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

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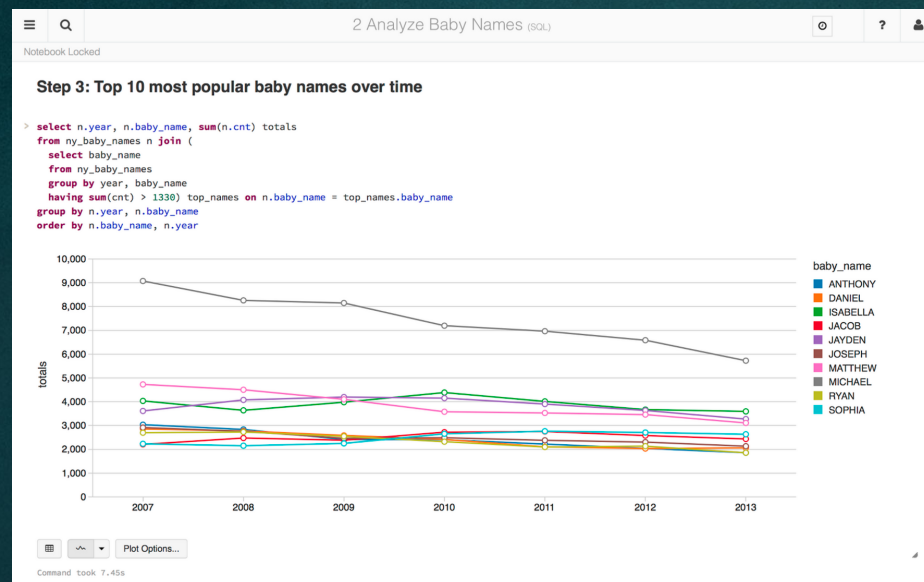
About Databricks

Founded by creators of Spark and remains largest contributor

Offers a hosted service:

- Spark on EC2
- Notebooks
- Plot visualizations
- Cluster management
- Scheduled jobs



Goals of Project Tungsten

Substantially improve the **memory and CPU** efficiency of Spark applications .

Push performance closer to the limits of modern hardware.

In this talk

- Motivation: why we're focusing on compute instead of IO
- How Tungsten optimizes memory + CPU
- Case study: aggregation
- Case study: record sorting
- Performance results
- Roadmap + next steps

Many big data workloads are now compute bound

NSDI'15:

Making Sense of Performance in Data Analytics Frameworks

Kay Ousterhout[*], Ryan Rasti[*†◇], Sylvia Ratnasamy[*], Scott Shenker[*†], Byung-Gon Chun[‡]
[*]UC Berkeley, [†]ICSI, [◇]VMware, [‡]Seoul National University

- "Network optimizations can only reduce job completion time by a median of at most 2%."
- "Optimizing or eliminating disk accesses can only reduce job completion time by a median of at most 19%."
- We've observed similar characteristics in many Databricks Cloud customer workloads.

Why is CPU the new bottleneck?

- Hardware has improved:
  - Increasingly large aggregate IO bandwidth, such as 10Gbps links in networks
  - High bandwidth SSD's or striped HDD arrays for storage
- Spark's IO has been optimized:
  - many workloads now avoid significant disk IO by pruning input data that is not needed in a given job
  - new shuffle and network layer implementations
- Data formats have improved:
  - Parquet, binary data formats
- Serialization and hashing are CPU-bound bottlenecks

How Tungsten improves CPU & memory efficiency

- **Memory Management and Binary Processing**: leverage application semantics to manage memory explicitly and eliminate the overhead of JVM object model and garbage collection
- **Cache-aware computation**: algorithms and data structures to exploit memory hierarchy
- **Code generation**: exploit modern compilers and CPUs; allow efficient operation directly on binary data

Generality has a cost, so we should use semantics and schema to exploit specificity instead

The overheads of Java objects

“abcd”

