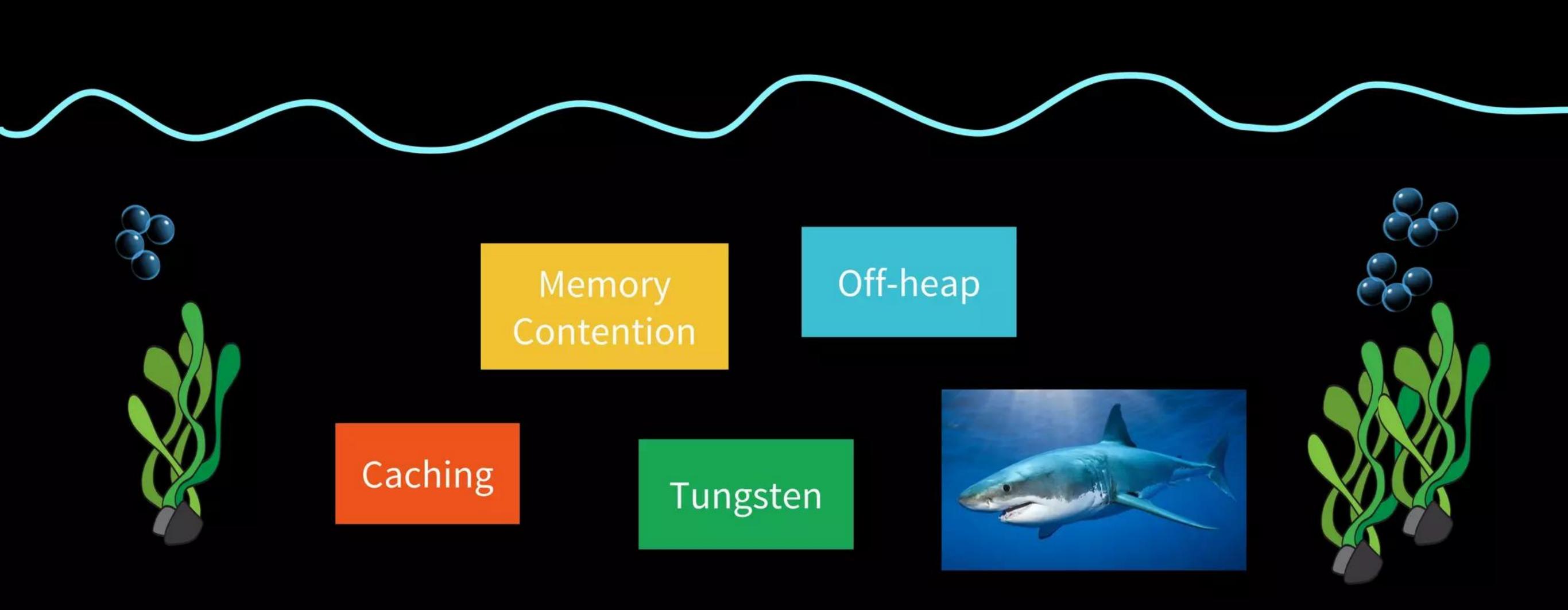
# Deep Dive: Memory Management in Apache Spark

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@andrewor14 🔰 June 8th, 2016



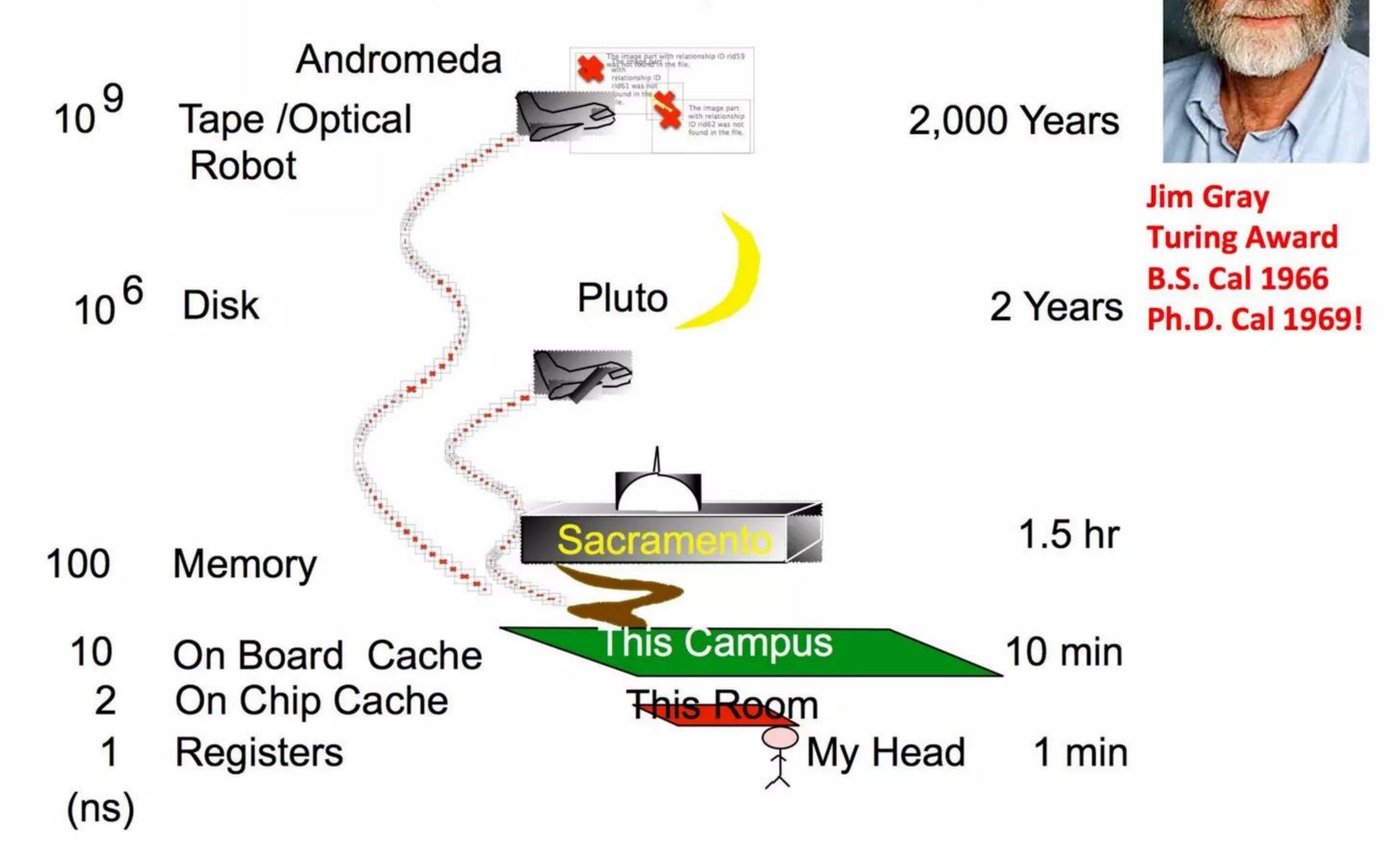
students.select("name").orderBy("age").cache().show()



# Efficient memory use is critical to good performance



## Jim Gray's Storage Latency Analogy: How Far Away is the Data?



## Memory contention poses three challenges for Apache Spark

How to arbitrate memory between execution and storage?

How to arbitrate memory across tasks running in parallel?

How to arbitrate memory across operators running within the same task?



#### Two usages of memory in Apache Spark

#### Execution

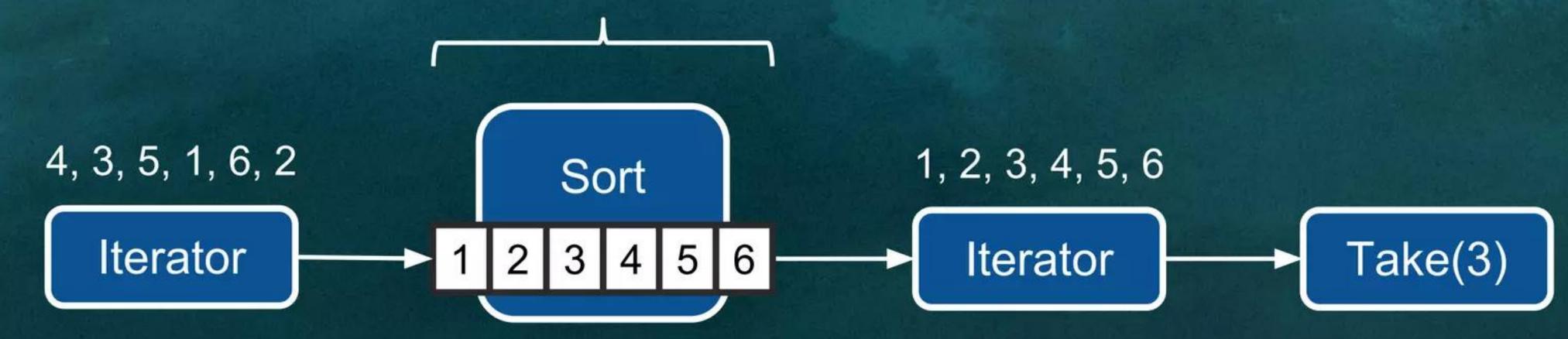
Memory used for shuffles, joins, sorts and aggregations

