TWO SIGMA

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Improving Python and Spark Performance and Interoperability

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Me

- Currently: Software Architect at Two Sigma Investments
- Creator of Python pandas project
- PMC member for Apache Arrow and Apache Parquet
- Other Python projects: Ibis, Feather, statsmodels
- Formerly: Cloudera, DataPad, AQR
- Author of *Python for Data Analysis*

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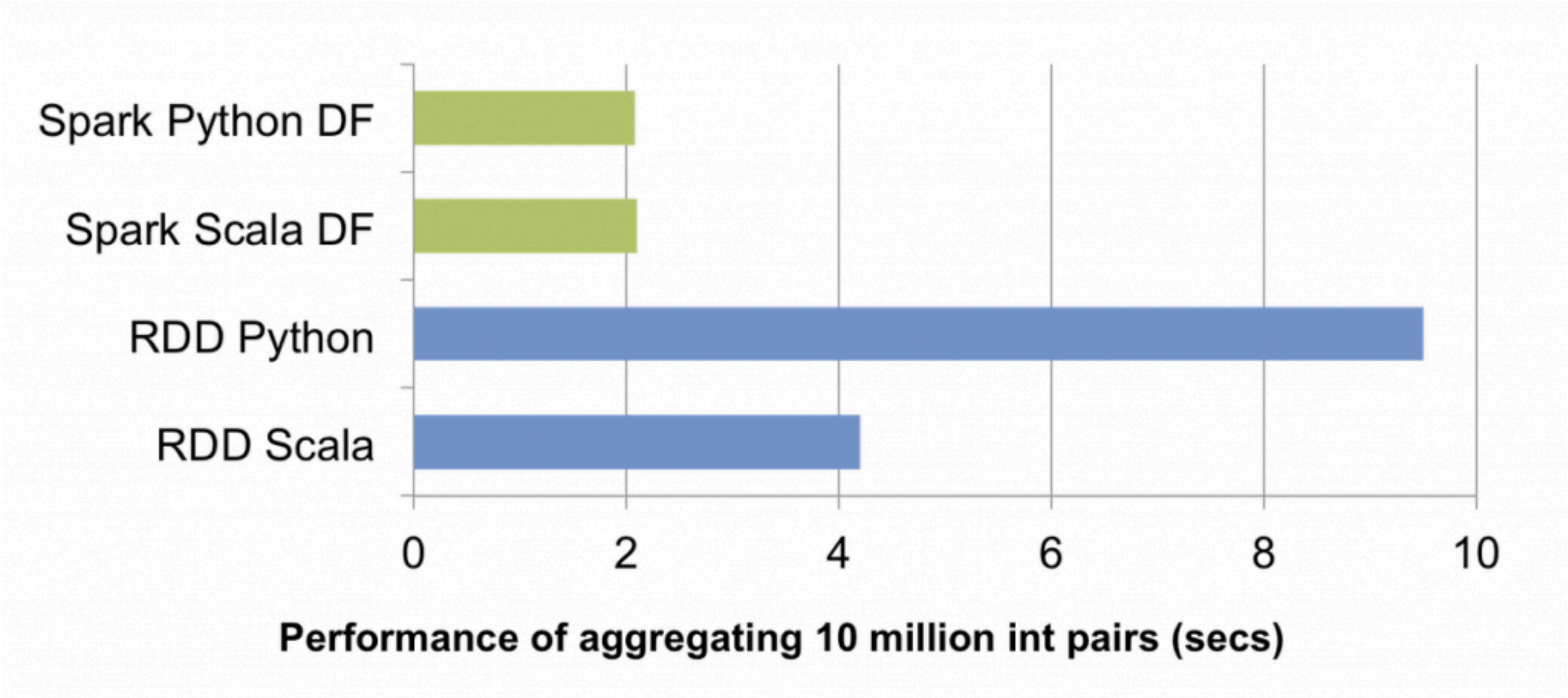
This talk

- Why some parts of PySpark are “slow”
- Technology that can help make things faster
- Work we have done to make improvements
- Future roadmap

