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

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Motivation

Many of existing data-flow based Big Data Processing systems like Apache Spark and Flink are using:

- ▷ Java Virtual Machine (JVM)
  - ▷ Abstracting hardware usage sacrificing additional computation
- ▷ Automated Memory Management
  - ▷ Generative Garbage Collection

Rust Programing Language is a promising candidate for development of Big Data analysis tools and libraries.

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 easier to write safe threaded code in Rust.
- ▷ Rust is a relatively new language (first appeared 2010).
- ▷ Rust uses LLVM compiler infrastructure and provides high performance.
- ▷ It is safer and easier to write code in Rust than C++

Different Rust Memory Management Strategies

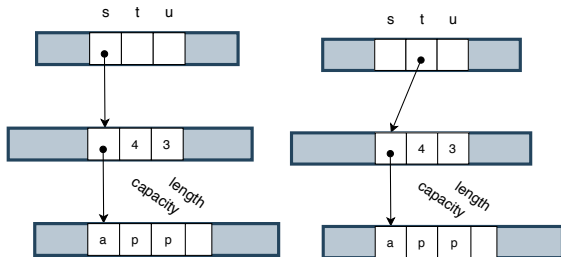Each one has different memory representation.

▷ Owner
▷ Reference
▷ Slice

```rust
let owner = String::from("hello world");
let slice = owner[7:10];
let reference = &owner;
```
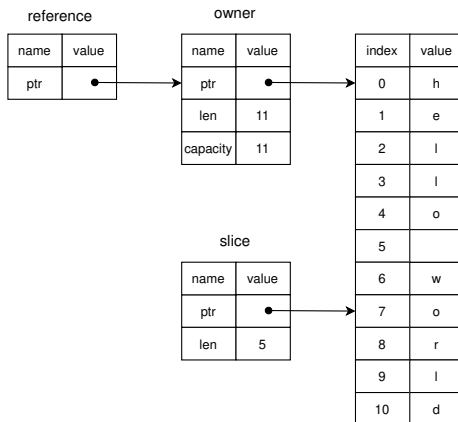

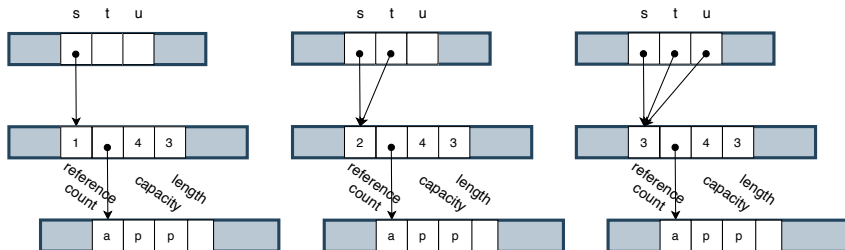Each one may have different memory access time.

Ownership

```
1    let s = "app".to_string();
2    let t = s;
3    let u = s;
4
```


▷ Each value is owned by single owner variable in Rust.
▷ Compiler error: **value "s" is dropped already.**

Reference Counting

```
1  let s = Rc::new("app".to_string());
2  let t = Rc::clone(&s);
3  let u = Rc::clone(&s);
```
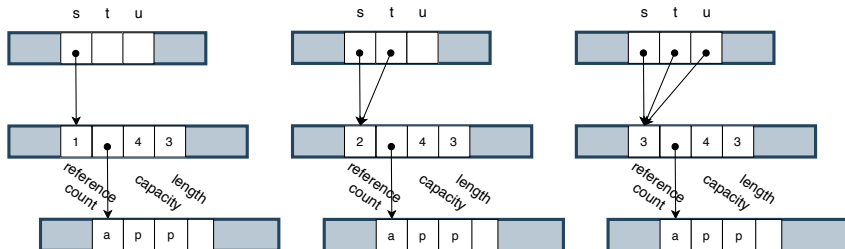

Advantage

▷ Sharing ownership
  ▷ Each value is owned by single owner variable in Rust.
▷ Dynamic memory de/allocation
  ▷ Rust usually determine lifetime of variable at compile time.

Reference Counting

```rust
1  let s = Rc::new(vec!["lemon".to_string(),
2                       "orange".to_string(),
3                       "apple".to_string()]);
4  let t = Rc::clone(&s);
5  let u = Rc::clone(&s);
```


Disadvantage

▷ Need to check reference count

▷ Heap allocation

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 - Memory Ownership and Borrowing

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

```
1  struct CustomerOwned {
2      key: i32,
3      total_purchase: f64,
4      zip_code: String,
5      order: OrderOwned,
6      ... 10 more
7      }
```

▷ All fields are owners.

```
1  struct CustomerBorrowed<'a> {
2      key: &'a i32,
3      total_purchase: &'a f64,
4      zip_code: &'a String,
5      order: &'a OrderBorrowed<'a>,
6      ... 10 more
7      }
```

▷ All fields are references.

▷ 'a is lifetime specifier.

▷ Rust compiler cannot determine lifetime automatically.