#### Storage

Memory used to cache data that will be reused later

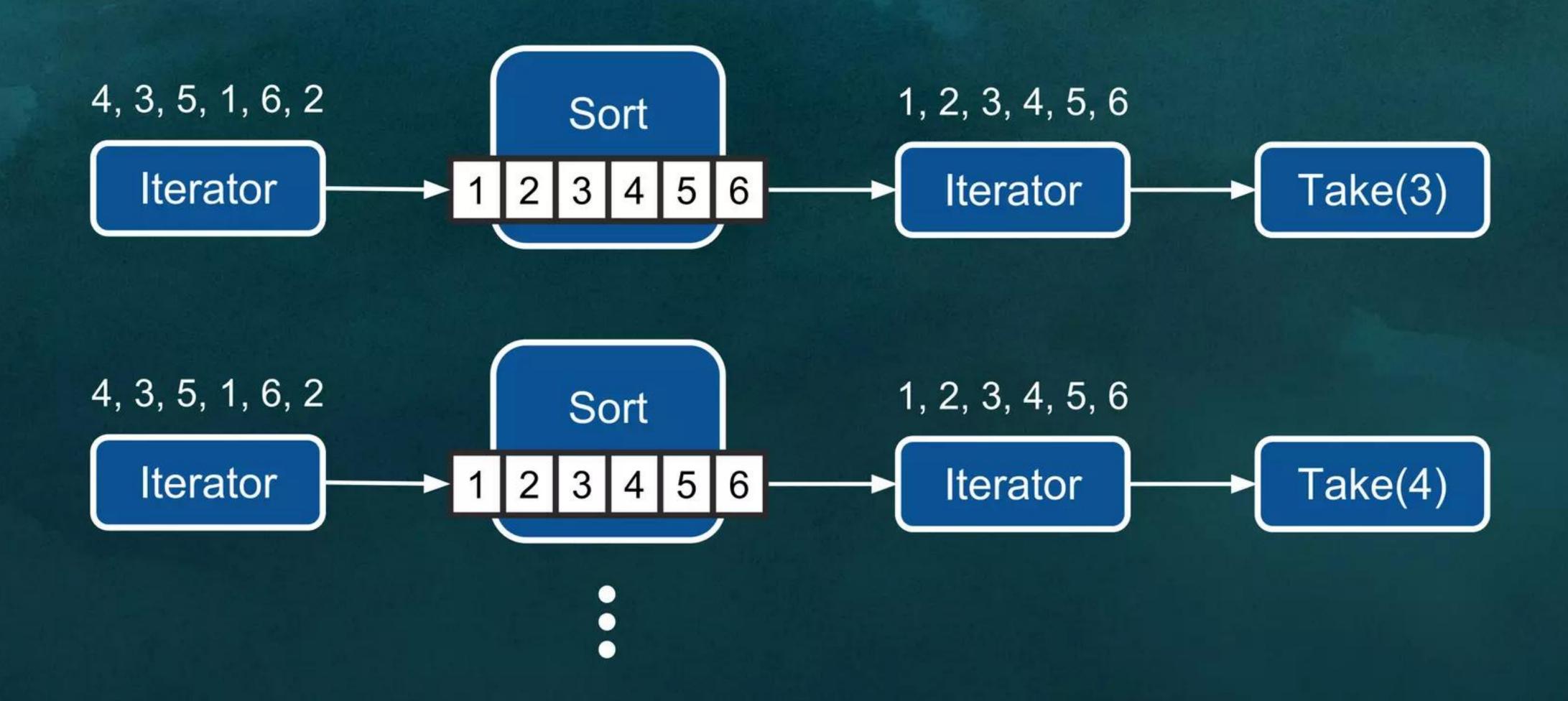


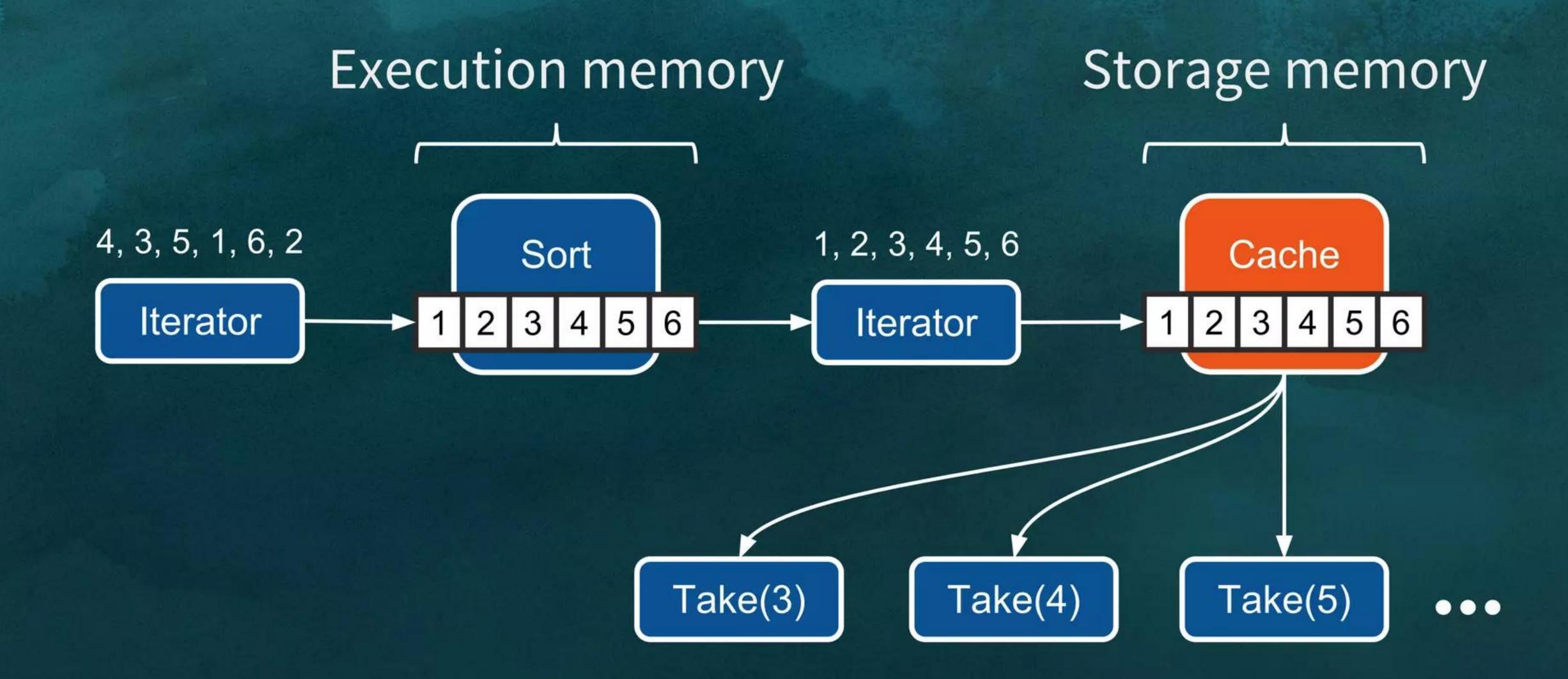
#### Execution memory



What if I want the sorted values again?







## Challenge #1

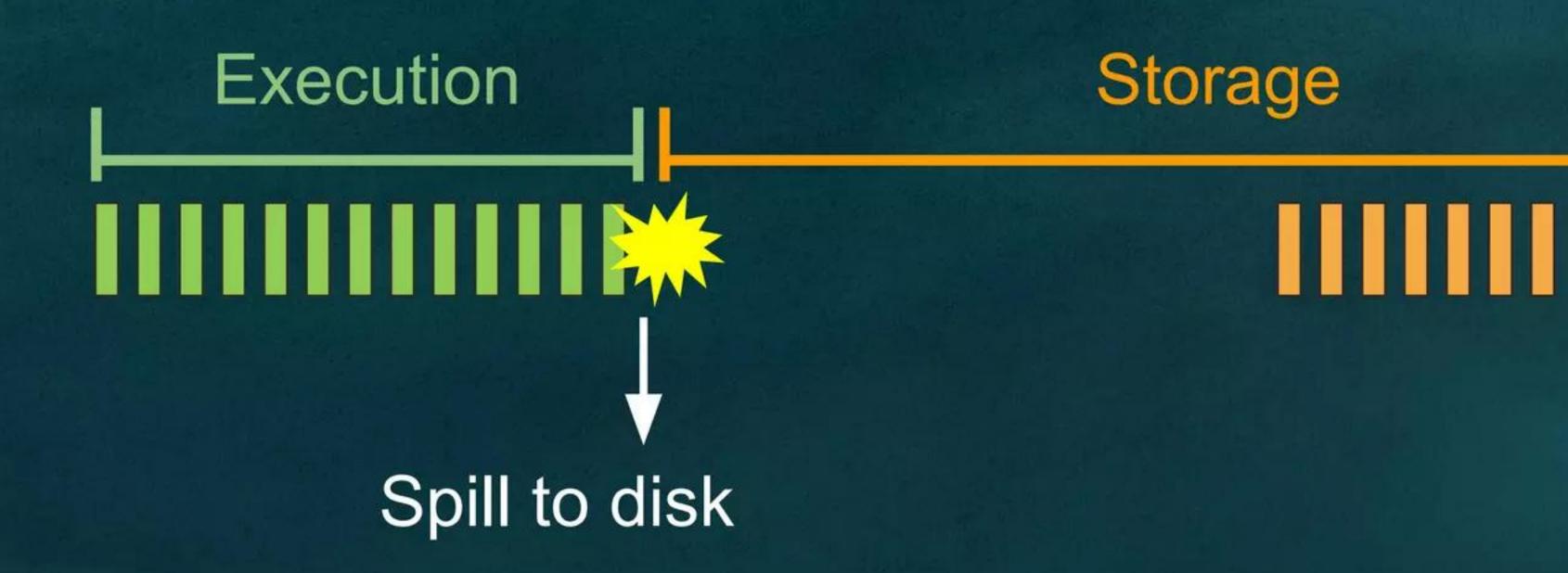
How to arbitrate memory between execution and storage?



