Improving Python and Spark Performance and Interoperability with Apache Arrow

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About Us

TWO SIGMA

Li Jin

@icexelloss

- Software Engineer at Two Sigma Investments
- Building a python-based analytics platform with PySpark
- Other open source projects:
  - Flint: A Time Series Library on Spark
  - Cook: A Fair Share Scheduler on Mesos

dremio

Julien Le Dem

@J_

- Architect at @DremioHQ
- Formerly Tech Lead at Twitter on Data Platforms
- Creator of Parquet
- Apache member
- Apache PMCs: Arrow, Kudu, Incubator, Pig, Parquet

Agenda

- Current state and limitations of PySpark UDFs
- Apache Arrow overview
- Improvements realized
- Future roadmap

Current state and limitations of PySpark UDFs

Why do we need User Defined Functions?

- Some computation is more easily expressed with Python than Spark built-in functions.
- Examples:
  - weighted mean
  - weighted correlation
  - exponential moving average

What is PySpark UDF

- PySpark UDF is a user defined function executed in **Python runtime**.
- Two types:
  - Row UDF:
    - lambda x: x + 1
    - lambda date1, date2: (date1 - date2).years
  - Group UDF (subject of this presentation):
    - lambda values: np.mean(np.array(values))

Row UDF

- Operates on a row by row basis
  - Similar to `map` operator
- Example …

```
df.withColumn(
    ‘v2’,
    udf(lambda x: x+1, DoubleType())(df.v1)
)
```

- Performance:
  - **60x** slower than build-in functions for simple case

Group UDF

- UDF that operates on more than one row
  - Similar to `groupBy` followed by `map` operator
- Example:
  - Compute weighted mean by month

Group UDF

- Not supported out of box:
  - Need boiler plate code to pack/unpack multiple rows into a nested row
- Poor performance
  - Groups are materialized and then converted to Python data structures

Example: Data Normalization

```
(values – values.mean()) / values.std()
```

Example: Data Normalization

```
group_columns = ['year', 'month']
non_group_columns = [col for col in df.columns if col not in group_columns]
s = StructType([f for f in df.schema.fields if f.name in non_group_columns])
cols = list([F.col(name) for name in non_group_columns])

df_norm = df.withColumn('values', F.struct(*cols))
df_norm = (df_norm.groupBy('year', 'month')
                  .agg(F.collect_list(df_norm.values).alias('values')))

s2 = StructType(s.fields + [StructField('v3', DoubleType())])
@udf(ArrayType(s2))
def normalize(values):
    v1 = pd.Series([r.v1 for r in values])
    v1_norm = (v1 - v1.mean()) / v1.std()
    return [values[i] + (float(v1_norm[i]),) for i in range(0, len(values))]

df_norm = (df_norm.withColumn('new_values', normalize(df_norm.values))
                  .drop('values')
                  .withColumn('new_values', F.explode(F.col('new_values'))))

for col in [f.name for f in s2.fields]:
    df_norm = df_norm.withColumn(col, F.col('new_values.{0}'.format(col)))

df_norm = df_norm.drop('new_values')
```

Example: Monthly Data Normalization

```
group_columns = ['year', 'month']
non_group_columns = [col for col in df.columns if col not in group_columns]
s = StructType([f for f in df.schema.fields if f.name in non_group_columns])
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for col in [f.name for f in s2.fields]:
    df_norm = df_norm.withColumn(col, F.col('new_values.{0}'.format(col)))

df_norm = df_norm.drop('new_values')
```

Useful bits

Example: Monthly Data Normalization

```
group_columns = ['year', 'month']
non_group_columns = [col for col in df.columns if col not in group_columns]
s = StructType([f for f in df.schema.fields if f.name in non_group_columns])
cols = list([F.col(name) for name in non_group_columns])

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df_norm = (df_norm.groupBy('year', 'month')
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s2 = StructType(s.fields + [StructField('v3', DoubleType())])
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def normalize(values):
    v1 = pd.Series([r.v1 for r in values])
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    return [values[i] + (float(v1_norm[i]),) for i in range(0, len(values))]

df_norm = (df_norm.withColumn('new_values', normalize(df_norm.values))
                  .drop('values')
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for col in [f.name for f in s2.fields]:
    df_norm = df_norm.withColumn(col, F.col('new_values.{0}'.format(col)))

df_norm = df_norm.drop('new_values')
```

Boilerplate

Boilerplate

Example: Monthly Data Normalization

- Poor performance - 16x slower than baseline

```
groupBy().agg(collect_list())
```

Problems

- Packing / unpacking nested rows
- Inefficient data movement (Serialization / Deserialization)
- Scalar computation model: object boxing and interpreter overhead

Apache Arrow

Arrow: An open source standard

- Common need for in memory columnar
- Building on the success of Parquet.
- Top-level Apache project
- Standard from the start
  - Developers from 13+ major open source projects involved
- Benefits:
  - Share the effort
  - Create an ecosystem

