# 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.

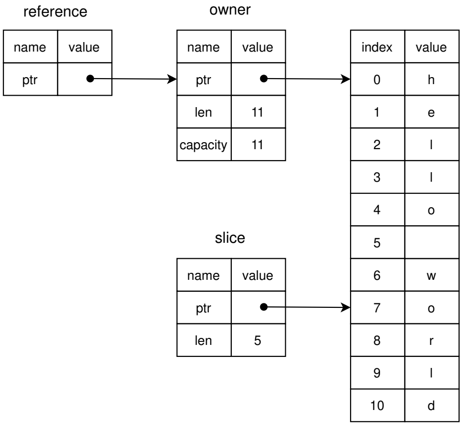
- A system language does not have Garbage Collection.
- Rust ensures memory safety.
- It is easier to write safe threaded code in Rust.
- Rust is a relatively new language (first appeared 2010).
- Rust uses LLVM compiler infrastructure and provides high performance.
- It is safer and easier to write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

# Different Rust Memory Management Strategies

Each one has different memory representation.

- Owner
- Reference
- Slice

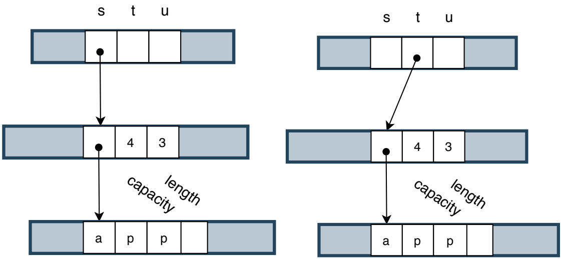
```rust
let owner = String::from("hello world");
let slice = owner[7:10];
let reference = &owner;
```




Each one may have different memory access time.

# Ownership

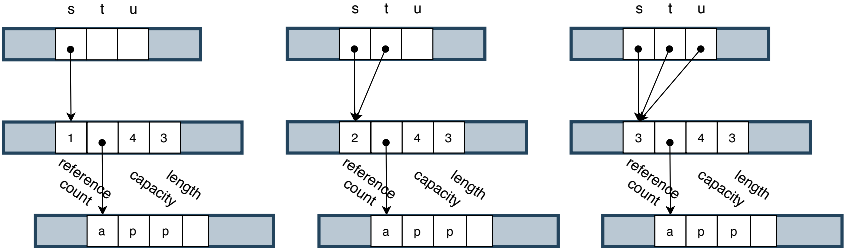
```
let s = "app".to_string();
let t = s;
let u = s;

