

# AMALTHEA-based GPU Response Time Analysis for NVidia's Jetson TX2

Daniel Leoncio Paredes Zevallos

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Doctor of Philosophy

Supervised by:  
Professor Dr. Carsten Wolff  
Herr Robert Hoettger

Fachhochschule Dortmund, Germany  
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*I, AUTHORNAME confirm that the work presented in this thesis is my own.  
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# Abstract

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# Abbreviations and Symbols

## Abbreviations

<b>API</b>	<b>A</b> pplication <b>P</b> rogramming <b>I</b> nterface
<b>CE</b>	<b>C</b> opy <b>E</b> ngine
<b>CPU</b>	<b>C</b> entral <b>P</b> rocessing <b>U</b> nit
<b>EE</b>	<b>E</b> xecution <b>E</b> ngine
<b>FIFO</b>	<b>F</b> irst <b>I</b> n <b>F</b> irst <b>O</b> ut
<b>GPU</b>	<b>G</b> raphics <b>P</b> rocessing <b>U</b> nit
<b>HMP</b>	<b>H</b> eterogeneous <b>M</b> ulti- <b>P</b> rocessor
<b>SM</b>	<b>S</b> treaming <b>M</b> ultiprocessor
<b>OS</b>	<b>O</b> perating <b>S</b> ystem

## Symbols

$\tau$	Set of tasks or kernels
$\tau_i$	Task or kernel $i$
$i$	Period of $\tau_i$
$g_i$	Grid size of $\tau_i$
$b_i$	Number of thread per block within $g_i$
$C_i$	Execution time workload of a thread within $b_i$
$u_i$	Utilization of $\tau_i$
$r_i$	Release time of $\tau_i$
$f_i$	Completion time of $\tau_i$

$R_i$	Response time of $\tau_i$
$U_t$	Total utilization of $\tau$
$b_{max}$	Maximum amount of threads in a SM
$g_{max}$	Maximum amount of blocks that can be allocated in a SM
$g_f$	Available blocks at some point in time
$t_a$	Point in ime at which a block will be allocated

# Chapter 1

## Introduction

### 1.1 Motivation

Car manufactures want to reduce cost in terms of money and time required to develop, test and validate a new piece of software due to a change of supplier. For that reason, centralized end-to-end architectures are the solution they are aiming to, because for car companies such as BWW and Audi the car of future will be similar to a “data center on wheels” [1].

Centralized end-to-end architectures would be the first step stone toward to decoupling software and hardware [2]. This type of architectures not only will take advantage of internet connectivity, cloud computing and powerful heterogeneous processing units, but also will allow scalable, hierarchical and highly integrated system.

In other words, car manufactures prefer now a days low-latency, hierarchical and cost effectiveness of centralized end-to-end architectures, because today requirements of computational power, bandwidth, integration, safety and real-time [3].

However, car manufactures don’t forget that at the end, in centralized end-to-end architectures, different types of software would run on top of an heterogeneous hardware supplied by companies such as NVIDIA, Mobileye or Qualcomm. Thus, it’s important to analyze and understand how software

will behave under those conditions, in order to ensure a predictable and efficient system.

## 1.2 Industrial challenge WATERS 2019

Predictability is a key property for safety-critical and hard real-time systems [4]. Analyzing time related characteristics is an important step to design predictable embedded systems. However, in multi-core or heterogeneous systems based on centralized end-to-end architectures is harder to satisfy timing constraints due to scheduling, caches, pipelines, out-of-order executions, and different kinds of speculation [5]. Thus, development of timing-analysis methods for these types of architectures has become, nowadays, one of the main focus of research in both industry and academic environment.

Robert Bosch GmbH or Bosch, the German multinational engineering and electronics company, and one of the top leaders in development technology for the automotive industry announces every year *the WATERS Challenge*. The purpose of the WATERS industrial challenge is to share ideas, experiences and solutions to concrete timing verification problems issued from real industrial case studies [6].

This year, 2019, the challenge focuses on timing-analysis for heterogeneous software-hardware systems based on centralized end-to-end architectures. The platform chosen for this purpose is the NVIDIA® Jetson™ TX2 platform which has an heterogeneous architecture equipped with a Quad ARM A57 processor, a Dual Denver processor, 8GB of LPDDR4 memory and 256 CUDA cores of NVIDIA's Pascal Architecture. For the challenge it is available an Amalthea model for this platform to design a solution, and test it later on real hardware.

### 1.3 NVIDIA Jetson TX2: Architecture Overview

NVIDIA Jetson TX2 is an embedded system-on-module (SOM). It is ideal for deploying advanced AI to remote field locations with poor or expensive internet connectivity, Robotics, Gaming Devices, Virtual Reality (VR), Augmented Reality (AR) and Portable Medical Devices. In addition, it offers near-real-time responsiveness and minimal latency—key for intelligent machines that need mission-critical autonomy [7].

The main components of the Jetson TX2 are dual-core ARMv8 based NVIDIA Denver2, quad-core ARMv8 Cortex-A57, 8GB 128-bit LPDDR4 and integrated 256-core Pascal NVIDIA GPU. The quad-core Cortex-A57 and dual-core NVIDIA Denver2 can be seen as a cluster of heterogeneous multiprocessors (HMP) [8]. Both HMP and GPU shares a 8GB SRAM memory as shown in Figure 1.1. Hereafter, whenever we use the term **host**, we will refer to HMP, similarly we will use **device** to refer to GPU.

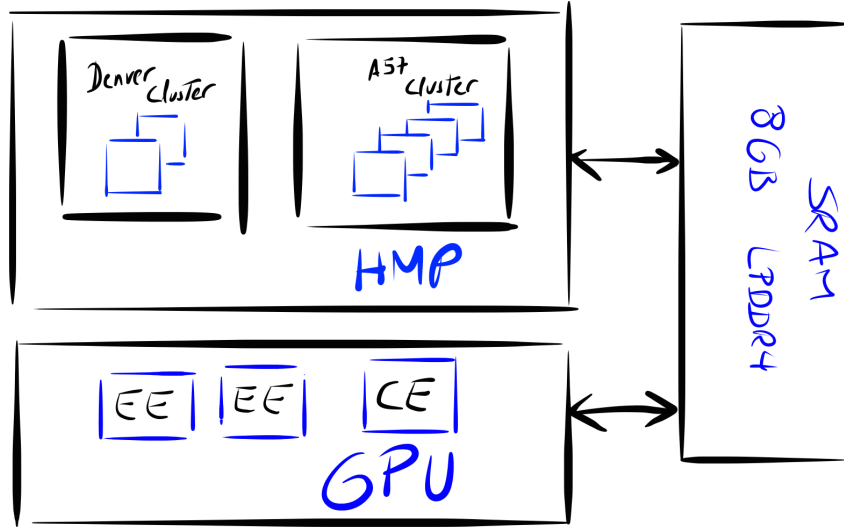


Figure 1.1: Jetson TX2 Architecture Overview

Any NVIDIA GPU has two types of engines, **Copy Engines** (CE) and **Execution Engines** (EE). The Jetson TX2 has only one CE and two EE also known as **Streaming multiprocessors**. CE is in charge of data transfers from host to device and viceversa. There is, moreover, the possibility that

EE and CE can run concurrently.

The GPU uses **streams** to run applications. The number of streams depends on the GPU resources. An application can run in one or multiple streams, the GPU scheduler, by default, manages how to application will be allocated on streams in order to maximize throughput. In Chapter 2, we will discuss in more detail how the TX2 GPU scheduler behave in case of multiple applications.

## 1.4 Jetson TX2 Amalthea Model

AMALTHEA is a platform for engineering multi- and many-core embedded systems. This platform enables the creation and management of complex tool chains including simulation and validation [9]. In the context of WATERS Challenge 2019, Bosch offers an AMALTHEA model of the Jetson TX2. In this model, a CPU runnable will read data from memory, execute some computation (Ticks) and write back data into memory as shown in Figure 1.2.

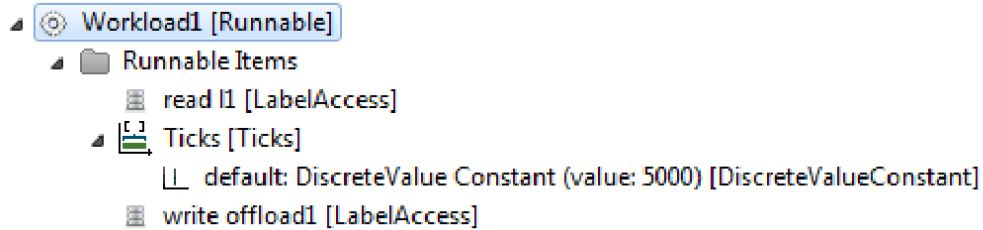


Figure 1.2: Runnable example for a CPU [6]

In the case of GPU modeling, the runnable will follow the same pattern as in the CPU case: read, execution, write back. However, the reading operation is actually to copy memory from host to device, thus it is modeled as *memory reading from host* and then as *memory writing to device*. On the other hand, the writing back operation requires to copy memory from device to host, therefore it is modeled as *memory reading from device* and then as *memory writing to host* as shown in Figure 1.3.



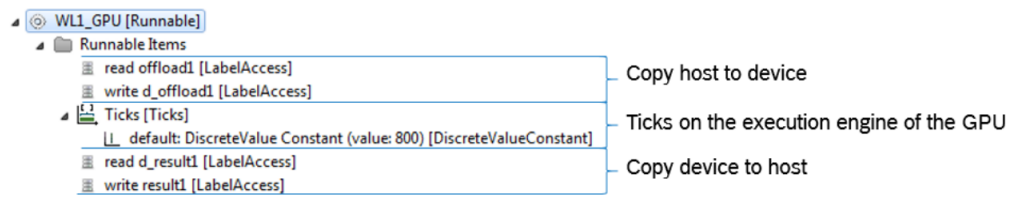


Figure 1.3: Runnable example for a GPU [6]

# Chapter 2

## CUDA and Jetson TX2

In this chapter...blablabla

### 2.1 NVIDIA GPU Software Model

Now a days computer applications run on heterogeneous hardware and GPUs are important in order to achieve high performance computing. Since 2006 running software on NVIDIA GPUs are known as a *CUDA application* [10]. A CUDA application will run concurrently multiple instances of special functions called **kernels**. Each instance runs on a **thread**. Moreover, these threads are arranged in **blocks**, and blocks compose **grids** as shown in Figure 2.1.

