Profiling GPU Code

Jeremy Appleyard, February 2016

What is Profiling?

Measuring Performance

- Measuring application performance
  - Usually the aim is to reduce runtime
- Simple profiling:
  - How long does an operation take?
- Advanced profiling:
  - Why does an operation take a long time?

Profiling Workflow

1. Find which parts of the code take time
2. Work out why they take time
3. Optimize
4. GOTO 1.

GPU Performance

Quick overview

- A processor has two key performance limits
  - Floating point throughput (FLOP/s)
    - Peak ~6 TFLOP/s
  - Memory throughput (GB/s)
    - Peak ~300 GB/s (DRAM)
- GPUs also need parallelism
  - This is how they can be so fast

Profiling Tools

General GPU Profiling

From NVIDIA

- nvprof
- NVIDIA Visual profiler
  - Standalone (nvvp)
  - Integrated into Nsight Eclipse Edition (nsight)
- Nsight Visual Studio Edition

Third Party

- Tau Performance System
- VampirTrace
- PAPI CUDA component

In this talk

- We will focus on nvprof and nvvp
- nvprof => NVIDIA Profiler
    - Command line
- nvvp => NVIDIA Visual Profiler
    - GUI based

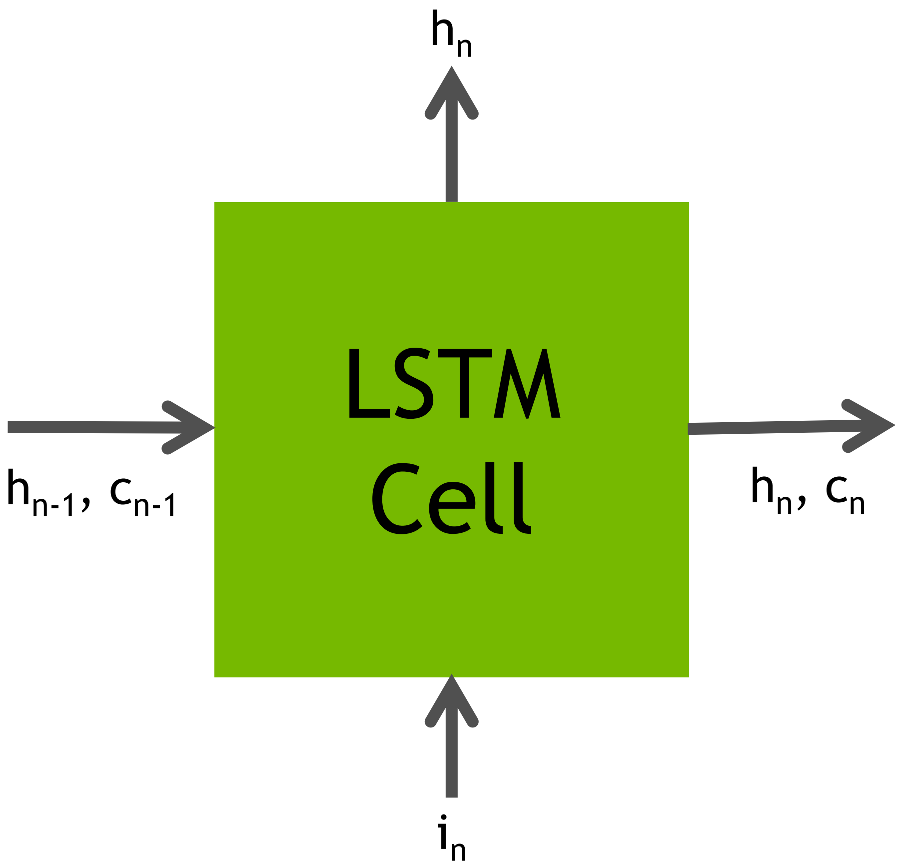
Case Study

Recurrent Neural Network - LSTM

- Uses:
  - Natural language processing
  - Sequences of images (eg. video)
  - Bio/medical
- We will look at optimisation of a single iteration of LSTM

