

Effectively memory profiling distributed PySpark code

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PyCon Taiwan 2024
September 22, 2024

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Topics we will cover

- Why some pandas code can't scale to large datasets
- Migrating from pandas to PySpark - dos and don'ts
- Diagnosing and fixing PySpark memory issues
- Profiling native libraries (C++, Rust) used in Apache Spark executors

Initial problem

- We have **Parquet files** stored in S3
- We want to compute a weighted average
- The aggregation logic comes from a **native library**
- Constraint: Each node has **1 GB** of memory

Note: This example is scaled down

What does our data look like?

```
$ parquet-tools show input.parquet
```

weight	value
10.0	2.0
20.0	1.0

In this case, we can compute the weighted average:

$$(10 * 2 + 20 * 1) / (20 + 10) = 1.333$$

However, in practice, aggregation can be much more complex!

What does our aggregation module look like?

```
import ctypes
import numpy as np
from numpy.ctypeslib import ndpointer
```

```
lib = ctypes.cdll.LoadLibrary("/examples/libfinance.so")
native_wavg = lib.weighted_avg
native_wavg.restype = None
native_wavg.argtypes = [
    ndpointer(ctypes.c_double, flags="C_CONTIGUOUS"),
    ctypes.c_size_t,
    ndpointer(ctypes.c_double, flags="C_CONTIGUOUS")
]
```

Binding to native shared
library with C FFI

```
def weighted_avg(np_array):
    arr = np.ascontiguousarray(np_array)
    result = np.array([0.0, 0.0])
    native_wavg(arr, arr.size, result)
    return result
```

NumPy-compatible
Python interface

Example #1: Typical pandas code

```
import pandas as pd
import finance

# Read a single small parquet file
df = pd.read_parquet("/examples/input.parquet")

# Returns weighted average and total weight
print(finance.weighted_avg(df.to_numpy()))
```

Example #1: Typical pandas code

```
$ python example1.py  
(np.float64(-1301.4259223484928),  
np.float64(21.851472001775814))
```

Example #2: Dataset grows larger than available RAM

```
import pandas as pd
import finance

# Read many large parquet files
df = pd.read_parquet("/examples/big_data/")

# Returns weighted average and total weight
print(finance.weighted_avg(df.to_numpy()))
```


Example #2: Dataset grows larger than available RAM

```
$ python example2.py  
Killed
```

- Exits with code 137 = SIGKILL
- Killed by the kernel's OOM Killer (out of memory)

Using Memray to diagnose OOM

- [Memray](#) is a Python memory profiler
- Published as open source project by Bloomberg in 2022
- Can profile native (e.g., C/C++/Rust) code
- Use `python -m memray run script.py`
- Generates readable HTML reports with detailed stats

