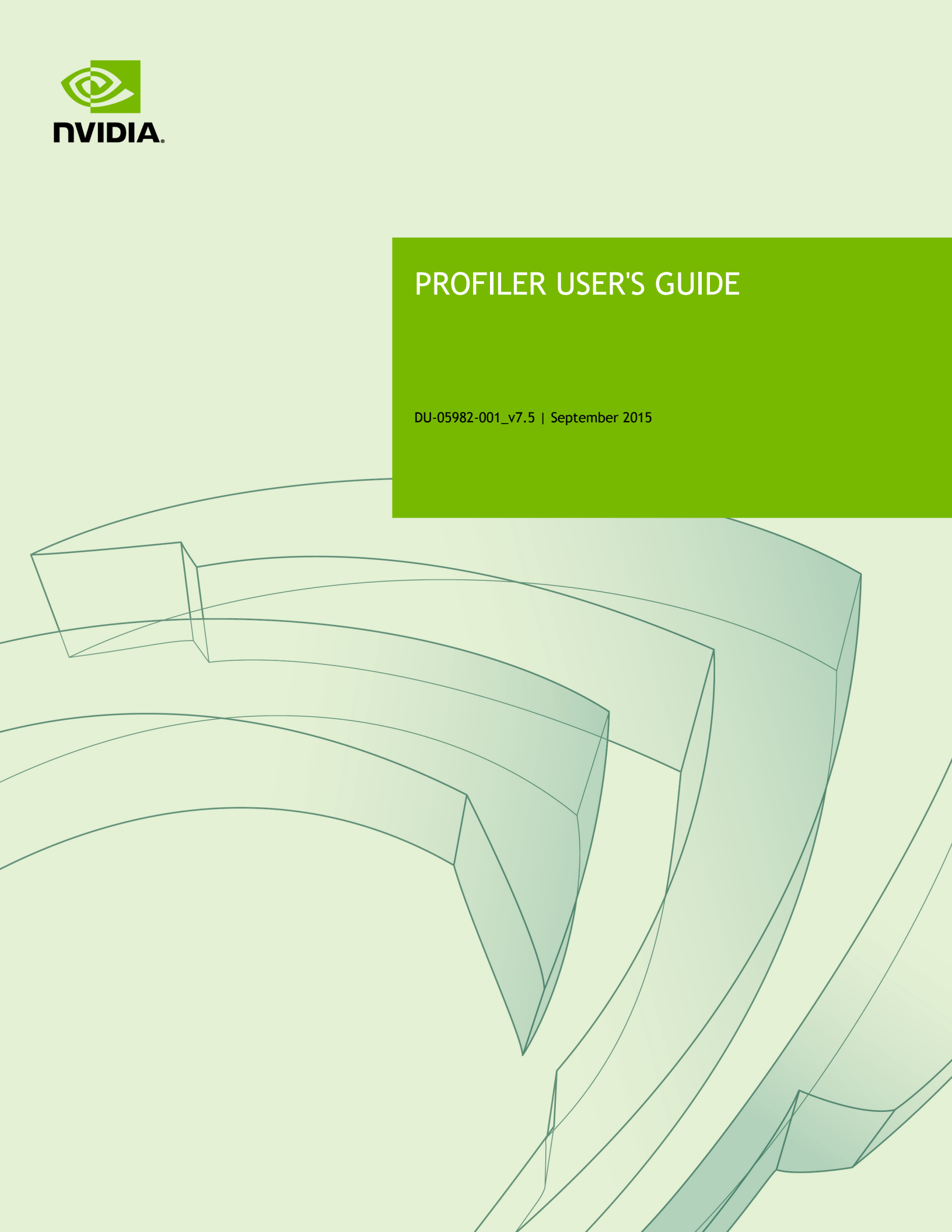


PROFILER USER'S GUIDE

DU-05982-001_v7.5 | September 2015

TABLE OF CONTENTS

LIST OF TABLES

PROFILING OVERVIEW

This document describes NVIDIA profiling tools and APIs that enable you to understand and optimize the performance of your CUDA application. The Visual Profiler is a graphical profiling tool that displays a timeline of your application's CPU and GPU activity, and that includes an automated analysis engine to identify optimization opportunities. The Visual Profiler is available as both a standalone application, **`nvvp`**, and as part of Nsight Eclipse Edition. The nvprof profiling tool enables you to collect and view profiling data from the command-line. The existing command-line profiler continues to be supported.

What's New

The profiling tools contain a number of changes and new features as part of the CUDA Toolkit 7.5 release.

- **`Visual Profiler`** now supports PC sampling for devices with compute capability 5.2. Warp state including stall reasons are shown at source level for kernel latency analysis. See PC sampling view for more information.
- **`Visual Profiler`** now supports profiling child processes and profiling all processes launched on the same system. See Creating a Session for more information on the new multi-process profiling options. For profiling CUDA applications using Multi-Process Service(MPS) see MPS profiling with Visual Profiler
- **`Visual Profiler`** import now supports browsing and selecting files on a remote system.
- **`nvprof`** now supports CPU profiling. See CPU Sampling for more information.
- All events and metrics for devices with compute capability 5.2 can now be collected accurately in presence of multiple contexts on the GPU.

Terminology

An **event** is a countable activity, action, or occurrence on a device. It corresponds to a single hardware counter value which is collected during kernel execution. To see a list of all available events on a particular NVIDIA GPU, type **`nvprof --query-events`**.

A **metric** is a characteristic of an application that is calculated from one or more event values. To see a list of all available metrics on a particular NVIDIA GPU, type **`nvprof --query-metrics`**. You can also refer to the metrics reference .

Chapter 1. PREPARING AN APPLICATION FOR PROFILING

The CUDA profiling tools do not require any application changes to enable profiling; however, by making some simple modifications and additions, you can greatly increase the usability and effectiveness of the profilers. This section describes these modifications and how they can improve your profiling results.

1.1. Focused Profiling

By default, the profiling tools collect profile data over the entire run of your application. But, as explained below, you typically only want to profile the region(s) of your application containing some or all of the performance-critical code. Limiting profiling to performance-critical regions reduces the amount of profile data that both you and the tools must process, and focuses attention on the code where optimization will result in the greatest performance gains.

There are several common situations where profiling a region of the application is helpful.

1. The application is a test harness that contains a CUDA implementation of all or part of your algorithm. The test harness initializes the data, invokes the CUDA functions to perform the algorithm, and then checks the results for correctness. Using a test harness is a common and productive way to quickly iterate and test algorithm changes. When profiling, you want to collect profile data for the CUDA functions implementing the algorithm, but not for the test harness code that initializes the data or checks the results.
2. The application operates in phases, where a different set of algorithms is active in each phase. When the performance of each phase of the application can be optimized independently of the others, you want to profile each phase separately to focus your optimization efforts.
3. The application contains algorithms that operate over a large number of iterations, but the performance of the algorithm does not vary significantly across those iterations. In this case you can collect profile data from a subset of the iterations.

To limit profiling to a region of your application, CUDA provides functions to start and stop profile data collection. **`cudaProfilerStart()`** is used to start profiling and **`cudaProfilerStop()`** is used to stop profiling (using the CUDA driver API, you get the same functionality with **`cuProfilerStart()`** and **`cuProfilerStop()`**). To use these functions you must include **`cuda_profiler_api.h`** (or **`cudaProfiler.h`** for the driver API).

When using the start and stop functions, you also need to instruct the profiling tool to disable profiling at the start of the application. For **`nvprof`** you do this with the **`--profile-from-start off`** flag. For the Visual Profiler you use the **Start execution with profiling enabled** checkbox in the Settings View.

1.2. Marking Regions of CPU Activity

The Visual Profiler can collect a trace of the CUDA function calls made by your application. The Visual Profiler shows these calls in the Timeline View, allowing you to see where each CPU thread in the application is invoking CUDA functions. To understand what the application's CPU threads are doing outside of CUDA function calls, you can use the NVIDIA Tools Extension API (NVTX). When you add NVTX markers and ranges to your application, the Timeline View shows when your CPU threads are executing within those regions.

`nvprof` also supports NVTX markers and ranges. Markers and ranges are shown in the API trace output in the timeline. In summary mode, each range is shown with CUDA activities associated with that range.

1.3. Naming CPU and CUDA Resources

The Visual Profiler Timeline View shows default naming for CPU thread and GPU devices, context and streams. Using custom names for these resources can improve understanding of the application behavior, especially for CUDA applications that have many host threads, devices, contexts, or streams. You can use the NVIDIA Tools Extension API to assign custom names for your CPU and GPU resources. Your custom names will then be displayed in the Timeline View.

`nvprof` also supports NVTX naming. Names of CUDA devices, contexts and streams are displayed in summary and trace mode. Thread names are displayed in summary mode.

1.4. Flush Profile Data

To reduce profiling overhead, the profiling tools collect and record profile information into internal buffers. These buffers are then flushed asynchronously to disk with low priority to avoid perturbing application behavior. To avoid losing profile information that has not yet been flushed, the application being profiled should make sure, before exiting, that all GPU work is done (using CUDA sychronization calls), and then call **`cudaProfilerStop()`** or **`cuProfilerStop()`**. Doing so forces buffered profile information on corresponding context(s) to be flushed.

If your CUDA application includes graphics that operate using a *display* or *main* loop, care must be taken to call **`cudaProfilerStop()`** or **`cuProfilerStop()`** before the thread executing that loop calls **`exit()`**. Failure to call one of these APIs may result in the loss of some or all of the collected profile data.

For some graphics applications like the ones use OpenGL, the application exits when the escape key is pressed. In those cases where calling the above functions before exit is not feasible, use **`nvprof`** option **`--timeout`** or set the "Exection timeout" in the Visual Profiler. The profiler will force a data flush just before the timeout.

1.5. Profiling CUDA Fortran Applications

CUDA Fortran applications compiled with the PGI CUDA Fortran compiler can be profiled by **`nvprof`** and the Visual Profiler. In cases where the profiler needs source file and line information (kernel profile analysis, global memory access pattern analysis, divergent execution analysis, etc.), use the "-Mcuda=lineinfo" option when compiling. This option is supported on linux x86 64-bit targets in PGI 2014 version 14.9 or later.

Chapter 2. VISUAL PROFILER

The NVIDIA Visual Profiler allows you to visualize and optimize the performance of your CUDA application. The Visual Profiler displays a timeline of your application's activity on both the CPU and GPU so that you can identify opportunities for performance improvement. In addition, the Visual Profiler will analyze your application to detect potential performance bottlenecks and direct you on how to take action to eliminate or reduce those bottlenecks.

The Visual Profiler is available as both a standalone application and as part of Nsight Eclipse Edition. The standalone version of the Visual Profiler, **`nvvp`**, is included in the CUDA Toolkit for all supported OSes. Within Nsight Eclipse Edition, the Visual Profiler is located in the Profile Perspective and is activated when an application is run in profile mode. Nsight Eclipse Edition, **`nsight`**, is included in the CUDA Toolkit for Linux and Mac OSX.

2.1. Getting Started

This section describes the steps you need to take to get started with the Visual Profiler.

2.1.1. Modify Your Application For Profiling

The Visual Profiler does not require any application changes; however, by making some simple modifications and additions, you can greatly increase its usability and effectiveness. Section Preparing An Application For Profiling describes how you can focus your profiling efforts and add extra annotations to your application that will greatly improve your profiling experience.

2.1.2. Creating a Session

The first step in using the Visual Profiler to profile your application is to create a new profiling *session*. A session contains the settings, data, and results associated with your application. Sessions gives more information on working with sessions.

You can create a new session by selecting the **Profile An Application** link on the Welcome page, or by selecting **New Session** from the **File** menu. In the **Create New**

Session dialog enter the executable for your application. Optionally, you can also specify the working directory, arguments, multi-process profiling option and environment.

The muti-process profiling options are:

- **Profile child processes** - If selected, profile all processes launched by the specified application.
- **Profile all processes** - If selected, profile every CUDA process launched on the same system by the same user who launched nvprof. In this mode Visual Profiler will launch nvprof and user needs to run his application in another terminal outside Visual profiler. User can exit this mode by pressing "Cancel" button on progress dialog in Visual Profiler to load the profile data
- **Profile current process only** - If selected, only profile specified application.

Press **Next** to choose some additional profiling options. The options are:

- **Start execution with profiling enabled** - If selected profile data is collected from the start of application execution. If not selected profile data is not collected until `cudaProfilerStart()` is called in the application. See Focused Profiling for more information about `cudaProfilerStart()`.
- **Enable concurrent kernel profiling** - This option should be selected for an application that uses CUDA streams to launch kernels that can execute concurrently. If the application uses only a single stream (and therefore cannot have concurrent kernel execution), deselecting this option may decrease profiling overhead.
- **Enable power, clock, and thermal profiling** - If selected, power, clock, and thermal conditions on the GPUs will be sampled and displayed on the timeline. Collection of this data is not supported on all GPUs. See the description of the Device timeline in Timeline View for more information.
- **Don't run guided analysis** - By default guided analysis is run immediately after the creation of a new session. Select this option to disable this behavior.

Press **Finish**.

2.1.3. Analyzing Your Application

If the **Don't run guided analysis** option was not selected when you created your session, the Visual Profiler will immediately run your application to collect the data needed for the first stage of guided analysis. As described in Analysis View, you can use the guided analysis system to get recommendations on performance limiting behavior in your application.

2.1.4. Exploring the Timeline

In addition to the guided analysis results, you will see a timeline for your application showing the CPU and GPU activity that occurred as your application executed. Read Timeline View and Properties View to learn how to explore the profiling information that is available in the timeline. Navigating the Timeline describes how you can zoom and scroll the timeline to focus on specific areas of your application.

2.1.5. Looking at the Details

In addition to the results provided in the Analysis View, you can also look at the specific metric and event values collected as part of the analysis. Metric and event values are displayed in the Details View. You can collect specific metric and event values that reveal how the kernels in your application are behaving. You collect metrics and events as described in the Details View section.

2.1.6. Improve Loading of Large Profiles

Some applications launch many tiny kernels, making them prone to very large (100s of megabytes or larger) **nvprof** output, even for application runs of only a few seconds. The Visual Profiler needs roughly the same amount of memory as the size of the profile it is opening/importing. The Java virtual machine may use a fraction of the main memory if no "max heap size" setting is specified. So depending on the size of main memory, Visual Profiler may fail to load some large files.

If the Visual Profiler fails to load a large profile, try setting the max heap size that JVM is allowed to use according to main memory size. You can modify the config file in **libnvvp/nvvp.ini** in the toolkit installation directory. The **nvvp.ini** configuration file looks like this:

```
-startup
plugins/org.eclipse.equinox.launcher_1.3.0.v20140415-2008.jar
--launcher.library
plugins/org.eclipse.equinox.launcher.gtk.linux.x86_64_1.1.200.v20140603-1326
-data
@user.home/nvvp_workspace
-vm
../jre/bin/java
-vmargs
-Dorg.eclipse.swt.browser.DefaultType=mozilla
```

To force the JVM to use 3 gigabytes of memory, for example, add a new line with **-Xmx3G** after **-vmargs**. The -Xmx setting should be tailored to the available system memory and input size. For example, if your system has 24GB of system memory, and you happen to know that you won't need to run any other memory-intensive applications at the same time as the Visual Profiler, so its okay for the profiler to take up the vast majority of that space. So you might pick, say, 22GB as the maximum heap size, leaving a few gigabytes for the OS, GUI, and any other programs that might be running.

Some other **nvvp.ini** configuration settings can also be tweaked:

- Increase the default heap size (the one Java automatically starts up with) to, say, 2GB. (**-Xms**)
- Tell Java to run in 64-bit mode instead of the default 32-bit mode (only works on 64-bit systems); this is required if you want heap sizes >4GB. (**-d64**)
- Enable Javas parallel garbage collection system, which helps both to decrease the required memory space for a given input size as well as to catch out of memory errors more gracefully. (**-XX:+UseConcMarkSweepGC -XX:+CMSIncrementalMode**)

Note: most CUDA installations require administrator/root-level access to modify this file.

The modified **nvvp.ini** file as per examples given above is as follows:

```
-data
@user.home/nvvp_workspace
-vm
../jre/bin/java
-d64
-vmargs
-Xms2g
-Xmx22g
-XX:+UseConcMarkSweepGC
-XX:+CMSIncrementalMode
-Dorg.eclipse.swt.browser.DefaultType=Mozilla
```

For more details on JVM settings, consult the Java virtual machine manual.

2.2. Sessions

A session contains the settings, data, and profiling results associated with your application. Each session is saved in a separate file; so you can delete, move, copy, or share a session by simply deleting, moving, copying, or sharing the session file. By convention, the file extension **.nvvp** is used for Visual Profiler session files.

There are two types of sessions: an executable session that is associated with an application that is executed and profiled from within the Visual Profiler, and an import session that is created by importing data generated by nvprof or the command-line profiler.

2.2.1. Executable Session

You can create a new executable session for your application by selecting the **Profile An Application** link on the **Welcome** page, or by selecting **New Session** from the **File** menu. Once a session is created, you can edit the session's settings as described in the Settings View.

You can open and save existing sessions using the open and save options in the **File** menu.

To analyze your application and to collect metric and event values, the Visual Profiler will execute your application multiple times. To get accurate profiling results, it is important that your application conform to the requirements detailed in Application Requirements.

2.2.2. Import Session

You create an import session from the output of **nvprof** or the command-line profiler by using the **Import...** option in the **File** menu. Selecting this option opens the import wizard which guides you through the import process.

Because an executable application is not associated with an import session, the Visual Profiler cannot execute the application to collect additional profile data. As a result, analysis can only be performed with the data that is imported. Also, the Details View will show any imported event and metrics values but new metrics and events cannot be selected and collected for the import session.

2.2.2.1. Import Single-Process `nvprof` Session

Using the import wizard you can select one or more **`nvprof`** data files for import into the new session.

You must have one **`nvprof`** data file that contains the timeline information for the session. This data file should be collected by running nvprof with the **`--export-profile`** option. You can optionally enable other options such as **`--system-profiling on`**, but you should not collect any events or metrics as that will distort the timeline so that it is not representative of the applications true behavior.

You may optionally specify one or more event/metric data files that contain event and metric values for the application. These data files should be collected by running nvprof with one or both of the **`--events`** and **`--metrics`** options. To collect all the events and metrics that are needed for the guided analysis system, you can simply use the **`--analysis-metrics`** option along with the **`--kernels`** option to select the kernel(s) to collect events and metrics for. See Remote Profiling for more information.

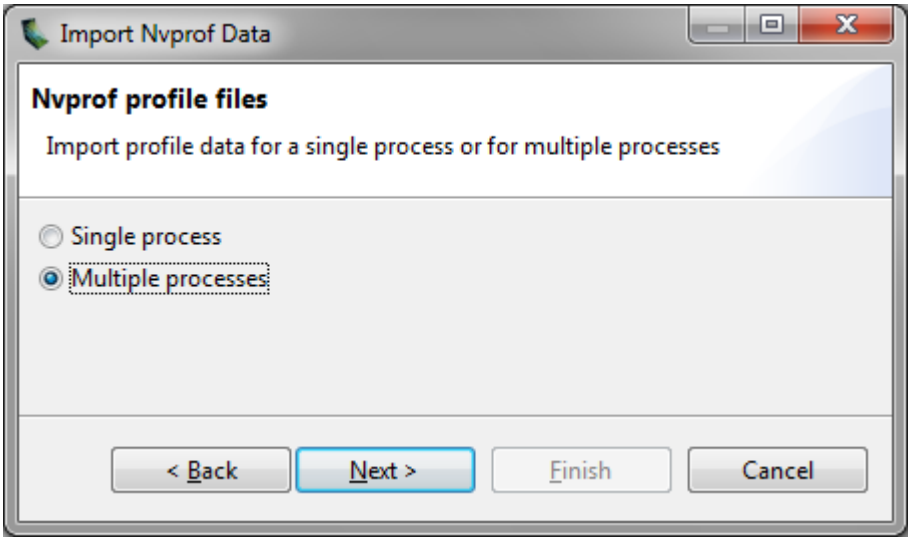
If you are importing multiple **`nvprof`** output files into the session, it is important that your application conform to the requirements detailed in Application Requirements.

2.2.2.2. Import Multi-Process `nvprof` Session

Using the import wizard you can select multiple **`nvprof`** data files for import into the new multi-process session.

Each **`nvprof`** data file must contain the timeline information for one of the processes. This data file should be collected by running nvprof with the **`--export-profile`** option. You can optionally enable other options such as **`--system-profiling on`**, but you should not collect any events or metrics as that will distort the timeline so that it is not representative of the applications true behavior.

Select the **Multiple Processes** option in the **Import Nvprof Data** dialog as shown in the figure below.



When importing timeline data from multiple processes you may not specify any event/metric data files for those processes. Multi-processes profiling is only supported for timeline data.

2.2.2.3. Import Command-Line Profiler Session

Using the import wizard you can select one or more command-line profiler generated CSV files for import into the new session. When you import multiple CSV files, their contents are combined and displayed in a single timeline.

When using the command-line profiler to create a CSV file for import into the Visual Profiler, the following requirement must be met:

- **COMPUTE_PROFILE_CSV** must be 1 to generate CSV formatted output.
- **COMPUTE_PROFILE_CONFIG** must point to a file that contains gpustarttimestamp and streamid configuration parameters. The configuration file may also contain other configuration parameters, including events.