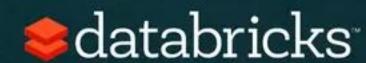


















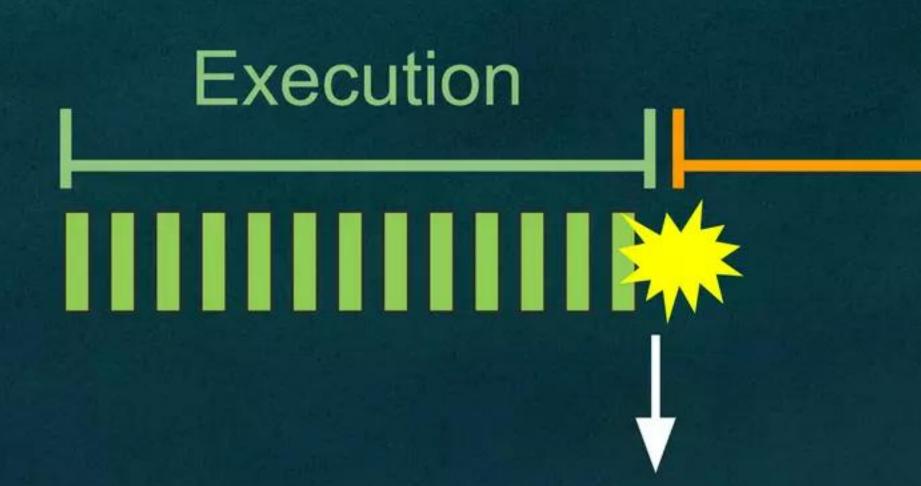






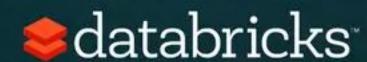
# Inefficient memory use leads to bad performance





Storage

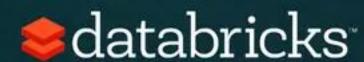
Execution can only use a fraction of the memory, even when there is no storage!





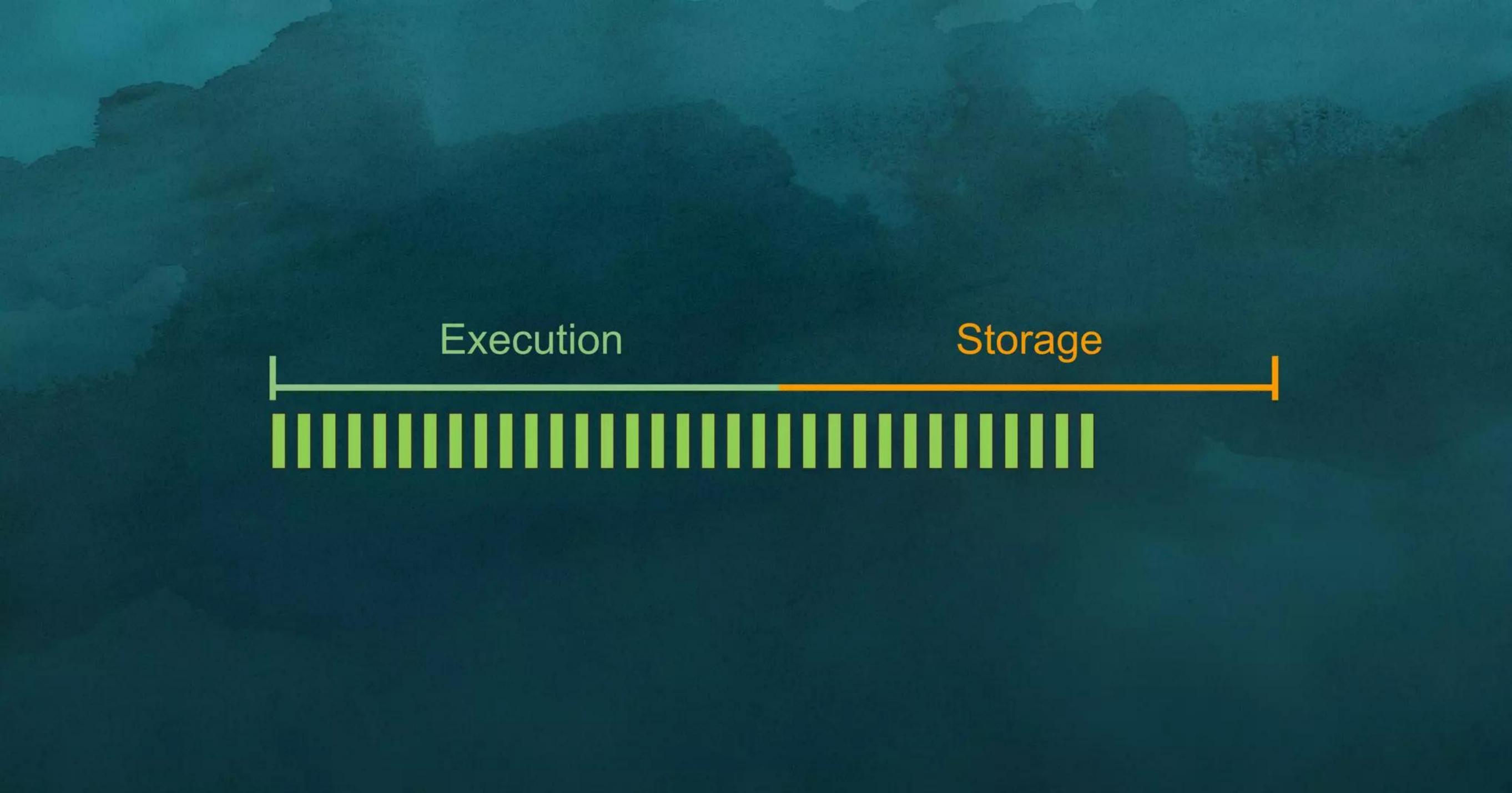


Efficient use of memory required user tuning



# Fast forward to 2016... How could we have done better?





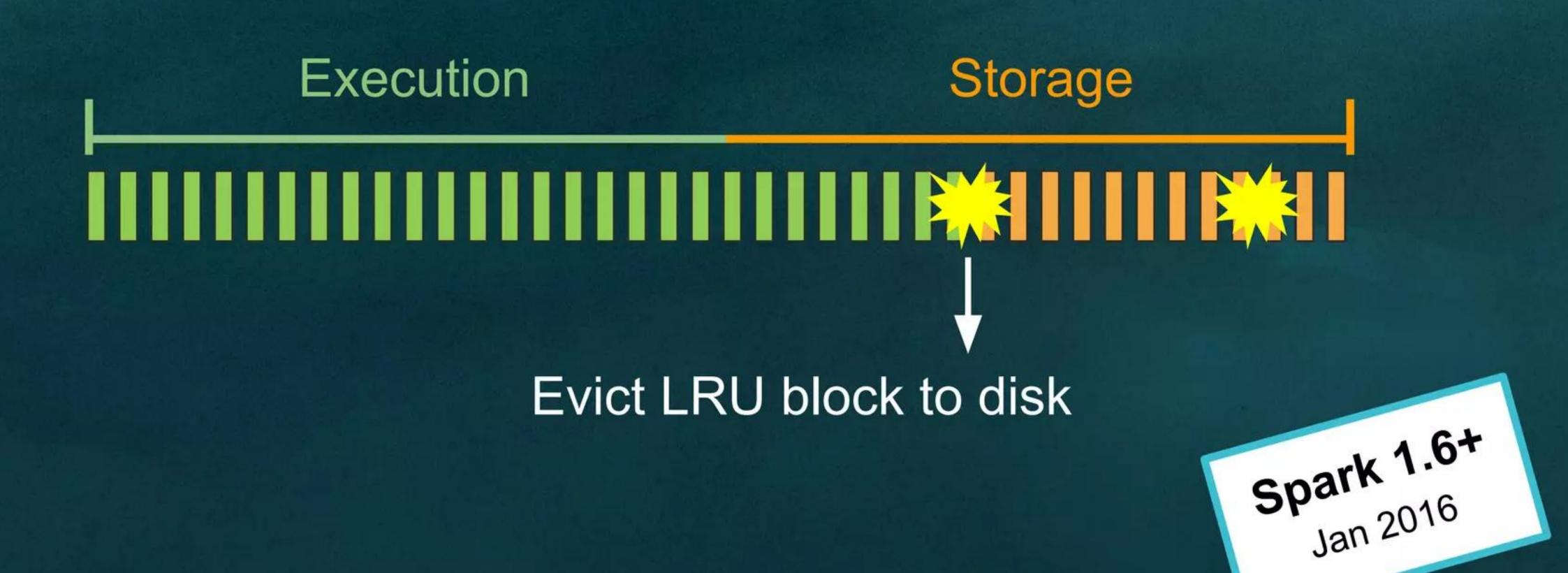
Execution

Storage

What happens if there is already storage?

