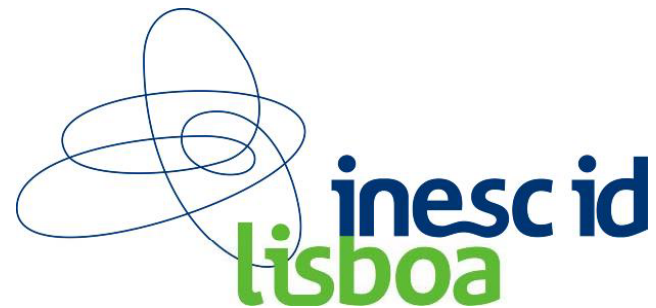


Cooperative Execution on Heterogeneous Multi-core Systems

Leonel Sousa and Aleksandar Ilić
INESC-ID/IST, TU Lisbon



COMMODITY COMPUTERS = HETEROGENEOUS SYSTEMS

- Multi-core General-Purpose Processors (CPUs)
- Many-core Graphic Processing Units (GPUs)
- ...
- Special accelerators, co-processors, FPGAs

=> **HUGE COMPUTING POWER**

- Not yet completely explored for **COLLABORATIVE COMPUTING**

HETEROGENEITY MAKES PROBLEMS MUCH MORE COMPLEX!

- Performance modeling and load balancing
- Different programming models and languages

COLLABORATIVE ENVIRONMENT FOR HETEROGENEOUS COMPUTERS

PERFORMANCE MODELING AND LOAD BALANCING

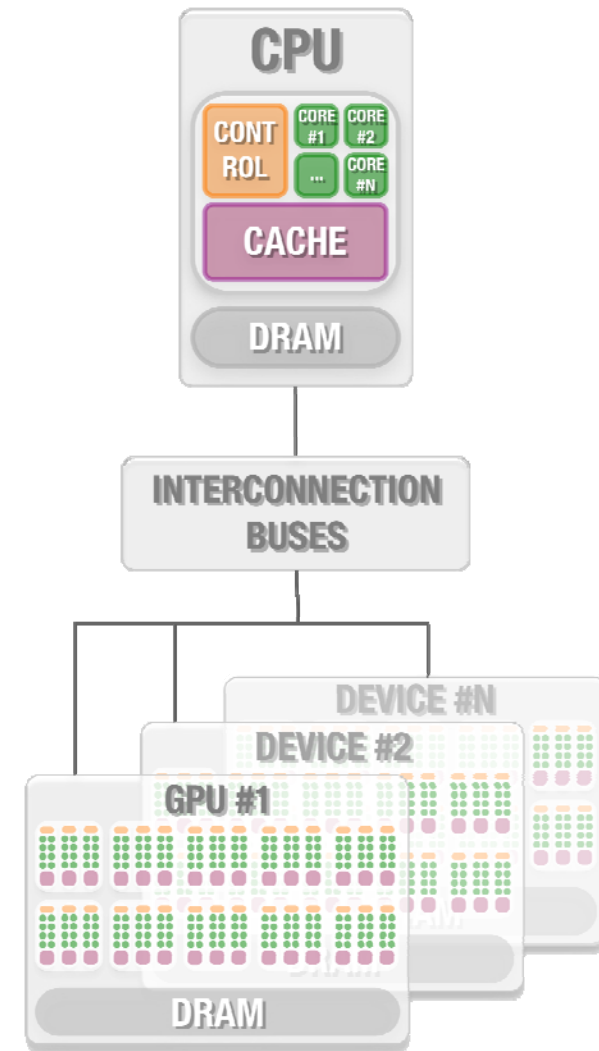
- State of the art for heterogeneous systems
- for CPU+GPU

CASE STUDY: 2D BATCH FAST FOURIER TRANSFORM

CONCLUSIONS AND FUTURE WORK

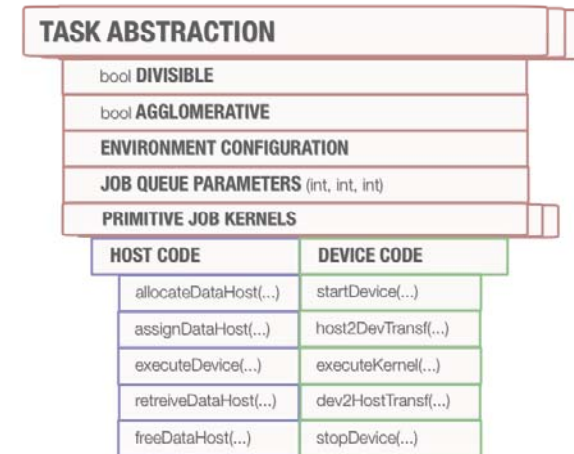
MASTER-SLAVE paradigm

- CPU (Master)
 - Global execution controller
 - Access the whole global memory
- INTERCONNECTION BUSES
 - Limited and asymmetric communication bandwidth
 - Potential execution bottleneck
- UNDERLYING DEVICES (Slaves)
 - Different architectures and programming models
 - Computation performed using local memories



TASK – basic programming unit (coarser-grained)

- CONFIGURATION PARAMETERS
 - Task: application and task dependency information
 - Environment: device type, number of devices...
- PRIMITIVE JOB WRAPPER
 - DIVISIBLE TASK – comprise several finer-grained Primitive Jobs
 - AGGLOMERATIVE TASK – allows grouping of Primitive Jobs



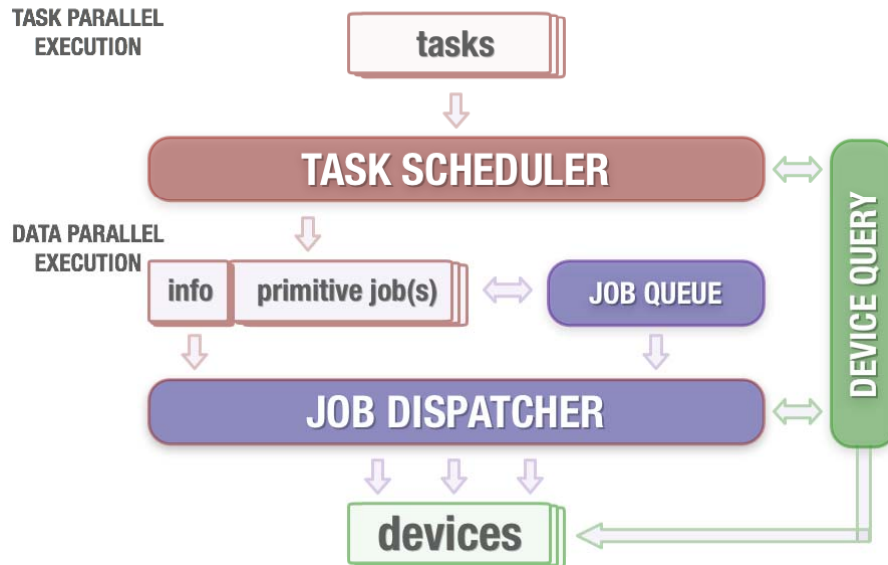
PRIMITIVE JOB – minimal program portion for parallel execution

- CONFIGURATION PARAMETERS
 - I/O and performance specifics, ...
- CARRIES PER-DEVICE-TYPE IMPLEMENTATIONS
 - Vendor-specific programming models and tools
 - Specific optimization techniques

Primitive Job Granularity	Task Type	
	Divisible	Agglomerative
Coarser-grained	NO	--
Balanced	YES	NO
Finer/Balanced	YES	YES

Collaborative Execution Environment for Heterogeneous Systems*

technology
from seed



Task Type	
Divisible	Agglomerative
NO	--
YES	NO
YES	YES

Task Level Parallelism

- TASK SCHEDULER submits independent tasks to JOB DISPATCHER in respect to task and environment configuration parameters and current platform state from DEVICE QUERY structure

Data Level Parallelism

- PRIMITIVE JOBS may be arranged into JOB QUEUES (currently, 1D-3D grid organization) for DIVISIBLE (AGGLOMERATIVE) TASKS
- JOB DISPATCHER uses DEVICE QUERY and JOB QUEUE information to map (agglomerated) PRIMITIVE JOBS to the requested devices; then initiates and controls further execution;

Nested Parallelism

- If provided, JOB DISPATCHER can be configured to perceive certain number of cores of a multi-core device as a single device

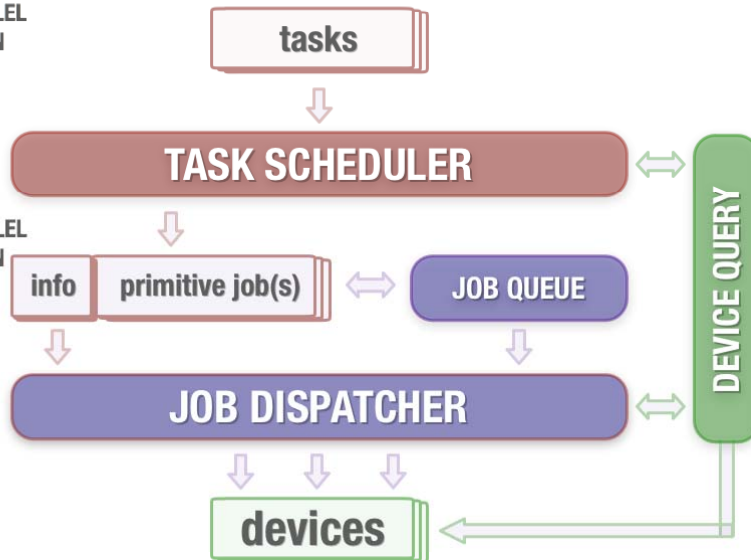
Collaborative Execution Environment for Heterogeneous Systems*

technology
from seed



TASK PARALLEL
EXECUTION

DATA PARALLEL
EXECUTION



PROBLEM

How to make good DYNAMIC LOAD BALANCING decisions using PERFORMANCE MODELS of the devices aware of :

- application demands
- implementation specifics
- platform / device heterogeneity
- complex memory hierarchies
- limited asymmetric communication bandwidth
- ...

Task Type	
Divisible	Agglomerative
NO	--
YES	NO
YES	YES

Heterogeneous Performance Modeling and Computation Distribution



technology
from seed

CONSTANT PERFORMANCE MODELS (CPM)

- DEVICE PERFORMANCE (SPEED) : constant positive number
 - Typically represents relative speed when executing a serial benchmark of a given size
- COMPUTATION DISTRIBUTION : proportional to the speed of device

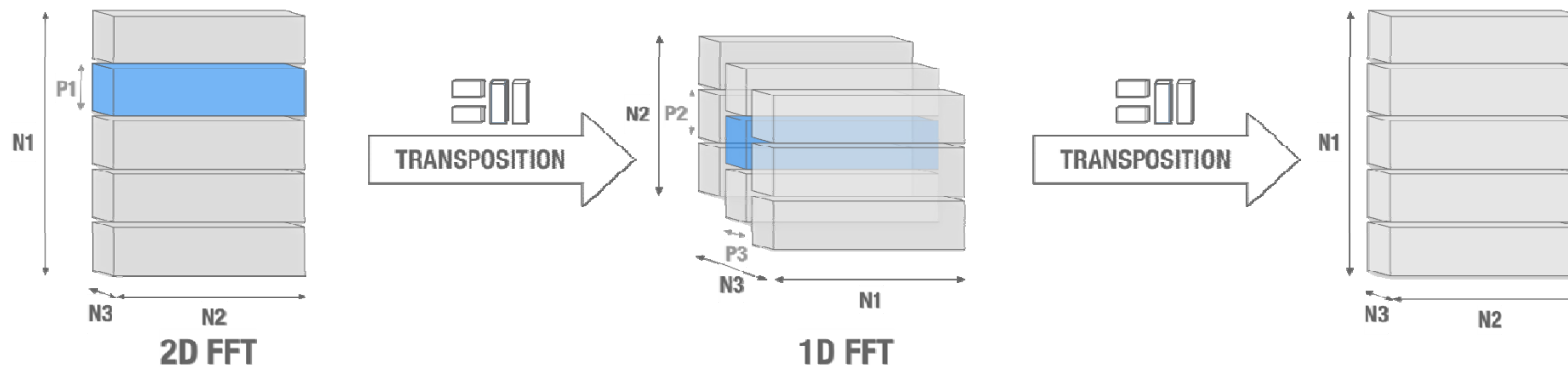
FUNCTIONAL PERFORMANCE MODELS (FPM)

- DEVICE PERFORMANCE (SPEED) : continuous function of the problem size
 - Typically require several benchmark runs and significant amount of time for building it
- COMPUTATION DISTRIBUTION : relies on the “functional speed” of the processor

FPM vs. CPM

- MORE REALISTIC : integrates features of heterogeneous processor
 - Processor heterogeneity, the heterogeneity of memory structure, and the other effects (such as paging)
- MORE ACCURATE DISTRIBUTION of computation across heterogeneous devices
- APPLICATION-CENTRIC approach characterize speed for different applications with different functions

Case Study : 2D FFT Batches



Part of a PARALLEL 3D FFT PROCEDURE : $H = FFT_{1D}(FFT_{2D}(h))$

– Very HIGH COMMUNICATION-TO-COMPUTATION ratio

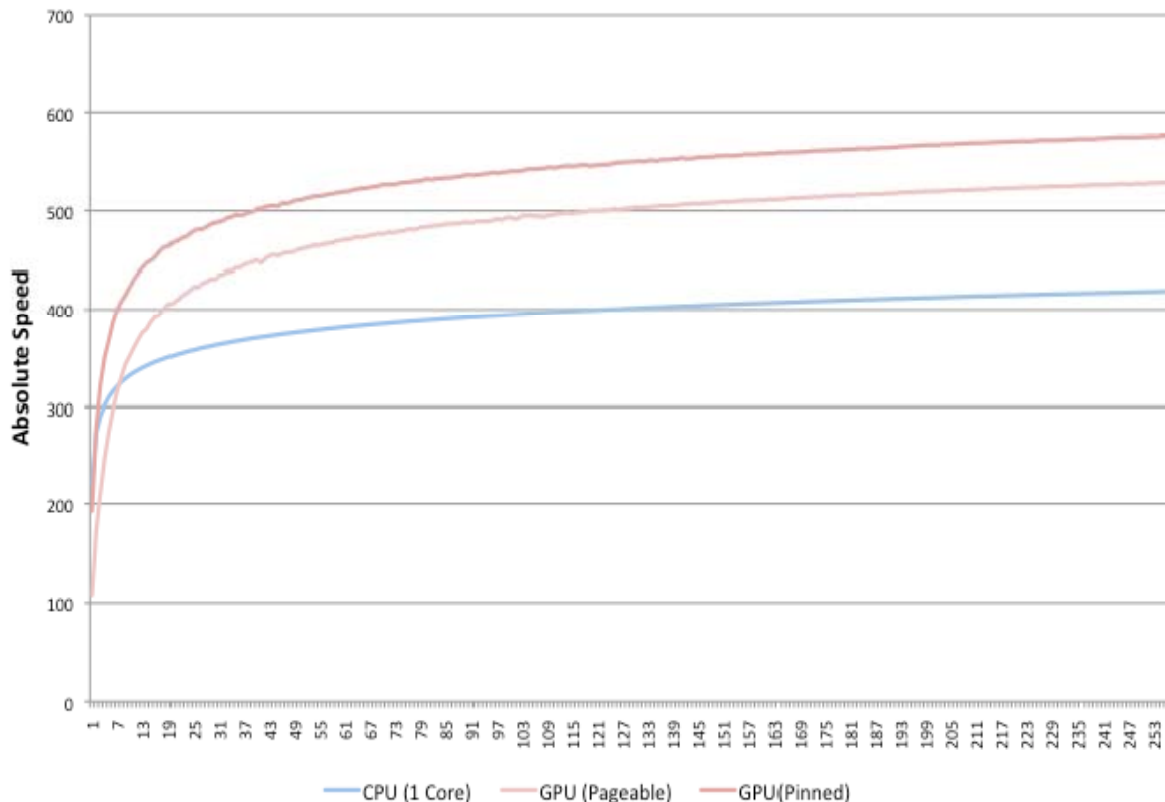
PROBLEM DEFINITION

- $N_{in} = N_{out} = N_1 N_2 N_3 * \text{sizeof}(\text{data})$
- Performance [FLOPS] : $N_1 N_2 N_3 * \log(N_1 N_2 N_3)$
- $N_2 = \text{const}; N_3 = \text{const};$
- N_1 – total number of computational chunks (PRIMITIVE JOBS)