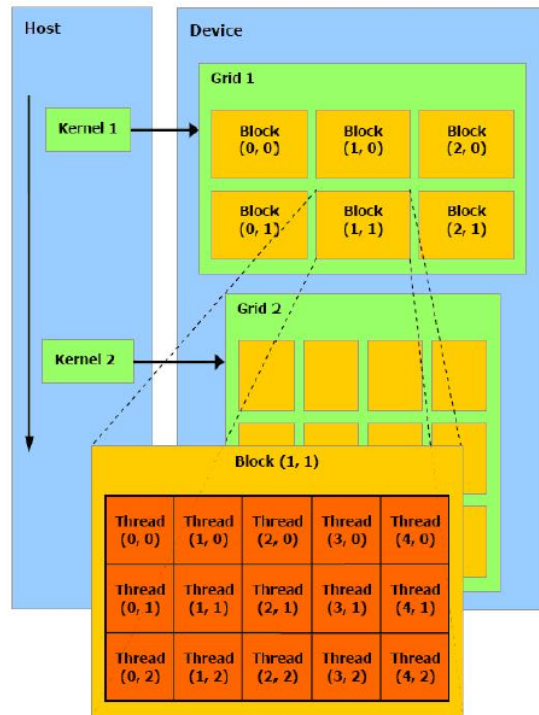


Figure 2.1: Organisation of grids, blocks, threads, and kernels [11].

It's logical to think that there is also a hierarchical memory structure. Threads, blocks and grids have access to different memory spaces as illustrated in Figure 2.2. The types of memory are summarized in Table 2.1.

Table 2.1: Types of memories in a GPU

Memory	Main Characteristics	Scope	Lifetime
Global	R/W, Slow and big	Grid	Application
Texture	ROM, Fast, Optimized for 2D/3D access	Grid	Application
Constant	ROM, Fast, Constants and kernel parameters	Grid	Application
Shared	R/W, Fast, it's on-chip	Block	Block
Local	R/W, Slow as global, when registers are full	Thread	Thread
Registers	R/W, Fast	Thread	Thread

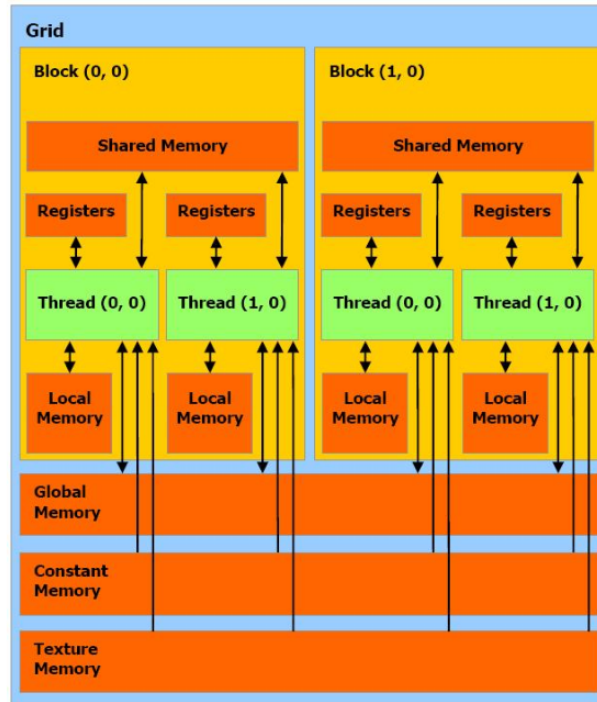


Figure 2.2: Memory hierarchy [11].

In summary, CUDA application solve problems that were modeled based on *divide and conquer* principle. Moreover, CUDA software model not only allow users to achieve high computational performance, but also CUDA application are highly scalable.

## 2.2 NVIDIA GPU Hardware Model

The CUDA architecture is based on **Streaming Multiprocessors** (SM) which perform the actual computation. Each SM has its own control units, registers, execution pipelines and local memories, but they also have access to global memory as illustrated in Figure 2.3. A **stream** is a queue of CUDA operations, memory copy and kernel launch. We will talk more about streams in following sections.

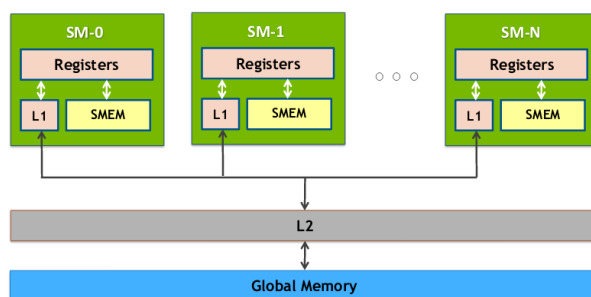


Figure 2.3: Memory hierarchy

When a kernel grid is launch blocks are enumerated and assigned to the SMs. Once the blocks are assigned, threads are managed in **wraps** by the **wrap scheduler**. A wraps is a group of 32 threads that run in parallel. Thus, it's highly recommendable to use block sizes of size  $32N$ ,  $N \in \mathbb{N}$ , otherwise there would be “inactive” threads. A example is shown in Figure 2.4, where there is a block of 140 threads but since the wrap scheduler works with wraps, 20 threads are wasted and no other block can make use of them.

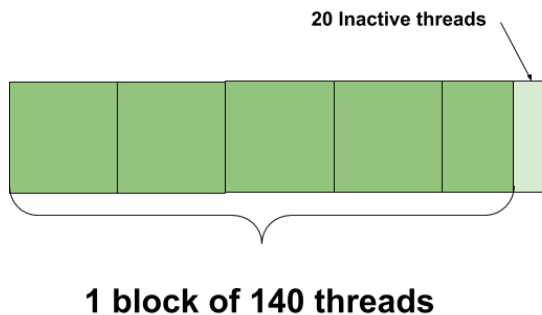


Figure 2.4: Inactive threads

The amount of threads and blocks that can run concurrently per SM depends on the number of 32-bit registers and shared memory within SM, as well as the CUDA computing capability of the GPU. Information related to maximum amount of blocks or threads, as well as the computing capability of the GPU can be display executing `deviceQuery` tool. Some information about Jetson TX2 is presented below:

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

Detected 1 CUDA Capable device(s)

Device 0: "NVIDIA Tegra X2"

CUDA Driver Version / Runtime Version	9.0 / 9.0
CUDA Capability:	6.2
Total amount of global memory:	7850 MBytes
( 2) SM, (128) CUDA Cores/SM:	256 CUDA Cores
L2 Cache Size:	524288 bytes
Total amount of shared memory per block:	49152 bytes
Total number of registers per block:	32768
Warp size:	32
Max. number of threads per SM:	2048
Max. number of threads per block:	1024
Max dim. size of a thread block (x,y,z):	(1024, 1024, 64)
Max dim. size of a grid size (x,y,z):	(2 <sup>31</sup> -1, 65535, 65535)

## 2.3 NVIDIA Jetson TX2's GPU Scheduler

It's common to use several kernels in an application. In order to reduce computation time and maximize GPU utilization, it's desire to run multiple kernels in parallel. CUDA uses streams to achieve this goal. As mentioned before, a stream is a queue of CUDA operations, memory copy and kernel launch. Thus, it is possible either to launch multiple kernels within one streams or multiple kernels on multiple streams. Operations within the same stream are managed in FIFO (First In First Out) fashion, thus, we will also use the term **stream queue** when we talk about FIFO queues within a stream. The Jeston TX2's GPU assigns resources to streams using its

internal scheduler.

Predictability is an important characteristic of safety-critical systems. It requires both functional and timing correctness. However, a detailed information about the Jetson TX2's GPU scheduler behaviour is not publicly available. Without such details, it is impossible to analyze timing constraints. Nevertheless, there are some efforts [12], [13] and [14] aimed at revealing these details through black-box experimentation.

NVIDIA GPU scheduling policies depend on whether the GPU workloads are launched by a CPU executing OS threads or OS processes. We will focus on the first case, because GPU computations launched by OS processes have more unpredictable behaviours, as stated in [12] and [13]. In this section, we will present GPU scheduling policies derived by [12] and use them in an example to clarify their use.

Let's start by defining some terms. When one block of a kernel has been scheduled for execution on a SM it's said that the block was **assigned**. Moreover, it's said a kernel was **dispatched** as soon as one of its blocks were assigned, and **fully dispatched** once all its blocks were assigned. The same applies to copy operations and CE.

There are, in addition, FIFO CE queues used to schedule copy operations, and FIFO EE queues used to schedule kernel launches. Stream queues feed CE and EE queues. Below we will present the rules that determine scheduler and queues behaviours.

- **General Scheduling Rules:**

- **G1** A copy operation or kernel is enqueued on the stream queue for its stream when the associated CUDA API function (memory transfer or kernel launch) is invoked.
- **G2** A kernel is enqueued on the EE queue when it reaches the head of its stream queue.
- **G3** A kernel at the head of the EE queue is dequeued from that queue once it becomes fully dispatched.
- **G4** A kernel is dequeued from its stream queue once all of its blocks complete execution.

- **Non-preemptive execution:**
  - **X1** Only blocks of the kernel at the head of the EE queue are eligible to be assigned.
- **Rules governing thread resources:**
  - **R1** A block of the kernel at the head of the EE queue is eligible to be assigned only if its resource constraints are met.
  - **R2** A block of the kernel at the head of the EE queue is eligible to be assigned only if there are sufficient thread resources available on some SM.
- **Rules governing shared-memory resources:**
  - **R3** A block of the kernel at the head of the EE queue is eligible to be assigned only if there are sufficient shared-memory resources available on some SM.
- **Copy operations:**
  - **C1** A copy operation is enqueued on the CE queue when it reaches the head of its stream queue.
  - **C2** A copy operation at the head of the CE queue is eligible to be assigned to the CE.
  - **C3** A copy operation at the head of the CE queue is dequeued from the CE queue once the copy is
  - **C4** A copy operation is dequeued from its stream queue once the CE has completed the copy.
- **Streams with priorities:**
  - **A1** A kernel can only be enqueued on the EE queue matching the priority of its stream.
  - **A2** A block of a kernel at the head of any EE queue is eligible to be assigned only if all higher-priority EE queues (priority-high over priority-low) are empty.

Authors in [12] mentioned that rules related to **registry resources** are expected to have exactly the same impact as threads and shared-memory rules.