2.3. Application Requirements

To collect performance data about your application, the Visual Profiler must be able to execute your application repeatedly in a deterministic manner. Due to software and hardware limitations, it is not possible to collect all the necessary profile data in a single execution of your application. Each time your application is run, it must operate on the same data and perform the same kernel and memory copy invocations in the same order. Specifically,

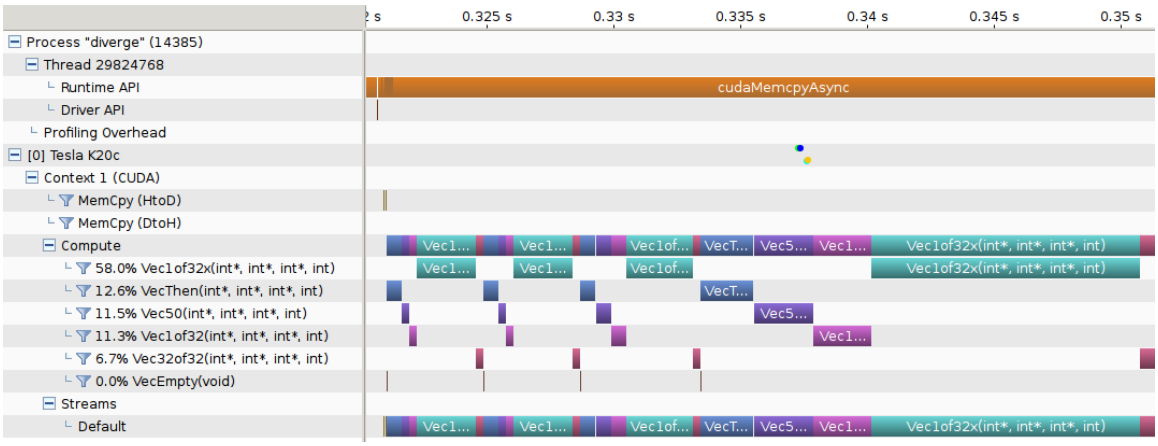
- For a device, the order of context creation must be the same each time the application executes. For a multi-threaded application where each thread creates its own context(s), care must be taken to ensure that the order of those context creations is consistent across multiple runs. For example, it may be necessary to create the contexts on a single thread and then pass the contexts to the other threads. Alternatively, the NVIDIA Tools Extension API can be used to provide a custom name for each context. As long as the same custom name is applied to the same context on each execution of the application, the Visual Profiler will be able to correctly associate those contexts across multiple runs.
- For a context, the order of stream creation must be the same each time the application executes. Alternatively, the NVIDIA Tools Extension API can be used to provide a custom name for each stream. As long as the same custom name is applied to the same stream on each execution of the application, the Visual Profiler will be able to correctly associate those streams across multiple runs.
- Within a stream, the order of kernel and memcpy invocations must be the same each time the application executes.

2.4. Visual Profiler Views

The Visual Profiler is organized into views. Together, the views allow you to analyze and visualize the performance of your application. This section describes each view and how you use it while profiling your application.

2.4.1. Timeline View

The Timeline View shows CPU and GPU activity that occurred while your application was being profiled. Multiple timelines can be opened in the Visual Profiler at the same time. Each opened timeline is represented by a different instance of the view. The following figure shows a Timeline View for a CUDA application.



Along the top of the view is a horizontal ruler that shows elapsed time from the start of application profiling. Along the left of the view is a vertical ruler that describes what is being shown for each horizontal row of the timeline, and that contains various controls for the timeline. These controls are described in Timeline Controls

The timeline view is composed of timeline rows. Each row shows intervals that represent the start and end times of the activities that correspond to the type of the row. For example, timeline rows representing kernels have intervals representing the start and end times of executions of that kernel. In some cases (as noted below) a timeline row can display multiple sub-rows of activity. Sub-rows are used when there is overlapping activity. These sub-rows are created dynamically as necessary depending on how much activity overlap there is. The placement of intervals within certain sub-rows does not convey any particular meaning. Intervals are just packed into sub-rows using a heuristic that attempts to minimize the number of needed sub-rows. The height of the sub-rows is scaled to keep vertical space reasonable.

The types of timeline rows that are displayed in the Timeline View are:

Process

A timeline will contain a **Process** row for each application profiled. The process identifier represents the pid of the process. The timeline row for a process does not contain any intervals of activity. Threads within the process are shown as children of the process.

Thread
A timeline will contain a **Thread** row for each CPU thread in the profiled application that performed either a CUDA driver or CUDA runtime API call. The thread identifier is a unique id for that CPU thread. The timeline row for a thread is does not contain any intervals of activity.

Runtime API
A timeline will contain a **Runtime API** row for each CPU thread that performs a CUDA Runtime API call. Each interval in the row represents the duration of the call on the corresponding thread.

Driver API
A timeline will contain a **Driver API** row for each CPU thread that performs a CUDA Driver API call. Each interval in the row represents the duration of the call on the corresponding thread.

Markers and Ranges
A timeline will contain a single **Markers and Ranges** row for each CPU thread that uses the NVIDIA Tools Extension API to annotate a time range or marker. Each interval in the row represents the duration of a time range, or the instantaneous point of a marker. This row will have sub-rows if there are overlapping ranges.

Profiling Overhead
A timeline will contain a single **Profiling Overhead** row for each process. Each interval in the row represents the duration of execution of some activity required for profiling. These intervals represent activity that does not occur when the application is not being profiled.

Device
A timeline will contain a **Device** row for each GPU device utilized by the application being profiled. The name of the timeline row indicates the device ID in square brackets followed by the name of the device. After running the **Compute Utilization** analysis, the row will contain an estimate of the compute utilization of the device over time. If power, clock, and thermal profiling are enabled, the row will also contain points representing those readings.

Context
A timeline will contains a **Context** row for each CUDA context on a GPU device. The name of the timeline row indicates the context ID or the custom context name if the NVIDIA Tools Extension API was used to name the context. The row for a context does not contain any intervals of activity.

Memcpy
A timeline will contain memory copy row(s) for each context that performs memcpys. A context may contain up to four memcpy rows for device-to-host, host-to-device, device-to-device, and peer-to-peer memory copies. Each interval in a row represents the duration of a memcpy executing on the GPU.

Compute
A timeline will contain a **Compute** row for each context that performs computation on the GPU. Each interval in a row represents the duration of a kernel on the GPU device. The **Compute** row indicates all the compute activity for the context. Sub-rows are used when concurrent kernels are executed on the context. All kernel activity, including kernels launched using CUDA Dynamic Parallelism, is shown on the Compute row. The **Kernel** rows following the Compute row show activity of each individual application kernel.

Kernel

A timeline will contain a **Kernel** row for each kernel executed by the application. Each interval in a row represents the duration of execution of an instance of that kernel in the containing context. Each row is labeled with a percentage that indicates the total execution time of all instances of that kernel compared to the total execution time of all kernels. For each context, the kernels are ordered top to bottom by this execution time percentage. Sub-rows are used to show concurrent kernel execution. For CUDA Dynamic Parallelism applications, the kernels are organized in a hierarchy that represents the parent/child relationship between the kernels. Host-launched kernels are shown as direct children of the Context row. Kernels that use CUDA Dynamic Parallelism to launch other kernels can be expanded using the '+' icon to show the kernel rows representing those child kernels. For kernels that don't launch child kernels, the kernel execution is represented by a solid interval, showing the time that that instance of the kernel was executing on the GPU. For kernels that launch child kernels, the interval can also include a hollow part at the end. The hollow part represents the time after the kernel has finished executing where it is waiting for child kernels to finish executing. The CUDA Dynamic Parallelism execution model requires that a parent kernel not complete until all child kernels complete and this is what the hollow part is showing. The **Focus** control described in Timeline Controls can be used to control display of the parent/child timelines.

Stream

A timeline will contain a **Stream** row for each stream used by the application (including both the default stream and any application created streams). Each interval in a **Stream** row represents the duration of a memcpy or kernel execution performed on that stream.

2.4.1.1. Timeline Controls

The Timeline View has several controls that you use to control how the timeline is displayed. Some of these controls also influence the presentation of data in the Details View and the Analysis View.

Resizing the Vertical Timeline Ruler

The width of the vertical ruler can be adjusted by placing the mouse pointer over the right edge of the ruler. When the double arrow pointer appears, click and hold the left mouse button while dragging. The vertical ruler width is saved with your session.

Reordering Timelines

The **Kernel** and **Stream** timeline rows can be reordered. You may want to reorder these rows to aid in visualizing related kernels and streams, or to move unimportant kernels and streams to the bottom of the timeline. To reorder a row, left-click on the row label. When the double arrow pointer appears, drag up or down to position the row. The timeline ordering is saved with your session.

Filtering Timelines

Memcpy and **Kernel** rows can be filtered to exclude their activities from presentation in the Details View and the Analysis View. To filter out a row, left-click on the filter icon just to the left of the row label. To filter all Kernel or Memcpy rows, **Shift**-left-click one of the rows. When a row is filtered, any intervals on that row are dimmed to indicate their filtered status.

Expanding and Collapsing Timelines

Groups of timeline rows can be expanded and collapsed using the **[+]** and **[-]** controls just to the left of the row labels. There are three expand/collapse states:

Collapsed
No timeline rows contained in the collapsed row are shown.

Expanded
All non-filtered timeline rows are shown.

All-Expanded
All timeline rows, filtered and non-filtered, are shown.

Intervals associated with collapsed rows may not be shown in the Details View and the Analysis View, depending on the filtering mode set for those views (see view documentation for more information). For example, if you collapse a device row, then all memcpys, memsets, and kernels associated with that device are excluded from the results shown in those views.

Coloring Timelines

There are three modes for timeline coloring. The coloring mode can be selected in the **View** menu, in the timeline context menu (accessed by right-clicking in the timeline view), and on the Visual Profiler toolbar. In **kernel** coloring mode, each type of kernel is assigned a unique color (that is, all activity intervals in a kernel row have the same color). In **stream** coloring mode, each stream is assigned a unique color (that is, all memcpy and kernel activity occurring on a stream are assigned the same color). In **process** coloring mode, each process is assigned a unique color (that is, all memcpy and kernel activity occurring in a process are assigned the same color).

Focusing Kernel Timelines

For applications using CUDA Dynamic Parallelism, the Timeline View displays a hierarchy of kernel activity that shows the parent/child relationship between kernels. By default all parent/child relationships are shown simultaneously. The focus timeline control can be used to focus the displayed parent/child relationships to a specific, limited set of "family trees". The focus timeline mode can be selected and deselected in the timeline context menu (accessed by right-clicking in the timeline view), and on the Visual Profiler toolbar.

To see the "family tree" of a particular kernel, select a kernel and then enable Focus mode. All kernels except those that are ancestors or descendants of the selected kernel will be hidden. Ctrl-select can be used to select multiple kernels before enabling Focus mode. Use the "Don't Focus" option to disable focus mode and restore all kernels to the Timeline view.

2.4.1.2. Navigating the Timeline

The timeline can be scrolled, zoomed, and focused in several ways to help you better understand and visualize your application's performance.

Zooming

The zoom controls are available in the **View** menu, in the timeline context menu (accessed by right-clicking in the timeline view), and on the Visual Profiler toolbar. Zoom-in reduces the timespan displayed in the view, zoom-out increases the timespan displayed in the view, and zoom-to-fit scales the view so that the entire timeline is visible.

You can also zoom-in and zoom-out with the mouse wheel while holding the **Ctrl** key (for MacOSX use the **Command** key).

Another useful zoom mode is zoom-to-region. Select a region of the timeline by holding **Ctrl** (for MacOSX use the **Command** key) while left-clicking and dragging the mouse. The highlighted region will be expanded to occupy the entire view when the mouse button is released.

Scrolling

The timeline can be scrolled vertically with the scrollbar of the mouse wheel. The timeline can be scrolled horizontally with the scrollbar or by using the mouse wheel while holding the **Shift** key.

Highlighting/Correlation

When you move the mouse pointer over an activity interval on the timeline, that interval is highlighted in all places where the corresponding activity is shown. For example, if you move the mouse pointer over an interval representing a kernel execution, that kernel execution is also highlighted in the **Stream** and in the **Compute** timeline row. When a kernel or memcpy interval is highlighted, the corresponding driver or runtime API interval will also highlight. This allows you to see the correlation between the invocation of a driver or runtime API on the CPU and the corresponding activity on the GPU. Information about the highlighted interval is shown in the Properties View.

Selecting

You can left-click on a timeline interval or row to select it. Multi-select is done using **Ctrl**-left-click. To unselect an interval or row simply **Ctrl**-left-click on it again. When a single interval or row is selected, the information about that interval or row is pinned in the Properties View. In the Details View, the detailed information for the selected interval is shown in the table.

Measuring Time Deltas

Measurement rulers can be created by left-click dragging in the horizontal ruler at the top of the timeline. Once a ruler is created it can be activated and deactivated by left-clicking. Multiple rulers can be activated by **Ctrl**-left-click. Any number of rulers can be created. Active rulers are deleted with the **Delete** or **Backspace** keys. After a ruler is created, it can be resized by dragging the vertical guide lines that appear over the timeline. If the mouse is dragger over a timeline interval, the guideline will snap to the nearest edge of that interval.

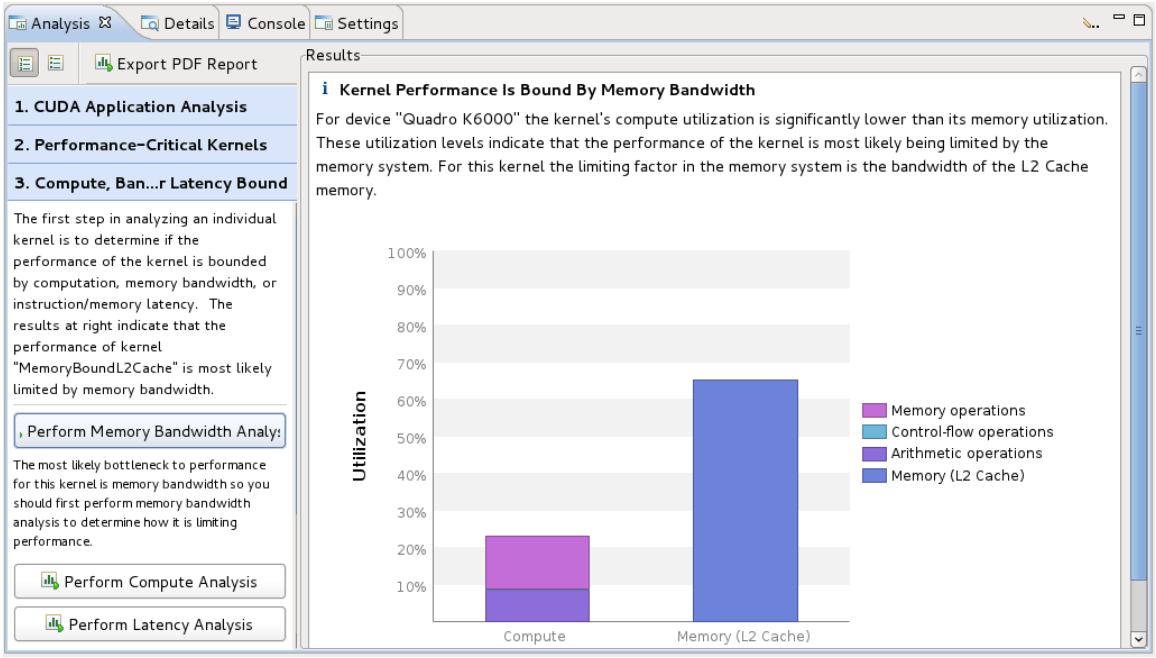
2.4.1.3. Timeline Refreshing

The Visual Profiler loads the timeline gradually as it reads the data. This is more visible if the data file being loaded is big, or the application has generated a lot of data. In such cases, the timeline may be partially rendered. At the same time, a spinning circle replaces the icon of the current session tab, indicating the timeline is not fully loaded. Loading is finished when the icon changes back.

To reduce memory footprint, the Visual Profiler may skip loading some timeline contents if they are not visible at the current zoom level. These contents will be automatically loaded when they become visible on a new zoom level.

2.4.2. Analysis View

The Analysis View is used to control application analysis and to display the analysis results. There are two analysis modes: *guided* and *unguided*. In guided mode the analysis system will guide you though multiple analysis stages to help you understand the likely performance limiters and optimization opportunities in your application. In unguided mode you can manually explore all the analysis results collect for you application. The following figure shows the analysis view in guided analysis mode. The left part of the view provides step-by-step directions to help you analyse and optimize your application. The right part of the view shows you detailed analysis results appropriate for each part of the analysis.



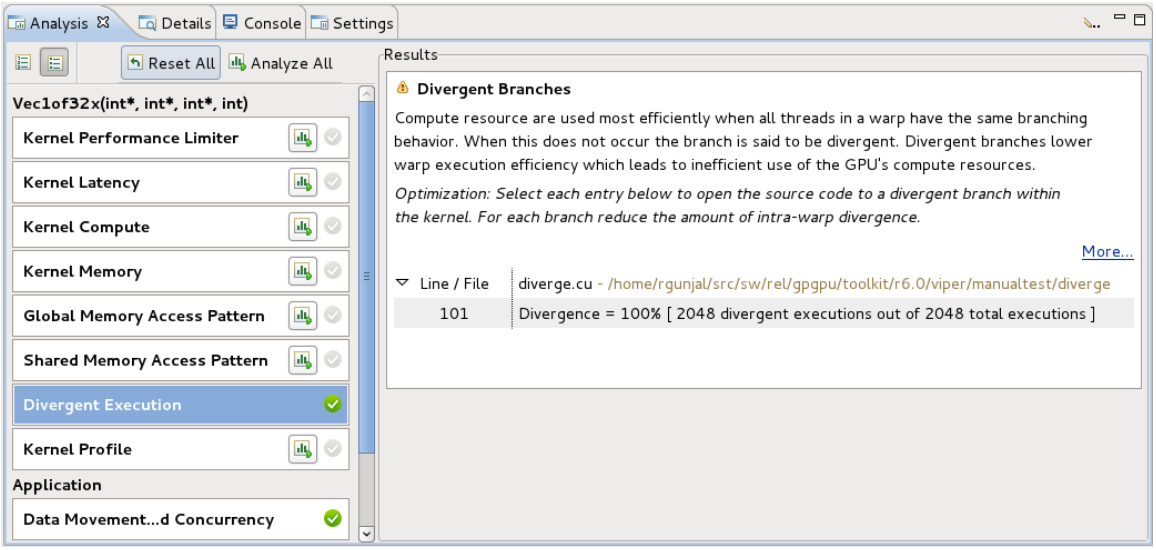
2.4.2.1. Guided Application Analysis

In guided mode, the analysis view will guide you step-by-step though analysis of your entire application with specific analysis guidance provided for each kernel within your application. Guided analysis starts with **CUDA Application Analysis** and from there will guide you to optimization opportunities within your application.

2.4.2.2. Unguided Application Analysis

In unguided analysis mode each application analysis stage has a **Run analysis** button that can be used to generate the analysis results for that stage. When the **Run analysis** button is selected, the Visual Profiler will execute the application to collect the profiling data needed to perform the analysis. The green check-mark next to an analysis stage indicates that the analysis results for that stage are available. Each analysis result contains a brief description of the analysis and a **More...** link to detailed documentation on the analysis. When you select an analysis result, the timeline rows or intervals associated with that result are highlighted in the Timeline View.

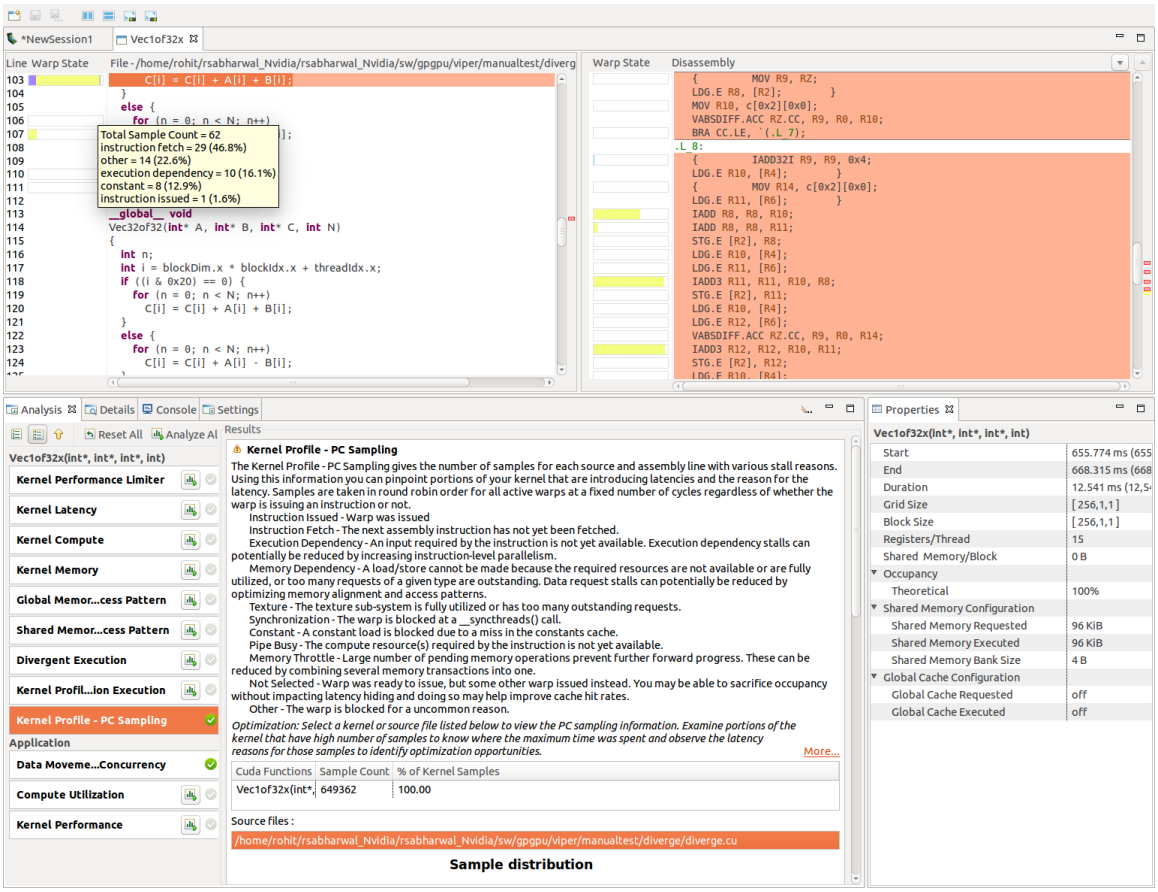
When a single kernel instance is selected in the timeline, additional kernel-specific analysis stages are available. Each kernel-specific analysis stage has a **Run analysis** button that operates in the same manner as for the application analysis stages. The following figure shows the analysis results for the **Divergent Execution** analysis stage. Some kernel instance analysis results, like **Divergent Execution** are associated with specific source-lines within the kernel. To see the source associated with each result, select an entry from the table. The source-file associated with that entry will open.