Example #2: Dataset grows larger than available RAM

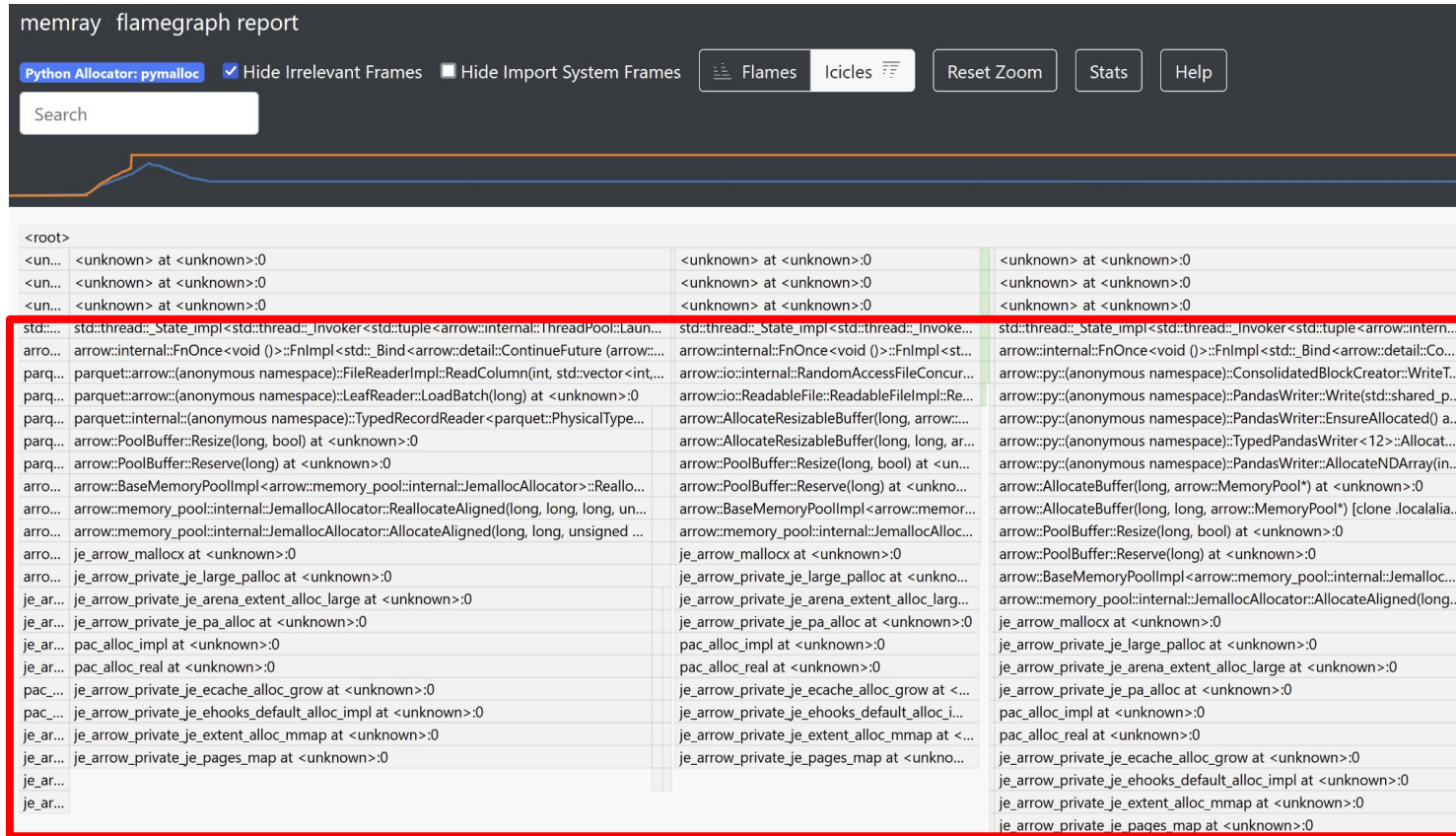
```
$ python -m memray run example2.py
Writing profile results into
memray-example2.py.6584.bin
Killed
```

Run code using Memray

```
$ python -m memray flamegraph
memray-example2.py.6584.bin
Wrote memray-example2.py.6584.html
```

Generate HTML report of
peak memory usage

Examining our Memray profile



C++ stack frames are visible

parquet::arrow::{anonymous}::
FileReaderImpl allocates a lot!