Spark 1.6+ Jan 2016





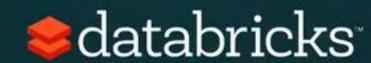


Execution

Storage

What about the other way round?

Spark 1.6+ Jan 2016







#### Design considerations

#### Why evict storage, not execution?

Spilled execution data will always be read back from disk, whereas cached data may not.

#### What if the application relies on caching?

Allow the user to specify a minimum unevictable amount of cached data (not a reservation!).

Spark 1.6+
Spark 1.6+



## Challenge #2

How to arbitrate memory across tasks running in parallel?



Worker machine has 4 cores

Each task gets 1/4 of the total memory

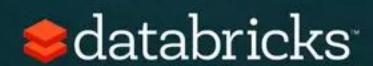
Slot 2 Slot 3 Slot 4



The share of each task depends on number of actively running tasks (N)



Now, another task comes along so the first task will have to spill



Each task is now assigned 1/N of the memory, where N = 2

Task 1



Each task is now assigned 1/N of the memory, where N = 4

Task 1 Task 2 Task 3 Task 4



Last remaining task gets all the memory because N = 1





#### Static vs dynamic assignment

Both are fair and starvation free

Static assignment is simpler

Dynamic assignment handles stragglers better



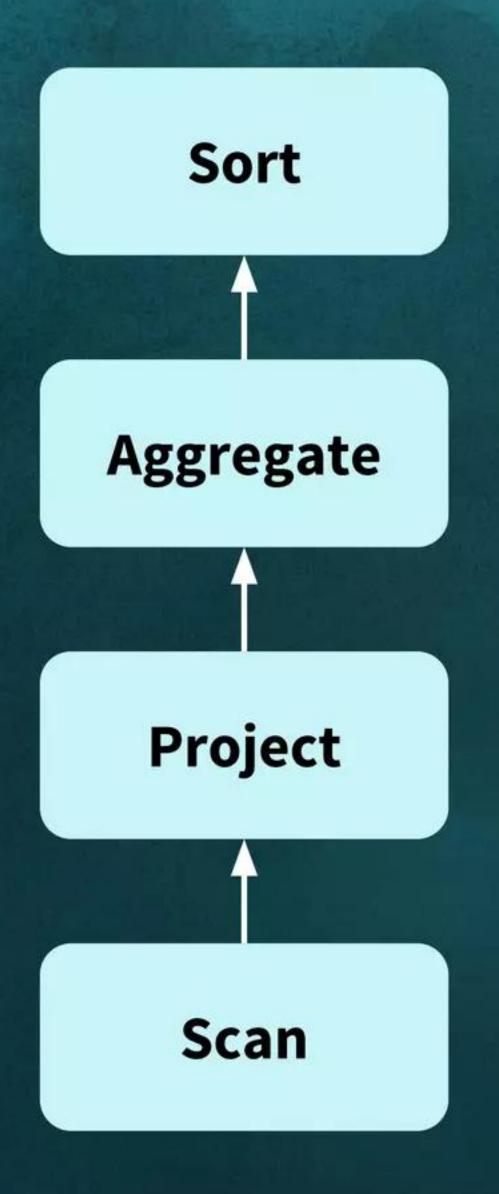
## Challenge #3

How to arbitrate memory across operators running within the same task?



```
SELECT age, avg(height)
FROM students
GROUP BY age
ORDER BY avg(height)
```

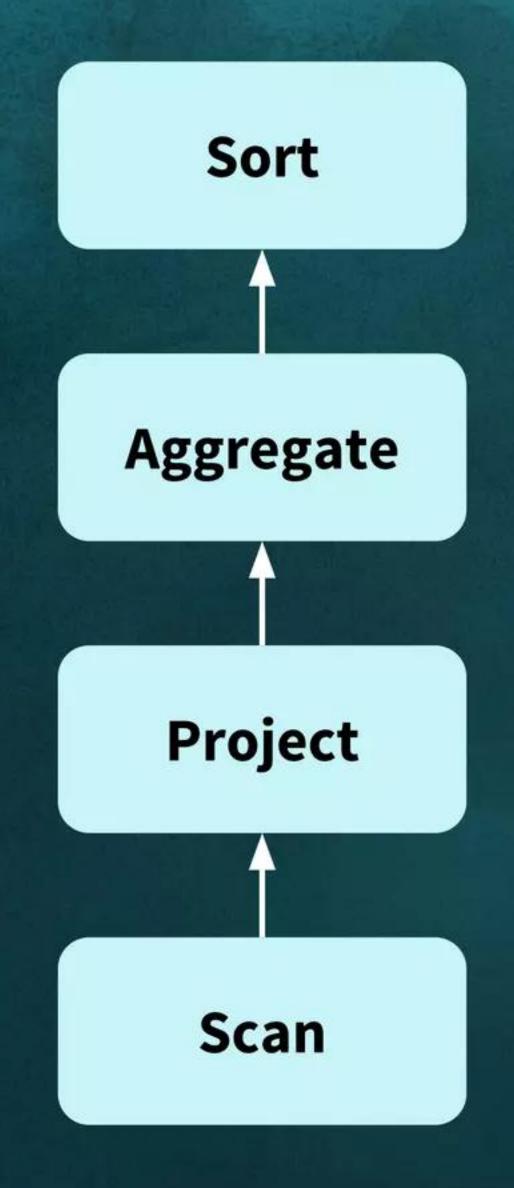
```
students.groupBy("age")
   .avg("height")
   .orderBy("avg(height)")
   .collect()
```