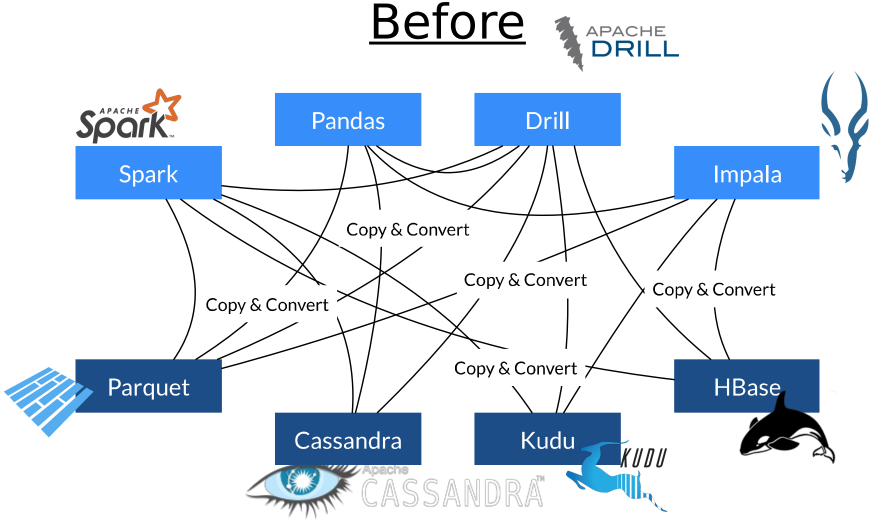
Calcite
Cassandra
Deeplearning4j
Drill
Hadoop
HBase
Ibis
Impala
Kudu
Pandas
Parquet
Phoenix
Spark
Storm
R

Arrow goals

- Well-documented and cross language compatible
- Designed to take advantage of modern CPU
- Embeddable
  - In execution engines, storage layers, etc.
- Interoperable

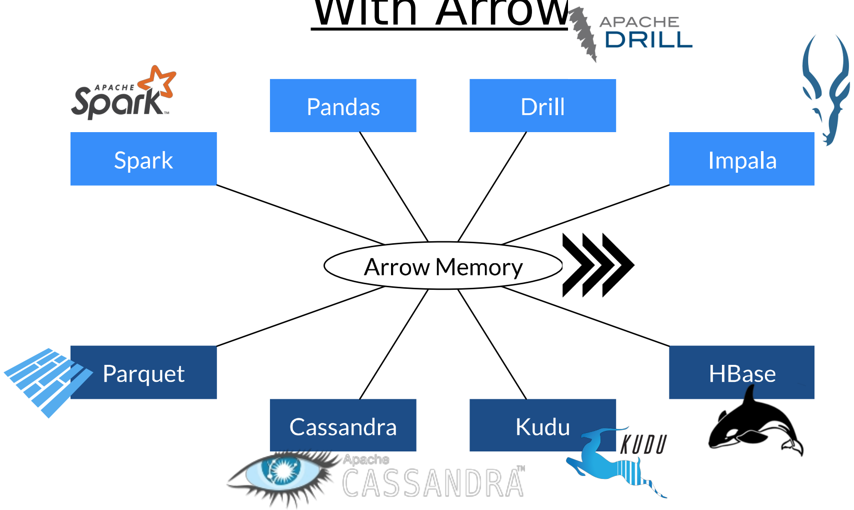
High Performance Sharing & Interchange

Before



- Each system has its own internal memory format
- 70-80% CPU wasted on serialization and deserialization
- Functionality duplication and unnecessary conversions