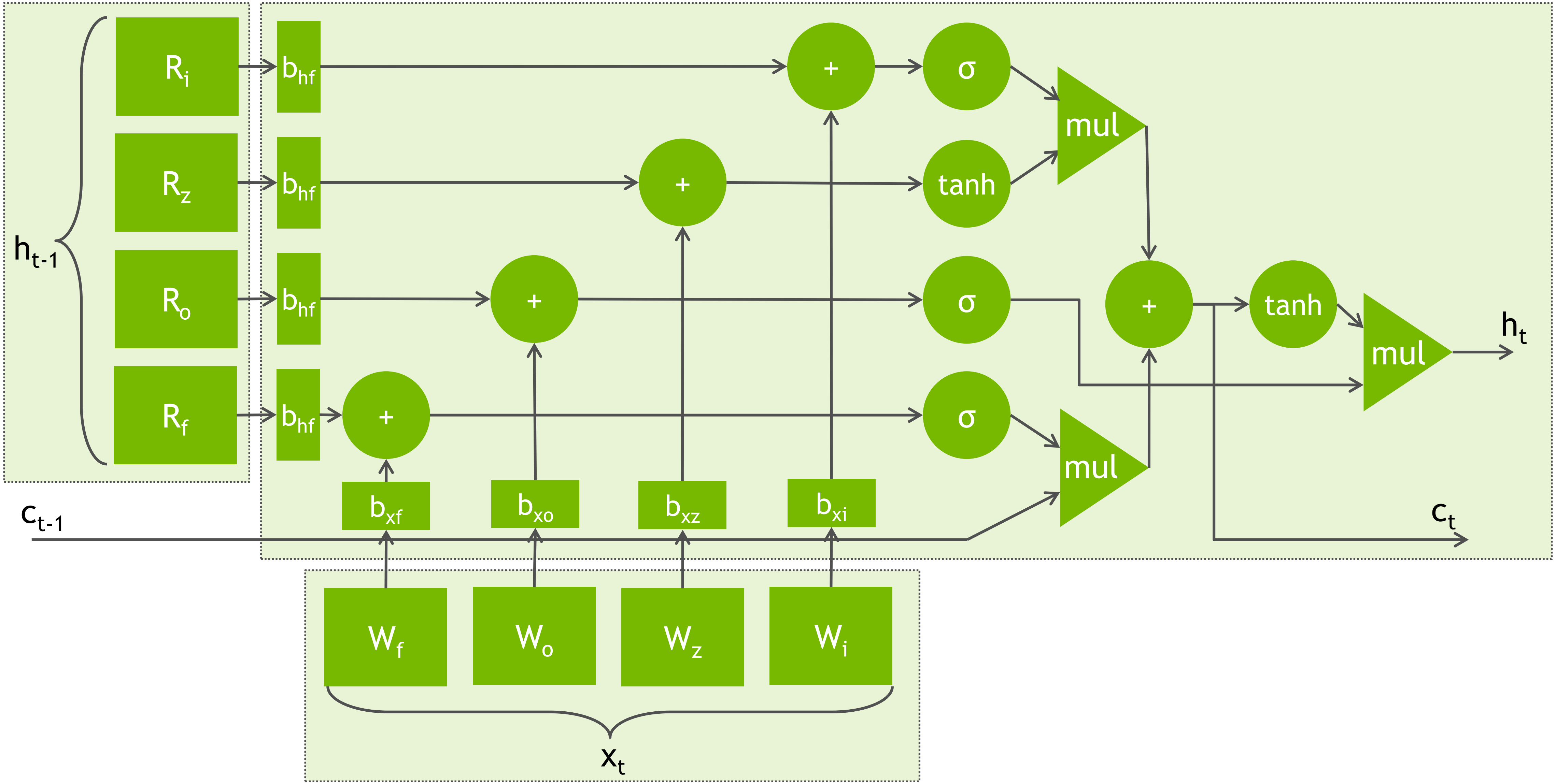
LSTM

Viewed as a black box



- Inputs and outputs are “batched vectors”.
  - ie. A minibatch
- Typical length is 256-2048
- Typical batch size is 32-128

