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METROPOLITAN COLLEGE

Thesis

BIG DATA PROCESSING FOR MACHINE LEARNING TASKS WITH RUST

by

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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.

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Janusz Konrad

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BIG DATA PROCESSING FOR MACHINE LEARNING TASKS WITH RUST

SHINSAKU OKAZAKI

ABSTRACT

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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.

Chapter 2

Related Work

2.1 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.

2.2 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 com-

putation 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.

2.3 BLAS LAPACK

Basic Linear Algebra Subprograms (BLAS) are standard building blocks for basic vector and matrix operations. There are 3 levels of operation. The level 1 BLAS performs scalar, vector and vector-vector operations, the level 2 BLAS performs matrix-vector operation, and the level 3 BLAS performs matrix-matrix operation.

LAPACK is developed on BLAS and has advanced functionalities such as LU decomposition and Singular Value Decomposition (SVD). Dense and banded matrices are handled, but not general sparse matrices. The initial motivation of development of LAPACK was to make the widely used EISPACK and LINPACK libraries run efficiently on shared-memory vector and parallel processors. LINPACK and EISPACK are inefficient because their memory access patterns disregard the multi-layered memory hierarchies of the machines, thereby spending too much time moving data. LAPACK addresses this problem by recognizing the algorithms to use block matrix operations, such as matrix multiplication, in the innermost loops. These block operations can be optimized for each architecture to account for the memory hierarchy, and so provide a portable way to achieve high efficiency on diverse modern machines.

However, LAPACK requires that highly optimized block matrix operations be already implemented on each machine.

The original BLAS and LAPACK are written in Fortran90. Linear algebra library used for Spark is netlib-java, which is a Java wrapper library for Netlib, C API of BLAS and LAPACK. The reason why the developers addressed to use this package is that the BLAS and LAPACK are already bug free and implementing linear algebra library from scratch can usually buggy.

However, the main advantage of use of BLAS and LAPACK is system optimized implementation. So if we implement original Fortran linear algebra library, it cannot perform as well as BLAS and LAPACK. And the performance would not be such different from one of implementation in Java or Rust. If we want to test only memory management between Rust and Java, it can be enough implementation of linear algebra operation from pure Java and Rust sacrificing the best performance taking advantage of system optimization. My concern is implementing linear algebra operation from scratch can be buggy and cause a lot of problems when we test on machine learning algorithms.

2.4 Matrix Computation and Optimization in Apache Spark

Matrix operation is a fundamental part of machine learning. Apache Spark provides implementation for distributed and local matrix operation. To translate single-node algorithms to run on a distributed cluster, Spark addresses separating matrix operations from vector operations and run matrix operations on the cluster, while keeping vector operations local to the driver.

Spark changes its behavior for matrix operations depending on the type of operations and shape of matrices. For example, Singular Value Decomposition (SVD) for a square matrix is performed in distributed cluster, but SVD for a tall and skinny ma-

trix is on a driver node. This is because the matrix derived among the computation of SVD for tall and skinny matrix is usually small so that it can fit to single node.

Spark uses ARPACK to solve square SVD. ARPACK is a collection of Fortran77 designed to solve eigenvalue problems. ARPACK is based upon an algorithmic variant of the Arnoldi process called the Implicitly Restarted Arnoldi Method (IRAM). When the matrix A is symmetric it reduces to a variant of the Lanczos process called the Implicitly Restarted Lanczos Method (IRLM). ARPACK calculate matrix multiplication by performing matrix-vector multiplication. So we can distribute matrix-vector multiplies, and exploit the computational resources available in the entire cluster. The other method to distribute matrix operations is Spark TFOCS. Spark TFOCS supports several optimization methods.

To allow full use of hardware-specific linear algebraic operations on single node, Spark uses the BLAS (Basic Linear Algebra Systems) interface with relevant libraries for CPU and GPU acceleration. Native libraries can be used in Scala are ones with C BLAS interface or wrapper and called through the Java native interface implemented in Netlib-java library and wrapped by the Scala library called Breeze. Following is some of the implementation of BLAS.

- f2jblas - Java implementation of Fortran BLAS
- OpenBLAS - open source CPU-optimized C implementation of BLAS
- MKL - CPU-optimized C and Fortran implementation of BLAS by Intel

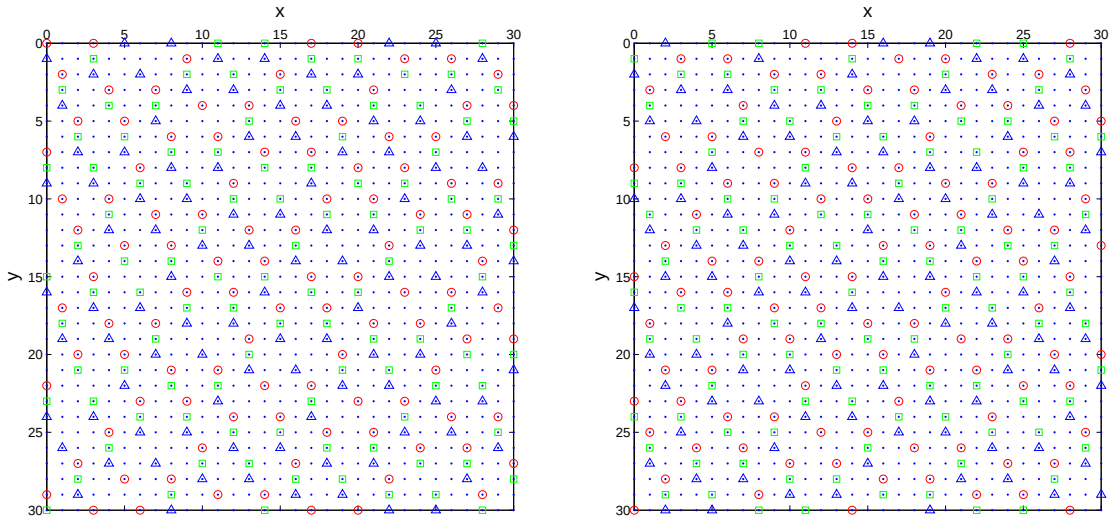
These have different implementation and they perform differently for the type of operation and matrices shape. In Sark, OpenBlas is the default method of choice. BLAS interface is made specifically for dense linear algebra. Then, there are few libraries that efficiently handle sparse matrix operations.

Chapter 3

Body of my thesis

3.1 Some results

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



(a) (b)

Figure 3·1: 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 3.1: Absolute disparity error per pixel for the test data from Fig. 3·1 and different parameter values. In each experiment one parameter is adjusted while other parameters are unchanged.

$\eta = 6000$, $\mu = 2000$

K	u_1	u_2
3	0.52	0.46
7	0.47	0.43
10	0.35	0.36
12	0.37	0.36

$K = 10$, $\mu = 2000$

η	u_1	u_2
1000	0.54	0.45
3000	0.43	0.40
6000	0.35	0.36
9000	0.37	0.37

$K = 10$, $\eta = 6000$

μ	u_1	u_2
100	1.00	1.16
1000	0.53	0.47
2000	0.35	0.36
3000	0.44	0.43

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

Chapter 4

Conclusions

4.1 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). *LaTeX—A Document Preparation System—User's Guide and Reference Manual*. Addison-Wesley.

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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.