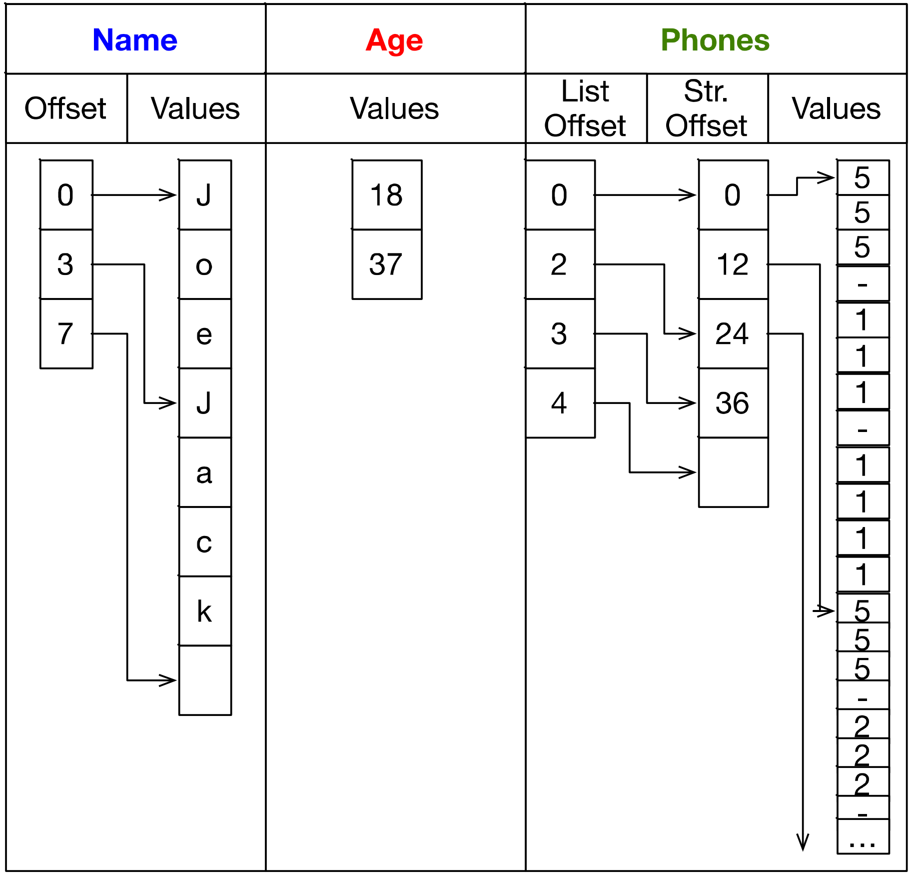
With Arrow



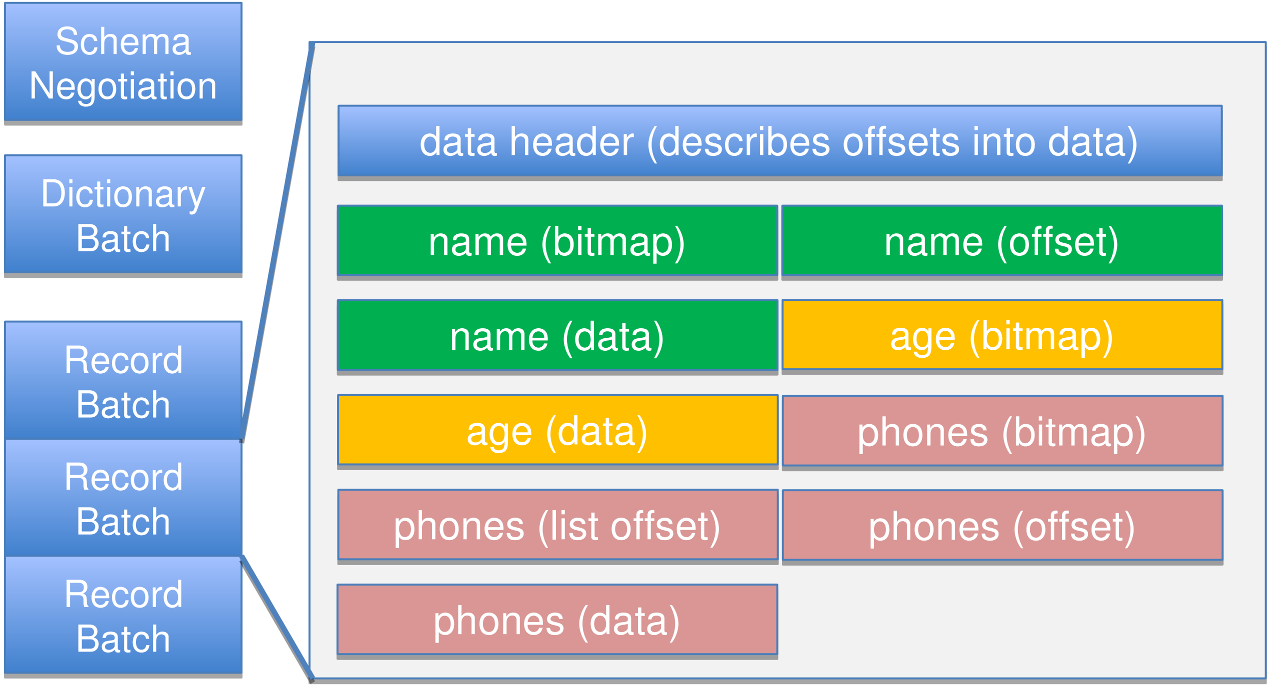
- All systems utilize the same memory format
- No overhead for cross-system communication
- Projects can share functionality (eg: Parquet-to-Arrow reader)

Columnar data

```
persons = [{
    name: 'Joe',
    age: 18,
    phones: [
        '555-111-1111',
        '555-222-2222'
    ]
},{
    name: 'Jack',
    age: 37,
    phones: [ '555-333-3333' ]
}]
```



Record Batch Construction




```
{
    name: 'Joe',
    age: 18,
    phones: [
        '555-111-1111',
        '555-222-2222'
    ]
}
```

Each box (vector) is contiguous memory
The entire record batch is contiguous on wire

In memory columnar format for speed

- Maximize CPU throughput
  - Pipelining
  - SIMD
  - cache locality
- Scatter/gather I/O