Case Study: Performance Modeling

What we already know ...* (1)

technology
from seed



METRIC : ABSOLUTE SPEED

- p devices: P_1, P_2, \dots, P_p
- N_1 total #Primitive Jobs (chunks)
- Device Load [chunks]: n_1, n_2, \dots, n_p
- Absolute speed:

$$s_i(n_i) = n_i/t_i(n_i), 1 \leq i \leq p$$

SOLUTION: OPTIMAL LOAD BALANCING

Lies on the straight line that passes through the origin of coordinate system, such that:

$$x_1/s_1(x_1) = x_2/s_2(x_2) = \dots = x_p/s_p(x_p)$$

$$x_1 + x_2 + \dots + x_p = N_1$$

Case Study: Performance Modeling

What we already know ...* (2)

Performance Metric



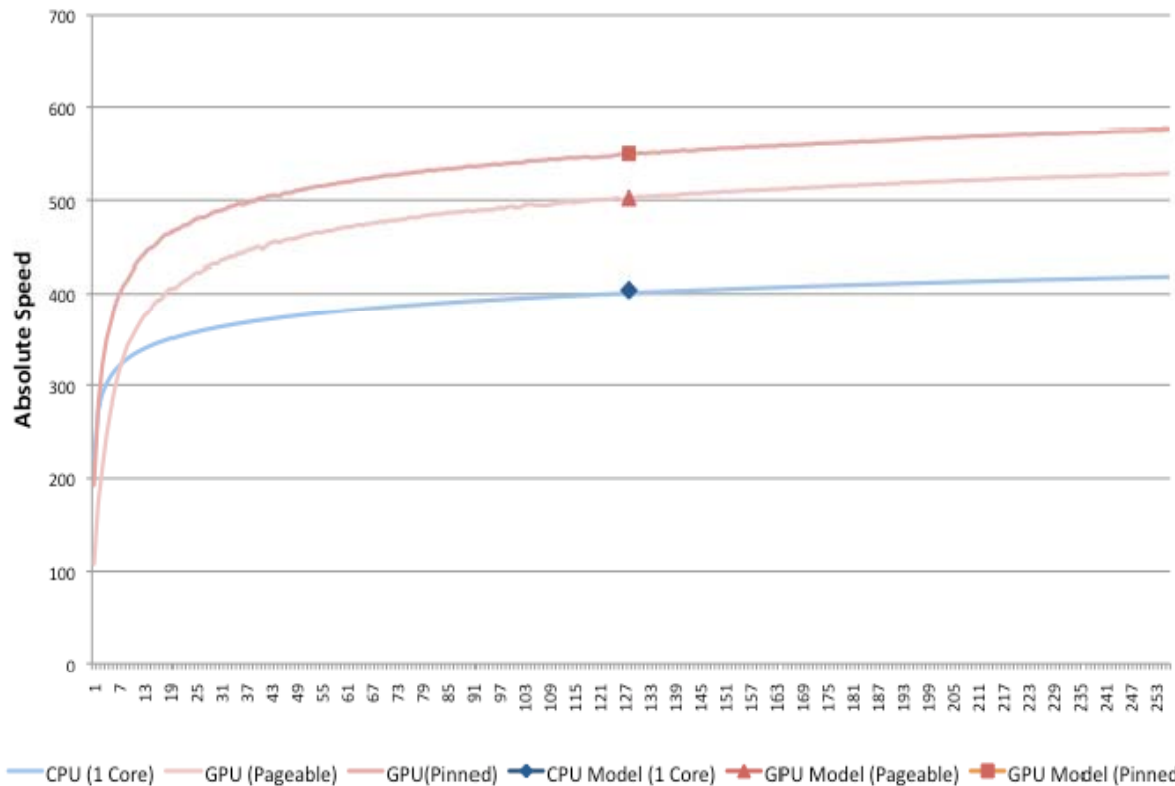
Initialization



Approximation



Iteration



① All the P computational units execute N_1/p 2D FFT Batches **in parallel**

$$n_i = N_1/p, \quad 1 \leq i \leq p$$

② Record execution times: $t_i(N_1/p)$

③ IF $\max_{1 \leq i, j \leq p} \{ (t_i(N_1/p) - t_j(N_1/p)) / t_i(N_1/p) \} \leq \epsilon$ THEN even distribution solves the problem and the algorithm stops;

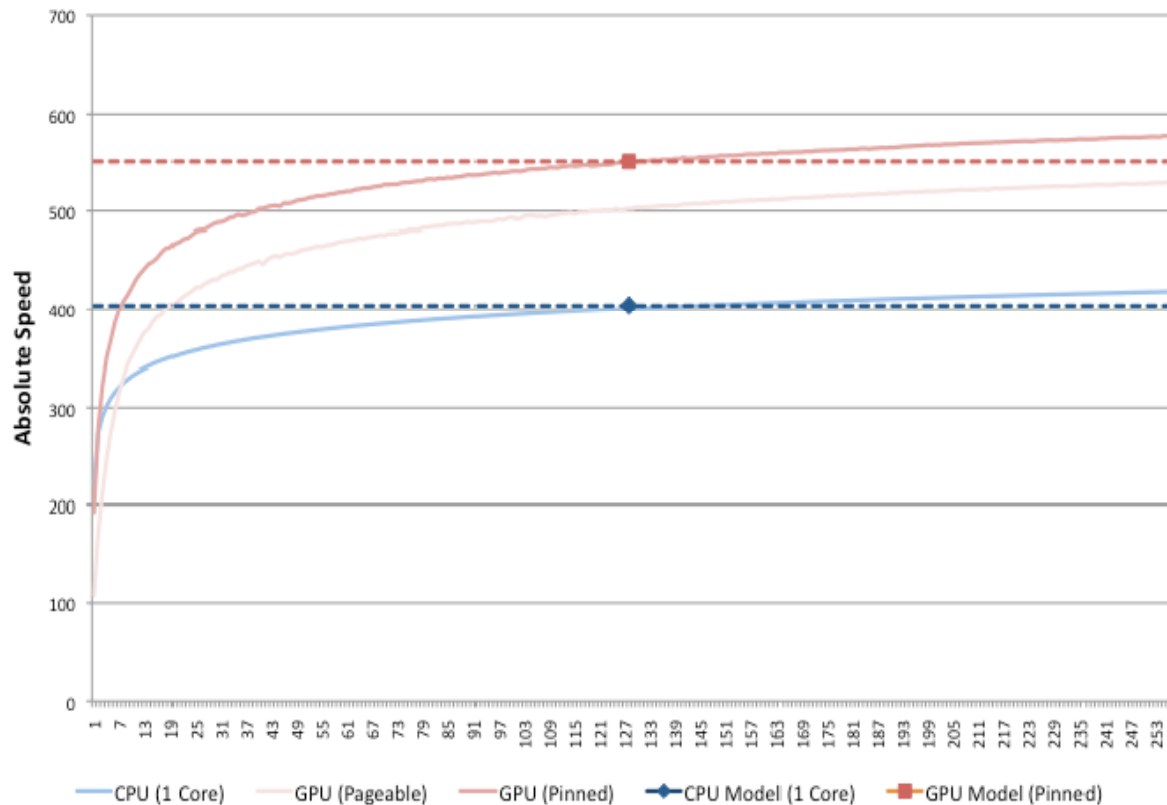
ELSE absolute speeds of devices are calculated, such that:

$$s_i(N_1/p) = (N_1/p) / t_i(N_1/p), \quad 1 \leq i \leq p$$

Case Study: Performance Modeling

What we already know ...* (3)

technology
from seed



① Performance of each device is modeled as a constant

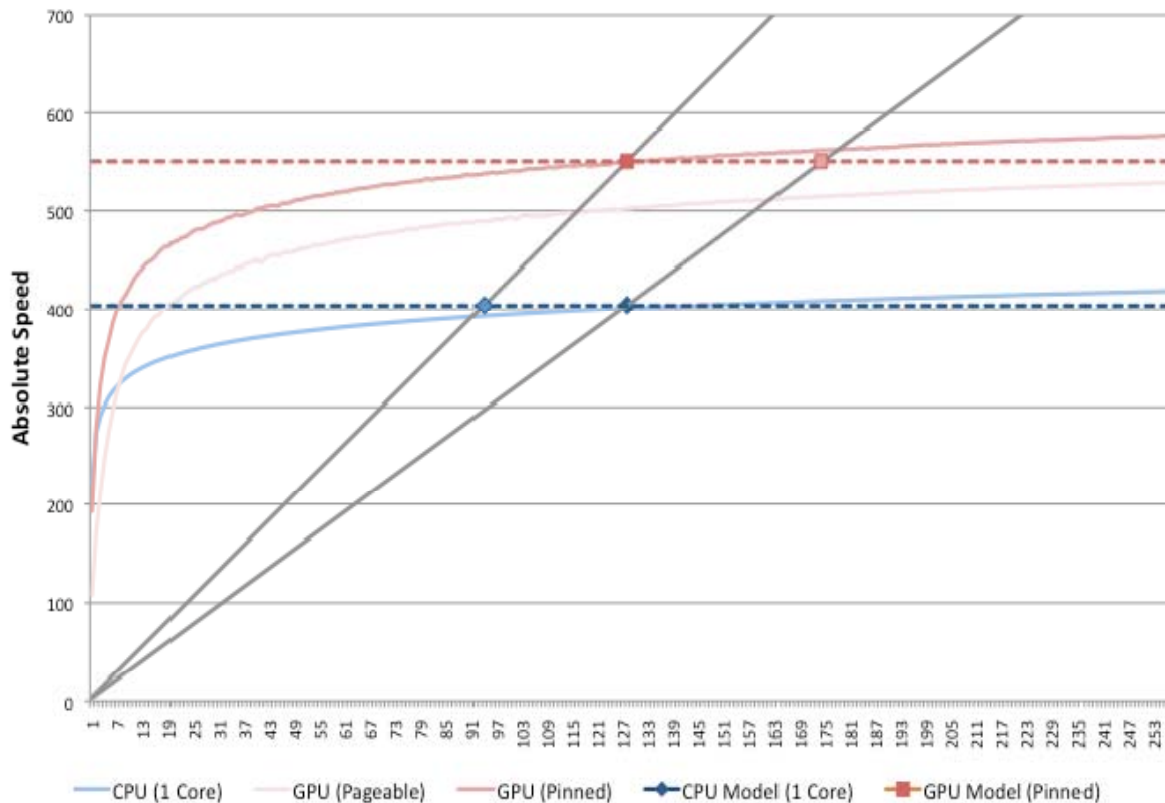
$$s_i(x) = s_i(N_1/p), 1 \leq i \leq p$$



*Lastovetsky, A., and R. Reddy, "Distributed Data Partitioning for Heterogeneous Processors Based on Partial Estimation of their Functional Performance Models", *HeteroPar 2009, Netherlands, Lecture Notes in Computer Science, vol. 6043, Springer, pp. 91-101, 25/9/2009, 2010.*

Case Study: Performance Modeling

What we already know ...** (4)



① Draw Upper U and Lower L lines through the following points:

$$(0, 0), (N_1/p, \max_i \{s_i(N_1/p)\})$$

$$(0, 0), (N_1/p, \min_i \{s_i(N_1/p)\})$$

② Let $x_1^{(U)}, x_1^{(L)}$ be the intersections with $s_i(x)$ IF exists $x_1^{(L)} - x_1^{(U)} \geq 1$
THEN go to 3
ELSE go to 5

Case Study: Performance Modeling

What we already know ...** (5)

Performance Metric



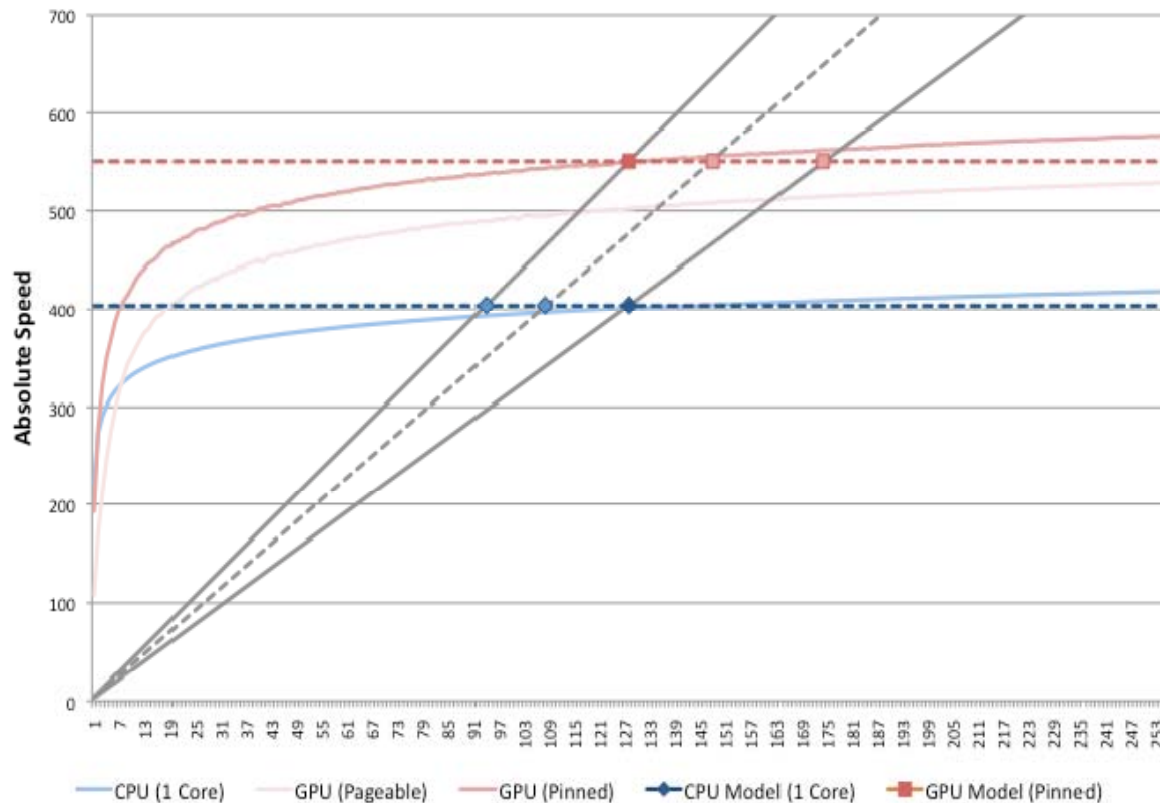
Initialization



Approximation



Iteration



- 1 Draw Upper U and Lower L lines through the following points:
 $(0, 0), (N_1/p, \max_i \{s_i(N_1/p)\})$
 $(0, 0), (N_1/p, \min_i \{s_i(N_1/p)\})$
- 2 Let $x_1^{(U)}, x_1^{(L)}$ be the intersections with $s_i(x)$ IF exists $x_1^{(L)} - x_1^{(U)} \geq 1$
 THEN go to 3
 ELSE go to 5
- ③ Bisect the angle between U and L by the line M , and calculate intersections $x_1^{(M)}$

Case Study: Performance Modeling

What we already know ...** (6)

