BOSTON UNIVERSITY METROPOLITAN COLLEGE

Thesis

BIG DATA PROCESSING FOR MACHINE LEARNING TASKS WITH RUST

by

SHINSAKU OKAZAKI

B.S., Seikei University, 2018

Submitted in partial fulfillment of the requirements for the degree of

Master of Science

2020

Approved by

First Reader

Kia Teymourian, PhD

Professor of Computer Science

Second Reader

First M. Last

Associate Professor of . . .

Third Reader

First M. Last

Assistant Professor of ...

Facilis descensus Averni;
Noctes atque dies patet atri janua Ditis;
Sed revocare gradum, superasque evadere ad auras,
Hoc opus, hic labor est.

Virgil (from Don's thesis!)

Acknowledgments

Here go all your acknowledgments. You know, your advisor, funding agency, lab

mates, etc., and of course your family.

As for me, I would like to thank Jonathan Polimeni for cleaning up old LaTeX style

files and templates so that Engineering students would not have to suffer typesetting

dissertations in MS Word. Also, I would like to thank IDS/ISS group (ECE) and

CV/CNS lab graduates for their contributions and tweaks to this scheme over the

years (after many frustrations when preparing their final document for BU library).

In particular, I would like to thank Limor Martin who has helped with the transition

to PDF-only dissertation format (no more printing hardcopies – hooray !!!)

The stylistic and aesthetic conventions implemented in this LaTeX thesis/dissertation

format would not have been possible without the help from Brendan McDermot of

Mugar library and Martha Wellman of CAS.

Finally, credit is due to Stephen Gildea for the MIT style file off which this current

version is based, and Paolo Gaudiano for porting the MIT style to one compatible

with BU requirements.

Janusz Konrad

Professor

ECE Department

V

BIG DATA PROCESSING FOR MACHINE LEARNING TASKS WITH RUST

SHINSAKU OKAZAKI

ABSTRACT

Abstract Many of popular open source cluster computing frameworks for large scale data analysis, such as Hadoop and Spark, allow programmers to define objects in a host languages, such as Java. The objects are then managed in RAM by the language and its runtime, Java Virtual Machine in the case of Java and Scala. Storing objects in memory enables machine to process iterative computation. One of the fundamental tasks for recent big data analysis is analysis using Machine Learning Algorithms, which require iterative process. As the amount of data increases, memory is required to keep many objects. Therefore, memory management plays a critical role in this task.

Memory management in Java and Scala is performed by garbage collection. The garbage collection brings a significant advantage for programmers by removing responsibility for planning memory management by themselves. Instead, JVM monitors the state of memory and performs garbage collection at certain points. However, these monitoring and auto-execution of garbage collection cost additional computation and might consume computation resources which should be used for data processing. This can significantly decrease performance of the computation.

In contrast, memory management in system language, such as C++, relies on programmers' decision for when to allocate and deallocate memory. The functions, malloc/free consume most of the memory management. Proper implementation of system language for big data processing can be overperform the implementation in

host language. Nevertheless, implementing C++ performing proper memory management and guaranteeing security can be unproductive and complicated.

Considering the issue of memory management, we introduce solution based on unique memory management methods implemented in Rust, ownership and borrowing. This unique concepts in Rust secure codes and perform memory management without monitoring memory or calling functions. We introduce implementations of machine learning algorithms in both Java and Rust to assess performances of each memory management system for iterative big data processing tasks.

Contents

1	Introduction		1
	1.1	Problem Description	1
	1.2	Memory Management in Rust	2
	1.3	Spark and RDD Catching	3
2	Bod	ly of my thesis	4
	2.1	Some results	4
3	Con	aclusions	6
	3.1	Summary of the thesis	6
\mathbf{A}	Pro	of of xyz	7
Re	efere	nces	8
Cı	ırric	ulum Vitae	9

List of Tables

2.1	Absolute disparity error per pixel for the test data from Fig. 2.1 and	
	different parameter values. In each experiment one parameter is ad-	
	justed while other parameters are unchanged	5

List of Figures

$2 \cdot 1$	Assignment of single	e-view intensities	to RGB	components:	(a) view	
	#1: and (b) view #2	2				2

List of Abbreviations

The list below must be in alphabetical order as per BU library instructions or it will be returned to you for re-ordering.

CAD	 Computer-Aided Design
CO	 Cytochrome Oxidase
DOG	 Difference Of Gaussian (distributions)
FWHM	 Full-Width at Half Maximum
LGN	 Lateral Geniculate Nucleus
ODC	 Ocular Dominance Column
PDF	 Probability Distribution Function
\mathbb{R}^2	 the Real plane

Chapter 1

Introduction

1.1 Problem Description

Many of popular open source cluster computing frameworks for large scale data analysis, such as Hadoop and Spark, allow programmers to define objects in a host languages, such as Java. The objects are then managed in RAM by the language and its runtime, Java Virtual Machine in the case of Java and Scala. Storing objects in memory enables machine to process iterative computation. One of the fundamental tasks for recent big data analysis is analysis using Machine Learning Algorithms, which require iterative process. As the amount of data increases, memory is required to keep many objects. Therefore, memory management plays a critical role in this task.

Memory management in Java and Scala is performed by garbage collection. The garbage collection brings a significant advantage for programmers by removing responsibility for planning memory management by themselves. Instead, JVM monitors the state of memory and performs garbage collection at certain points. However, these monitoring and auto-execution of garbage collection cost additional computation and might consume computation resources which should be used for data processing. This can significantly decrease performance of the computation.

