General-Purpose Computing on Graphics Processing Units for Storage Networks

A Major Qualifying Project Report

submitted to the Faculty of

Worcester Polytechnic Institute

in partial fulfilment of the requirements for the

Degree of Bachelor of Science

By

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Date: March 15, 2014

Sponsoring Organization: EMC Corporation

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1 ABSTRACT

The purpose of this Major Qualifying Project was to investigate different areas in which Graphics Processing Units (GPUs) could be used by EMC to increase performance. The project researched various CUDA GPU programming tools and libraries that could be of use to EMC. CUDA implementations of linear algebra operations such as dot products, matrix multiplication, and SAXPY, which were of interest to multiple teams at EMC, were investigated. Finally, this paper discusses a SQLite3 virtual table using CUDA to accelerate SQL queries.

2 ACKNOWLEDGEMENTS

We would like to thank the following people, without whom our project would not have been possible.

Professor Emmanuel Agu, whose quick feedback and critical insights kept us focused from the beginning.

Jon Krasner, whose vision and big-picture perspective lent purpose to our time on this MQP.

Steve Chalmer, whose technical expertise and willingness to answer all our questions helped us to accomplish more than we could have by ourselves.

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3 INTRODUCTION

With the advancement of computing technologies and the need for computational power, companies are looking for methods to increase performance. General-purpose computing on graphics processing units, known as GPGPU, allows developers to utilize graphics processing units (GPUs) to accelerate computation tasks. NVIDIA's Compute Unified Device Architecture (CUDA), is a parallel computing language that enables a significant performance increase through the use of GPUs. As GPUs became more widely used, programmers leveraged their capabilities for problems such as floating-point arithmetic, matrices and vectors, and other parallelizable operations. Now, companies such as EMC Corporation, are searching for ways GPUs can be applied to enhance the performance of their products. This Major Qualifying Project (MQP) entails applying GPGPU and CUDA to the storage world.

3.1 The Goal of this MQP

Listed below are the major goals of this project:

- Research CUDA tools and libraries for GPU programming
- Program GPUs using CUDA for linear-algebra operations and benchmark performance
- Explore performance enhancements for SQL queries using SQLite
- Implement a SQLite virtual table with CUDA

4 BACKGROUND

4.1 EMC

This project is sponsored by EMC Corporation. EMC, founded in 1979 [1], provides IT solutions to businesses, such as data storage, cloud computing, and information security. The company currently has a market capitalization of approximately 58 billion dollars [2], and is one of the world's largest providers of data storage solutions. Some of their competitors in this area include companies such as HP, Dell, IBM, and Cisco [3].

4.2 Databases

At its core, a database is just an organized collection of digital data. Database management systems provide an interface that allows users to add, view, and modify data within the database.

4.2.1 Relational Databases

One common type of database is the relational database, which is based on E.F. Codd's relational model of data [4]. Codd represents all data as sets of primitive data types and their associations. In a relational database, data is stored in a collection of tables. Figure 1 shows a sample layout of a table in a relational database.

Students				
Student_ID	**Lname**	**Fname**	**City**	**Major**
1	Chaulk	Adam	Boston	Computer Science
2	Paon	Andrew	Providence	Computer Science

Figure 1. Example relational database table

A relational database is made up of a list of rows, or entries. There are two entries in Figure 1, and each contains information about one student. Each entry in a table has the same data structure [5], or schema. The schema for the table in Figure 1 is described in Figure 2.

Field name	**Data Type**
Student_ID	INTEGER
Lname	STRING
Fname	STRING
City	STRING
Major	STRING

Figure 2. Example table schema

Each element of the schema describes one column in the table. Thus, the first element in every row is an integer valued student ID number; the second column is a string for last name, etc.

4.2.2 SQL

Structured Query Language, or SQL, was developed in 1974 by scientists at the IBM research laboratory [6]. SQL is a declarative language used to manage data in a relational database. The commands in SQL are divided into two main categories: the Data Definition Language (DDL) and the Data Manipulation Language (DML) [7].

The DDL is used to express the structure of the information contained in a database. In order to create a table structured like that in Figure 1, a user would use the CREATE command.

```
CREATE Table Students
{
 Student_ID INTEGER,
 Lname TEXT,
 Fname TEXT,
 City TEXT,
 Major TEXT
};
```

In contrast, the DML is used to modify the data contained in a database. This data abides by the outline created using the DDL. For example, if the user wished to add a new student to the table defined in Figure 1, they would use the INSERT command. This statement enables the user to add a new row to the table.

```
INSERT INTO Students VALUES(3, “Smith”, “John”, “Worcester”, “ECE”);
```

Via the use of the SELECT command, the DML also allows the retrieval of rows that have already been added. In order to retrieve all records stored in the database, a user would likely use the following command.

```
SELECT * FROM Students;
```

This project, which is primarily intended as a proof of concept, concerns itself mainly with the use of SQL INSERT and SELECT statements. SQL offers many other capabilities, including the editing of data already added to the database through the use of the UPDATE command and the removal of data from the database through the use of the DELETE command.

4.2.3 Overview of Relational Database Management Systems

There is an assortment of Relational Database Management Systems (DBMS) that implement SQL commands and Codd's relational model. Some of the most prevalent systems include Oracle, Microsoft SQL Server, PostgreSQL, and SQLite [8].

Oracle and Microsoft SQL Server Databases are proprietary enterprise-grade database solutions. They are intended to handle vast amounts of data stored centrally on a database server [9] [10]. PostgreSQL is an open-source DBMS; it boasts enterprise-grade power and exceptional SQL standards compliance [11].

4.2.4 SQLite

The implementation chosen for this project is SQLite, version 3.7.6.3. SQLite is an open source DBMS that is fundamentally different from the implementations discussed above. Instead of following a client-server model, it is meant to "provide local data storage for individual applications and devices" [12]. It claims to compete not with the larger scale server-client database systems discussed previously, but with the fopen() system call. It is used in many areas, including embedded systems, small websites, and data analysis. However, SQLite is not well suited for most networking applications, high concurrency, or data sets larger than a terabyte. Given these simplifications, SQLite is much more lightweight than other DBMSs available. This fact makes it more straightforward for a developer to understand and make changes to the system.

4.3 Classification of Machine Architectures

In 1966, Michael J. Flynn proposed a classification for computer architectures. The system describes the number of concurrent operations and the amount of data the instructions operate on. The classification is broken into four classes: Single Instruction – Single Data (SISD), Single Instruction – Multiple Data (SIMD), Multiple Instruction – Single Data (MISD), and Multiple Instruction, Multiple Data (MIMD) [13]. This project will focus on two of these architectures, namely SISD and SIMD.

4.3.1 Single Instruction – Single Data

The simplest of Flynn's classifications, SISD, is implemented as a single core processor. In this architecture, single machine instructions are run sequentially on single pieces of data in memory. Figure 3 demonstrates this behavior; each arrow signifies a single instruction, and each instruction is executed at a different point on the arbitrary time scale.

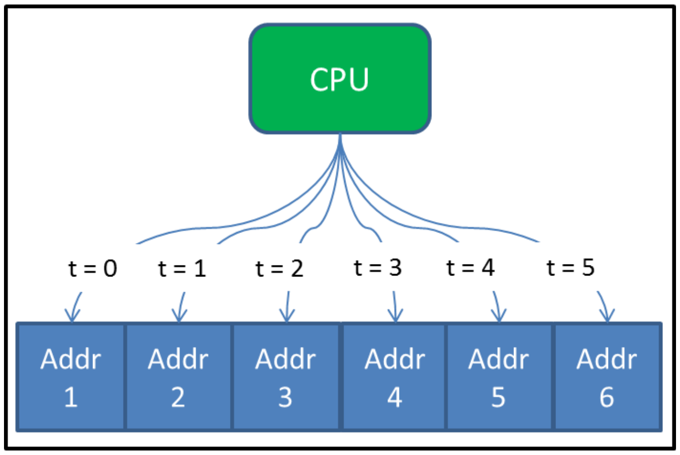


Figure 3. Single Instruction, Single Data

4.3.2 Single Instruction – Multiple Data

In contrast to the traditional CPU SISD architecture the SIMD architecture executes a single instruction on multiple memory locations in parallel (SIMD). Figure 4 demonstrates this behavior; it shows the data at each location in memory being operated on simultaneously.

