

# 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.

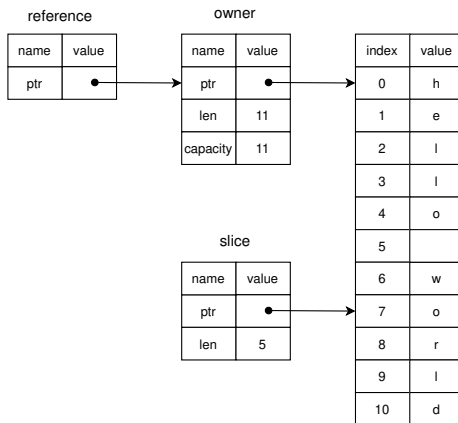
- ▷ A system language does not have Garbage Collection.
- ▷ Rust ensures memory safety.
- ▷ It is easier to write safe threaded code in Rust.
- ▷ Rust is a relatively new language (first appeared 2010).
- ▷ Rust uses LLVM compiler infrastructure and provides high performance.
- ▷ It is safer and easier to write code in Rust than C++

# Different Rust Memory Management Strategies

Each one has different memory representation.

- ▷ Owner
- ▷ Reference
- ▷ Slice

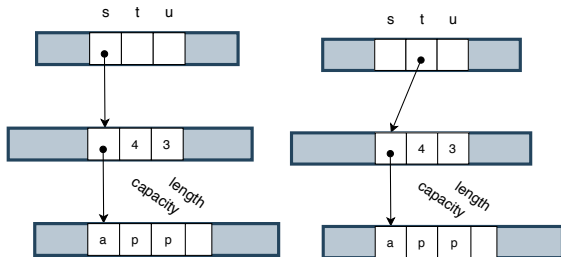
```
1 let owner = String::from("hello_world");  
2 let slice = owner[7:10];  
3 let reference = &owner;
```



Each one may have different memory access time.

# Ownership

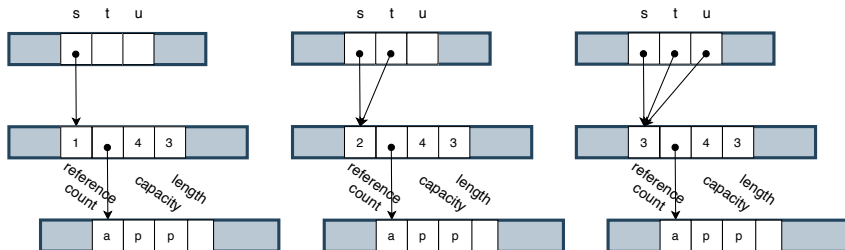
```
1 let s = "app".to_string();
2 let t = s;
3 let u = s;
4
```



- ▷ 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);
```

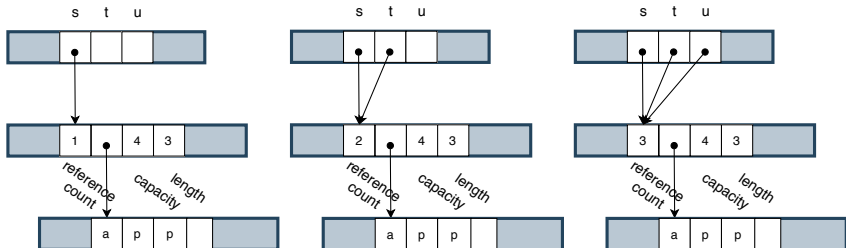


## Advantage

- ▷ **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

```
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

In this thesis, our goal is to determine the magnitude of performance change regarding the following aspects on overall performance of Big Data processing.

- ▷ High Complex Nested Objects vs. Simple Objects/Primitive Types
- ▷ Different Rust Memory Management Strategies: Ownership vs. Borrowing vs. Slicing
- ▷ Automated Reference Counting (Rc) vs. Normal Reference
- ▷ Multithreading using Atomic Reference Counting (Arc) vs. Normal Reference
- ▷ Arc vs. Deep Copy

We have specified 5 different experiments.



# 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

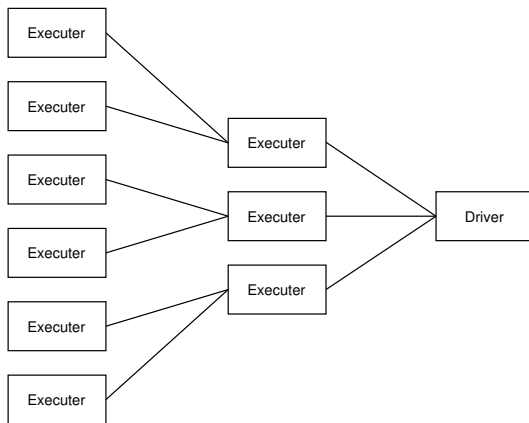
## Merge-sort

- ▷ 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-aggregate

- ▷ Many intermediate HashMap like data structures
- ▷ Many de/allocation of intermediate data
- ▷ Common memory and network usage pattern in 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:  $100 \times 10^3$  pages
  - ▷ testing set:  $18 \times 10^3$  pages