- **Native:** 4 bytes with UTF-8 encoding
- **Java:** 48 bytes

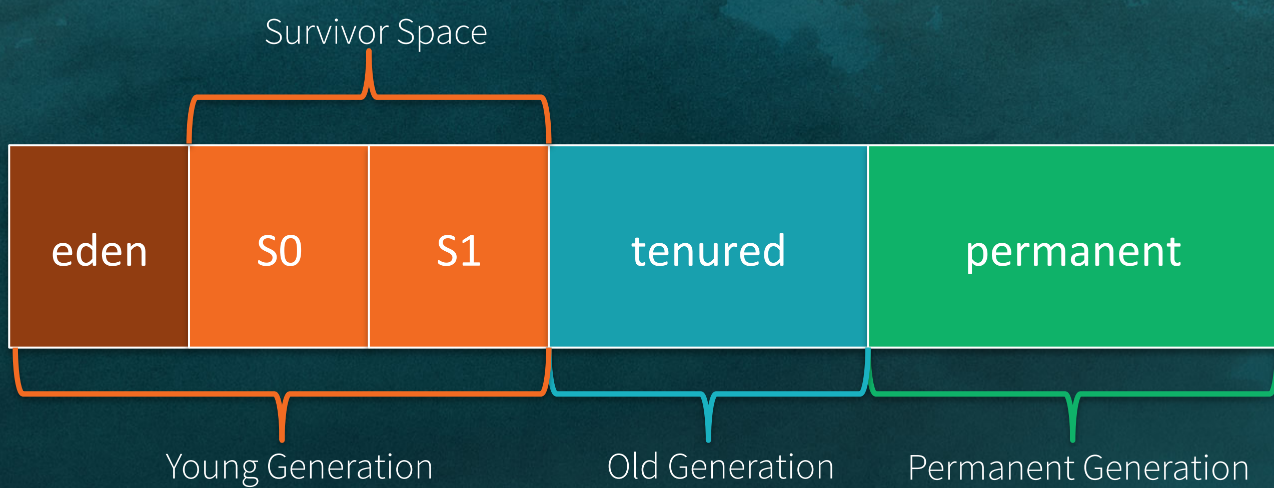
```
java.lang.String object internals:
OFFSET  SIZE   TYPE DESCRIPTION                    VALUE
     0     4        (object header)                ...
     4     4        (object header)                ...
     8     4        (object header)                ...
    12     4 char[] String.value                   []
    16     4    int String.hash                    0
    20     4    int String.hash32                  0
Instance size: 24 bytes (reported by Instrumentation API)
```

12 byte object header

20 bytes of overhead + 8 bytes for chars

8 byte hashcode

Garbage collection challenges



- Many big data workloads create objects in ways that are unfriendly to regular Java GC.
- Guest blog on GC tuning: tinyurl.com/db-gc-tuning

sun.misc.Unsafe

- JVM internal API for directly manipulating memory without safety checks (hence “unsafe”)
- We use this API to build data structures in both on- and off-heap memory

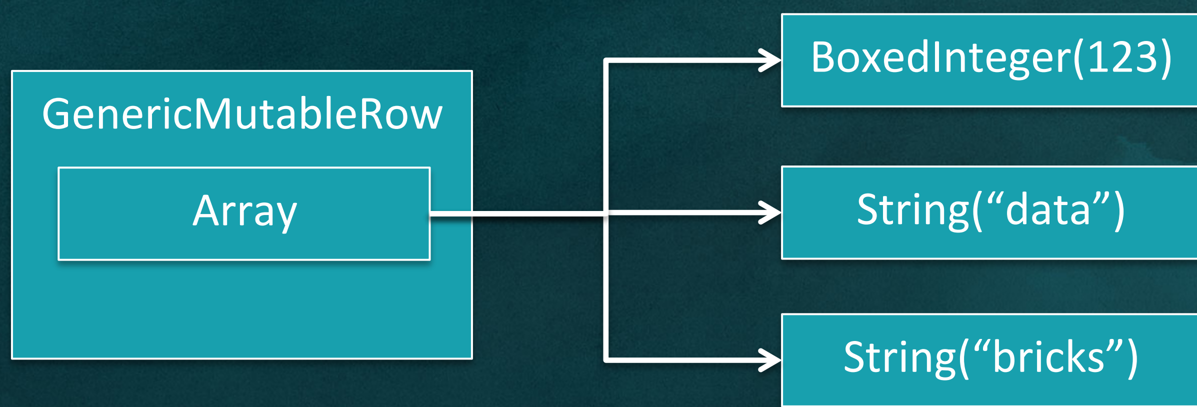
Flat data structures

Data structures with pointers

Complex examples

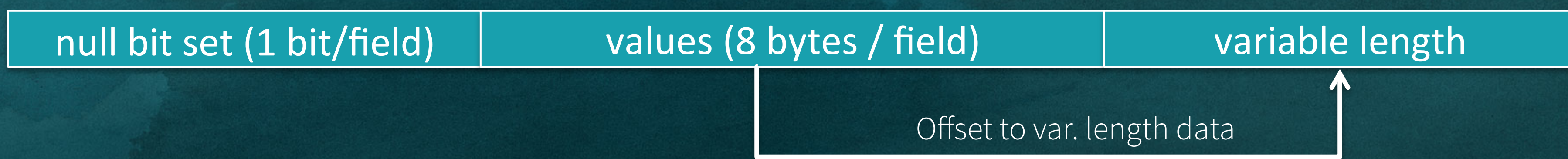
Java object-based row representation

3 fields of type (int, string, string)
with value (123, “data”, “bricks”)