Worker has 6 pages of memory







```
Map \{ // \text{ age } \rightarrow \text{ heights} \}

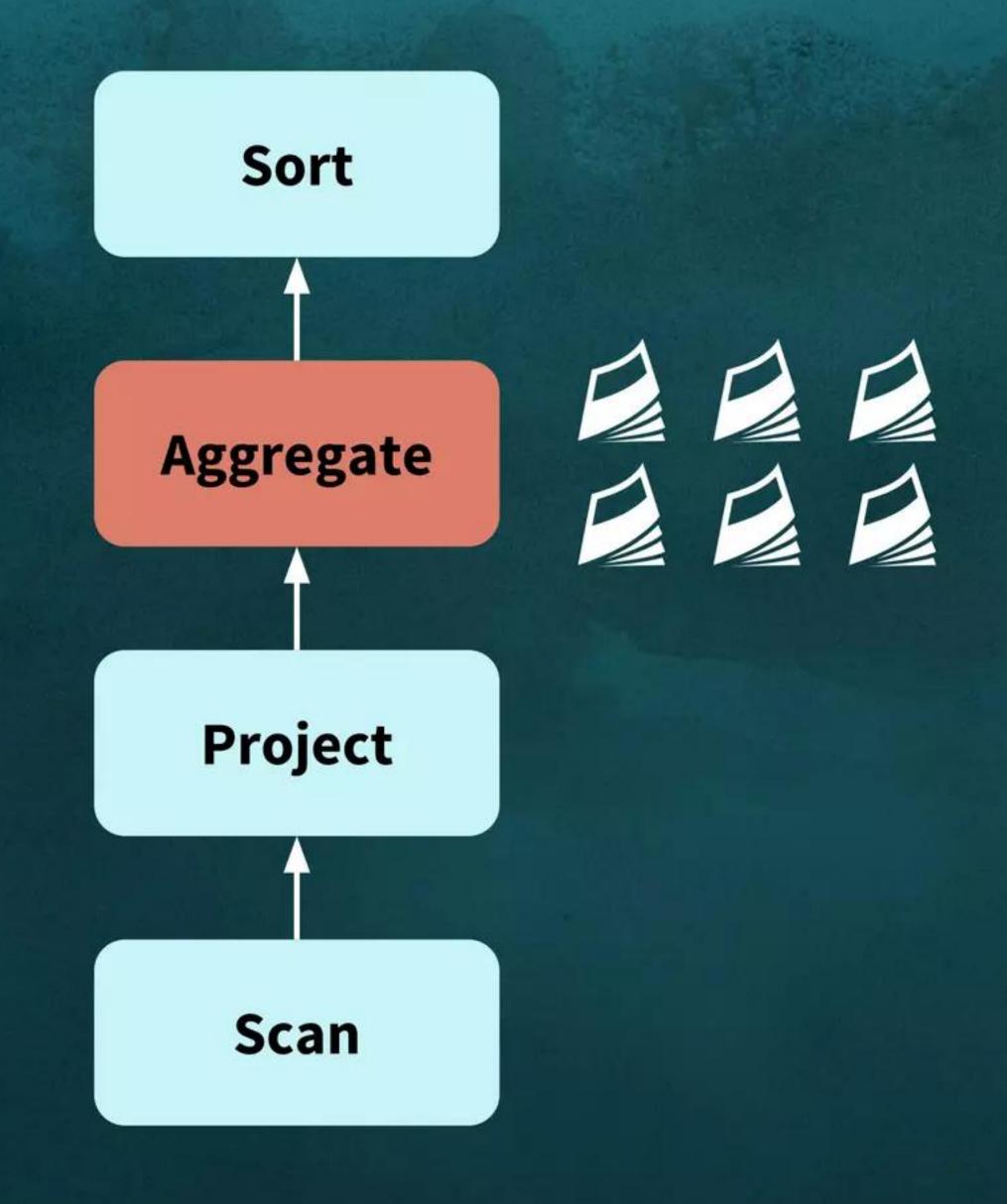
20 \rightarrow [154, 174, 175]

21 \rightarrow [167, 168, 181]

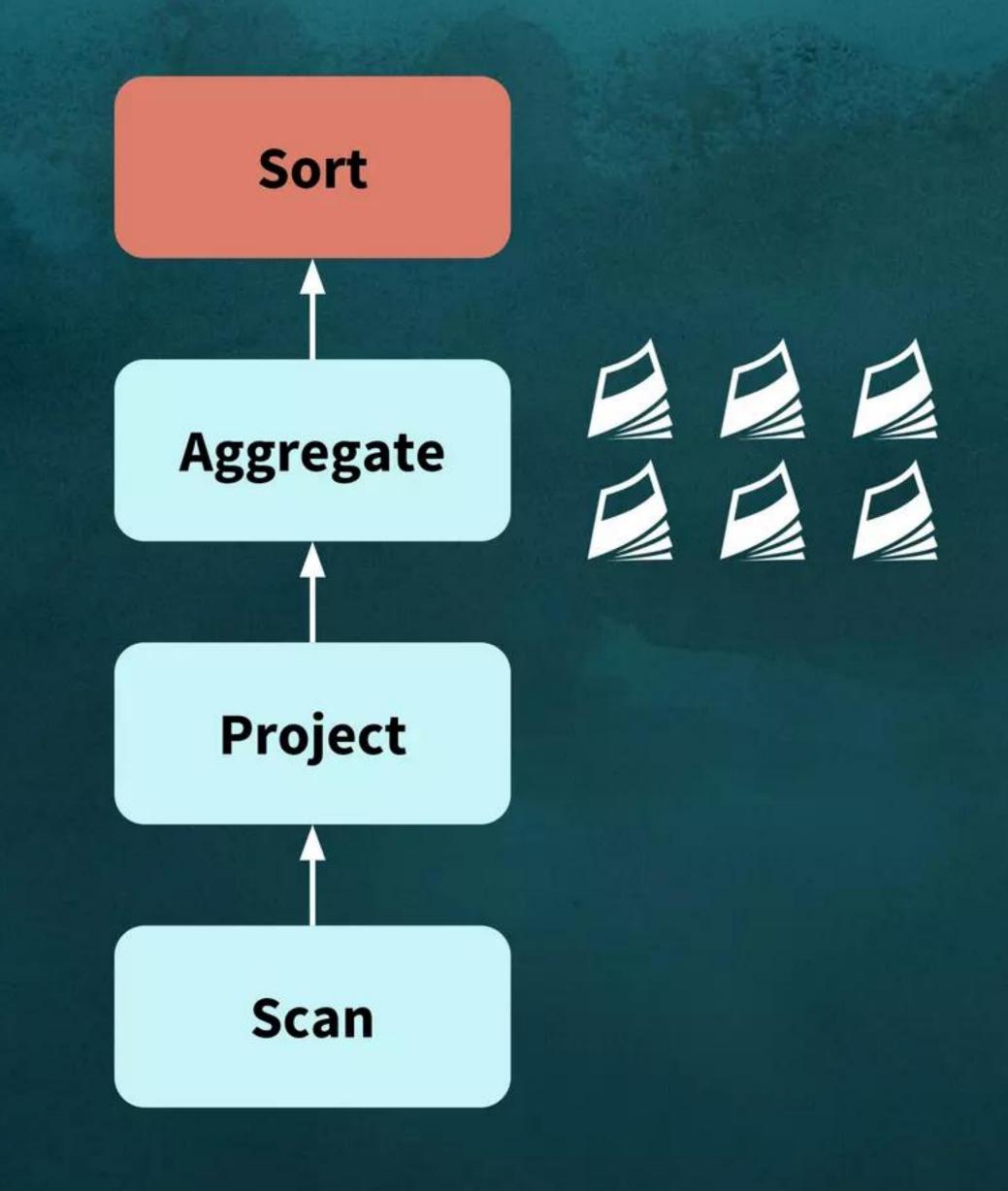
22 \rightarrow [155, 166, 188]

23 \rightarrow [160, 168, 178, 183]

\}
```



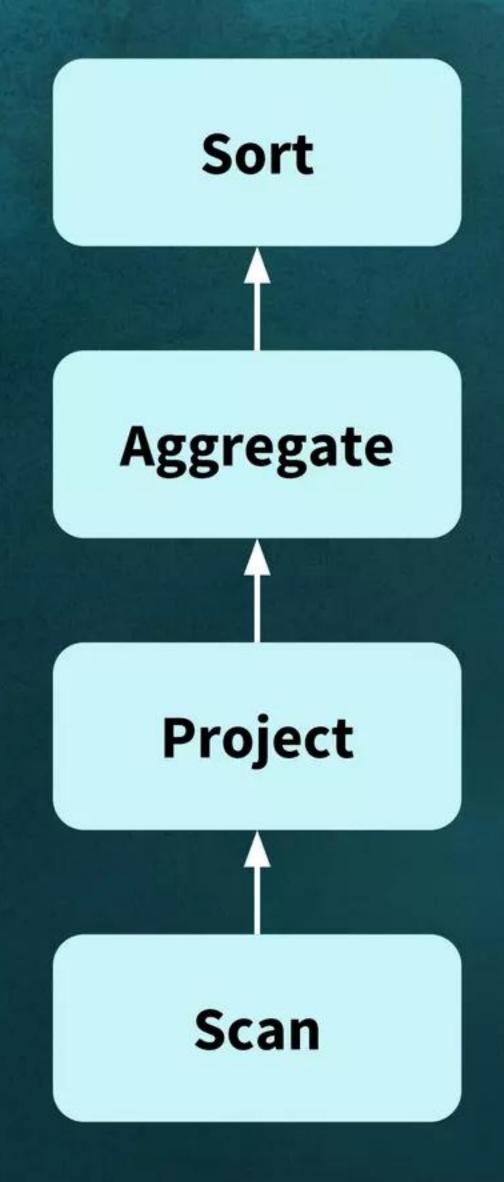
All 6 pages were used by *Aggregate*, leaving no memory for *Sort*!