Results

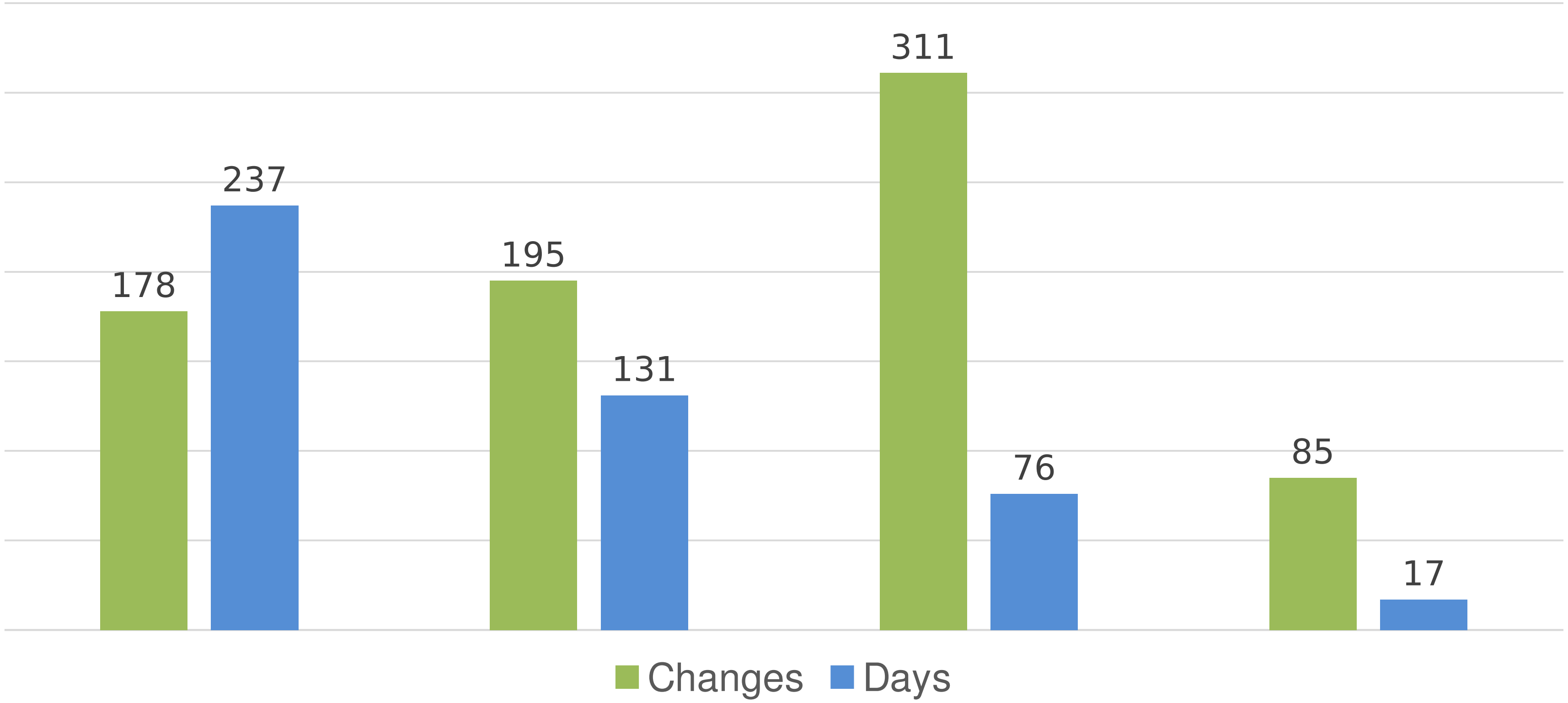
- PySpark Integration:
  53x speedup (IBM spark work on SPARK-13534)
  http://s.apache.org/arrowresult1

- Streaming Arrow Performance
  7.75GB/s data movement
  http://s.apache.org/arrowresult2