Performance Metric



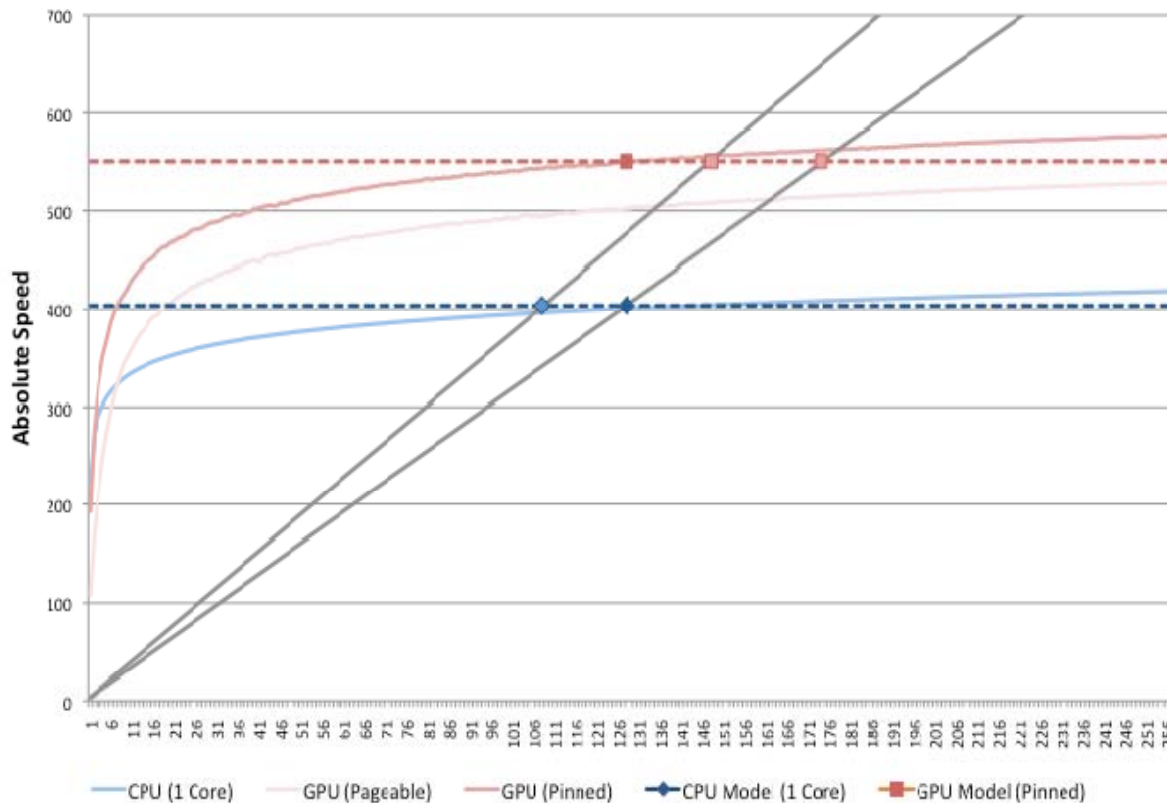
Initialization



Approximation



Iteration

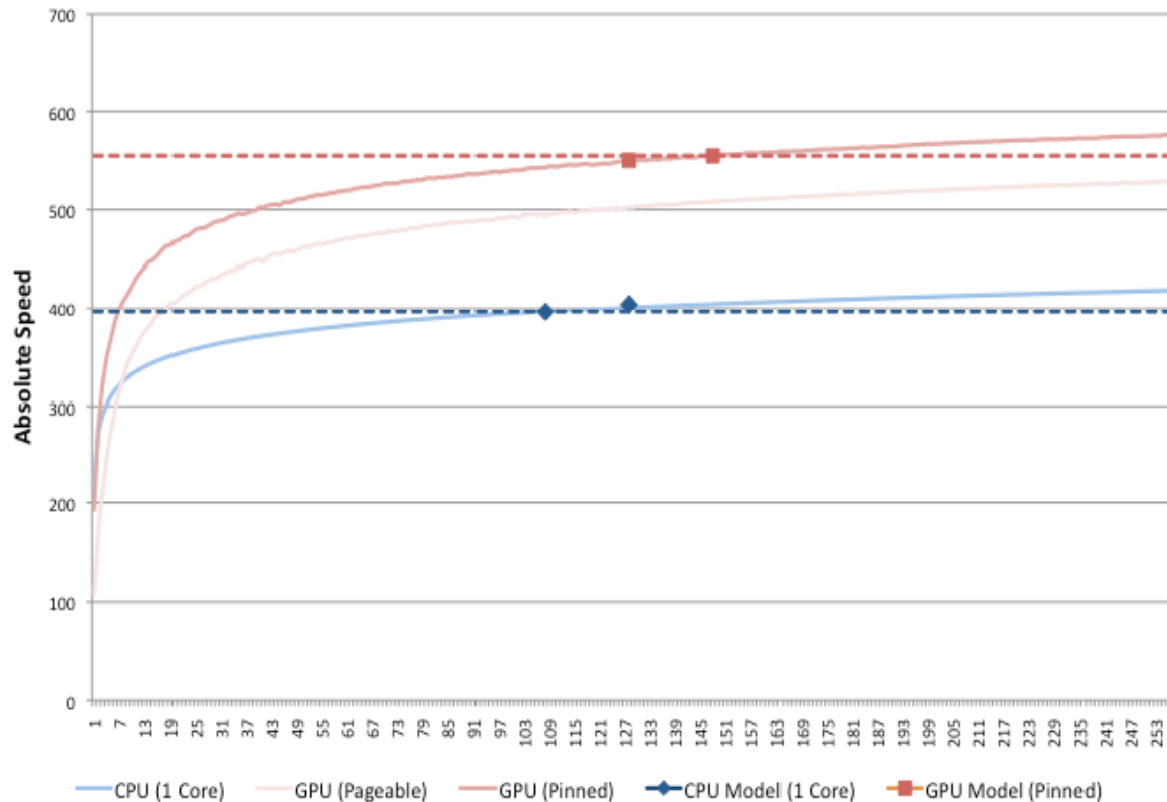


- 1 Draw Upper U and Lower L lines through the following points:
 - $(0, 0), (N_1/p, \max_i \{s_i(N_1/p)\})$
 - $(0, 0), (N_1/p, \min_i \{s_i(N_1/p)\})$
- 2 Let $x_1^{(U)}, x_1^{(L)}$ be the intersections with $s_i(x)$ IF exists $x_1^{(L)} - x_1^{(U)} \geq 1$
THEN go to 3
ELSE go to 5
- 3 Bisect the angle between U and L by the line M , and calculate intersections $x_1^{(M)}$
- ④ IF $\sum_i x_i^{(M)} \leq N_1$
THEN $U=M$
ELSE $L=M$
REPEAT 2

Case Study: Performance Modeling

What we already know ... (7)

technology
from seed



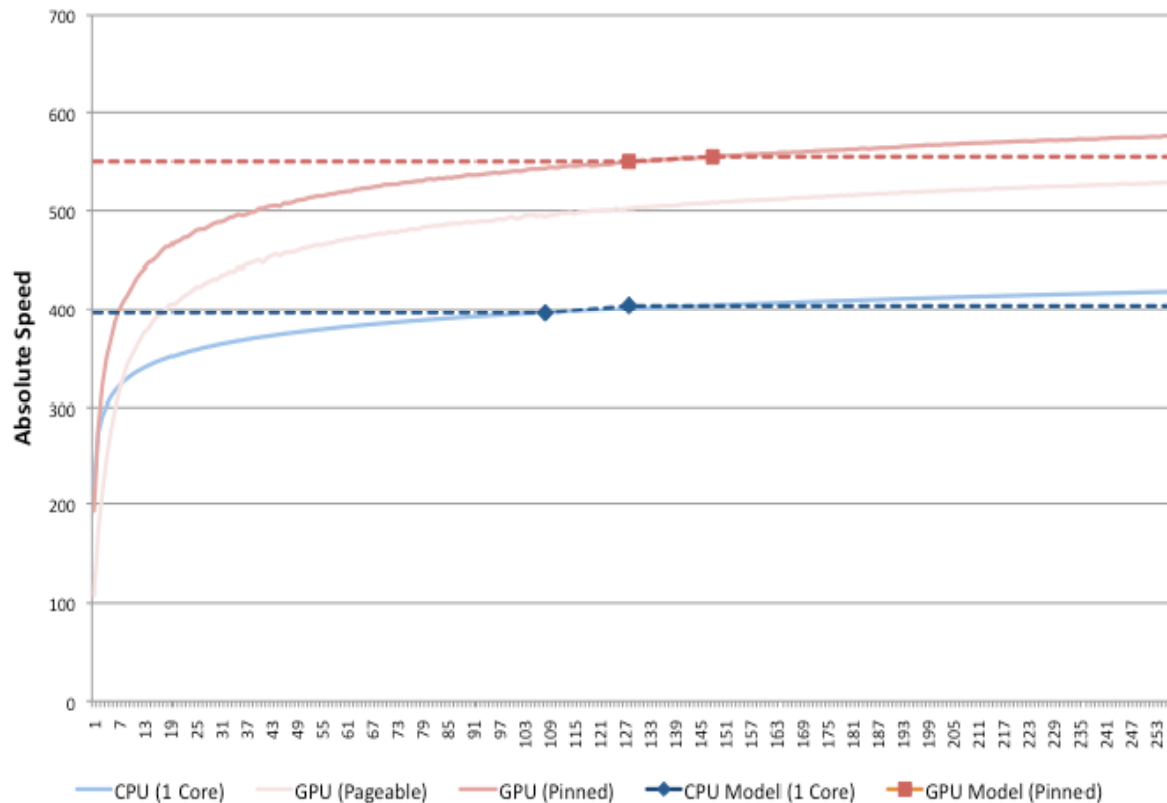
A. Speeds of each device are modeled as **constants** equal to the observed values [1]

$$s_i(x) = s_i(n_i), \quad 1 \leq i \leq p$$

Case Study: Performance Modeling

What we already know ... (8)

technology
from seed



A. Speeds of each device are modeled as **constants** equal to the observed values [1]

$$s_i(x) = s_i(n_i), \quad 1 \leq i \leq p$$

B. Functional performance modeling using **piecewise linear approximation** [2]



[1] Galindo I., Almeida F., and Badía-Contelles J.M., "Dynamic Load Balancing on Dedicated Heterogeneous Systems", In EuroPVM/MPI 2008, Springer, pp. 64-74, 2008.

[2] Lastovetsky, A., and R. Reddy, "Distributed Data Partitioning for Heterogeneous Processors Based on Partial Estimation of their Functional Performance Models", HeteroPar 2009, vol. 6043, Springer, pp. 91-101, 25/9/2009, 2010

ONLINE PERFORMANCE MODELING

- PERFORMANCE ESTIMATION of all heterogeneous devices DURING THE EXECUTION
 - No prior knowledge on the performance of an application is available on any of the devices
 - Modeling of the overall CPU and GPU performance for different problem sizes (+ kernel-only GPU performance)

DYNAMIC LOAD BALANCING

- OPTIMAL DISTRIBUTION OF COMPUTATIONS (PRIMITIVE JOBS)
 - Partial estimations of the performance should be built and used to decide on optimal mapping
 - Returned solution should provide load balancing within a given accuracy

COMMUNICATION AWARENESS

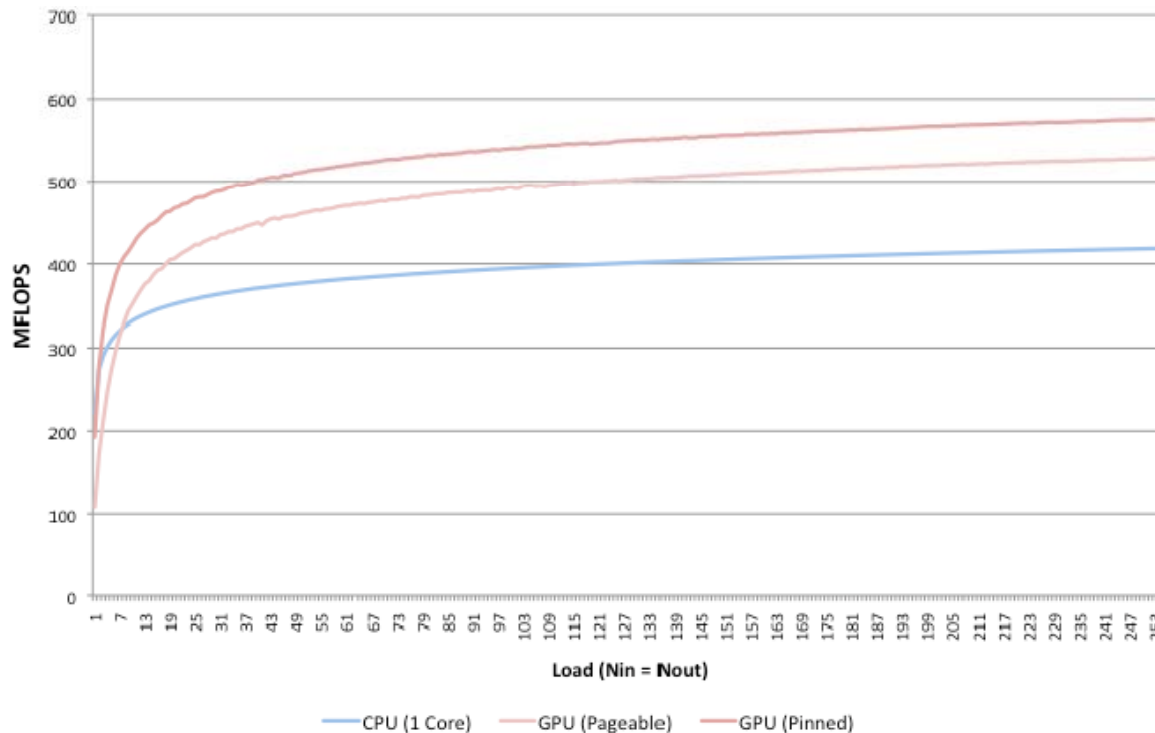
- MODELING THE BANDWIDTH for interconnection busses DURING THE EXECUTION
 - To select problem sizes that maximize the interconnection bandwidth
 - The algorithm should be aware of asymmetric bandwidth for Host-To-Device and Device-To-Host transfers

CPU+GPU ARCHITECTURAL SPECIFICS

- Make use of ENVIRONMENT-SPECIFIC FUNCTIONS to ease performance modeling
 - Asynchronous transfers and CUDA streams to overlap communication with computation
 - Be aware of diverse capabilities of different devices, but also for devices of the same type (e.g. GT200 vs. Fermi)

Case Study: Building Full Performance Models

technology
from seed



FULL PERFORMANCE MODELS: PER-DEVICE REAL PERFORMANCE

- Experimentally obtained using CPU+ GPU platform specifics (*Pageable/Pinned Memory*)
- Exhaustive search on the full range of problem sizes
- High cost of building it !!!

Experimental Setup	CPU	GPU
	Intel Core 2 Quad	nVIDIA GeForce 285GTX
Speed/Core (GHz)	2.83	1.476
Global Memory (MB)	4096	1024

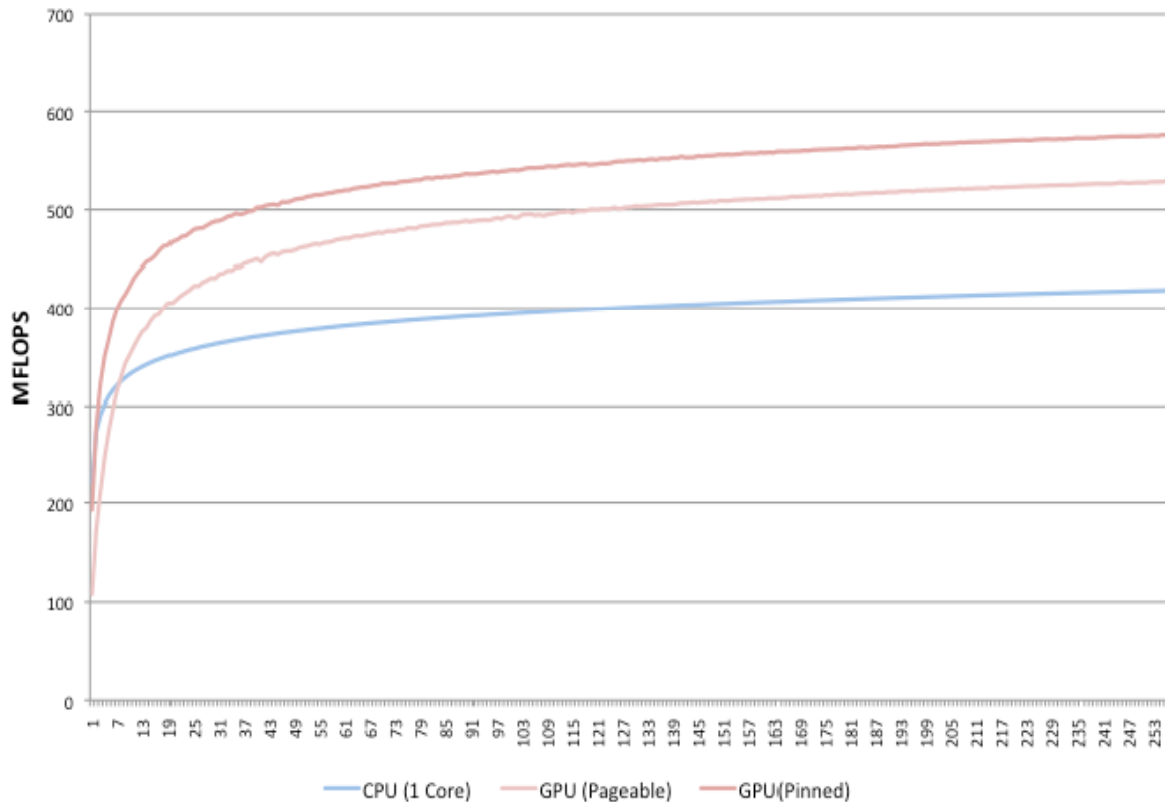
2D FFT Batch	CPU	GPU
FFT Type	Complex; Double Precision	
Total Size ($N_1 \times N_2 \times N_3$)	256x256x256	
High Performance Software		
FFT	Intel MKL 10.2	CUFFT 3.1