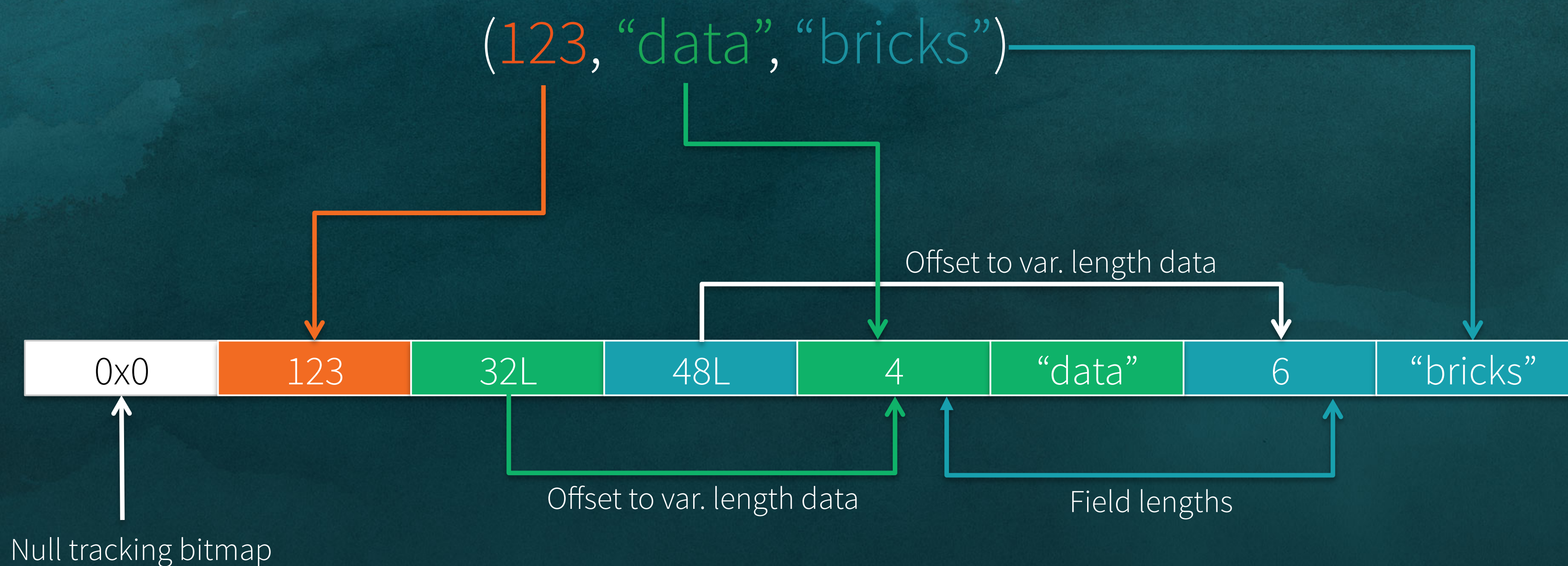
5+ objects; high space overhead; expensive hashCode()

Tungsten's UnsafeRow format



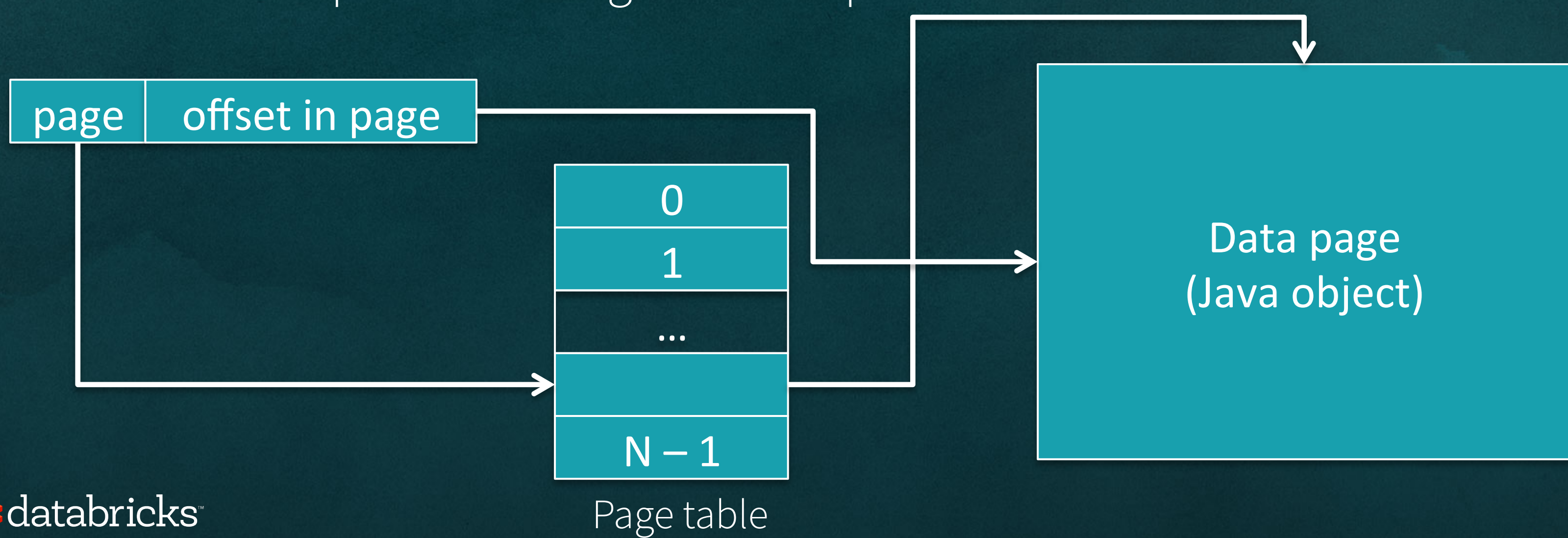
- Bit set for tracking null values
- Every column appears in the fixed-length values region:
  - Small values are inlined
  - For variable-length values (strings), we store a relative offset into the variable-length data section
- Rows are always 8-byte word aligned (size is multiple of 8 bytes)
- Equality comparison and hashing can be performed on raw bytes without requiring additional interpretation