LSTM Details



LSTM Profile

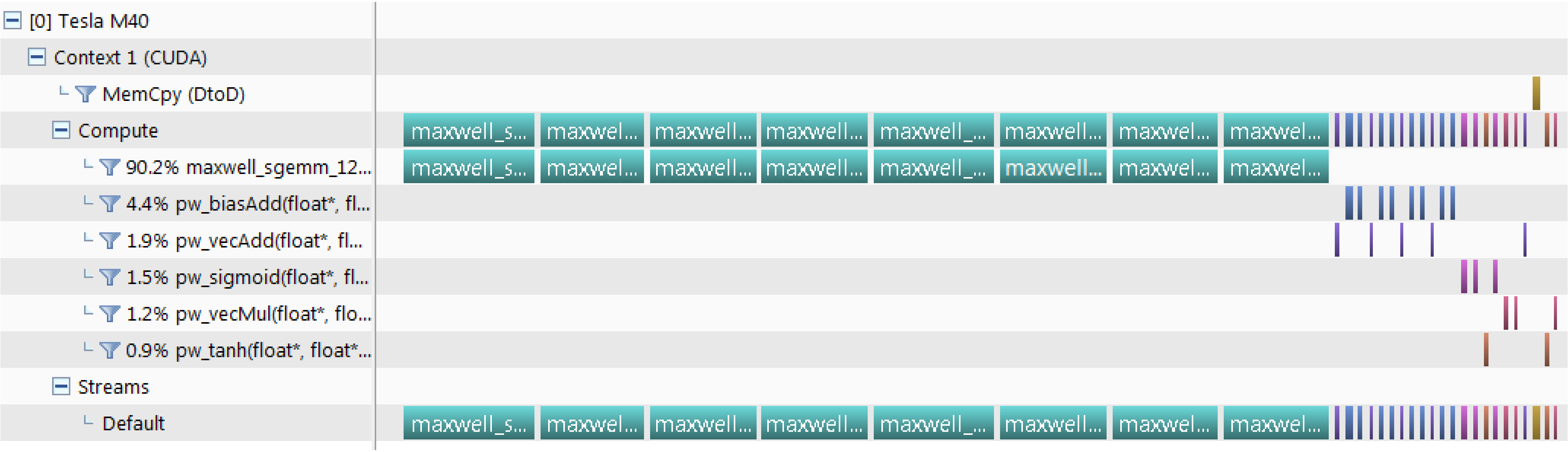
Using nvprof

```
>> nvprof ./RNN 512 64
==6805== NVPROF is profiling process 6805, command: ./RNN 512 64
==6805== Profiling application: ./RNN 512 64
==6805== Profiling result:
Time(%)      Time     Calls       Avg       Min       Max  Name
 88.46%  512.07us         8  64.009us  60.449us  75.618us  maxwell_sgemm_128x64_tn
  4.26%  24.673us         8  3.0840us  2.9120us  4.1600us  pw_biasAdd(float*, float*, int, int)
  1.93%  11.200us         5  2.2400us  2.0160us  2.9760us  pw_vecAdd(float*, float*, float*, int)
  1.92%  11.136us         3  3.7120us  3.4560us  4.1920us  [CUDA memcpy DtoD]
  1.39%  8.0650us         3  2.6880us  2.3040us  3.4570us  pw_sigmoid(float*, float*, int)
  1.15%  6.6560us         3  2.2180us  1.9840us  2.6560us  pw_vecMul(float*, float*, float*, int)
  0.88%  5.0880us         2  2.5440us  2.3040us  2.7840us  pw_tanh(float*, float*, int)
```

LSTM Profile

Using nvvp

- Can run interactively
- Or use `nvprof -o a.nvp` and import file



SGEMM Performance

Back of the envelope

- SGEMM is a well known operation
- With the inputs chosen each should perform about 33 million floating point operations
- 33 million / 64us = ~516 GFLOPs.
    - GPU can do ~6000 GFLOPs!
- What is wrong?

