Demystifying DataFrame and Dataset

#SFdev20

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About Me – Kazuaki Ishizaki

- Researcher at IBM Research in compiler optimizations
- Working for IBM Java virtual machine over 20 years
  - In particular, just-in-time compiler
- Contributor to SQL package in Apache Spark
- Committer of GPUEnabler
  - Apache Spark Plug-in to execute GPU code on Spark
    - https://github.com/IBMSparkGPU/GPUEnabler
- Homepage: http://ibm.biz/ishizaki
- Github: https://github.com/kiszk, Twitter: @kiszk

Spark 2.2 makes Dataset Faster Compared to Spark 2.0 (also 2.1)

- 1.6x faster for `map()` with scalar variable

```
ds = (1 to ...).toDS.cache
ds.map(value => value + 1)
```

- 4.5x faster for `map()` with primitive array

```
ds = Seq(Array(…), Array(…), …).toDS.cache
ds.map(array => Array(array(0)))
```

from enhancements in Catalyst optimizer and codegen

How Does It Matter?

- Application programmers
  - ML pipeline will become faster ☺
- Library developers
  - You will want to use Dataset instead of RDD ☺
- SQL package developers
  - You will know detail on Dataset 😮

DataFrame, Dataset, and RDD

DataFrame (DF)

SQL

```
df = (1 to 100).toDF.cache
df.selectExpr(“value + 1”)
```

Based on SQL operation

Dataset (DS)

Scala

```
ds = (1 to 100).toDS.cache
ds.map(value => value + 1)
```

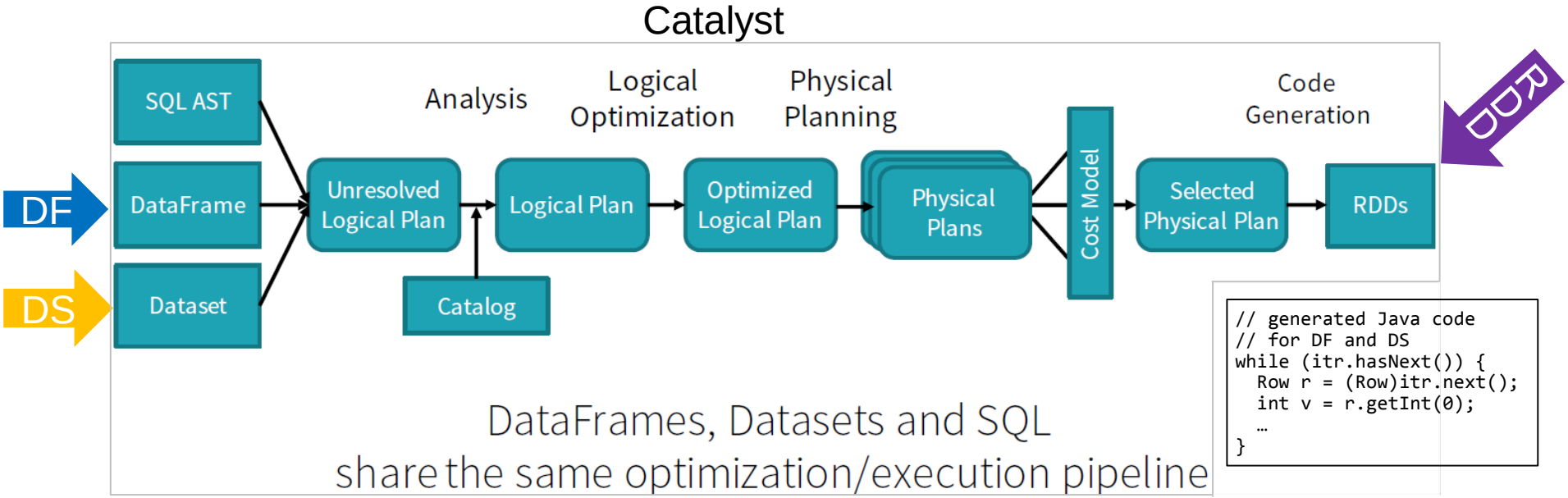
RDD

Scala

```
rdd = sc.parallelize(
  (1 to 100)).cache
rdd.map(value => value + 1)
```

Based on lambda expression

How DF, DS, and RDD Work



From Structuring Apache Spark 2.0: SQL, DataFrames, Datasets And Streaming - by Michael Armbrust