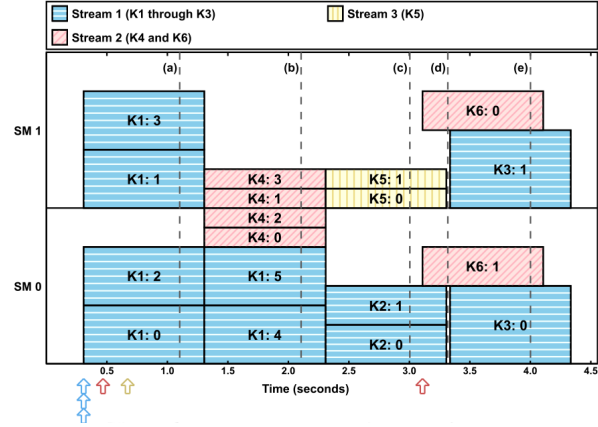


Figure 2.5: Basic GPU scheduling experiment [12]

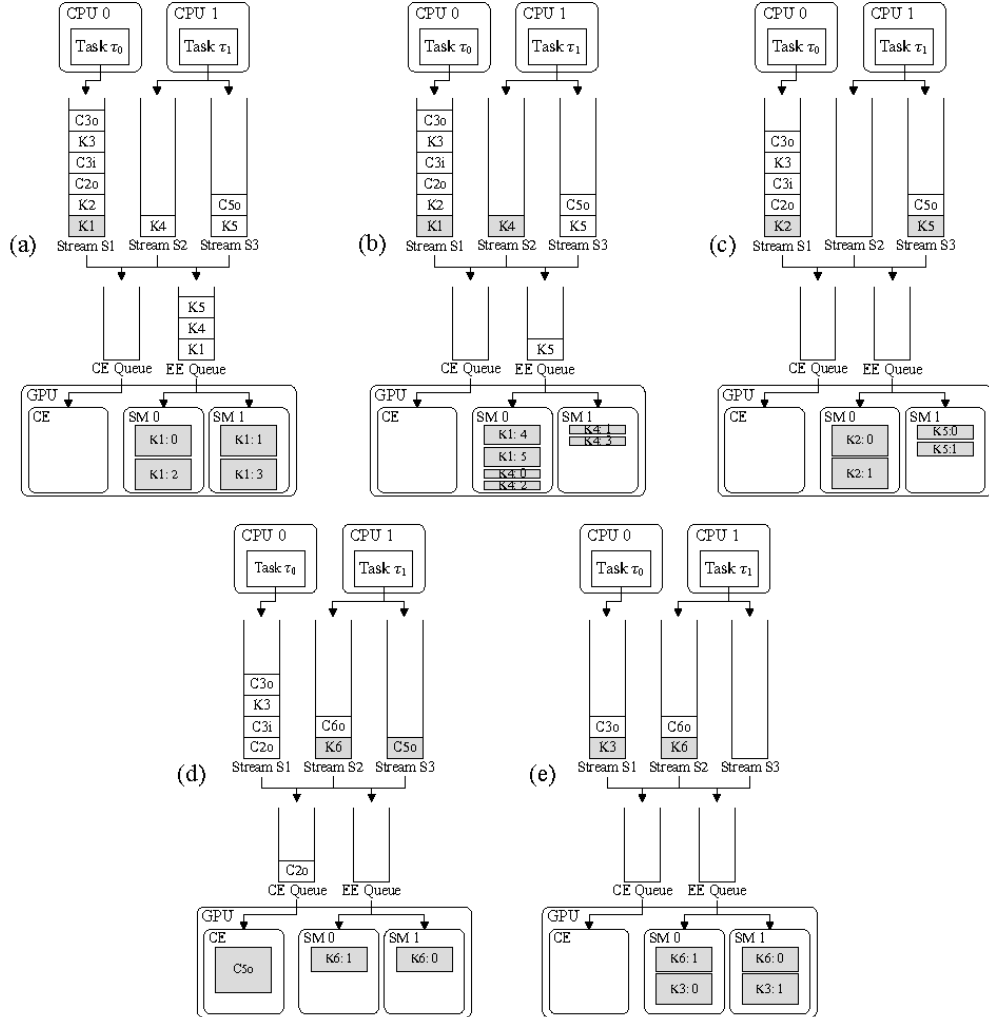


Figure 2.6: Detailed state information at various time points in Fig. 2.5 [12] .

# Chapter 3

## Jetson TX2's GPU scheduler response time analysis

### 3.1 Introduction

In this chapter, we present our approach to calculate the response time analysis for Jetson TX2's GPU scheduler based on the set of scheduling rules explained in the last chapter. **Need a better introduction**

### 3.2 Task model

There is a set of tasks or kernels  $\tau$  of  $n$  independent kernels  $\{\tau_1, \tau_2, \dots, \tau_n\}$  on a single GPU. Each kernel has a period  $T_i$  defined as the separation between two consecutive releases of  $\tau_i$ , thread execution time workload  $C_i$  and a grid of blocks  $g_i$ . Each block contains  $b_i$  threads.

$$\tau = \{\tau_i\}; \quad i \geq n \wedge n \in \mathbb{N} \quad (3.1)$$

$$\tau_i = \{T_i, C_i, g_i, b_i\} \quad (3.2)$$

Thus each kernel  $\tau_i$  has a total of  $g_i \cdot b_i$  threads, and the total execution time workload of  $\tau_i$  is  $C_i \cdot g_i \cdot b_i$ . The utilization of each kernel is defined as the total execution time workload divided by the period, as stated in [15].

$$u_i = \frac{C_i g_i b_i}{T_i} \quad (3.3)$$

In addition, the total utilization of the set of tasks  $\tau$  is defined as:

$$U_t = \sum_{\tau_i \in \tau} u_i \quad (3.4)$$

For a kernel  $\tau_i$  we denote the release time as  $r_i$ , the completion time as  $f_i$  and response time as  $R_i = f_i - r_i$ . We assume that a kernel  $\tau_i$  has a deadline equal to its period  $T_i$ .

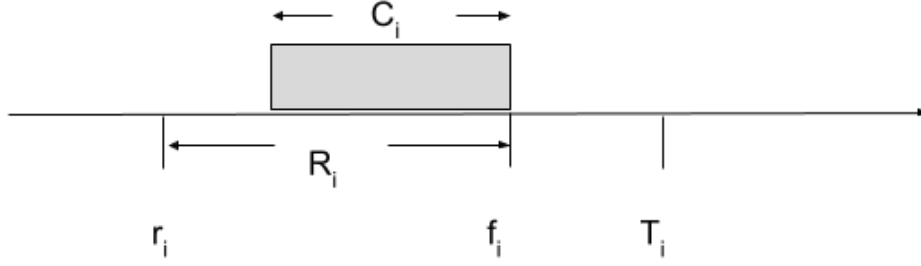


Figure 3.1: Time chart

### 3.3 Assumptions

For the calculation of the response time we have two assumption:

#### 3.3.1 ALL BLOCKS HAVE THE SAME AMOUNT OF THREADS

The election of the optimum number of threads for a specific kernel is a hard task, for that reason there have been some efforts towards that direction [16], [17], [18], [19]. However, NVIDIA developers recommend, for practical

purposes, on their official guides [20] and [21] to use block sizes equals to either 128, 256, 512 or 1024, because it has been documented that these values are more likely to take full advantage of the GPU resources. In our case we will assume that all the blocks, regardless the kernel, are the same size.

$$b_i = b, \quad \forall \tau_i \in \tau \quad (3.5)$$

### 3.3.2 ONE BIG STREAMING MULTIPROCESSOR

This assumption is derived from the previous one. Each streaming multiprocessor in the Jetson TX2 has 2048 available threads and since  $b_i$  can be either 128, 256, 512 or 1024 ( $2048/b_i = k, k \in \mathbb{N}$ ), we can think of the two streaming multiprocessors as a big one of 4096 threads.

It means that it could be allocated  $2048/b_i$  blocks per SM or  $4096/b_i$  blocks in the big SM. Hereafter we will refer the big SM as it were the only SM in the Jetson TX2's GPU. Thus, we defined  $g_{max}$  as the maximum number of blocks that can be allocated in the SM at some point in time.

$$g_{max} = \frac{b_{max}}{b}, \quad g_{max} \in \mathbb{N} \quad (3.6)$$

Where  $b_{max}$  is the maximum amount of threads in the GPU, in the case of Jetson TX2 is 4096.

## 3.4 Introduction to GPU Response Time Analysis

In addition to the variables defined in our assumptions we define  $g_f$  as the number of blocks that are available at some point in time  $t$ , and  $t_a$  as the point in time in which a block  $b_i \in g_i$  can be allocated.

For example in Figure 3.2a is shown that for a  $t = t_1$  the amount of free blocks  $g_f$  is lower than  $g_{max}$  while in Figure 3.2b for a  $t = t_2$ ,  $g_f = g_{max}$ .

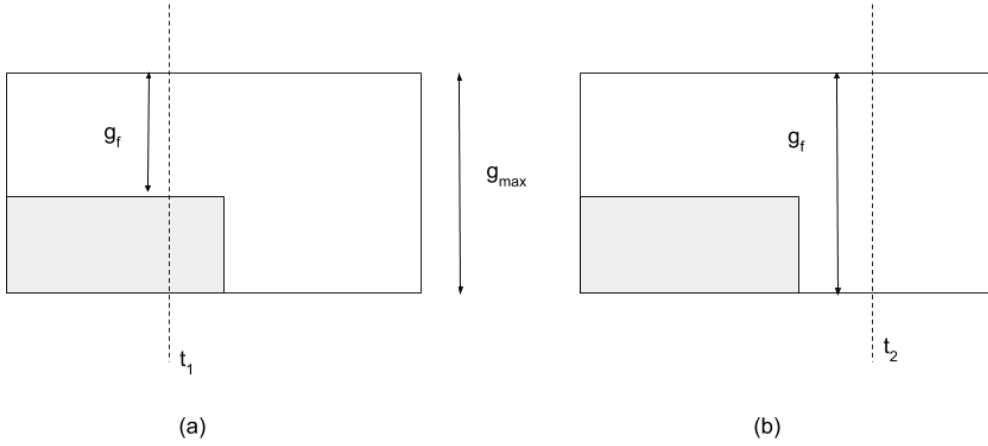


Figure 3.2: Free blocks (a) at  $t = t_1$ ,  $g_f < g_{max}$  (b) at  $t = t_2$ ,  $g_f = g_{max}$

In Figure 3.3 we present two cases. Let's assume there is a new kernel K4 which wants to allocate a block  $b_i \in g_i$ . In Figure 3.3a the release time  $r_4$  of the kernel 4 is lower than  $t_1$ , which means that  $t_a = t_1$  because  $r_4 \leq t_1$  and kernel 3 (K3) was already dequeued. In Figure 3.3b  $r_4$  lies between  $t_2$  and  $t_3$ , in that case  $t_a = r_4$ , because all previous kernels were already dequeued and there are enough resources.