Instituto de Engenharia de Sistemas e Computadores Investigação e Desenvolvimento em Lisboa

Case Study: Performance Modeling in CPU + GPU Environment (1)

technology
from seed



PROBLEM DEFINITION: PRIMITIVE JOB

- n^{in} - input data requirements
- n^{out} - output data requirements
- n^{size} - problem size
- n^{flops} - #float-point operations

METRIC : FLOPS

- p devices: P_1, P_2, \dots, P_p
- N_1 total #Primitive Jobs (chunks)
- Device Load [chunks]: n_1, n_2, \dots, n_p
- $n_i = \{n_i^{in}, n_i^{out}, n_i^{size}, n_i^{flops}\}$

- FLOPS:

$$Perf_i(n_i) = n_i^{flops} / t_i(n_i), \quad 1 \leq i \leq p$$

SOLUTION: OPTIMAL LOAD BALANCING

Lies on the straight line that passes through the origin of coordinate system, such that:

$$x_i^{flops} = nf(x_i), \quad x_i \text{ as } n_i^{size}$$

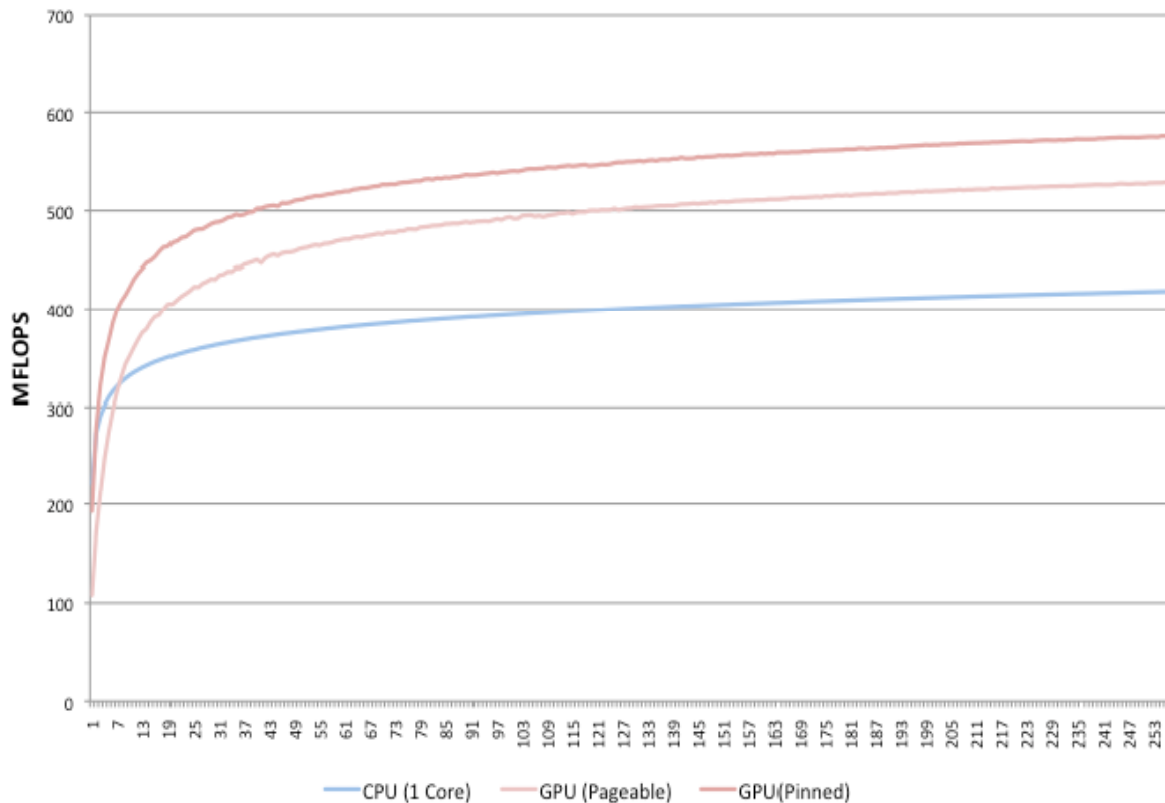
$$nf(x_1) / Perf_1(x_1) = \dots = nf(x_p) / Perf_p(x_p)$$

$$x_1 + x_2 + \dots + x_p = N_1$$



Case Study: Performance Modeling in CPU + GPU Environment (2)

technology
from seed



- ① All the P computational units execute N_1/p 2D FFT Batches **in parallel**

$$n_i = N_1/p, 1 \leq i \leq p$$
- ② IF (device is GPU) AND (task is Divisible and Agglomerative)
 THEN go to 3
 ELSE go to 4
- ③ Split given computational load into streams and use asynchronous transfers to overlap communication with computation

Case Study: Performance Modeling in CPU + GPU Environment (3)

technology
from seed



- SUBDIVIDE n_i computational chunks using DIV2 STRATEGY
 - No prior knowledge on the performance of an application!
 - The next stream has half the load of a previous stream
 - Algorithm may continue splitting the workload until the last stream is assigned with load equal to 1
- BANDWIDTH-AWARE DIV2 STRATEGY
 - Interconnection bandwidth is a subject to the amount of data that should be transferred and not to the application-specific demands
 - Run small pre-calibration tests for HOST-TO-DEVICE AND DEVICE-TO-HOST transfers
 - Tests can be stopped when saturation points are detected, or when transfers reach desired value (e.g. 60% of its theoretical)
 - CASE STUDY: $n^{\min_size} = 4$

- 1 All the P computational units execute N_1/p 2D FFT Batches **in parallel**
$$n_i = N_1/p, 1 \leq i \leq p$$
- 2 IF (device is GPU) AND (task is Divisible and Agglomerative)
THEN go to 3
ELSE go to 4
- ③ Split given computational load into streams and use asynchronous transfers to overlap communication with computation



Case Study: Performance Modeling in CPU + GPU Environment (4)

Performance Metric



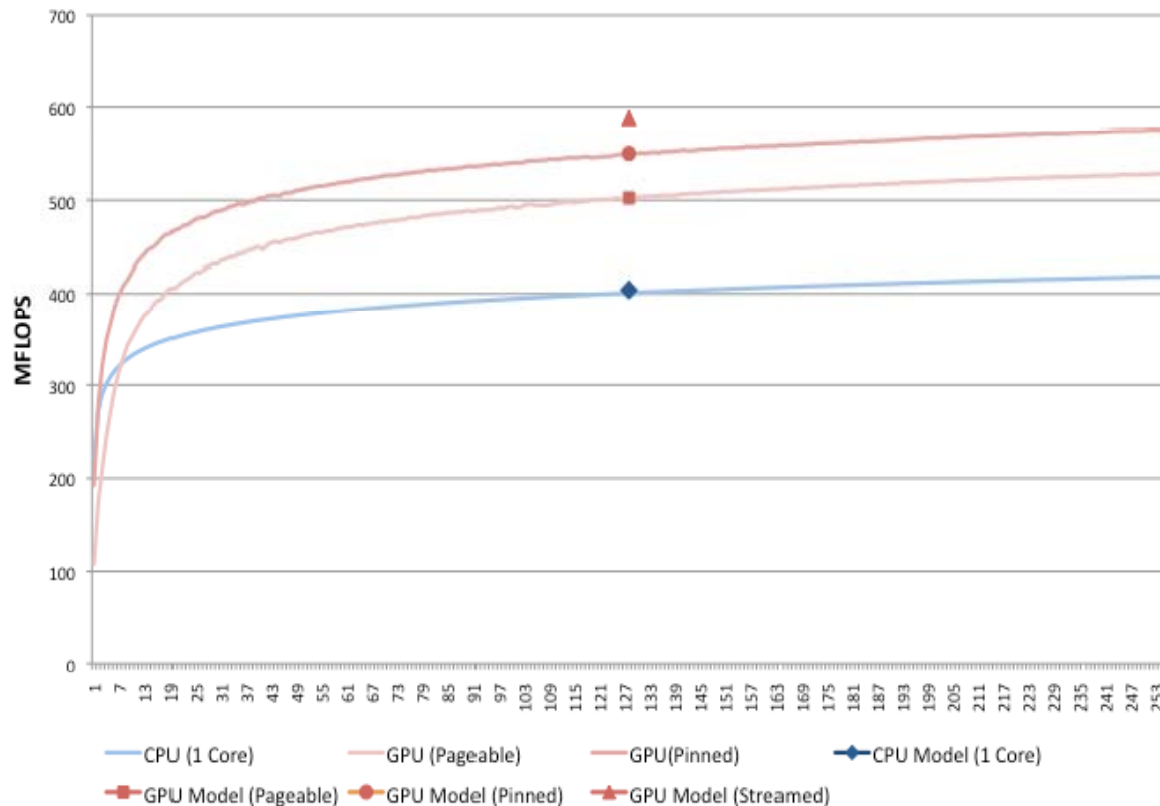
Initialization



Approximation



Iteration



- 1 All the P computational units execute N_1/p 2D FFT Batches **in parallel**

$$n_i = N_1/p, \quad 1 \leq i \leq p$$

- 2 IF (device is GPU) AND (task is Divisible and Agglomerative)
THEN go to 3
ELSE go to 4

- 3 Split given computational load into streams and use asynchronous transfers to overlap communication with computation

- ④ Execute & record execution times: $t_i(N_1/p)$

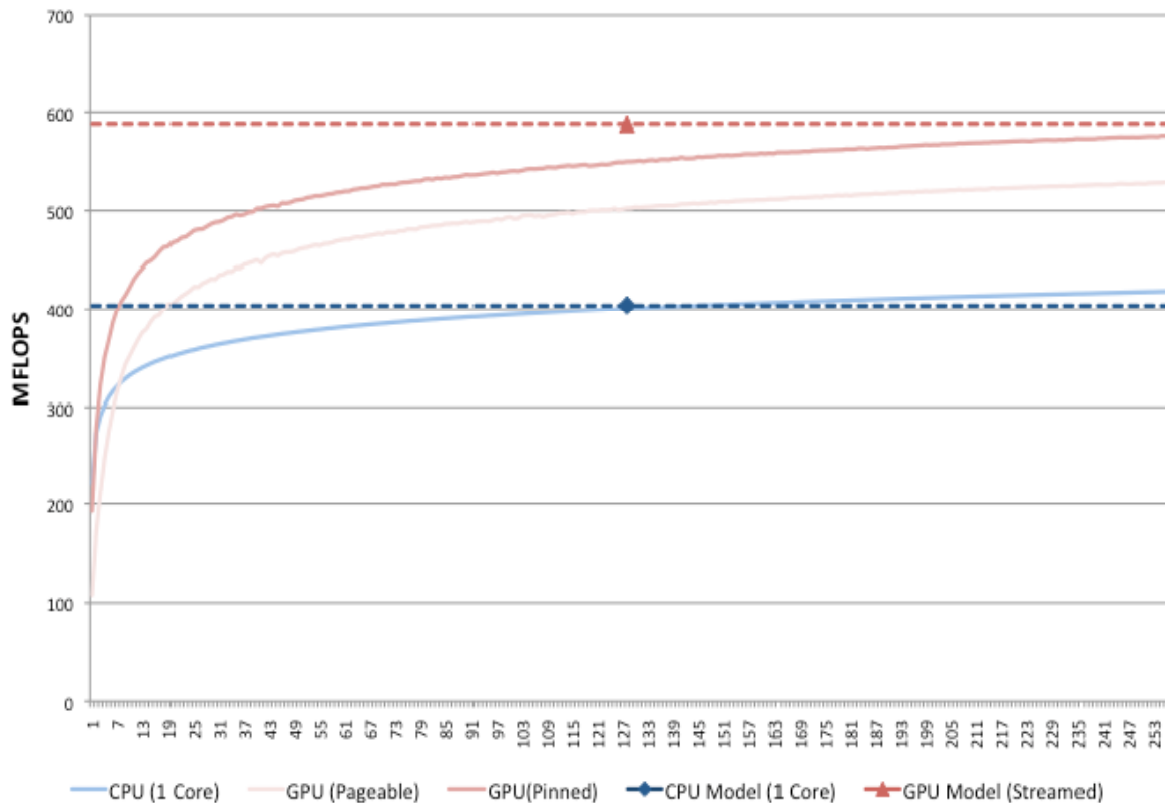
- ⑤ IF $\max_{1 \leq i, j \leq p} \{ (t_i(N_1/p) - t_j(N_1/p)) / t_i(N_1/p) \} \leq \epsilon$
THEN even distribution solves the problem and the algorithm stops;

ELSE performance of devices is calculated, such that:

$$\text{Perf}_i(N_1/p) = nf(N_1/p) / t_i(N_1/p), \quad 1 \leq i \leq p$$

Case Study: Performance Modeling in CPU + GPU Environment (5)

technology
from seed

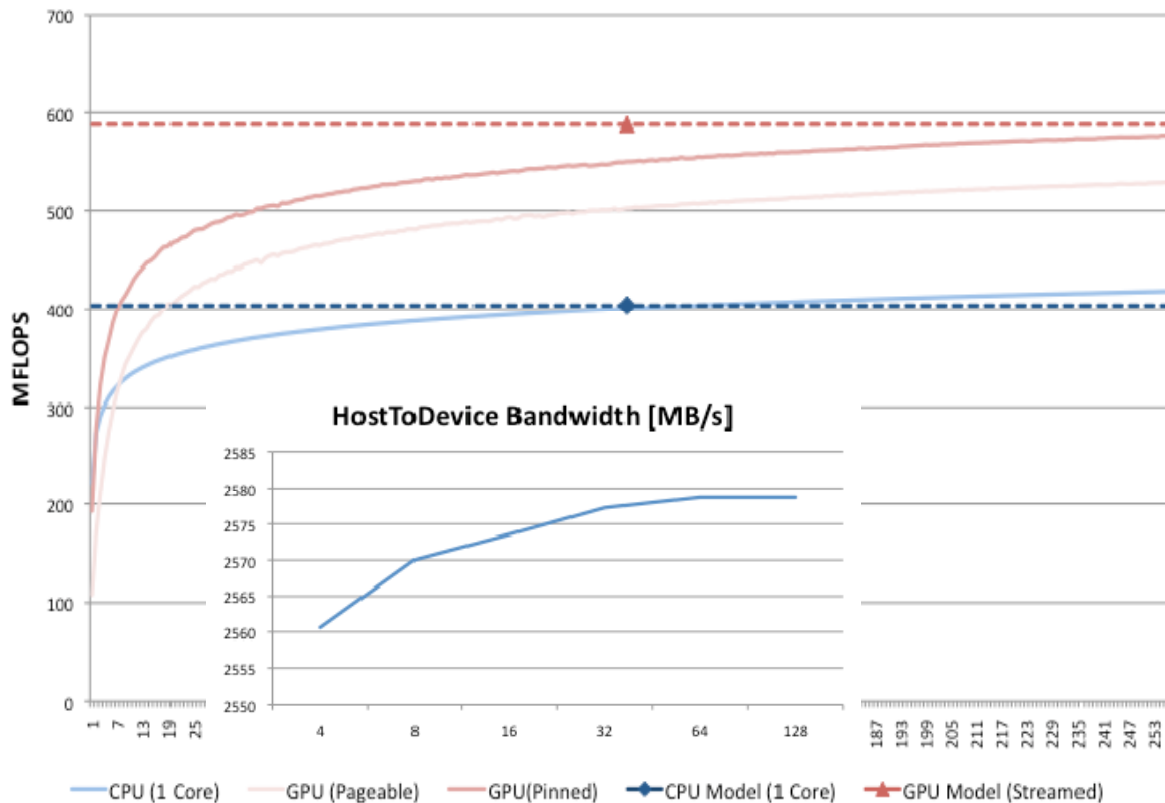


① Traditional approach: **Performance** of each device is **modeled as a constant**

$$Perf_i(x) = Perf_i(N_1/p), 1 \leq i \leq p$$

Case Study: Performance Modeling in CPU + GPU Environment (6)

technology
from seed



1 Traditional approach: **Performance** of each device is **modeled as a constant**

$$Perf_i(x) = Perf_i(N_1/p), 1 \leq i \leq p$$

② GPU-specific Modeling: Using the obtained values from streaming execution

– *HostToDevice* Bandwidth

Case Study: Performance Modeling in CPU + GPU Environment (7)

