Distributed/Cluster Computing for Data Stream Mining: Draft Notes

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Abstract

The thesis is focused on elucidating GPU computing feasibility for clustering tasks

Acknowledgements

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Introduction

In real world applications such as industrial monitoring, sensor networks, financial data generate large unbounded streams of data which has to be processed with pre-defined response time. The processors capabilities limit the bandwidth of the stream which can be processed. Parallelizing processing algorithm will increase maximum bandwidth while maintaining the response time requirement.

Chapter 1

General Purpose GPU Computing Frameworks

General Purpose GPU Technology Tree

The tree of the GP-GPU technologies is presented in the Figure 1.

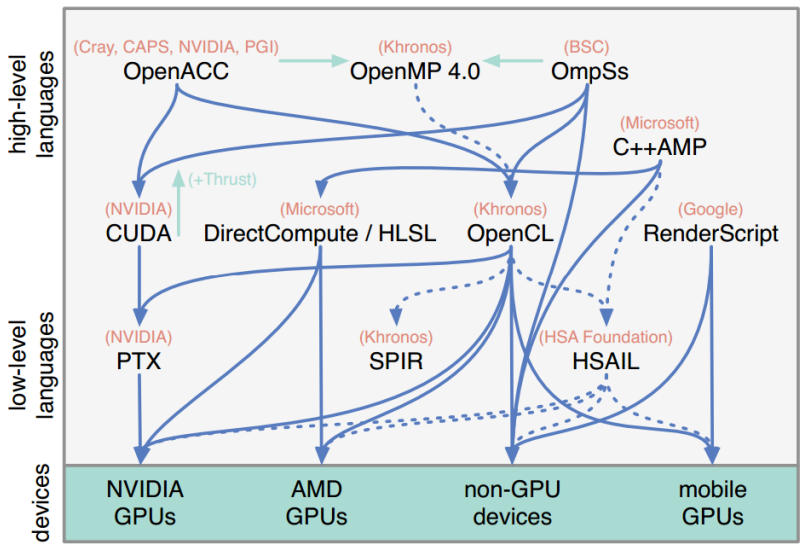

Figure 1.1: GP GPU technologies tree. Reproduced from C. Nugteren, Improving the Programmability of GPU Architecture, p. 21 [23]

GPU-specific Languages

GPU-specific languages provide a programming model consistent with the GPU hardware implementation. Modern GPUs implement SIMT (Single Instruction - Multple Thread) execution model (NB. AMD/NVIDIA desktop GPUs) first introduced by NVIDIA in G80 model[5]. The single unit of scalar instructions called *kernel* is scheduled to execute in blocks of data-parallel threads on SIMT hardware. Each instruction in a block is executed in a lock-step. The control divergence is emulated by *masking* - the device executes instructions from both branches of the conditional statement[9][21].

The memory on GPU is divided in 3 tiers:

- *private/register* - private to the current thread
- *local* - shared within a *threadblock*
- *global* - accessible by every thread

Each of the listed languages provides following abstractions:

- *Kernel* - a unit of execution
- *Thread* - a single unit of processed data
- *Threadblock* - a group of *threads* sharing same *kernel* and *local* memory.

The unit of scheduling is called *wavefront* in AMD terminology or *warp* in NVIDIA and typically consists of 32 threads on NVIDIA and 64 on AMD hardware. The GPU chip is equipped with a number of SIMT cores which execute same instruction for each *warp*. Divergence of control results in underload of the processing units and reduces performance. The branching should be reduced to wavefront granularity to avoid wasting execution cycles[26][21] It should be noted that the wavefront size is a hardware specific feature and the optimization should be performed at the run-time.

- CUDA - A programming language for NVIDIA hardware based on C language. Kernels are expressed as C-functions for one thread with parallelism defined at run-time by specifying dimensions of execution grid and thread blocks[21]

- OpenCL 1.X builds upon ideas implemented in CUDA by adding device management APIs and providing hardware-agnostic programming specification. OpenCL gives *write once-run anywhere* guarantee but does not give any performance consistency guarantees across different hardware[28].

- RenderScript - Android GPU computing component which uses OpenCL with Java binding programming model - C-style kernels and Java-based control code. RenderScript does not provide any APIs for the *work-group* size control in the bid to provide performance portability between different devices[8].

- DirectCompute/HLSL - Microsoft Parallel Computing.

Low-Level Languages

The low level assembly representation is used to abstract compiler implementation from the actual hardware since each model or even revision may have a different instruction set. The translation is performed by *Just-In-Time* compiler before kernel execution. Each vendor provides different low level specification:

- PTX - NVIDA CUDA[7]

- SPIR - Standard Portable Intermediate Representation from Khronos group. OpenCL assembly.