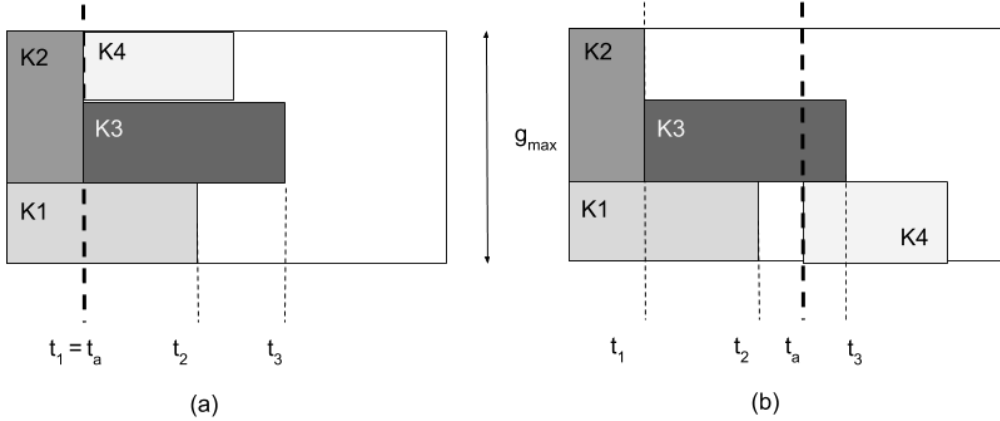


Figure 3.3: (a)  $t_a = t_1 \quad \forall r_4 \text{ s.t. } r_4 \leq t_1$  (b)  $t_a = r_4 \quad \forall r_4 \text{ s.t. } t_2 \leq r_4 \leq t_3$

Assuming  $t_a$  is known, we would need to calculate how many blocks can be allocated at that point of time. In other words, we need to know the value of  $g_f$  at  $t_a$ . In Figure 3.4a a new kernel K3 with 6 blocks  $g_3 = 6$  is going

to be allocation on the Jetson's GPU. Each block have 512 threads, which means that  $g_{max} = 8$ . The GPU is not executing any kernel at  $t = t_a$  as shown in Figure 3.4b therefore  $g_f = g_{max} = 8$  at  $t = t_a$ . Given that  $g_3 < g_f$  all the blocks of K3 will be allocated at the same time as shown in Figure 3.4c. The completion time  $f_3$  of kernel K3 is  $t_a$  plus the thread execution time given by  $C_3$ ,  $f_3 = C_3 + t_a$ . If we assume that the release time  $r_3$  is the same as  $t_a$  then the completion time for K3 is the same as the response time  $R_3$ , otherwise  $R_3 \geq f_3$ .

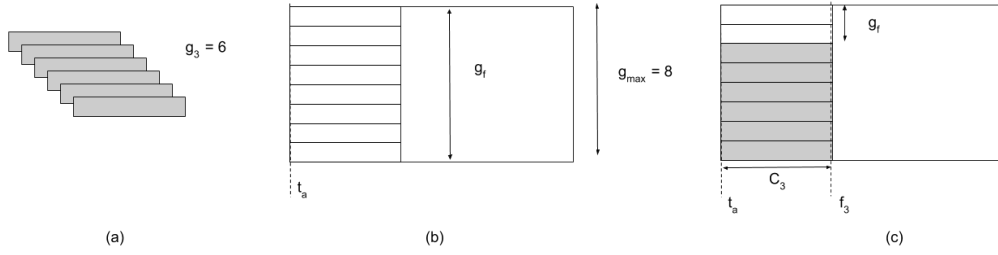


Figure 3.4: (a) New kernel  $K_3$  with 6 blocks to allocate  $g_3 = 6$ . (b) State prior to  $K_3$  of the GPU (c) state after  $K_3$  allocation

Once  $f_3$  and  $R_3$  are calculated, it's important to update the values of  $t_a$  and  $g_f$ , because these values will be used by the following kernel. Let's start with  $g_f$ , it is easy to notice that after  $K_3$  allocation there are two free blocks  $g_f - g_3 = 2$  as a result the new value of  $g_f = 2$ . On the other hand, by definition  $t_a$  is the point in time in which a block  $b_i \in g_i$  can be allocated, therefore  $t_a$  will not change because  $g_f > 0$ .

In Figure 3.5 we analyze another highly probable scenario. We use the same kernel  $K_3$  as in the last example ( $g_3 = 6$ ). However, as shown in Figure 3.5b, there were two kernels allocated previously to  $K_3$ . Kernel  $K_1$  with 5 allocated blocks  $g_1 = 5$  and  $K_2$  with 3 allocated blocks  $g_2 = 3$ . Note that these kernels have different completion time  $f_2 > f_1$ . Nevertheless, what matters is not either  $K_1$  or  $K_2$  completion time but the value of  $t_a$  and  $g_f$ . In this example,  $t_a$  is the same as  $K_1$  completion time and  $g_f$  has the same value as  $g_1$ ,  $g_f = 5$ . Thus, 5 blocks from  $K_3$  will be allocated first as shown in Figure 3.5c.

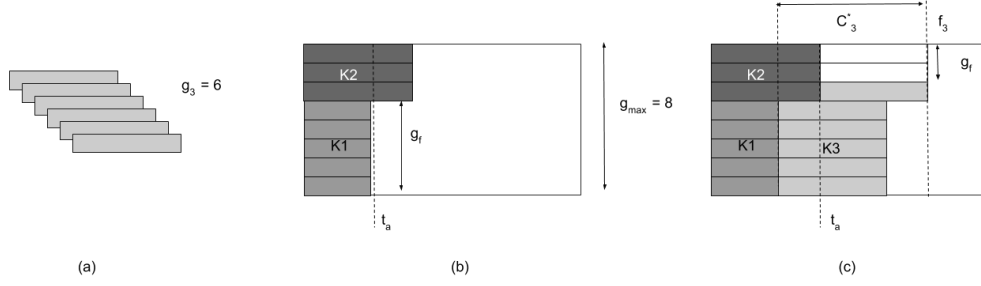


Figure 3.5: (a) New kernel  $K_3$  with 6 blocks to allocate  $g_3 = 6$ . (b) State prior to  $K_3$  of the GPU. Kernels  $K_1$  and  $K_2$  were previously allocated (c) state after  $K_3$  allocation

The next logic question is where the last block of  $K_3$  should be allocated. The answer again is given by the updated values of  $t_a$  and  $g_f$ . Looking at Figure 3.5c is easy to get these new values. The new value of  $t_a$  is  $f_2$  since  $f_2 < (t_a + C_3)$ , and for  $t = t_a$  the corresponding  $g_f$  is  $g_2$ . Thus, the last  $K_3$  block is allocated at  $t = t_a = f_2$  and that give us the completion time for  $K_3$  that is  $f_3 = f_2 + C_3$  or  $f_3 = t_a + C_3$ . In Figure 3.5c, we defined a new variable  $C_3^*$  as the total amount of time in which  $K_3$  was using GPU resources.

After  $K_3$  allocation,  $t_a$  and  $g_f$  should be updated again. In this example, the new  $g_f$  is the old value of  $g_f$  minus the last allocated  $K_3$  blocks  $g_f = g_f - 1 = 2$ , while  $t_a$  remains the same  $t_a = f_2$  because the conditions are the same as in the later example where there was only one kernel.

### 3.5 Response Time Analysis Algorithm

Our algorithm is focused on the calculation of  $t_a$  and  $g_f$  for each block regardless from which kernel  $t_i$  comes. In addition, it is important to notice that  $t_a$  and  $g_f$  depend on how previous blocks were allocated and on the GPU state at some point in time, as it was described above and illustrated in the Figure 3.4 and Figure 3.5.

The output of our algorithm is a set of release times  $f_1, f_2, \dots, f_n$  where  $n$  is the length of  $\tau$  which values  $f_i$  depend on  $t_a$  and  $C_i$ .

$$f_i = f(t_a, C_i) \quad (3.7)$$

A basic version of our algorithm is described in Algorithm 1. This version is derived directly from the examples illustrated in Figure 3.4 and Figure 3.5, in other words, this basic algorithm is a summary of the section above. We have omitted details such as how  $t_a$  and  $g_f$  are updated in the case that  $g_f \geq g_i$ , however we still keep the big picture of what is necessary at each step.

```

Input :  $\tau$ 
Output:  $f_1, \dots, f_n$ 
Initialization:  $t_a = 0, g_f = g_{max}, i = 1$ 
while  $i \leq n$  do
    if  $g_f \geq g_i$  then
         $f_i = t_a + C_i$ ;
        Update  $g_f$  and  $t_a$ ;
         $i++$  ; // Next kernel
    else
         $g_i = g_i - g_f$ ;
        Update  $g_f$  and  $t_a$ ;
    end
end

```

**Algorithm 1:** Basic real time analysis algorithm

In order to analyze a new kernel  $\tau_i$  and update  $t_a$  and  $g_f$  we need to track old values of  $g_f \quad \forall t \leq t_a$ . Fortunately, it is necessary only to track  $g_f$  at specific points of time. Some relevant points of time, as it was shown in the previous example described by Figure 3.5, are given by completion times of previous kernels, in other words we must track  $g_{i-k}$  and  $f_{i-k}$  where  $k \in 1, 2, \dots, i-1$ , because updated values of  $g_f$  and  $t_a$  depend as well on these them.

Let's define a set  $h$  of pair of values  $(t_k, g_k)$  where  $g_k$  are the number of free blocks at  $t = t_k$  such that  $t_k \geq t_a$ . In a further example we will show step by step how this array  $h$  is filled and updated in order to have a better understanding.

A complete version of our algorithm is presented in Algorithm 2.



**Input** :  $\tau$   
**Output**:  $f_1, \dots, f_n$   
 Initialization:  $t_a = 0, g_f = g_{max}, i = 1, h = \{\}$   
**while**  $i \leq n$  **do**  
     **if**  $g_f \geq g_i$  **then**  
          $f_i = t_a + C_i$ ;  
          $h = \{h; (f_i, g_i)\}$ ;  
          $t_a = t_a$ ;  
          $g_f = g_f - g_i$ ;  
          $i++$  ; // Next kernel  
     **else**  
          $g_i = g_i - g_f$ ;  
          $h = \{h; (t_a + C_i, g_f)\}$ ;  
          $[t_a, \text{index}] = \min(h[:, 1])$ ;  
          $g_f = h[\text{index}, 2]$ ;  
     **end**  
**end**

**Algorithm 2:** Real time analysis algorithm

Our algorithm is based on three main updates:  $h$ ,  $t_a$  and  $g_f$ . The set  $h$  can be seen as an array of size  $N \times 2$ , where  $N$  is the number of tracked pairs. For this reason, when  $g_f > g_i$  we used MATLAB notation of `min` function `[value, index] = min(A)`, where `index` is the position of the pair or row  $(t_k, g_k) \in h$  that has the minimum of all time values saved in  $h$ . Once we know which pair has the minimum time, we just assign  $t_a = t_k$  and  $g_f = g_k$ . It is important to mention again that by definition of  $h$ , all the tracked times should be greater or equal than the current  $t_a$ , meaning that pairs that have tracked times lower than  $t_a$  must be removed.