Performance Metric



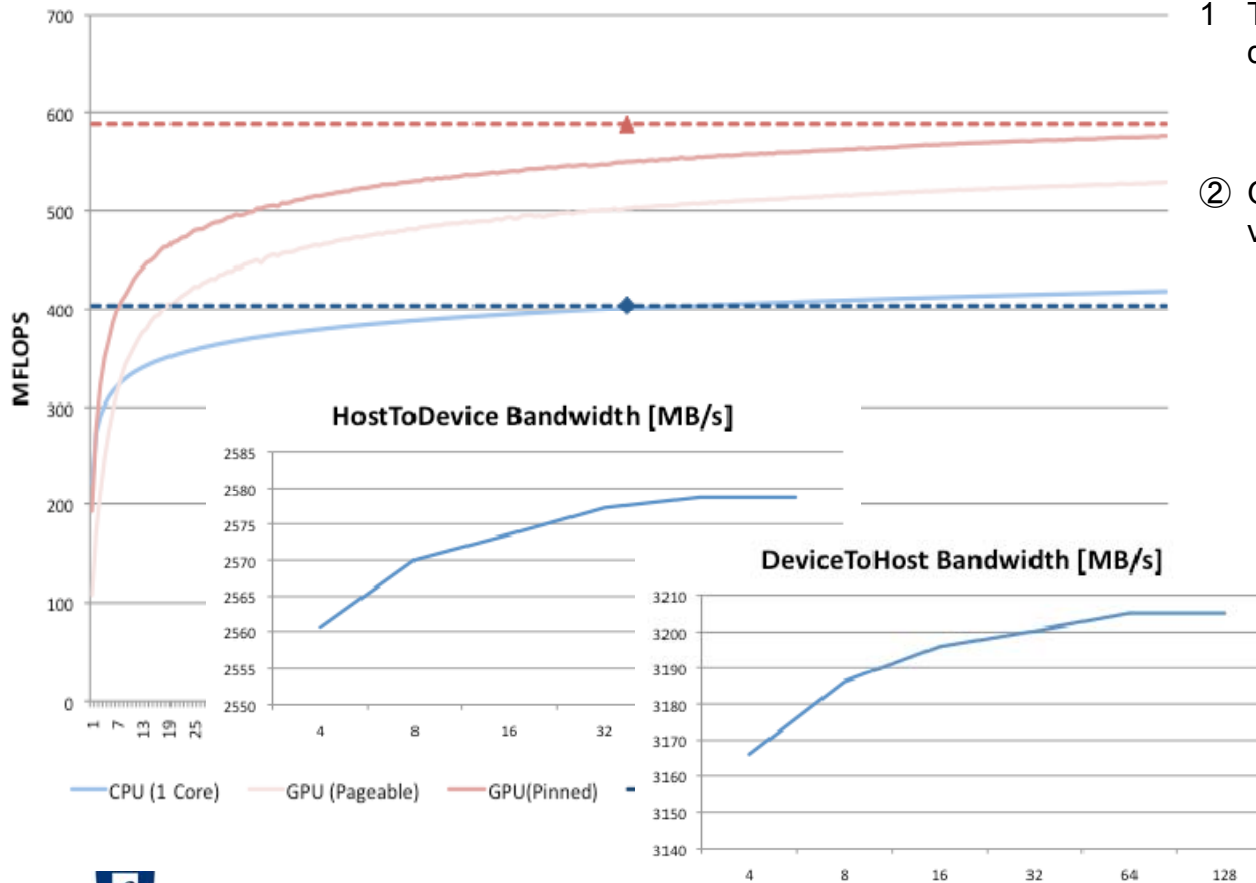
Initialization



Approximation



Iteration



1 Traditional approach: **Performance** of each device is **modeled as a constant**

$$\text{Perf}_i(x) = \text{Perf}_i(N_1/p), 1 \leq i \leq p$$

② GPU-specific Modeling: Using the obtained values from streaming execution

- *HostToDevice* Bandwidth
- *DeviceToHost* Bandwidth

Case Study: Performance Modeling in CPU + GPU Environment (8)

Performance Metric



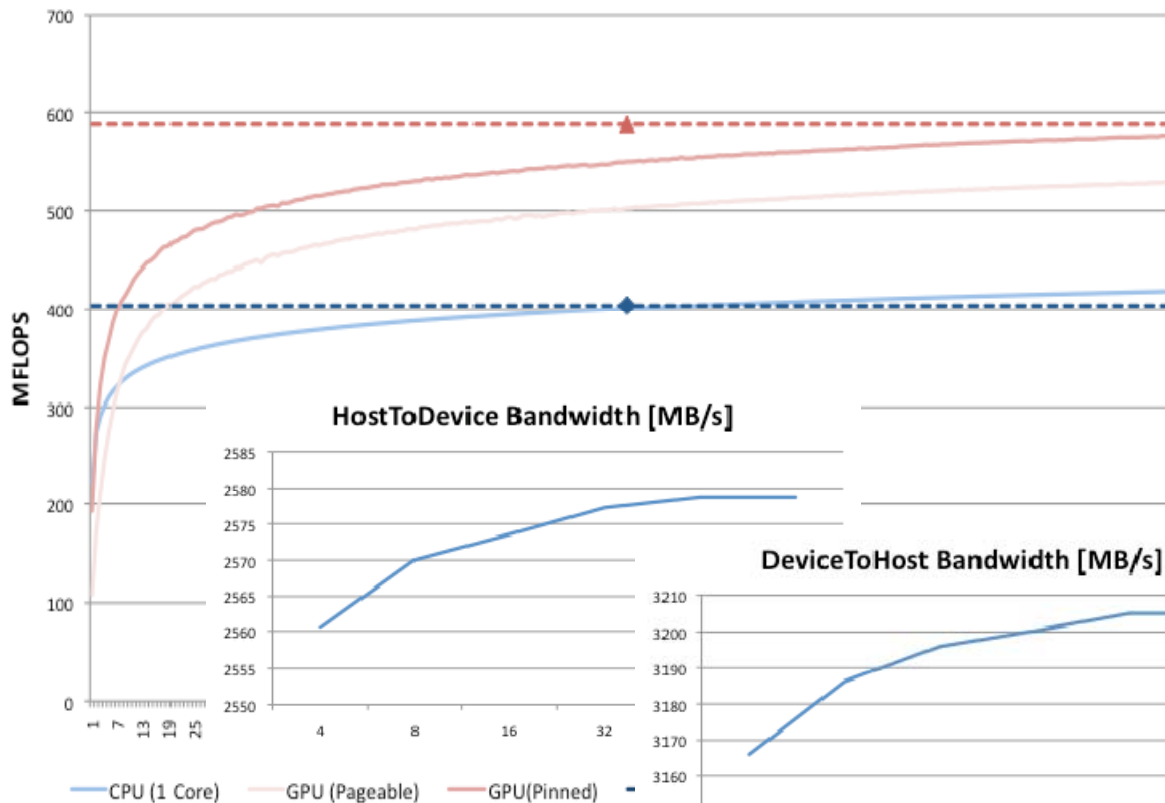
Initialization



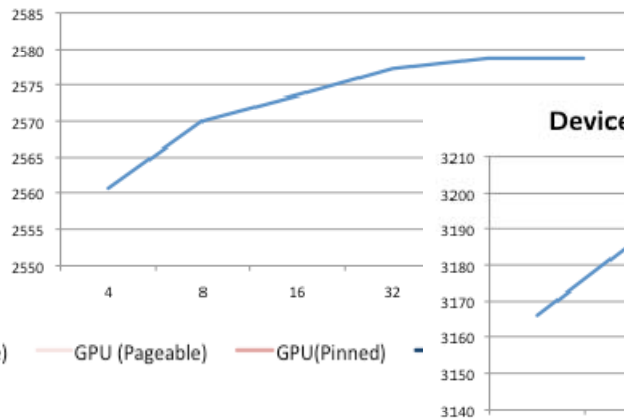
Approximation



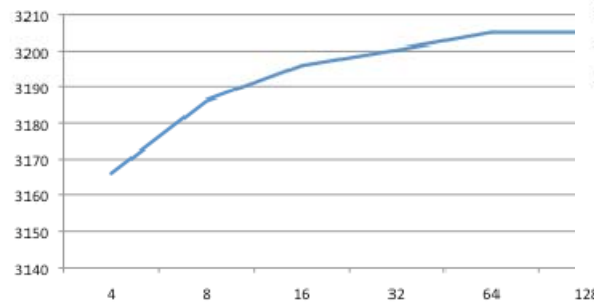
Iteration



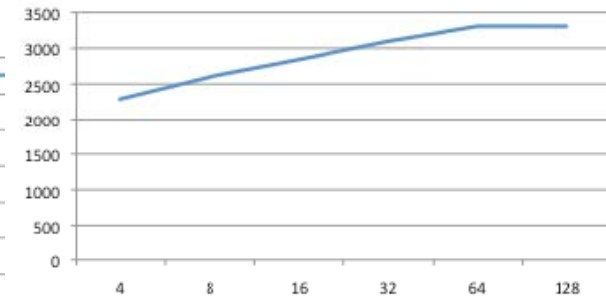
HostToDevice Bandwidth [MB/s]



DeviceToHost Bandwidth [MB/s]



GPU Kernel [MFLOPS]



1 Traditional approach: **Performance** of each device is **modeled as a constant**

$$\text{Perf}_i(x) = \text{Perf}_i(N_1/p), 1 \leq i \leq p$$

② GPU-specific Modeling: Using the obtained values from streaming execution

- *HostToDevice* Bandwidth
- *DeviceToHost* Bandwidth
- *GPU Kernel* Performance

Case Study: Performance Modeling in CPU + GPU Environment (9)

Performance Metric



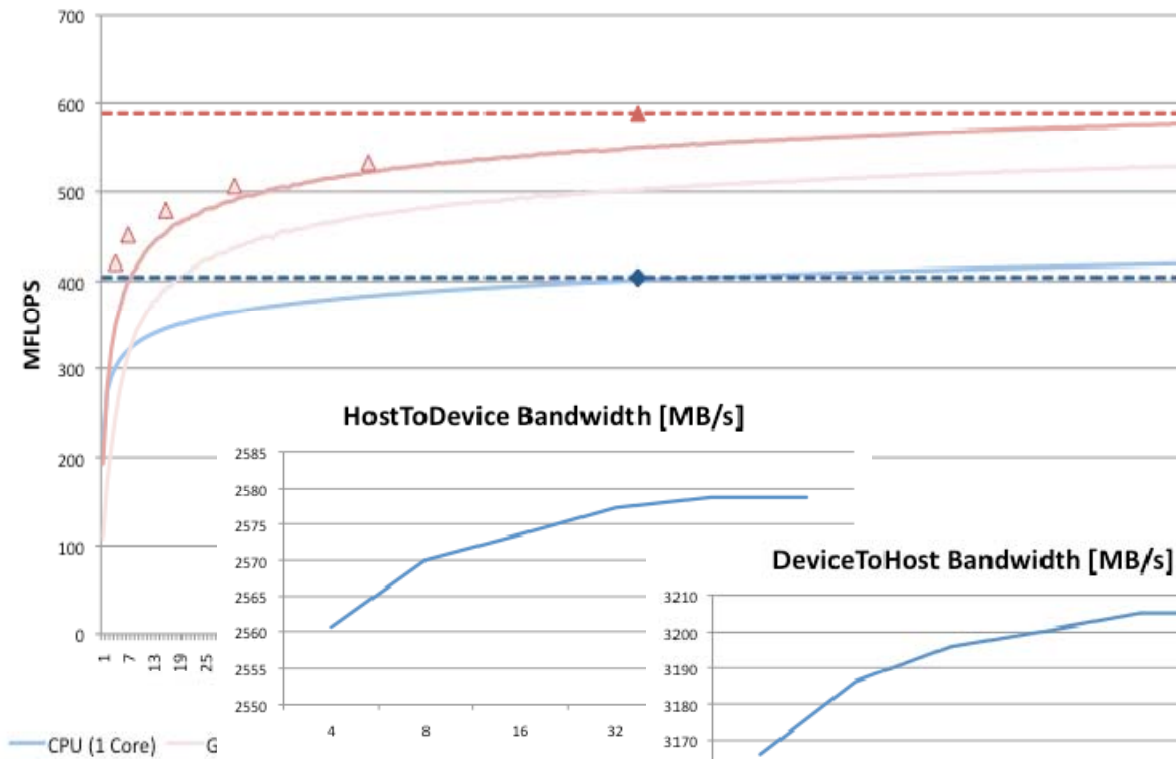
Initialization



Approximation



Iteration



1 Traditional approach: **Performance** of each device is **modeled as a constant**

$$\text{Perf}_i(x) = \text{Perf}_i(N_1/p), 1 \leq i \leq p$$

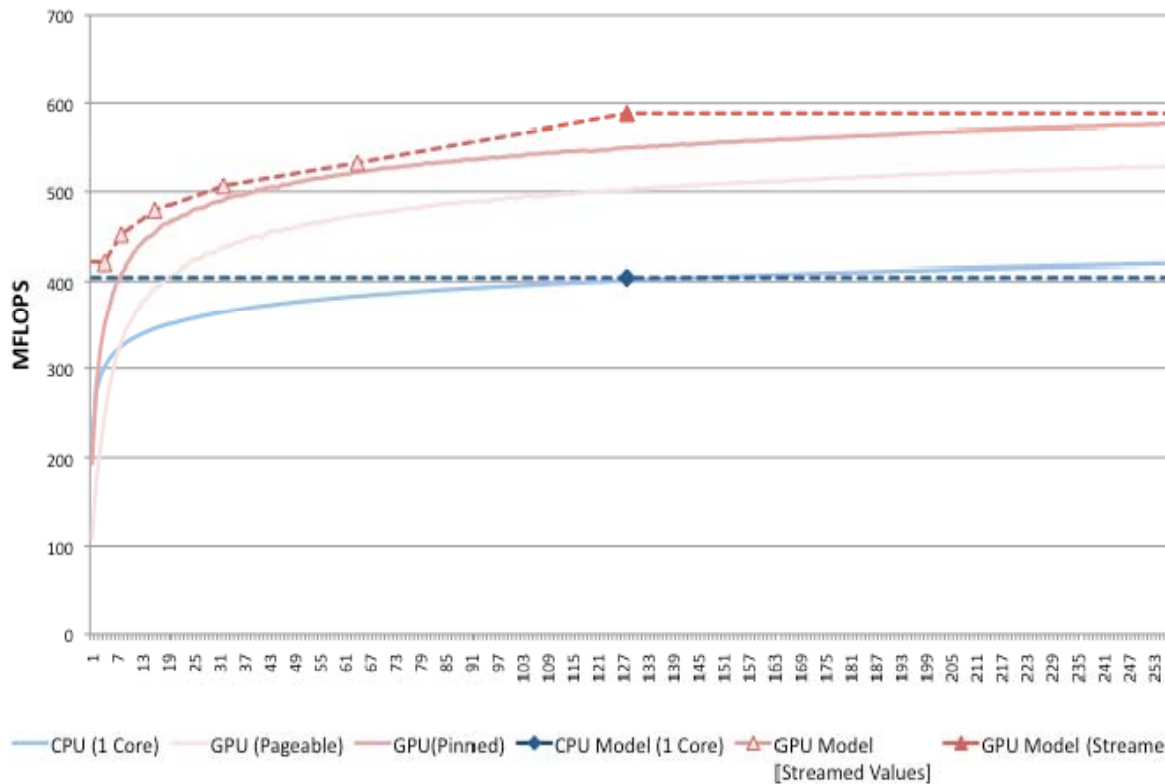
② GPU-specific Modeling: Using the obtained values from streaming execution

- *HostToDevice* Bandwidth
- *DeviceToHost* Bandwidth
- *GPU Kernel* Performance

③ Incorporate streaming results

Case Study: Performance Modeling in CPU + GPU Environment (10)

technology
from seed



1 Traditional approach: **Performance** of each device is **modeled as a constant**

$$Perf_i(x) = Perf_i(N_1/p), 1 \leq i \leq p$$

2 GPU-specific Modeling: Using the obtained values from streaming execution

- *HostToDevice* Bandwidth
- *DeviceToHost* Bandwidth
- *GPU Kernel* Performance

③ Incorporate streaming results

Case Study: Performance Modeling in CPU + GPU Environment (11)