## Execution

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

# Experiment 1: Accessing Object with Different Variable Type

## Question

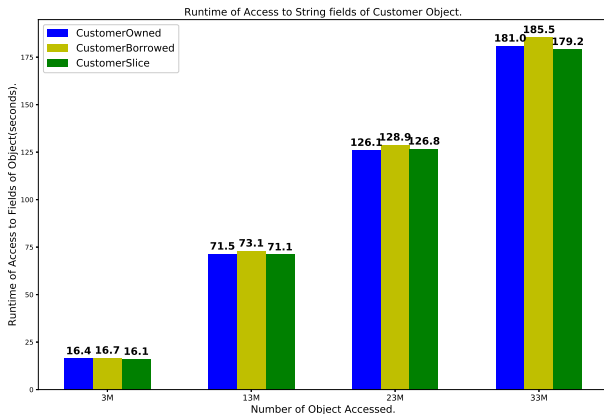
- ▷ What is the performance differences among different memory management strategies?

## 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



## 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

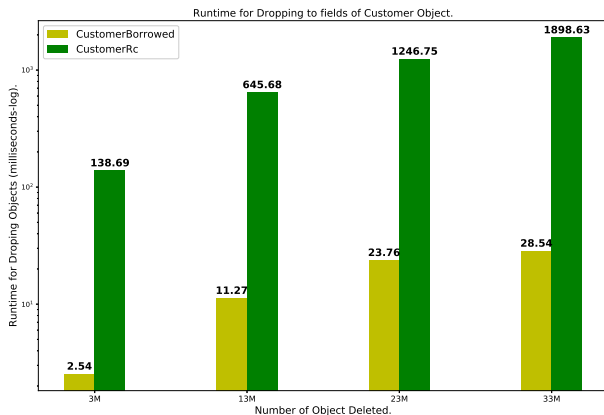
## Question

- ▷ 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



### 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

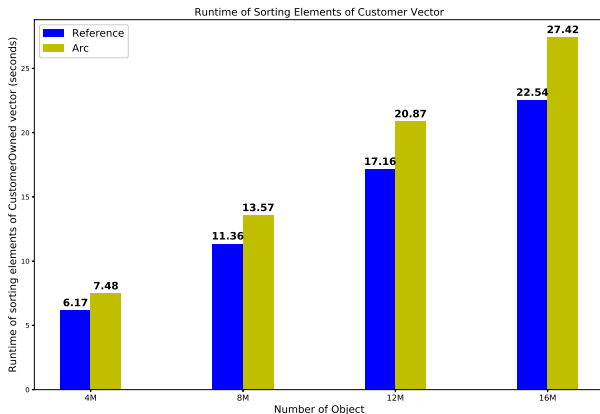
## Question

- ▷ 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



## 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

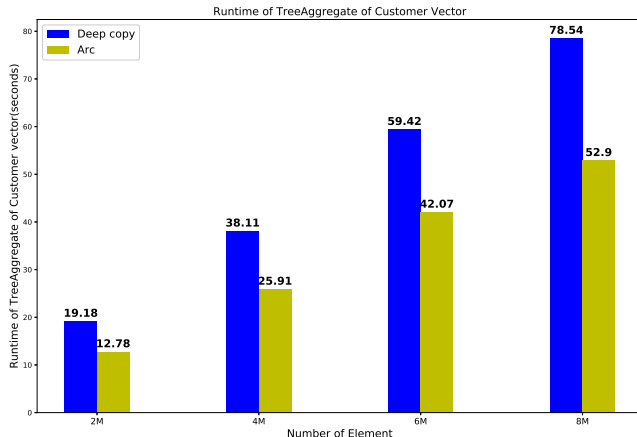
### Question

- ▷ - 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



### 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:  $100 \times 10^3$  pages
  - ▷ testing set:  $18 \times 10^3$  pages
- ▷ Preprocessing phase: calculating **Term-Frequencies (TFs)**
- ▷ String manipulation
- ▷ Measure runtime of **preprocessing time of KNN algorithms**

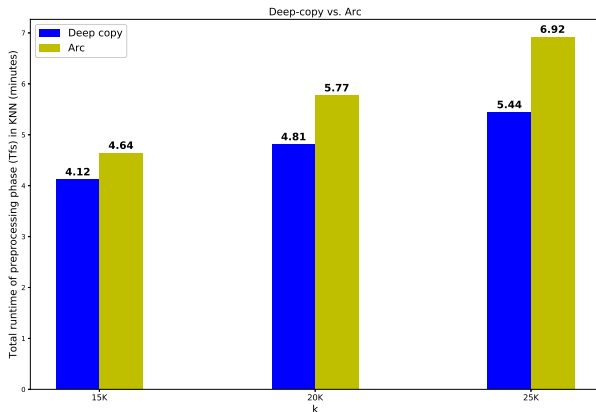


# Experiment 5: K-Nearest-Neighbors (KNN)

## Parameters

- ▷ Data Acquisition
  - ▷ **Atomic Reference Counting** (Arc)
  - ▷ **Deep-copy**
- ▷ Dimensions of feature matrices
  - ▷ 15K
  - ▷ 20K
  - ▷ 25K

## Experiment 5: K-Nearest-Neighbors



### 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.