- Arrow Parquet C++ Integration
  4GB/s reads
  http://s.apache.org/arrowresult3

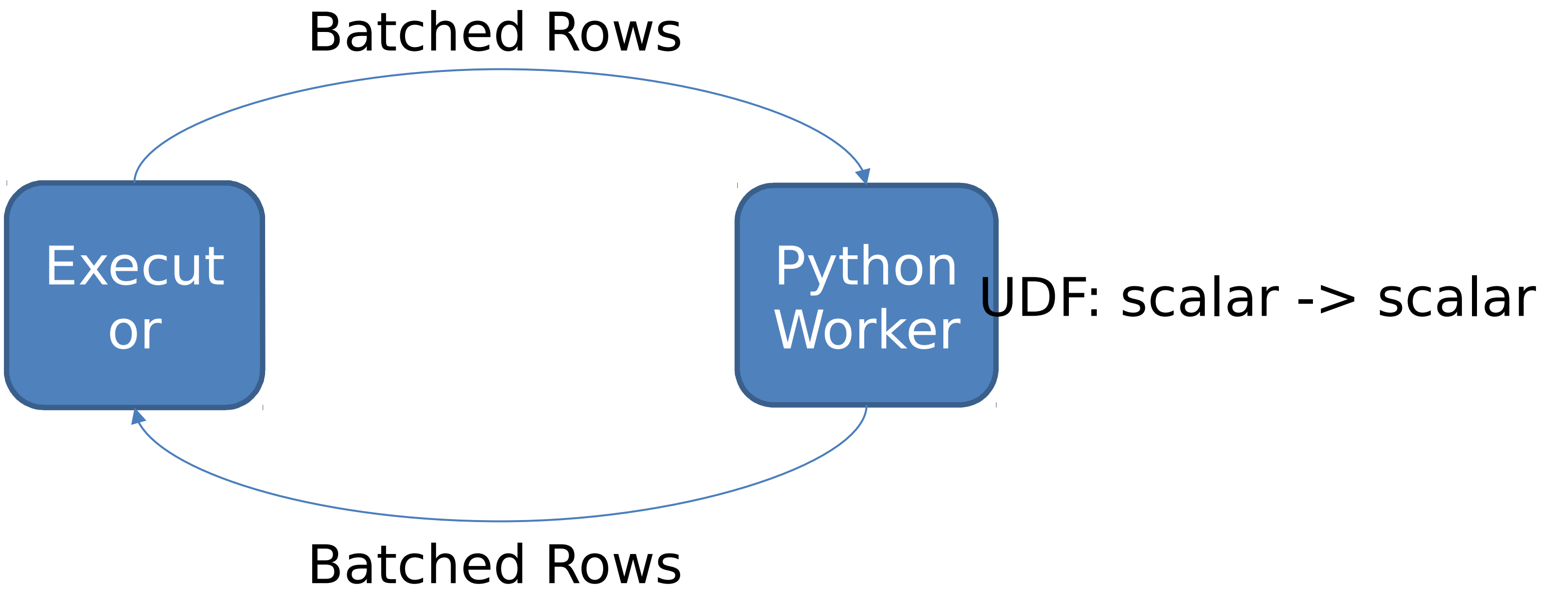
- Pandas Integration
  9.71GB/s
  http://s.apache.org/arrowresult4

Arrow Releases



Improvements to PySpark with Arrow

How PySpark UDF works



Current Issues with UDF

- Serialize / Deserialize in Python
- Scalar computation model (Python for loop)

Profile lambda x: x+1

Actual Runtime is **2s** without profiling.
8 Mb/s

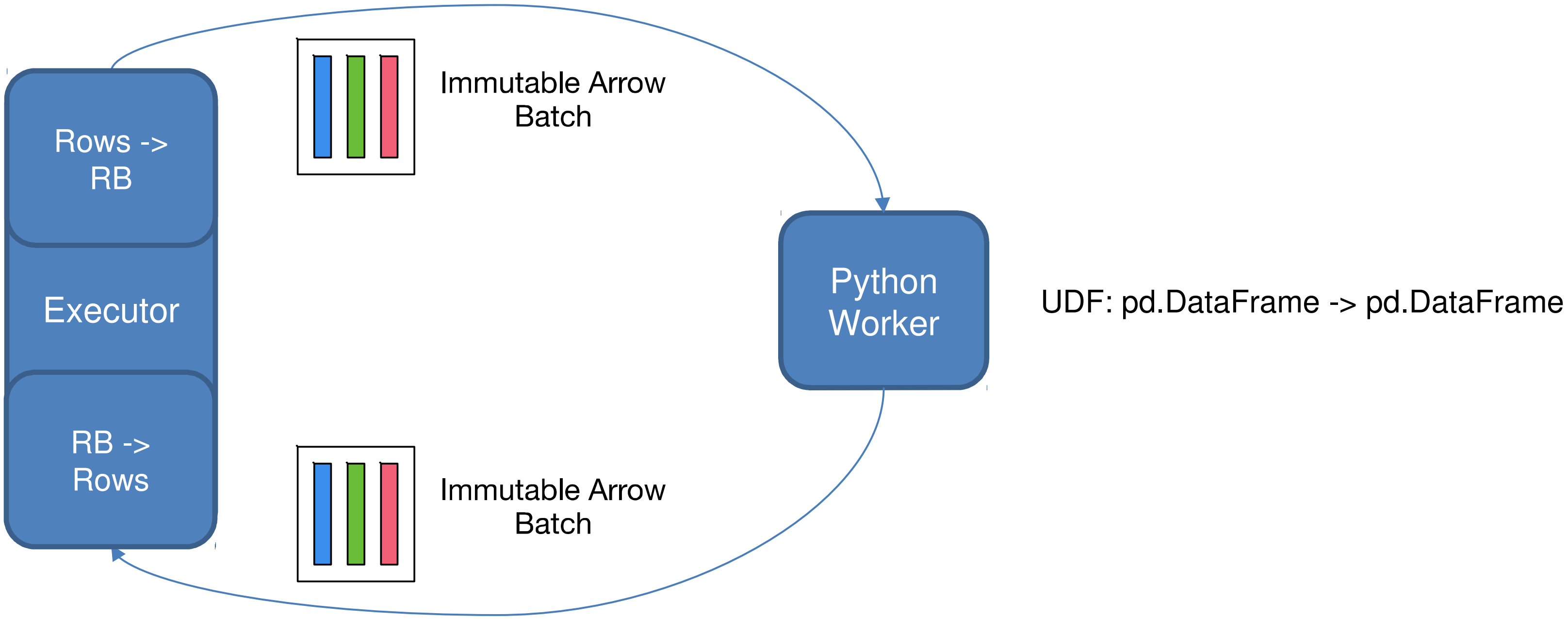
```
8787091 function calls in 4.084 seconds

Ordered by: internal time

ncalls  tottime  percall  cumtime  percall filename:lineno(function)
 20973    1.296    0.000    3.820    0.000 serializers.py:223(_batched)
2097152   0.800    0.000    2.004    0.000 worker.py:107(<lambda>)
2097152   0.761    0.000    1.204    0.000 worker.py:72(<lambda>)
2097152   0.443    0.000    0.443    0.000 <ipython-input-2-853f857cd265>:14(<lambda>)
2097152   0.214    0.000    0.214    0.000 {method 'append' of 'list' objects}
 20972    0.153    0.000    0.153    0.000 {built-in method _pickle.loads}
 20972    0.086    0.000    0.086    0.000 {built-in method _pickle.dumps}
[redacted]
```