Solution #1:
Reserve a page for each operator



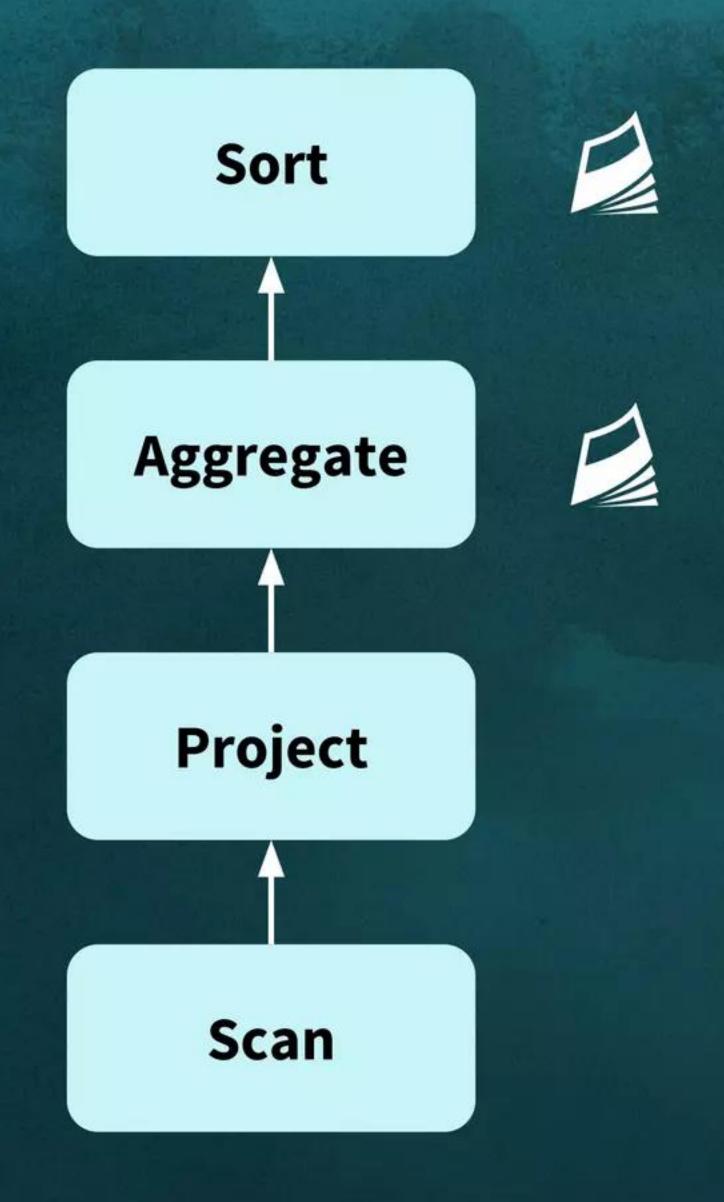




Solution #1:
Reserve a page for each operator

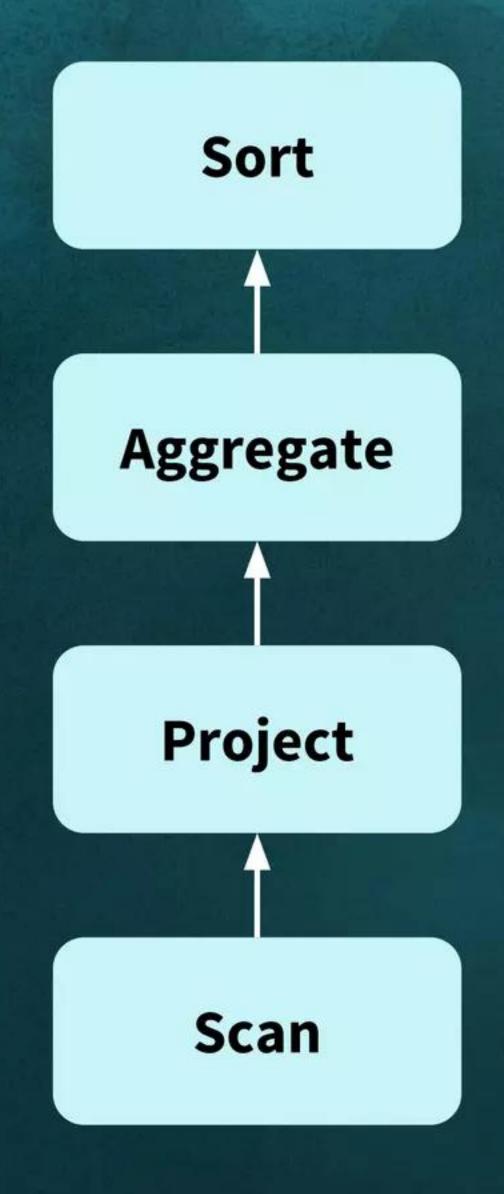


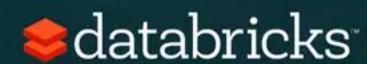
Starvation free, but still not fair... What if there were more operators?

