An Experimental Study of Memory Management in Rust Programming for Big Data Processing

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May, 2020

Motivation

Many of existing data-flow based Big Data Processing systems like Apache Spark and Flink have the following weaknesses!

- Using Java Virtual Machine (JVM)
  - Using additional computation
- Automated Memory Management
  - Generative Garbage Collection

Rust is a promising candidate for development of Big Data processing tools.

Rust

Rust is a **"system language"** which has unique memory management concept.

- A system language does not have Garbage Collection.
- Rust ensures memory safety.
- It is easy to write safe threaded code in Rust.
- Rust uses LLVM compiler infrastructure and provides high performance.

Problem Description

Our goal is to determine the magnitude of performance change regarding the following aspects.

- Memory Management for High Complex Nested Objects
- Different Rust Memory Management Strategies
- Automated Reference Counting (Rc) vs. Reference
- Multithreading using Atomic Reference Counting (Arc)
- Arc vs. Deep Copy on Overall Performance of Big Data Processing

Different Rust Memory Management Strategies

Each one has different memory representation.

- Owner
- Reference
- Slice

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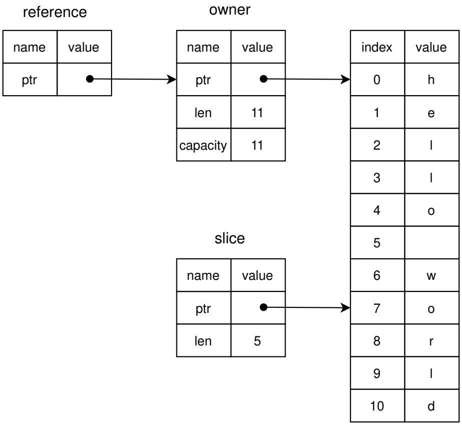


Each one may have different memory access time.

Reference Counting

Advantage

- ▷ Sharing ownership
- ▷ Dinamic memory de/allocation

Disadvantage

- ▷ Need to check reference count
- ▷ Heap allocation

Complex Object - Memory Ownership and Borrowing

A Complex Object like a nested Customer Object like those defined in the complete Web-based shop.

Memory Ownership

```
struct CustomerOwned {
                key: i32,
                total_purchase: f64,
                zip_code: String,
                order: OrderOwned
                ... 10 more
        }
```

Memory Borrowing

```
struct CustomerBorrowed<'a> {
                key: &'a i32,
                total_purchase: &'a f64,
                zip_code: &'a String,
                order: &'a OrderBorrowed<'a>
                ... 10 more
        }
```

Complex Object - Slicing and Reference Counting

Memory Slicing and Atomic Reference Counting

Memory Slicing

```
struct CustomerSlice<'a> {
                key: &'a i32,
                total_purchase: &'a f64,
                zip_code: &'a str,
                order: &'a OrderSlice<'a>
                        ... 10 more
       }
```

Atomic Reference Counting

```
struct CustomerRc {
                key: Rc<i32>,
                total_purchase: Rc<f64>,
                zip_code: Rc<String>,
                order: Rc<OrderRc>
                                ... 10 more
        }
```

Multithreading with Atomic Reference Counting

Atomic Reference Counting

Advantage

- ▷ Sharing ownership
- ▷ Dinamic memory de/allocation
- ▷ Sharing among multithreads

Disadvantage

- ▷ Need to check reference count
- ▷ Heap allocation
- ▷ Atomic operation

Impact of Memory Management on performance of Big Data Processing

- **Merge-sort**
  - Many contiguous memory de/allocations
- **Tree-aggtegate**
  - Many intermediate HashMap like data structures
- **K-Nearest-Neighbors (KNN)**
  - Document preprocessing