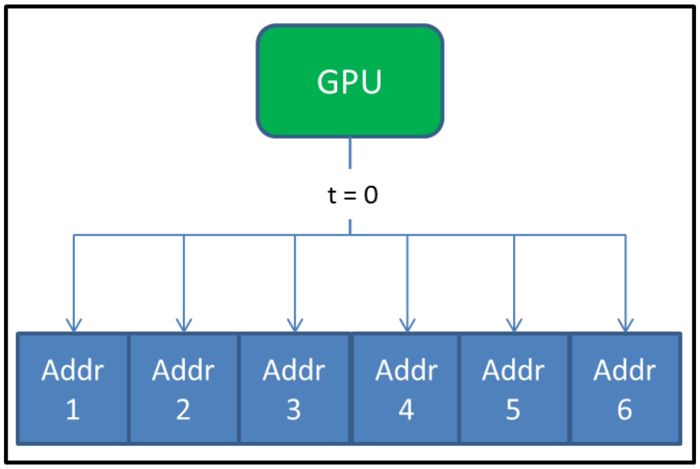


Figure 4. Single Instruction, Multiple Data

This design is implemented by a piece of hardware called the Graphics Processing Unit, or GPU.

4.4 GPU

4.4.1 History of the GPU

GPUs, known colloquially as video cards, emerged out of necessity in the early 1990s to accelerate the 2d graphics in GUI systems like Microsoft Windows. At a similar time, a company called Silicon Graphics released a programming interface called OpenGL to its graphics hardware. They did this for two ends: to popularize 3d graphics, and to secure OpenGL a place as the industry standard in graphics programming [14].

In 2001, NVIDIA released their GeForce 3 series chip, which implemented Microsoft's DirectX 8.0. This meant their hardware contained programmable vertex and pixel shaders, which allowed developers some precise control over the actual operations being performed on the GPU [14].

4.4.2 Graphics Operations on GPUs

GPUs can now be used to speed up graphics as well as non-graphics tasks. Graphics operations are achieved by processing data through a pipeline of smaller, parallelizable tasks. Figure 5 demonstrates the DirectX pipeline as an example of a graphics pipeline.

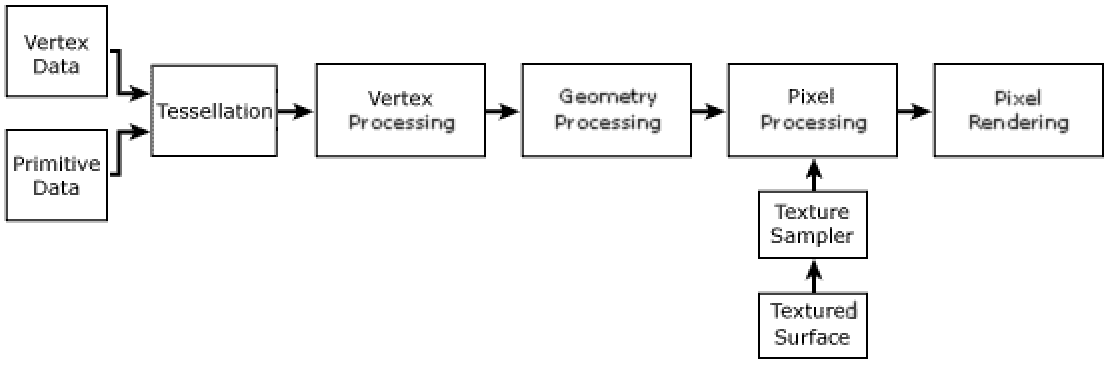


Figure 5. DirectX Graphics Pipeline [15]

A simplified diagram of the OpenGL graphics pipeline is shown in Figure 5, and is at a level of depth adequate for this explanation [16]. Each stage of the graphics pipeline is very similar in concept, so the Vertex Processing stage is chosen for further analysis. The primary purpose of the Vertex Processing stage is to transform the information in a vertex data structure to a location on-screen [17]. This is accomplished through the use of a program called the vertex shader. One instance of the vertex shader is run on the GPU for each vertex element to be displayed [18]. Ideally, every vertex would be operated on in parallel, but this is limited in practice by the number of cores available on the GPU.

4.4.3 General Purpose GPU Programming

These shaders expect to receive graphics data (e.g. color, location) as arguments, and expect to return modified graphical data as outputs. However, within the shader, these values are simply arbitrary numeric values on which the programmer can perform arbitrary operations.

Developers soon began to write code in the shaders for more generic number-crunching tasks, by transferring arbitrary information posing as graphical information back and forth between the CPU and GPU. This was the birth of General Purpose GPU (GPGPU) Programming [14].

4.4.4 CPU vs. GPU

The modern CPU typically has a higher clock rate than the GPU. While the current generation Intel and AMD processors typically have clock rates on the order of 3-4GHz [19] [20], current NVIDIA cards like the GeForce GTX 980 falls just over 1GHz [21]. However, while a CPU will likely have 2-4 processing cores, a GPU may have as many as 1-2 thousand [21]. Each of these cores is lower power than a CPU core, and thus is suited to less complex operations. GPUs work well in environments where many small tasks can be performed in parallel to achieve some larger goal.

4.4.5 GPGPU Applications

Many numerical algorithms can be made faster through GPGPU programming. Successful acceleration has been achieved in the areas of crypto-currency mining, scientific computing, image processing, and many others [22].

GPUs have been successfully used to speed up many diverse applications. For instance, there exists a program called cRARk, whose purpose is to crack forgotten passwords on Windows RAR archives. Developed by a man named Pavel Semjanov, this program runs on any modern NVIDIA GPU [23]. CRARk boasts a speedup from 283 password checks per second on traditional CPU-based methods to 4281 per second on GPUs [24].

NVIDIA lists a wide variety of GPGPU applications on their website [25]. Some of the more interesting uses include: acceleration for MATLAB (up to 22 times speedup) [26], a molecular dynamics simulator called LAMMPS (up to 18 times speedup) [27], and a life sciences 3D visualizer called Amira (up to 70 times speedup) [28].

4.4.6 GPGPU Restrictions

Perhaps the largest restriction on the processing of a GPU is data transfer rate between the CPU and GPU [29]. In order for the GPU to process data, the CPU must transfer data from its memory across the computer's bus to GPU memory. This is a slow process, and must be repeated in the opposite direction once the GPU has finished its work. Figure 6 illustrates these transfers.

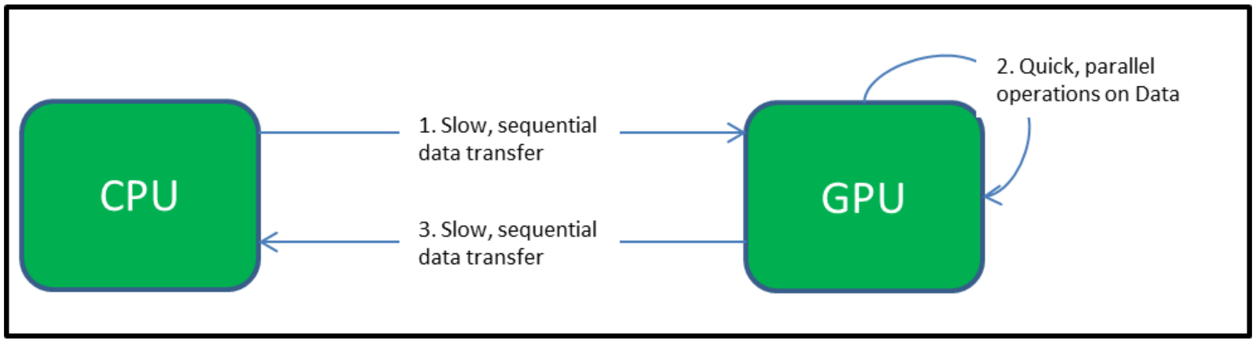

2. Quick, parallel operations on Data
1. Slow, sequential data transfer
CPU
GPU
3. Slow, sequential data transfer

Figure 6. Data Transfer between CPU & GPU

Consequently, the use of the GPU is best suited in situations where many operations can be performed on data, with relatively few data transfers. Otherwise, the relative processing speed on the GPU may become irrelevant due to the transfer overhead.