### 3.6 Example

Let's say there are four kernels we want to allocate, all with the same period  $T = 15$  and block size of 512 threads,  $b = 512$ , which means  $g_{max} = 8$ . The four tasks are defined as  $\tau = \{\tau_1 = \{15, 4, 2, 512\}, \tau_2 = \{15, 6, 7, 512\}, \tau_3 = \{15, 6, 2, 512\}, \tau_4 = \{15, 5, 5, 512\}\}$ .

At the beginning  $t_a = 0, i = 1, h = \{\}$  and  $g_f = g_{max} = 8$ . Let's start

with  $\tau_1$ . Kernel  $\tau_1$  and initial state of GPU are shown in Figure 3.6(a) and Figure 3.6(b) respectively.

- $g_f \geq g_1$ ? yes, because  $g_1 = 2$
- $f_1 = t_a + C_1 = 0 + 4 = 4$
- $h = \{h, (f_1, g_1)\} = \{(4, 2)\}$
- $t_a = 0$
- $g_f = g_f - g_1 = 8 - 2 = 6$
- $i = 2$

After  $\tau_1$  allocation the GPU state is as shown in Figure 3.6(c), as it is observed,  $t_a$  remains the same but  $g_f$  now is 6. Furthermore, that is the initial GPU state when  $\tau_2$  arrives.

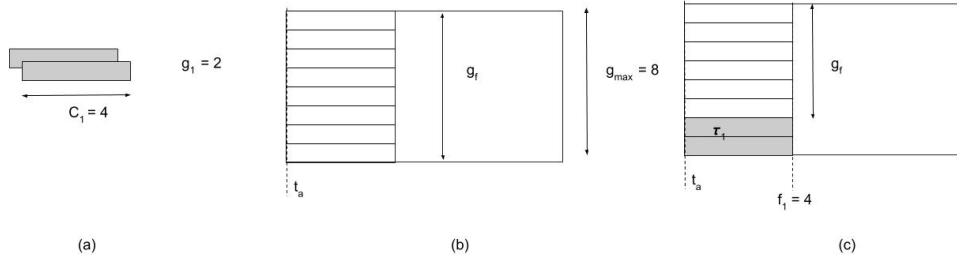


Figure 3.6: (a) Kernel  $\tau_1$  (b) GPU state prior to  $\tau_1$  allocation (c) GPU state after  $\tau_1$  allocation

Since  $i = 2$ , it's time to analyze  $\tau_2$ . Figure 3.7(a) shows the number of blocks that should be allocated for  $\tau_2$ . In this case  $t_a = 0$  and  $g_f = 6$  as shown in Figure 3.7(b).

- $g_f \geq g_2$ ? no, because  $g_i = 7$
- $g_2 = g_2 - g_f = 7 - 6 = 1$
- $h = \{h, (t_a + C_2, g_f)\} = \{(4, 2), (6, 6)\}$
- $[t_a, \text{index}] = \min(h[:, 1]) = \min([4, 6])$
- $[t_a, \text{index}] = [4, 1]$
- $g_f = h[\text{index}, 2] = h[1, 2] = 2$
- $h = h - \{(4, 2)\} = \{(4, 2), (6, 6)\} - \{(4, 2)\}$

- $h = \{(6, 6)\}$

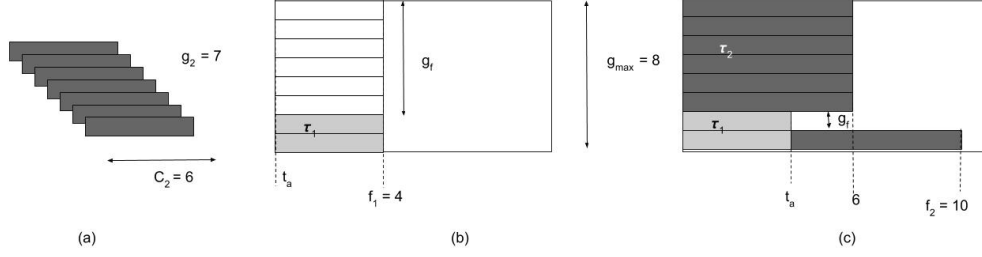


Figure 3.7: (a) Kernel  $\tau_2$  (b) GPU state prior to  $\tau_2$  allocation (c) GPU state after  $\tau_2$  allocation

Values for  $t_a$ ,  $g_f$ ,  $g_2$  and  $h$  were updated. Notice that current value of  $t_a$  is the completion time of  $\tau_1$  and  $g_f$  is  $g_1$ , that is why, as mention before, it is important to track  $f_1$  and  $g_1$ . However, completion time for  $\tau_2$  is not known yet. Let's continue with the analysis.

- $g_f \geq g_2$ ? yes, because  $g_2 = 1$
- $f_2 = t_a + C_2 = 4 + 6 = 10$
- $h = \{h, (f_2, g_2)\} = \{(6, 6), (10, 1)\}$
- $t_a = 4$
- $g_f = g_f - g_2 = 2 - 1 = 1$
- $i = 3$

In Figure 3.7(c) is shown the GPU state,  $t_a$  and  $g_f$  values after  $\tau_2$  allocation. This setup is the starting point for the analysis of  $\tau_3$  as observed in Figure 3.8(b). Since we already described step by step analysis for  $\tau_1$  and  $\tau_2$ , we skip some details in  $\tau_3$  analysis, however we will point out something important about  $h$ .

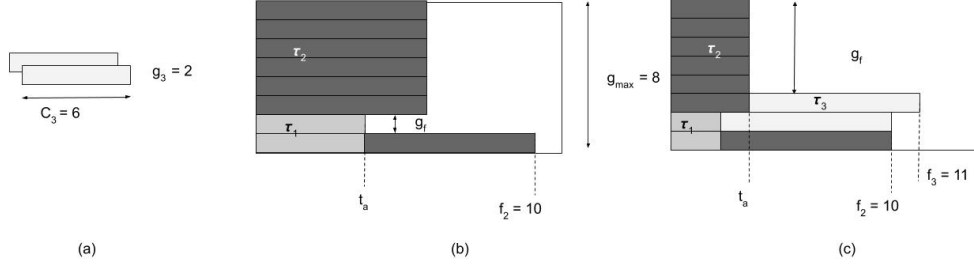


Figure 3.8: (a) Kernel  $\tau_3$  (b) GPU state prior to  $\tau_3$  allocation (c) GPU state after  $\tau_3$  allocation

The initial setup for  $\tau_3$  is  $t_a = 4$ ,  $g_f = 1$  and  $h = \{(6, 6), (10, 1)\}$ . The number of blocks and thread execution time of  $\tau_3$  is illustrated in Figure 3.8.

- $g_f \geq g_3$ ? no
- $g_3 = g_2 - g_f = 1$
- $h = \{(6, 6), (10, 1), (10, 1)\}$
- $h = \{(6, 6), (10, 2)\}$
- $[t_a, \text{index}] = [6, 1]$
- $g_f = h[\text{index}, 2] = h[1, 2] = 6$
- $h = \{(10, 2)\}$

As mention before, we performed an *extra* step with  $h$  in which  $h$  went from having three pairs to having just two. The reason behind it lies on the definition of  $h$ . The set  $h$  of pair of values  $(t_k, g_k)$  where  $g_k$  are the number of free blocks at  $t = t_k$ ; notice that at  $t = 10$  there are two *free* tracked blocks, one that comes from  $\tau_2$  and other from  $\tau_3$  as shown is Figure 3.8(c), as well as the results of the following  $\tau_3$  analysis.

- $g_f \geq g_3$ ? yes
- $f_3 = t_a + C_3 = 12$
- $h = \{(10, 2), (12, 1)\}$
- $t_a = 6$
- $g_f = g_f - g_3 = 5$
- $i = 4$

The analysis for  $\tau_4$  is straightforward. The blocks and thread execution time for  $\tau_4$ , the GPU state prior to  $\tau_4$  allocation and GPU state after  $\tau_4$  allocation are shown in Figure 3.9. It is easy to find out that the completion time  $f_4$  is 11.

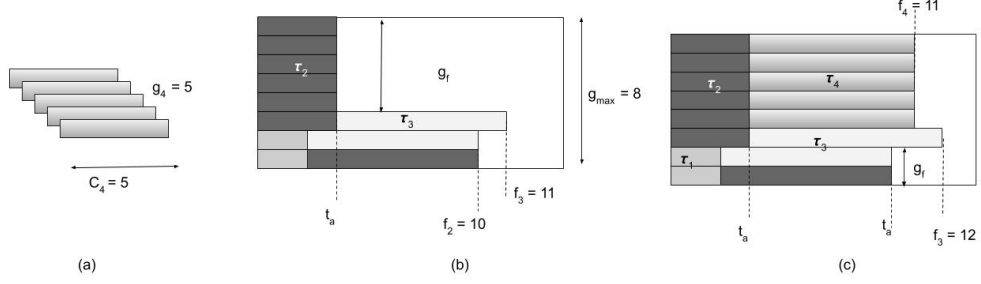


Figure 3.9: (a) Kernel  $\tau_4$  (b) GPU state prior to  $\tau_4$  allocation (c) GPU state after  $\tau_4$  allocation

We have calculated the completion times  $f_i \quad \forall i \in \tau, f = \{4, 10, 12, 11\}$ . Given the fact that all kernel were scheduled at the same time, the release time for all kernels is 0. Thus, the response time for each kernel is the same as their completion times. Furthermore, we can conclude that all the kernels can be scheduled because  $R_i \leq T \quad \forall i \in \tau$ .

### 3.7 A Special case

In this section we demonstrate that if all kernels are released at the same time and also have the same thread execution time,  $C_i = C \quad \forall i \in \tau$ , our response time analysis has not algorithmic behavior, instead it's a set of three equations.

In this special case, there is no need of  $h$ , because  $t_a$  and  $g_f$  can be calculated directly with two equations. The goal is as always to find  $t_a$ ,  $g_f$  and  $f_i$ , however, we will exploit the fact that  $C_i$  is the same for all kernels. The case in which  $g_i \leq g_f$  is trivial to analyze, therefore we will analyze the other case. If Figure 3.10 is shown the block distribution when  $g_i > g_f$ , thus in order to find  $g_f^*$  and  $t_a^*$ , that are the updated values, we must calculate  $K$ .

