

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

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Motivation

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

- ▷ Java Virtual Machine (JVM)
- ▷ Automated Memory Management

[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 multithreading code in Rust.
- ▷ Rust uses LLVM 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

Complex Object

In Big Data processing, data is represented by complex objects.

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

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

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

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

Different Rust Memory Management Strategies

Each one has different memory representation.

- ▷ Owner
- ▷ Reference
- ▷ Slice

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

Multithreading

Atomic Reference Counting

Advantage

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

Disadvantage

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

Common Big Data algorithms

- ▷ Merge-sort
- ▷ Tree-aggregate
- ▷ K-Nearest-Neighbors (KNN)

Experiment 1: Accessing Object with Different Variable Type

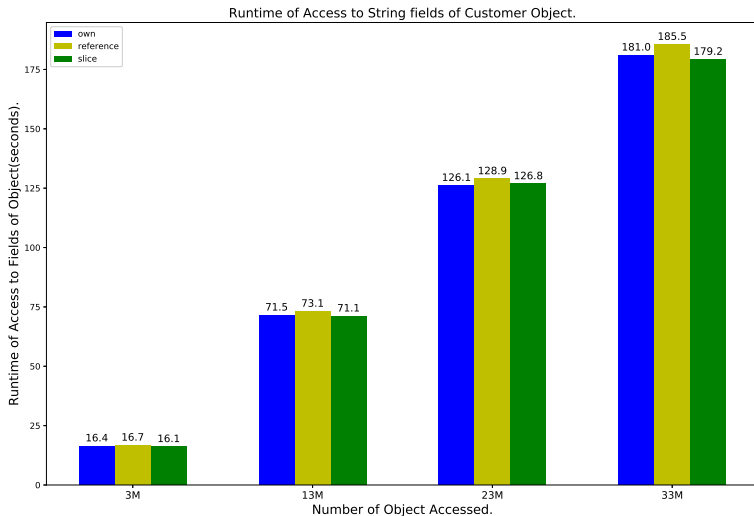
Question

- ▷ How much are memory access times different among different variable types used in complex objects?

Evaluation

- ▷ **Custruct complex objects**
- ▷ With different variable types: **Owner, Reference, Slice**
- ▷ Measure time to **access to fields of complex objects**

Experiment 1: Accessing Object with Different Variable Type



Experiment 2: Assessment of different reference methods in Rust

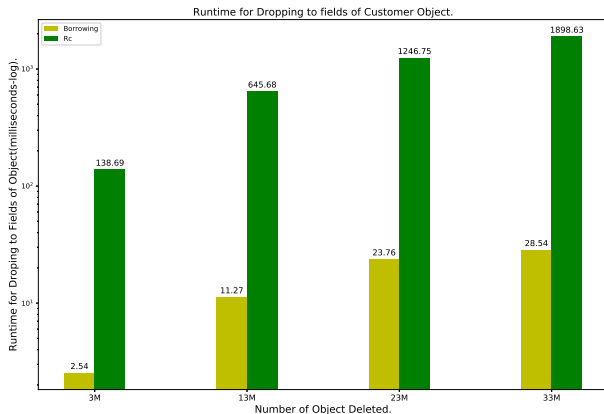
Question

- ▷ How much does Reference Counting slowdown time for dropping its variable?

Evaluation

- ▷ **Custruct complex objects**
- ▷ **Reference Counting** vs **reference**
- ▷ Measure time to **drop variables of complex objects**

Experiment 2: Assessment of different reference methods in Rust



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

Experiment 3: Merge-sort

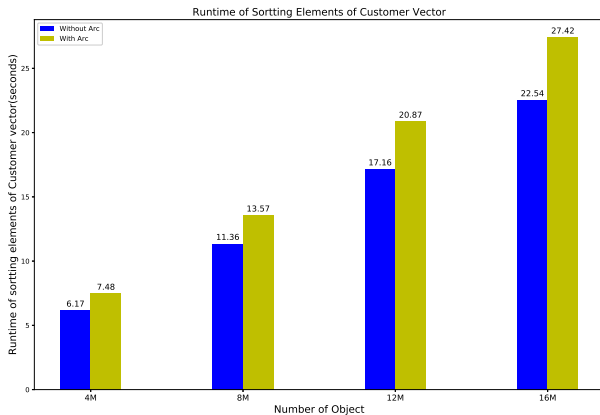
Question

- ▷ 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



Algorithms with Arc are about **21% slower**.

Experiment 4: Tree-aggregate

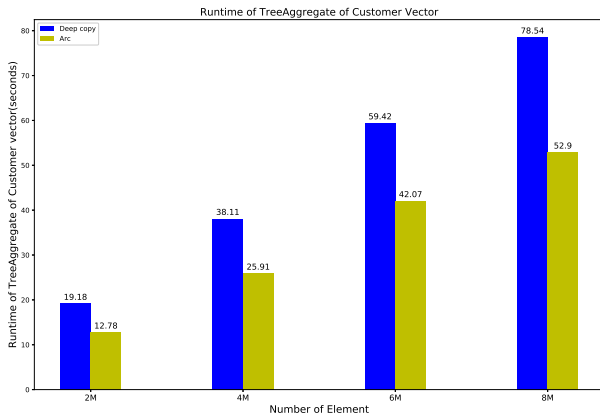
Question

- ▷ 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



Algorithms with deep-copy are from **40 to 50% slower**.

Experiment 5: K-Nearest-Neighbors (KNN)

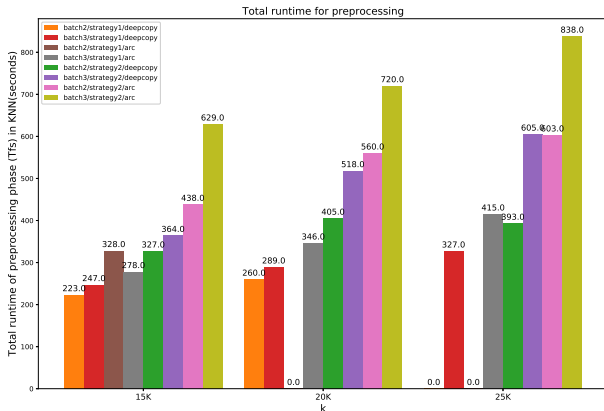
Question

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

Evaluation

- ▷ Document classification on Wikipedia page dataset
- ▷ Preprocessing phase: calculating **Term-frequencies (Tfs)**
- ▷ String manipulation
- ▷ **Atomic Reference Counting (Arc)** vs **Deep copy**
- ▷ **Frequency of memory de/allocation**
 - ▷ batch number
 - ▷ strategy
 - 1: keep intermediate objects in memory until owner is changed
 - 2: remove intermediate objects as soon as it is not needed
- ▷ Measure runtime of **preprocessing time of KNN algorithms**

Experiment 5: K-Nearest-Neighbors



- ▷ Algorithms with **Arc** are **at most 38 % slower** than deep-copy.
- ▷ Algorithms with **strategy 2** are **at most 85 % slower** than strategy 1.
- ▷ Algorithms with **3 batches** are **at most 40 % slower** than 2 batches.

Conclusion

- ▷ 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.