- HSAIL - HSA Foundation assembly languange

High Level Languages

OpenACC and OpenMP are high level parallel programming frameworks that specify a set of annotations, environment variables and library routines for shared memory parallelism in C/C++ and Fortran programs[**?**][**?**]. Microsoft C++ AMP[2] is a C++ library which enables parallel computations for CPU and GPUs (using Microsoft DirectX Shading Language) Rootbear GPU compiler provides a transparent compilation of Java code into CUDA[24]. Aparapi provides a way to generate OpenCL kernel code from Java, theoretically allowing code which can be executed on CPU and offloaded to GPU if needed[1]. Project Sumatra is a OpenJDK project which focuses on development of the Hotspot virtual machine capable of offloading JDK 8 Stream API[3] computations to the GPU[6].

Limitations

Input Size The massively parallel nature of GPU platforms require a certain amount of data to be passed to the kernel to achieve maximum performance. Table 1.1 shows execution time of a kernel which assigns index to each array element $X_i = i$ on AMD A8-7600. The execution time starts to increase when input size is above 1024 and remains constant for lower values. To maximum performance on AMD A8-7600 will be achieved when input size will exceed 1024 elements.

GPU Memory Size and Host-GPU Transfer The discrete GPU requires transfer of data from the host to the GPU memory which adds additional overhead to the computations and requires task partitioning according to the memory specification of GPU[25]. Memory transfer is a bottleneck for Aparapi and its developers allow explicit memory management[1]. This effectively reduces framework which promises CPU-GPU interoperability to the Java wrapper of the OpenCL API.

Global Size	Execution Time (μsec)
256	8
512	8
768	8
1024	8
1280	9
2560	9
2816	10
3072	10
3584	11
4608	11
4864	12

Table 1.1: Input Size and Execution Time

Kernel Launch There is a constant time needed to setup kernel launch which might offset any gain from parallelization if the data can be processed sequentially faster.(NB. Amdahl's law) It is impossible to schedule kernel execution from within the kernel itself requiring a mix of kernel and host code if several iterations are required.

OpenCL 2.0

OpenCL 2.0 standard[4] introduces several features which attempt to address limitations of GPU programming:

- Shared Virtual Memory - both host and kernel code share same address space thus either hiding memory transfers (discreet GPU driver stack) or if backed by the hardware architecture such as HSA eliminate its need[**?**]
- Dynamic Parallelism - OpenCL 2.0 allows scheduling of kernels from within a kernel without host interaction reducing host CPU bottleneck.
- Pipes - (did not check the feature - sample not available)
- Atomics - (TODO)

HSA Platform

AMD introduced Heterogeneous System Architecture plaftorm as an optimized platform architecture for OpenCL 2.0. Its specifiction introduces a set of requirements that allow both GPUs and CPU share same memory space, synchronize execution using signals and atomics and schedule execution both from GPU and CPU[10]. *Check Pipes*

Software Available: At the moment (Feb 2014) there is a OpenCL 2.0-¿HSAIL compiler available[**?**] and a Linux-based runtime environment[**?**].

HSA Memory Model *TODO*

HSA Queues HSA uses queues to schedule code execution. A HSA *queue* is a ringbuffer which contains *packets* with either call or synchronization parameters. The queue maintains two indexes - read index and write index. Write index is modified by the user and used to submit packets to the queue. The read index is updated by the packet processor whenever the packet is taken for execution. As soon as packet is written to the queue the ownership is taken by the HSA packet processor and it may change packet contents at any time[10]. Compared to traditional dispatch where the execution is scheduled via user-mode and kernel-mode driver layers the HSA dispatch intends to be lightweight and source-agnostic way of scheduling execution. The packet can be scheduled both by CPU and GPU.

HSA Signals HSA uses *signals* to perform synchronization between host and kernels being executed or to signal completion of the task. *TODO: Continue*

Implementation Notes Scenario: submit packet, wait for completion, submit another one yields 8 μsec per packet and submit N packets with a shared completion flag, wait for the completion flag become updated by N results in 193 μsec per packet. According to AMD support this is caused by CPU go-

ing into power-saving mode while kernel is running. There is a constant time needed to setup kernel launch, e.g. for AMD A8-7600, it is 6 μsec using HSA.

Chapter 2

k-Nearest Neighbours

Problem Statement

k-Nearest Neighbours method is a non-parametric method used for the classification and regression. It computes a given instance distance to the examples with the known label and either provides a class membership for the classification which is a class most common among nearest neighbours or an object property value which is an average of the nearest neighbours. The error rate bound by the twice the Bayes error if the number of examples approaches infinity[**?**]. The naive approach computes distance to each example and has computational complexity $O(N^d)$ where N - number of examples and d - cardinality of the example. [**?**] The method optimizations deal with organizing the search space to reduce number of distance calculations. Examples would be branch and bounds [**?**] methods - [list trees], and approximate methods, e.g. - Locality sensivity hash.[**?**] In relation to data stream classification there are two problems:

- Forward k-NN - for an given sliding window of examples find classification of the variable query
- Reverse k-NN - for a given fixed query form a window of examples nearest to it. This approach is discussed in Efficiently Processing Continuous k-NN Queries on Data Streams[13].