91.8%

Vectorize Row UDF



Why pandas.DataFrame

- Fast, feature-rich, widely used by Python users
- Already exists in PySpark (toPandas)
- Compatible with popular Python libraries:
  - NumPy, StatsModels, SciPy, scikit-learn…
- Zero copy to/from Arrow

Scalar vs Vectorized UDF

Actual Runtime is **2s** without profiling

```
 8787091 function calls in 4.084 seconds

 Ordered by: internal time

 ncalls  tottime  percall  cumtime  percall filename:lineno(function)
   20973    1.296    0.000    3.820    0.000 serializers.py:223(_batched)
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   20972    0.086    0.000    0.086    0.000 {built-in method _pickle.dumps}
   20972    0.046    0.000    0.230    0.000 serializers.py:148(_write_with_length)
   41944    0.045    0.000    0.045    0.000 {method 'write' of '_io.BufferedWriter' objects}
   20973    0.044    0.000    0.287    0.000 serializers.py:161(_read_with_length)
   41945    0.039    0.000    0.039    0.000 {method 'read' of '_io.BufferedReader' objects}
```

```
 1245 function calls (1226 primitive calls) in 0.092 seconds

 Ordered by: internal time

 ncalls  tottime  percall  cumtime  percall filename:lineno(function)
      3    0.013    0.004    0.013    0.004 {method 'read' of '_io.BufferedReader' objects}
      2    0.012    0.006    0.012    0.006 {method 'write' of '_io.BufferedWriter' objects}
      1    0.012    0.012    0.012    0.012 {built-in method _operator.add}
      2    0.011    0.006    0.011    0.006 {method 'copy' of 'numpy.ndarray' objects}
      1    0.011    0.011    0.012    0.012 {method 'to_pandas' of 'pyarrow._table.RecordBatch' objects}
      1    0.009    0.009    0.009    0.009 {built-in method from_pandas}
      1    0.006    0.006    0.006    0.006 {method 'get_result' of 'pyarrow._io.InMemoryOutputStream' objects}
      1    0.006    0.006    0.006    0.006 {method 'to_pybytes' of 'pyarrow._io.Buffer' objects}
      1    0.005    0.005    0.005    0.005 {method 'write_batch' of 'pyarrow._io._StreamWriter' objects}
      1    0.003    0.003    0.003    0.003 internals.py:329(set)
```

20x Speed Up

Scalar vs Vectorized UDF

```
8787091 function calls in 4.084 seconds

Ordered by: internal time

ncalls   tottime  percall  cumtime  percall filename:lineno(function)
  20973    1.296    0.000    3.820    0.000 serializers.py:223(_batched)
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  41944    0.045    0.000    0.045    0.000 {method 'write' of '_io.BufferedWriter' objects}
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  41945    0.039    0.000    0.039    0.000 {method 'read' of '_io.BufferedReader' objects}
```