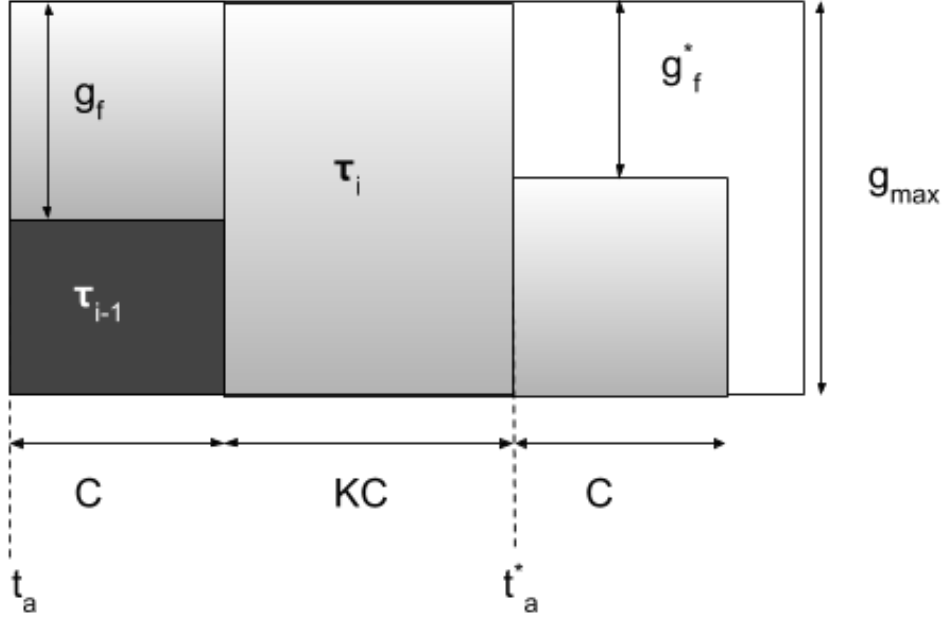


Figure 3.10: New kernel allocation

It is not hard to see that  $K$  is given by equation 3.8. The interpretation is that  $K$  is the maximum amount of times that  $g_{max}$  blocks can be allocated.

$$K = \lfloor \frac{g_i - g_f}{g_{max}} \rfloor \quad (3.8)$$

From  $K$ , the value of  $g_f^*$  is calculated using equation 3.9. If we observed the blocks in Figure 3.10, we notice that  $g_f^*$  can be calculated using geometry. The area of the first block is  $g_f$ , of the second one  $Kg_{max}$  and the last one is  $g_i - g_f - Kg_{max}$ .

$$g_f^* = g_{max} - (g_i - g_f - Kg_{max}) \quad (3.9)$$

The value of  $t_a^*$  is calculated in similar fashion and is given by equation 3.10. On the other hand, the calculation of  $f_i$  remains the same.

$$t_a^* = t_a + C + KC \quad (3.10)$$

We are at a point at which we are able to calculate with formulas the updated values of  $t_a$  and  $g_f$ , nonetheless, we still have the algorithmic behavior given by the **if** condition. Therefore to no longer use that dependency, we will make use of the absolute value and the signum function. The signum function of a real number  $x$  is defined as follows:

$$\text{sgn}(x) = \begin{cases} -1 & \text{if } x < 0, \\ 0 & \text{if } x = 0, \\ 1 & \text{if } x > 0. \end{cases} \quad (3.11)$$

We redefine  $K$  with the absolute value using equation 3.12, we use absolute value in 3.12 because we want  $K$  to be zero when  $g_i \leq g_f$ .

$$K = \lfloor \frac{\|g_i - g_f\|}{g_{max}} \rfloor \quad (3.12)$$

In addition, we define  $\alpha$  which value is given by equation 3.13. The value of  $\alpha$  is zero when  $g_i \leq g_f$  and one otherwise.

$$\alpha = \frac{\text{sgn}(g_i - g_f) + 1}{2} \quad (3.13)$$

With 3.12 and 3.13 we eliminate the **if** condition and at the same time the algorithmic behavior. Therefore, the updated values of  $t_a$  and  $g_f$  are calculated using 3.14 and 3.15. To emphasize again, when  $g_i \leq g_f$  3.14 and 3.15 are the same steps described in Algorithm 2.

$$t_a = t_a + \alpha C + KC \quad (3.14)$$

$$g_f = \alpha g_{max} - (g_i - g_f - Kg_{max}) \quad (3.15)$$

### 3.8 Computational Complexity

Our algorithm described in Algorithm 2 has two branches, inside the **while** loop, given by an **if** conditional. In Table 3.1 is shown the computational complexity of each step of the real time analysis algorithm.

Table 3.1: Computational Complexity

Step	Type of operation	Average
		Cost
$f_i = t_a + C_i$	Sum	O(1)
$h = \{h; (f_i, g_i)\}$	Append	O(1)
$t_a = t_a$	Sum	O(1)
$g_f = g_f - g_i$	Sum	O(1)
$i++$	Sum	O(1)
$g_i = g_i - g_f$	Sum	O(1)
$h = \{h; (t_a + C_i, g_f)\}$	Append	O(1)
$[t_a, \text{index}] = \min(h[:, 1])$	Min	O(n)
$g_f = h[\text{index}, 2]$	Index	O(1)

The first branch is when  $g_f \geq g_i$ . The computational complexity, given by big O notation, of that branch is O(1), because all the operations in this branch are O(1).

In the case of the second branch the computational complexity is O(n), because **min** function is the most costly operation. In the worst case scenario **n** is the number of kernels we want to allocate, it is important to highlight that only on the first branch the length of  $h$  increases. Thus, the computational complexity of the **if** statement is O(n).

Let us analyze the outer **while** loop. The number of iterations depends on number of kernels, their grid sizes  $g_i$  and how many blocks can be allocated in total in the GPU or  $g_{max}$ . An estimation can be given by  $\frac{g}{g_{max}}$ , where  $g$  is  $\sum g_i$ ,  $g$  contains the information about number of kernels and their grid sizes. Thus, computational complexity of our algorithm is  $O(\frac{gn}{g_{max}})$ .



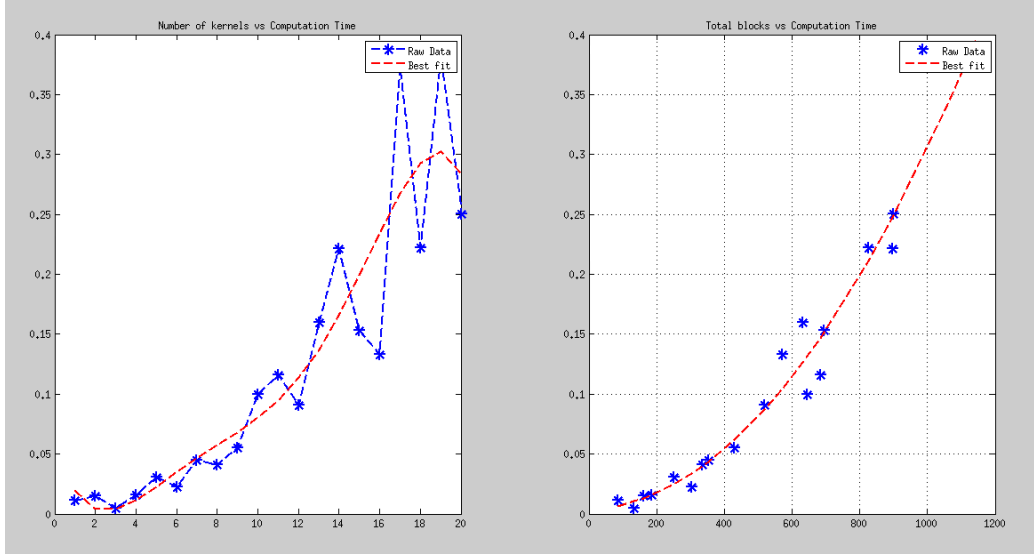


Figure 3.11: Best fit for computational complexity

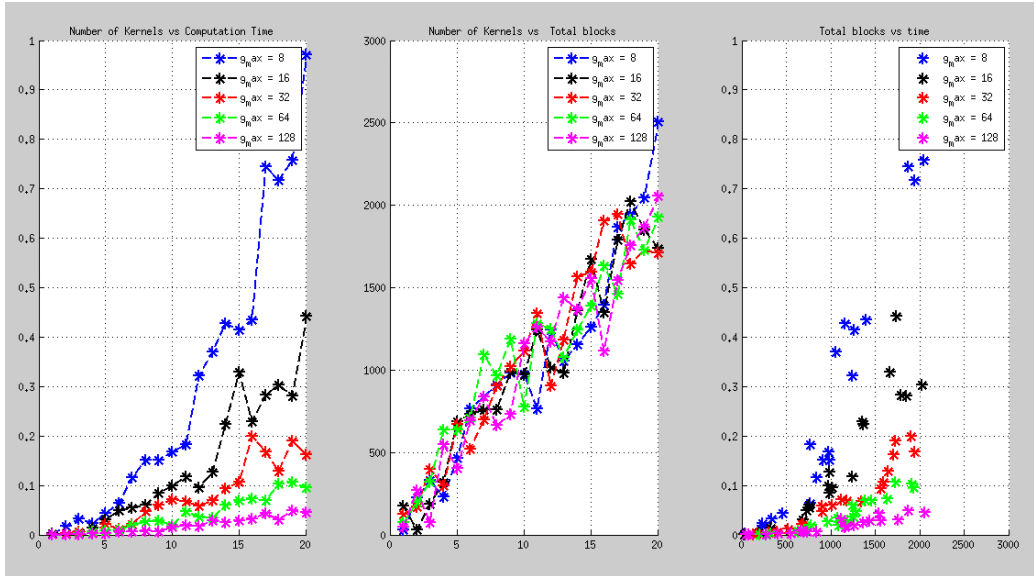


Figure 3.12: Analysis of computational complexity when  $g_{max}$  is variable

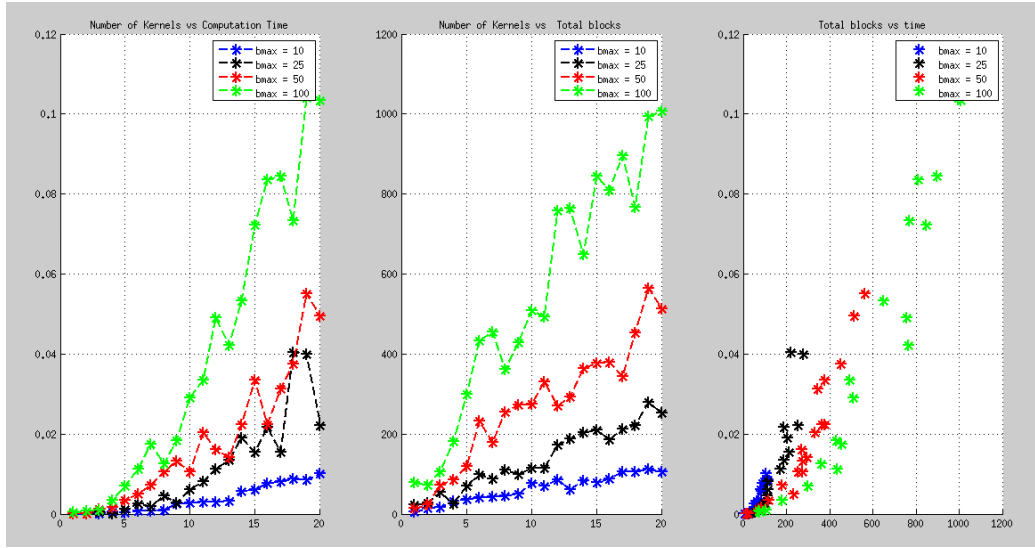


Figure 3.13: Analysis of computational complexity when  $b_{max}$  is variable

# Chapter 4

## Experimental Results

In this chapter we presents our experimental results. We compare results from Jetson TX2 platfrom againts our Octave implementation. The former are used as ground truth to verify our implementation and assumptions.