Experiment 1: Accessing Object with Different Variable Type

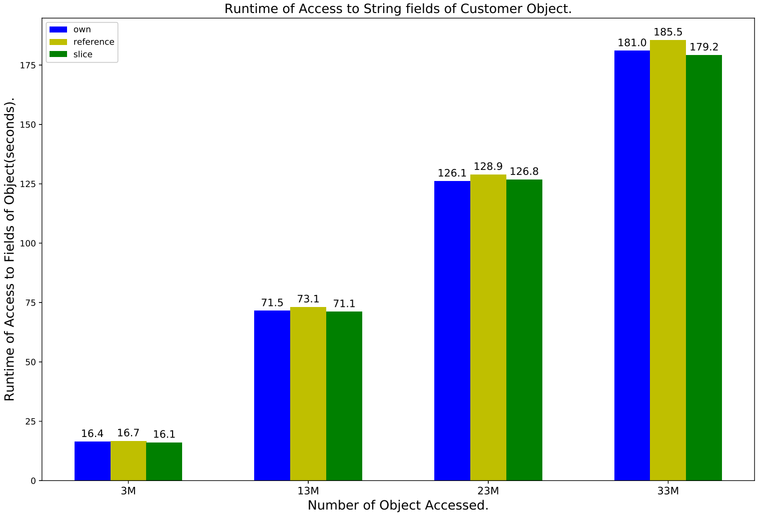
Question

- How much memory access time are different among different memory management strategies used in complex objects specification?

Evaluation

- **Construct Complex objects**
- With different memory management strategies: **Owner, Reference, Slice**
- **CustomerOwned** vs. **CustomerBorrowed** vs. **CustomerSlice**
- Measure access time of different **fields of complex objects**

Experiment 1: Accessing Object with Different Variable Type



Experiment 2: Assessment of different reference methods in Rust

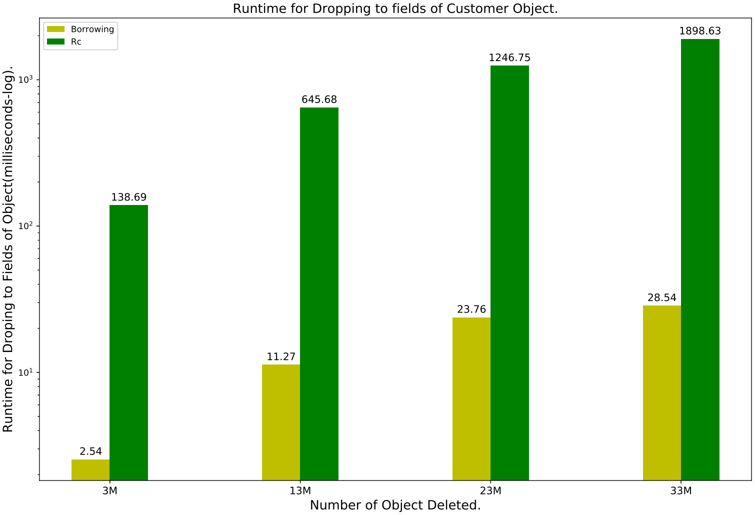
Question

- How much does Reference Counting hits performance?

Evaluation

- **Custruct complext objects**
- **Reference Counting** vs **reference**
- CustomerRc vs. CustomerBorrowed
- Measure time to **drop variables of complex objects**

Experiment 2: Assessment of different reference methods in Rust



Experiment 2: Assessment of different reference methods in Rust

Result

- Dropping Reference Counting is about **60 times slower** than normal reference.

Discussion

- Reference Counting needs some CPU cycles to check reference count.
- In complex objects, overhead is significant.