4.5 CUDA

In 2006, NVIDIA Corporation released CUDA (Compute Unified Device Architecture) as a platform for general purpose parallel computing using their GPUs. CUDA allows the programmer to interface with the GPU using extensions to the C programming language. This code is compiled to PTX, which is CUDA's instruction set architecture, through the use of nvcc: NVIDIA's proprietary compiler. The language is based on three key abstractions: its hierarchy of thread groups, shared memory between threads, and barrier synchronization.

From a developer's perspective, the primary difference between ANSI C and CUDA C is the introduction of a semantic element called a kernel. A kernel, which is a small program that is run on the GPU rather than the CPU, introduces a double angle bracket syntax that defines the amount of parallelism [30].

```
cudaFunc<<N, M>>();
```

In the above code, cudaFunc is the name of a pre-defined kernel function, M is the number of threads to instantiate, and N is the number of parallel executions per thread. If N=3 and M=4, the kernel would run twelve times: three times for each of four threads. A function definition is denoted as a kernel with the __global__ qualifier. A function that is declared __global__ can be called from the CPU or the GPU, but is always run on the GPU [30].

In addition to __global__, CUDA defines new function qualifiers __device__ and __host__. The __device__ qualifier is used in the definition of a function that both runs on and is called from the GPU; this keyword can also be used to declare a variable stored in GPU memory. On the other hand, __host__ is used to designate a function that both runs on and is called from the CPU [30].

5 METHODOLOGY

Figure 7 gives an overview of the procedures taken in order to achieve a working virtual table.

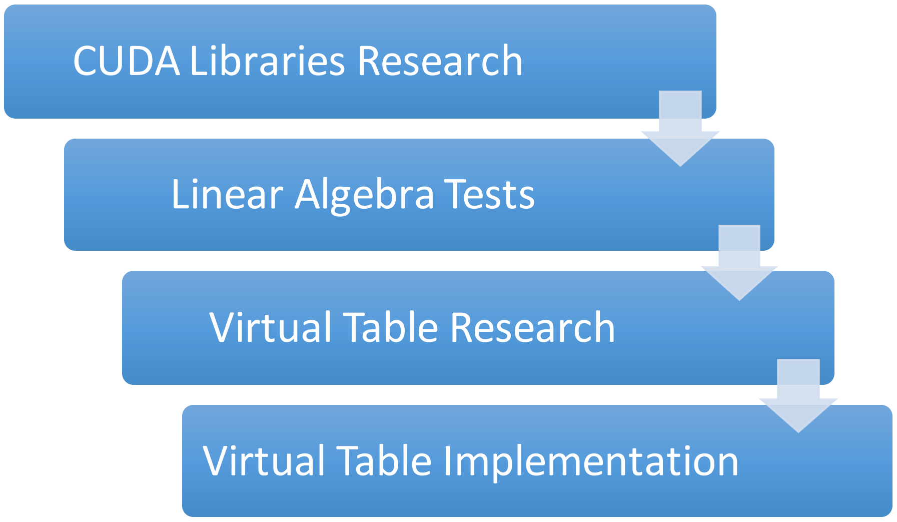


Figure 7: Methodology Overview

5.1 Research

The first phase of the project consisted of researching CUDA, SQLite, and GPGPU in general. The sections below outline the steps taken to gain an understanding of the technologies prevalent to this MQP.

5.1.1 Tools & libraries

As a first step into the world of CUDA, the first major accomplishment was researching many of the tools and libraries available. These components were organized in a spreadsheet, and split into three key sections: infrastructure, libraries, and tools. The three categories are listed in ascending order of abstraction: infrastructure APIs are low-level building blocks, and libraries are higher-level collections of infrastructure components. The tools category is an assortment of programs used to improve the CUDA programming experience (e.g. IDEs and profilers). The complete spreadsheet is available in Appendix B, but a small snippet is shown below.

	General Libraries	
Name	**Description**	**URL**
AmgX	acceleration in the computationally intense linear solver portion of simulations	https://developer.nvidia.com/amgx
ArrayFire	GPU function library, including functions for math, signal and image processing, statistics	https://developer.nvidia.com/arrayfire
cuBLAS	GPU-accelerated version of the complete standard BLAS library	https://developer.nvidia.com/cublas
cuBLAS-XT	set of routines which accelerate Level 3 BLAS (Basic Linear Algebra Subroutine)	https://developer.nvidia.com/cublasxt
CUDA Math Library	collection of standard mathematical functions, providing high performance on NVIDIA GPUs	https://developer.nvidia.com/cuda-math-library
CULA Tools	dramatically improve the computation speed of sophisticated mathematics	https://developer.nvidia.com/em-photonics-cula-tools

Figure 8: CUDA Spreadsheet Snippet

The following sections contain tools, libraries, and resources directly of interest to this project.

5.1.1.1 cuBLAS

cuBLAS, or the CUDA Basic Linear Algebra Subroutines (cuBLAS) library, is a GPU-optimized set of Linear Algebra functions. Just as Thrust is a CUDA analogue to the C++ STL, cuBLAS is based on Intel's MKL BLAS. cuBLAS boasts support for all standard BLAS routines, as well as tremendous speedup. cuBLAS was used in the tests to perform matrix multiplication, specifically using the *cublasSgemm()* function. This is useful because this function performs the matrix multiplications and allows us to transpose the matrices all in one function call.

5.1.1.2 Thrust

One of the most prevalent API sets available is Thrust. Thrust is a library that closely emulates the C++ Standard Template Library. One useful element of Thrust is the provision of data structures, such as vectors, that can be created in CPU or GPU-space. The Thrust library was specifically used in the GPU integer SAXPY algorithm in order to create and populate vectors on the CPU and GPU, and performing vector transformations.