Python and Spark

- Spark is implemented in Scala, runs on the Java virtual machine (JVM)
- Spark has Python and R APIs with partial or full coverage for many parts of the Scala Spark API
- In some Spark tasks, **Python is only a scripting front-end.**
  - **This means no interpreted Python code is executed once the Spark job starts**
- Other PySpark jobs suffer performance and interoperability issues that we're going to analyze in this talk

Spark DataFrame performance



Source: https://databricks.com/blog/2015/02/17/introducing-dataframes-in-spark-for-large-scale-data-science.html

Spark DataFrame performance can be misleading

- Spark DataFrames are an example of Python as a DSL / scripting front end
- Excepting UDFs (.map(…) or sqlContext.registerFunction), no Python code is evaluated in the Spark job
- Python API calls create SQL query plans inside the JVM — so Scala and Python versions are computationally identical

Spark DataFrames as deferred DSL

```
young = users[users.age < 21]
young.groupBy(“gender”).count()
```

Spark DataFrames as deferred DSL

```
SELECT gender, COUNT(*)
FROM users
WHERE age < 21
GROUP BY 1
```

Spark DataFrames as deferred DSL

```
Aggregation[table]
  table:
    Table: users
  metrics:
    count = Count[int64]
      Table: ref_0
  by:
    gender = Column[array(string)] 'gender' from users
  predicates:
    Less[array(boolean)]
      age = Column[array(int32)] 'age' from users
      Literal[int8]
        21
```

Where Python code and Spark meet

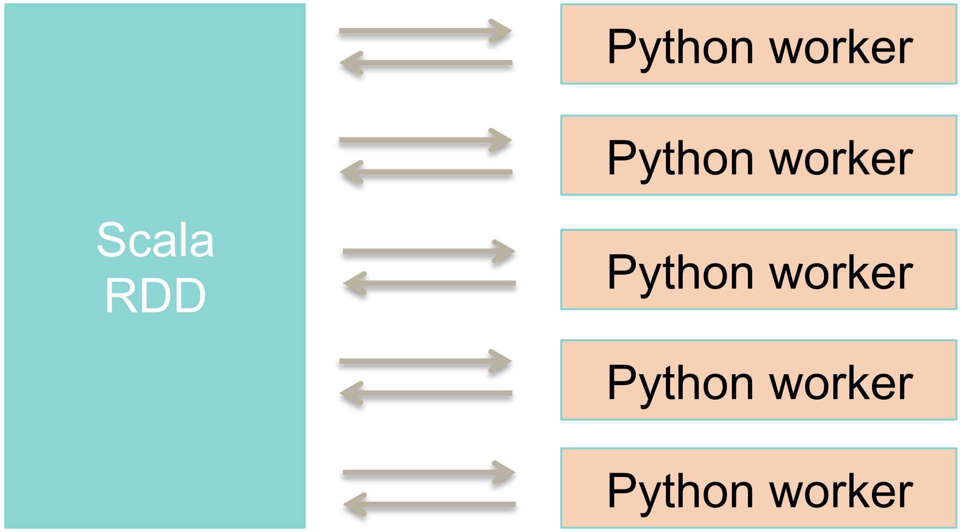
- Unfortunately, many PySpark jobs cannot be expressed entirely as DataFrame operations or other built-in Scala constructs

- Spark-Scala interacts with in-memory Python in key ways:
  - **Reading and writing in-memory datasets to/from the Spark driver**
  - **Evaluating custom Python code (user-defined functions)**

How PySpark lambda functions work

- The anatomy of

```
rdd.map(lambda x: … )
df.withColumn(py_func(...))
```



see PythonRDD.scala

PySpark lambda performance problems

- See 2016 talk “High Performance Python on Apache Spark”
  - http://www.slideshare.net/wesm/high-performance-python-on-apache-spark
- Problems
  - Inefficient data movement (serialization / deserialization)
  - Scalar computation model: object boxing and interpreter overhead
- General summary: PySpark is not currently designed to achieve high performance in the way that pandas and NumPy are.