Overhead Removed

```
1245 function calls (1226 primitive calls) in 0.092 seconds

Ordered by: internal time

ncalls  tottime  percall  cumtime  percall filename:lineno(function)
     3    0.013    0.004    0.013    0.004 {method 'read' of '_io.BufferedReader' objects}
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     1    0.012    0.012    0.012    0.012 {built-in method _operator.add}
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     1    0.006    0.006    0.006    0.006 {method 'get_result' of 'pyarrow._io.InMemoryOutputStream' objects}
     1    0.006    0.006    0.006    0.006 {method 'to_pybytes' of 'pyarrow._io.Buffer' objects}
     1    0.005    0.005    0.005    0.005 {method 'write_batch' of 'pyarrow._io._StreamWriter' objects}
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Scalar vs Vectorized UDF

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     1    0.003    0.003    0.003    0.003 internals.py:329(set)
```
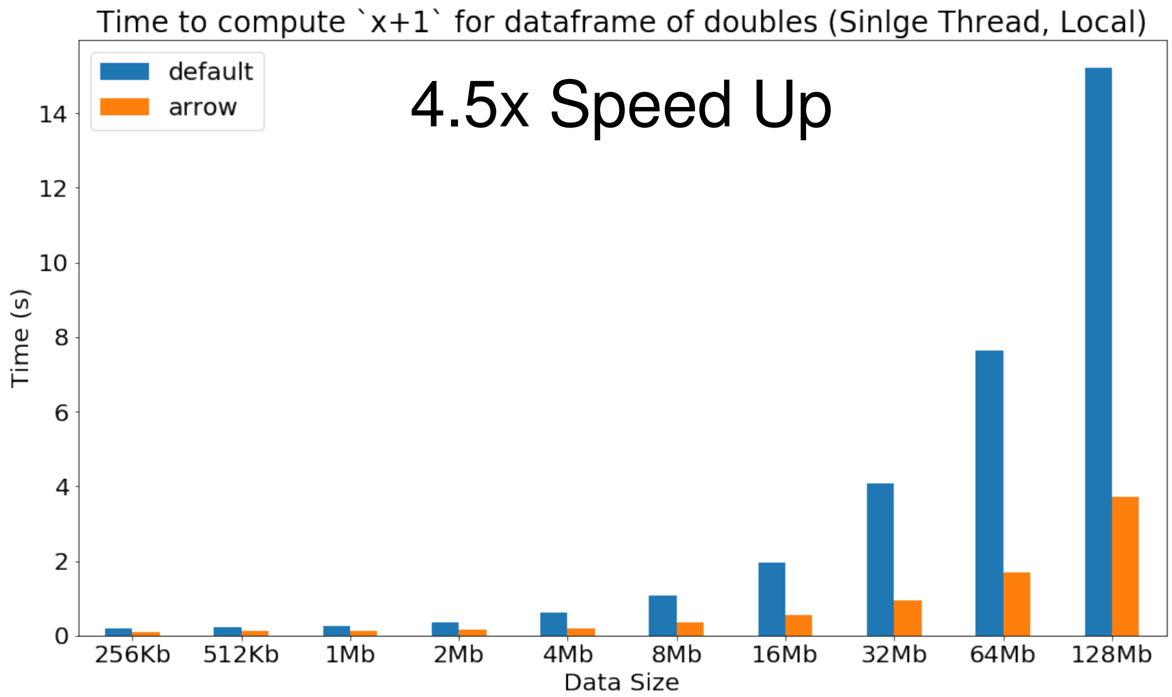

Less System Call
Faster I/O

Scalar vs Vectorized UDF



Support Group UDF

- Split-apply-combine:
  - Break a problem into smaller pieces
  - Operate on each piece independently
  - Put all pieces back together
- Common pattern supported in SQL, Spark, Pandas, R …

Split-Apply-Combine (Current)

- Split: groupBy, window, …
- Apply: mean, stddev, collect_list, rank …
- Combine: Inherently done by Spark

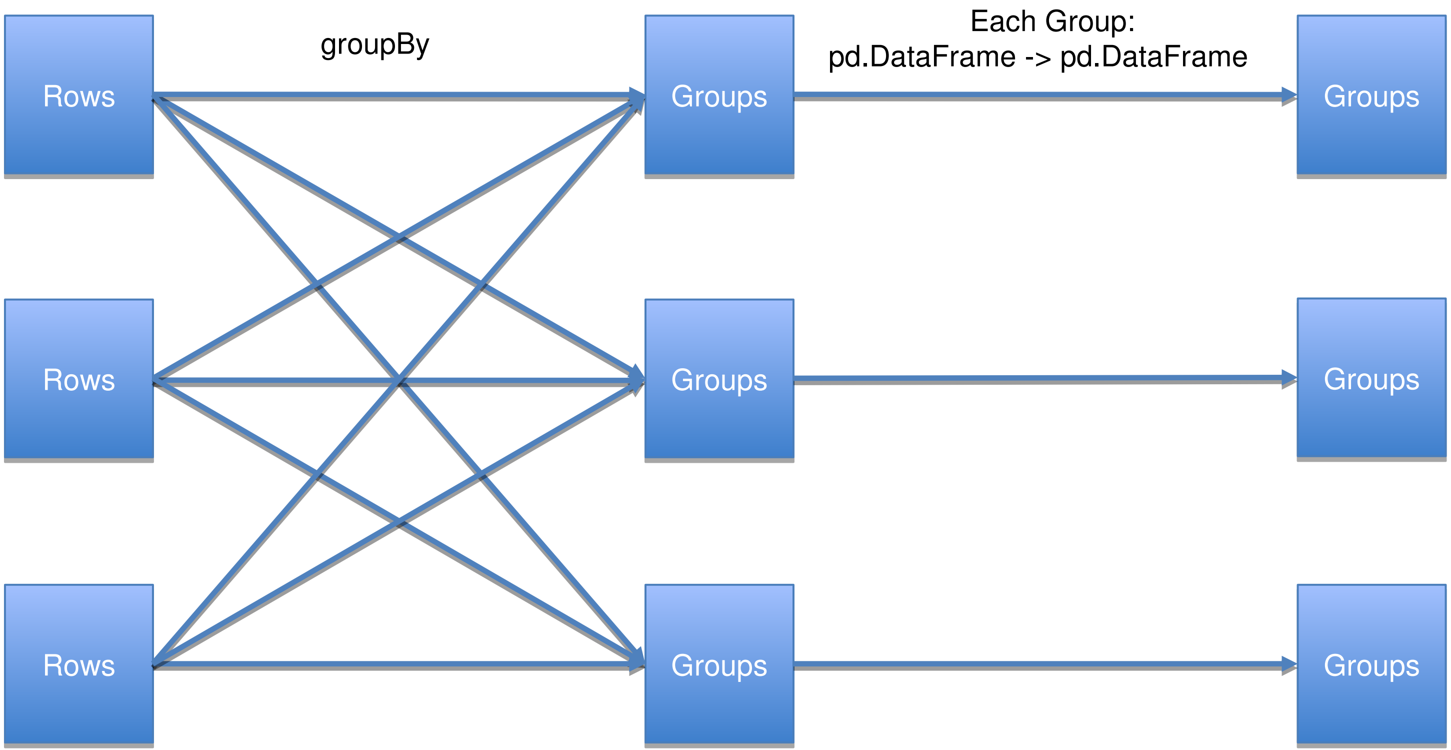
Split-Apply-Combine (with Group UDF)