2.4.2.3. PC sampling view

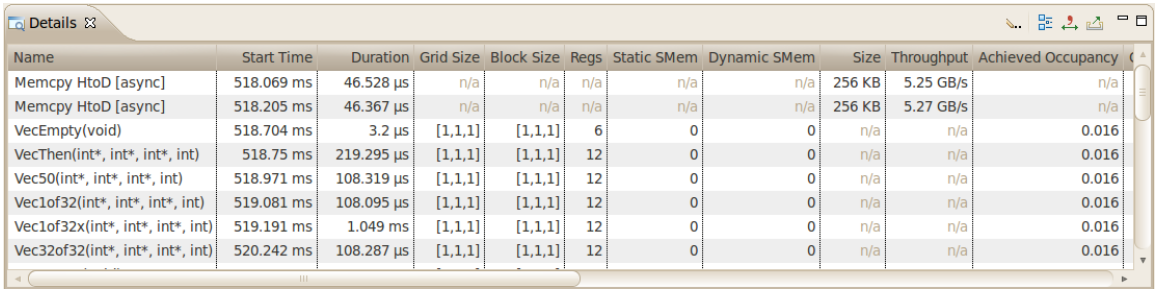
Devices with compute capability 5.2 have a feature for PC sampling. In this feature PC and state of warp is sampled at regular interval for one of the active warps per SM. The warp state indicates if the warp issued in that cycle or the stall reason why it could not issue in that cycle. When a warp that is sampled has a stall reason, there is a possibility that in the same cycle some other warp is issuing an instruction. Hence the stall for the sampled warp need not necessarily indicate that there is a hole in instruction issue pipeline. Refer the Warp State section for a description of different states.

The Visual Profiler collects this information and presents it in the **Kernel Profile - PC Sampling** view. In this view, in the **Results** sample distribution for all functions called from the kernel is given in the table. Also a pie chart is shown that gives the distribution of stall reasons collected for the kernel using sampling. After clicking on the source file or device function the **Kernel Profile - PC Sampling** view is opened. The hotspots shown next to the vertical scroll bar are decided based on number of samples collected for each source and assembly line. The distribution of the stall reasons is shown as a stacked bar for each source and assembly line. This helps in pinpointing the latency reasons at the source level.



2.4.3. Details View

The Details View displays a table of information for each memory copy and kernel execution in the profiled application. The following figure shows the table containing several memcpy and kernel executions. Each row of the table contains general information for a kernel execution or memory copy. For kernels, the table will also contain a column for each metric or event value collected for that kernel. In the figure, the **Achieved Occupancy** column shows the value of that metric for each of the kernel executions.



Name	Start Time	Duration	Grid Size	Block Size	Regs	Static SMem	Dynamic SMem	Size	Throughput	Achieved Occupancy
Memcpy HtoD [async]	518.069 ms	46.528 µs	n/a	n/a	n/a	n/a	n/a	256 KB	5.25 GB/s	n/a
Memcpy HtoD [async]	518.205 ms	46.367 µs	n/a	n/a	n/a	n/a	n/a	256 KB	5.27 GB/s	n/a
VecEmpty(void)	518.704 ms	3.2 µs	[1,1,1]	[1,1,1]	6	0	0	n/a	n/a	0.016
VecThen(int*, int*, int*, int)	518.75 ms	219.295 µs	[1,1,1]	[1,1,1]	12	0	0	n/a	n/a	0.016
Vec50(int*, int*, int*, int)	518.971 ms	108.319 µs	[1,1,1]	[1,1,1]	12	0	0	n/a	n/a	0.016
Vec1of32(int*, int*, int*, int)	519.081 ms	108.095 µs	[1,1,1]	[1,1,1]	12	0	0	n/a	n/a	0.016
Vec1of32x(int*, int*, int*, int)	519.191 ms	1.049 ms	[1,1,1]	[1,1,1]	12	0	0	n/a	n/a	0.016
Vec32of32(int*, int*, int*, int)	520.242 ms	108.287 µs	[1,1,1]	[1,1,1]	12	0	0	n/a	n/a	0.016

You can sort the data by a column by left clicking on the column header, and you can rearrange the columns by left clicking on a column header and dragging it to its new location. If you select a row in the table, the corresponding interval will be selected in the

Timeline View. Similarly, if you select a kernel or memcpy interval in the Timeline View the table will be scrolled to show the corresponding data.

If you hover the mouse over a column header, a tooltip will display describing the data shown in that column. For a column containing event or metric data, the tooltip will describe the corresponding event or metric. Section Metrics Reference contains more detailed information about each metric.

The information shown in the Details View can be filtered in various ways, controlled by the menu accessible from the Details View toolbar. The following modes are available:

- **Filter By Selection** - If selected, the Details View shows data only for the selected kernel and memcpy intervals.
- **Show Hidden Timeline Data** - If not selected, data is shown only for kernels and memcpys that are visible in the timeline. Kernels and memcpys that are not visible because they are inside collapsed parts of the timeline are not shown.
- **Show Filtered Timeline Data** - If not selected, data is shown only for kernels and memcpys that are in timeline rows that are not filtered.

Collecting Events and Metrics

Specific event and metric values can be collected for each kernel and displayed in the details table. Use the toolbar icon in the upper right corner of the view to configure the events and metrics to collect for each device, and to run the application to collect those events and metrics.

Show Summary Data

By default the table shows one row for each memcpy and kernel invocation. Alternatively, the table can show summary results for each kernel function. Use the toolbar icon in the upper right corner of the view to select or deselect summary format.

Formatting Table Contents

The numbers in the table can be displayed either with or without grouping separators. Use the toolbar icon in the upper right corner of the view to select or deselect grouping separators.

Exporting Details

The contents of the table can be exported in CSV format using the toolbar icon in the upper right corner of the view.

2.4.4. Properties View

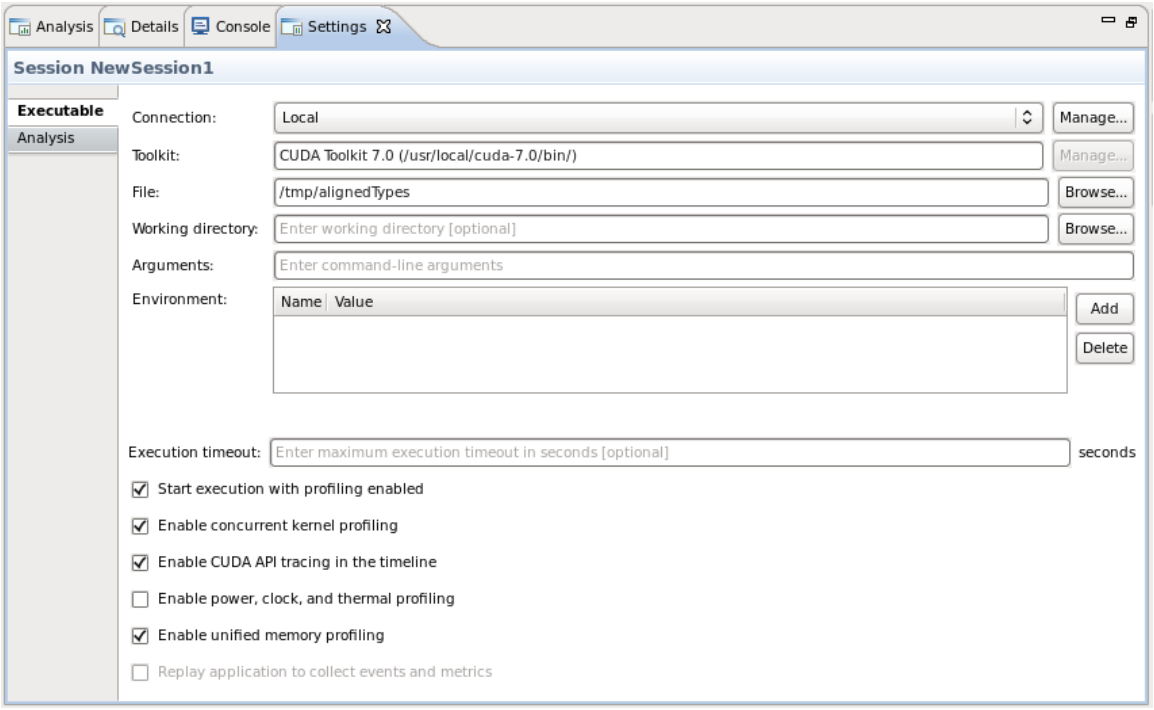
The Properties View shows information about the row or interval highlighted or selected in the Timeline View. If a row or interval is not selected, the displayed information tracks the motion of the mouse pointer. If a row or interval is selected, the displayed information is pinned to that row or interval.

2.4.5. Console View

The Console View shows the stdout and stderr output of the application each time it executes. If you need to provide stdin input to you application, you do so by typing into the console view.

2.4.6. Settings View

The Settings View allows you to specify execution settings for the application being profiled. As shown in the following figure, the **Executable** settings tab allows you to specify the executable file for the application, the working directory for the application, the command-line arguments for the application, and the environment for the application. Only the executable file is required, all other fields are optional.



Exection timeout

The **Executable** settings tab also allows you to specify and optional execution timeout. If the execution timeout is specified, the application execution will be terminated after that number of seconds. If the execution timeout is not specified, the application will be allowed to continue execution until it terminates normally.

Timeout starts counting from the moment the CUDA driver is initialized. If the application doesn't call any CUDA APIs, timeout won't be triggered.

Start execution with profiling enabled

The **Start execution with profiling enabled** checkbox is set by default to indicate that application profiling begins at the start of application execution. If you are using `cudaProfilerStart()` and `cudaProfilerStop()` to control profiling within your application as described in Focused Profiling, then you should uncheck this box.

Enable concurrent kernels profiling

The **Enable concurrent kernel profiling** checkbox is set by default to enable profiling of applications that exploit concurrent kernel execution. If this checkbox is unset, the profiler will disable concurrent kernel execution. Disabling concurrent kernel execution can reduce profiling overhead in some cases and so may be appropriate for applications that do not exploit concurrent kernels.

Enable power, clock, and thermal profiling

The **Enable power, clock, and thermal profiling** checkbox can be set to enable low frequency sampling of the power, clock, and thermal behavior of each GPU used by the application.

2.5. Customizing the Visual Profiler

When you first start the Visual Profiler, and after closing the **Welcome** page, you will be presented with a default placement of the views. By moving and resizing the views, you can customize the Visual Profiler to meet you development needs. Any changes you make to the Visual Profiler are restored the next time you start the profiler.

2.5.1. Resizing a View

To resize a view, simply left click and drag on the dividing area between the views. All views stacked together in one area are resized at the same time.

2.5.2. Reordering a View

To reorder a view in a stacked set of views, left click and drag the view tab to the new location within the view stack.

2.5.3. Moving a View

To move a view, left click the view tab and drag it to its new location. As you drag the view, an outline will show the target location for the view. You can place the view in a new location, or stack it in the same location as other views.

2.5.4. Undocking a View

You can undock a view from the Visual Profiler window so that the view occupies its own stand-alone window. You may want to do this to take advantage of multiple monitors or to maximum the size of an individual view. To undock a view, left click the view tab and drag it outside of the Visual Profiler window. To dock a view, left click the view tab (not the window decoration) and drag it into the Visual Profiler window.

2.5.5. Opening and Closing a View

Use the **X** icon on a view tab to close a view. To open a view, use the **View** menu.

2.6. Command Line Arguments

When the Visual Profiler is started from the command line, it is possible, using command line arguments, to specify executable to start new session with or import profile files exported from nvprof using one of the following patterns:

- Start new executable session by launching nvvp with name of executable followed, optionally, by its arguments:

```
nvvp executableName [[executableArguments]...]
```

- Import single-process nvprof session by launching nvvp with single .nvprof file as argument(see nvprof's export/import options section for more details):

```
nvvp data.nvprof
```

- Import multi-process nvprof session, by launching nvvp with multiple .nvprof files as arguments:

```
nvvp data1.nvprof data2.nvprof ...
```

Chapter 3. NVPROF

The **nvprof** profiling tool enables you to collect and view profiling data from the command-line. **nvprof** enables the collection of a timeline of CUDA-related activities on both CPU and GPU, including kernel execution, memory transfers, memory set and CUDA API calls. **nvprof** also enables you to collect events/metrics for CUDA kernels. Profiling options are provided to **nvprof** through command-line options. Profiling results are displayed in the console after the profiling data is collected, and may also be saved for later viewing by either **nvprof** or the Visual Profiler.

The textual output is redirected to **stderr** by default. Use **--log-file** to redirect the output to another file. See Redirecting Output.

nvprof is included in the CUDA Toolkit for all supported OSes. Here's how to use nvprof to profile a CUDA application:

```
nvprof [options] [CUDA-application] [application-arguments]
```

nvprof and the Command Line Profiler are mutually exclusive profiling tools. If **nvprof** is invoked when the command-line profiler is enabled, **nvprof** will report an error and exit.

To view the full help page, type **nvprof --help**.

3.1. Profiling Modes

nvprof operates in one of the modes listed below.

3.1.1. Summary Mode

Summary mode is the default operating mode for **nvprof**. In this mode, **nvprof** outputs a single result line for each kernel function and each type of CUDA memory copy/set performed by the application. For each kernel, **nvprof** outputs the total time of all instances of the kernel or type of memory copy as well as the average, minimum, and maximum time. The time for a kernel is the kernel execution time on the device. By default, **nvprof** also prints a summary of all the CUDA runtime/driver API calls.

Output of **nvprof** (except for tables) are prefixed with **==<pid>==**, **<pid>** being the process ID of the application being profiled. Here's a simple example of running **nvprof** on the CUDA sample **matrixMul**:

```
$ nvprof matrixMul
[Matrix Multiply Using CUDA] - Starting...
==27694== NVPROF is profiling process 27694, command: matrixMul
GPU Device 0: "GeForce GT 640M LE" with compute capability 3.0

MatrixA(320,320), MatrixB(640,320)
Computing result using CUDA Kernel...
done
Performance= 35.35 GFlop/s, Time= 3.708 msec, Size= 131072000 Ops,
 WorkgroupSize= 1024 threads/block
Checking computed result for correctness: OK

Note: For peak performance, please refer to the matrixMulCUBLAS example.
==27694== Profiling application: matrixMul
==27694== Profiling result:
Time(%)      Time     Calls       Avg       Min       Max  Name
 99.94%  1.11524s       301  3.7051ms  3.6928ms  3.7174ms  void
 matrixMulCUDA<int=32>(float*, float*, float*, int, int)
  0.04%  406.30us         2  203.15us  136.13us  270.18us  [CUDA memcpy HtoD]
  0.02%  248.29us         1  248.29us  248.29us  248.29us  [CUDA memcpy DtoH]

==27964== API calls:
Time(%)      Time     Calls       Avg       Min       Max  Name
 49.81%  285.17ms         3  95.055ms  153.32us  284.86ms  cudaMalloc
 25.95%  148.57ms         1  148.57ms  148.57ms  148.57ms  cudaEventSynchronize
 22.23%  127.28ms         1  127.28ms  127.28ms  127.28ms  cudaDeviceReset
  1.33%  7.6314ms       301  25.353us  23.551us  143.98us  cudaLaunch
  0.25%  1.4343ms         3  478.09us  155.84us  984.38us  cudaMemcpy
  0.11%  601.45us         1  601.45us  601.45us  601.45us  cudaDeviceSynchronize
  0.10%  564.48us      1505     375ns     313ns  3.6790us  cudaSetupArgument
  0.09%  490.44us        76  6.4530us     307ns  221.93us  cuDeviceGetAttribute
  0.07%  406.61us         3  135.54us  115.07us  169.99us  cudaFree
  0.02%  143.00us       301     475ns     431ns  2.4370us  cudaConfigureCall
  0.01%  42.321us         1  42.321us  42.321us  42.321us  cuDeviceTotalMem
  0.01%  33.655us         1  33.655us  33.655us  33.655us
 cudaGetDeviceProperties
  0.01%  31.900us         1  31.900us  31.900us  31.900us  cuDeviceGetName
  0.00%  21.874us         2  10.937us  8.5850us  13.289us  cudaEventRecord
  0.00%  16.513us         2  8.2560us  2.6240us  13.889us  cudaEventCreate
  0.00%  13.091us         1  13.091us  13.091us  13.091us  cudaEventElapsedTime
  0.00%  8.1410us         1  8.1410us  8.1410us  8.1410us  cudaGetDevice
  0.00%  2.6290us         2  1.3140us     509ns  2.1200us  cuDeviceGetCount
  0.00%  1.9970us         2     998ns     520ns  1.4770us  cuDeviceGet
```

API trace can be turned off, if not needed, by using **--profile-api-trace none**. This reduces some of the profiling overhead, especially when the kernels are short.

If multiple CUDA capable devices are profiled, **nvprof --print-summary-per-gpu** can be used to print one summary per GPU.

nvprof supports CUDA Dynamic Parallelism in summary mode. If your application uses Dynamic Parallelism, the output will contain one column for the number of host-

launched kernels and one for the number of device-launched kernels. Here's an example of running **nvprof** on the CUDA Dynamic Parallelism sample **cdpSimpleQuicksort**:

```
$ nvprof cdpSimpleQuicksort
==27325== NVPROF is profiling process 27325, command: cdpSimpleQuicksort
Running on GPU 0 (Tesla K20c)
Initializing data:
Running quicksort on 128 elements
Launching kernel on the GPU
Validating results: OK
==27325== Profiling application: cdpSimpleQuicksort
==27325== Profiling result:
Time(%)      Time  Calls (host)  Calls (device)       Avg       Min       Max  Name
 99.71%  1.2114ms             1              14  80.761us  5.1200us  145.66us  cdp_simple_quicksort(unsigned
 int*, int, int, int)
  0.18%  2.2080us             1               -  2.2080us  2.2080us  2.2080us  [CUDA memcpy DtoH]
  0.11%  1.2800us             1               -  1.2800us  1.2800us  1.2800us  [CUDA memcpy HtoD]
```

3.1.2. GPU-Trace and API-Trace Modes

GPU-Trace and API-Trace modes can be enabled individually or at the same time. GPU-trace mode provides a timeline of all activities taking place on the GPU in chronological order. Each kernel execution and memory copy/set instance is shown in the output. For each kernel or memory copy detailed information such as kernel parameters, shared memory usage and memory transfer throughput are shown. The number shown in the square brackets after the kernel name correlates to the CUDA API that launched that kernel.