Complex Object - Slicing and Reference Counting

```
1  struct CustomerSlice<'a> {
2      key: &'a i32,
3      total_purchase: &'a f64,
4      zip_code: &'a str,
5      order: &'a OrderSlice<'a>
6      ... 10 more
7      }
```

▷ Fields are mix of references and slices.

▷ Slice is obtained only for contiguously allocated data structure, such as String and Vec.

```
1  struct CustomerRc {
2      key: Rc<i32>,
3      total_purchase: Rc<f64>,
4      zip_code: Rc<String>,
5      order: Rc<OrderRc>
6      ... 10 more
7      }
```

▷ All fields are Reference Counting

Multithreading with Atomic Reference Counting

Atomic Reference Counting

Advantage

  ▷ Sharing ownership
  ▷ Dynamic 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

    ▷ Common memory usage pattern in sorting algorithms for Big Data Processing.

        ▷ ex. External-sort

Impact of Memory Management on performance of Big Data Processing

Tree-aggtegate

▷ Many intermediate HashMap like data structures

▷ Many de/allocations of intermediate data

▷ Common memory and network usage pattern in Big Data Processing

Impact of Memory Management on performance of Big Data Processing
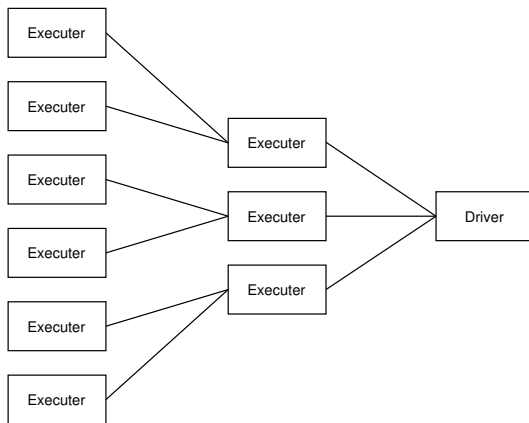
K-Nearest-Neighbors (KNN)

- ▷ Text document preprocessing
- ▷ String manipulations
- ▷ An example of Machine Learning algorithm that requires Big Data processing.
- ▷ We are interested only in preprocessing phase.
- ▷ It is just matrix read operation after preprocessing phase.

Experimental Setting

Machine Specification
- ▷ Google Cloud Platform: n1-standard-8
- ▷ CPU : 8 cores
- ▷ RAM: 30 GB
- ▷ Standard persistent disk: 10 GB

Data Set
- ▷ Customer object
  - ▷ CustomerOwned
  - ▷ CustomerBorrowed
  - ▷ CustomerSlice
  - ▷ CustomerRc
- ▷ Wikipedia page data set
  - ▷ training set: 100×10^3 pages
  - ▷ testing set: 18×10^3 pages

Execution
- ▷ Run each experiment 5 time
- ▷ Take average of the 5 runs

# Experiment 1: Accessing Object with Different Variable Type

Question

▷ What is the proformance differences among different memory management strategies?

Evaluation

▷ **Construct Complex objects**

▷ With different memory management strategies like **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

Runtime of Access to String fields of Customer Object.
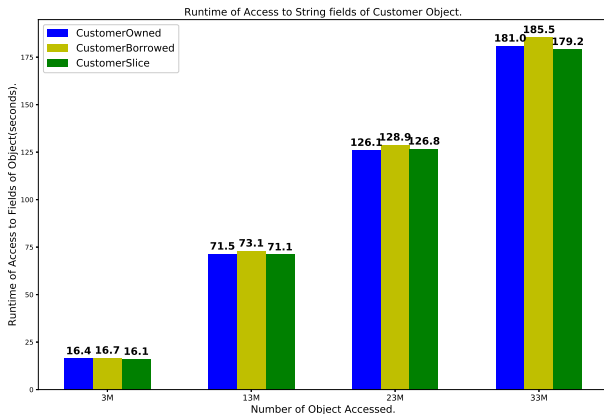
Result

▷ No differences of memory access time among Customer objects using different memory management strategies.

Discussion

▷ Selection of different memory management strategies does not have impact on memory access time.

# Experiment 2: Assessment of different reference methods in Rust

Question

▷ How much does Reference Counting hits performance?

Evaluation

▷ **Construct complex 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

Runtime for Dropping to fields of Customer Object.
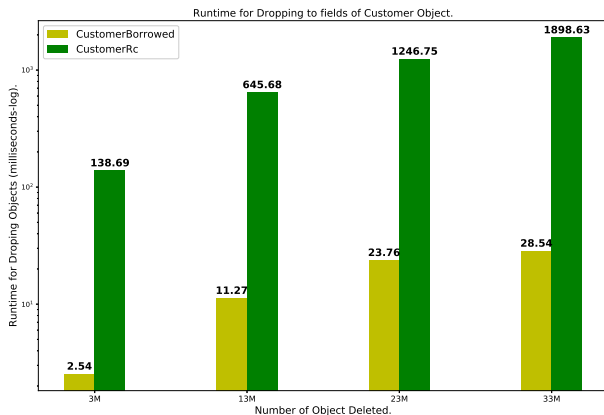
Result

▷ 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

▷ What is performance hit of Merge-sort algorithm using Arc vs, normal reference?