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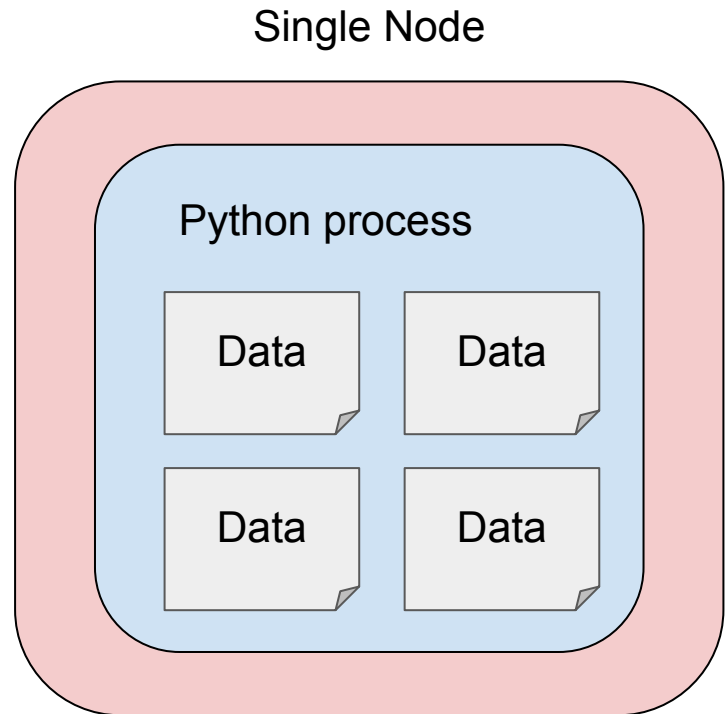
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Examining our Memray profile

- More memory is required to even run `pd.read_parquet`!
- Needs more than 1 GB RAM
- We need to avoid loading all of our data into the memory on one machine

pandas' Computation Model



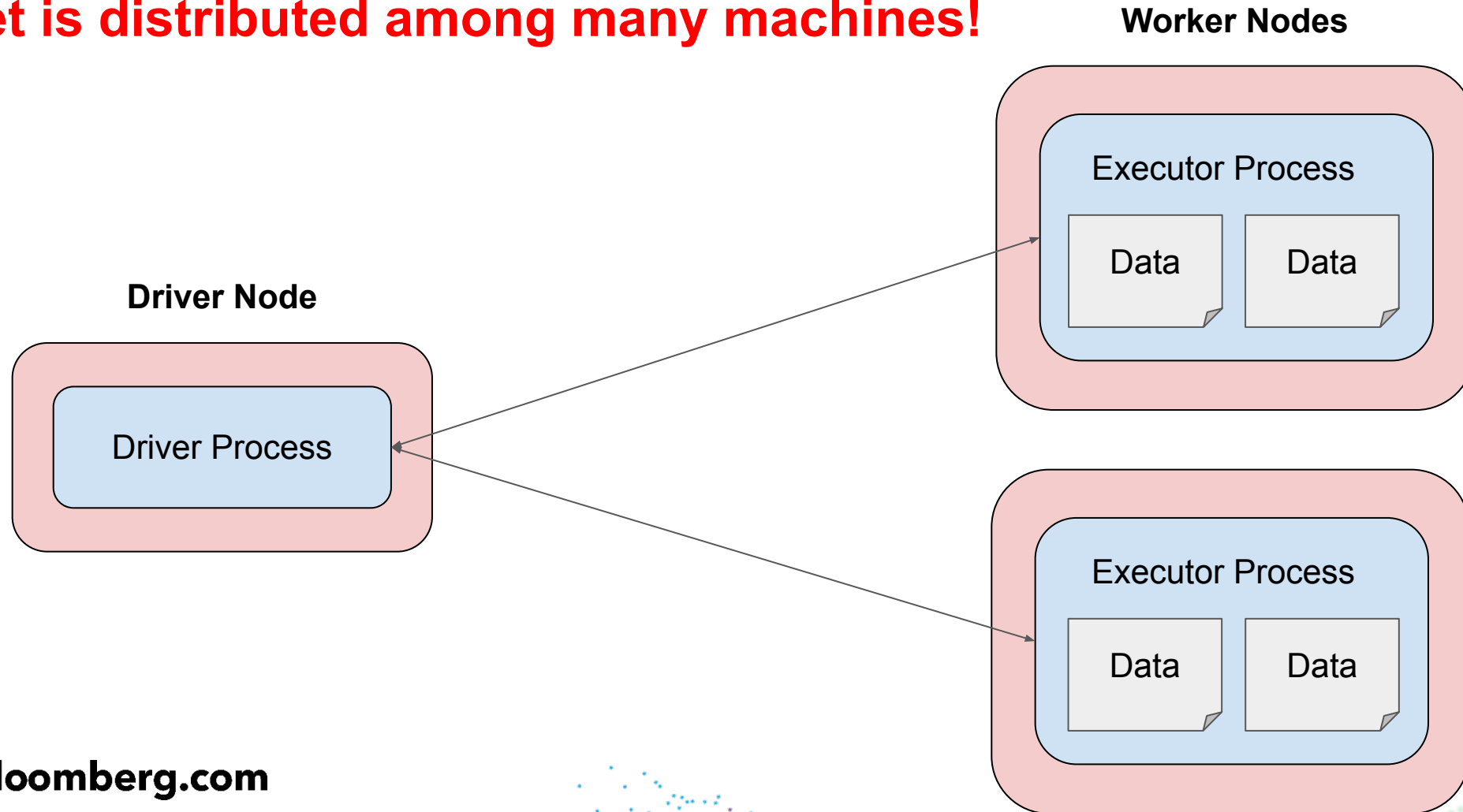
- All data **in memory on one machine**
- Doesn't scale to arbitrarily large (>1 TB) datasets
- To handle larger datasets, we must distribute the dataset across **multiple machines**