5.1.1.3 Nsight

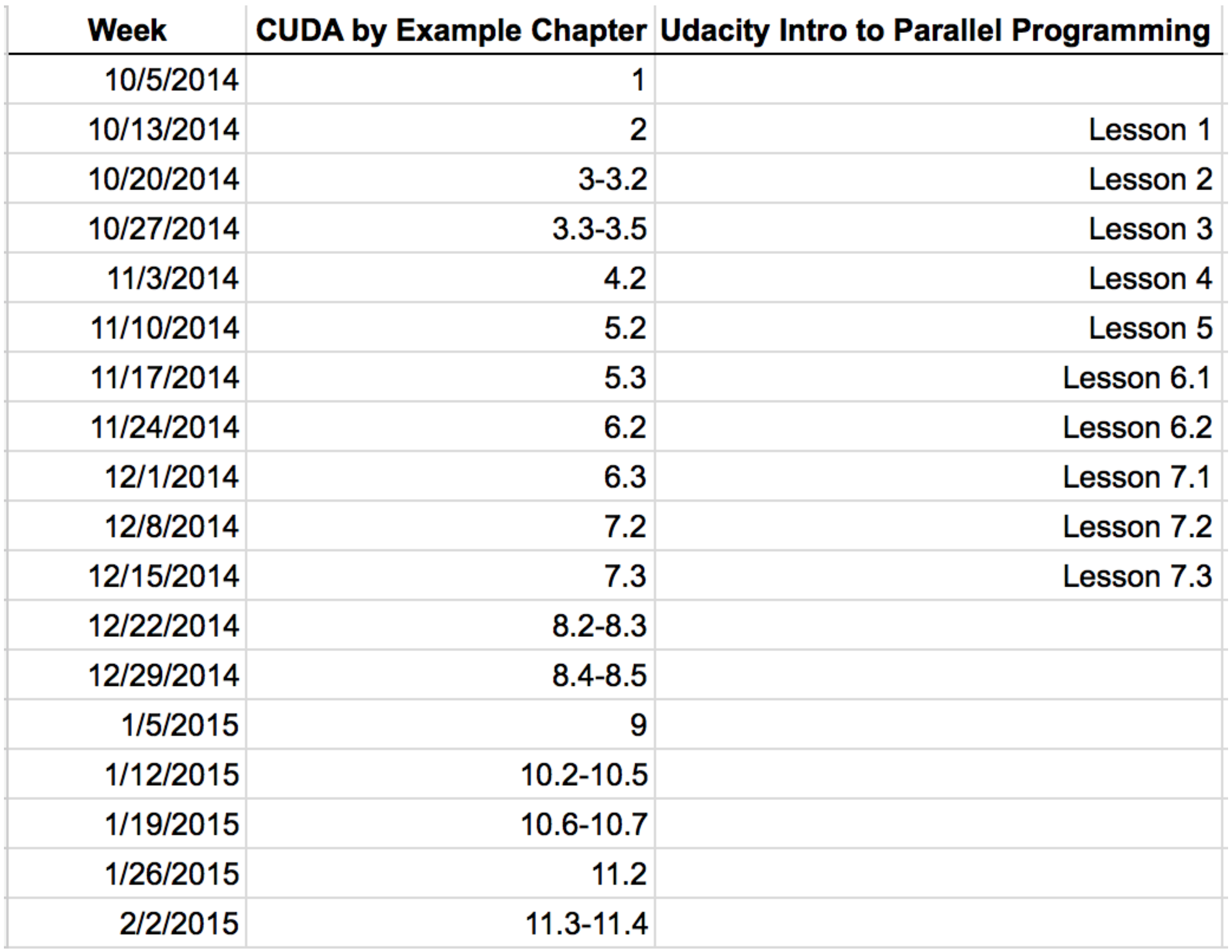
Nsight is a CUDA development platform released by NVIDIA, with editions for Visual Studio and Eclipse. This is a useful tool, containing features like GPU-oriented debugging functionality and code profiling. Because much of this development was performed on a virtual machine, Nsight was not directly used in this project.

5.1.2 CUDA by Example

CUDA by Example [31] is a book written by senior developers of the CUDA platform team. It contains lessons and examples aimed to get readers working with CUDA as quickly as possible. In order to gain as much knowledge in this area as possible, a schedule of chapters to read was designed in order to complete the book in its entirety by the end of the MQP.

5.1.3 Udacity Intro to Parallel Programming

Udacity offers an introductory-level course on Parallel Programming. Although this course does not dive as deeply into the language as *CUDA by Example*, it is a useful resource that should provide much insight prior to the start of coding. A lesson plan from this course was arranged to supplement the readings from *CUDA by Example*, as shown in Figure 9.



Week	CUDA by Example Chapter	Udacity Intro to Parallel Programming
10/5/2014	1	
10/13/2014	2	Lesson 1
10/20/2014	3-3.2	Lesson 2
10/27/2014	3.3-3.5	Lesson 3
11/3/2014	4.2	Lesson 4
11/10/2014	5.2	Lesson 5
11/17/2014	5.3	Lesson 6.1
11/24/2014	6.2	Lesson 6.2
12/1/2014	6.3	Lesson 7.1
12/8/2014	7.2	Lesson 7.2
12/15/2014	7.3	Lesson 7.3
12/22/2014	8.2-8.3	
12/29/2014	8.4-8.5	
1/5/2015	9	
1/12/2015	10.2-10.5	
1/19/2015	10.6-10.7	
1/26/2015	11.2	
2/2/2015	11.3-11.4	

Figure 9: CUDA Lesson Plan

5.1.4 Using SQLite

The main resource used to gain a proper understanding of certain aspects of SQLite was Jay A. Kreibich's text, *Using SQLite* [31]. This book outlines uses of SQLite, the SQL language, APIs available, the C programming interface, as well as other topics. The main interest in this book, however, were chapters nine and ten. These sections outlined SQLite functions and extensions, as well as virtual tables and modules, which directly pertain to this project. The examples provided in the chapters proved to be a substantial resource for developing a custom virtual table.

5.2 Environment

The following sections describe the environment uses to complete this project.

5.2.1 VirtualBox and Debian

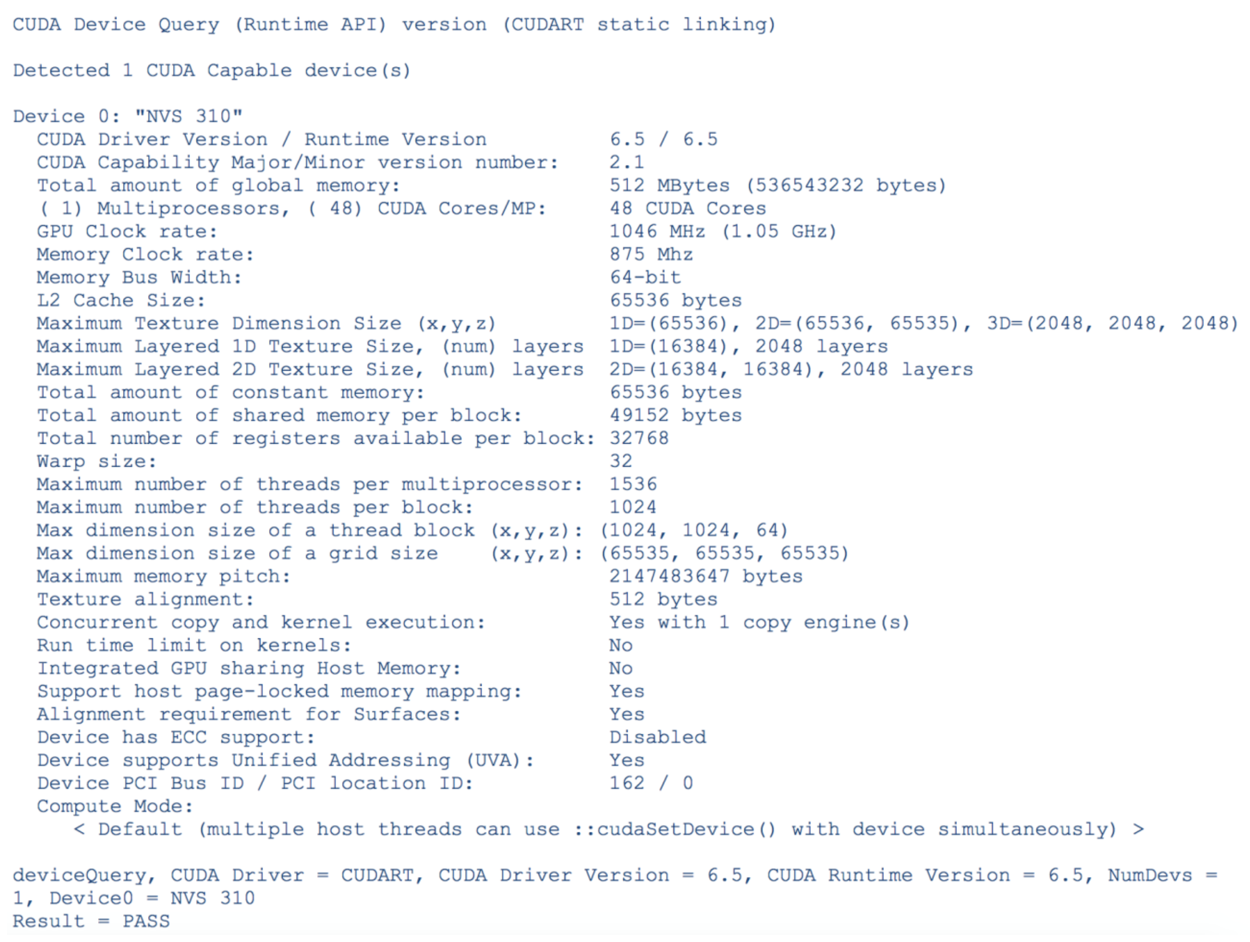
Because of the complexity of installing CUDA on a Windows machine, VirtualBox and a Linux distribution were required. Debian 7 was the Linux version chosen.