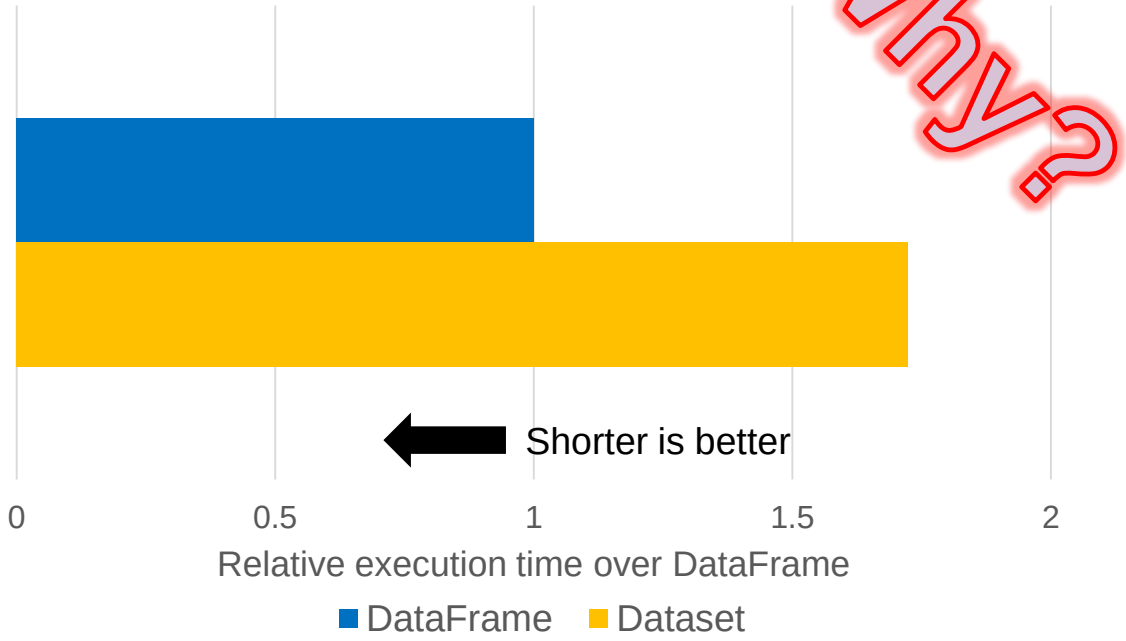
- We expect the same performance on DF and DS

Dataset for Int Value is Slow on Spark 2.0

- 1.7x slow for addition to scalar int value

```
df.selectExpr(“value + 1”)
```

```
ds.map(value => value + 1)
```



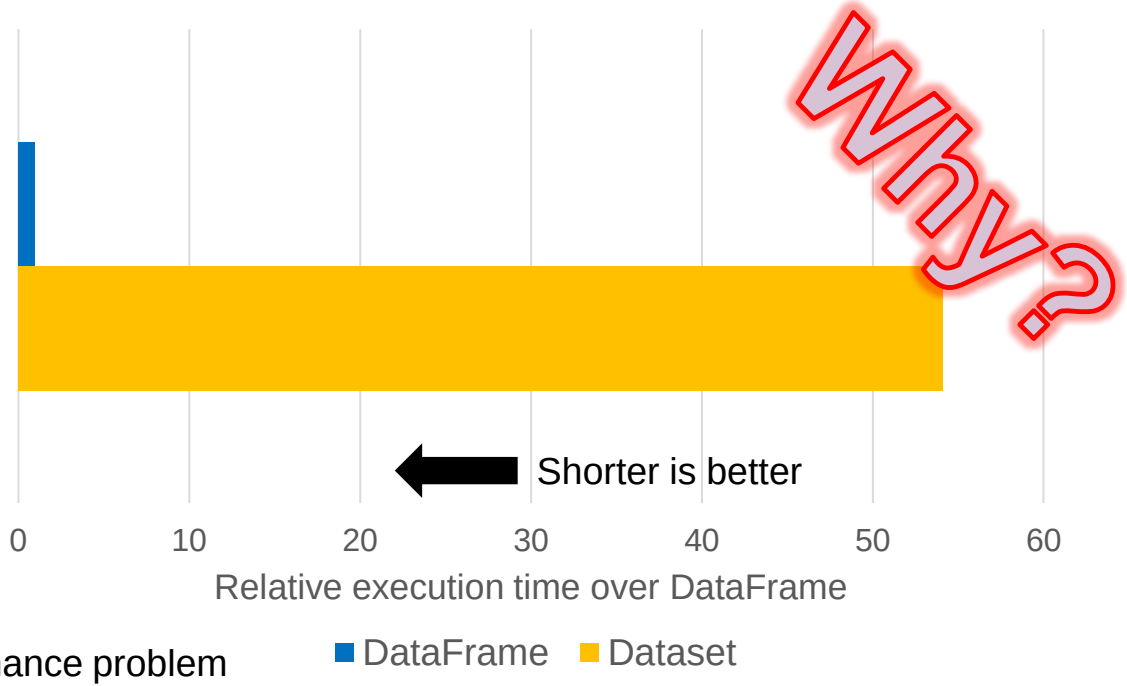
All experiments are done using
16-core Intel E2667-v3 3.2GHz, with 384GB mem, Ubuntu 16.04,
OpenJDK 1.8.0u212-b13 with 256GB heap, Spark master=local[1]
Spark branch-2.0 and branch-2.2, ds/df/rdd are cached