Solution: Distributed data processing

- [Apache Spark](#) is a framework for distributed data processing
- Distributes datasets across multiple nodes' memory
- Parallelizes computations across multiple nodes
- PySpark offers Python bindings for Spark

Spark's Computation Model

Dataset is distributed among many machines!



Example #3: Naively translated PySpark code

```
import pyspark.pandas as ps  
import finance
```

Attempt a drop-in replacement for
pandas

```
# Read many Parquet files  
# DataFrame is distributed across workers  
df = ps.read_parquet("/examples/big_data/")  
  
print(finance.weighted_avg(df.to_numpy()))
```

Example #3: Naive PySpark code

```
$ spark-submit.sh /examples/example3.py
```

```
py4j.protocol.Py4JJavaError: An error occurred  
while calling o58.collectToPython.  
: org.apache.spark.SparkException: Job aborted due  
to stage failure: Total size of serialized results  
of 6 tasks (1049.9 MiB) is bigger than  
spark.driver.maxResultSize (1024.0 MiB)
```

- `df.to_numpy()` loads all data into the driver
- Spark blocks this pattern by default

Example #3 (second attempt!)

```
$ spark-submit.sh --conf spark.driver.maxResultSize=2g  
/examples/example3.py
```

```
py4j.protocol.Py4JJavaError: An error occurred while  
calling o59.collectToPython.
```

```
: org.apache.spark.SparkException: Job aborted due to  
stage failure: Exception while getting task result:
```

```
java.lang.IllegalStateException: unread block data
```

- Increases [spark.driver.maxResultSize](#)
- collectToPython still errors out!
- This error results from OOM in the driver

Dangers of misusing pandas on Spark API

- Just replacing `import pandas as pd` with `import pyspark.pandas as pd` will lead to scaling issues
- Many APIs are fast with pandas on a small dataset, but slow/unusable on large datasets – even with `pyspark.pandas`
 - `DataFrame.to_numpy`
 - `DataFrame.shape`
 - `DataFrame.apply`

`pyspark.pandas.DataFrame.to_numpy`

Symptoms (already seen these!):

- An error occurred while calling `o59.collectToPython`.
- `spark.driver.maxResultSize` **issues**
- `java.lang.IllegalStateException: unread block data`

Why?

- Loads the entire dataset into the driver
- Not how you're supposed to use Spark!

`pyspark.pandas.DataFrame.shape`

Issues:

- Very slow compared to `pandas.DataFrame.shape`
- Even for small datasets!

Why?

- `pandas.DataFrame.__len__` is close to free
- `pyspark.pandas.DataFrame.__len__` is very expensive!

`pandas.DataFrame.__len__` is close to free!

```
>>> df = pd.read_parquet("examples/big_data")
>>> df.index
RangeIndex(start=0, stop=1000000000, step=1)
>>> len(df)
1000000000
```

- `len(df)` just takes the length of a range ($O(1)$)
- We don't need to look at the data, just the index

See the [pandas source code](#) – it really *is* that simple!