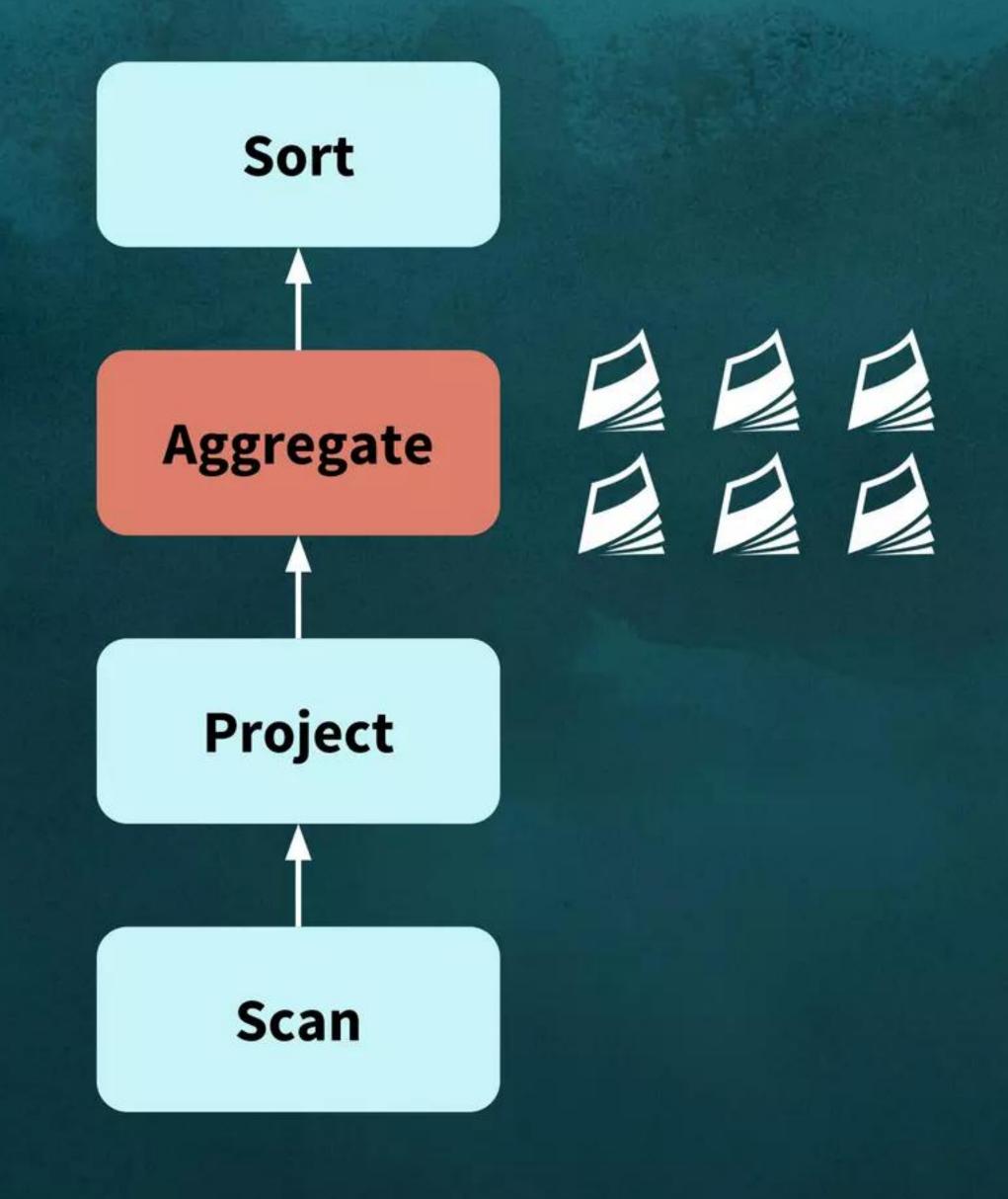






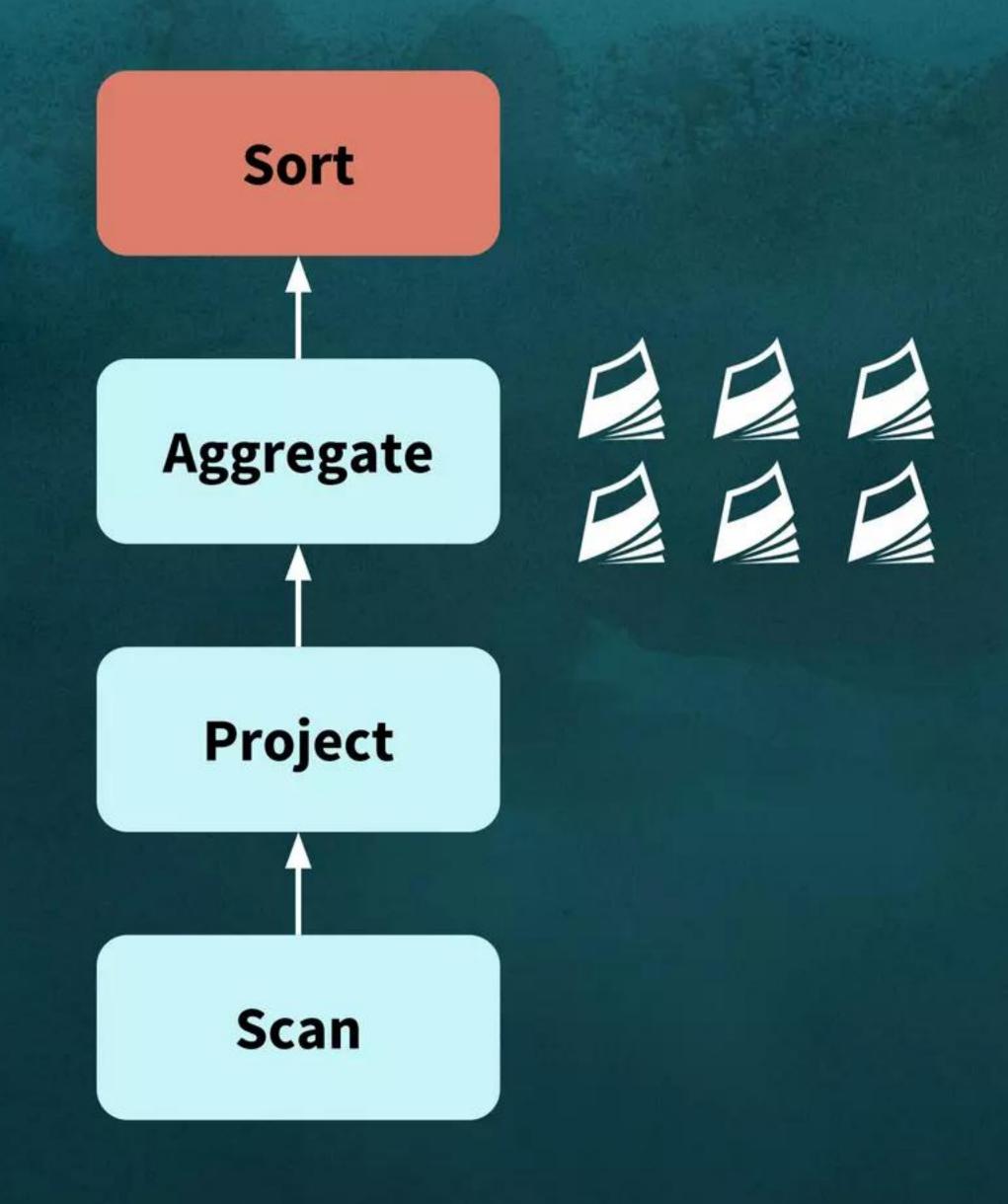






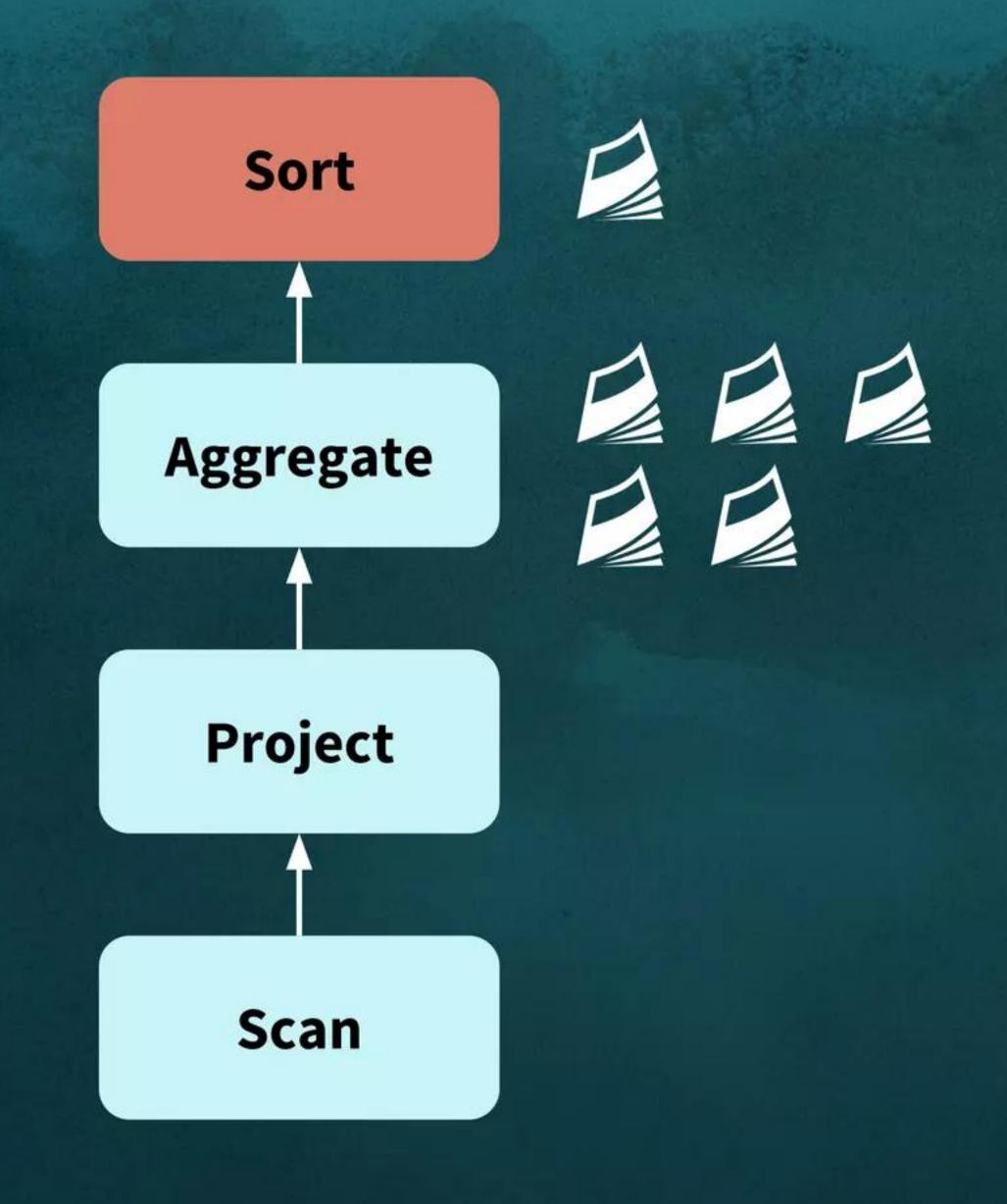


Sort forces Aggregate to spill a page to free memory





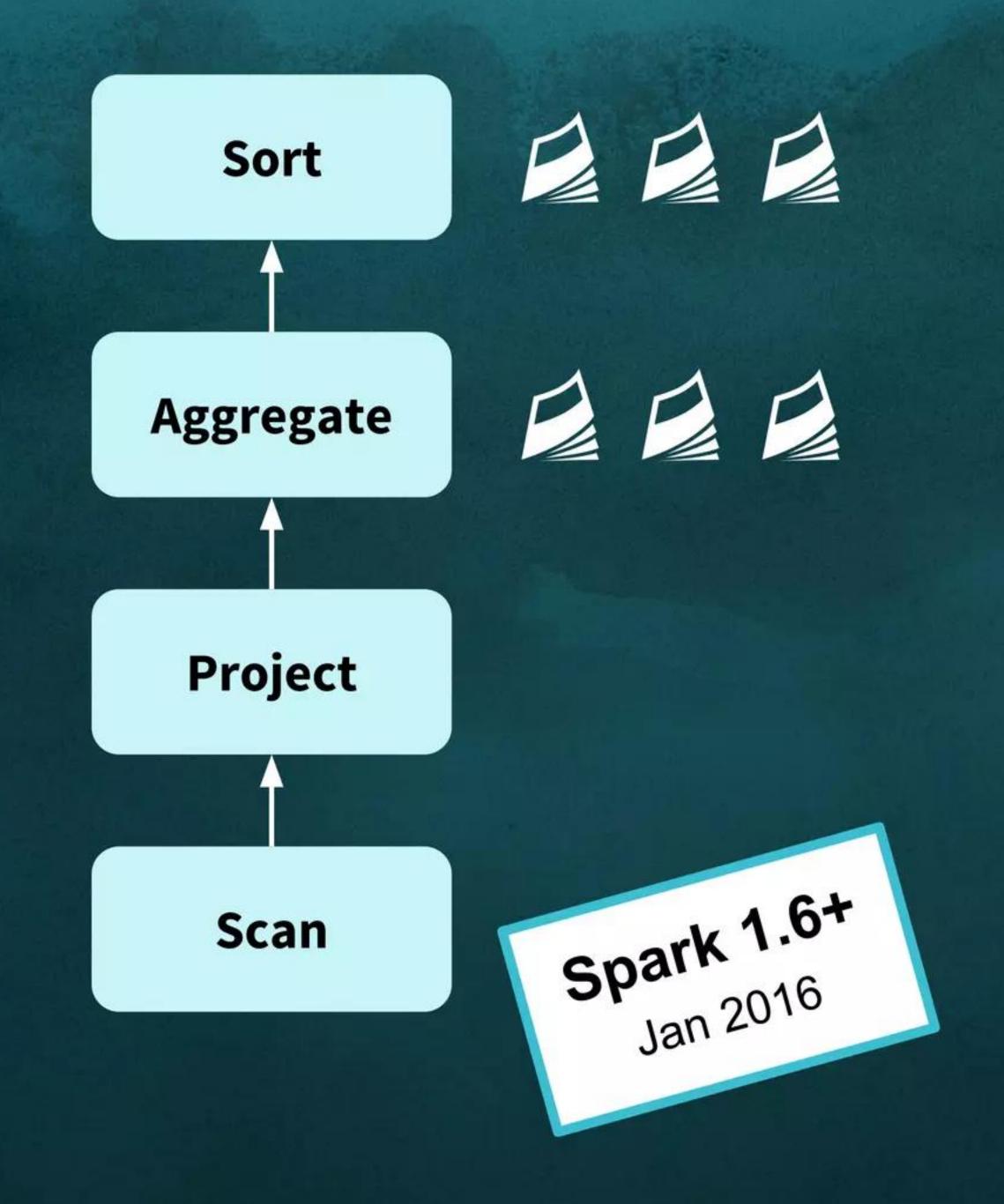
Sort needs more memory so it forces Aggregate to spill another page (and so on)





Sort finishes with 3 pages

Aggregate does not have to spill its remaining pages





## Recap: Three sources of contention

How to arbitrate memory ...

- between execution and storage?
- across tasks running in parallel?
- across operators running within the same task?