Experiment 3: Merge-sort

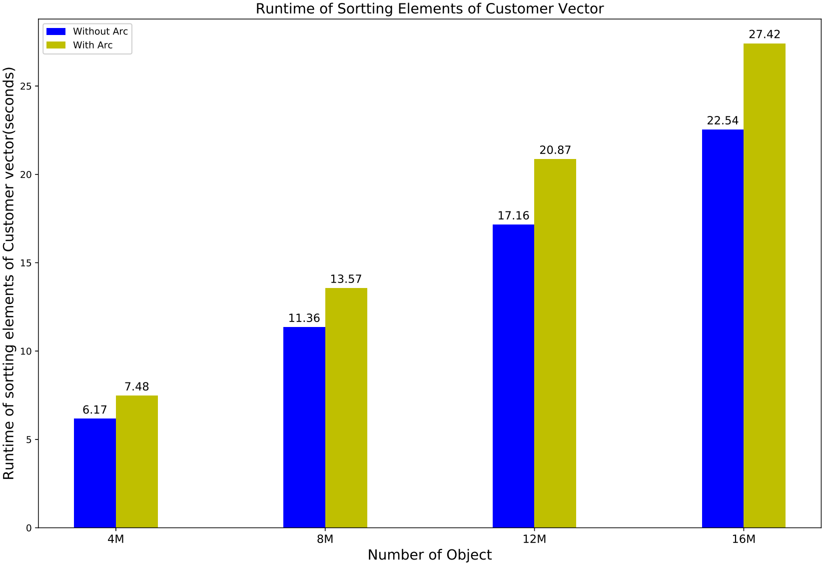
Question

- How much does sharing set of data with Atomic Reference Counting slowdown merge-sort algorithms?

Evaluation

- Share **vector** of complex objects
- **Atomic Reference Counting (Arc)** vs **normal reference**
- Measure **runtime of merge-sort algorithms**

Experiment 3: Merge-sort



Experiment 3: Merge-sort

Result

- Arc are about **21% slower** than normal reference.

Discussion

- Atomic Reference Counting needs to check reference count.
- Atomic operations are more expensive than ordinal operations.

Experiment 4: Tree-aggregate

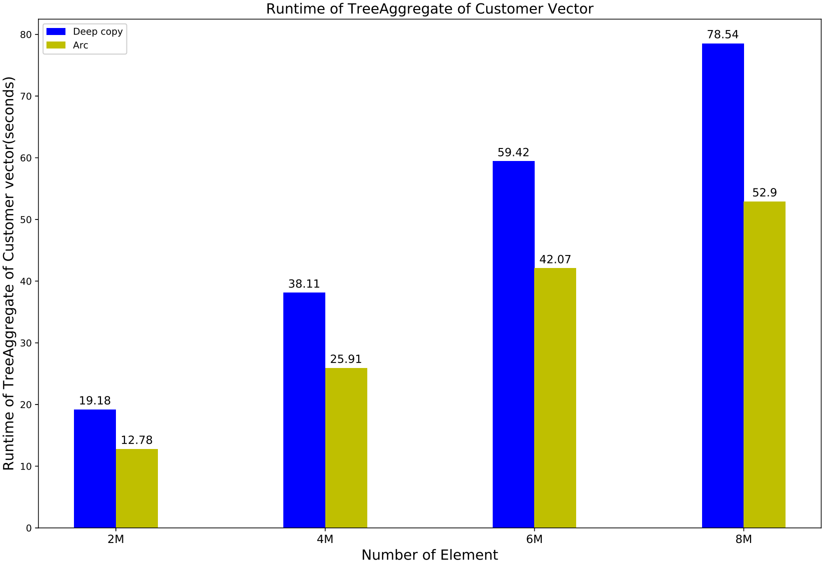
Question

- How much are runtime differences between sharing elements of data with Arc and deep-copying elements of data?

Evaluation

- Share **elements** of complex object
- **Atomic Reference Counting (ARC)** vs **Deep copy**
- Measure **runtime of Tree-aggregate algorithms**

Experiment 4: Tree-aggregate



Experiment 4: Tree-aggregate

Result

- Deep-copies are from **40 to 50% slower** than Arc.

Discussion

- Deep-copy of complex object is expensive.
- Performing deep-copy many times may lead significant overhead.

Experiment 5: K-Nearest-Neighbors (KNN)

Question

- What are better memory management strategies for common Machine Learning Algorithms?