```




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

# Reference Counting

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

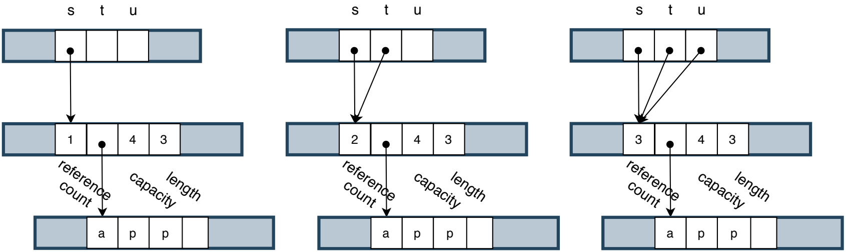



### Advantage

- 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

```
let s = Rc::new(vec!["lemon".to_string(),
                      "orange".to_string(),
                      "apple".to_string()]);
let t = Rc::clone(&s);
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 using different memory strategies: Ownership vs. Borrowing vs. Slicing vs. Reference Counting
- 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.

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

- All fields are owners.

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

- All fields are references.
- 'a is lifetime specifier.
- Rust compiler cannot determine lifetime automatically.

# Complex Object - Slicing and Reference Counting

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

- Fields are mix of references and slices.
- Slice is obtained only for contiguously allocated data structure, such as String and Vec.

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

- 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

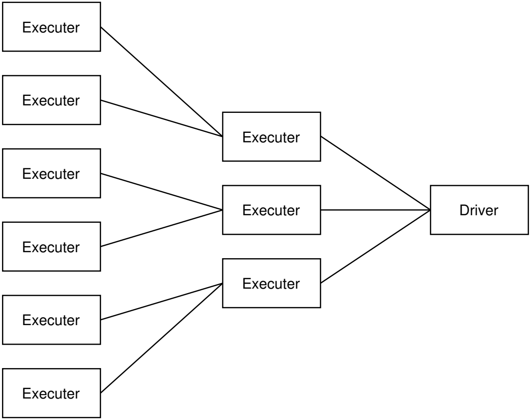
**Merge-sort**

- 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



**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**

- Randomized generated data of **Customer objects** (Synthetic Data)
  - CustomerOwned
  - CustomerBorrowed
  - CustomerSlice
  - CustomerRc
- **Wikipedia Text data** set (Real-World Data)
  - Training set: $100 \times 10^3$ wiki pages
  - Testing set: $18 \times 10^3$ wiki pages

**Execution**

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

# Experiment 1: Accessing Object with Different Variable Type

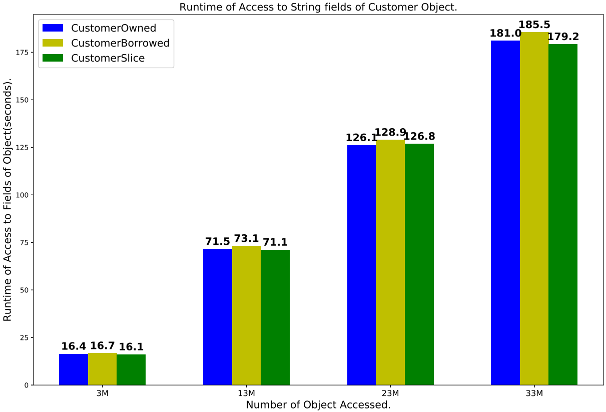
**Question**

- 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




## 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

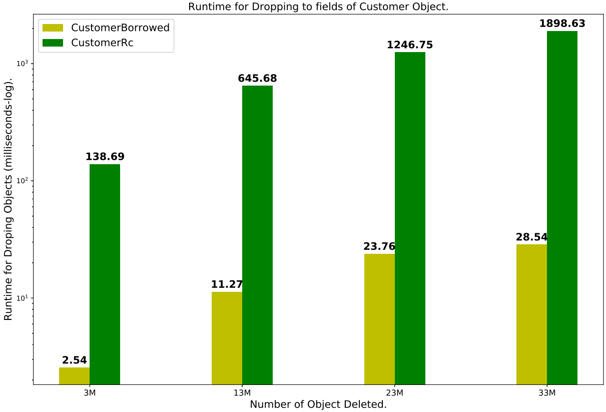
**Question**

- 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

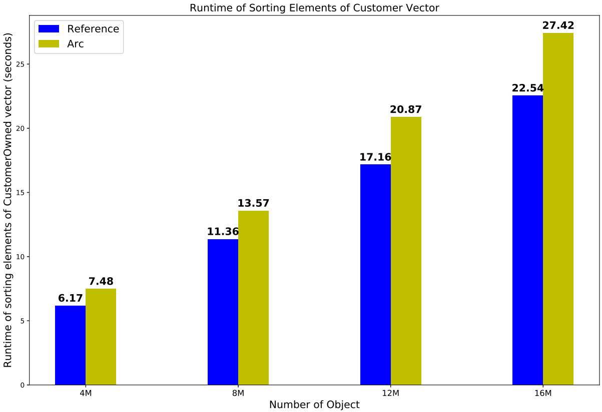
**Question**

- 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

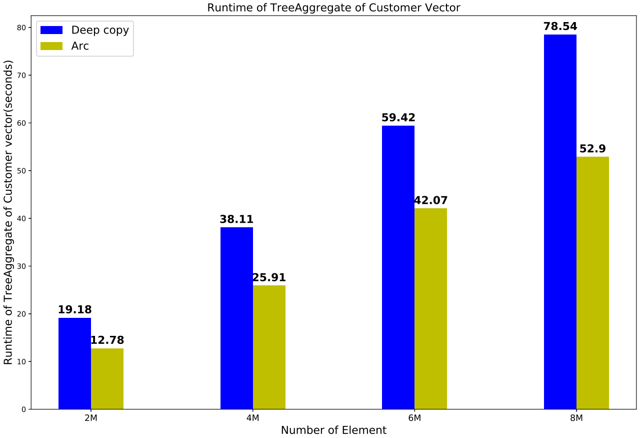
**Question**

- \- 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**

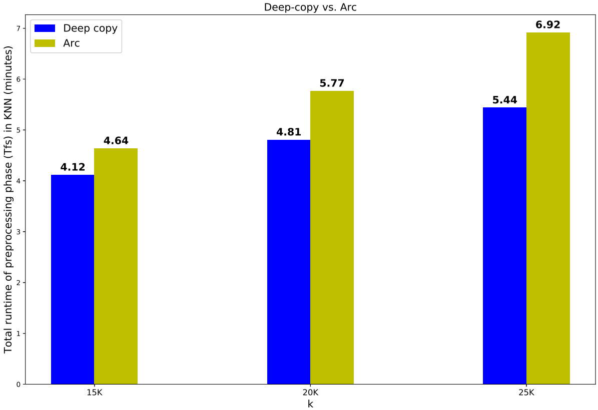
- Document classification on Wikipedia page dataset
  - Training set: $100 \times 10^3$ wiki pages
  - Testing set: $18 \times 10^3$ wiki pages
- Preprocessing phase: calculating **Term-Frequencies (TFs)**
- String manipulation
- Measure runtime of **preprocessing time of KNN algorithms**

# 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 - Preprocessing Time




**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.