Other issues with PySpark lambdas

- Computation model unlike what pandas users are used to
  - In `dataframe.map(f)`, the Python function `f` only sees one Row at a time
- A more natural and efficient vectorized API would be:
  - `dataframe.map_pandas(lambda df: …)`

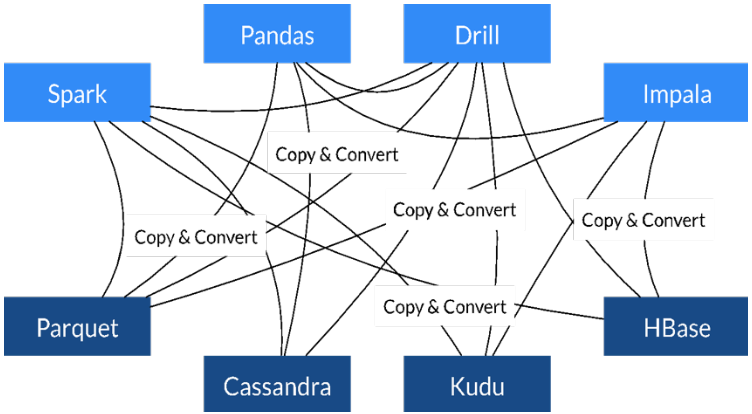
Apache Arrow

Apache Arrow: Process and Move Data Fast

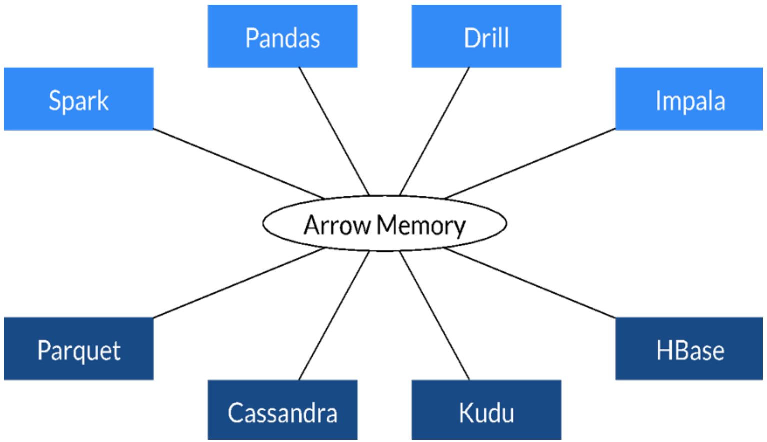
- New Top-level Apache project as of February 2016
- Collaboration amongst broad set of OSS projects around shared needs
- Language-independent columnar data structures
- Metadata for describing schemas / chunks of data
- Protocol for moving data between processes with minimal serialization overhead