5.2.2 SSH

The local machines used did not have a GPU, so an external resource to run the CUDA code was necessary. The remote machine all of the code ran on was a SUSE Linux machine. SSH was used to gain terminal access to modify and run code.

5.2.3 GPU Information

The CUDA installation provides a useful program called *deviceQuery* that provides all of the necessary information about the GPU installed in the machine. Figure 10 shows the output of program for the GPU used in this project.



```
CUDA Device Query (Runtime API) version (CUDART static linking)

Detected 1 CUDA Capable device(s)

Device 0: "NVS 310"
  CUDA Driver Version / Runtime Version          6.5 / 6.5
  CUDA Capability Major/Minor version number:    2.1
  Total amount of global memory:                 512 MBytes (536543232 bytes)
  ( 1) Multiprocessors, ( 48) CUDA Cores/MP:     48 CUDA Cores
  GPU Clock rate:                                1046 MHz (1.05 GHz)
  Memory Clock rate:                             875 Mhz
  Memory Bus Width:                              64-bit
  L2 Cache Size:                                 65536 bytes
  Maximum Texture Dimension Size (x,y,z)         1D=(65536), 2D=(65536, 65535), 3D=(2048, 2048, 2048)
  Maximum Layered 1D Texture Size, (num) layers  1D=(16384), 2048 layers
  Maximum Layered 2D Texture Size, (num) layers  2D=(16384, 16384), 2048 layers
  Total amount of constant memory:               65536 bytes
  Total amount of shared memory per block:       49152 bytes
  Total number of registers available per block: 32768
  Warp size:                                     32
  Maximum number of threads per multiprocessor:  1536
  Maximum number of threads per block:           1024
  Max dimension size of a thread block (x,y,z): (1024, 1024, 64)
  Max dimension size of a grid size    (x,y,z): (65535, 65535, 65535)
  Maximum memory pitch:                          2147483647 bytes
  Texture alignment:                             512 bytes
  Concurrent copy and kernel execution:          Yes with 1 copy engine(s)
  Run time limit on kernels:                     No
  Integrated GPU sharing Host Memory:            No
  Support host page-locked memory mapping:       Yes
  Alignment requirement for Surfaces:            Yes
  Device has ECC support:                        Disabled
  Device supports Unified Addressing (UVA):      Yes
  Device PCI Bus ID / PCI location ID:           162 / 0
  Compute Mode:
     < Default (multiple host threads can use ::cudaSetDevice() with device simultaneously) >

deviceQuery, CUDA Driver = CUDART, CUDA Driver Version = 6.5, CUDA Runtime Version = 6.5, NumDevs =
1, Device0 = NVS 310
Result = PASS
```

Figure 10: Information of GPU used in this Project

5.3 Linear Algebra Tests

A first area of investigation was to find the types of problems most likely to yield the most performance improvements, specifically linear algebra operations. These types of problems directly apply to different users in EMC, specifically the FAST(Fully Automated Storage Tiering) Engine and the meta-data paging developers. The FAST team runs algorithms that determine which back-end devices data lives on, ranging from solid-state drives, Serial Attached SCSI (SAS) drives, and Serial ATA (SATA) drives. The meta-data paging team develops algorithms to ensure the meta-data associated with active drives are already in memory, using a variety of database algorithms to keep track of this data.

5.3.1 Dot Products

The first test performed was the integer dot product algorithm. The dot product is calculated with the formula below, given two vectors X and Y with a size of N:

$$X \cdot Y = X_1 * Y_1 + X_2 * Y_2 + \ldots + X_N * Y_N$$

This test was completed by starting with a size of N=100, and incrementing by 1000 until N < 100100. The dot product is one type of linear algebra operation that could be useful to some of the meta-data paging developers at EMC, who run algorithms to determine if meta-data is already in memory.

5.3.2 Matrix Multiply

The second test executed to become accustomed to programming in CUDA was the matrix multiplication algorithm. This test uses the CUBLAS, a commonly used Linear Algebra Subroutine library, for matrix functions, providing an easy interface to run operations on matrices with C code. A major issue was the column ordering of the matrices. The CUBLAS library uses column ordering, while C matrices are stored in row order. Hence, a function was needed to transpose the matrices when the matrices are transferred onto the GPU, and transpose the data again once it is transferred onto the host. Square matrices were used in this example (NxN).

5.3.3 SAXPY

SAXPY (Single-Precision A·X Plus Y) is a combination of scalar multiplication and vector addition. The chart below shows the timing for running { (a* X) + Y } using on both the CPU and GPU using the thrust library functions. Thrust here is used to generate the CPU and GPU vectors, and performs the transformation operations for the GPU. In this graph, the y-axis is a log scale in milliseconds. The vectors the vector size on the x-axis ranges from 100 to 100100 in increments of 1000. Below is the function used to calculate SAXPY on the CPU.

```
void saxpy_cpu_float(float A, thrust::host_vector<float>& X,
thrust::host_vector<float>& Y)
{
  for(int i = 0; i < X.size(); i++)
  {
    Y[i] = (A * X[i]) + Y[i];
  }
}
```

5.3.4 Linear Algebra Test Parameters

The table below represent parameters used for each linear algebra test ran.

Type	Range	Increment Value	Data Type
Dot Product	100-100100	1000	Vector
Matrix Multiply	10-1000	25	Square Matrix (NxN)
SAXPY	100-100100	1000	Vector

5.4 Virtual Tables

Virtual tables are described as an extension to SQLite that allows a developer to define table structure and behavior through C code. When running typical SQL commands, virtual tables use custom implemented functions to process the data. This allows a CUDA implementation to perform tailored operations on datasets. Custom virtual table implementations are known as modules. The author [31] explains two primary examples of SQLite modules, both of which proved to be quite useful references for this implementation. Finally, SQLite provides the ability to develop and load extensions, which consists of custom functions and virtual tables packaged into one bundle. Modules can be developed then load and run through the SQLite shell. The table below shows the parameters used to test the CPU vs. GPU comparison for SQLite insert statements.

Elements	CPU	GPU	Ratio (GPU/CPU)
10	54.546	46.655	0.855333
50	55.836	51.607	0.92426
100	63.451	55.617	0.876535
500	76.378	76.987	1.007974
1000	80.424	111.846	1.390704
5000	190.073	362.673	1.908072
10000	377.843	618.979	1.638191
50000	1621.624	3319.754	2.047179
100000	2716.473	6451.976	2.37513
500000	13766.28	29348.19	2.13189
1000000	30754.51	60059.45	1.952867

Table 1: Parameters for SQLite Insertion Benchnmark

6 RESULTS

6.1 Linear Algebra Results

The following sections show the performance increases found from CPU to GPU for linear algebra operations. These performance increases shown below are important for the FAST(Fully Automated Storage Tiering) Engine and the meta-data paging teams.

6.1.1 Dot Products

As Figure 11 shows, GPUs perform at a relatively consistent level, while the CPU increases logarithmically as the number of elements in the vector increases. Even as the vector size increases, the GPU performs at a steady pace. Vector size represents the number of elements in each of the two vectors input into the dot product algorithm. The crossover point in which the GPU outperforms the CPU occurs at a vector size of around 200 elements.