Performance Metric



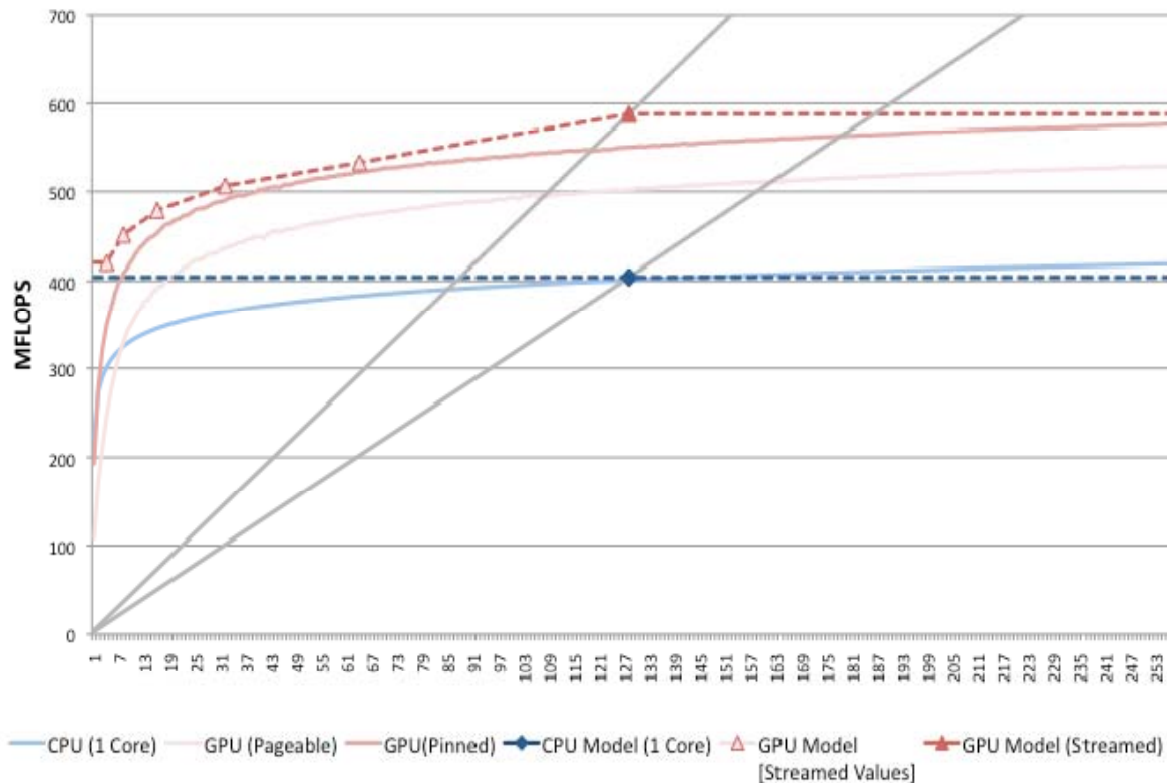
Initialization



Approximation



Iteration



- ① Draw Upper U and Lower L lines through the following points:
 $(0, 0)$, $(N_1/p, \max_i \{ \text{Perf}_i(N_1/p) \})$
 $(0, 0)$, $(N_1/p, \min_i \{ \text{Perf}_i(N_1/p) \})$
- ② Let $x_i^{(U)}$ and $x_i^{(L)}$ be the intersections with $\text{Perf}_i(x)$
 IF exists $x_i^{(L)} - x_i^{(U)} \geq 1$
 THEN go to 3
 ELSE go to 5
- ③ Bisect the angle between U and L by the line M , and calculate intersections $x_i^{(M)}$
- ④ IF $\sum_i x_i^{(M)} \leq N_1$
 THEN $U=M$
 ELSE $L=M$
 REPEAT 2

Case Study: Performance Modeling in CPU + GPU Environment (12)

Performance Metric



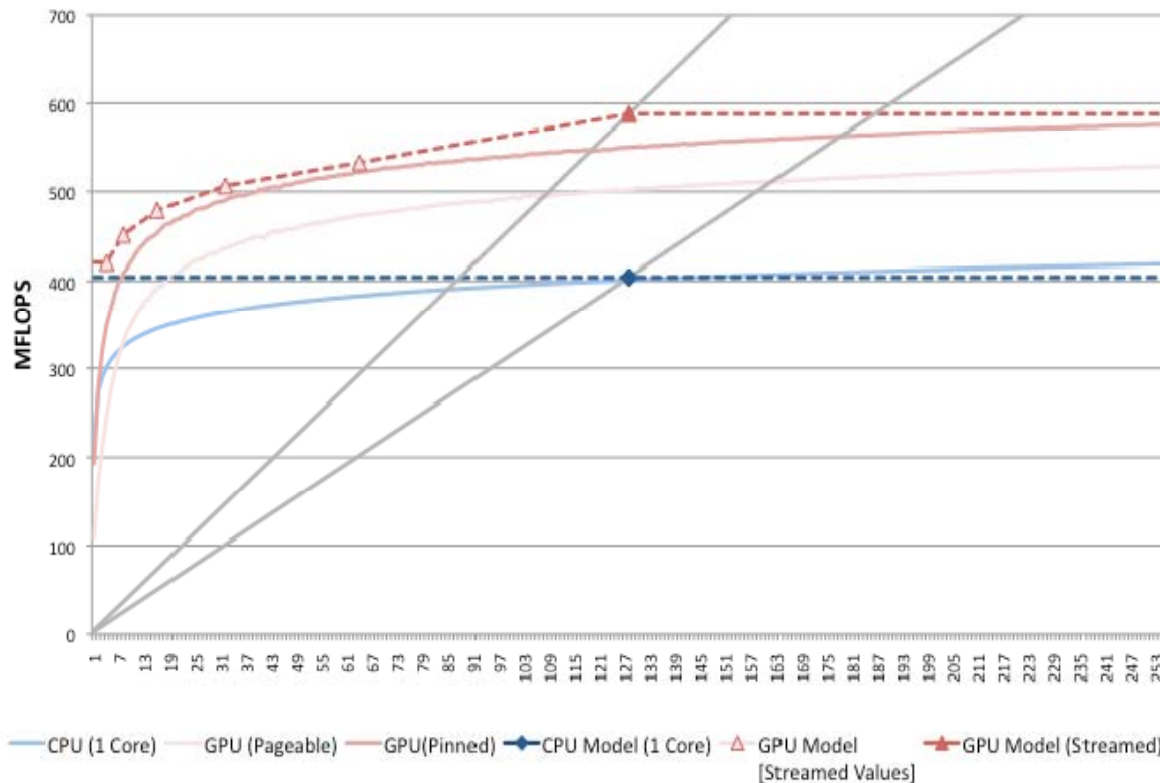
Initialization



Approximation



Iteration



- 1 Draw Upper U and Lower L lines through the following points:
 $(0, 0), (N_1/p, \max_i \{Perf_i(N_1/p)\})$
 $(0, 0), (N_1/p, \min_i \{Perf_i(N_1/p)\})$
- 2 Let $x_i^{(U)}$ and $x_i^{(L)}$ be the intersections with $Perf_i(x)$
 IF exists $x_i^{(L)} - x_i^{(U)} \geq 1$
 THEN go to 3
 ELSE go to 5
- 3 Bisect the angle between U and L by the line M , and calculate intersections $x_i^{(M)}$
- 4 IF $\sum_i x_i^{(M)} \leq N_1$
 THEN $U=M$
 ELSE $L=M$
 REPEAT 2
- ⑤ Employ **streaming strategy** on the calculated workload value

Case Study: Performance Modeling in CPU + GPU Environment (13)

technology
from seed



Performance Metric



Initialization



Approximation



Iteration

Streaming

– STREAMING STRATEGY

- Results obtained using DIV2 STRATEGY consider application characterization (e.g. communication-to-computation ratio)
- Workload size for the next stream should be chosen in order to OVERLAP TRANSFERS WITH COMPUTATION in the previous stream

– BANDWIDTH-AWARE STREAMING STRATEGY

- Reuses the MINIMAL WORKLOAD SIZE FROM DIV2 STRATEGY (obtained via HOST-TO-DEVICE and DEVICE-TO-HOST tests)
 - IF $(n^{curr} \geq n^{min_size})$
 - THEN use strategy (cont. overlapping)
 - ELSE restart strategy on n^{curr} load
- In case that load drops under n^{min_size} , strategy is restarted on remaining load

1 Draw Upper U and Lower L lines through the following points:

$$(0, 0), (N_1/p, \max_i \{Perf_i(N_1/p)\})$$

$$(0, 0), (N_1/p, \min_i \{Perf_i(N_1/p)\})$$

2 Let $x_i^{(U)}$ and $x_i^{(L)}$ be the intersections with $Perf_i(x)$

IF exists $x_i^{(L)} - x_i^{(U)} \geq 1$

THEN go to 3

ELSE go to 5

3 Bisect the angle between U and L by the line M , and calculate intersections $x_i^{(M)}$

4 IF $\sum_i x_i^{(M)} \leq N_1$

THEN $U=M$

ELSE $L=M$

REPEAT 2

⑤ Employ **streaming strategy** on the calculated workload value

Case Study: Performance Modeling in CPU + GPU Environment (14)

technology
from seed

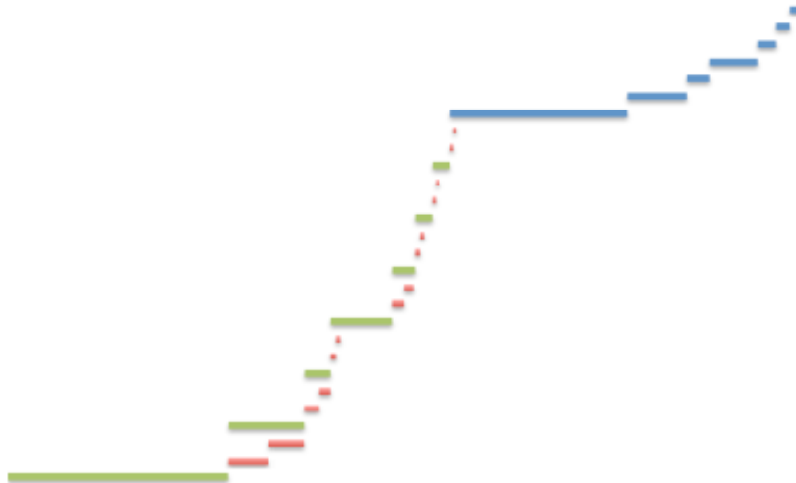


– CASE STUDY: 2D FFT BATCH

- About 83% of total execution time goes on data transfers
 - **HOSTTODEVICE Transfers** – 46%
 - **KERNEL Execution** – 17%
 - **DEVICETOHOST Transfers** – 37%

– BANDWIDTH-AWARE STREAMING STRATEGY

- $n_{\min_size} = 4$, overlap HOSTTODEVICE transfers and KERNEL execution of two streams



1 Draw Upper U and Lower L lines through the following points:

$$(0, 0), (N_1/p, \max_i \{Perf_i(N_1/p)\})$$

$$(0, 0), (N_1/p, \min_i \{Perf_i(N_1/p)\})$$

2 Let $x_i^{(U)}$ and $x_i^{(L)}$ be the intersections with $Perf_i(x)$

$$\text{IF exists } x_i^{(L)} - x_i^{(U)} \geq 1$$

THEN go to 3

ELSE go to 5

3 Bisect the angle between U and L by the line M , and calculate intersections $x_i^{(M)}$

4 IF $\sum_i x_i^{(M)} \leq N_1$

THEN $U=M$

ELSE $L=M$

REPEAT 2

⑤ Employ **streaming strategy** on the calculated workload value

Case Study: Performance Modeling in CPU + GPU Environment (15)

Performance Metric



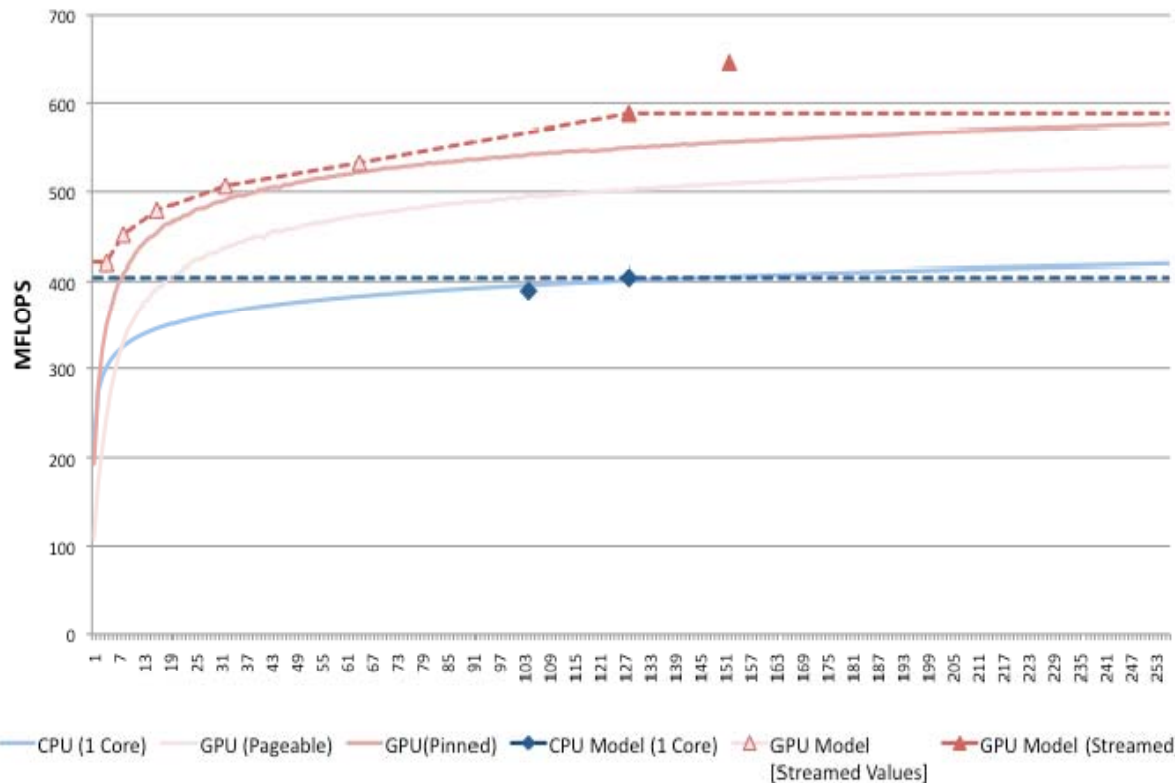
Initialization



Approximation



Iteration



1 Draw Upper U and Lower L lines through the following points:

$$(0, 0), (N_1/p, \max_i \{ \text{Perf}_i(N_1/p) \})$$

$$(0, 0), (N_1/p, \min_i \{ \text{Perf}_i(N_1/p) \})$$

2 Let $x_i^{(U)}$ and $x_i^{(L)}$ be the intersections with $\text{Perf}_i(x)$

IF exists $x_i^{(L)} - x_i^{(U)} \geq 1$

THEN go to 3

ELSE go to 5

3 Bisect the angle between U and L by the line M , and calculate intersections $x_i^{(M)}$

4 IF $\sum_i x_i^{(M)} \leq N_1$

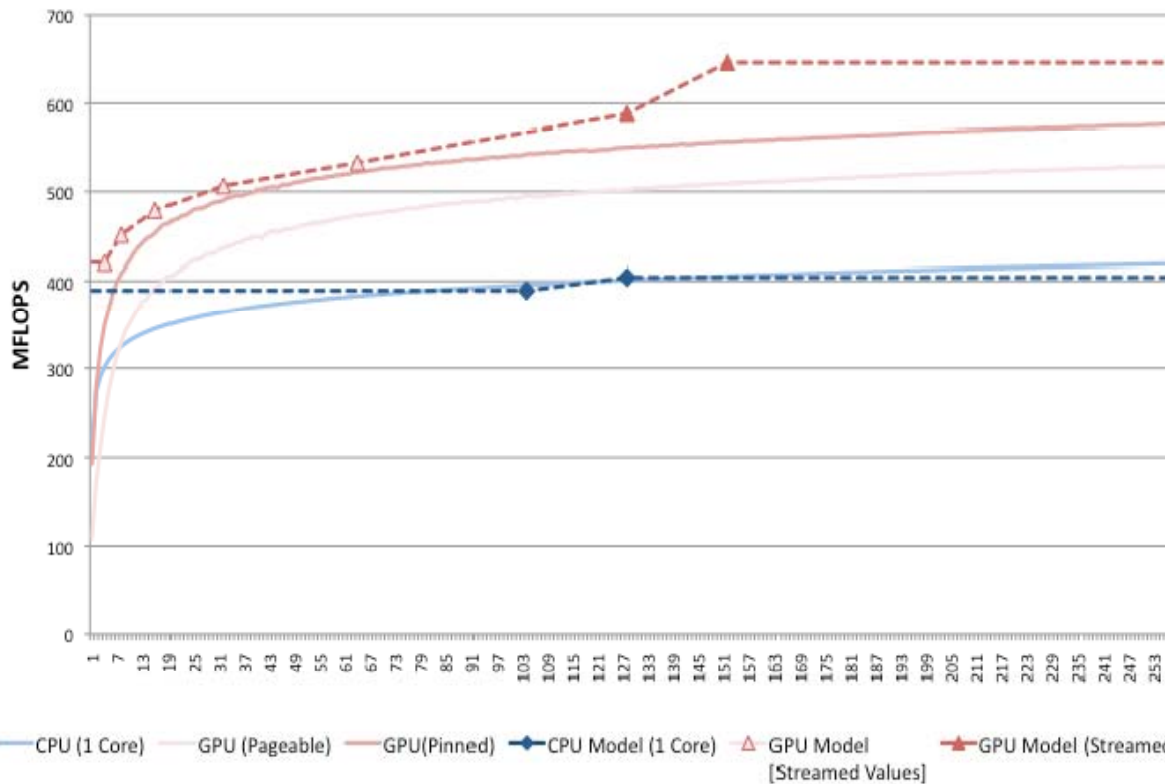
THEN $U=M$

ELSE $L=M$

REPEAT 2

5 Employ streaming strategy on the calculated workload value

Case Study: Performance Modeling in CPU + GPU Environment (16)