SGEMM Performance

What is wrong?

- Collect performance metrics:
  - Either via nvprof --analysis-metrics …
  - Or interactively
- A lot of information available
  - Guided analysis helps filter this down
  - Leads me to: “Optimization: Increase the number of blocks executed by the kernel.”
  - Expose more parallelism!

SGEMM Performance

Improvement #1

$$[A_1][h] = [y_1]$$

$$[A_2][h] = [y_2]$$

$$[A_3][h] = [y_3]$$

$$[A_4][h] = [y_4]$$

$$\begin{bmatrix} \\ A \\ \\ \end{bmatrix} [h] = \begin{bmatrix} \\ y \\ \\ \end{bmatrix}$$

- As our matrix operations share inputs we can combine them

SGEMM Performance

Improvement #1

Before:

Time(%)	Time	Calls	Avg	Min	Max	Name
88.46%	**512.07us**	8	64.009us	60.449us	75.618us	maxwell_sgemm_128x64_tn

After:

Time(%)	Time	Calls	Avg	Min	Max	Name
75.97%	**213.19us**	2	106.59us	104.90us	108.29us	maxwell_sgemm_128x64_tn

SGEMM Performance

Improvement #2

- We are still doing two independent matrix products
  - We can combine them
  - Or compute them simultaneously

$$\begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{bmatrix} [h] = \begin{bmatrix} y \end{bmatrix} \qquad \begin{bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \end{bmatrix} [i] = \begin{bmatrix} z \end{bmatrix}$$

SGEMM Performance

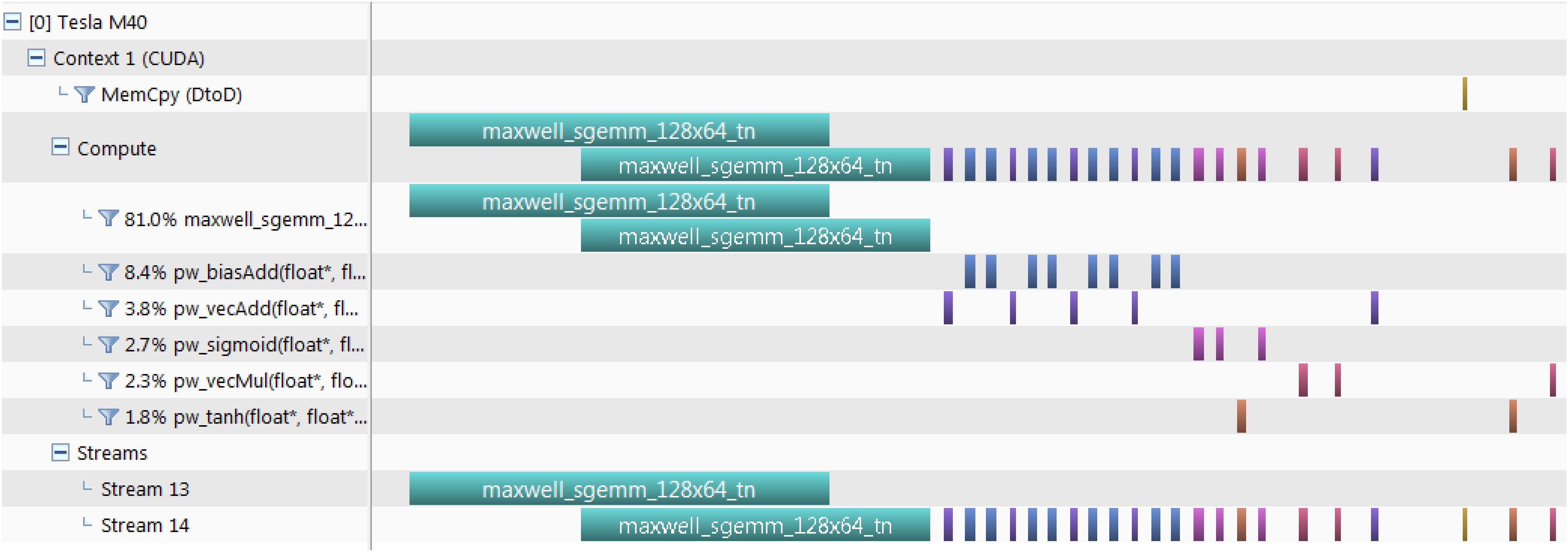
Improvement #2

- We are still doing two independent matrix products
  - We can combine them
  - **Or compute them simultaneously**