High performance data interchange

Today



With Arrow

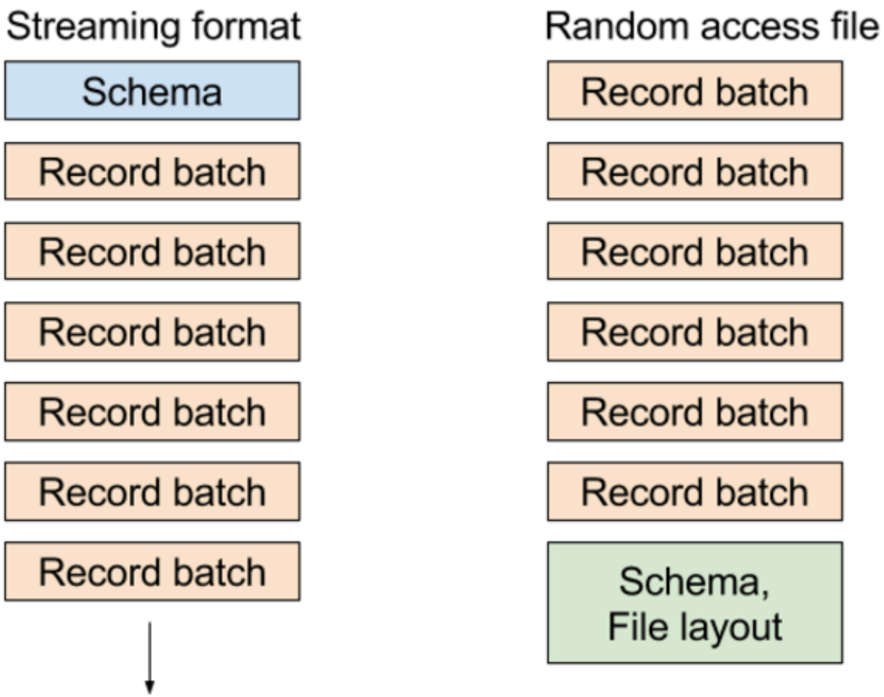


Source: Apache Arrow

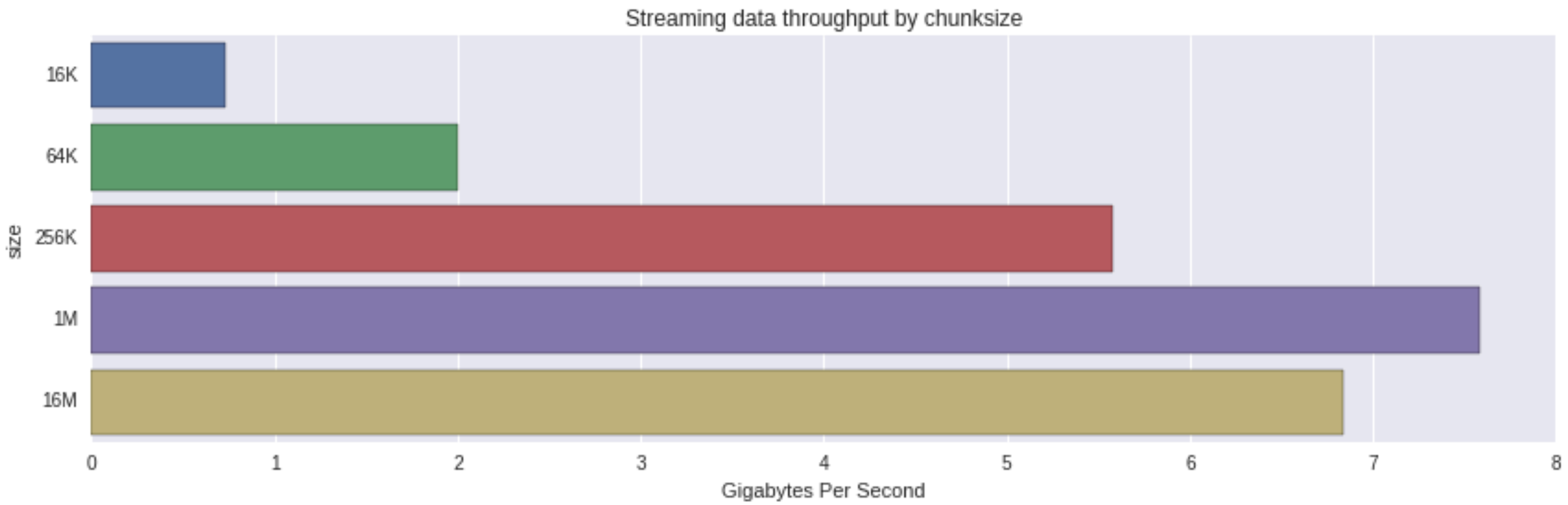
What does Apache Arrow give you?

- **Zero-copy columnar data:** Complex table and array data structures that can reference memory without copying it
- **Ultrafast messaging:** Language-agnostic metadata, batch/file-based and streaming binary formats
- **Complex schema support**: Flat and nested data types
- **C++, Python, and Java Implementations**: with integration tests

Arrow binary wire formats



Extreme performance to pandas from Arrow streams



PyArrow file and streaming API

```
from pyarrow import StreamReader

reader = StreamReader(stream)

# pyarrow.Table
table = reader.read_all()

# Convert to pandas
df = table.to_pandas()
```

Making DataFrame.toPandas faster

- Background
  - Spark's toPandas transfers in-memory from the Spark driver to Python and converts it to a pandas.DataFrame. It is very slow
  - Joint work with Bryan Cutler (IBM), Li Jin (Two Sigma), and Yin Xusen (IBM). See SPARK-13534 on JIRA

- Test case: transfer 128MB Parquet file with 8 DOUBLE columns

```
conda install pyarrow -c conda-forge
```

Making DataFrame.toPandas faster

```
df = sqlContext.read.parquet('example2.parquet')
df = df.cache()
df.count()
```