Example of an UnsafeRow

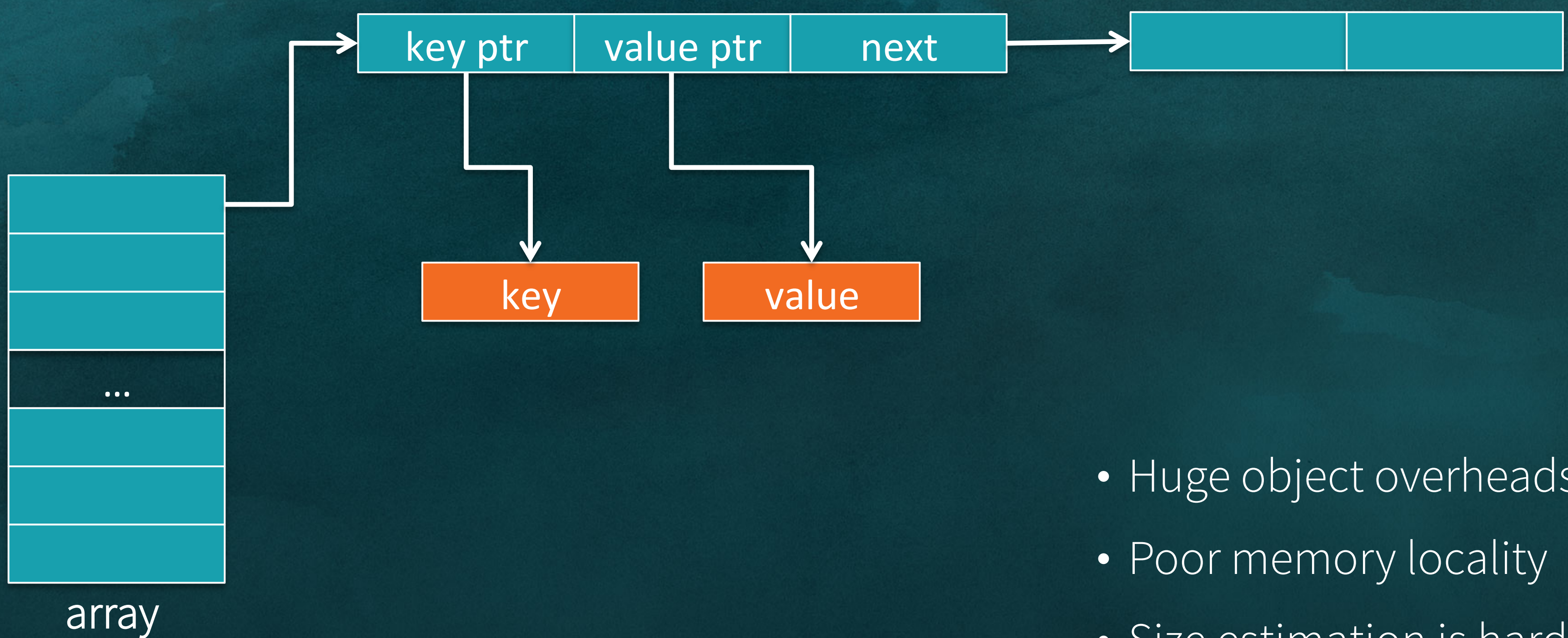


How we encode memory addresses

- Off heap: addresses are raw memory pointers.
- On heap: addresses are base object + offset pairs.
- We use our own "page table" abstraction to enable more compact encoding of on-heap addresses:



java.util.HashMap



- Huge object overheads
- Poor memory locality
- Size estimation is hard

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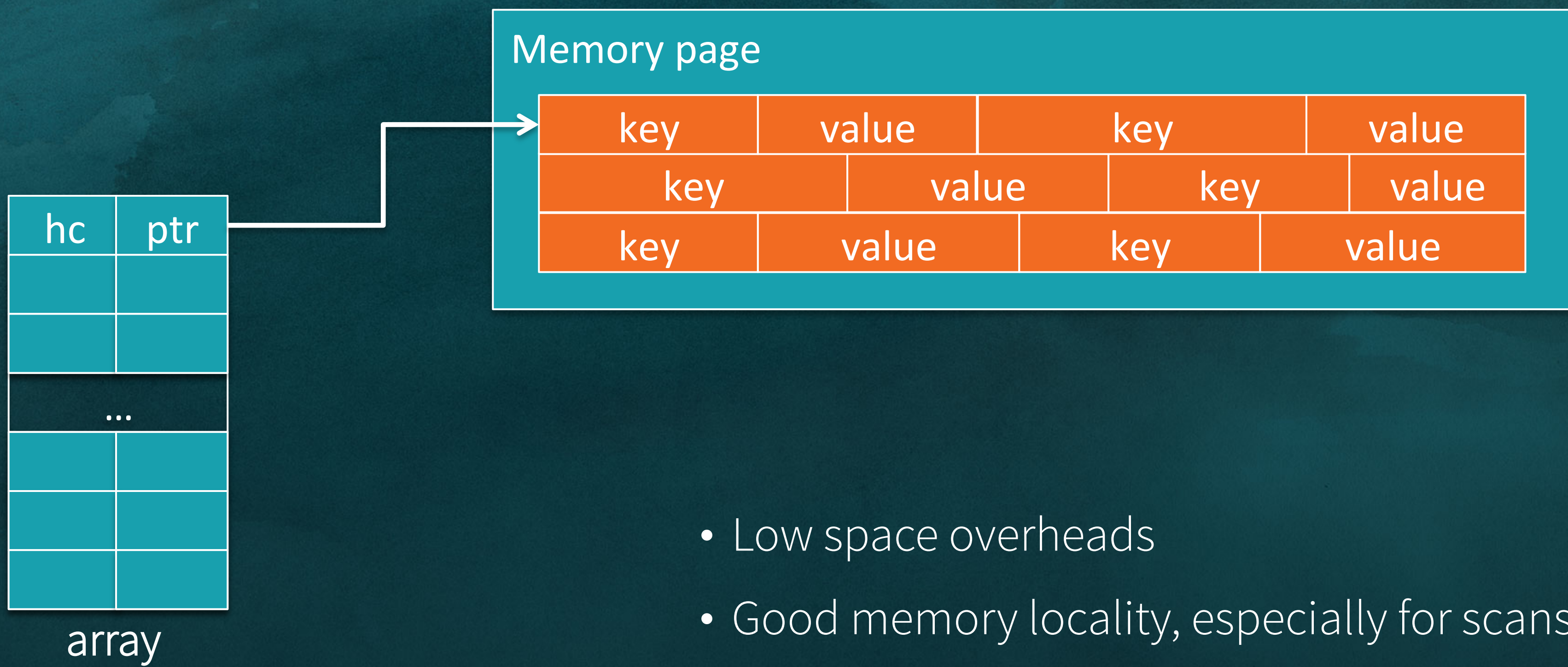
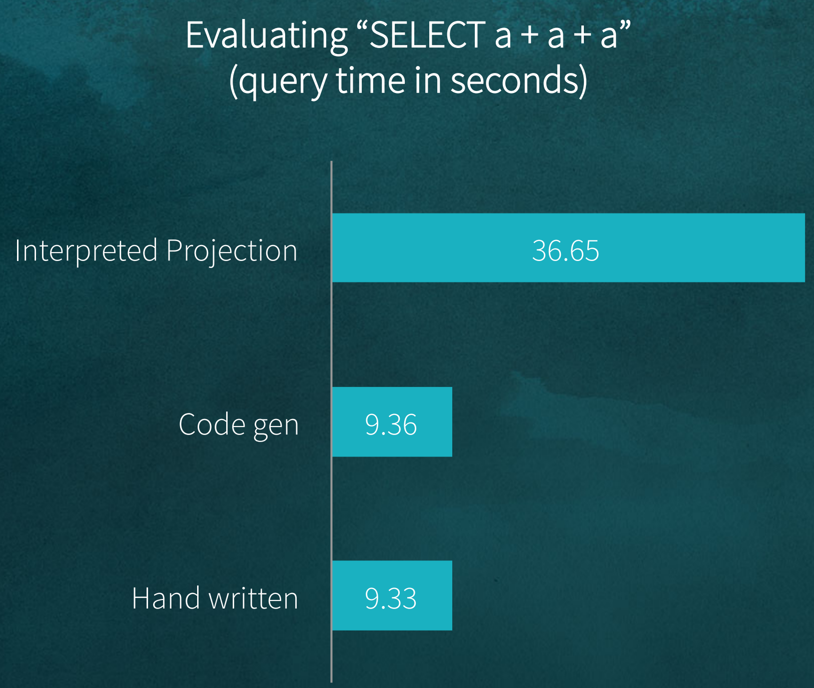
Tungsten’s BytesToBytesMap