### 4.1 Ground truth generation

Amert et. al [12] published their code in github. They developed a CUDA Scheduling Viewer, which is a tool for examining block-level scheduling behavior and co-scheduling performance on CUDA devices. The input are configuration files on the JSON format, and the output can be displayed as figure using a Python script, which is provided as well. An example output is shown in Figure 4.1

Our test scenario was similar to the example presented in the last chapter. We had four kernels we wanted to allocate. The parameters were: block size = 512 threads, and  $g_{max} = 8$ . The four kernels were defined as  $\tau = \{\tau_1 = \{15, 4, 2, 512\}, \tau_2 = \{15, 6, 7, 512\}, \tau_3 = \{15, 6, 2, 512\}, \tau_4 = \{15, 5, 5, 512\}\}$ .

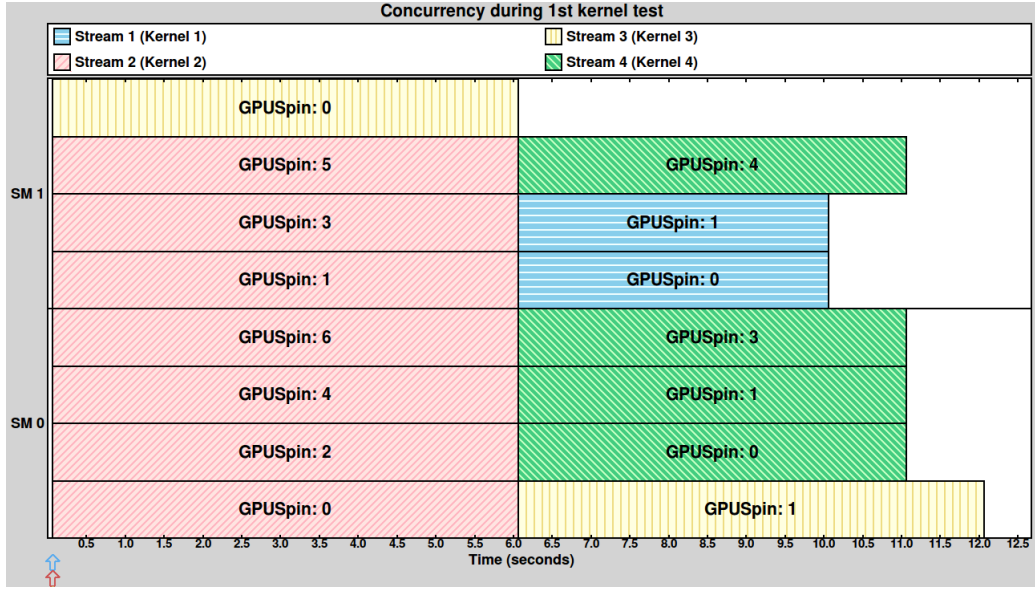


Figure 4.1: Output of the CUDA Scheduling Viewer

An example of a kernel description in the configuration file was as follows:

```
"filename": "./bin/timer_spin.so",
"log_name": "k3.json",
"label": "Kernel 3",
"thread_count": 512,
"block_count": 2,
"additional_info": 6000000000
```

The `filename` is the benchmark binary file we used as a kernel. For all the kernels was `timer_spin.so`. This file defines a bare-bones CUDA benchmark which spins waiting for a user-specified amount of time to complete. The execution time in nanoseconds or  $C_i$  was set as `additional_info`. The `log_name` was the JSON file that contained metadata and results related to a specified kernel (`label`). In addition, `thread_count` and `block_count` were the values of  $b_i$  and  $g_i$  respectively.

## 4.2 Implementation results

We implemented our algorithm in GNU Octave, a software for scientific programming similar to MATLAB but open source, because it was an easy way to test whether our algorithm was correct. The goal was not to test how many kernel the Jetson could manage, instead we focused on verifying our assumptions and therefore our algorithm.

We set up three test scenarios. The four previously described kernels were launched in different order. The first scenario was the one presented in Figure 4.1. The kernels were launched on the following order: K2, K3, K4, K1. As showed in Figure 4.1 the completion times were  $f = \{6, 12, 11, 10\}$ . The results from Octave are shown in Figure 4.2.

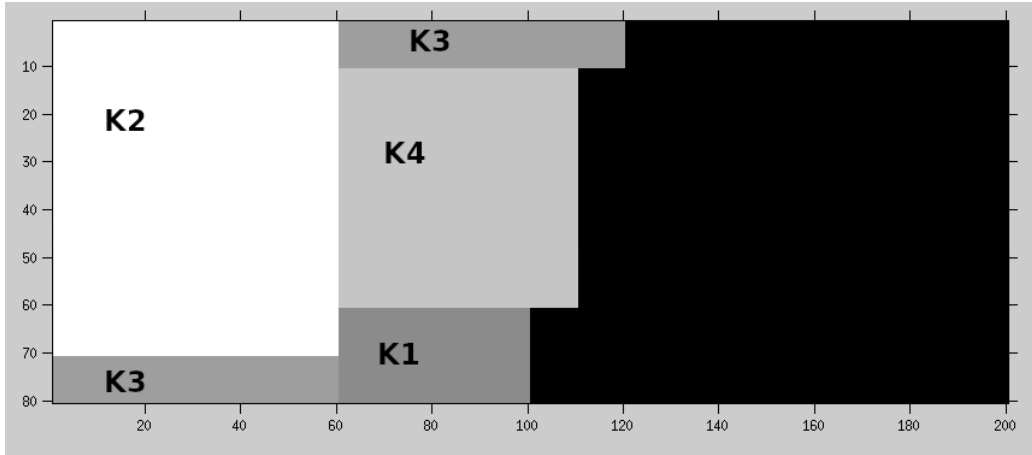


Figure 4.2: Octave: Scenario 1 - K2,K3,K4,K1

In the second scenario kernels were launched on the following order: K2, K4, K1, K3. As observed in Figure 4.3 the completion times were  $f = \{6, 11, 10, 12\}$ . Notice that *GPUSping: 5* for kernel 4 should be shown, but there is a bug in the code from [12] in which sometimes the log file doesn't contain all the data. On the other hand, results from Octave are shown in Figure 4.4. The block allocation differ from Jetson's allocation because our code follows our assumption described in section 3.3.2.

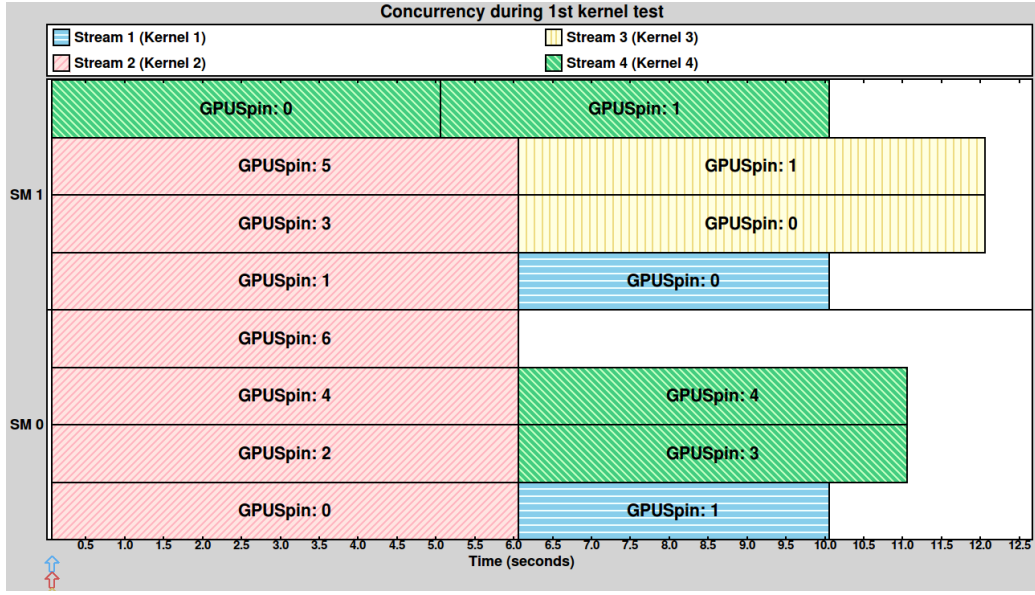


Figure 4.3: JetsonTX2: Scenario 2 - K2,K4,K1,K3

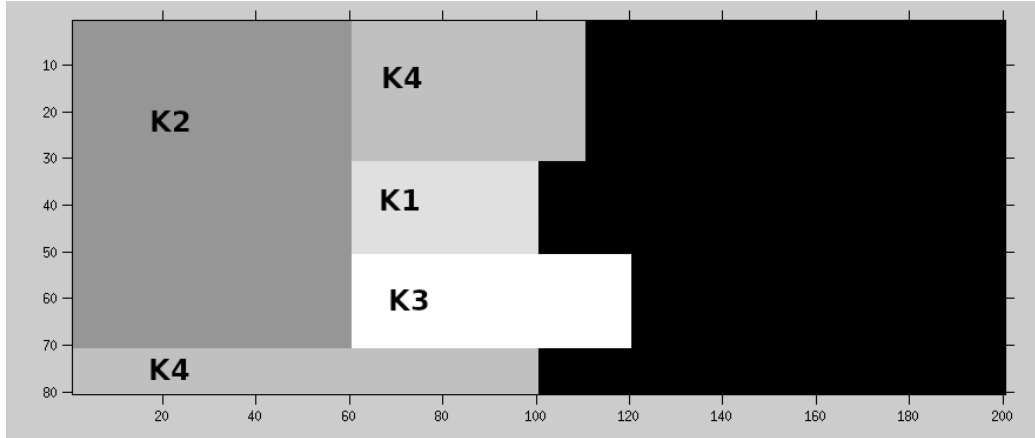


Figure 4.4: Octave: Scenario 2 - K2,K4,K1,K3

In the third scenario kernels were launched on the following order: K2, K1, K3, K4. As observed in Figure 4.5 the completion times were  $f = \{6, 8, 12, 11\}$ . Notice in this case that *GPUSpin:4* from kernel 4 and *GPUSpin:1* from kernel 5 overlap in the figure. This is again an error on how the log file was created. We tested [12] C implementation using `printf`, and the values were correct. Nevertheless, results from Octave shown in Figure 4.4 remain congruent with the results of its counterpart.