Dataset for Int Array is Extremely Slow on Spark 2.0

- 54x slow for creating a new array for primitive int array

```
df = Seq(Array(…), Array(…), …)
       .toDF(“a”).cache
df.selectExpr(“Array(a[0])”)
```

```
ds = Seq(Array(…), Array(…), …)
       .toDS.cache
ds.map(a => Array(a(0)))
```



SPARK-16070 pointed out this performance problem

Outline

- How DataFrame and Dataset are executed?
- Deep dive for two cases
  - Why Dataset was slow
  - How Spark 2.2 improves performance
- Deep dive for another case
  - Why Dataset is slow
  - How future Spark will improve performance
- How Dataset is used in ML pipeline?
- Next Steps

Simple Generated Code for int with DF

- Generated code performs `+` to `int`
  - Use strongly-typed ‘`int`’ variable

```
// df: DataFrame for int …
df.selectExpr(“value + 1”)
```

Catalyst

Catalyst generates Java code

```
1: while (itr.hasNext()) { // execute a row
2:   // get a value from a row in DF
3:   int value =((Row)itr.next()).getInt(0);
4:   // compute a new value
5:   int mapValue = value + 1;
6:   // store a new value to a row in DF
7:   outRow.write(0, mapValue);
8:   append(outRow);
9: }
```

Weird Generated Code with DS

- Generated code performs four data conversions
  - Use standard API with generic type method `apply(Object)`

```
// ds: Dataset[Int] …
ds.map(value => value + 1)
```

Catalyst

Catalyst generates Java code

```
while (itr.hasNext()) {
  int value = ((Row)itr.next()).getInt(0);
  Object objValue = new Integer(value);
  int mapValue = ((Integer)
    mapFunc.apply(objVal)).toValue();
  outRow.write(0, mapValue);
  append(outRow);
}
```

Scalac generates these functions from lambda expression

```
Object apply(Object obj) {
  int value = Integer(obj).toValue();
  return new Integer(apply$II(value));
}
int apply$II(int value) { return value + 1; }
```

Simple Generated Code with DS on Spark 2.2

- SPARK-19008 enables generated code to use `int` value
  - Use non-standard API with type-specialized method `apply$II(int)`

```
// ds: Dataset[Int] …
ds.map(value => value + 1)
```

Catalyst

```
while (itr.hasNext()) {
  int value = ((Row)itr.next()).getInt(0);
  int mapValue = mapFunc.apply$II(value);
  outRow.write(0, mapValue);
  append(outRow);
}
```