Then

```
%%prun -s cumulative
dfs = [df.toPandas() for i in range(5)]
```


Making DataFrame.toPandas faster

```
94483943 function calls (94478223 primitive calls) in 62.492 seconds

  ncalls  tottime  percall  cumtime  percall filename:lineno(function)
       5    1.458    0.292   62.492   12.498 dataframe.py:1570(toPandas)
       5    0.661    0.132   54.759   10.952 dataframe.py:382(collect)
10485765    0.669    0.000   46.823    0.000 rdd.py:121(_load_from_socket)
     715    0.002    0.000   46.139    0.065 serializers.py:141(load_stream)
     710    0.002    0.000   45.950    0.065 serializers.py:448(loads)
10485760    4.969    0.000   32.853    0.000 types.py:595(fromInternal)
    1391    0.004    0.000    7.445    0.005 socket.py:562(readinto)
      18    0.000    0.000    7.283    0.405 java_gateway.py:1006(send_command)
       5    0.000    0.000    6.262    1.252 frame.py:943(from_records)
```

Making DataFrame.toPandas faster

Now, using pyarrow

```
%%prun -s cumulative
dfs = [df.toPandas(useArrow) for i in range(5)]
```


Making DataFrame.toPandas faster

```
38585 function calls (38535 primitive calls) in 9.448 seconds

  ncalls  tottime  percall  cumtime  percall filename:lineno(function)
       5    0.001    0.000    9.448    1.890 dataframe.py:1570(toPandas)
       5    0.000    0.000    9.358    1.872 dataframe.py:394(collectAsArrow)
    6271    9.330    0.001    9.330    0.001 {method 'recv_into' of '_socket.socket‘}
      15    0.000    0.000    9.229    0.615 java_gateway.py:860(send_command)
      10    0.000    0.000    0.123    0.012 serializers.py:141(load_stream)
       5    0.085    0.017    0.089    0.018 {method 'to_pandas' of 'pyarrow.Table‘}
```

pip install memory_profiler

```
%%memit -i 0.0001
pdf = None
pdf = df.toPandas()
gc.collect()

peak memory: 1223.16 MiB,
increment: 1018.20 MiB
```

Plot thickens: memory use

```
%%memit -i 0.0001
pdf = None
pdf = df.toPandas(useArrow=True)
gc.collect()

peak memory: 334.08 MiB,
increment: 258.31 MiB
```

Summary of results

- Current version: average 12.5s (10.2 MB/s)
  - **Deseralization accounts for 88% of time**; the rest is waiting for Spark to send the data
  - Peak memory use 8x (~1GB) the size of the dataset
- Arrow version
  - Average wall clock time of 1.89s (6.61x faster, 67.7 MB/s)
  - **Deserialization accounts for 1% of total time**
  - Peak memory use 2x the size of the dataset (1 memory doubling)
  - Time for Spark to send data 25% higher (1866ms vs 1488 ms)

Aside: reading Parquet directly in Python

```
import pyarrow.parquet as pq


%%timeit
df = pq.read_table('example2.parquet').to_pandas()
10 loops, best of 3: 175 ms per loop
```

Digging deeper

- Why does it take Spark ~1.8 seconds to send 128MB of data over the wire?

```
val collectedRows = queryExecution.executedPlan.executeCollect()
cnvtr.internalRowsToPayload(collectedRows, this.schema)
```