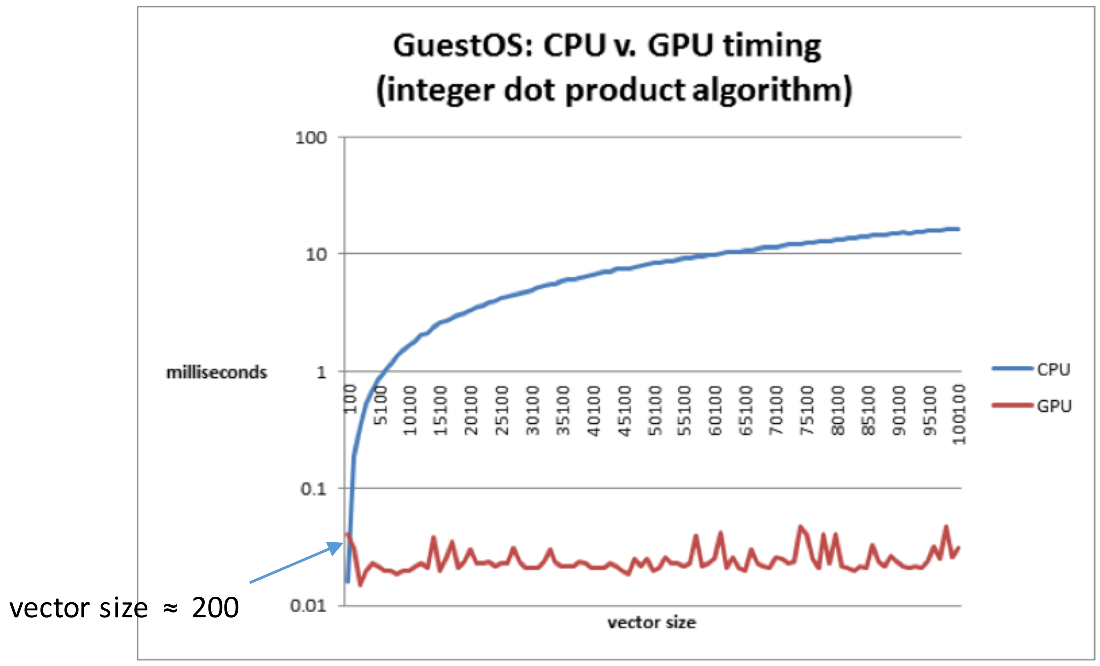


Figure 11: Dot Product Algorithm

6.1.2 Matrix Multiply

Figure 12 shows the results from the matrix multiplication test. As can be observed, the GPU again significantly outperforms the CPU in linear algebra operations. Here, the GPU shows a logarithmic type of curve, but still overcomes the CPU by factors of ten. The crossover point in which the GPU outperforms the CPU occurs at a matrix size of 25x25.

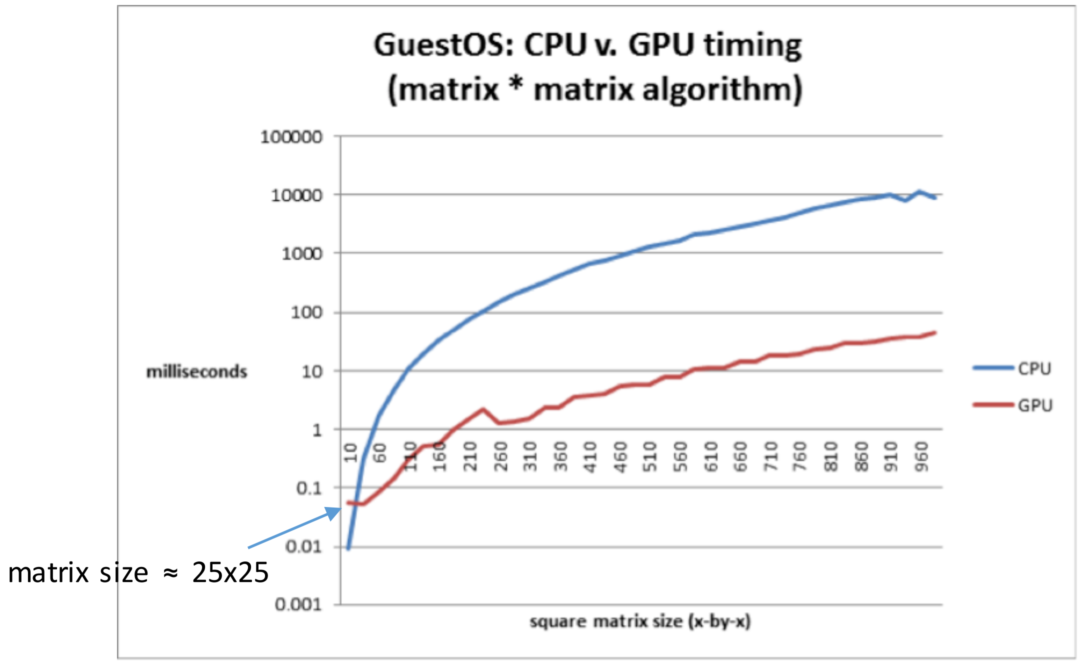


Figure 12: Matrix Multiplication Algorithm

6.1.3 SAXPY

Figure 13 shows that whenever the size of the vectors is over about 40 entries, it is much faster to use the GPU. Similar to the other tests, the GPU performs at a relatively steady rate. The vector size in this test refers to the number of elements in the two input vectors for the SAXPY algorithm. The crossover point in which the GPU outperforms the CPU occurs at a vector size of around 400 elements.

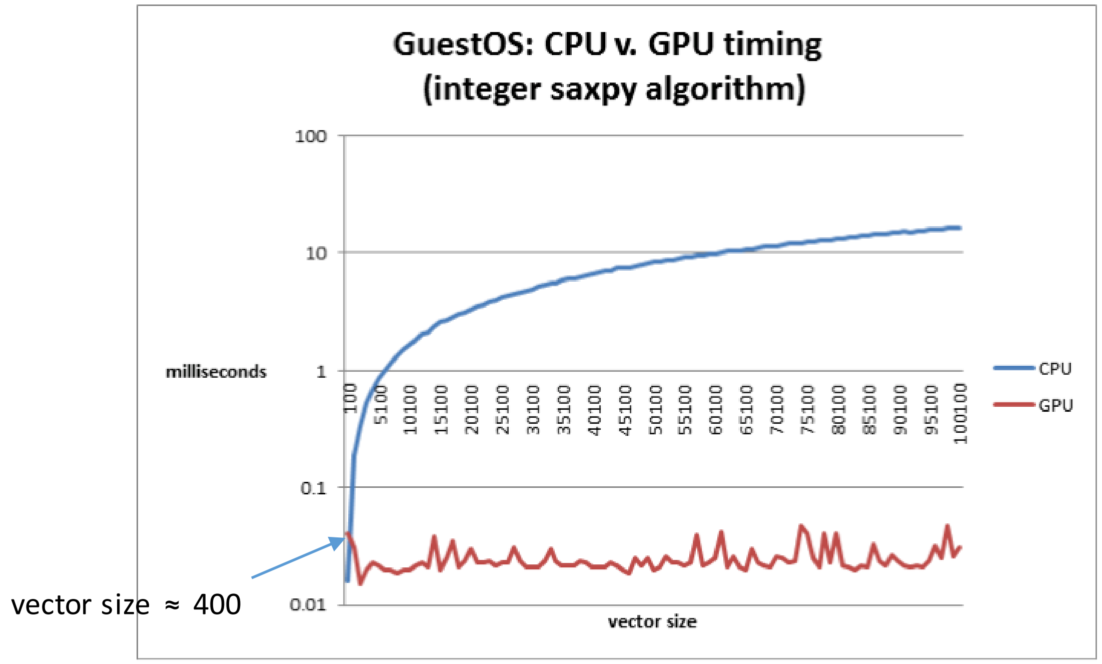


Figure 13: Integer SAXPY Algorithm

6.1.4 Column-major vs. row-major

When writing CUDA code concerning matrices, the ordering of the matrix must be considered. The CUBLAS matrixes functions require column-major ordering, while C and C++ want row-major ordering. Hence, a transpose operator is required for CUBLAS when transferring data to the GPU, and the data must be converted to its original ordering when it returns to the CPU.