Scalac generates this function from lambda expression

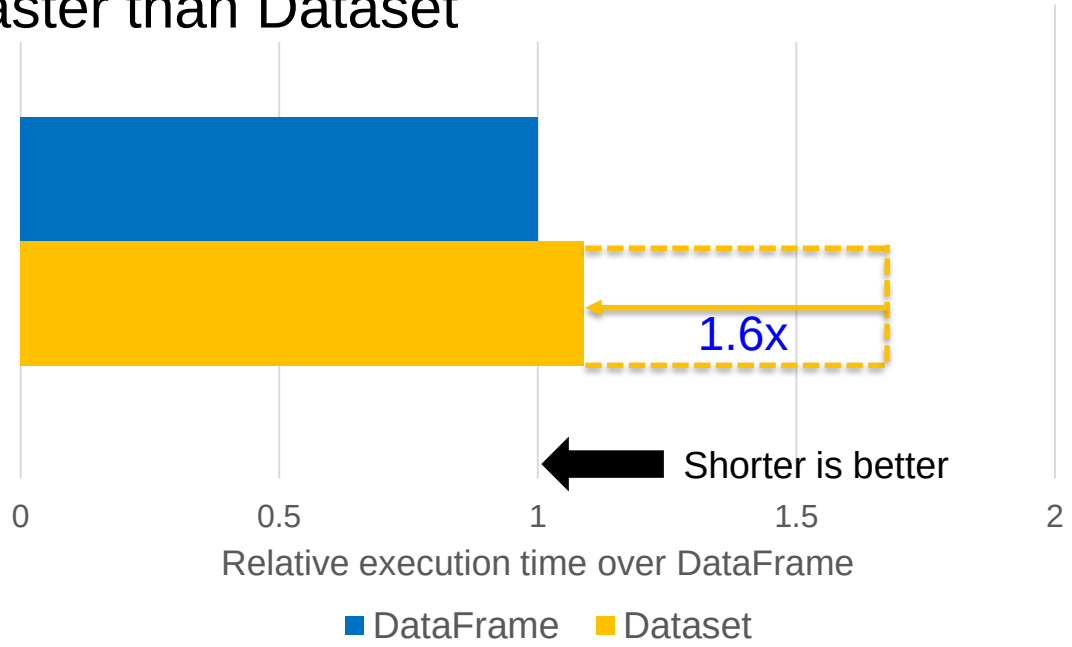
```
int apply$II(int value) { return value + 1;}
```

Dataset is Not Slow on Spark 2.2

- Improve performance by 1.6x compared to Spark 2.0
  - DataFrame is 9% faster than Dataset

```
df.selectExpr(“value + 1”)
```

```
ds.map(value => value + 1)
```



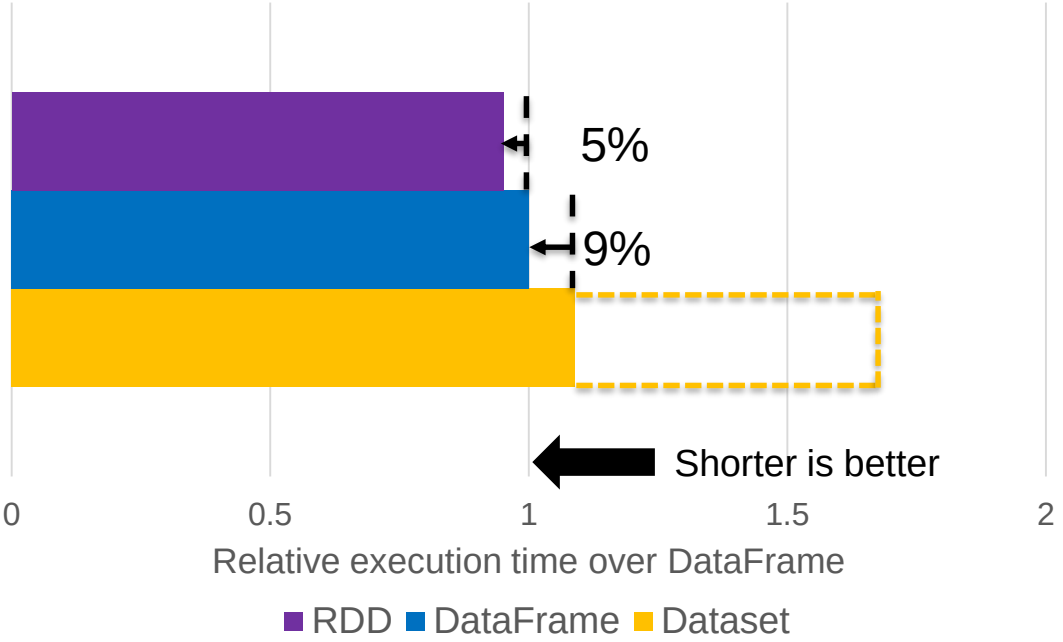
RDD/DF/DS achieve close performance on Spark 2.2

- RDD is 5% faster than DataFrame

```
rdd.map(value => value + 1)
```

```
df.selectExpr(“value + 1”)
```

```
ds.map(value => value + 1)
```