Here's an example:

```
$ nvprof --print-gpu-trace matrixMul
==27706== NVPROF is profiling process 27706, command: matrixMul
==27706== Profiling application: matrixMul
[Matrix Multiply Using CUDA] - Starting...
GPU Device 0: "GeForce GT 640M LE" with compute capability 3.0

MatrixA(320,320), MatrixB(640,320)
Computing result using CUDA Kernel...
done
Performance= 35.36 GFlop/s, Time= 3.707 msec, Size= 131072000 Ops, WorkgroupSize= 1024 threads/block
Checking computed result for correctness: OK

Note: For peak performance, please refer to the matrixMulCUBLAS example.
==27706== Profiling result:
   Start  Duration            Grid Size      Block Size     Regs*    SSMem*    DSMem*      Size  Throughput
        Device   Context    Stream  Name
133.81ms  135.78us                  -               -         -         -         -  409.60KB  3.0167GB/s
 GeForce GT 640M         1         2  [CUDA memcpy HtoD]
134.62ms  270.66us                  -               -         -         -         -  819.20KB  3.0267GB/s
 GeForce GT 640M         1         2  [CUDA memcpy HtoD]
134.90ms  3.7037ms            (20 10 1)        (32 32 1)        29  8.1920KB        0B         -           -
 GeForce GT 640M         1         2  void matrixMulCUDA<int=32>(float*, float*, float*, int, int) [94]
138.71ms  3.7011ms            (20 10 1)        (32 32 1)        29  8.1920KB        0B         -           -
 GeForce GT 640M         1         2  void matrixMulCUDA<int=32>(float*, float*, float*, int, int) [105]
<...more output...>
1.24341s  3.7011ms            (20 10 1)        (32 32 1)        29  8.1920KB        0B         -           -
 GeForce GT 640M         1         2  void matrixMulCUDA<int=32>(float*, float*, float*, int, int) [2191]
1.24711s  3.7046ms            (20 10 1)        (32 32 1)        29  8.1920KB        0B         -           -
 GeForce GT 640M         1         2  void matrixMulCUDA<int=32>(float*, float*, float*, int, int) [2198]
1.25089s  248.13us                  -               -         -         -         -  819.20KB  3.3015GB/s
 GeForce GT 640M         1         2  [CUDA memcpy DtoH]

Regs: Number of registers used per CUDA thread. This number includes registers used internally by the CUDA
 driver and/or tools and can be more than what the compiler shows.
SSMem: Static shared memory allocated per CUDA block.
DSMem: Dynamic shared memory allocated per CUDA block.
```

nvprof supports CUDA Dynamic Parallelism in GPU-trace mode. For host kernel launch, the kernel ID will be shown. For device kernel launch, the kernel ID, parent kernel ID and parent block will be shown. Here's an example:

```
$nvprof --print-gpu-trace cdpSimpleQuicksort
==28128== NVPROF is profiling process 28128, command: cdpSimpleQuicksort
Running on GPU 0 (Tesla K20c)
Initializing data:
Running quicksort on 128 elements
Launching kernel on the GPU
Validating results: OK
==28128== Profiling application: cdpSimpleQuicksort
==28128== Profiling result:
   Start  Duration            Grid Size      Block Size     Regs*    SSMem*    DSMem*      Size  Throughput           Device
 Context    Stream          ID   Parent ID         Parent Block  Name
192.76ms  1.2800us                    -             -         -         -         -      512B  400.00MB/s   Tesla K20c (0)
   1         2           -           -                   -  [CUDA memcpy HtoD]
193.31ms  146.02us              (1 1 1)         (1 1 1)        32        0B        0B         -           -   Tesla K20c (0)
   1         2           2           -                   -  cdp_simple_quicksort(unsigned int*, int, int, int) [171]
193.41ms  110.53us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2          -5           2                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.45ms  125.57us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2          -6           2                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.48ms  9.2480us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2          -7          -5                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.52ms  107.23us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2          -8          -5                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.53ms  93.824us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2          -9          -6                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.57ms  117.47us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2         -10          -6                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.58ms  5.0560us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2         -11          -8                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.62ms  108.06us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2         -12          -8                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.65ms  113.34us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2         -13         -10                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.68ms  29.536us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2         -14         -12                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.69ms  22.848us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2         -15         -10                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.71ms  130.85us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2         -16         -13                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.73ms  62.432us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2         -17         -12                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.76ms  41.024us              (1 1 1)         (1 1 1)        32        0B      256B         -           -   Tesla K20c (0)
   1         2         -18         -13                (0 0 0)  cdp_simple_quicksort(unsigned int*, int, int, int)
193.92ms  2.1760us                    -             -         -         -         -      512B  235.29MB/s   Tesla K20c (0)
   1         2           -           -                   -  [CUDA memcpy DtoH]

Regs: Number of registers used per CUDA thread. This number includes registers used internally by the CUDA driver and/or tools and
 can be more than what the compiler shows.
SSMem: Static shared memory allocated per CUDA block.
DSMem: Dynamic shared memory allocated per CUDA block.
```

API-trace mode shows the timeline of all CUDA runtime and driver API calls invoked on the host in chronological order. Here's an example:

```
$nvprof --print-api-trace matrixMul
==27722== NVPROF is profiling process 27722, command: matrixMul
==27722== Profiling application: matrixMul
[Matrix Multiply Using CUDA] - Starting...
GPU Device 0: "GeForce GT 640M LE" with compute capability 3.0

MatrixA(320,320), MatrixB(640,320)
Computing result using CUDA Kernel...
done
Performance= 35.35 GFlop/s, Time= 3.708 msec, Size= 131072000 Ops, WorkgroupSize=
 1024 threads/block
Checking computed result for correctness: OK

Note: For peak performance, please refer to the matrixMulCUBLAS example.
==27722== Profiling result:
   Start  Duration  Name
108.38ms  6.2130us  cuDeviceGetCount
108.42ms     840ns  cuDeviceGet
108.42ms  22.459us  cuDeviceGetName
108.45ms  11.782us  cuDeviceTotalMem
108.46ms     945ns  cuDeviceGetAttribute
149.37ms  23.737us  cudaLaunch (void matrixMulCUDA<int=32>(float*, float*,
 float*, int, int) [2198])
149.39ms  6.6290us  cudaEventRecord
149.40ms  1.10156s  cudaEventSynchronize
<...more output...>
1.25096s  21.543us  cudaEventElapsedTime
1.25103s  1.5462ms  cudaMemcpy
1.25467s  153.93us  cudaFree
1.25483s  75.373us  cudaFree
1.25491s  75.564us  cudaFree
1.25693s  10.901ms  cudaDeviceReset
```

Due to the way the profiler is setup, the first "culnit()" driver API call is never traced.

3.1.3. Event/metric Summary Mode

To see a list of all available events on a particular NVIDIA GPU, type **`nvprof --query-events`**. To see a list of all available metrics on a particular NVIDIA GPU, type **`nvprof --query-metrics`**. **`nvprof`** is able to collect multiple events/metrics at the same time. Here's an example:

```
$ nvprof --events warps_launched,local_load --metrics ipc matrixMul
[Matrix Multiply Using CUDA] - Starting...
==6461== NVPROF is profiling process 6461, command: matrixMul
GPU Device 0: "GeForce GTX TITAN" with compute capability 3.5

MatrixA(320,320), MatrixB(640,320)
Computing result using CUDA Kernel...
==6461== Warning: Some kernel(s) will be replayed on device 0 in order to collect all events/metrics.
done
Performance= 6.39 GFlop/s, Time= 20.511 msec, Size= 131072000 Ops, WorkgroupSize= 1024 threads/block
Checking computed result for correctness: Result = PASS

NOTE: The CUDA Samples are not meant for performance measurements. Results may vary when GPU Boost is enabled.
==6461== Profiling application: matrixMul
==6461== Profiling result:
==6461== Event result:
Invocations                                Event Name         Min         Max         Avg
Device "GeForce GTX TITAN (0)"
    Kernel: void matrixMulCUDA<int=32>(float*, float*, float*, int, int)
          301                           warps_launched        6400        6400        6400
          301                               local_load           0           0           0

==6461== Metric result:
Invocations                               Metric Name                        Metric Description         Min         Max
 Avg
Device "GeForce GTX TITAN (0)"
    Kernel: void matrixMulCUDA<int=32>(float*, float*, float*, int, int)
          301                                       ipc                              Executed IPC    1.282576    1.299736
 1.291500
```

If the specified events/metrics can't be profiled in a single run of the application, **nvprof** by default replays each kernel multiple times until all the events/metrics are collected.

Option **--replay-mode <mode>** can be used to change the replay mode. In "application replay" mode, **nvprof** re-runs the whole application instead of replaying each kernel, in order to collect all events/metrics. This in some cases can be faster than kernel replay mode if the application allocates large amount of device memory. Replay can also be turned off, in which case the profiler will fail to collect some events/metrics.

To collect all events available on each device, use option **--events all**.

To collect all metrics available on each device, use option **--metrics all**.

If a large number of events or metrics are requested, no matter which replay mode is chosen, the overall application execution time may increase significantly.

3.1.4. Event/metric Trace Mode

In event/metric trace mode, event and metric values are shown for each kernel execution. By default, event and metric values are aggregated across all units in the GPU. For example, by default multiprocessor specific events are aggregated across all multiprocessors on the GPU. If **--aggregate-mode off** is specified, values of each unit are shown. For example, in the following example, the "branch" event value is shown for each multiprocessor on the GPU.

```
$ nvprof --aggregate-mode off --events local_load --print-gpu-trace matrixMul
[Matrix Multiply Using CUDA] - Starting...
==6740== NVPROF is profiling process 6740, command: matrixMul
GPU Device 0: "GeForce GTX TITAN" with compute capability 3.5

MatrixA(320,320), MatrixB(640,320)
Computing result using CUDA Kernel...
done
Performance= 16.76 GFlop/s, Time= 7.822 msec, Size= 131072000 Ops, WorkgroupSize= 1024 threads/block
Checking computed result for correctness: Result = PASS

NOTE: The CUDA Samples are not meant for performance measurements. Results may vary when GPU Boost is
 enabled.
==6740== Profiling application: matrixMul
==6740== Profiling result:
          Device           Context           Stream                Kernel  local_load (0)  local_load (1)  ...
GeForce GTX TIT                 1                7  void matrixMulCUDA<i               0               0  ...
GeForce GTX TIT                 1                7  void matrixMulCUDA<i               0               0  ...
<...more output...>
```

--aggregate-mode also applies to metrics. However some metrics are only available in aggregate mode and some are only available in non-aggregate mode.

3.2. Profiling Controls

3.2.1. Timeout

A timeout (in seconds) can be provided to **nvprof**. The CUDA application being profiled will be killed by **nvprof** after the timeout. Profiling result collected before the timeout will be shown.

Timeout starts counting from the moment the CUDA driver is initialized. If the application doesn't call any CUDA APIs, timeout won't be triggered.

3.2.2. Concurrent Kernels

Concurrent-kernel profiling is supported, and is turned on by default. To turn the feature off, use the option **--concurrent-kernels off**. This forces concurrent kernel executions to be serialized when a CUDA application is run with **nvprof**.

3.2.3. Profiling Scope

When collecting events/metrics, **nvprof** profiles all kernels launched on all visible CUDA devices by default. This profiling scope can be limited by the following options.

--devices <device IDs> applies to **--events**, **--metrics**, **--query-events** and **--query-metrics** options **that follows it**. It limits these options to collect events/metrics only on the devices specified by **<device IDs>**, which can be a list of device ID numbers separated by comma.

--kernels <kernel filter> applies to **--events** and **--metrics** options **that follows it**. It limits these options to collect events/metrics only on the kernels specified by **<kernel filter>**, which has the following syntax:

```
<kernel name>
```

or

```
<context id/name>:<stream id/name>:<kernel name>:<invocation>
```

Each string in the angle brackets can be a standard Perl regular expression. Empty string matches any number or character combination.

Invocation number *n* indicates the *n*th invocation of the kernel. If invocation is a positive number, it's strictly matched against the invocation of the kernel. Otherwise it's treated as a regular expression. Invocation number is counted separately for each kernel. So for instance **:::3** will match the 3rd invocation of every kernel.

If the context/stream string is a positive number, it's strictly matched against the cuda context/stream ID. Otherwise it's treated as a regular expression and matched against the context/stream name provided by the NVIDIA Tools Extension.

Both **--devices** and **--kernels** can be specified multiple times, with distinct events/metrics associated.

--events, **--metrics**, **--query-events** and **--query-metrics** are controlled by the nearest scope options before them.

As an example, the following command,

```
nvprof --devices 0 --metrics ipc --kernels "1:foo:bar:2" --events local_load
 a.out
```

collects metric **ipc** on all kernels launched on device 0. It also collects event **local_load** for any kernel whose name contains **bar** and is the 2nd instance launched on context 1 and on stream named **foo** on device 0.

3.2.4. Multiprocess Profiling

By default, **nvprof** only profiles the application specified by the command-line argument. It doesn't trace child processes launched by that process. To profile all processes launched by an application, use the **--profile-child-process** option.

nvprof cannot profile processes that **fork()** but do not then **exec()**.

nvprof also has a "profile all processes" mode, in which it profiles every CUDA process launched on the same system by the same user who launched **nvprof**. Exit this mode by typing "Ctrl-c".

3.2.5. System Profiling

For devices that support system profiling, nvprof can enable low frequency sampling of the power, clock, and thermal behavior of each GPU used by the application. This feature is turned off by default. To turn on this feature, use **--system-profiling on**. To see the detail of each sample point, combine the above option with **--print-gpu-trace**.

3.2.6. Unified Memory Profiling

For devices that support Unified Memory, **nvprof** collects the Unified Memory related memory traffic to and from each GPU on your system. This feature is turned off by default. To turn on this feature, use **--unified-memory-profiling <per-process-device|off>**. To see the detail of each memory transfer, combine the above option with **--print-gpu-trace**.

On multi-GPU configurations without P2P support between any pair of devices that support Unified Memory, managed memory allocations are placed in zero-copy memory. In this case Unified Memory profiling is not supported. In certain cases, the environment variable **CUDA_MANAGED_FORCE_DEVICE_ALLOC** can be set to force managed allocations to be in device memory and to enable migration on these hardware configurations. In this case Unified Memory profiling is supported. Normally, using the environment variable **CUDA_VISIBLE_DEVICES** is recommended to restrict CUDA to

only use those GPUs that have P2P support. Please refer to the environment variables section in the CUDA C Programming Guide for further details.

3.3. Output

3.3.1. Adjust Units

By default, **nvprof** adjusts the time units automatically to get the most precise time values. The **--normalized-time-unit** options can be used to get fixed time units throughout the results.

3.3.2. CSV

For each profiling mode, option **--csv** can be used to generate output in comma-separated values (CSV) format. The result can be directly imported to spreadsheet software such as Excel.

3.3.3. Export/Import

For each profiling mode, option **--export-profile** can be used to generate a result file. This file is not human-readable, but can be imported to **nvprof** using the option **--import-profile**, or into the Visual Profiler.

The profilers use SQLite as the format of the export profiles. Writing files in such format may require more disk operations than writing a plain file. Thus, exporting profiles to slower devices such as a network drive may slow down the execution of the application.

3.3.4. Demangling

By default, **nvprof** demangles C++ function names. Use option **--demangling off** to turn this feature off.

3.3.5. Redirecting Output

By default, **nvprof** sends most of its output to **stderr**. To redirect the output, use **--log-file**. **--log-file %1** tells **nvprof** to redirect all output to **stdout**. **--log-file <filename>** redirects output to a file. Use **%p** in the filename to be replaced by the process ID of **nvprof**, **%h** by the hostname , **%q{ENV}** by the value of environment variable **ENV**, and **%%** by **%**.

3.4. CPU Sampling

Sometimes it's useful to profile the CPU portion of your application, in order to better understand the bottlenecks and identify potential hotspots for the entire CUDA application. For the CPU portion of the application, **nvprof** is able to sample the

program counter and call stacks at a certain frequency. The data is then used to construct a graph, with nodes being frames in each call stack. Function and library symbols are also extracted if available. A sample graph is shown below:

```
======== CPU profiling result (bottom up):
45.45% cuInit
| 45.45% cudart::globalState::loadDriverInternal(void)
|   45.45% cudart::__loadDriverInternalUtil(void)
|     45.45% pthread_once
|       45.45% cudart::cuosOnce(int*, void (*) (void))
|         45.45% cudart::globalState::loadDriver(void)
|           45.45% cudart::globalState::initializeDriver(void)
|             45.45% cudaMalloc
|               45.45% main
33.33% cuDevicePrimaryCtxRetain
| 33.33% cudart::contextStateManager::initPrimaryContext(cudart::device*)
|   33.33% cudart::contextStateManager::tryInitPrimaryContext(cudart::device*)
|     33.33% cudart::contextStateManager::initDriverContext(void)
|       33.33% cudart::contextStateManager::getRuntimeContextState(cudart::contextState**, bool)
|         33.33% cudart::getLazyInitContextState(cudart::contextState**)
|           33.33% cudart::doLazyInitContextState(void)
|             33.33% cudart::cudaApiMalloc(void**, unsigned long)
|               33.33% cudaMalloc
|                 33.33% main
18.18% cuDevicePrimaryCtxReset
| 18.18% cudart::device::resetPrimaryContext(void)
|   18.18% cudart::cudaApiThreadExit(void)
|     18.18% cudaThreadExit
|       18.18% main
3.03% cudbgGetAPIVersion
  3.03% start_thread
    3.03% clone
```

The graph can be presented in different "views" (**`top-down`**, **`bottom-up`** or **`flat`**), allowing the user to analyze the sampling data from different perspectives. For instance, the **`bottom-up`** view (shown above) can be useful in identifying the "hot" functions in which the application is spending most of its time. The **`top-down`** view gives a break-down of the application execution time, starting from the **`main`** function, allowing you to find "call paths" which are executed frequently.

By default the CPU sampling feature is disabled. To enable it, use the option **`--cpu-profiling on`**. The next section describes all the options controlling the CPU sampling behavior.

CPU sampling is supported on Linux, Mac OS and Windows for Intel x86/x86_64 architecture, and IBM Power 8 architecture.

When using the CPU profiling feature on POSIX systems, the profiler samples the application by sending periodic signals. Applications should therefore ensure that system calls are handled appropriately when interrupted.

On Windows, nvprof requires Visual Studio installation (2010 or later) and compiler-generated .PDB (program database) files to resolve symbol information. When building your application, ensure that .PDB files are created and placed next to the profiled executable and libraries.

3.4.1. CPU Sampling Options

Table 1 contains CPU sampling related command-line options of **`nvprof`**, along with a description of what each option does. Most of the generic options (e.g. export/import) work with CPU sampling too.

Table 1 CPU Sampling Options

Option	Description
`--cpu-profiling <on|off>`	Turn on CPU profiling. Note: CPU profiling is not supported in multi-process mode.
`--cpu-profiling-frequency <frequency>`	Set the CPU profiling frequency, in samples per second. The maximum value is 500.
`--cpu-profiling-scope <scope>`	Choose the profiling scope. Allowed values: "function" - Each level in the stack trace represents a distinct function (default). "instruction" - Each level in the stack trace represents a distinct instruction address.
`--cpu-profiling-max-depth <depth>`	Set the maximum depth of each call stack. Zero means no limit. Default is zero.
`--cpu-profiling-mode <mode>`	Set the output mode of CPU profiling. Allowed values: "top-down" - Show parent functions at the top. "bottom-up" - Show parent functions at the bottom (default). "flat" - Show flat profile.
`--cpu-profiling-percentage-threshold <threshold>`	Filter out the entries that are below the set percentage threshold. The limit should be an integer between 0 and 100, inclusive. Zero means no limit. Default is zero.
`--cpu-profiling-show-ccff <on|off>`	Whether to print Common Compiler Feedback Format (CCFF) messages embedded in the binary. Note: this option implies "--cpu-profiling-scope instruction".
`--cpu-profiling-thread-mode <mode>`	Set the thread mode of CPU profiling. Allowed values: "separated" - Show separate profile for each thread. "aggregated" - Aggregate data from all threads.

3.4.2. CPU Sampling Limitations

The following are known issues with the current release.

- CPU sampling is currently not supported in multi-process profiling mode.
- The result stack traces might not be complete under some compiler optimizations, notably frame pointer omission and function inlining.
- The CPU sampling result doesn't support CSV mode.
- On Mac OSX, the profiler may hang in a rare case.

Chapter 4. COMMAND LINE PROFILER

The Command Line Profiler is a profiling tool that can be used to measure performance and find potential opportunities for optimization for CUDA applications executing on NVIDIA GPUs. The command line profiler allows users to gather timing information about kernel execution and memory transfer operations. Profiling options are controlled through environment variables and a profiler configuration file. Profiler output is generated in text files either in Key-Value-Pair (KVP) or Comma Separated (CSV) format.

4.1. Command Line Profiler Control

The command line profiler is controlled using the following environment variables:

COMPUTE_PROFILE: is set to either 1 or 0 (or unset) to enable or disable profiling.

COMPUTE_PROFILE_LOG: is set to the desired file path for profiling output. In case of multiple contexts you must add '%d' in the COMPUTE_PROFILE_LOG name. This will generate separate profiler output files for each context - with '%d' substituted by the context number. Contexts are numbered starting with zero. In case of multiple processes you must add '%p' in the COMPUTE_PROFILE_LOG name. This will generate separate profiler output files for each process - with '%p' substituted by the process id. If there is no log path specified, the profiler will log data to "cuda_profile_%d.log" in case of a CUDA context ('%d' is substituted by the context number).

COMPUTE_PROFILE_CSV: is set to either 1 (set) or 0 (unset) to enable or disable a comma separated version of the log output.

COMPUTE_PROFILE_CONFIG: is used to specify a config file for selecting profiling options and performance counters.

Configuration details are covered in a subsequent section.

The following old environment variables used for the above functionalities are still supported:

CUDA_PROFILE

CUDA_PROFILE_LOG

CUDA_PROFILE_CSV

CUDA_PROFILE_CONFIG

4.2. Command Line Profiler Default Output

Table 2 describes the columns that are output in the profiler log by default.

Table 2 Command Line Profiler Default Columns

Column	Description
method	This is character string which gives the name of the GPU kernel or memory copy method. In case of kernels the method name is the mangled name generated by the compiler.
gputime	This column gives the execution time for the GPU kernel or memory copy method. This value is calculated as (gpuendtimestamp - gpustarttimestamp)/1000.0. The column value is a single precision floating point value in microseconds.
cputime	For non-blocking methods the cputime is only the CPU or host side overhead to launch the method. In this case: walltime = cputime + gputime For blocking methods cputime is the sum of gputime and CPU overhead. In this case: walltime = cputime Note all kernel launches by default are non-blocking. But if any of the profiler counters are enabled kernel launches are blocking. Also asynchronous memory copy requests in different streams are non-blocking. The column value is a single precision floating point value in microseconds.
occupancy	This column gives the multiprocessor occupancy which is the ratio of number of active warps to the maximum number of warps supported on a multiprocessor of the GPU. This is helpful in determining how effectively the GPU is kept busy. This column is output only for GPU kernels and the column value is a single precision floating point value in the range 0.0 to 1.0.

4.3. Command Line Profiler Configuration

The profiler configuration file is used to select the profiler options and counters which are to be collected during application execution. The configuration file is a simple format text file with one option on each line. Options can be commented out using the **#** character at the start of a line. Refer the command line profiler options table for the column names in the profiler output for each profiler configuration option.

4.3.1. Command Line Profiler Options

Table 3 contains the options supported by the command line profiler. Note the following regarding the profiler log that is produced from the different options:

- Typically, each profiler option corresponds to a single column is output. There are a few exceptions in which case multiple columns are output; these are noted where applicable in Table 3.
- In most cases the column name is the same as the option name; the exceptions are listed in Table 3.
- In most cases the column values are 32-bit integers in decimal format; the exceptions are listed in Table 3.