There is a number of implementations of the offline k-NN algorithm for GP-GPU: brute force approach[14][18][17][25], kd-tree[16][29], approximate [20][19]. The brute force implementation consists of distance calculation and sorting phase. The distances to the query a computed as a vector-matrix multiplication or if several queries are processed at once as a matrix-matrix multiplication. GPU implementation of those routines is available as a part of cuBLAS library[**?**]. Sorting phase finds k nearest of all the computed distances[25]. Sismanis et. al[25] provide time complexity of reduced sort algorithms and evaluates their performance on GPU, proposes to interleave distance calculation and sorting phases to hide latency - the data for the distance calculation should be offloaded to GPU while it performs the sorting phase. The input data in the brute-force approach is partitioned according to the GPU memory capabilities and does not use examples's spatial information. The kd-tree approach presented by Gieske et. al focuses on parallel execution of nearest neighbour queries in a lazy fashion. The query points are accumulated in the leaf nodes of the kd-tree until enough of them is present and then processed as batch. This solves an issue of the GPU underutilization and low performance if leaf nodes are processed sequentially for each example[16]. The parallel kd-tree construction is explored by Zhou et. al[29].

TODO: Continue

Algorithm Implementations

Brute-Force Approach The algorithm maintains a sliding window of examples, calculates distance to the query point for each example and sorts them according to the least distance selecting nearest k neighbours.

Sliding Window The sliding window is implemented as a FIFO cyclic buffer. The OpenCL implementation uses partial mapping of the buffer to reduce memory transfers.

Distance Calculation The distance calculation between query vector and sliding window is a vector by matrix multiplication operation. For the dense matrices the naive implementation performs a serial computation of each distance:

```
1  // input − query vector
2  // samples − sliding window, matrix of window_size instances
3  // ranges − min/max values for each attribute
4  // result − resulting distance vector
5  // window_size − size of the window
6  // element_count − number of attributes in each instance
7  // numerics_size − number of numeric attributes
8  distance(double* input, double* samples,      _double2* ranges, double* result, int
       window_size, int element_count, int numerics_size)
9  {
10   forall result_offset ( 0 < result_offset < window_size) do in parallel
11     int vector_offset = element_count * result_offset;
12   double point_distance = 0;
13   double val;
14   double width;
15   int i;
16   for (i = 0; i < numerics_size ; i ++ )
17   {
18     double2 range = ranges[i];
19     width = ( range.y − range.x);
20     val = width > 0 ? (input[i] − range.x) / width − (samples[vector_offset + i] − range.
           x)/width : 0;
21     point_distance += val*val;
22   }
23
24   for (; i < element_count; i ++ )
25   {
26     point_distance += isnotequal( input[i] , samples[vector_offset + i]);
27   }
28   result[result_offset] = point_distance;
29 }
```

The optimal implementation depends on the size of the window and number of attributes present[27]. For the small instance size (¡100) and windows less than 10^4 elements naive implementation will provide the best solution. Best all around distance calculation should apply different strategies depending on the windowsize and number of attributes.[27].

Selection Alabi, et.al evaluated different selection strategies based on bucket sort algorithm and Merril-Grimshaw implementation of radix sort[11].

This implementation provides only select based bitonic sort[12] algorithm which is suboptimal as we can only truncate sorting at the last stage of the algorithm.

*TODO:*The work needs to provide several alternative selection strategies. While Merril's algorithm may be too complex for implementation, we might use k-bucket Selection[11] to provide alternative selection strategy.

KD-Tree based k-Nearest Neighbours Search The KD-Tree structure was implemented as a sequentially updated structure. The distance calculation for the leaves of KD-Tree was offloaded to GPU. The OpenCL implementation required transfer of the leaf nodes contents to the GPU memory and has shown performance worse than serial implementation due to the transfer overhead *Need table*

Some ideas to try: when updating tree do not remove instances - each instance has a timestamp and distance calcuation assigns max distance when instance is too old. Old instances are replaced by the new ones (see FIFO buffer in brute-force implementation). The NN-Search can be batched - to reduce kernel launch overhead accumulate N query instances at the leaf node and only then perform distance calcuation.[15]

LHS based k-Nearest Neighbours Search *TODO*

Chapter 3

Stochastic Gradient Descent

Problem Statement

TODO

Algorithm Implementation

The implementation relies on the fact that the weights vector can be updated without locking since the training instances are sparse and each instance contributes to a different part of the weights vector[22].

Chapter 4

Experimental Results

TODO Good benchmarks: OpenCL brute-force kNN, HSA brute-force kNN Bad benchmarks: OpenCL KD-Tree

k-Nearest Neihbours

TODO

Stochastic Gradient Descent

TODO Good benchmarks: HSA Hogwild! with batching Bad benchmarks: HSA Hogwild! without batching

Chapter 5

Conclusions and Future Work

TODO

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