- ① Refine performance models with the newly obtained results
- 2 GPU-specific Modeling: Using the obtained values from streaming execution
 - *HostToDevice* Bandwidth
 - *DeviceToHost* Bandwidth
 - *GPU Kernel* Performance
- 3 Incorporate streaming results

Case Study: Performance Modeling in CPU + GPU Environment (17)

Performance Metric



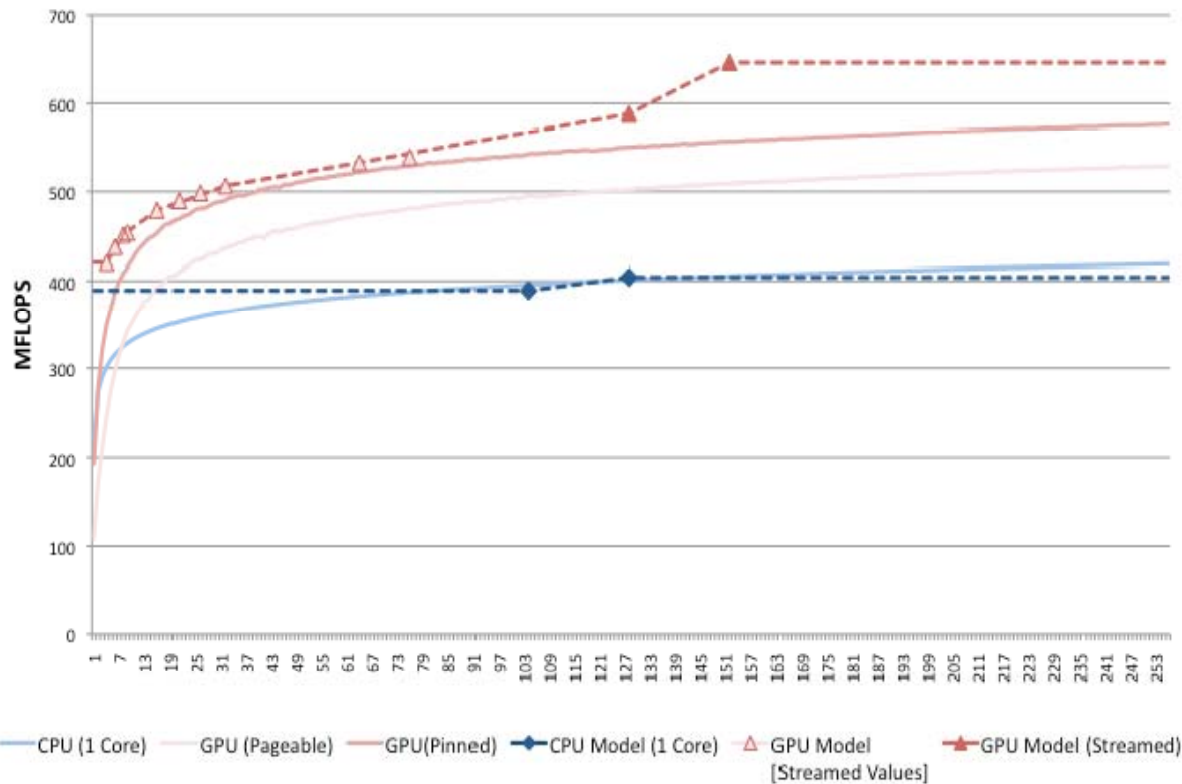
Initialization



Approximation



Iteration



- 1 Refine performance models with the newly obtained results
- ② GPU-specific Modeling: Using the obtained values from streaming execution
 - *HostToDevice* Bandwidth
 - *DeviceToHost* Bandwidth
 - *GPU Kernel* Performance
- ③ Incorporate streaming results
 - for each stream

Case Study: Performance Modeling in CPU + GPU Environment (18)

Performance Metric



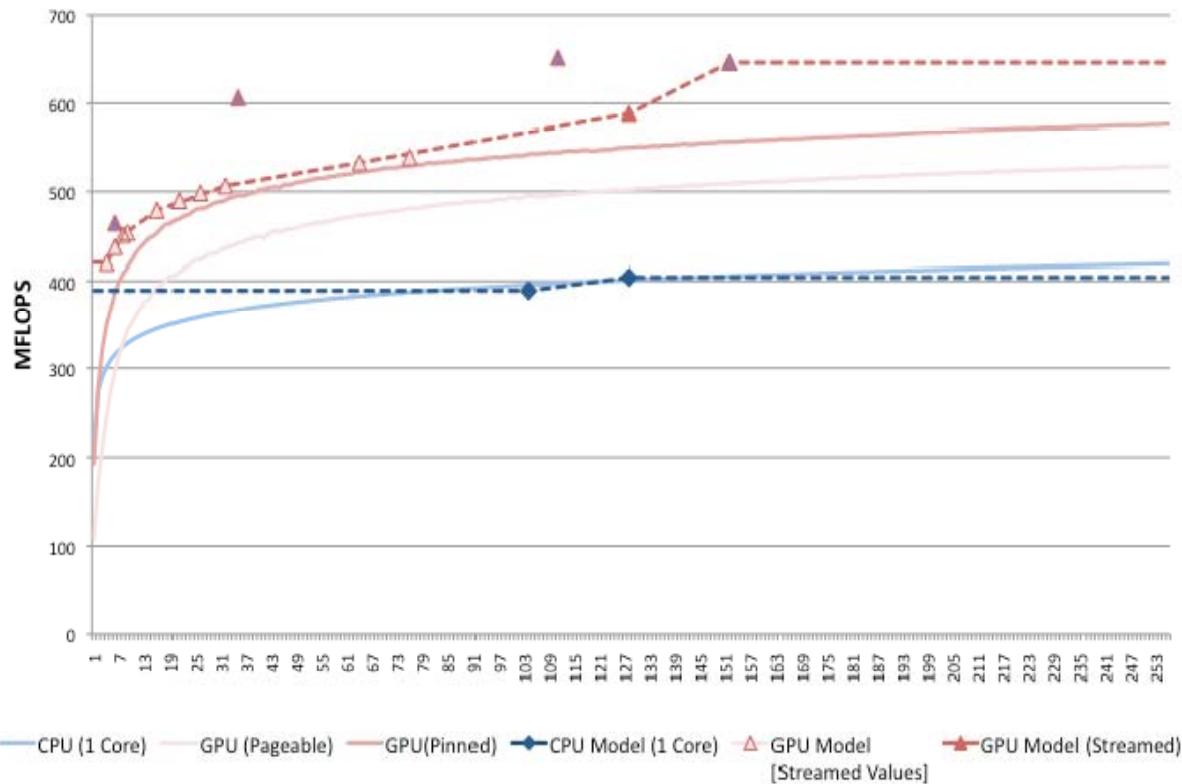
Initialization



Approximation



Iteration



- 1 Refine performance models with the newly obtained results
- ② GPU-specific Modeling: Using the obtained values from streaming execution
 - *HostToDevice* Bandwidth
 - *DeviceToHost* Bandwidth
 - *GPU Kernel* Performance
- ③ Incorporate streaming results
 - for each stream
 - for each stream restart

Case Study: Performance Modeling in CPU + GPU Environment (19)

Performance Metric



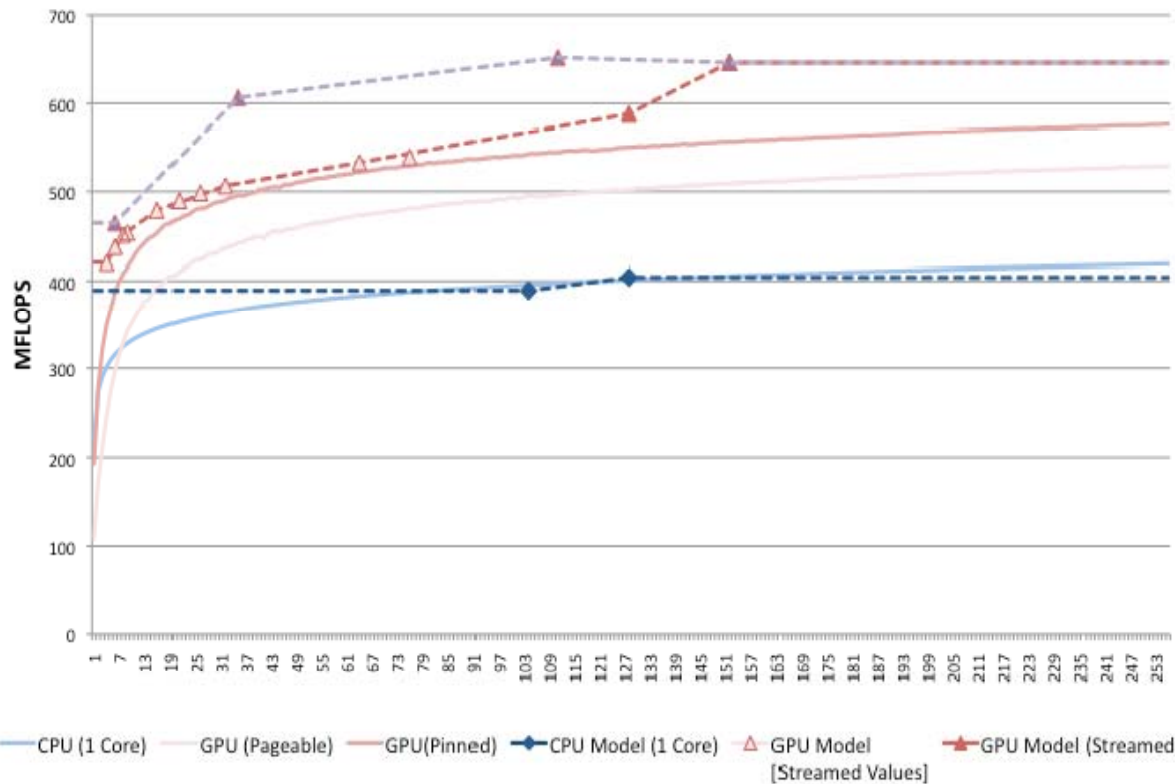
Initialization



Approximation



Iteration



- 1 Refine performance models with the newly obtained results
- ② GPU-specific Modeling: Using the obtained values from streaming execution
 - *HostToDevice* Bandwidth
 - *DeviceToHost* Bandwidth
 - *GPU Kernel* Performance
- ③ Incorporate streaming results
 - for each stream
 - for each stream restart

Case Study: Performance Modeling in CPU + GPU Environment (20)

technology
from seed



Performance Metric



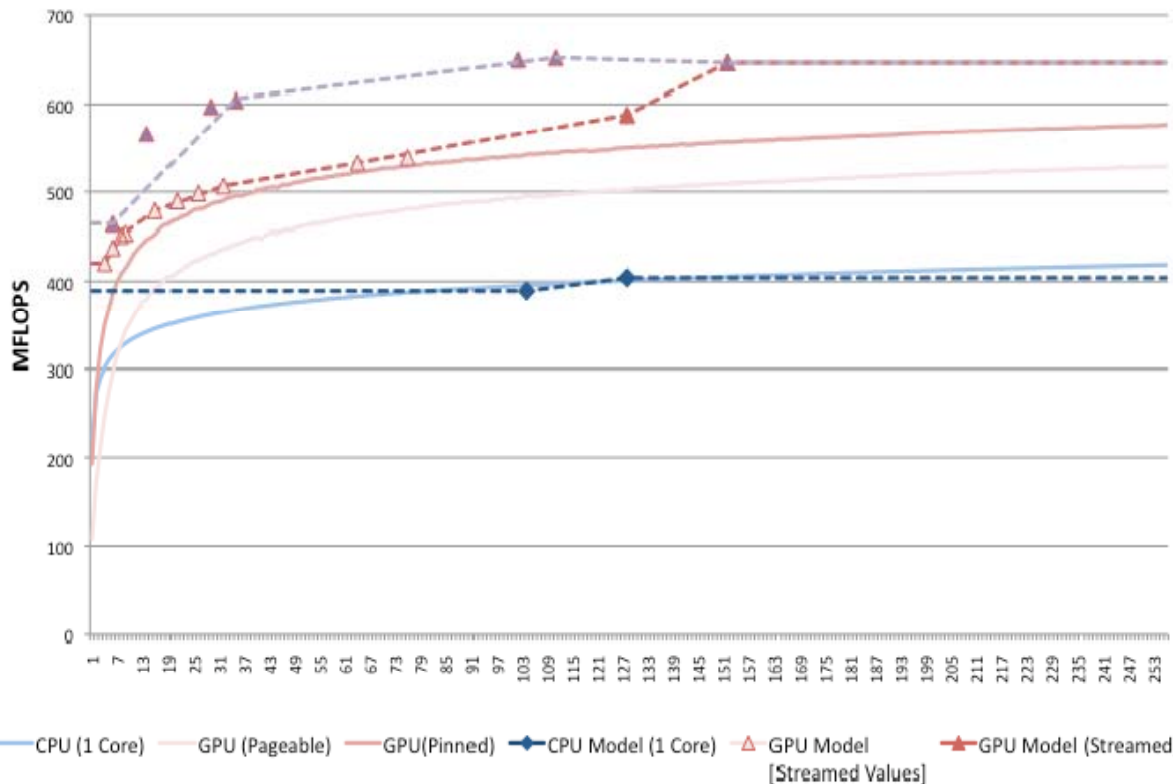
Initialization



Approximation



Iteration



- 1 Refine performance models with the newly obtained results
- ② GPU-specific Modeling: Using the obtained values from streaming execution
 - *HostToDevice* Bandwidth
 - *DeviceToHost* Bandwidth
 - *GPU Kernel* Performance
- ③ Incorporate streaming results
 - for each stream
 - for each stream restart
 - for every stream combination

Case Study: Performance Modeling in CPU + GPU Environment (21)