Table 3 Command Line Profiler Options

Option	Description
gpustarttimestamp	Time stamp when a kernel or memory transfer starts. The column values are 64-bit unsigned value in nanoseconds in hexadecimal format.
gpuendtimestamp	Time stamp when a kernel or memory transfer completes. The column values are 64-bit unsigned value in nanoseconds in hexadecimal format.
timestamp	Time stamp when a kernel or memory transfer starts. The column values are single precision floating point value in microseconds. Use of the gpustarttimestamp column is recommended as this provides a more accurate time stamp.
gridsize	Number of blocks in a grid along the X and Y dimensions for a kernel launch. This option outputs the following two columns: ▸ gridsizeX ▸ gridsizeY
gridsize3d	Number of blocks in a grid along the X, Y and Z dimensions for a kernel launch. This option outputs the following three columns: ▸ gridsizeX ▸ gridsizeY ▸ gridsizeZ
threadblocksize	Number of threads in a block along the X, Y and Z dimensions for a kernel launch. This option outputs the following three columns: ▸ threadblocksizeX ▸ threadblocksizeY ▸ threadblocksizeZ

Option	Description
dynsmemperblock	Size of dynamically allocated shared memory per block in bytes for a kernel launch. (Only CUDA)
stasmemperblock	Size of statically allocated shared memory per block in bytes for a kernel launch.
regperthread	Number of registers used per thread for a kernel launch.
memtransferdir	Memory transfer direction, a direction value of 0 is used for host to device memory copies and a value of 1 is used for device to host memory copies.
memtransfersize	Memory transfer size in bytes. This option shows the amount of memory transferred between source (host/device) to destination (host/device).
memtransferhostmemtype	Host memory type (pageable or page-locked). This option implies whether during a memory transfer, the host memory type is pageable or page-locked.
streamid	Stream Id for a kernel launch or a memory transfer.
localblocksize	This option is no longer supported and if it is selected all values in the column will be -1. This option outputs the following column: ▸ localworkgroupsize
cacheconfigrequested	Requested cache configuration option for a kernel launch: ▸ 0 CU_FUNC_CACHE_PREFER_NONE - no preference for shared memory or L1 (default) ▸ 1 CU_FUNC_CACHE_PREFER_SHARED - prefer larger shared memory and smaller L1 cache ▸ 2 CU_FUNC_CACHE_PREFER_L1 - prefer larger L1 cache and smaller shared memory ▸ 3 CU_FUNC_CACHE_PREFER_EQUAL - prefer equal sized L1 cache and shared memory
cacheconfigexecuted	Cache configuration which was used for the kernel launch. The values are same as those listed under cacheconfigrequested.

cudadevice <device_index>	This can be used to select different counters for different CUDA devices. All counters after this option are selected only for a CUDA device with index <device_index>.
	<device_index> is an integer value specifying the CUDA device index.
	Example: To select counterA for all devices, counterB for CUDA device 0 and counterC for CUDA device 1:
	`counterA`
	`cudadevice 0`
	`counterB`
	`cudadevice 1`
	`counterC`

profilelogformat [CSV|KVP]	Choose format for profiler log. ▸ CSV: Comma separated format ▸ KVP: Key Value Pair format

Option	Description
	The default format is KVP. This option will override the format selected using the environment variable COMPUTE_PROFILE_CSV.
countermodeaggregate	If this option is selected then aggregate counter values will be output. For a SM counter the counter value is the sum of the counter values from all SMs. For l1*, tex*, sm_cta_launched, uncached_global_load_transaction and global_store_transaction counters the counter value is collected for 1 SM from each GPC and it is extrapolated for all SMs. This option is supported only for CUDA devices with compute capability 2.0 or higher.
conckerneltrace	This option should be used to get gpu start and end timestamp values in case of concurrent kernels. Without this option execution of concurrent kernels is serialized and the timestamps are not correct. Only CUDA devices with compute capability 2.0 or higher support execution of multiple kernels concurrently. When this option is enabled additional code is inserted for each kernel and this will result in some additional execution overhead. This option cannot be used along with profiler counters. In case some counter is given in the configuration file along with "conckerneltrace" then a warning is printed in the profiler output file and the counter will not be enabled.
enableonstart 0|1	Use **`enableonstart 1`** option to enable or **`enableonstart 0`** to disable profiling from the start of application execution. If this option is not used then by default profiling is enabled from the start. To limit profiling to a region of your application, CUDA provides functions to start and stop profile data collection. **`cudaProfilerStart()`** is used to start profiling and **`cudaProfilerStop()`** is used to stop profiling (using the CUDA driver API, you get the same functionality with **`cuProfilerStart()`** and **`cuProfilerStop()`**). When using the start and stop functions, you also need to instruct the profiling tool to disable profiling at the start of the application. For command line profiler you do this by adding **`enableonstart 0`** in the profiler configuration file.

4.3.2. Command Line Profiler Counters

The command line profiler supports logging of event counters during kernel execution. The list of available events can be found using **`nvprof --query-events`** as described in Event/metric Summary Mode. The event name can be used in the command line profiler configuration file. In every application run only a few counter values can be collected. The number of counters depends on the specific counters selected.

4.4. Command Line Profiler Output

If the **`COMPUTE_PROFILE`** environment variable is set to enable profiling, the profiler log records timing information for every kernel launch and memory operation performed by the driver.

Example 1: CUDA Default Profiler Log- No Options or Counters Enabled (File name: cuda_profile_0.log) shows the profiler log for a CUDA application with no profiler configuration file specified.

Example 1: CUDA Default Profiler Log- No Options or Counters Enabled (File name: `cuda_profile_0.log`)

```
# CUDA_PROFILE_LOG_VERSION 2.0
# CUDA_DEVICE 0 Tesla C2075
# CUDA_CONTEXT 1
# TIMESTAMPFACTOR fffff6de60e24570
method,gputime,cputime,occupancy
method=[ memcpyHtoD ] gputime=[ 80.640 ] cputime=[ 278.000 ]
method=[ memcpyHtoD ] gputime=[ 79.552 ] cputime=[ 237.000 ]
method=[ _Z6VecAddPKfS0_Pfi ] gputime=[ 5.760 ] cputime=[ 18.000 ]
 occupancy=[ 1.000 ]
method=[ memcpyDtoH ] gputime=[ 97.472 ] cputime=[ 647.000 ]
```

The log above in Example 1: CUDA Default Profiler Log- No Options or Counters Enabled (File name: cuda_profile_0.log) shows data for memory copies and a kernel launch. The **`method`** label specifies the name of the memory copy method or kernel executed. The **`gputime`** and **`cputime`** labels specify the actual chip execution time and the driver execution time, respectively. Note that **`gputime`** and **`cputime`** are in microseconds. The 'occupancy' label gives the ratio of the number of active warps per multiprocessor to the maximum number of active warps for a particular kernel launch. This is the theoretical occupancy and is calculated using kernel block size, register usage and shared memory usage.

Example 2: CUDA Profiler Log- Options and Counters Enabled shows the profiler log of a CUDA application. There are a few options and counters enabled in this example using the profiler configuration file:

```
gpustarttimestamp
gridsize3d
threadblocksize
dynsmemperblock
stasmemperblock
regperthread
memtransfersize
memtransferdir
streamid
countermodeaggregate
active_warps
active_cycles
```

Example 2: CUDA Profiler Log- Options and Counters Enabled

```
# CUDA_PROFILE_LOG_VERSION 2.0
# CUDA_DEVICE 0 Tesla C2075
# CUDA_CONTEXT 1
# TIMESTAMPFACTOR fffff6de5e08e990
gpustarttimestamp,method,gputime,cputime,gridsizeX,gridsizeY,gridsizeZ,
 threadblocksizeX,threadblocksizeY,threadblocksizeZ,dynsmemperblock,
 stasmemperblock,regperthread,occupancy,streamid,active_warps,
 active_cycles,memtransfersize,memtransferdir
gpustarttimestamp=[ 124b9e484b6f3f40 ] method=[ memcpyHtoD ] gputime=[ 80.800 ]
 cputime=[ 280.000 ] streamid=[ 1 ] memtransfersize=[ 200000 ]
 memtransferdir=[ 1 ]
gpustarttimestamp=[ 124b9e484b7517a0 ] method=[ memcpyHtoD ] gputime=[ 79.744 ]
 cputime=[ 232.000 ] streamid=[ 1 ] memtransfersize=[ 200000 ]
 memtransferdir=[ 1 ]
gpustarttimestamp=[ 124b9e484b8fd8e0 ] method=[ _Z6VecAddPKfS0_Pfi ]
 gputime=[ 10.016 ] cputime=[ 57.000 ] gridsize=[ 196, 1, 1 ]
 threadblocksize=[ 256, 1, 1 ] dynsmemperblock=[ 0 ] stasmemperblock=[ 0 ]
 regperthread=[ 4 ] occupancy=[ 1.000 ] streamid=[ 1 ]active_warps=[ 1545830 ]
 active_cycles=[ 40774 ]
gpustarttimestamp=[ 124b9e484bb5a2c0 ] method=[ memcpyDtoH ] gputime=[ 98.528 ]
 cputime=[ 672.000 ] streamid=[ 1 ] memtransfersize=[ 200000 ]
 memtransferdir=[ 2 ]
```

The default log syntax is easy to parse with a script, but for spreadsheet analysis it might be easier to use the comma separated format.

When **COMPUTE_PROFILE_CSV** is set to 1, this same test produces the output log shown in Example 3: CUDA Profiler Log- Options and Counters Enabled in CSV Format.

Example 3: CUDA Profiler Log- Options and Counters Enabled in CSV Format

```
# CUDA_PROFILE_LOG_VERSION 2.0
# CUDA_DEVICE 0 Tesla C2075
# CUDA_CONTEXT 1
# CUDA_PROFILE_CSV 1
# TIMESTAMPFACTOR fffff6de5d77a1c0
gpustarttimestamp,method,gputime,cputime,gridsizeX,gridsizeY,gridsizeZ,
 threadblocksizeX,threadblocksizeY,threadblocksizeZ,dynsmemperblock,
 stasmemperblock,regperthread,occupancy,streamid,active_warps,
 active_cycles,memtransfersize,memtransferdir
124b9e85038d1800,memcpyHtoD,80.352,286.000,,,,,,,,,,1,,,200000,1
124b9e850392ee00,memcpyHtoD,79.776,232.000,,,,,,,,,,1,,,200000,1
124b9e8503af7460,_Z6VecAddPKfS0_Pfi,10.048,59.000,196,1,1,256,1,1,0,
 0,4,1.000,1,1532814,42030
```

Chapter 5. REMOTE PROFILING

Remote profiling is the process of collecting profile data from a *remote* system that is different than the *host* system at which that profile data will be viewed and analyzed. There are two ways to perform remote profiling. You can profile your remote application directly from **nsight** or **nvvp**. Or you can use **nvprof** to collect the profile data on the remote system and then use **nvvp** on the host system to view and analyze the data.

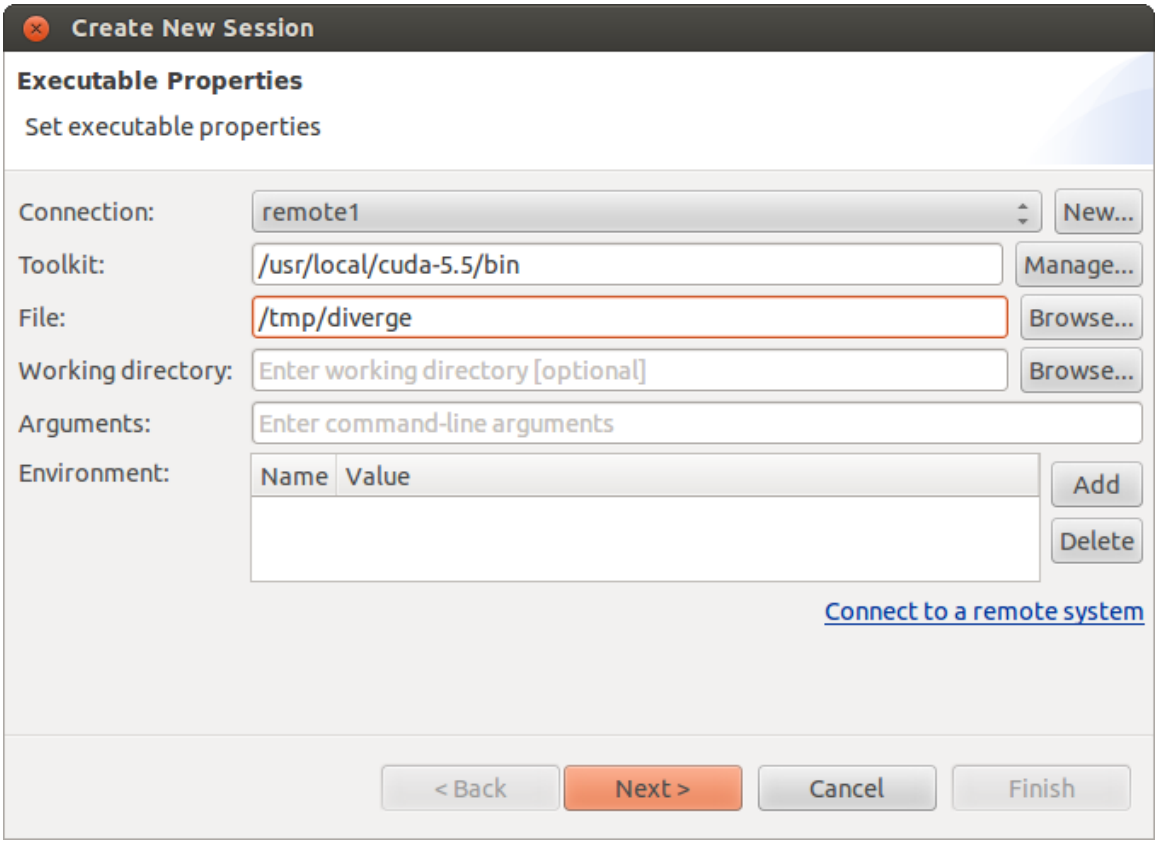
5.1. Remote Profiling With Visual Profiler

This section describes how to perform remote profiling by using the remote capabilities of **nsight** and **nvvp**.

Nsight Eclipse Edition supports full remote development including remote building, debugging, and profiling. Using these capabilities you can create a project and launch configuration that allows you to remotely profile your application. See the Nsight Eclipse Edition documentation for more information.

nvvp also enables remote profiling. As shown in the following figure, when creating a new session or editing an existing session you can specify that the application being profiled resides on a remote system. Once you have configured your session to use a remote application, you can perform all Visual Profiler functions in the same way as you would with a local application, including timeline generation, guided analysis, and event and metric collection.

To use **nvvp** remote profiling you must install the same version of the CUDA Toolkit on both the host and remote systems. It is not necessary for the host system to have an NVIDIA GPU. The host and remote systems may run different operating systems or have different CPU architectures. Only a remote system running Linux is supported. The remote system must be accessible via SSH.



5.2. Remote Profiling With **nvprof**

This section describes how to perform remote profiling by running **nvprof** manually on the remote system and then importing the collected profile data into **nvvp**.

5.2.1. Collect Data On Remote System

There are three common remote profiling use cases that can be addressed by using **nvprof** and **nvvp**.

Timeline

The first use case is to collect a timeline of the application executing on the remote system. The timeline should be collected in a way that most accurately reflects the behavior of the application. To collect the timeline execute the following on the remote system. See nvprof for more information on **nvprof** options.

```
$ nvprof --export-profile timeline.nvprof <app> <app args>
```

The profile data will be collected in `timeline.nvprof`. You should copy this file back to the host system and then import it into **nvvp** as described in the next section.

Metrics And Events

The second use case is to collect events or metrics for all kernels in an application for which you have already collected a timeline. Collecting events or metrics for all kernels will significantly change the overall performance characteristics of the application because all kernel executions will be serialized on the GPU. Even though overall application performance is changed, the event or metric values for individual kernels will be correct and so you can merge the collected event and metric values onto a previously collected timeline to get an accurate picture of the applications behavior. To collect events or metrics you use the **--events** or **--metrics** flag. The following shows an example using just the **--metrics** flag to collect two metrics.

```
$ nvprof --metrics achieved_occupancy,executed_ipc -o metrics.nvprof <app> <app
 args>
```

You can collect any number of events and metrics for each **nvprof** invocation, and you can invoke **nvprof** multiple times to collect multiple `metrics.nvprof` files. To get accurate profiling results, it is important that your application conform to the requirements detailed in Application Requirements.

The profile data will be collected in the `metrics.nvprof` file(s). You should copy these files back to the host system and then import it into **nvvp** as described in the next section.

Guided Analysis For Individual Kernel

The third common remote profiling use case is to collect the metrics needed by the guided analysis system for an individual kernel. When imported into **nvvp** this data will enable the guided analysis system to analyze the kernel and report optimization opportunities for that kernel. To collect the guided analysis data execute the following on the remote system. It is important that the **--kernels** option appear before the **--analysis-metrics** option so that metrics are collected only for the kernel(s) specified by **kernel specifier**. See Profiling Scope for more information on the **--kernels** option.

```
$ nvprof --kernels <kernel specifier> --analysis-metrics -o analysis.nvprof
 <app> <app args>
```

The profile data will be collected in `analysis.nvprof`. You should copy this file back to the host system and then import it into **nvvp** as described in the next section.

5.2.2. View And Analyze Data

The collected profile data is viewed and analyzed by importing it into **nvvp** on the host system. See Import Session for more information about importing.

Timeline, Metrics And Events

To view collected timeline data, the `timeline.nvprof` file can be imported into **nvvp** as described in Import Single-Process nvprof Session. If metric or event data was also collected for the application, the corresponding `metrics.nvprof` file(s) can be imported into **nvvp** along with the timeline so that the events and metrics collected for each kernel are associated with the corresponding kernel in the timeline.

Guided Analysis For Individual Kernel

To view collected analysis data for an individual kernel, the `analysis.nvprof` file can be imported into **nvvp** as described in Import Single-Process nvprof Session. The `analysis.nvprof` must be imported by itself. The timeline will show just the individual kernel that we specified during data collection. After importing, the guided analysis system can be used to explore the optimization opportunities for the kernel.

Chapter 6. NVIDIA TOOLS EXTENSION

NVIDIA Tools Extension (NVTX) is a C-based Application Programming Interface (API) for annotating events, code ranges, and resources in your applications. Applications which integrate NVTX can use the Visual Profiler to capture and visualize these events and ranges. The NVTX API provides two core services:

1. Tracing of CPU events and time ranges.
2. Naming of OS and CUDA resources.

NVTX can be quickly integrated into an application. The sample program below shows the use of marker events, range events, and resource naming.

```
void Wait(int waitMilliseconds) {
  nvtxNameOsThread(“MAIN”);
  nvtxRangePush(__FUNCTION__);
  nvtxMark("Waiting...");
  Sleep(waitMilliseconds);
  nvtxRangePop();
}

int main(void) {
  nvtxNameOsThread("MAIN");
  nvtxRangePush(__FUNCTION__);
  Wait();
  nvtxRangePop();
}
```

6.1. NVTX API Overview

Files

The core NVTX API is defined in file nvToolsExt.h, whereas CUDA-specific extensions to the NVTX interface are defined in nvToolsExtCuda.h and nvToolsExtCudaRt.h. On Linux the NVTX shared library is called **`libnvToolsExt.so`** and on Mac OSX the shared library is called **`libnvToolsExt.dylib`**. On Windows the library (.lib) and runtime components (.dll) are named **`nvToolsExt[bitness=32|64]_[version].{dll|lib}`**.

Function Calls

All NVTX API functions start with an nvtx name prefix and may end with one out of the three suffixes: A, W, or Ex. NVTX functions with these suffixes exist in multiple variants, performing the same core functionality with different parameter encodings. Depending on the version of the NVTX library, available encodings may include ASCII (A), Unicode (W), or event structure (Ex).

The CUDA implementation of NVTX only implements the ASCII (A) and event structure (Ex) variants of the API, the Unicode (W) versions are not supported and have no effect when called.

Return Values

Some of the NVTX functions are defined to have return values. For example, the **`nvtxRangeStart()`** function returns a unique range identifier and **`nvtxRangePush()`** function outputs the current stack level. It is recommended not to use the returned values as part of conditional code in the instrumented application. The returned values can differ between various implementations of the NVTX library and, consequently, having added dependencies on the return values might work with one tool, but may fail with another.

6.2. NVTX API Events

Markers are used to describe events that occur at a specific time during the execution of an application, while ranges detail the time span in which they occur. This information is presented alongside all of the other captured data, which makes it easier to understand the collected information. All markers and ranges are identified by a message string. The Ex version of the marker and range APIs also allows category, color, and payload attributes to be associated with the event using the event attributes structure.

6.2.1. NVTX Markers

A marker is used to describe an instantaneous event. A marker can contain a text message or specify additional information using the event attributes structure. Use **`nvtxMarkA`** to create a marker containing an ASCII message. Use **`nvtxMarkEx()`** to create a marker containing additional attributes specified by the event attribute structure. The **`nvtxMarkW()`** function is not supported in the CUDA implementation of NVTX and has no effect if called.

Code Example

```
nvtxMarkA("My mark");

nvtxEventAttributes_t eventAttrib = {0};
eventAttrib.version = NVTX_VERSION;
eventAttrib.size = NVTX_EVENT_ATTRIB_STRUCT_SIZE;
eventAttrib.colorType = NVTX_COLOR_ARGB;
eventAttrib.color = COLOR_RED;
eventAttrib.messageType = NVTX_MESSAGE_TYPE_ASCII;
eventAttrib.message.ascii = "my mark with attributes";
nvtxMarkEx(&eventAttrib);
```

6.2.2. NVTX Range Start/Stop

A start/end range is used to denote an arbitrary, potentially non-nested, time span. The start of a range can occur on a different thread than the end of the range. A range can contain a text message or specify additional information using the event attributes structure. Use **`nvtxRangeStartA()`** to create a marker containing an ASCII message. Use **`nvtxRangeStartEx()`** to create a range containing additional attributes specified by the event attribute structure. The **`nvtxRangeStartW()`** function is not supported in the CUDA implementation of NVTX and has no effect if called. For the correlation of a start/end pair, a unique correlation ID is created that is returned from **`nvtxRangeStartA()`** or **`nvtxRangeStartEx()`**, and is then passed into **`nvtxRangeEnd()`**.