- Low space overheads
- Good memory locality, especially for scans

Code generation

- Generic evaluation of expression logic is very expensive on the JVM
  - Virtual function calls
  - Branches based on expression type
  - Object creation due to primitive boxing
  - Memory consumption by boxed primitive objects
- Generating custom bytecode can eliminate these overheads



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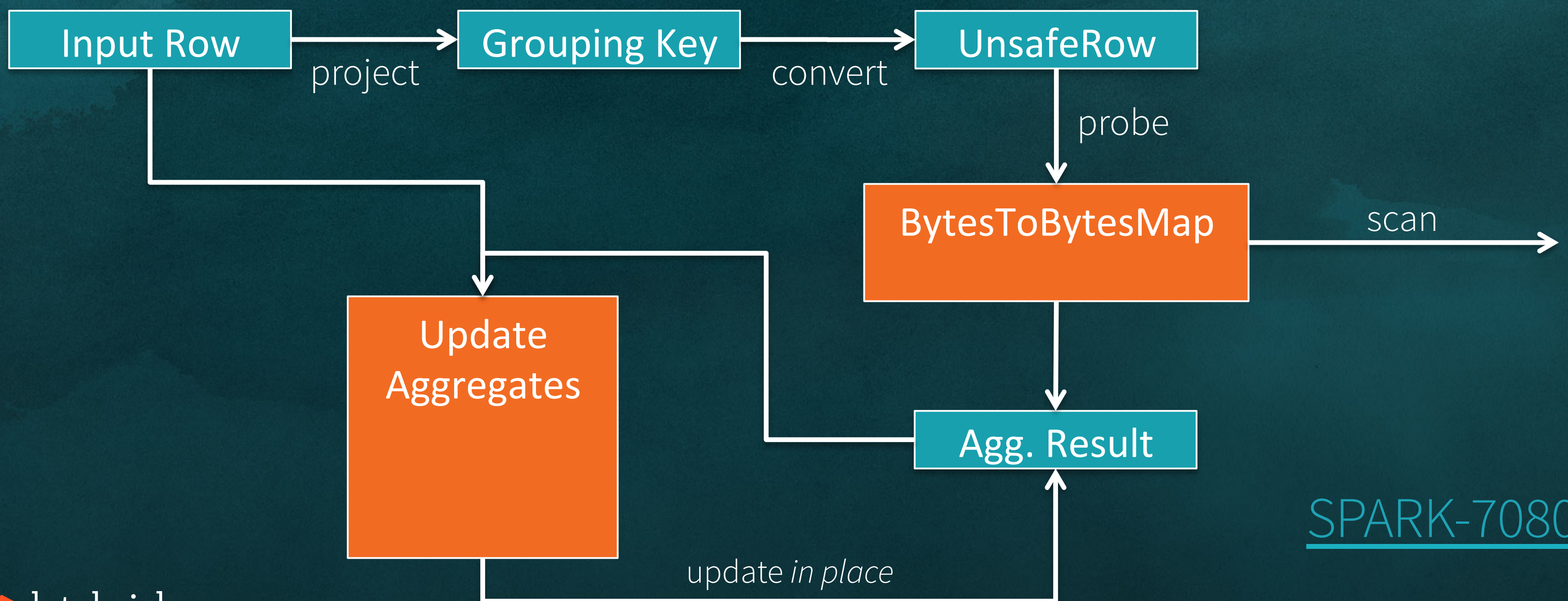
Code generation

- Project Tungsten uses the Janino compiler to reduce code generation time.
- Spark 1.5 will greatly expand the number of expressions that support code generation:
  - SPARK-8159

Example: aggregation optimizations in DataFrames and Spark SQL

```
df.groupBy("department").agg(max("age"), sum("expense"))
```