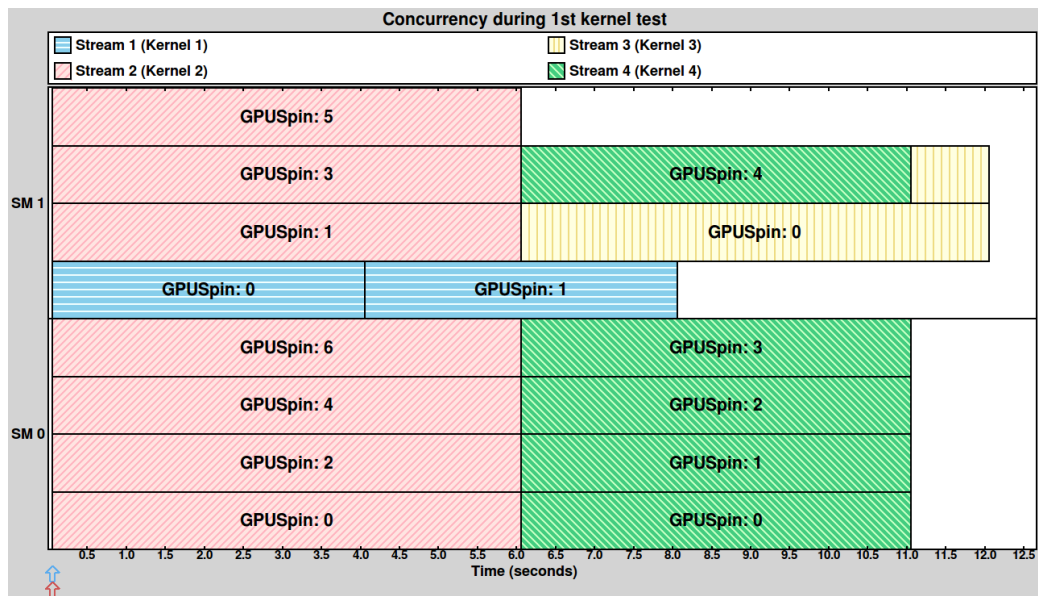


Figure 4.5: JetsonTX2: Scenario 3 - K2,K1,K3,K4

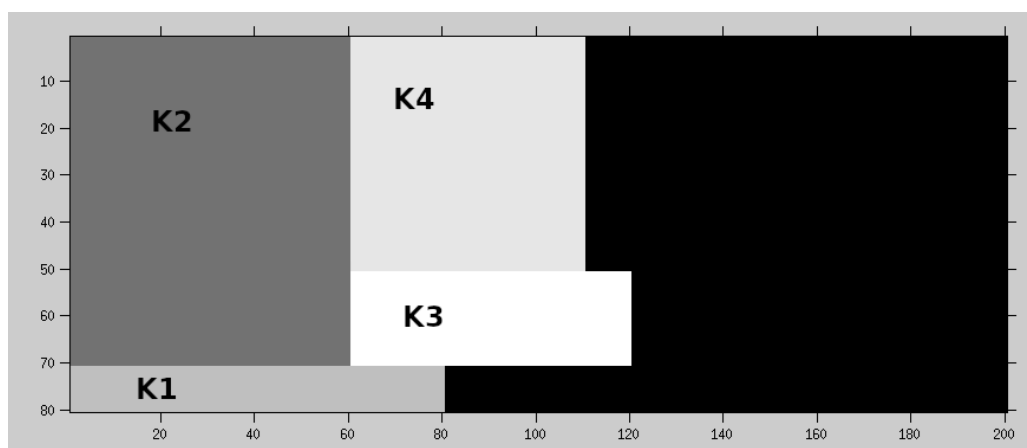


Figure 4.6: Octave: Scenario 3 - K2,K1,K3,K4

# Chapter 5

## Research containing a table

### 5.1 Introduction

This is the introduction. Phasellus non purus id mauris aliquam rutrum vitae quis tellus. Maecenas rhoncus ligula nulla, fringilla placerat mi consectetur eu. Aenean nec metus ac est ornare posuere. Nunc ipsum lacus, gravida commodo turpis quis, rutrum eleifend erat. Pellentesque id lorem eget ante porta tincidunt nec nec tellus.

### 5.2 Method

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#### 5.2.1 SUBSECTION 1

This is the first part of the methodology. Integer leo erat, commodo in lacus vel, egestas varius elit. Nulla eget magna quam. Nullam sollicitudin dolor ut ipsum varius tincidunt. Duis dignissim massa in ipsum accumsan imperdiet.



Maecenas suscipit sapien sed dui pharetra blandit. Morbi fermentum est vel quam pretium maximus.

### 5.2.2 SUBSECTION 2

This is the second part of the methodology. Nullam accumsan condimentum eros eu volutpat. Maecenas quis ligula tempor, interdum ante sit amet, aliquet sem. Fusce tellus massa, blandit id tempus at, cursus in tortor. Nunc nec volutpat ante. Phasellus dignissim ut lectus quis porta. Lorem ipsum dolor sit amet, consectetur adipiscing elit.

## 5.3 Results

Table 5.1 shows us how to add a table. Integer tincidunt sed nisl eget pellentesque. Mauris eleifend, nisl non lobortis fringilla, sapien eros aliquet orci, vitae pretium massa neque eu turpis. Pellentesque tincidunt aliquet volutpat. Ut ornare dui id ex sodales laoreet.

Table 5.1: This is the table caption. Suspendisse blandit dolor sed tellus venenatis, venenatis fringilla turpis pretium.

Column 1	Column 2	Column 3
Row 1	0.1	0.2
Row 2	0.3	0.3
Row 3	0.4	0.4
Row 4	0.5	0.6

## 5.4 Discussion

This is the discussion. Etiam sit amet mi eros. Donec vel nisi sed purus gravida fermentum at quis odio. Vestibulum quis nisl sit amet justo maximus molestie. Maecenas vitae arcu erat. Nulla facilisi. Nam pretium mauris eu enim porttitor, a mattis velit dictum. Nulla sit amet ligula non mauris volutpat fermentum quis vitae sapien.

## 5.5 Conclusion

This is the conclusion to the chapter. Nullam porta tortor id vehicula interdum. Quisque pharetra, neque ut accumsan suscipit, orci orci commodo tortor, ac finibus est turpis eget justo. Cras sodales nibh nec mauris laoreet iaculis. Morbi volutpat orci felis, id condimentum nulla suscipit eu. Fusce in turpis quis ligula tempus scelerisque eget quis odio. Vestibulum et dolor id erat lobortis ullamcorper quis at sem.

# Chapter 6

## Final research study

### 6.1 Introduction

This is the introduction. Nunc lorem odio, laoreet eu turpis at, condimentum sagittis diam. Phasellus metus ligula, auctor ac nunc vel, molestie mattis libero. Praesent id posuere ex, vel efficitur nibh. Quisque vestibulum accumsan lacus vitae mattis.

### 6.2 Method

In tincidunt viverra dolor, ac pharetra tellus faucibus eget. Pellentesque tempor a enim nec venenatis. Morbi blandit magna imperdiet posuere auctor. Maecenas in maximus est.

#### 6.2.1 SUBSECTION 1

This is the first part of the methodology. Praesent mollis sem diam, sit amet tristique lacus vulputate quis. Vivamus rhoncus est rhoncus tellus lacinia, a interdum sem egestas. Curabitur quis urna vel quam blandit semper vitae a leo. Nam vel lectus lectus.

### 6.2.2 SUBSECTION 2

This is the second part of the methodology. Aenean vel pretium tortor. Aliquam erat volutpat. Quisque quis lobortis mi. Nulla turpis leo, ultrices nec nulla non, ullamcorper laoreet risus.

## 6.3 Results

These are the results. Curabitur vulputate nisl non ante tincidunt tempor. Aenean porta nisi quam, sed ornare urna congue sed. Curabitur in sapien justo. Quisque pulvinar ullamcorper metus, eu varius mauris pellentesque et. In hac habitasse platea dictumst. Pellentesque nec porttitor libero. Duis et magna a massa lacinia cursus.

## 6.4 Discussion

This is the discussion. Curabitur gravida nisl id gravida congue. Duis est nisi, sagittis eget accumsan ullamcorper, semper quis turpis. Mauris ultricies diam metus, sollicitudin ultricies turpis lobortis vitae. Ut egestas vehicula enim, porta molestie neque consectetur placerat. Integer iaculis sapien dolor, non porta nibh condimentum ut.

## 6.5 Conclusion

This is the conclusion to the chapter. Nulla sed condimentum lectus. Duis sed tempor erat, at cursus lacus. Nam vitae tempus arcu, id vestibulum sapien. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus.

# Chapter 7

## Conclusion

### 7.1 Thesis summary

In summary, pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Nunc eleifend, ex a luctus porttitor, felis ex suscipit tellus, ut sollicitudin sapien purus in libero. Nulla blandit eget urna vel tempus. Praesent fringilla dui sapien, sit amet egestas leo sollicitudin at.

### 7.2 Future work

There are several potential directions for extending this thesis. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Aliquam gravida ipsum at tempor tincidunt. Aliquam ligula nisl, blandit et dui eu, eleifend tempus nibh. Nullam eleifend sapien eget ante hendrerit commodo. Pellentesque pharetra erat sit amet dapibus scelerisque.

Vestibulum suscipit tellus risus, faucibus vulputate orci lobortis eget. Nunc varius sem nisi. Nunc tempor magna sapien, euismod blandit elit pharetra sed. In dapibus magna convallis lectus sodales, a consequat sem euismod. Curabitur in interdum purus. Integer ultrices laoreet aliquet. Nulla vel dapibus urna. Nunc efficitur erat ac nisi auctor sodales.

# Appendix 1: Some extra stuff

Add appendix 1 here. Vivamus hendrerit rhoncus interdum. Sed ullamcorper et augue at porta. Suspendisse facilisis imperdiet urna, eu pellentesque purus suscipit in. Integer dignissim mattis ex aliquam blandit. Curabitur lobortis quam varius turpis ultrices egestas.

## Appendix 2: Some more extra stuff

Add appendix 2 here. Aliquam rhoncus mauris ac neque imperdiet, in mattis eros aliquam. Etiam sed massa et risus posuere rutrum vel et mauris. Integer id mauris sed arcu venenatis finibus. Etiam nec hendrerit purus, sed cursus nunc. Pellentesque ac luctus magna. Aenean non posuere enim, nec hendrerit lacus. Etiam lacinia facilisis tempor. Aenean dictum nunc id felis rhoncus aliquam.

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