In contrast, memory management in system language, such as C++, relies on programmers' decision for when to allocate and deallocate memory. The functions, malloc/free consume most of the memory management. Proper implementation of

system language for big data processing can be overperform the implementation in host language. Nevertheless, implementing C++ performing proper memory management and guaranteeing security can be unproductive and complicated.

Considering the issue of memory management, we introduce solution based on unique memory management methods implemented in Rust, ownership and borrowing. This unique concepts in Rust secure codes and perform memory management without monitoring memory or calling functions. We introduce implementations of machine learning algorithms in both Java and Rust to assess performances of each memory management system for iterative big data processing tasks.

1.2 Memory Management in Rust

Each value in Rust has a variable called its owner. This owner has information about the value, such as location in memory, length and capacity of the value. This owner can live on the scope associated with its life time. When the owner goes out of it's scope, the value will be dropped. When a value already assigned to a variable is assigned to another variable, if the value is allocated on heap its information is copied to the new owner and drop the old owner disabling old variable. Similar thing happens when we pass variable to parameter of function. After passing a variable to a parameter, all the information is copied to new owner through the parameter and old owner is no longer available. The new owner can only live in the function and the object will be dropped. In this case, we have no longer access to the object after the function. To avoid this, Rust has a concept called borrowing. We can set reference for the parameter of function and use the reference for operation within function and drop the reference, but not the ownership.

1.3 Spark and RDD Catching

Spark is one of the most used big data computing framework. Spark uses Resilient Distributed Datasets (RDDs) which implement in-memory data structures used to cache intermediate data across a set of nodes. This enables multiple rounds of computation on the same data, which is required for machine learning and graph analytics iteratively process the data.

In RDD caching, there are different stages of caching, such as MEMOR_YONLY and DISK_ONLY. Currently, for very large data sets, we need to pay attention to garbage collection (GC) and OS page swapping overhead, because these could degrades execution time significantly. Therefore, DISK_ONLY RDD caching can be better configuration in this case. However, writing and reading intermediate data among desk and memory could have bad effects for execution time, due to need of serialization and deserialization.

Chapter 2

Body of my thesis

2.1 Some results

Here goes all the important stuff, likely with a lot of graphics like this:

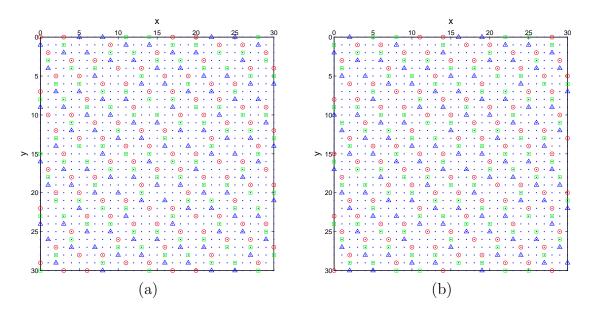


Figure 2·1: Assignment of single-view intensities to RGB components: (a) view #1; and (b) view #2.

You will also be using a lot of citations. Here is the format required in the dissertation: (Lamport, 1985), (Debreuve et al., 2001).

In all likelihood, you will need to insert tables. See one example on the next page.

Table 2.1: Absolute disparity error per pixel for the test data from Fig. 2·1 and different parameter values. In each experiment one parameter is adjusted while other parameters are unchanged.

$\eta = 6000, \mu = 2000$	$K = 10, \mu = 2000$	$K = 10, \eta = 6000$
$\begin{array}{c cccc} \hline K & u_1 & u_2 \\ \hline 3 & 0.52 & 0.46 \\ 7 & 0.47 & 0.43 \\ 10 & 0.35 & 0.36 \\ 12 & 0.37 & 0.36 \\ \end{array}$	$\begin{array}{c cccc} \hline \eta & u_1 & u_2 \\ \hline 1000 & 0.54 & 0.45 \\ 3000 & 0.43 & 0.40 \\ 6000 & 0.35 & 0.36 \\ 9000 & 0.37 & 0.37 \\ \hline \end{array}$	$\begin{array}{c cccc} \mu & u_1 & u_2 \\ \hline 100 & 1.00 & 1.16 \\ 1000 & 0.53 & 0.47 \\ 2000 & 0.35 & 0.36 \\ 3000 & 0.44 & 0.43 \\ \end{array}$

Of course, there must be a Table of Contents at the beginning of the thesis.

Chapter 3

Conclusions

3.1 Summary of the thesis

Time to get philosophical and wordy.

IMPORTANT: In the references at the end of thesis, all journal names must be spelled out in full, except for standard abbreviations like IEEE, ACM, SPIE, INFOCOM, ...

Appendix A

Proof of xyz

This is the appendix.

References

- Debreuve, E., Barlaud, M., Aubert, G., Laurette, I., and Darcourt, J. (2001). Space-time segmentation using level set active contours applied to myocardial gated SPECT. *IEEE Trans. Med. Imag.*, 20(7):643–659.
- Lamport, L. (1985). \(\mathbb{L}T_EX\)—A Document Preparation System—User's Guide and Reference Manual. Addison-Wesley.

CURRICULUM VITAE

Joe Graduate

Basically, this needs to be worked out by each individual, however the same format, margins, typeface, and type size must be used as in the rest of the dissertation.