Simple Generated Code for Array with DF

- All operations access data in internal data format for array `ArrayData` (devised in Project Tungsten)

```
// df: DataFrame for Array(Int) …
df.selectExpr("Array(a[0])")
```

Catalyst

Catalyst generates Java code

```
ArrayData inArray, outArray;
while (itr.hasNext()) {
  inArray = ((Row)itr.next()).getArray(0);
  int value = inArray.getInt(0));  //a[0]
  outArray = new UnsafeArrayData(); ...
  outArray.setInt(0, value); //Array(a[0])
  outArray.writeToMemory(outRow);
  append(outRow);
}
```

Internal data format (`ArrayData`)

```
inArray.getInt(0)
outArray.setInt(0, …)
```

Lambda Expression with DS requires Java Object

- Need serialization/deserialzation (Ser/De) between internal data format and Java object for lambda expression

```
// ds: DataSet[Array(Int)] …
ds.map(a => Array(a(0)))
```

Catalyst

```
ArrayData inArray, outArray;
while (itr.hasNext()) {
  inArray = ((Row)itr.next()).getArray(0);
  Ser/De
  int[] mapArray = Array(a(0));
  Ser/De
  append(outRow);
}
```

Array(a(0))

Java bytecode for lambda expression

Java object

Serialization

Deserialization

Internal data format

Extremely Weird Code for Array with DS on Spark 2.0

- Data conversion is too slow
- Element-wise copy is slow

```
// ds: DataSet[Array(Int)] …
ds.map(a => Array(a(0)))
```

Catalyst

```
ArrayData inArray, outArray;
while (itr.hasNext()) {
  inArray = ((Row)itr.next().getArray(0);
```

Data conversion
Element-wise data copy
Element-wise data copy

Ser

```
  int[] mapArray = Array(a(0));
```

Data conversion
Element-wise data copy

De

```
  append(outRow);
}
```

Data conversion — Copy with Java object creation

Element-wise data copy — Copy each element with null check

Simple Generated Code for Array on Spark 2.2

- SPARK-15985, SPARK-17490, and SPARK-15962 simplify Ser/De by using bulk data copy
  - Data conversion and element-wise copy are not used
  - Bulk copy is faster

```
// ds: DataSet[Array(Int)] …
ds.map(a => Array(a(0)))
```

Catalyst

```
while (itr.hasNext()) {
  inArray =((Row)itr.next()).getArray(0);
  Bulk data copy
  int[] mapArray = Array(a(0));
  Bulk data copy
  Bulk data copy
  append(outRow);
}
```

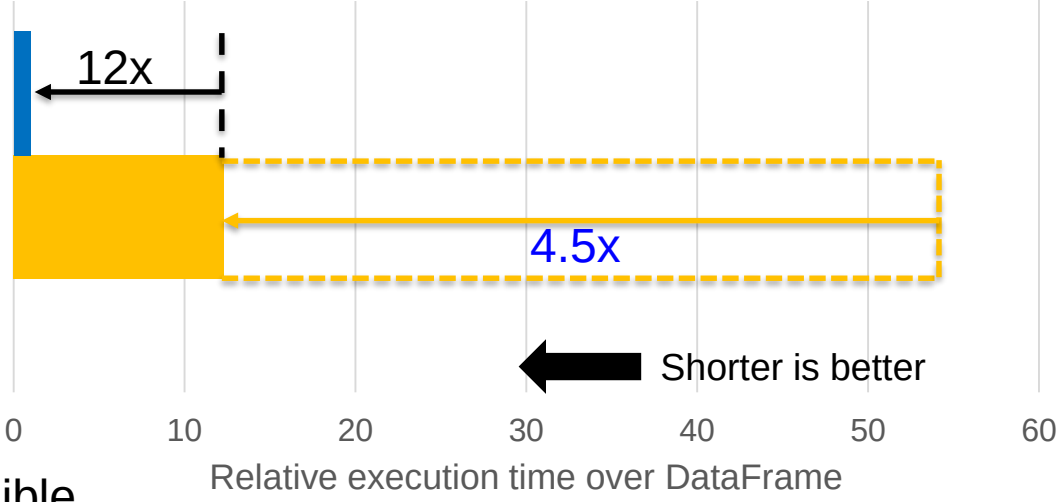
Bulk data copy Copy whole array using memcpy()

Dataset for Array is Not Extremely Slow over DataFrame

- Improve performance by 4.5 compared to Spark 2.0
  - DataFrame is 12x faster than Dataset

```
df = Seq(Array(…), Array(…), …)
       .toDF(”a”).cache
df.selectExpr(“Array(a[0])”)
```

```
ds = Seq(Array(…), Array(…), …)
       .toDS.cache
ds.map(a => Array(a(0)))
```



Would this overhead be negligible if `map()` is much computation intensive?