`pyspark.pandas.DataFrame.__len__` is expensive!

- Calls [`self.to_spark\(\).count\(\)`](#)
- Requires a full scan of the entire DataFrame ($O(n)$)
- **Do not assume `df.shape` is free!**

`pyspark.pandas.DataFrame.apply(f)`

- Different from pandas when using `axis=0`
 - pandas: `f` is called once with the whole column
 - pyspark.pandas: `f` is called once **per batch**
- Only guarantee: Union of batches is the whole dataset
- Row batch size can be anything!
- Global aggregations aren't possible

Example #4: `pandas.DataFrame.apply(f)`

```
import pandas as pd
df = pd.DataFrame(range(1_000_000))
print(df.apply(sum, axis=0))
```

This prints:

```
$ python examples/example4.py
0    499999500000
dtype: int64
```

Example #5: `pyspark.pandas.DataFrame.apply(f)`

```
import pyspark.pandas as ps
df = ps.DataFrame(range(1_000_000))
print(df.apply(sum, axis=0))
```

This prints:

```
$ python examples/example5.py
0    49995000
0   149995000
0   249995000
0   349995000
0   449995000
```

`pyspark.pandas.DataFrame.apply(f)`

- Do not naively translate pandas code
- It may appear to work for small datasets (e.g., your tests!)
- Read documentation! [pyspark.pandas docs](#) warn about this prominently!

Migration to PySpark: Conclusions

- Our dependency exposes a NumPy interface, so we must eventually convert to NumPy – it is unavoidable
- Strategy:
 - Aggregate each partition, then aggregate results
 - Use `pyspark.sql.DataFrame.mapInPandas`
- Danger! Floating point addition/multiplication is not commutative or associative – this will give slightly different answers

`pyspark.sql.DataFrame.mapInPandas(f)`

- Takes a function `f` to map over the DataFrame
- `f` has type `Iterator[pd.DataFrame] -> Iterator[pd.DataFrame]`
- PySpark distributes data and work across nodes

Example #6: More scalable PySpark code

```
import pandas as pd
from pyspark.sql import SparkSession
import finance
```

```
spark = SparkSession.builder.getOrCreate()
df = spark.read.parquet("/examples/big_data/")
```

```
def aggregate(dfs):
    return (pd.DataFrame(
        finance.weighted_avg(df.to_numpy())
        for df in dfs),)
```

```
averages = df.mapInPandas(aggregate, df.schema)
```

```
print(finance.weighted_avg(averages.toPandas().to_numpy()))
```

Step 1: Aggregate data
into list of averages

Step 2: Aggregate
into overall average



Example #6: More scalable PySpark code

```
$ spark-submit.sh /examples/example6.py
```

```
spark-worker-2 | 24/09/02 23:40:55 INFO Worker:  
Executor app-20240902234033-0000/1 finished with  
state EXITED message Command exited with code 137  
exitStatus 137
```

- OOM killed again!
- The executors are going OOM even on small chunks!

How can we profile memory usage of our executor code?

- Spark 3.5 has built-in memory profilers
 - Can profile memory use of Python/Java/Scala executor code
 - Uses memory_profiler for Python
- cProfile
 - Can profile run time, but not memory
- Memray
 - Can profile memory use of any Python code
 - Can see native stack frames!

PySpark's built-in memory profiler

1. Set `spark.python.profile.memory=true`
2. Add `sc.show_profiles()` at the end of your job
3. View your detailed memory profile!