Concerning the virtual table ordering, column major tables will speed up operations such as "like" and "match," since whole chunks of column data can be examined in parallel. This will also avoid the need to transpose the database storage from CPU memory to GPU memory, since the data will be put directly into the GPU.

6.2 Implementing the Virtual Table

The next major step in the project was the implementation of a virtual table with GPU functionality. The following sections outline the steps taken to complete that goal.

6.2.1 Stripping down book example

Virtual tables are fairly complex, and inherently difficult to debug. Each virtual table extension must implement a subset of virtual table functions (e.g. xCreate, xConnect, xDisconnect, etc.) depending on its purpose. To start, SQL functions needed to be mapped to CUDA, determining a minimal, working set of required virtual table functions. This was accomplished by starting with the virtual table example, "dblist.c," from Chapter 10 of *Using SQLite*. The dblist module provided from the book takes the “PRAGMA database_list” SQLite command output and presents it as a table. The purpose of this module is to show the necessary functions needed for a SQLite module.

The next step, for testing purposes, was a function call to the matrix tests described above. This allowed for CUDA code to be called within SQLite, as shown below.

```
sqlite3> select doMatrixTest() from sql_database_list where name=”main”;
```

In order to determine which virtual table functions were necessary, print statements were added within each function to show when it was being called. In order to create a barebones module, extraneous function implementations were removed and code simplifications were made. In the end, the functions that needed to be implemented were xConnect, xOpen, xFilter, xNext, xEof, and xColumn. The following section shows a step-by-step example of how these functions are used.

The xConnect() function is used to create a virtual table, and is called in response to the "CREATE VIRTUAL TABLE" statement. This function also establishes a connection to the newly created virtual table. The xOpen() function is used to create a new cursor for reading or writing to the virtual table. The xFilter() function is used to search the virtual table. This function takes in the cursor opened by xOpen(), as well as a search index chosen by the xBestIndex() function. The xFilter() and xBestIndex() functions are the primary areas in which query optimization occurs. xNext() is used by the xFilter() function and advances the virtual table cursor the next row. xColumn() is called multiple times per row, as it extracts the value of the N-th column for the current row. Finally, the xEof() function determines if the cursor points to a valid row of data. Hence, this function is called after every xFilter() and xNext() call.

The custom virtual implementation used in this project uses these functions described above, and removed non-essential functions. This allowed for the above functions to be implemented with CUDA code.

6.2.2 Memory management

One concern with virtual table performance is memory management. Because column-based ordering is required for the GPU implementation, memory management becomes considerably more complicated than row-based models. Hence, the memory management overhead cannot be greater than the performance gains from the column-based pattern matching. To achieve this, each column must be contiguous in memory. This becomes difficult, as it is uncertain how many rows may be added, which may lead to a large number of memory reallocations.

For the CPU implementation, memory is allocated based on a fixed amount defined in a constant. This approach is inefficient, but makes it easier to manage than having varying table sizes. The GPU table is designed to be relatively more efficient, since it uses a column-major ordering. This ordering allows for more efficient memory access for parallel searching and pattern matching, achieving performance gains over normal C row-major ordering. The GPU still uses a pre-allocated limit to the number of rows that the table can use. This technique is necessary in order to maintain contiguous memory and limits reallocation. If this strategy was not used, continuous memory allocations would cause fragmentation in the memory space available and non-contiguous memory would result in a significant performance hit for parallel searching. The major penalty on the GPU side occurs when string data is transferred from the CPU to the GPU and back. Because of this performance loss, it may be an improvement to perform the searches on the CPU.

6.3 Virtual Table Results

In order to test the effectiveness of a CUDA SQLite virtual table, a set of benchmarks were run in order to see the GPU comparison. As Figure 14 shows, the CPU significantly outperforms the GPU as the number of rows increase. This may be due to the memory transfer across the PCI barrier. A more optimized memory model would greatly increase the effectiveness of this study, but this implementation did not focus on code optimization as much as developing a working virtual table.

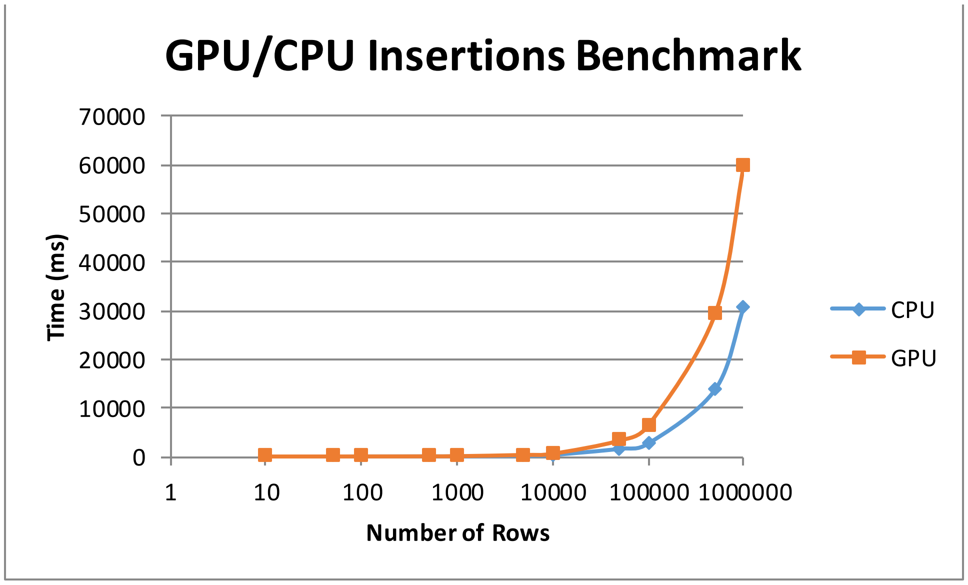


Figure 14: GPU/CPU Insertions Benchmark

Figure 15 shows a zoomed-in version of Figure 14, giving a clearer view of the compressed range of data points from 10-10000 rows.

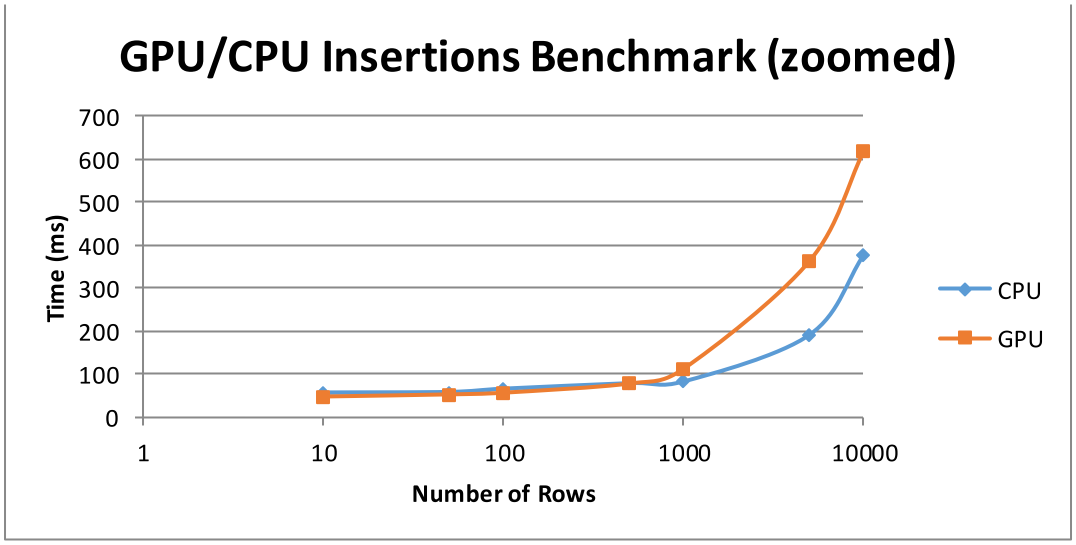


Figure 15: GPU/CPU Insertions Benchmark (zoomed)