Instead of avoid statically reserving memory in advance, deal with memory contention when it arises by forcing members to spill



# Project Tungsten

Binary in-memory data representation

Cache-aware computation

Code generation (next time)

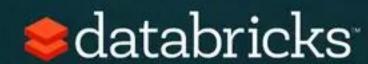




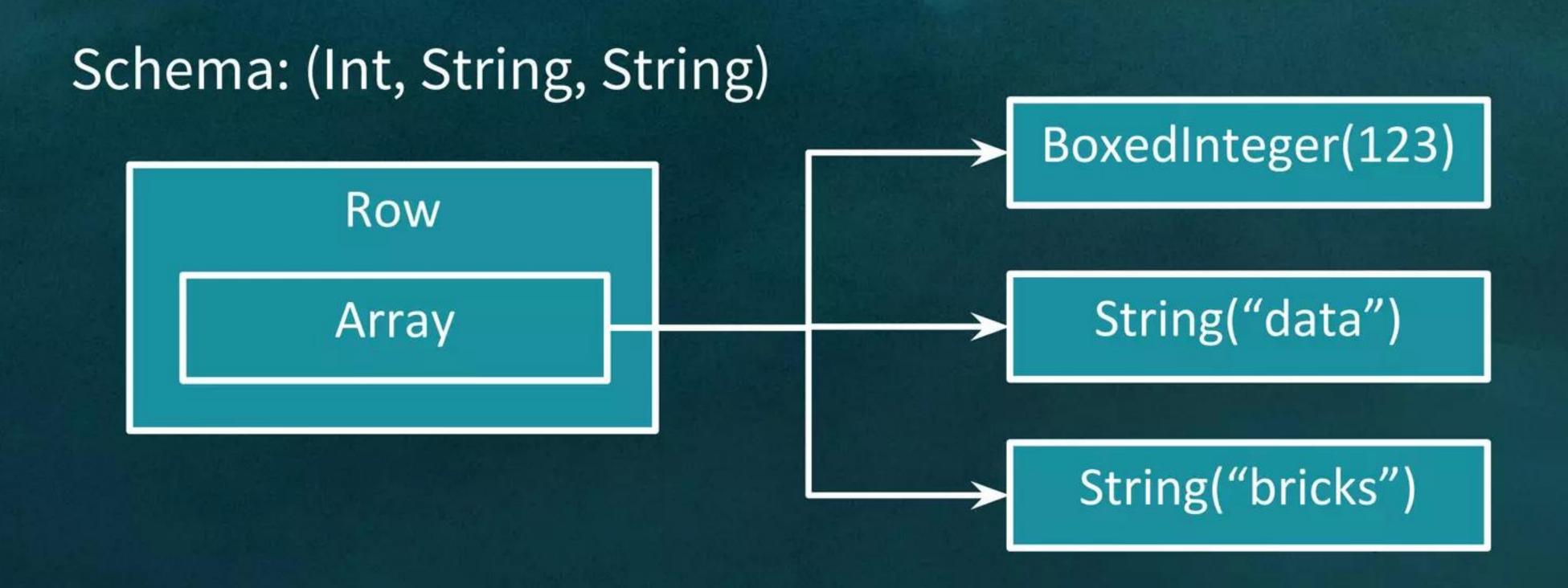
# Java objects have large overheads

# "abcd"

- Native: 4 bytes with UTF-8 encoding
- Java: 48 bytes
  - 12 byte header
  - 2 bytes per character (UTF-16 internal representation)
  - 20 bytes of additional overhead
  - 8 byte hash code



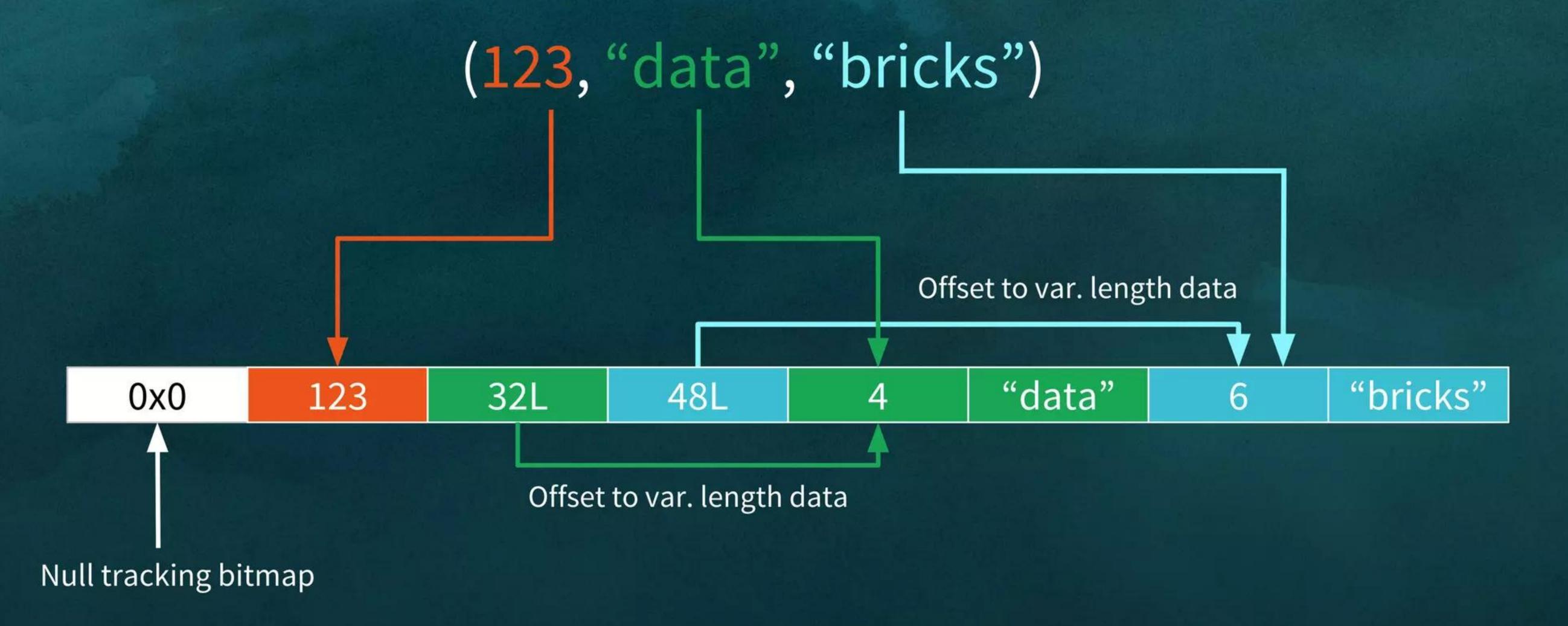
## Java objects based row format



5+ objects, high space overhead, expensive hashCode()



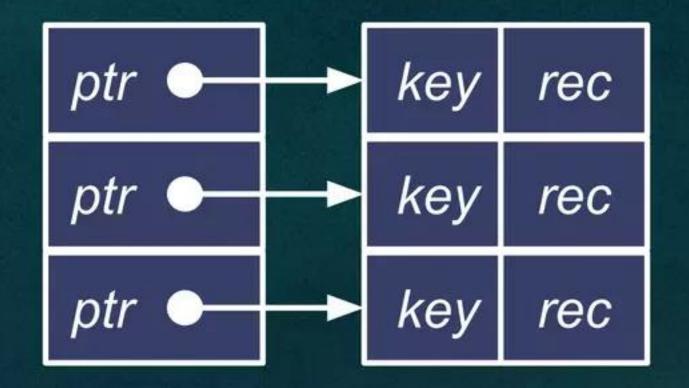
# Tungsten row format





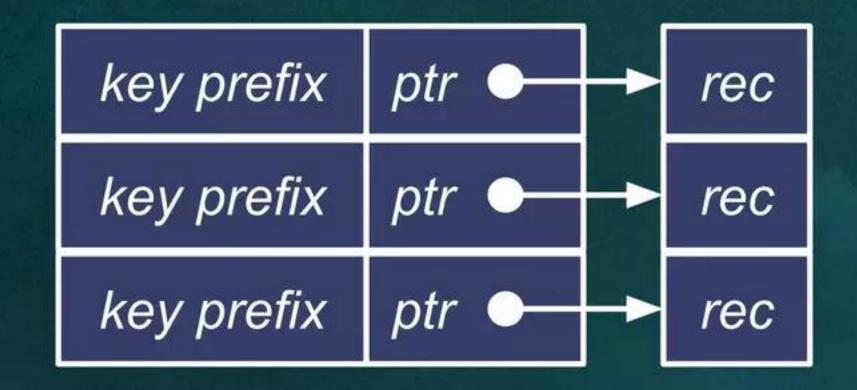
## Cache-aware computation

E.g. sorting a list of records

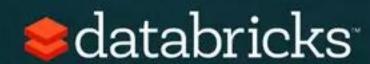


Naive layout

Poor cache locality



Cache-aware layout Good cache locality



# Off-heap memory

Available for execution since Apache Spark 1.6 Available for storage since Apache Spark 2.0

Very important for large heaps

Many potential advantages: memory sharing, zero copy I/O, dynamic allocation



#### For more info...

Deep Dive into Project Tungsten: Bringing Spark Closer to Bare Metal

https://www.youtube.com/watch?v=5ajs8EIPWGI

Spark Performance: What's Next

https://www.youtube.com/watch?v=JX0CdOTWYX4

Unified Memory Management

https://issues.apache.org/jira/browse/SPARK-10000





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