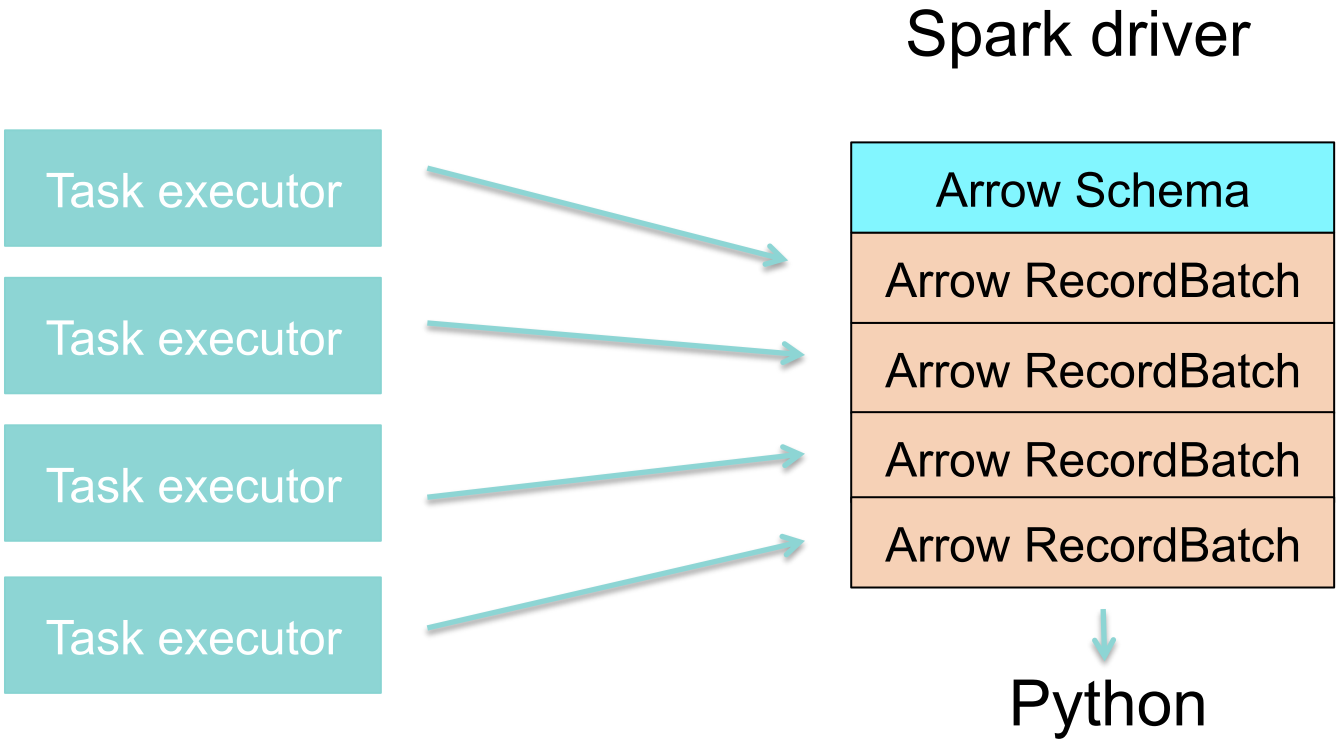
`Array[InternalRow]`

Digging deeper

- In our 128MB test case, on average:
  - **75%** of time is being spent collecting **`Array[InternalRow]`** from the task executors
  - **25%** of the time is spent on a **single-threaded** conversion of all the data from **`Array[InternalRow]`** to **`ArrowRecordBatch`**

- **We can go much faster by performing the Spark SQL -> Arrow conversion locally on the task executors, then streaming the batches to Python**

Future architecture



Hot off the presses

```
 ncalls  tottime  percall  cumtime  percall filename:lineno(function)
      5    0.000    0.000    5.928    1.186 dataframe.py:1570(toPandas)
      5    0.000    0.000    5.838    1.168 dataframe.py:394(collectAsArrow)
   5919    0.005    0.000    5.824    0.001 socket.py:561(readinto)
   5919    5.809    0.001    5.809    0.001 {method 'recv_into' of '_socket.socket‘}
...
      5    0.086    0.017    0.091    0.018 {method 'to_pandas' of 'pyarrow.Table‘}
```

Patch from February 8: 38% perf improvement

The work ahead

- Luckily, speeding up **toPandas** and speeding up Lambda / UDF functions is architecturally the same type of problem
- Reasonably clear path to making toPandas even faster
- **How can you get involved?**
  - Keep an eye on Spark ASF JIRA
  - Contribute to Apache Arrow (Java, C++, Python, other languages)
  - Join the Arrow and Spark mailing lists

Thank you

- Bryan Cutler, Li Jin, and Yin Xusen, for building the integration Spark-Arrow integration
- Apache Arrow community
- Spark Summit organizers
- Two Sigma and IBM, for supporting this work