Spark's built-in memory profiler

```
/opt/spark/python/lib/pyspark.zip/pyspark/sql/udf.py:350: UserWarning: Profiling UDFs with iterators  
input/output is not supported.
```

- Internally, `df.mapInPandas` uses a UDF
- UDF takes iterator input
- Not supported by PySpark profiler

Example #7: Memray instrumented code

```
def aggregate(dfs):  
    filename = f"/examples/memray{uuid4()}.bin"  
    with memray.Tracker(filename, native_traces=True):  
        return (pd.DataFrame(  
            finance.weighted_avg(df.to_numpy())  
            for df in dfs),)
```

Example #7: Memray instrumented code

```
<root>
runpy.run_path(args.script, run_name="__main__")
PyObject_Vectorcall at <unknown>:0
<unknown> at <unknown>:0
<unknown> at <unknown>:0
PyEval_EvalCode at <unknown>:0
print(finance.weighted_avg(df.to_numpy()))
rust_wavg(arr, arr.size, result)
_PyObject_MakeTpCall at <unknown>:0
<unknown> at <unknown>:0
<unknown> at <unknown>:0
<unknown> at <unknown>:0
<unknown> at <unknown>:0
weighted_avg at src/lib.rs:6
alloc::vec::Vec$LT$T$C$A$GT$::reserve::h7d01a06690a05000 at /rustc/3f5fd8dd41153bc5fdca9427e9e05be2c767ba23/library/alloc/src/vec/mod.rs:972
alloc::raw_vec::RawVec$LT$T$C$A$GT$::reserve::h87714e7769982b13 at /rustc/3f5fd8dd41153bc5fdca9427e9e05be2c767ba23/library/alloc/src/raw_vec.rs:355
alloc::raw_vec::RawVec$LT$T$C$A$GT$::reserve::do_reserve_and_handle::hae3916fad9ebaf63 at /rustc/3f5fd8dd41153bc5fdca9427e9e05be2c767ba23/library/alloc/src/raw_vec.rs:349
alloc::raw_vec::RawVec$LT$T$C$A$GT$::grow_amortized::h100f7f2ea893feaf at /rustc/3f5fd8dd41153bc5fdca9427e9e05be2c767ba23/library/alloc/src/raw_vec.rs:485
alloc::raw_vec::finish_grow::he76acc8f31b703eb at /rustc/3f5fd8dd41153bc5fdca9427e9e05be2c767ba23/library/alloc/src/raw_vec.rs:573
_$LT$alloc..alloc..Global$u20$as$u20$core..alloc..Allocator$GT$::allocate::h8d49a03a2518acc2 at /rustc/3f5fd8dd41153bc5fdca9427e9e05be2c767ba23/library/alloc/src/alloc.rs:243
alloc::alloc::Global::alloc_impl::h7ad93932524b1030 at /rustc/3f5fd8dd41153bc5fdca9427e9e05be2c767ba23/library/alloc/src/alloc.rs:183
alloc::alloc::alloc::h566e3d7c81c3bb7e at /rustc/3f5fd8dd41153bc5fdca9427e9e05be2c767ba23/library/alloc/src/alloc.rs:100
```

Python stack frame

C stack frame

Rust stack frames!

Pinpointing the issue in our Rust library

```
#[no_mangle]
pub extern "C" fn weighted_avg(indata: *const f64, size: isize, result: *mut f64) ->
() {
    let mut total_weight: f64 = 0.0;
    let mut dot_product: f64 = 0.0;
    let mut scratch: Vec<f64> = vec![];
    scratch.reserve(1000000000);

    for i in (0..size).step_by(2) {
        total_weight += unsafe { *indata.offset(i) };
        dot_product += unsafe { *indata.offset(i) * *indata.offset(i+1) };
    }

    unsafe {
        *result = total_weight;
        *result.offset(1) = dot_product / total_weight;
    }
}
```

Let's get rid of this allocation!

Success!

```
$ python final_example.py  
(np.float64(-1301.4259223484928),  
np.float64(21.851472001775814))
```

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Conclusions

- Be careful when converting pandas code to PySpark!
- pandas on Spark: While convenient, naive usage is dangerous
- Use **Memray** to diagnose memory issues in pandas, driver code, executor code, Python, C/C++/Rust
- Profile, profile, profile!

Thank you!

Learn more: TechAtBloomberg.com/Python

Try out Memray: <https://github.com/bloomberg/memray>

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