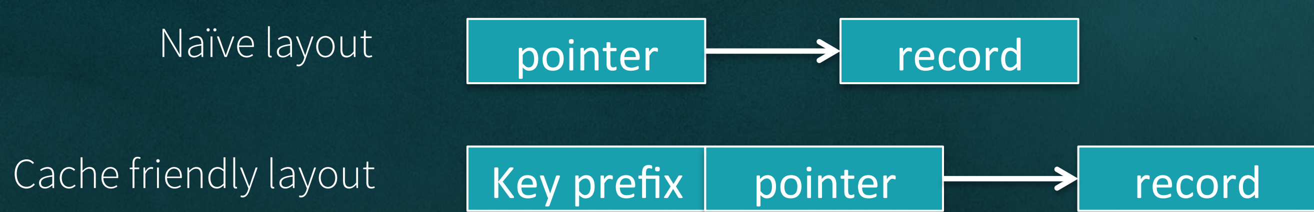
Example: aggregation optimizations in DataFrames and Spark SQL



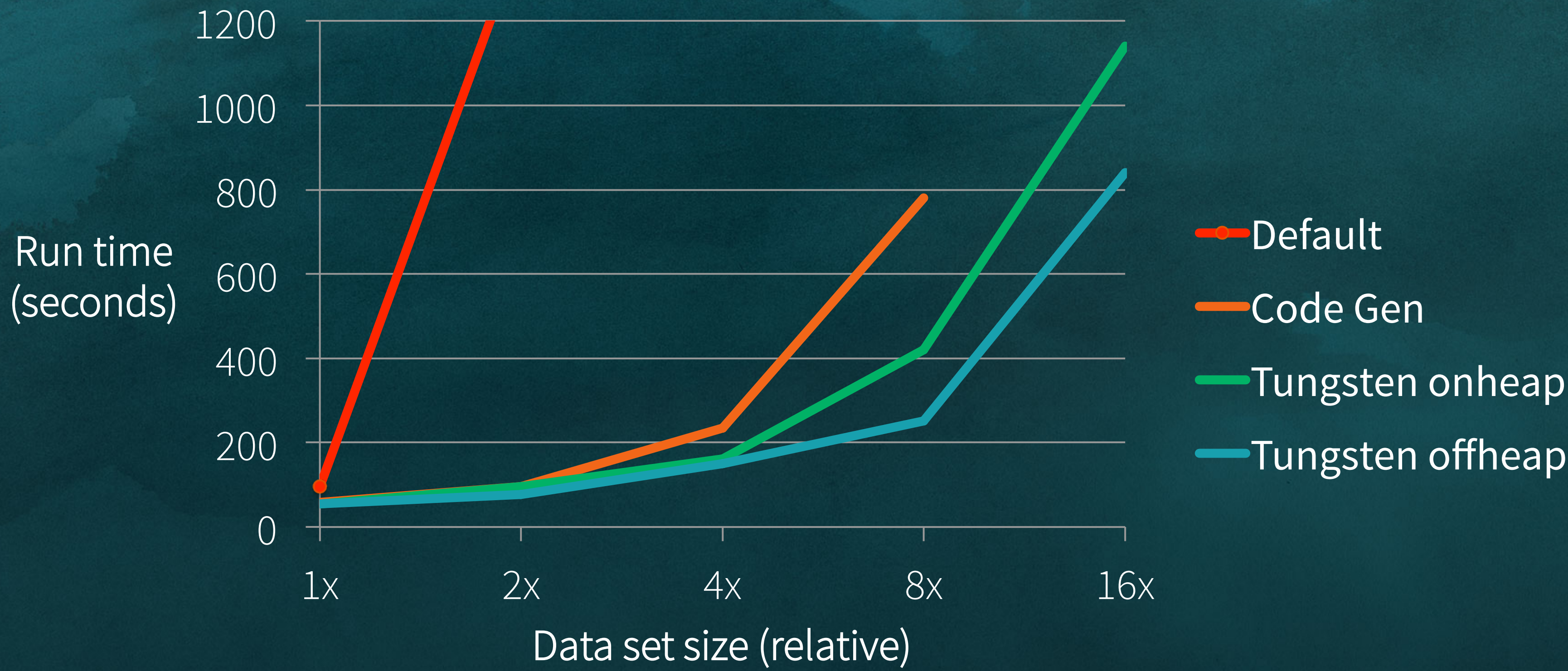
SPARK-7080

Optimized record sorting in Spark SQL + DataFrames (SPARK-7082)

- AlphaSort-style prefix sort:
  - Store prefixes of sort keys inside the sort pointer array
  - During sort, compare prefixes to short-circuit and avoid full record comparisons
- Use this to build external sort-merge join to support joins larger than memory



