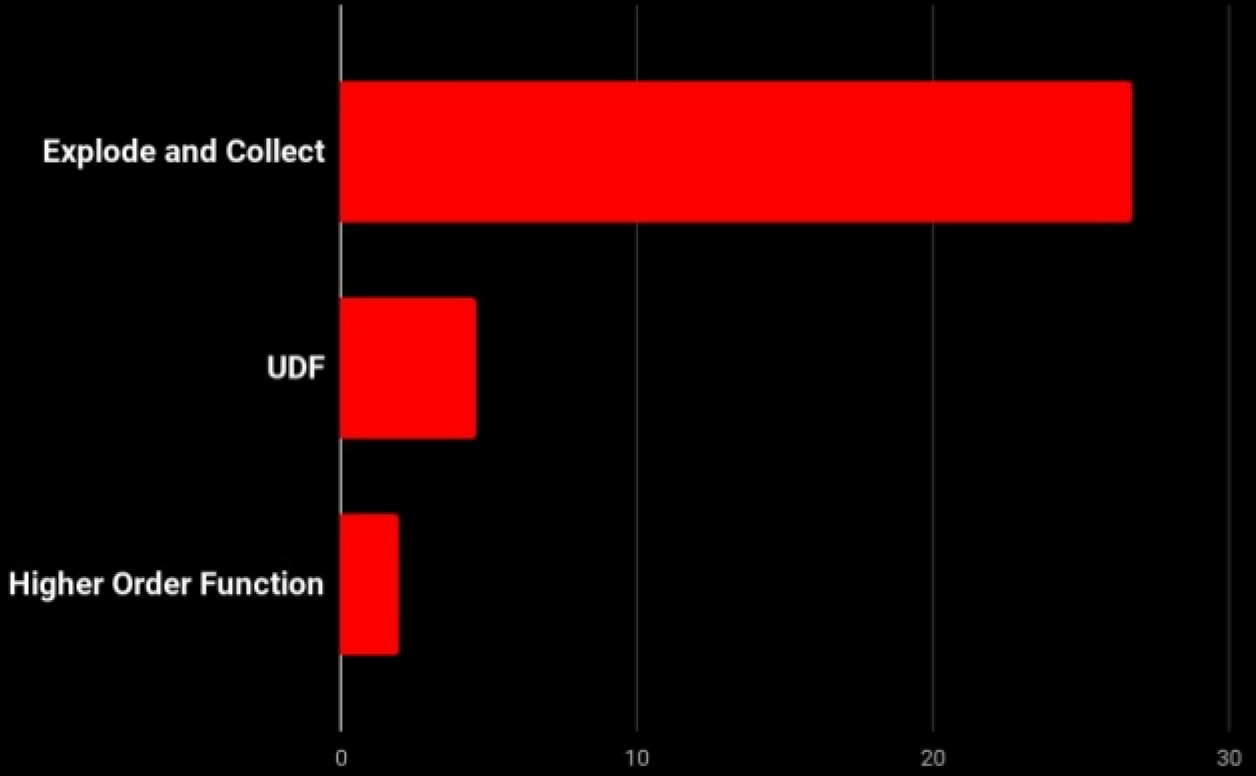
```
select  id,
        transform(vals, val ->
          transform(val, e -> e + 1)) as vals
from    nested_input_tbl
```

Capture

```
select  id,
        ref_value,
        transform(vals, val -> ref_value + val) as vals
from    nested_input_tbl
```

Didn't you say these were faster?

Performance



Higher Order Functions in Spark SQL

Spark 2.4 will ship with following higher order functions:

Array

- transform
- filter
- exists
- aggregate/reduce
- zip_with

Map

- transform_keys
- transform_values
- map_filter
- map_zip_with

A lot of new collection based expression were also added...

Future work

Arrays and Maps have received a lot of love. However working with wide structs fields is still non-trivial (a lot of typing). We can do better here:

- The following dataset functions should work for nested fields:
  - withColumn()
  - withColumnRenamed()
- The following functions should be added for struct fields:
  - select()
  - withColumn()
  - withColumnRenamed()

Disclaimer: *All of this is speculative and has not been discussed on the Dev list!*

Questions?

databricks