7 CONCLUSIONS

7.1 Viability of leveraging the GPU

Based on the linear algebra tests and the SQLite virtual table implementation, this proof of concept project could be useful in multiple areas in EMC. As stated above, the FAST Engine and the meta-data paging developers could benefit from the linear algebra and other types of problems. Using certain libraries, such as the Thrust or CUBLAS libraries could also be advantageous for some of their applications. The SQLite virtual table could also be of use for the meta-data paging team, as well as future work involving a complete port of SQLite to CUDA. This step would be time consuming, but beneficial for those users.

7.2 OpenCL

OpenCL is an open-source alternative to CUDA. It was developed by KHRONOS Group, well known as the developers of OpenGL. It will be wise for the successors in this project to consider migrating the existing codebase from CUDA to OpenCL. This provides a few key advantages; first and foremost is its multi-vendor support. Though CUDA claims more frequent updates than OpenCL, its use implies that only NVIDIA GPUs can be used. On the other hand, OpenCL boasts an ability to run code on any modern GPU [32].

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9 APPENDIX A: TABLE OF TOOLS AND LIBRARIES

Infrastructure		
Name	**Description**	**URL**
GPUDirect	Enables 3rd party network adapters and other devices to directly read and write CUDA host and device memory on NVIDIA Tesla™ and Quadro™ products. GPUDirect technology also includes direct transfers between GPUs	https://developer.nvidia.com/gpudirect
LLVM	open source compiler infrastructure on which NVIDIA's CUDA Compiler (NVCC) is based on. Developers can create or extend programming languages with support for GPU acceleration using the CUDA Compiler SDK	https://developer.nvidia.com/cuda-llvm-compiler
MPI Solutions for GPUs	enables applications threads to communicate across compute nodes, supports GPU accelerated nodes	https://developer.nvidia.com/mpi-solutions-gpus
OpenACC	collection of compiler directives to specify loops and regions of code in standard C, C++ and Fortran to be offloaded from a host CPU to an attached accelerator	http://www.openacc-standard.org/
Thrust	open source library of parallel algorithms and data structures. Perform GPU accelerated sort, scan, transform, and reductions with just a few lines of code	https://developer.nvidia.com/thrust https://code.google.com/p/thrust/
General Libraries		
Name	**Description**	**URL**
AmgX	acceleration in the computationally intense linear solver portion of simulations	https://developer.nvidia.com/amgx
ArrayFire	GPU function library, including functions for math, signal and image processing, statistics	https://developer.nvidia.com/arrayfire
cuBLAS	GPU-accelerated version of the complete standard BLAS library	https://developer.nvidia.com/cublas
cuBLAS-XT	set of routines which accelerate Level 3 BLAS (Basic Linear Algebra Subroutine)	https://developer.nvidia.com/cublasxt
CUDA Math Library	collection of standard mathematical functions, providing high performance on NVIDIA GPUs	https://developer.nvidia.com/cuda-math-library
CULA Tools	dramatically improve the computation speed of sophisticated mathematics	https://developer.nvidia.com/em-photonics-cula-tools
cuDNN	GPU accelerated library of primitives for deep neural networks	https://developer.nvidia.com/cuDNN
cuFFT	simple interface for computing FFTs up to 10x faster	https://developer.nvidia.com/cufft
cuRAND	library performs high quality GPU accelerated random number generation (RNG)	https://developer.nvidia.com/curand
cuSPARSE	collection of basic linear algebra subroutines	https://developer.nvidia.com/cu

	used for sparse matrices	sparse
Geometry Performance Primatives(GPP)	geometry engine that is optimized for GPU acceleration	https://developer.nvidia.com/geometric-performance-primitives-gpp
HiPLAR	(High Performance Linear Algebra in R) delivers high performance linear algebra (LA) routines for the R platform for statistical computing	https://developer.nvidia.com/hiplar
IMSL Fortran Numerical Library	set of mathematical and statistical functions that offloads work to GPUs	https://developer.nvidia.com/imsl-fortran-numerical-library
KALDI	The CUDA matrix library seamless wrapper of CUDA computation	http://kaldi.sourceforge.net/cudamatrix.html
Labview	LabView enables engineers and scientists to create applications using a powerful high level programming language and advanced tools	http://zone.ni.com/devzone/cda/tut/p/id/11972
MAGMA	collection of next gen linear algebra routines	https://developer.nvidia.com/magma
Math Premium	takes advantage of the NVIDIA CUDA architecture to dramatically accelerate mathematics on the .NET platform	https://developer.nvidia.com/nmath
Mathematics	Mathematicia by Wolfram is a comprehensive technical computing solution ,enabling complex computational applications to be build	https://developer.nvidia.com/matlab-cuda
Matlab	Matlab by Mathworks, has native support for CUDA in the Parallel Computing Toolbox	https://developer.nvidia.com/matlab-cuda
NPP	accelerated library with a very large collection of 1000's of image processing primitives and signal processing primitives	https://developer.nvidia.com/npp
NVBIO	C++ framework for High Throughput Sequence Sequence Analysis for both short and long read alignment	https://developer.nvidia.com/nvbio
OpenCV	open source library for computer vision, image processing and machine learning	https://developer.nvidia.com/opencv
Paralution	library for sparse iterative methods with special focus on multi-core and accelerator technology such as GPUs	https://developer.nvidia.com/paralution
	Tools	
Name	**Description**	**URL**
Allinea DDT	single tool that can debug hybrid MPI, OpenMP and CUDA applications on a single workstation or GPU cluster	https://developer.nvidia.com/allinea-ddt
CUDA-GDB	debugging experience that allows you to debug both the CPU and GPU portions of your application simultaneously	https://developer.nvidia.com/cuda-gdb

CUDA-MEMCHECK	Identifies memory access errors in your GPU code and allows you to locate and resolve problems quickly. reports runtime execution errors, identifying situations that could result in an "unspecified launch failure" error while your application is running	https://developer.nvidia.com/CUDA-MEMCHECK
NVIDIA CUDA Profiling Tools Interface (CUPTI)	performance analysis tools with detailed information about GPU usage in a system	https://developer.nvidia.com/cuda-profiling-tools-interface
NVIDIA Nsight	Development platform, debugging and profile tools	http://www.nvidia.com/nsight
NVIDIA Visual Profiler	performance profiling tool to give feedback to optimize CUDA aplications	https://developer.nvidia.com/nvidia-visual-profiler
PAPI CUDA Component	hardware performance counter measurement technology for the NVIDIA CUDA platform which provides access to the hardware counters inside the GPU. Provides detailed performance counter information regarding the execution of GPU kernels	https://developer.nvidia.com/papi-cuda-component
TAU Performance System	profiling and tracing toolkit for performance analysis of hybrid parallel programs written in CUDA, and pyCUDA., and HMPP	http://www.cs.uoregon.edu/research/tau/home.php
TotalView	GUI-based tool that allows you to debug one or many processes/threads with complete control over program execution	https://developer.nvidia.com/totalview-debugger
VampirTrace	performance monitor which comes with CUDA, and PyCUDA support to give detailed insight into the runtime behavior of accelerators. Enables extensive performance analysis and optimization of hybrid programs.	https://developer.nvidia.com/vampirtrace