Evaluation

▷ Share **vector** of complex objects in multithreads

▷ **Atomic Reference Counting (Arc)** vs. **normal reference**

▷ Measure **runtime of merge-sort algorithms**

Experiment 3: Merge-sort

Runtime of Sorting Elements of Customer Vector
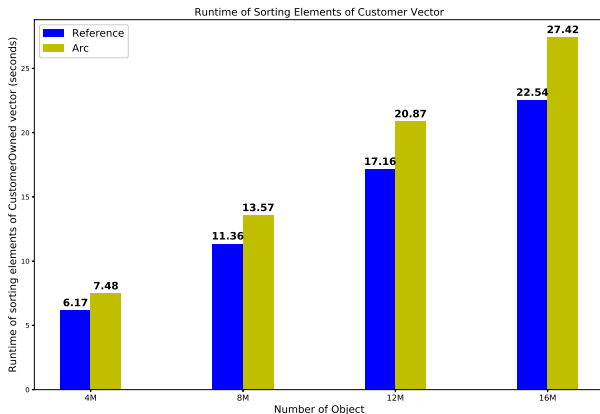
Result

▷ 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.
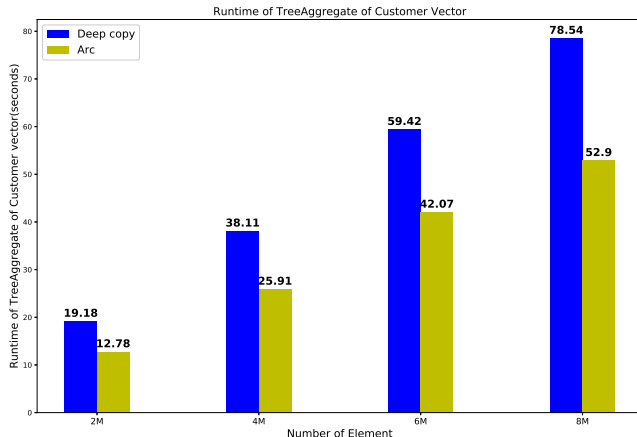
Experiment 4: Tree-aggregate

Question

▷ - What is performance hit of Tree-aggregate using Arc vs. deep-copy?

Evaluation

▷ Share **elements** of complex object in multithreads

▷ **Atomic Reference Counting (Arc)** vs. **Deep copy**

▷ Measure **runtime of Tree-aggregate algorithm**

Experiment 4: Tree-aggregate

Runtime of TreeAggregate of Customer Vector

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 to significant overhead.

Experiment 5: K-Nearest-Neighbors (KNN)

Question

▷ - What is performance hit of Machine learning algorithms using Arc vs. deep-copy?

Evaluation

▷ Document classification on Wikipedia page dataset
  ▷ training set: 100×10^3 pages
  ▷ testing set: 18×10^3 pages

▷ Preprocessing phase: calculating **Term-Frequencies (TFs)**

▷ String manipulation

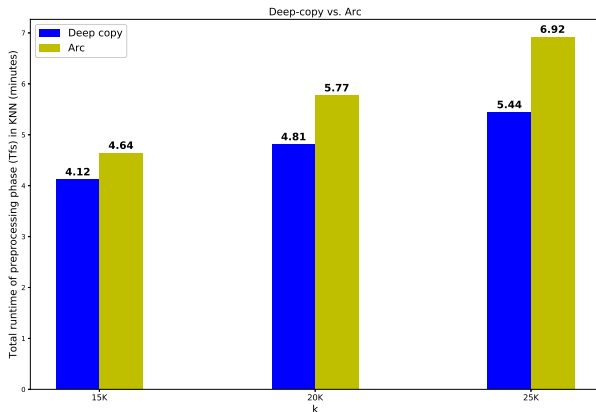▷ Measure runtime of **preprocessing time of KNN algorithms**

Experiment 5: K-Nearest-Neighbors (KNN)

Parameters

▷ Data Acquisition
  ▷ **Atomic Reference Counting** (Arc)
  ▷ **Deep-copy**

▷ Dimensions of feature matrices
  ▷ 15K
  ▷ 20K
  ▷ 25K

Experiment 5: K-Nearest-Neighbors

Deep-copy vs. Arc

Result

▷ **Arc** is **at most 27% slower** than deep-copy.

Discussion

▷ Deep-copying String is cheaper operation than Arc:
  ▷ Relatively simple object
  ▷ Contiguously allocated
▷ Overhead using Arc may become more significant as size of data increases

Findings

Arc vs. Deep-Copy

▷ Use Arc instead of deep-copy, when **complexity of objects is large**.

▷ Use deep-copy when dealing with **low complex objects/primitive types** like String.

Arc vs. Normal Reference

▷ Use normal reference rather than Reference Counting whenever it is possible.

▷ **Avoid using Arc** when we can use reference.

Conclusion

▷ We have seen that impact of memory memory Management is very large, especially when working on High Complex Object structures and large volume of data set.

▷ Using a System Language like Rust is very promising to avoid using large CPU computation for memory management.

▷ When using Rust, writing memory-safe multithreaded code is fairly easy.