Code Example

```
// non-overlapping range
nvtxRangeId_t id1 = nvtxRangeStartA("My range");
nvtxRangeEnd(id1);

nvtxEventAttributes_t eventAttrib = {0};
eventAttrib.version = NVTX_VERSION;
eventAttrib.size = NVTX_EVENT_ATTRIB_STRUCT_SIZE;
eventAttrib.colorType = NVTX_COLOR_ARGB;
eventAttrib.color = COLOR_BLUE;
eventAttrib.messageType = NVTX_MESSAGE_TYPE_ASCII;
eventAttrib.message.ascii = "my start/stop range";
nvtxRangeId_t id2 = nvtxRangeStartEx(&eventAttrib);
nvtxRangeEnd(id2);

// overlapping ranges
nvtxRangeId_t r1 = nvtxRangeStartA("My range 0");
nvtxRangeId_t r2 = nvtxRangeStartA("My range 1");
nvtxRangeEnd(r1);
nvtxRangeEnd(r2);
```

6.2.3. NVTX Range Push/Pop

A push/pop range is used to denote nested time span. The start of a range must occur on the same thread as the end of the range. A range can contain a text message or specify additional information using the event attributes structure. Use **`nvtxRangePushA()`** to create a marker containing an ASCII message. Use **`nvtxRangePushEx()`** to create a range containing additional attributes specified by the event attribute structure. The

nvtxRangePushW() function is not supported in the CUDA implementation of NVTX and has no effect if called. Each push function returns the zero-based depth of the range being started. The **nvtxRangePop()** function is used to end the most recently pushed range for the thread. **nvtxRangePop()** returns the zero-based depth of the range being ended. If the pop does not have a matching push, a negative value is returned to indicate an error.

Code Example

```
nvtxRangePushA("outer");
nvtxRangePushA("inner");
nvtxRangePop();  // end "inner" range
nvtxRangePop();  // end "outer" range

nvtxEventAttributes_t eventAttrib = {0};
eventAttrib.version = NVTX_VERSION;
eventAttrib.size = NVTX_EVENT_ATTRIB_STRUCT_SIZE;
eventAttrib.colorType = NVTX_COLOR_ARGB;
eventAttrib.color = COLOR_GREEN;
eventAttrib.messageType = NVTX_MESSAGE_TYPE_ASCII;
eventAttrib.message.ascii = "my push/pop range";
nvtxRangePushEx(&eventAttrib);
nvtxRangePop();
```

6.2.4. Event Attributes Structure

The events attributes structure, **nvtxEventAttributes_t**, is used to describe the attributes of an event. The layout of the structure is defined by a specific version of NVTX and can change between different versions of the Tools Extension library.

Attributes

Markers and ranges can use attributes to provide additional information for an event or to guide the tool's visualization of the data. Each of the attributes is optional and if left unspecified, the attributes fall back to a default value.

Message

The message field can be used to specify an optional string. The caller must set both the **messageType** and **message** fields. The default value is **NVTX_MESSAGE_UNKNOWN**. The CUDA implementation of NVTX only supports ASCII type messages.

Category

The category attribute is a user-controlled ID that can be used to group events. The tool may use category IDs to improve filtering, or for grouping events. The default value is 0.

Color

The color attribute is used to help visually identify events in the tool. The caller must set both the **colorType** and **color** fields.

Payload

The payload attribute can be used to provide additional data for markers and ranges. Range events can only specify values at the beginning of a range. The caller must specify valid values for both the **payloadType** and **payload** fields.

Initialization

The caller should always perform the following three tasks when using attributes:

- Zero the structure
- Set the version field
- Set the size field

Zeroing the structure sets all the event attributes types and values to the default value. The version and size field are used by NVTX to handle multiple versions of the attributes structure.

It is recommended that the caller use the following method to initialize the event attributes structure.

```
nvtxEventAttributes_t eventAttrib = {0};
eventAttrib.version = NVTX_VERSION;
eventAttrib.size = NVTX_EVENT_ATTRIB_STRUCT_SIZE;
eventAttrib.colorType = NVTX_COLOR_ARGB;
eventAttrib.color = ::COLOR_YELLOW;
eventAttrib.messageType = NVTX_MESSAGE_TYPE_ASCII;
eventAttrib.message.ascii = "My event";
nvtxMarkEx(&eventAttrib);
```

6.3. NVTX Resource Naming

NVTX resource naming allows custom names to be associated with host OS threads and CUDA resources such as devices, contexts, and streams. The names assigned using NVTX are displayed by the Visual Profiler.

OS Thread

The **nvtxNameOsThreadA()** function is used to name a host OS thread. The **nvtxNameOsThreadW()** function is not supported in the CUDA implementation of NVTX and has no effect if called. The following example shows how the current host OS thread can be named.

```
// Windows
nvtxNameOsThread(GetCurrentThreadId(), "MAIN_THREAD");

// Linux/Mac
nvtxNameOsThread(pthread_self(), "MAIN_THREAD");
```

CUDA Runtime Resources

The **nvtxNameCudaDeviceA()** and **nvtxNameCudaStreamA()** functions are used to name CUDA device and stream objects, respectively. The **nvtxNameCudaDeviceW()** and **nvtxNameCudaStreamW()** functions are not supported in the CUDA implementation of NVTX and have no effect if called. The **nvtxNameCudaEventA()** and **nvtxNameCudaEventW()** functions are also not supported. The following example shows how a CUDA device and stream can be named.

```
nvtxNameCudaDeviceA(0, "my cuda device 0");

cudaStream_t cudastream;
cudaStreamCreate(&cudastream);
nvtxNameCudaStreamA(cudastream, "my cuda stream");
```

CUDA Driver Resources

The **nvtxNameCuDeviceA()**, **nvtxNameCuContextA()** and **nvtxNameCuStreamA()** functions are used to name CUDA driver device, context and stream objects, respectively. The **nvtxNameCuDeviceW()**, **nvtxNameCuContextW()** and **nvtxNameCuStreamW()** functions are not supported in the CUDA implementation of NVTX and have no effect if called. The **nvtxNameCuEventA()** and **nvtxNameCuEventW()** functions are also not supported. The following example shows how a CUDA device, context and stream can be named.

```
CUdevice device;
cuDeviceGet(&device, 0);
nvtxNameCuDeviceA(device, "my device 0");

CUcontext context;
cuCtxCreate(&context, 0, device);
nvtxNameCuContextA(context, "my context");

cuStream stream;
cuStreamCreate(&stream, 0);
nvtxNameCuStreamA(stream, "my stream");
```

Chapter 7. MPI PROFILING

The nvprof profiler and the Command Line Profiler can be used to profile individual MPI processes. The resulting output can be used directly, or can be imported into the Visual Profiler.

7.1. MPI Profiling With nvprof

To use nvprof to collect the profiles of the individual MPI processes, you must tell **nvprof** to send its output to unique files. In CUDA 5.0 and earlier versions, it was recommended to use a script for this. However, you can now easily do it utilizing the **%h** , **%p** and **%q{ENV}** features of the **--export-profile** argument to the **nvprof** command. Below is example run using Open MPI.

```
$ mpirun -np 2 -host c0-0,c0-1 nvprof -o output.%h.%p.%q{OMPI_COMM_WORLD_RANK}
 a.out
```

Alternatively, one can make use of the new feature to turn on profiling on the nodes of interest using the **--profile-all-processes** argument to **nvprof**. To do this, you first log into the node you want to profile and start up **nvprof** there.

```
$ nvprof --profile-all-processes -o output.%h.%p.%q{OMPI_COMM_WORLD_RANK}
```

Then you can just run the MPI job as your normally would.

```
$ mpirun -np 2 -host c0-0,c0-1 a.out
```

Any processes that run on the node where the **--profile-all-processes** is running will automatically get profiled. The profiling data will be written to the output files.

With CUDA 7.5 you can name threads and CUDA contexts just as you name output files with the options --process-name and --context-name, by passing a string like "MPI Rank %q{OMPI_COMM_WORLD_RANK}" as a parameter. This feature is useful to spot

resources associated with a specific rank when user imports multiple files into the same time-line in the Visual Profiler.

```
$ nvprof --profile-all-processes --process-name "MPI Rank
 %q{OMPI_COMM_WORLD_RANK}" --context-name "MPI Rank %q{OMPI_COMM_WORLD_RANK}" -o
 output.%h.%p.%q{OMPI_COMM_WORLD_RANK}
```

Details about what types of additional arguments to use with **nvprof** can be found in the Multiprocess Profiling and Redirecting Output section. Additional information about how to view the data with **nvvp** can be found in the Import Single-Process nvprof Session and Import Multi-Process nvprof Session sections.

The blog post Profiling MPI Applications shows how to use new output file naming of nvprof introduced in CUDA 6.5 and NVTX library to name various resources to analyze the performance of a MPI application.

The blog post Track MPI Calls in the Visual Profiler shows how Visual Profiler, combined with PMPI and NVTX can give interesting insights into how the MPI calls in your application interact with the GPU.

7.2. MPI Profiling With The Command-Line Profiler

The command-line profiler is enabled and controlled by environment variables and a configuration file. To correctly profile MPI jobs, the profile output produced by the command-line profiler must be directed to unique output files for each MPI process. The command-line profiler uses the COMPUTE_PROFILE_LOG environment variable for this purpose. You can use special substitute characters in the log name to ensure that different devices and processes record their profile information to different files. The '%d' is replaced by the device ID, and the '%p' is replaced by the process ID.

```
setenv COMPUTE_PROFILE_LOG cuda_profile.%d.%p
```

If you are running on multiple nodes, you will need to store the profile logs locally, so that processes with the same ID running on different nodes don't clobber each others log file.

```
setenv COMPUTE_PROFILE_LOG /tmp/cuda_profile.%d.%p
```

COMPUTE_PROFILE_LOG and the other command-line profiler environment variables must get passed to the remote processes of the job. Most **mpiruns** have a way to do this. Examples for Open MPI and MVAPICH2 are shown below using the simpleMPI program from the CUDA Software Development Toolkit.

Open MPI

```
> setenv COMPUTE_PROFILE_LOG /tmp/cuda_profile.%d.%p
> setenv COMPUTE_PROFILE_CSV 1
> setenv COMPUTE_PROFILE_CONFIG /tmp/compute_profile.config
> setenv COMPUTE_PROFILE 1
> mpirun -x COMPUTE_PROFILE_CSV -x COMPUTE_PROFILE -x COMPUTE_PROFILE_CONFIG -x
 COMPUTE_PROFILE_LOG -np 6 -host c0-5,c0-6,c0-7 simpleMPI
Running on 6 nodes
Average of square roots is: 0.667282
PASSED
```

MVAPICH2

```
> mpirun_rsh -np 6 c0-5 c0-5 c0-6 c0-6 c0-7 c0-7 COMPUTE_PROFILE_CSV=1
 COMPUTE_PROFILE=1 COMPUTE_PROFILE_CONFIG=/tmp/compute_profile.config
 COMPUTE_PROFILE_LOG=cuda_profile.%d.%p simpleMPI
Running on 6 nodes
Average of square roots is: 0.667282
PASSED
```

Chapter 8. MPS PROFILING

You can collect profiling data for a CUDA application using Multi-Process Service(MPS) with **nvprof** and then view the timeline by importing the data in **Visual Profiler**.

8.1. MPS profiling with Visual Profiler

Visual Profiler can be run on a particular MPS client or for all MPS clients. Timeline profiling can be done for all MPS clients on the same server. Event or metric profiling results in serialization - only one MPS client will execute at a time.

To profile a CUDA application using MPS:

1) Launch the MPS daemon. Refer the MPS document for details.

```
nvidia-cuda-mps-control -d
```

2) In Visual Profiler open "New Session" wizard using main menu "File->New Session". Select "Profile all processes" option from drop down, press "Next" and then "Finish".

3) Run the application in a separate terminal

4) To end profiling press the "Cancel" button on progress dialog in Visual Profiler.

Note that the profiling output also includes data for the CUDA MPS server processes which have process name **nvidia-cuda-mps-server**.

8.2. MPS profiling with nvprof

nvprof can be run on a particular MPS client or for all MPS clients. Timeline profiling can be done for all MPS clients on the same server. Event or metric profiling results in serialization - only one MPS client will execute at a time.

To profile a CUDA application using MPS:

1) Launch the MPS daemon. Refer the MPS document for details.

```
nvidia-cuda-mps-control -d
```

2) Run **nvprof** with **--profile-all-processes** argument and to generate separate output files for each process use the **%p** feature of the **--export-profile** argument. Note that **%p** will be replaced by the process id.

```
nvprof --profile-all-processes -o output_%p
```

3) Run the application in a separate terminal

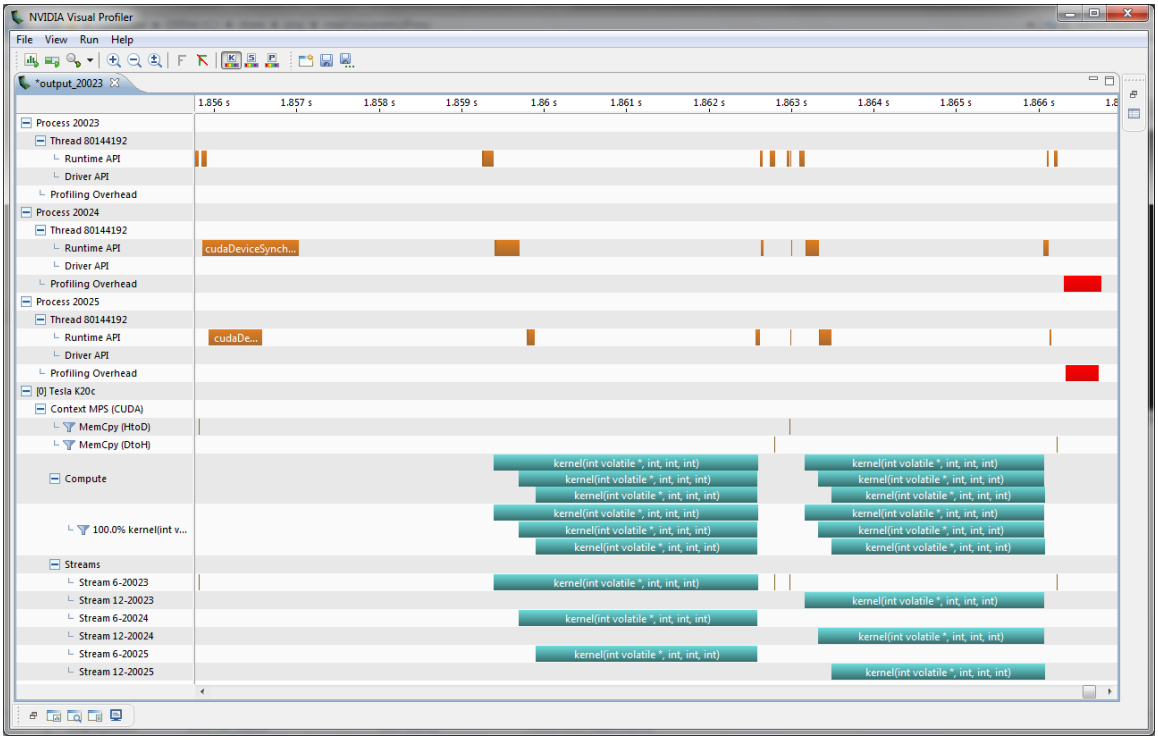
4) Exit **nvprof** by typing "Ctrl-c".

Note that the profiling output also includes data for the CUDA MPS server processes which have process name **nvidia-cuda-mps-server**.

8.3. Viewing nvprof MPS timeline in Visual Profiler

Import the nvprof generated data files for each process using the multi-process import option. Refer the Import Multi-Process nvprof Session section.

The figure below shows the MPS timeline view for three processes. The MPS context is identified in the timeline row label as **Context MPS**. Note that the **Compute** and **kernel** timeline row shows three kernels overlapping.



Chapter 9. METRICS REFERENCE

This section contains detailed descriptions of the metrics that can be collected by **nvprof** and the Visual Profiler. A scope value of single-context indicates that the metric can only be accurately collected when a single context (CUDA or graphic) is executing on the GPU. A scope value of multi-context indicates that the metric can be accurately collected when multiple contexts are executing on the GPU.

Devices with compute capability between 2.0, inclusive, and 3.0 implement the metrics shown in the following table.

Table 4 Capability 2.x Metrics

Metric Name	Description	Scope
achieved_occupancy	Ratio of the average active warps per active cycle to the maximum number of warps supported on a multiprocessor	Multi-context
alu_fu_utilization	The utilization level of the multiprocessor function units that execute integer and floating-point arithmetic instructions on a scale of 0 to 10	Multi-context
atomic_replay_overhead	Average number of replays due to atomic and reduction bank conflicts for each instruction executed	Multi-context
atomic_throughput	Global memory atomic and reduction throughput	Multi-context
atomic_transactions	Global memory atomic and reduction transactions	Multi-context
atomic_transactions_per_request	Average number of global memory atomic and reduction transactions performed for each atomic and reduction instruction	Multi-context

Metric Name	Description	Scope
branch_efficiency	Ratio of non-divergent branches to total branches expressed as percentage	Multi-context
cf_executed	Number of executed control-flow instructions	Multi-context
cf_fu_utilization	The utilization level of the multiprocessor function units that execute control-flow instructions on a scale of 0 to 10	Multi-context
cf_issued	Number of issued control-flow instructions	Multi-context
dram_read_throughput	Device memory read throughput	Single-context
dram_read_transactions	Device memory read transactions	Single-context
dram_utilization	The utilization level of the device memory relative to the peak utilization on a scale of 0 to 10	Single-context
dram_write_throughput	Device memory write throughput	Single-context
dram_write_transactions	Device memory write transactions	Single-context
ecc_throughput	ECC throughput from L2 to DRAM	Single-context
ecc_transactions	Number of ECC transactions between L2 and DRAM	Single-context
eligible_warps_per_cycle	Average number of warps that are eligible to issue per active cycle	Multi-context
flop_count_dp	Number of double-precision floating-point operations executed by non-predicated threads (add, multiply, multiply-accumulate and special). Each multiply-accumulate operation contributes 2 to the count.	Multi-context
flop_count_dp_add	Number of double-precision floating-point add operations executed by non-predicated threads	Multi-context
flop_count_dp_fma	Number of double-precision floating-point multiply-accumulate operations executed by non-predicated threads. Each multiply-accumulate operation contributes 1 to the count.	Multi-context

Metric Name	Description	Scope
flop_count_dp_mul	Number of double-precision floating-point multiply operations executed by non-predicated threads	Multi-context
flop_count_sp	Number of single-precision floating-point operations executed by non-predicated threads (add, multiply, multiply-accumulate and special). Each multiply-accumulate operation contributes 2 to the count.	Multi-context
flop_count_sp_add	Number of single-precision floating-point add operations executed by non-predicated threads	Multi-context
flop_count_sp_fma	Number of single-precision floating-point multiply-accumulate operations executed by non-predicated threads. Each multiply-accumulate operation contributes 1 to the count.	Multi-context
flop_count_sp_mul	Number of single-precision floating-point multiply operations executed by non-predicated threads	Multi-context
flop_count_sp_special	Number of single-precision floating-point special operations executed by non-predicated threads	Multi-context
flop_dp_efficiency	Ratio of achieved to peak double-precision floating-point operations	Multi-context
flop_sp_efficiency	Ratio of achieved to peak single-precision floating-point operations	Multi-context
gld_efficiency	Ratio of requested global memory load throughput to required global memory load throughput expressed as percentage. Values greater than 100% indicate that, on average, the load requests of multiple threads in a warp fetched from the same memory address. If the code has surface loads then the metric will report lower values than actual efficiency. Refer limitation-1* listed below the table.	Single-context
gld_requested_throughput	Requested global memory load throughput	Multi-context

Metric Name	Description	Scope
gld_throughput	Global memory load throughput. Refer limitation-1* listed below the table.	Single-context
gld_transactions	Number of global memory load transactions. Refer limitation-1* listed below the table.	Single-context
gld_transactions_per_request	Average number of surface and global memory load transactions performed for each surface and global memory load. Refer limitation-1* listed below the table.	Single-context
global_cache_replay_overhead	Average number of replays due to global memory cache misses for each instruction executed. Refer limitation-1* listed below the table.	Single-context
gst_efficiency	Ratio of requested global memory store throughput to required global memory store throughput expressed as percentage. Values greater than 100% indicate that, on average, the store requests of multiple threads in a warp targeted the same memory address.	Single-context
gst_requested_throughput	Requested global memory store throughput	Multi-context
gst_throughput	Global memory store throughput	Single-context
gst_transactions	Number of global memory store transactions. Refer limitation-1* listed below the table.	Single-context
gst_transactions_per_request	Average number of surface and global memory store transactions performed for each surface and global memory store.	Single-context
inst_bit_convert	Number of bit-conversion instructions executed by non-predicated threads	Multi-context
inst_compute_ld_st	Number of compute load/store instructions executed by non-predicated threads	Multi-context
inst_control	Number of control-flow instructions executed by non-predicated threads (jump, branch, etc.)	Multi-context
inst_executed	The number of instructions executed	Multi-context