Initial performance results for agg. query



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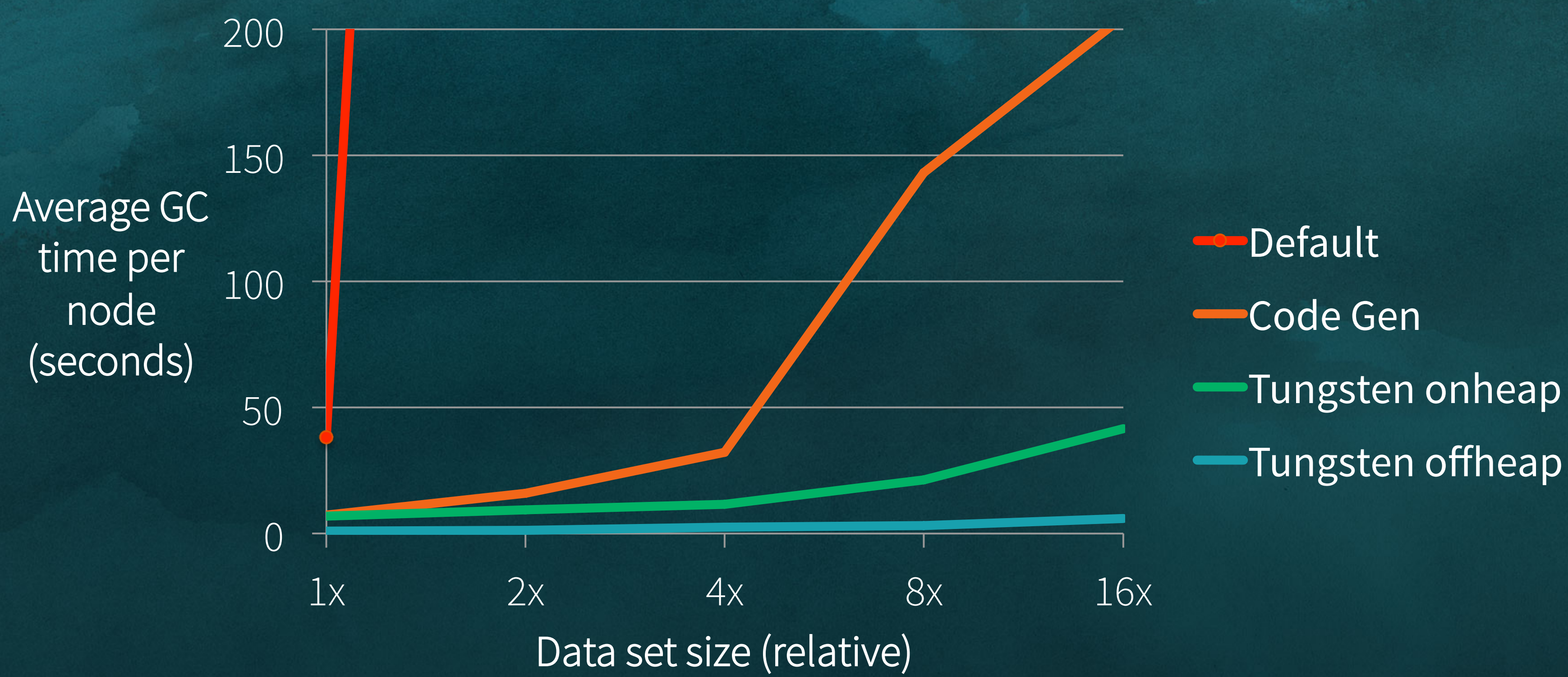
Initial performance results for agg. query



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Project Tungsten Roadmap

Spark 1.4	Spark 1.5	Spark 1.6
• Binary processing for aggregation in Spark SQL / DataFrames • New Tungsten shuffle manager • Compression & serialization optimizations	• Optimized code generation • Optimized sorting in Spark SQL / DataFrames • End-to-end processing using binary data representations • External aggregation	• Vectorized / batched processing • ???

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Which Spark jobs can benefit from Tungsten?

- DataFrames
  - Java
  - Scala
  - Python
  - R
- Spark SQL queries
- **Some Spark RDD API programs**, via general serialization + compression optimizations

```
logs.join(
  users,
  logs.userId == users.userId,
  "left_outer") \
.groupBy("userId").agg({"*": "count"})
```

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How to enable all of Spark 1.4's Tungsten optimizations

Warning! These features are experimental in 1.4!

```
spark.sql.codegen = true
spark.sql.unsafe.enabled = true
spark.shuffle.manager = tungsten-sort
```

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Thank you.

Follow our progress on JIRA: [SPARK-7075]

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