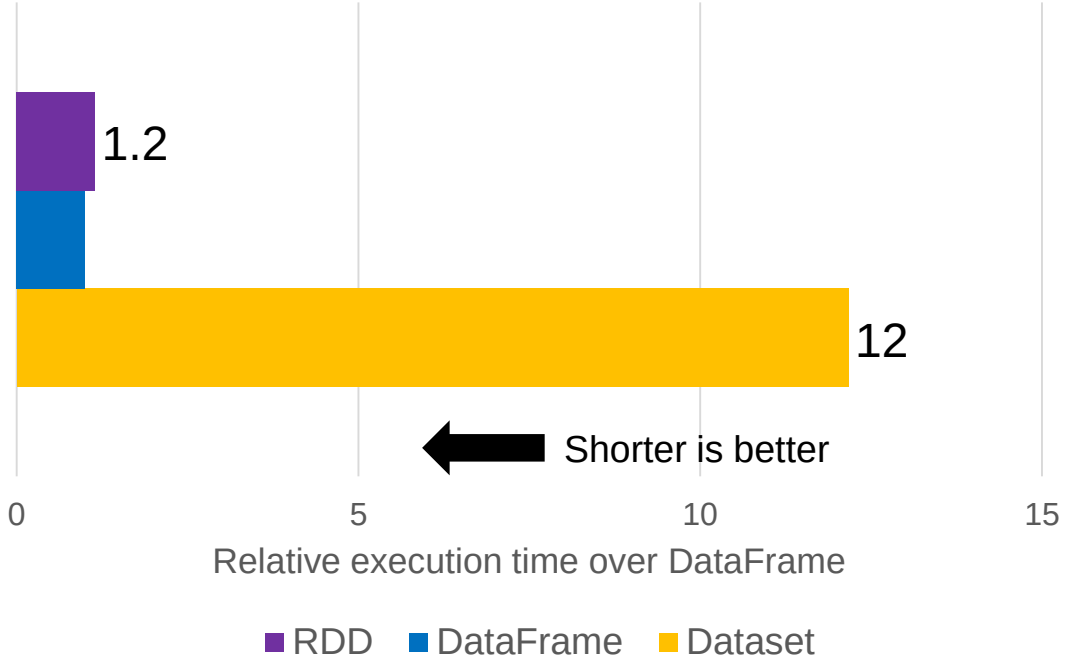
RDD and DataFrame for Array Achieve Close Performance

- DataFrame is 1.2x faster than RDD

```
rdd = sc.parallelize(Seq(
  Array(…), Array(…), …)).cache
rdd.map(a => Array(a(0)))
```

```
df = Seq(Array(…), Array(…), …)
        .toDF(”a”).cache
df.selectExpr(“Array(a[0])”)
```

```
ds = Seq(Array(…), Array(…), …)
       .toDS.cache
ds.map(a => Array(a(0)))
```



Enable Lambda Expression to Use Internal Data Format

- Our prototype modifies Java bytecode of lambda expression to access internal data format
  - We improved performance by avoiding Ser/De

```
// ds: DataSet[Array(Int)] …
ds.map(a => Array(a(0)))
```

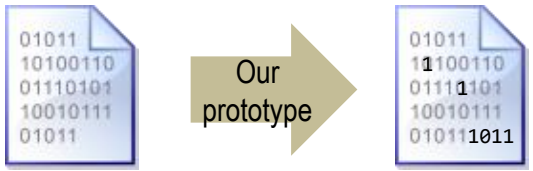
Catalyst

Catalyst generates Java code

```
while (itr.hasNext()) {
  inArray = ((Row)itr.next().getArray(0);
  outArray = mapFunc.applyTungsten(inArray);
  outArray.writeToMemory(outRow);
  append(outRow);
}
```

apply(Object)

applyTungsten(ArrayData)



Internal data format

"Accelerating Spark Datasets by inlining deserialization", our academic paper at IPDPS2017