$$\begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{bmatrix} [h] = \begin{bmatrix} y \end{bmatrix} \qquad \begin{bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \end{bmatrix} [i] = \begin{bmatrix} z \end{bmatrix}$$

SGEMM Performance

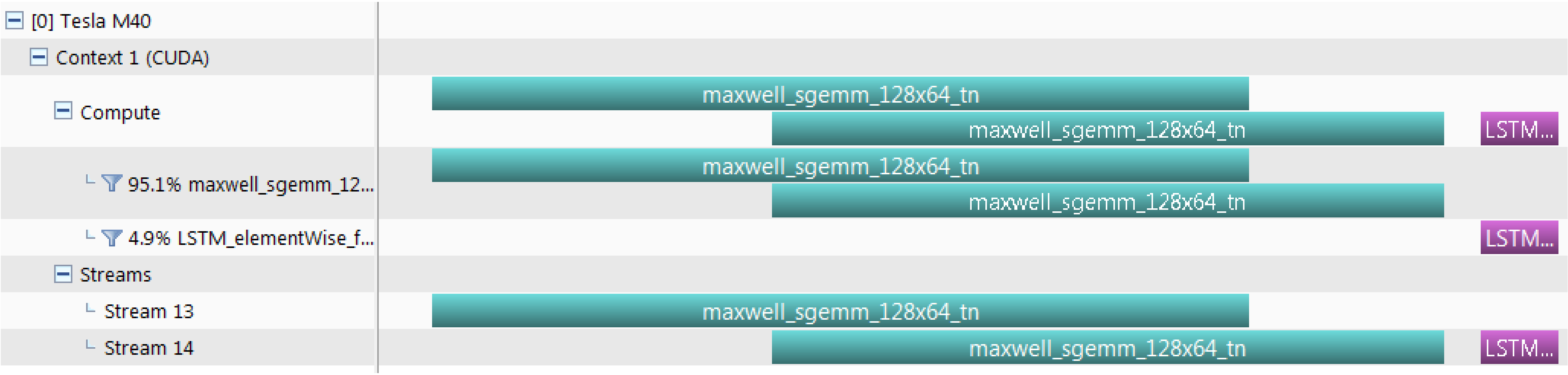
Matrix overlapping



NVIDIA.

Final optimization

Fuse element-wise operations



LSTM

Performance

Optimisation	Runtime	Speedup
Naïve	661us	(1.0x)
Combined matrices	357us	1.9x
Matrix streaming	250us	2.6x
Fused element-wise ops	136us	4.9x

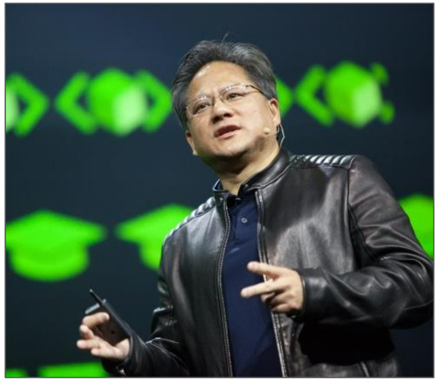
Profiling

5x performance improvement

- Profiling helped to quickly identify the slow parts
- It showed that SGEMM was underusing the GPU
  - This was fixed by exposing more parallelism
- It showed that the pointwise operations were taking a significant proportion of our runtime
  - This was fixed by fusing them

GPU TECHNOLOGY CONFERENCE

April 4-7, 2016 | Silicon Valley | #GTC16
www.gputechconf.com



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