Metric Name	Description	Scope
inst_fp_32	Number of single-precision floating-point instructions executed by non-predicated threads (arithmetic, compare, etc.)	Multi-context
inst_fp_64	Number of double-precision floating-point instructions executed by non-predicated threads (arithmetic, compare, etc.)	Multi-context
inst_integer	Number of integer instructions executed by non-predicated threads	Multi-context
inst_inter_thread_communication	Number of inter-thread communication instructions executed by non-predicated threads	Multi-context
inst_issued	The number of instructions issued	Multi-context
inst_misc	Number of miscellaneous instructions executed by non-predicated threads	Multi-context
inst_per_warp	Average number of instructions executed by each warp	Multi-context
inst_replay_overhead	Average number of replays for each instruction executed	Multi-context
ipc	Instructions executed per cycle	Multi-context
ipc_instance	Instructions executed per cycle for a single multiprocessor	Multi-context
issue_slot_utilization	Percentage of issue slots that issued at least one instruction, averaged across all cycles	Multi-context
issue_slots	The number of issue slots used	Multi-context
issued_ipc	Instructions issued per cycle	Multi-context
l1_cache_global_hit_rate	Hit rate in L1 cache for global loads. Refer limitation-1* listed below the table.	Single-context
l1_cache_local_hit_rate	Hit rate in L1 cache for local loads and stores. Refer limitation-1* listed below the table.	Single-context
l1_shared_utilization	The utilization level of the L1/shared memory relative to peak utilization on a scale of 0 to 10. Refer limitation-1* listed below the table.	Single-context
l2_atomic_throughput	Memory read throughput seen at L2 cache for atomic and reduction requests	Sinlge-context

Metric Name	Description	Scope
l2_atomic_transactions	Memory read transactions seen at L2 cache for atomic and reduction requests	Single-context
l2_l1_read_hit_rate	Hit rate at L2 cache for all read requests from L1 cache	Sinlge-context
l2_l1_read_throughput	Memory read throughput seen at L2 cache for read requests from L1 cache	Single-context
l2_l1_read_transactions	Memory read transactions seen at L2 cache for all read requests from L1 cache	Single-context
l2_l1_write_throughput	Memory write throughput seen at L2 cache for write requests from L1 cache	Single-context
l2_l1_write_transactions	Memory write transactions seen at L2 cache for all write requests from L1 cache	Single-context
l2_read_throughput	Memory read throughput seen at L2 cache for all read requests	Single-context
l2_read_transactions	Memory read transactions seen at L2 cache for all read requests	Single-context
l2_tex_read_transactions	Memory read transactions seen at L2 cache for read requests from the texture cache	Single-context
l2_texture_read_hit_rate	Hit rate at L2 cache for all read requests from texture cache	Single-context
l2_texure_read_throughput	Memory read throughput seen at L2 cache for read requests from the texture cache	Sinlge-context
l2_utilization	The utilization level of the L2 cache relative to the peak utilization on a scale of 0 to 10	Single-context
l2_write_throughput	Memory write throughput seen at L2 cache for all write requests	Single-context
l2_write_transactions	Memory write transactions seen at L2 cache for all write requests	Single-context
ldst_executed	Number of executed load and store instructions	Multi-context
ldst_fu_utilization	The utilization level of the multiprocessor function units that execute global, local and shared memory instructions on a scale of 0 to 10	Multi-context

Metric Name	Description	Scope
ldst_issued	Number of issued load and store instructions	Multi-context
local_load_throughput	Local memory load throughput. Refer limitation-1* listed below the table.	Single-context
local_load_transactions	Number of local memory load transactions. Refer limitation-1* listed below the table.	Single-context
local_load_transactions_per_request	Average number of local memory load transactions performed for each local memory load. Refer limitation-1* listed below the table.	Single-context
local_memory_overhead	Ratio of local memory traffic to total memory traffic between the L1 and L2 caches expressed as percentage. Refer limitation-1* listed below the table.	Single-context
local_replay_overhead	Average number of replays due to local memory accesses for each instruction executed. Refer limitation-1* listed below the table.	Single-context
local_store_throughput	Local memory store throughput. Refer limitation-1* listed below the table.	Single-context
local_store_transactions	Number of local memory store transactions. Refer limitation-1* listed below the table.	Single-context
local_store_transactions_per_request	Average number of local memory store transactions performed for each local memory store. Refer limitation-1* listed below the table.	Single-context
shared_efficiency	Ratio of requested shared memory throughput to required shared memory throughput expressed as percentage. Refer limitation-1* listed below the table.	Single-context
shared_load_throughput	Shared memory load throughput. Refer limitation-1* listed below the table.	Single-context
shared_load_transactions	Number of shared memory load transactions. Refer limitation-1* listed below the table.	Single-context
shared_load_transactions_per_request	Average number of shared memory load transactions performed for each shared	Single-context

Metric Name	Description	Scope
	memory load. Refer limitation-1* listed below the table.	
shared_replay_overhead	Average number of replays due to shared memory conflicts for each instruction executed. Refer limitation-1* listed below the table.	Single-context
shared_store_throughput	Shared memory store throughput. Refer limitation-1* listed below the table.	Single-context
shared_store_transactions	Number of shared memory store transactions. Refer limitation-1* listed below the table.	Single-context
shared_store_transactions_per_request	Average number of shared memory store transactions performed for each shared memory store. Refer limitation-1* listed below the table.	Single-context
sm_efficiency	The percentage of time at least one warp is active on a multiprocessor averaged over all multiprocessors on the GPU	Single-context
sm_efficiency_instance	The percentage of time at least one warp is active on a specific multiprocessor	Single-context
stall_data_request	Percentage of stalls occurring because a memory operation cannot be performed due to the required resources not being available or fully utilized, or because too many requests of a given type are outstanding	Multi-context
stall_exec_dependency	Percentage of stalls occurring because an input required by the instruction is not yet available	Multi-context
stall_inst_fetch	Percentage of stalls occurring because the next assembly instruction has not yet been fetched	Multi-context
stall_other	Percentage of stalls occurring due to miscellaneous reasons	Multi-context
stall_sync	Percentage of stalls occurring because the warp is blocked at a __syncthreads() call	Multi-context

Metric Name	Description	Scope
stall_texture	Percentage of stalls occurring because the texture sub-system is fully utilized or has too many outstanding requests	Multi-context
sysmem_read_throughput	System memory read throughput	Single-context
sysmem_read_transactions	System memory read transactions	Single-context
sysmem_utilization	The utilization level of the system memory relative to the peak utilization on a scale of 0 to 10	Single-context
sysmem_write_throughput	System memory write throughput	Single-context
sysmem_write_transactions	System memory write transactions	Single-context
tex_cache_hit_rate	Texture cache hit rate. Refer limitation-1* listed below the table.	Single-context
tex_cache_throughput	Texture cache throughput. Refer limitation-1* listed below the table.	Single-context
tex_cache_transactions	Texture cache read transactions. Refer limitation-1* listed below the table.	Single-context
tex_fu_utilization	The utilization level of the multiprocessor function units that execute texture instructions on a scale of 0 to 10	Multi-context
tex_utilization	The utilization level of the texture cache relative to the peak utilization on a scale of 0 to 10. Refer limitation-1* listed below the table.	Single-context
warp_execution_efficiency	Ratio of the average active threads per warp to the maximum number of threads per warp supported on a multiprocessor expressed as percentage	Multi-context

*** Limitation-1: The metric value may not be accurate as some of the events used are collected only for few multiprocessor instances and are extrapolated to cover total number of multiprocessors available in the GPU.**

Devices with compute capability between 3.0, inclusive, and 4.0 implement the metrics shown in the following table. Note that for some metrics the multi-context scope is supported only for specific devices. Such metrics are marked with "Multi-context*" under the "Scope" column. Refer the note at the bottom of the table.

Table 5 Capability 3.x Metrics

Metric Name	Description	Scope
achieved_occupancy	Ratio of the average active warps per active cycle to the maximum number of warps supported on a multiprocessor	Multi-context
alu_fu_utilization	The utilization level of the multiprocessor function units that execute integer and floating-point arithmetic instructions on a scale of 0 to 10	Multi-context
atomic_replay_overhead	Average number of replays due to atomic and reduction bank conflicts for each instruction executed	Multi-context
atomic_throughput	Global memory atomic and reduction throughput	Multi-context
atomic_transactions	Global memory atomic and reduction transactions	Multi-context
atomic_transactions_per_request	Average number of global memory atomic and reduction transactions performed for each atomic and reduction instruction	Multi-context
branch_efficiency	Ratio of non-divergent branches to total branches expressed as percentage. This is available for compute capability 3.0.	Multi-context
cf_executed	Number of executed control-flow instructions	Multi-context
cf_fu_utilization	The utilization level of the multiprocessor function units that execute control-flow instructions on a scale of 0 to 10	Multi-context
cf_issued	Number of issued control-flow instructions	Multi-context
dram_read_throughput	Device memory read throughput. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
dram_read_transactions	Device memory read transactions. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
dram_utilization	The utilization level of the device memory relative to the peak utilization on a scale of 0 to 10	Multi-context*

Metric Name	Description	Scope
dram_write_throughput	Device memory write throughput. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
dram_write_transactions	Device memory write transactions. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
ecc_throughput	ECC throughput from L2 to DRAM. This is available for compute capability 3.5 and 3.7.	Multi-context*
ecc_transactions	Number of ECC transactions between L2 and DRAM. This is available for compute capability 3.5 and 3.7.	Multi-context*
eligible_warps_per_cycle	Average number of warps that are eligible to issue per active cycle	Multi-context
flop_count_dp	Number of double-precision floating-point operations executed by non-predicated threads (add, multiply, multiply-accumulate and special). Each multiply-accumulate operation contributes 2 to the count.	Multi-context
flop_count_dp_add	Number of double-precision floating-point add operations executed by non-predicated threads	Multi-context
flop_count_dp_fma	Number of double-precision floating-point multiply-accumulate operations executed by non-predicated threads. Each multiply-accumulate operation contributes 1 to the count.	Multi-context
flop_count_dp_mul	Number of double-precision floating-point multiply operations executed by non-predicated threads	Multi-context
flop_count_sp	Number of single-precision floating-point operations executed by non-predicated threads (add, multiply, multiply-accumulate and special). Each multiply-accumulate operation contributes 2 to the count.	Multi-context
flop_count_sp_add	Number of single-precision floating-point add operations executed by non-predicated threads	Multi-context

Metric Name	Description	Scope
flop_count_sp_fma	Number of single-precision floating-point multiply-accumulate operations executed by non-predicated threads. Each multiply-accumulate operation contributes 1 to the count.	Multi-context
flop_count_sp_mul	Number of single-precision floating-point multiply operations executed by non-predicated threads	Multi-context
flop_count_sp_special	Number of single-precision floating-point special operations executed by non-predicated threads	Multi-context
flop_dp_efficiency	Ratio of achieved to peak double-precision floating-point operations	Multi-context
flop_sp_efficiency	Ratio of achieved to peak single-precision floating-point operations	Multi-context
gld_efficiency	Ratio of requested global memory load throughput to required global memory load throughput. If the code has surface loads then the metric will report lower values than actual efficiency	Multi-context*
gld_requested_throughput	Requested global memory load throughput	Multi-context
gld_throughput	Global memory load throughput	Multi-context*
gld_transactions	Number of global memory load transactions expressed as percentage	Multi-context*
gld_transactions_per_request	Average number of global memory load transactions performed for each global memory load. The metric can give higher values than expected if the code has surface loads	Multi-context*
global_cache_replay_overhead	Average number of replays due to global memory cache misses for each instruction executed	Multi-context
global_replay_overhead	Average number of replays due to global memory cache misses	Multi-context

Metric Name	Description	Scope
gst_efficiency	Ratio of requested global memory store throughput to required global memory store throughput expressed as percentage	Multi-context*
gst_requested_throughput	Requested global memory store throughput	Multi-context
gst_throughput	Global memory store throughput	Multi-context*
gst_transactions	Number of global memory store transactions	Multi-context*
gst_transactions_per_request	Average number of global memory store transactions performed for each global memory store. The metric can give higher values than expected if the code has surface stores.	Multi-context*
inst_bit_convert	Number of bit-conversion instructions executed by non-predicated threads	Multi-context
inst_compute_ld_st	Number of compute load/store instructions executed by non-predicated threads	Multi-context
inst_control	Number of control-flow instructions executed by non-predicated threads (jump, branch, etc.)	Multi-context
inst_executed	The number of instructions executed	Multi-context
inst_fp_32	Number of single-precision floating-point instructions executed by non-predicated threads (arithmetic, compare, etc.)	Multi-context
inst_fp_64	Number of double-precision floating-point instructions executed by non-predicated threads (arithmetic, compare, etc.)	Multi-context
inst_integer	Number of integer instructions executed by non-predicated threads	Multi-context
inst_inter_thread_communication	Number of inter-thread communication instructions executed by non-predicated threads	Multi-context
inst_issued	The number of instructions issued	Multi-context
inst_misc	Number of miscellaneous instructions executed by non-predicated threads	Multi-context

Metric Name	Description	Scope
inst_per_warp	Average number of instructions executed by each warp	Multi-context
inst_replay_overhead	Average number of replays for each instruction executed	Multi-context
ipc	Instructions executed per cycle	Multi-context
ipc_instance	Instructions executed per cycle for a single multiprocessor	Multi-context
issue_slot_utilization	Percentage of issue slots that issued at least one instruction, averaged across all cycles	Multi-context
issue_slots	The number of issue slots used	Multi-context
issued_ipc	Instructions issued per cycle	Multi-context
l1_cache_global_hit_rate	Hit rate in L1 cache for global loads	Multi-context*
l1_cache_local_hit_rate	Hit rate in L1 cache for local loads and stores	Multi-context*
l1_shared_utilization	The utilization level of the L1/shared memory relative to peak utilization on a scale of 0 to 10. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
l2_atomic_throughput	Memory read throughput seen at L2 cache for atomic and reduction requests	Multi-context*
l2_atomic_transactions	Memory read transactions seen at L2 cache for atomic and reduction requests	Multi-context*
l2_l1_read_hit_rate	Hit rate at L2 cache for all read requests from L1 cache. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
l2_l1_read_throughput	Memory read throughput seen at L2 cache for read requests from L1 cache. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
l2_l1_read_transactions	Memory read transactions seen at L2 cache for all read requests from L1 cache. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
l2_l1_write_throughput	Memory write throughput seen at L2 cache for write requests from L1 cache. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*

Metric Name	Description	Scope
l2_l1_write_transactions	Memory write transactions seen at L2 cache for all write requests from L1 cache. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
l2_read_throughput	Memory read throughput seen at L2 cache for all read requests	Multi-context*
l2_read_transactions	Memory read transactions seen at L2 cache for all read requests	Multi-context*
l2_tex_read_transactions	Memory read transactions seen at L2 cache for read requests from the texture cache	Multi-context*
l2_texture_read_hit_rate	Hit rate at L2 cache for all read requests from texture cache. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
l2_texture_read_throughput	Memory read throughput seen at L2 cache for read requests from the texture cache	Multi-context*
l2_utilization	The utilization level of the L2 cache relative to the peak utilization on a scale of 0 to 10	Multi-context*
l2_write_throughput	Memory write throughput seen at L2 cache for all write requests	Multi-context*
l2_write_transactions	Memory write transactions seen at L2 cache for all write requests	Multi-context*
ldst_executed	Number of executed load and store instructions	Multi-context
ldst_fu_utilization	The utilization level of the multiprocessor function units that execute global, local and shared memory instructions on a scale of 0 to 10	Multi-context
ldst_issued	Number of issued load and store instructions	Multi-context
local_load_throughput	Local memory load throughput	Multi-context*
local_load_transactions	Number of local memory load transactions	Multi-context*
local_load_transactions_per_request	Average number of local memory load transactions performed for each local memory load	Multi-context*
local_memory_overhead	Ratio of local memory traffic to total memory traffic between the L1 and L2 caches	Multi-context*

Metric Name	Description	Scope
	expressed as percentage. This is available for compute capability 3.0, 3.5 and 3.7.	
local_replay_overhead	Average number of replays due to local memory accesses for each instruction executed	Multi-context
local_store_throughput	Local memory store throughput	Multi-context*
local_store_transactions	Number of local memory store transactions	Multi-context*
local_store_transactions_per_request	Average number of local memory store transactions performed for each local memory store	Multi-context*
nc_cache_global_hit_rate	Hit rate in non coherent cache for global loads	Multi-context*
nc_gld_efficiency	Ratio of requested non coherent global memory load throughput to required non coherent global memory load throughput expressed as percentage	Multi-context*
nc_gld_requested_throughput	Requested throughput for global memory loaded via non-coherent cache	Multi-context
nc_gld_throughput	Non coherent global memory load throughput	Multi-context*
nc_l2_read_throughput	Memory read throughput for non coherent global read requests seen at L2 cache	Multi-context*
nc_l2_read_transactions	Memory read transactions seen at L2 cache for non coherent global read requests	Multi-context*
shared_efficiency	Ratio of requested shared memory throughput to required shared memory throughput expressed as percentage	Multi-context*
shared_load_throughput	Shared memory load throughput	Multi-context*
shared_load_transactions	Number of shared memory load transactions	Multi-context*
shared_load_transactions_per_request	Average number of shared memory load transactions performed for each shared memory load	Multi-context*
shared_replay_overhead	Average number of replays due to shared memory conflicts for each instruction executed	Multi-context

Metric Name	Description	Scope
shared_store_throughput	Shared memory store throughput	Multi-context*
shared_store_transactions	Number of shared memory store transactions	Multi-context*
shared_store_transactions_per_request	Average number of shared memory store transactions performed for each shared memory store	Multi-context*
sm_efficiency	The percentage of time at least one warp is active on a multiprocessor averaged over all multiprocessors on the GPU	Multi-context*
sm_efficiency_instance	The percentage of time at least one warp is active on a specific multiprocessor	Multi-context*
stall_constant_memory_dependency	Percentage of stalls occurring because of immediate constant cache miss. This is available for compute capability 3.2, 3.5 and 3.7.	Multi-context
stall_exec_dependency	Percentage of stalls occurring because an input required by the instruction is not yet available	Multi-context
stall_inst_fetch	Percentage of stalls occurring because the next assembly instruction has not yet been fetched	Multi-context
stall_memory_dependency	Percentage of stalls occurring because a memory operation cannot be performed due to the required resources not being available or fully utilized, or because too many requests of a given type are outstanding.	Multi-context
stall_memory_throttle	Percentage of stalls occurring because of memory throttle.	Multi-context
stall_not_selected	Percentage of stalls occurring because warp was not selected.	Multi-context
stall_other	Percentage of stalls occurring due to miscellaneous reasons	Multi-context
stall_pipe_busy	Percentage of stalls occurring because a compute operation cannot be performed due to the required resources not being available. This is available for compute capability 3.2, 3.5 and 3.7.	Multi-context

Metric Name	Description	Scope
stall_sync	Percentage of stalls occurring because the warp is blocked at a __syncthreads() call	Multi-context
stall_texture	Percentage of stalls occurring because the texture sub-system is fully utilized or has too many outstanding requests	Multi-context
sysmem_read_throughput	System memory read throughput. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
sysmem_read_transactions	System memory read transactions. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
sysmem_utilization	The utilization level of the system memory relative to the peak utilization on a scale of 0 to 10. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
sysmem_write_throughput	System memory write throughput. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
sysmem_write_transactions	System memory write transactions. This is available for compute capability 3.0, 3.5 and 3.7.	Multi-context*
tex_cache_hit_rate	Texture cache hit rate	Multi-context*
tex_cache_throughput	Texture cache throughput	Multi-context*
tex_cache_transactions	Texture cache read transactions	Multi-context*
tex_fu_utilization	The utilization level of the multiprocessor function units that execute texture instructions on a scale of 0 to 10	Multi-context
tex_utilization	The utilization level of the texture cache relative to the peak utilization on a scale of 0 to 10	Multi-context*
warp_execution_efficiency	Ratio of the average active threads per warp to the maximum number of threads per warp supported on a multiprocessor expressed as percentage	Multi-context
warp_nonpred_execution_efficiency	Ratio of the average active threads per warp executing non-predicated instructions to	Multi-context

Metric Name	Description	Scope
	the maximum number of threads per warp supported on a multiprocessor expressed as percentage	

*** The multi-context scope is supported for devices with compute capability 3.0, 3.5 and 3.7.**

Devices with compute capability greater than or equal to 5.0 implement the metrics shown in the following table. Note that for some metrics the multi-context scope is supported only for specific devices. Such metrics are marked with "Multi-context*" under the "Scope" column. Refer the note at the bottom of the table.