Outline

- How DataFrame and Dataset are executed?
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  - Why Dataset is slow
  - How Spark 2.2 improve performance
- Deep dive for another case
  - Why Dataset is slow
- How Dataset are used in ML pipeline?
- Next Steps

Dataset for Two Scalar Adds is Slow on Spark 2.2

☺ DataFrame and Dataset are faster than RDD

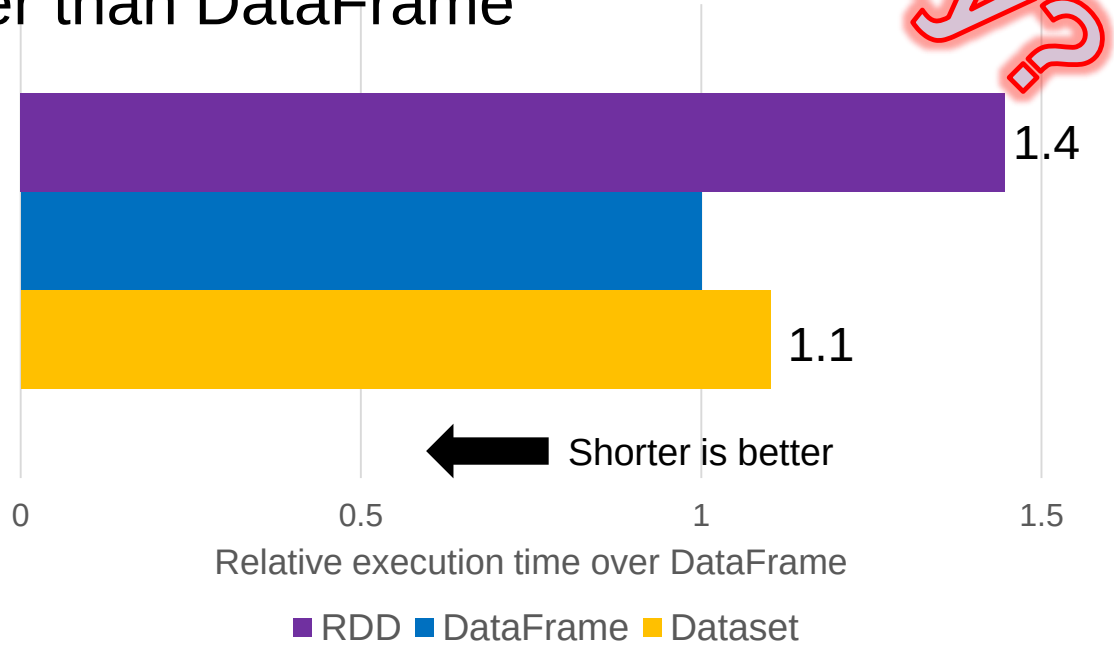
☹ Dataset is 1.1x slower than DataFrame

Why?

```
rdd.map(value => value + 1)
   .map(value => value + 2)
```

```
df.selectExpr("value + 1")
  .selectExpr("value + 2")
```

```
ds.map(value => value + 1)
  .map(value => value + 2)
```



Adds are Combined with DF

- Spark 2.2 understands operations in `selectExpr()` and combines two adds into one add ‘`value + 3`’

```
// df: DataFrame for Int …
df.selectExpr(“value + 1”)
  .selectExpr(“value + 2”)
```

Catalyst

Catalyst generates Java code

```
while (itr.hasNext()) {
  Row row = (Row)itr.next();
  int value = row.getInt(0);
  int mapValue = value + 3;
  projectRow.write(0, mapValue);
  append(projectRow);
}
```

Two Method Calls for Adds Remain with DS

- Spark 2.2 cannot understand lambda expressions stored as Java bytecode

```
// ds: Dataset[Int] …
ds.map(value => value + 1)
  .map(value => value + 2)
```

Catalyst

```
while (itr.hasNext()) {
  int value = ((Row)itr.next()).getInt(0);
  int mapValue = mapFunc1.apply$II(value);
  mapValue    += mapFunc2.apply$II(mapValue);
  outRow.write(0, mapValue);
  append(outRow);
}
```

Scalac generates these functions from lambda expression

```
class MapFunc1 {
  int apply$II(int value) { return value + 1;}}
class MapFunc2 {
  int apply$II(int value) { return value + 2;}}
```