- Split: groupBy, window, …
- Apply: UDF
- Combine: Inherently done by Spark

Introduce groupBy().apply()

- UDF: pd.DataFrame -> pd.DataFrame
  - Treat each group as a pandas DataFrame
  - Apply UDF on each group
  - Assemble as PySpark DataFrame

Introduce groupBy().apply()



Previous Example: Data Normalization

```
(values – values.mean()) / values.std()
```

Previous Example: Data Normalization

Current:

```
group_columns = ['year', 'month']
non_group_columns = [col for col in df.columns if col not in group_columns]
s = StructType([f for f in df.schema.fields if f.name in non_group_columns])
cols = list([F.col(name) for name in non_group_columns])

df_norm = df.withColumn('values', F.struct(*cols))
df_norm = (df_norm.groupBy('year', 'month')
                  .agg(F.collect_list(df_norm.values).alias('values')))

s2 = StructType(s.fields + [StructField('v3', DoubleType())])
@udf(ArrayType(s2))
def normalize(values):
    v1 = pd.Series([r.v1 for r in values])
    v1_norm = (v1 - v1.mean()) / v1.std()
    return [values[i] + (float(v1_norm[i]),) for i in range(0, len(values))]

df_norm = (df_norm.withColumn('new_values', normalize(df_norm.values))
                  .drop('values')
                  .withColumn('new_values', F.explode(F.col('new_values'))))

for col in [f.name for f in s2.fields]:
    df_norm = df_norm.withColumn(col, F.col('new_values.{0}'.format(col)))

df_norm = df_norm.drop('new_values')
```

Group UDF:

```
schema = StructType(df.schema.fields + [StructField('v3', DoubleType())])

def normalize(df):
    v1 = df.v1
    df['v3'] = (v1 - v1.mean()) / v1.std()
    return df

df_norm = (df.groupby('year', 'month')
              .apply(F.UserDefinedFunction(normalize, schema)))
```

5x Speed Up

Limitations

- Requires Spark Row <-> Arrow RecordBatch conversion
  - Incompatible memory layout (row vs column)
- (groupBy) No local aggregation
  - Difficult due to how PySpark works. See https://issues.apache.org/jira/browse/SPARK-10915

Future Roadmap

What’s Next (Arrow)

- Arrow RPC/REST
- Arrow IPC
- Apache {Spark, Drill, Kudu} to Arrow Integration
  - Faster UDFs, Storage interfaces

What's Next (PySpark UDF)

- Continue working on SPARK-20396
- Support Pandas UDF with more PySpark functions:
  - groupBy().agg()
  - window

What’s Next (PySpark UDF)

```
import numpy as np
@pandas_udf(Scalar, DoubleType())
def weighted_mean_udf(v1, w):
    return np.average(v1, weights=w)

df.groupBy('id').agg(weighted_mean_udf(df.v1, df.w).as('v1_wm'))
```

```
w = Window.partitionBy('id')

@pandas_udf(Series, DoubleType())
def rank_udf(v):
    return v.rank(pct=True)

df.withColumn('rank', rank_udf(df.v).over(w))
```

Get Involved

- Watch SPARK-20396
- Join the Arrow community
  - dev@arrow.apache.org
  - Slack:
    - https://apachearrowslackin.herokuapp.com/
  - http://arrow.apache.org
  - Follow @ApacheArrow

Thank you

- Bryan Cutler (IBM), Wes McKinney (Two Sigma Investments) for helping build this feature
- Apache Arrow community
- Spark Summit organizers
- Two Sigma and Dremio for supporting this work