Table 6 Capability 5.x Metrics

Metric Name	Description	Scope
achieved_occupancy	Ratio of the average active warps per active cycle to the maximum number of warps supported on a multiprocessor	Multi-context
atomic_transactions	Global memory atomic and reduction transactions	Multi-context
atomic_transactions_per_request	Average number of global memory atomic and reduction transactions performed for each atomic and reduction instruction	Multi-context
branch_efficiency	Ratio of non-divergent branches to total branches expressed as percentage	Multi-context
cf_executed	Number of executed control-flow instructions	Multi-context
cf_fu_utilization	The utilization level of the multiprocessor function units that execute control-flow instructions on a scale of 0 to 10	Multi-context
cf_issued	Number of issued control-flow instructions	Multi-context
double_precision_fu_utilization	The utilization level of the multiprocessor function units that execute double-precision floating-point instructions and integer instructions on a scale of 0 to 10	Multi-context
dram_read_throughput	Device memory read throughput	Multi-context*
dram_read_transactions	Device memory read transactions	Multi-context*

Metric Name	Description	Scope
dram_utilization	The utilization level of the device memory relative to the peak utilization on a scale of 0 to 10	Multi-context*
dram_write_throughput	Device memory write throughput	Multi-context*
dram_write_transactions	Device memory write transactions	Multi-context*
ecc_throughput	ECC throughput from L2 to DRAM	Multi-context*
ecc_transactions	Number of ECC transactions between L2 and DRAM	Multi-context*
eligible_warps_per_cycle	Average number of warps that are eligible to issue per active cycle	Multi-context
flop_count_dp	Number of double-precision floating-point operations executed by non-predicated threads (add, multiply, multiply-accumulate and special). Each multiply-accumulate operation contributes 2 to the count.	Multi-context
flop_count_dp_add	Number of double-precision floating-point add operations executed by non-predicated threads	Multi-context
flop_count_dp_fma	Number of double-precision floating-point multiply-accumulate operations executed by non-predicated threads. Each multiply-accumulate operation contributes 1 to the count.	Multi-context
flop_count_dp_mul	Number of double-precision floating-point multiply operations executed by non-predicated threads	Multi-context
flop_count_sp	Number of single-precision floating-point operations executed by non-predicated threads (add, multiply, multiply-accumulate and special). Each multiply-accumulate operation contributes 2 to the count.	Multi-context
flop_count_sp_add	Number of single-precision floating-point add operations executed by non-predicated threads	Multi-context
flop_count_sp_fma	Number of single-precision floating-point multiply-accumulate operations executed	Multi-context

Metric Name	Description	Scope
	by non-predicated threads. Each multiply-accumulate operation contributes 1 to the count.	
flop_count_sp_mul	Number of single-precision floating-point multiply operations executed by non-predicated threads	Multi-context
flop_count_sp_special	Number of single-precision floating-point special operations executed by non-predicated threads	Multi-context
flop_dp_efficiency	Ratio of achieved to peak double-precision floating-point operations	Multi-context
flop_sp_efficiency	Ratio of achieved to peak single-precision floating-point operations	Multi-context
gld_efficiency	Ratio of requested global memory load throughput to required global memory load throughput expressed as percentage	Multi-context*
gld_requested_throughput	Requested global memory load throughput	Multi-context
gld_throughput	Global memory load throughput	Multi-context*
gld_transactions	Number of global memory load transactions	Multi-context*
gld_transactions_per_request	Average number of global memory load transactions performed for each global memory load	Multi-context*
global_hit_rate	Hit rate for global loads	Multi-context*
gst_efficiency	Ratio of requested global memory store throughput to required global memory store throughput expressed as percentage	Multi-context*
gst_requested_throughput	Requested global memory store throughput	Multi-context
gst_throughput	Global memory store throughput	Multi-context*
gst_transactions	Number of global memory store transactions	Multi-context*
gst_transactions_per_request	Average number of global memory store transactions performed for each global memory store	Multi-context*
inst_bit_convert	Number of bit-conversion instructions executed by non-predicated threads	Multi-context

Metric Name	Description	Scope
inst_compute_ld_st	Number of compute load/store instructions executed by non-predicated threads	Multi-context
inst_control	Number of control-flow instructions executed by non-predicated threads (jump, branch, etc.)	Multi-context
inst_executed	The number of instructions executed	Multi-context
inst_fp_32	Number of single-precision floating-point instructions executed by non-predicated threads (arithmetic, compare, etc.)	Multi-context
inst_fp_64	Number of double-precision floating-point instructions executed by non-predicated threads (arithmetic, compare, etc.)	Multi-context
inst_integer	Number of integer instructions executed by non-predicated threads	Multi-context
inst_inter_thread_communication	Number of inter-thread communication instructions executed by non-predicated threads	Multi-context
inst_issued	The number of instructions issued	Multi-context
inst_misc	Number of miscellaneous instructions executed by non-predicated threads	Multi-context
inst_per_warp	Average number of instructions executed by each warp	Multi-context
inst_replay_overhead	Average number of replays for each instruction executed	Multi-context
ipc	Instructions executed per cycle	Multi-context
issue_slot_utilization	Percentage of issue slots that issued at least one instruction, averaged across all cycles	Multi-context
issue_slots	The number of issue slots used	Multi-context
issued_ipc	Instructions issued per cycle	Multi-context
l2_atomic_throughput	Memory read throughput seen at L2 cache for atomic and reduction requests	Multi-context
l2_atomic_transactions	Memory read transactions seen at L2 cache for atomic and reduction requests	Multi-context*

Metric Name	Description	Scope
l2_read_throughput	Memory read throughput seen at L2 cache for all read requests	Multi-context*
l2_read_transactions	Memory read transactions seen at L2 cache for all read requests	Multi-context*
l2_tex_read_hit_rate	Hit rate at L2 cache for all read requests from texture cache	Multi-context*
l2_tex_read_throughput	Memory read throughput seen at L2 cache for read requests from the texture cache	Multi-context*
l2_tex_read_transactions	Memory read transactions seen at L2 cache for read requests from the texture cache	Multi-context*
l2_tex_write_hit_rate	Hit Rate at L2 cache for all write requests from texture cache	Multi-context*
l2_tex_write_throughput	Memory write throughput seen at L2 cache for write requests from the texture cache	Multi-context*
l2_tex_write_transactions	Memory write transactions seen at L2 cache for write requests from the texture cache	Multi-context*
l2_utilization	The utilization level of the L2 cache relative to the peak utilization on a scale of 0 to 10	Multi-context*
l2_write_throughput	Memory write throughput seen at L2 cache for all write requests	Multi-context*
l2_write_transactions	Memory write transactions seen at L2 cache for all write requests	Multi-context*
ldst_executed	Number of executed load and store instructions	Multi-context
ldst_fu_utilization	The utilization level of the multiprocessor function units that execute global, local and shared memory instructions on a scale of 0 to 10	Multi-context
ldst_issued	Number of issued load and store instructions	Multi-context
local_hit_rate	Hit rate for local loads and stores	Multi-context*
local_load_throughput	Local memory load throughput	Multi-context*
local_load_transactions	Number of local memory load transactions	Multi-context*

Metric Name	Description	Scope
local_load_transactions_per_request	Average number of local memory load transactions performed for each local memory load	Multi-context*
local_memory_overhead	Ratio of local memory traffic to total memory traffic between the L1 and L2 caches expressed as percentage	Multi-context*
local_store_throughput	Local memory store throughput	Multi-context*
local_store_transactions	Number of local memory store transactions	Multi-context*
local_store_transactions_per_request	Average number of local memory store transactions performed for each local memory store	Multi-context*
shared_efficiency	Ratio of requested shared memory throughput to required shared memory throughput expressed as percentage	Multi-context*
shared_load_throughput	Shared memory load throughput	Multi-context*
shared_load_transactions	Number of shared memory load transactions	Multi-context*
shared_load_transactions_per_request	Average number of shared memory load transactions performed for each shared memory load	Multi-context*
shared_store_throughput	Shared memory store throughput	Multi-context*
shared_store_transactions	Number of shared memory store transactions	Multi-context*
shared_store_transactions_per_request	Average number of shared memory store transactions performed for each shared memory store	Multi-context*
shared_utilization	The utilization level of the shared memory relative to peak utilization on a scale of 0 to 10	Multi-context*
single_precision_fu_utilization	The utilization level of the multiprocessor function units that execute single-precision floating-point instructions and integer instructions on a scale of 0 to 10	Multi-context
sm_efficiency	The percentage of time at least one warp is active on a multiprocessor	Multi-context*
special_fu_utilization	The utilization level of the multiprocessor function units that execute sin, cos, ex2,	Multi-context

Metric Name	Description	Scope
	popc, flo, and similar instructions on a scale of 0 to 10	
stall_constant_memory_dependency	Percentage of stalls occurring because of immediate constant cache miss	Multi-context
stall_exec_dependency	Percentage of stalls occurring because an input required by the instruction is not yet available	Multi-context
stall_inst_fetch	Percentage of stalls occurring because the next assembly instruction has not yet been fetched	Multi-context
stall_memory_dependency	Percentage of stalls occurring because a memory operation cannot be performed due to the required resources not being available or fully utilized, or because too many requests of a given type are outstanding	Multi-context
stall_memory_throttle	Percentage of stalls occurring because of memory throttle	Multi-context
stall_not_selected	Percentage of stalls occurring because warp was not selected	Multi-context
stall_other	Percentage of stalls occurring due to miscellaneous reasons	Multi-context
stall_pipe_busy	Percentage of stalls occurring because a compute operation cannot be performed due to the required resources not being available	Multi-context
stall_sync	Percentage of stalls occurring because the warp is blocked at a __syncthreads() call	Multi-context
stall_texture	Percentage of stalls occurring because the texture sub-system is fully utilized or has too many outstanding requests	Multi-context
sysmem_read_throughput	System memory read throughput	Multi-context*
sysmem_read_transactions	System memory read transactions	Multi-context*
sysmem_utilization	The utilization level of the system memory relative to the peak utilization on a scale of 0 to 10	Multi-context*
sysmem_write_throughput	System memory write throughput	Multi-context*

Metric Name	Description	Scope
sysmem_write_transactions	System memory write transactions	Multi-context*
tex_cache_hit_rate	Texture cache hit rate	Multi-context*
tex_cache_throughput	Texture cache throughput	Multi-context*
tex_cache_transactions	Texture cache read transactions	Multi-context*
tex_fu_utilization	The utilization level of the multiprocessor function units that execute texture instructions on a scale of 0 to 10	Multi-context
tex_utilization	The utilization level of the texture cache relative to the peak utilization on a scale of 0 to 10	Multi-context*
warp_execution_efficiency	Ratio of the average active threads per warp to the maximum number of threads per warp supported on a multiprocessor expressed as percentage	Multi-context
warp_nonpred_execution_efficiency	Ratio of the average active threads per warp executing non-predicated instructions to the maximum number of threads per warp supported on a multiprocessor	Multi-context

*** The Multi-context scope for this metric is supported only for devices with compute capability 5.0 and 5.2.**

Chapter 10. WARP STATE

This section contains a description of each warp state. The warp can have following states:

- **Instruction issued** - An instruction or a pair of independent instructions was issued from a warp.

- **Stalled** - Warp can be stalled for one of the following reasons. The stall reason distribution can be seen at source level in PC sampling view or at kernel level in Latency analysis using 'Examine Stall Reasons'

  - **Stalled for instruction fetch** - The next instruction was not yet available.

    To reduce instruction fetch stalls:

    - If large loop have been unrolled in kernel, try reducing them.
    - If the kernel contains many calls to small function, try inlining more of them with the __inline__ or __forceinline__ qualifiers. Conversely, if inlining many functions or large functions, try __noinline__ to disable inlining of those functions.
    - For very short kernels, consider fusing into a single kernels.
    - If blocks with fewer threads are used, consider using fewer blocks of more threads. Occasional calls to synchthreads() will then keep the warps in synch which may improve instruction cache hit rate.

  - **Stalled for execution dependency** - The next instruction is waiting for one or more of its inputs to be computed by earlier instruction(s).

    To reduce execution dependency stalls, try to increase instruction-level parallelism (ILP). This can be done by, for example, increasing loop unrolling or processing several elements per thread. This prevents the thread from idling through the full latency of each instruction.

  - **Stalled for memory dependency** - The next instruction is waiting for a previous memory accesses to complete.

    To reduce the memory dependency stalls

- Try to improve memory coalescing and/or efficiency of bytes fetched (alignment, etc.). Look at the source level analysis 'Global Memory Access Pattern' and/or the NVVP/nvprof profiler metrics gld_efficiency and gst_efficiency.
- Try to increase memory-level parallelism (MLP): the number of independent memory operations in flight per thread. Loop unrolling, loading vector types such as float4, and processing multiple elements per thread are all ways to increase memory-level parallelism.
- Consider moving frequently-accessed data closer to SM, such as by use of shared memory or read-only data cache.
- Consider re-computing data where possible instead of loading it from device memory.
- If local memory accesses are high, consider increasing register count per thread to reduce spilling, even at the expense of occupancy since local memory accesses are cached only in L2 for GPUs with compute capability major = 5.

- **Stalled for memory throttle** - A large number of outstanding memory requests prevents forward progress. On GPUs with compute capability major = 3, memory throttle indicates high number of memory replays.

  To reduce memory throttle stalls:

  - Try to find ways to combine several memory transactions into one (e.g., use 64-bit memory requests instead of two 32-bit requests).
  - Check for un-coalesced memory accesses using the source level analysis 'Global Memory Access Pattern' and/or the profiler metrics gld_efficiency and gst_efficiency; minimize them wherever possible.
  - On GPUs with compute capability major >= 3, consider using read-only data cache using LDG for un-coalesced global reads

- **Stalled for texture** - The texture sub-system is fully utilized or has too many outstanding requests.

  To reduce texture stalls:

  - Consider combining several texture fetch operations into one (e.g., packing data in texture and unpacking in SM or using vector loads).
  - Consider moving frequently-accessed data closer to SM by use of shared memory.
  - Consider re-computing data where possible instead of fetching it from memory.
  - On GPUs with compute capability major < 5: Consider changing some texture accesses into regular global loads to reduce pressure on the texture unit, especially if you do not use texture-specific features such as interpolation.
  - On GPUs with compute capability major = 3: If global loads through the read-only data cache (LDG) are the source of texture accesses for this kernel,

consider changing some of them back to regular global loads. Note that if LDG is being generated due to use of the __ldg() intrinsic, this simply means changing back to a normal pointer dereference, but if LDG is being generated automatically by the compiler due to the use of the const and __restrict__ qualifiers, this may be more difficult.

- **Stalled for sync** - The warp is waiting for all threads to synchronize after a barrier instruction.

  To reduce sync stalls:

  - Try to improve load balancing i.e. try to increase work done between synchronization points; consider reducing thread block size.
  - Minimize use of threadfence_*().
  - On GPUs with compute capability major >= 3: If __syncthreads() is being used because of data exchange through shared memory within a threadblock, consider whether warp shuffle operations can be used in place of some of these exchange/synchronize sequences.

- **Stalled for constant memory dependency** - The warp is stalled on a miss in the cache for __constant__ memory and immediates.

  This may be high the first time each constant is accessed (e.g., at the beginning of a kernel). To reduce these stalls,

  - Consider reducing use of __constant__ or increase kernel runtime by increasing block count
  - Consider increasing number of items processed per thread
  - Consider merging several kernels that use the same __constant__ data to amortize the cost of misses in the constant cache.
  - Try using regular global memory accesses instead of constant memory accesses.

- **Stalled for pipe busy** - The warp is stalled because the functional unit required to execute the next instruction is busy.

  To reduce stalls due to pipe busy:

  - Prefer high-throughput operations over low-throughput operations. If precision doesn't matter, use float instead of double precision arithmetic.
  - Look for arithmetic improvements (e.g., order-of-operations changes) that may be mathematically valid but unsafe for the compiler to do automatically. due to e.g. floating-point non-associativity.

- **Stalled for not selected** - Warp was ready but did not get a chance to issue as some other warp was selected for issue. This reason generally indicates that kernel is possibly optimized well but in some cases, you may be able to decrease

occupancy without impacting latency hiding, and doing so may help improve cache hit rates.

- **Stalled for other** - Warp is blocked for an uncommon reason like compiler or hardware reasons. Developers do not have control over these stalls.

Chapter 11. PROFILER KNOWN ISSUES

The following are known issues with the current release.

- To ensure that all profile data is collected and flushed to a file, cudaDeviceSynchronize() followed by either cudaProfilerStop() or cuProfilerStop() should be called before the application exits. Refer the section Flush Profile Data.
- Concurrent kernel mode can add significant overhead if used on kernels that execute a large number of blocks and that have short execution durations.
- If the kernel launch rate is very high, the device memory used to collect profiling data can run out. In such a case some profiling data might be dropped. This will be indicated by a warning.
- When profiling an application that uses Dynamic Parallelism there are several limitations to the profiling tools.
  - The Visual Profiler timeline does not display CUDA API calls invoked from within device-launched kernels.
  - The Visual Profiler does not display detailed event, metric, and source-level results for device-launched kernels. Event, metric, and source-level results collected for CPU-launched kernels will include event, metric, and source-level results for the entire call-tree of kernels launched from within that kernel.
  - The **`nvprof`** event/metric output and the command-line profiler event output does not include results for device-launched kernels. Events/metrics collected for CPU-launched kernels will include events/metrics for the entire call-tree of kernels launched from within that kernel.
- Profiling APK binaries is not supported.
- Visual Profiler is not supported on the ARM architecture. You can use Remote Profiling. Refer the Remote Profiling section for more information.
- Unified memory profiling counters are not supported on the ARM architecture.
- When profiling an application in which a device kernel was stopped due to an assertion the profiling data will be incomplete and a warning or error message is displayed. But the message is not precise as the exact cause of the failure is not detected.
- The following are known issues related to Visual Profiler:

- Some analysis results require metrics that are not available on all devices. When these analyses are attempted on a device where the metric is not available the analysis results will show that the required data is "not available".
- Note that "Examine stall reasons" analysis does not work for compute capability 3.0. But in this case no results or message is displayed and so it can be confusing.
- Using the mouse wheel button to scroll does not work within the Visual Profiler on Windows.
- Since Visual Profiler uses **nvprof** for collecting profiling data, **nvprof** limitations also apply to Visual Profiler.
- The Visual Profiler cannot correctly import profiler data generated by **nvprof** when the option **--kernels kernel-filter** is used. Visual Profiler reports a warning, "Some collected events or source-level results could not be associated with the session timeline." One workaround is to use the **nvprof** option **--kernels :::1** to profile the first invocation for all kernels.
- Visual Profiler cannot load profiler data larger than the memory size limited by JVM or available memory on the system. Refer Improve Loading of Large Profiles for more information.
- Visual Profiler requires Java version 6 or later to be installed on the system. On some platforms the required Java version is installed as part of the CUDA Toolkit installation. But in some cases you may need to install Java version 6 or later separately.
- Visual Profiler events and metrics do not work correctly on OS X 10.8.5. Please upgrade to OS X 10.9.2 to use Visual Profiler events and metrics.
- Visual Profiler global menus do not show properly or are empty on some versions of Ubuntu. One workaround is to set environment variable "UBUNTU_MENUPROXY=0" before running Visual Profiler

- The following are known issues related to **nvprof**:
  - **nvprof** cannot profile processes that **fork()** but do not then **exec()**.
  - **nvprof** assumes it has access to the temporary directory on the system, which it uses to store temporary profiling data. On Linux/Mac the default is **/tmp**. On Windows it's specified by the system environment variables. To specify a custom location, change **$TMPDIR** on Linux/Mac or **%TMP%** on Windows.
  - To profile application on Android **$TMPDIR** environment variable has to be defined and point to a user-writable folder.
  - Profiling results might be inconsistent when auto boost is enabled. **nvprof** tries to disable auto boost by default, it might fail to do so in some conditions, but profiling will continue. **nvprof** will report a warning when auto boost cannot be disabled. Note that auto boost is supported only on certain Tesla devices from the Kepler+ family.
- The following are known issues related to Events and Metrics:
  - In event or metric profiling, kernel launches are blocking. Thus kernels waiting on host updates may hang.
  - For some metrics, the required events can only be collected for a single CUDA context. For an application that uses multiple CUDA contexts, these metrics will

only be collected for one of the contexts. The metrics that can be collected only for a single CUDA context are indicated in the metric reference tables.

- Some metric values are calculated assuming a kernel is large enough to occupy all device multiprocessors with approximately the same amount of work. If a kernel launch does not have this characteristic, then those metric values may not be accurate.
- Some metrics are not available on all devices. To see a list of all available metrics on a particular NVIDIA GPU, type **`nvprof --query-metrics`**. You can also refer to the metric reference tables.
- For compute capability 2.x devices, the achieved_occupancy metric can report inaccurate values that are greater than the actual achieved occupancy. In rare cases this can cause the achieved occupancy value to exceed the theoretical occupancy value for the kernel.
- The profilers may fail to collect events or metrics when "application replay" mode is turned on. This is most likely to happen if the application is multi-threaded and non-deterministic. Instead use "kernel replay" mode in this case.
- Here are a couple of reasons why Visual Profiler may fail to gather metric or event information.
  - More than one tool is trying to access the GPU. To fix this issue please make sure only one tool is using the GPU at any given point. Tools include the CUDA command line profiler, Parallel NSight Analysis Tools and Graphics Tools, and applications that use either CUPTI or PerfKit API (NVPM) to read event values.
  - More than one application is using the GPU at the same time Visual Profiler is profiling a CUDA application. To fix this issue please close all applications and just run the one with Visual Profiler. Interacting with the active desktop should be avoided while the application is generating event information. Please note that for some types of event Visual Profiler gathers events for only one context if the application is using multiple contexts within the same application.
- When collecting events or metrics with the **`--events`**, **`--metrics`**, or **`--analysis-metrics`** options, **`nvprof`** will use kernel replay to execute each kernel multiple times as needed to collect all the requested data. If a large number of events or metrics are requested then a large number of replays may be required, resulting in a significant increase in application execution time.
- Profiler events and metrics do not work correctly on OS X 10.8.5 and OS X 10.9.3. OS X 10.9.2 or OS X 10.9.4 or later can be used.
- Some events are not available on all devices. To see a list of all available events on a particular device, type **`nvprof --query-events`**.
- Enabling certain events can cause GPU kernels to run longer than the driver's watchdog time-out limit. In these cases the driver will terminate the GPU kernel resulting in an application error and profiling data will not be available. Please disable the driver watchdog time out before profiling such long running CUDA kernels.
  - On Linux, setting the X Config option Interactive to false is recommended.

- For Windows, detailed information on disabling the Windows TDR is available at http://msdn.microsoft.com/en-us/windows/hardware/gg487368.aspx#E2

Notice

Trademarks

Copyright