Evaluation

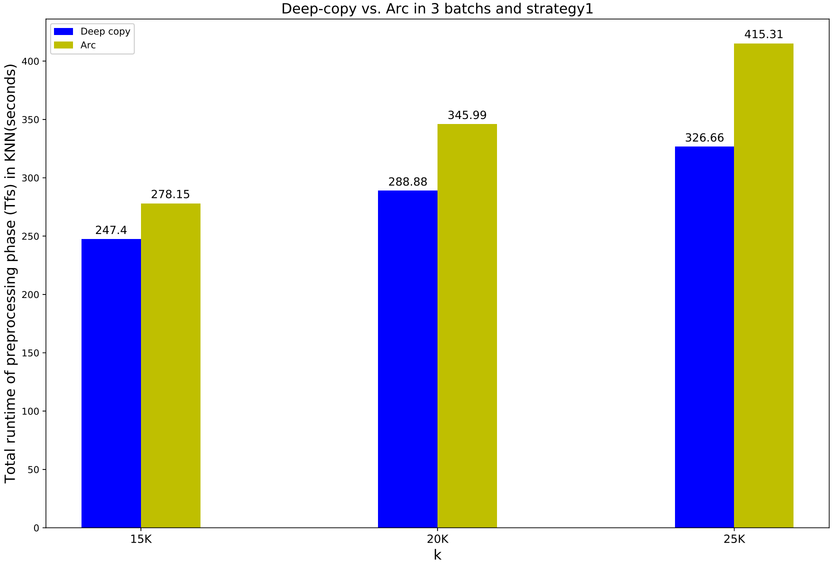
- Document classification on Wikipedia page dataset
  - train set: 100×10^3 pages
  - test set: 18×10^3 pages
- Preprocessing phase: calculating **Term-Frequencies (TFs)**
- String manipulation
- Measure runtime of **preprocessing time of KNN algorithms**

Experiment 5: K-Nearest-Neighbors (KNN)

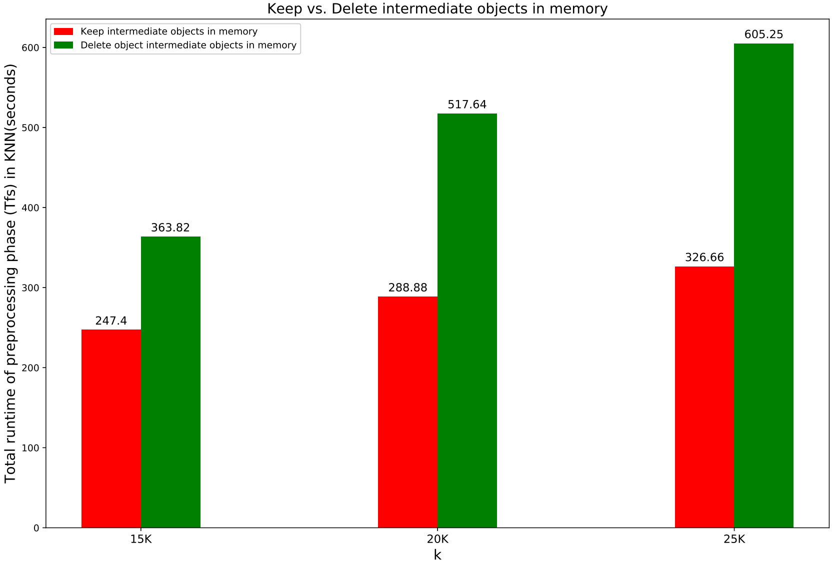
Parameters

- Data Acquisition
  - **Atomic Reference Counting** (Arc)
  - **Deep-copy**
- Strategy
  - keep intermediate objects in memory until owner is changed
  - remove intermediate objects as soon as it is not needed
- Dimensions of feature matrices
  - 15K
  - 20K
  - 25K

Experiment 5: K-Nearest-Neighbors



Experiment 5: K-Nearest-Neighbors



Experiment 5: K-Nearest-Neighbors

Result

- **Arc** is **at most 38% slower** than deep-copy.
- Removing intermediate objects is **at most 85% slower** than keeping the objects.

Discussion

- Deep-copying String is cheaper operation than Arc:
  - reference checking
  - atomic operation
- More frequent deallocation of intermediate objects may lead to overhead.

Findings

- Use normal reference rather than Reference Counting whenever it is possible.
- Trade-off between **runtime performance** and **lifetime tracking**.
- **Avoid using Arc** when we can use reference.
- Use Arc instead of deep-copy, when **complexity of objects is large**.
- Use deep-copy, when **complexity of objects is small**, like String.

Conclusion

- There are not notable differences among times to access memory with different memory management strategies.
- When we drop complex objects constructed with Reference Counting, additional computation for counting reference results in huge overhead.
- Sharing set of data with Arc is more expensive than reference.
- Deep-copying complex objects is more expensive than sharing them with Arc.
- Sharing Strings with Arc is faster than deep-copying them.