Adds Will be Combined on Future Spark 2.x

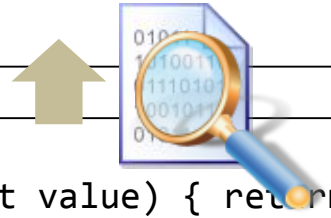
- SPARK-14083 will allow future Spark to understand Java byte code lambda expressions and to combine them

Dataset will become faster

```
// ds: Dataset[Int] …
ds.map(value => value + 1)
  .map(value => value + 2)
```

Catalyst

```
while (itr.hasNext()) {
  int value = ((Row)itr.next()).getInt(0);
  int mapValue = value + 3;
  outRow.write(0, mapValue);
  append(outRow);
}
```



```
class MapFunc1 {
  int apply$II(int value) { return value + 1;}}
class MapFunc2 {
  int apply$II(int value) { return value + 2;}}
```

Outline

- How DataFrame and Dataset are executed?
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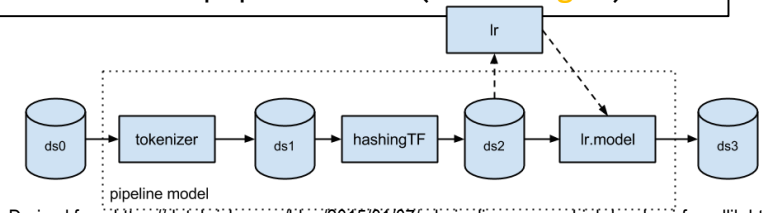
  - How Spark 2.2 improve performance
- Deep dive for another case
  - Why Dataset is slow
- How Dataset are used in ML pipeline?
- Next Steps

How Dataset is Used in ML Pipeline

- ML Pipeline is constructed by using DataFrame/Dataset
- Algorithm still operates on data in RDD
  - **Conversion** overhead between Dataset and RDD

ML pipeline

```
val trainingDS: Dataset = ...
val tokenizer = new Tokenizer()
val hashingTF = new HashingTF()
val lr = new LogisticRegression()
val pipeline = new Pipeline().setStages(
  Array(tokenizer, hashingTF, lr))
val model = pipeline.fit(trainingDS)
```



Derived from https://databricks.com/blog/2015/01/07/ml-pipelines-a-new-high-level-api-for-mllib.html

Machine learning algorithm (LogisticRegression)

```
def fit(ds: Dataset[_]) = {
  ...
  train(ds)
}
def train(ds:Dataset[_]):LogisticRegressionModel = {
  val instances: RDD[Instance] =
    ds.select(...).rdd.map {  // convert DS to RDD
      case Row(...) => ...
    }
  instances.persist(...)
  instances.treeAggregate(...)
}
```

If We Use Dataset for Machine Learning Algorithm

- ML Pipeline is constructed by using DataFrame/Dataset
- Algorithm also operates on data in DataFrame/Dataset
  - No conversion between Dataset and RDD
  - Optimizations applied by Catalyst
  - Writing of control flows

ML pipeline

```
val trainingDataset: Dataset = ...
val tokenizer = new Tokenizer()
val hashingTF = new HashingTF()
val lr = new LogisticRegression()
val pipeline = new Pipeline().setStages(
  Array(tokenizer, hashingTF, lr))
val model = pipeline.fit(trainingDataset)
```

Machine learning algorithm (LogisticRegression)

```
def train(ds:Dataset[_]):LogisticRegressionModel = {
  val instances: Dataset[Instance] =
    ds.select(...).rdd.map {
      case Row(...) => ...
    }
  instances.persist(...)
  instances.treeAggregate(...)
}
```

Next Steps

- Achieve further performance improvements for Dataset
  - Implement Java bytecode analysis and modification
    - Exploit optimizations in Catalyst (SPARK-14083)
    - Reduce overhead of data conversion (Our paper)
- Exploit SIMD/GPU in Spark by using simple generated code
  - http://www.spark.tc/simd-and-gpu/

Takeaway

- Dataset on Spark 2.2 is much faster than on Spark 2.0/2.1
- How Dataset was executed and was improved
  - Data conversion
  - Serialization/deserialization
  - Java bytecode of lambda expression
- Continue to improve performance of Dataset
- Let us start using Dataset from Today!

Thank you

- @sameeragarwal, @hvanhovell, @gatorsmile, @cloud-fan, @ueshin, @davies, @rxin, @joshrosen, @maropu, @viirya
- Spark Technology Center

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