Performance Metric



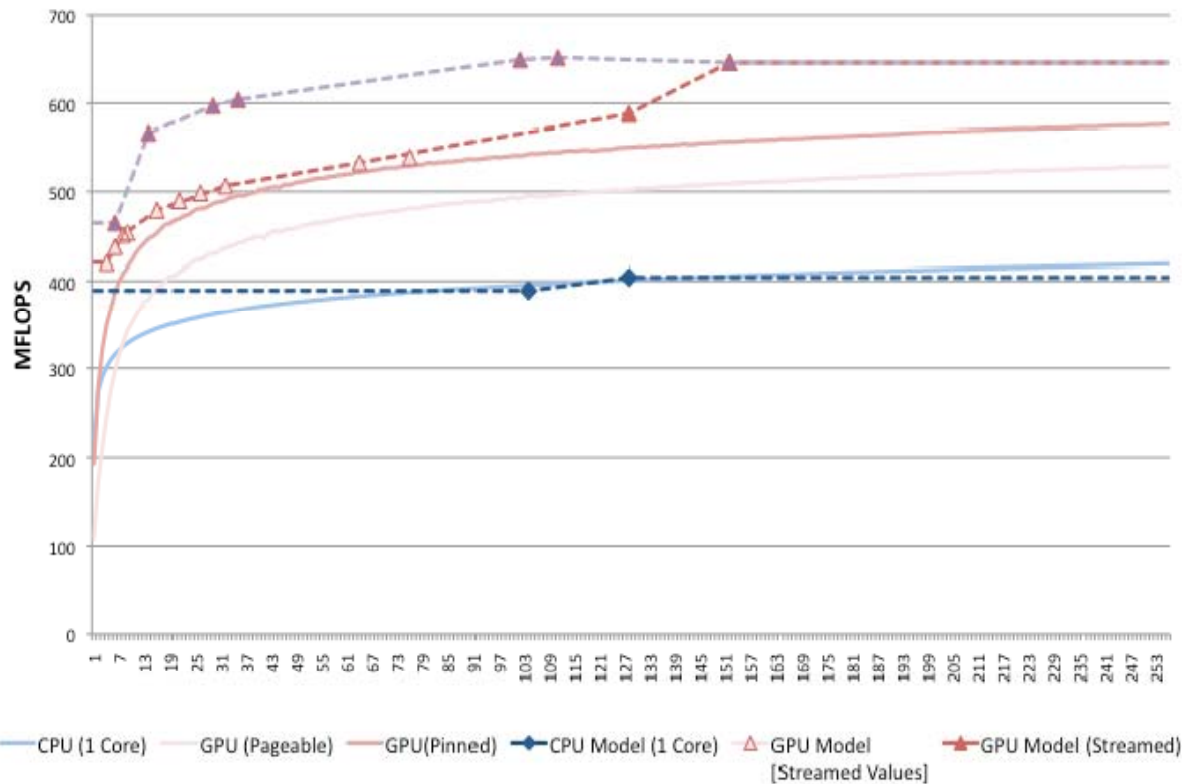
Initialization



Approximation



Iteration



- 1 Refine performance models with the newly obtained results
- ② GPU-specific Modeling: Using the obtained values from streaming execution
 - *HostToDevice* Bandwidth
 - *DeviceToHost* Bandwidth
 - *GPU Kernel* Performance
- ③ Incorporate streaming results
 - for each stream
 - for each stream restart
 - for every stream combination

Case Study: Performance Modeling in CPU + GPU Environment (22)

Performance Metric



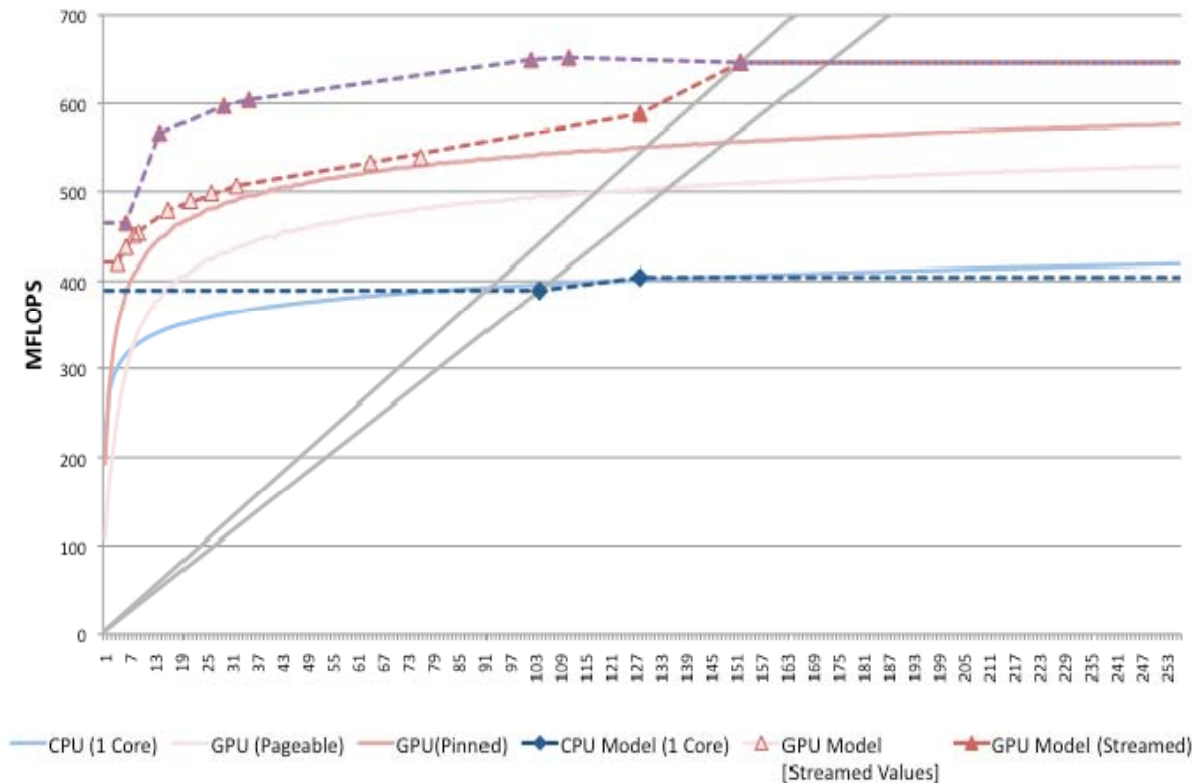
Initialization



Approximation



Iteration



① Draw Upper U and Lower L lines through the following points:

$$(0, 0), (N_1/p, \max_i \{ \text{Perf}_i(N_1/p) \})$$

$$(0, 0), (N_1/p, \min_i \{ \text{Perf}_i(N_1/p) \})$$

② Let $x_i^{(U)}$ and $x_i^{(L)}$ be the intersections with $\text{Perf}_i(x)$

IF exists $x_i^{(L)} - x_i^{(U)} \geq 1$

THEN go to 3

ELSE go to 5

③ Bisect the angle between U and L by the line M , and calculate intersections $x_i^{(M)}$

④ IF $\sum_i x_i^{(M)} \leq N_1$

THEN $U=M$

ELSE $L=M$

REPEAT 2

⑤ Employ streaming strategy on the calculated workload value

Case Study: Performance Modeling in CPU + GPU Environment (23)

Performance Metric



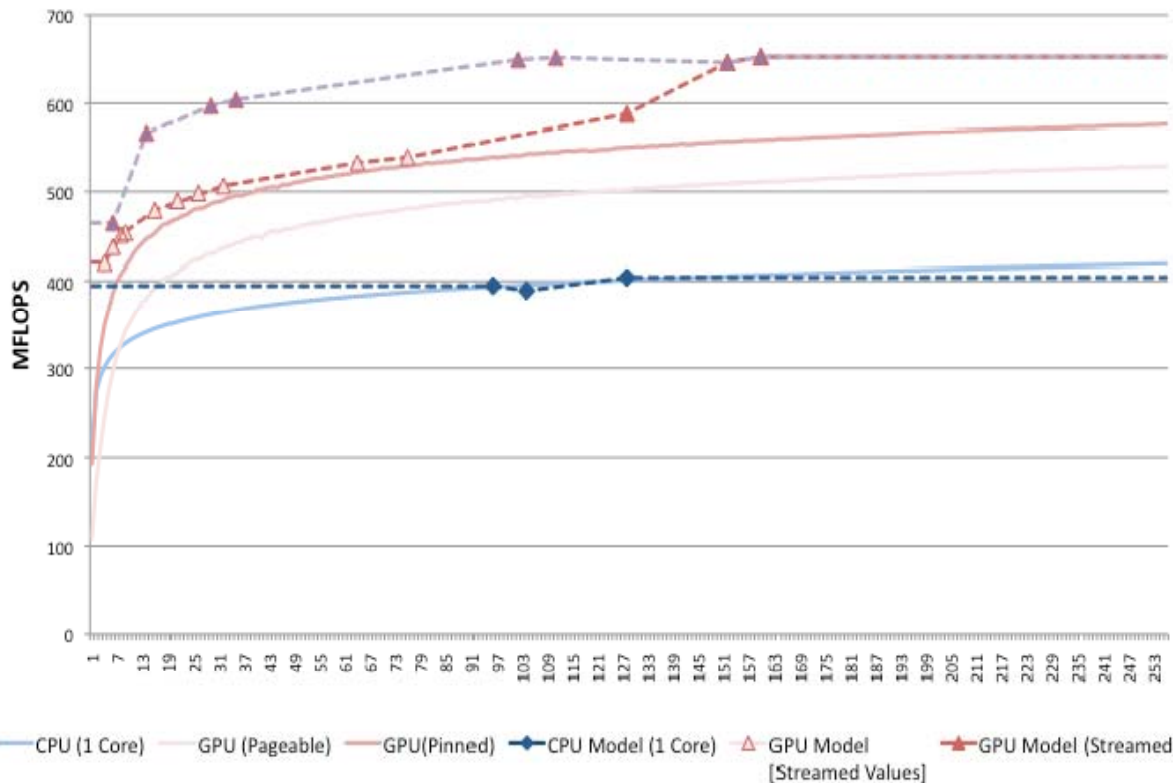
Initialization



Approximation



Iteration



- ① Refine performance models with the newly obtained results
- 2 GPU-specific Modeling: Using the obtained values from streaming execution
 - *HostToDevice* Bandwidth
 - *DeviceToHost* Bandwidth
 - *GPU Kernel* Performance
- 3 Incorporate streaming results
 - for each stream
 - for each stream restart
 - for every stream combination

Case Study: Performance Modeling in CPU + GPU Environment (24)

Performance Metric



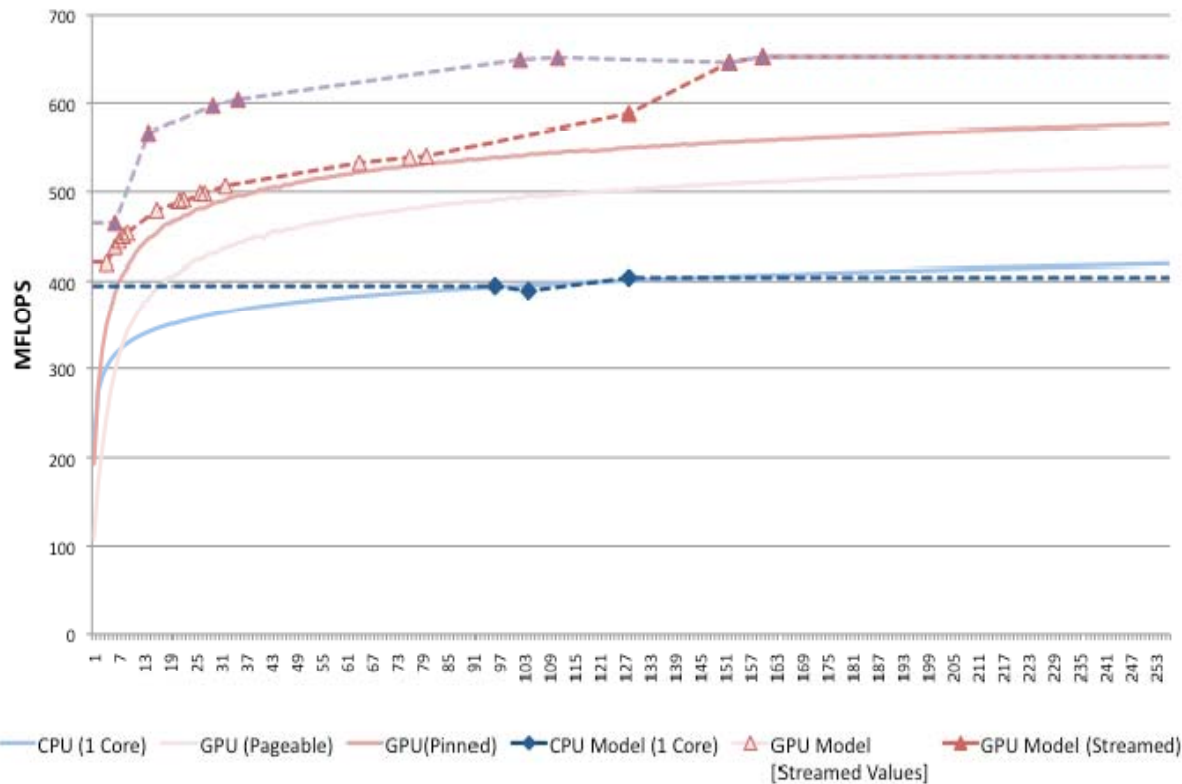
Initialization



Approximation



Iteration



- 1 Refine performance models with the newly obtained results
- ② GPU-specific Modeling: Using the obtained values from streaming execution
 - *HostToDevice* Bandwidth
 - *DeviceToHost* Bandwidth
 - *GPU Kernel* Performance
- ③ Incorporate streaming results
 - for each stream
 - for each stream restart
 - for every stream combination

Case Study: Performance Modeling in CPU + GPU Environment (25)

Performance Metric



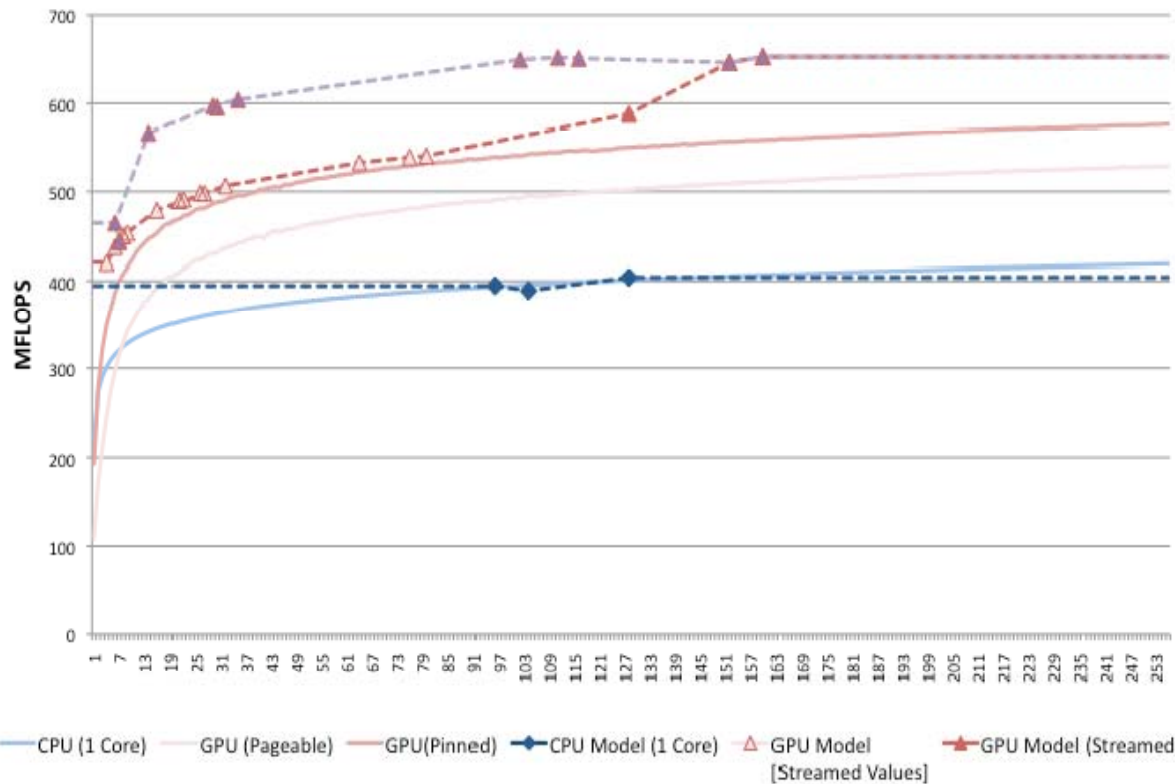
Initialization



Approximation



Iteration



- 1 Refine performance models with the newly obtained results
- ② GPU-specific Modeling: Using the obtained values from streaming execution
 - *HostToDevice* Bandwidth
 - *DeviceToHost* Bandwidth
 - *GPU Kernel* Performance
- ③ Incorporate streaming results
 - for each stream
 - for each stream restart
 - for every stream combination

Case Study: Performance Modeling in CPU + GPU Environment (26)

Performance Metric



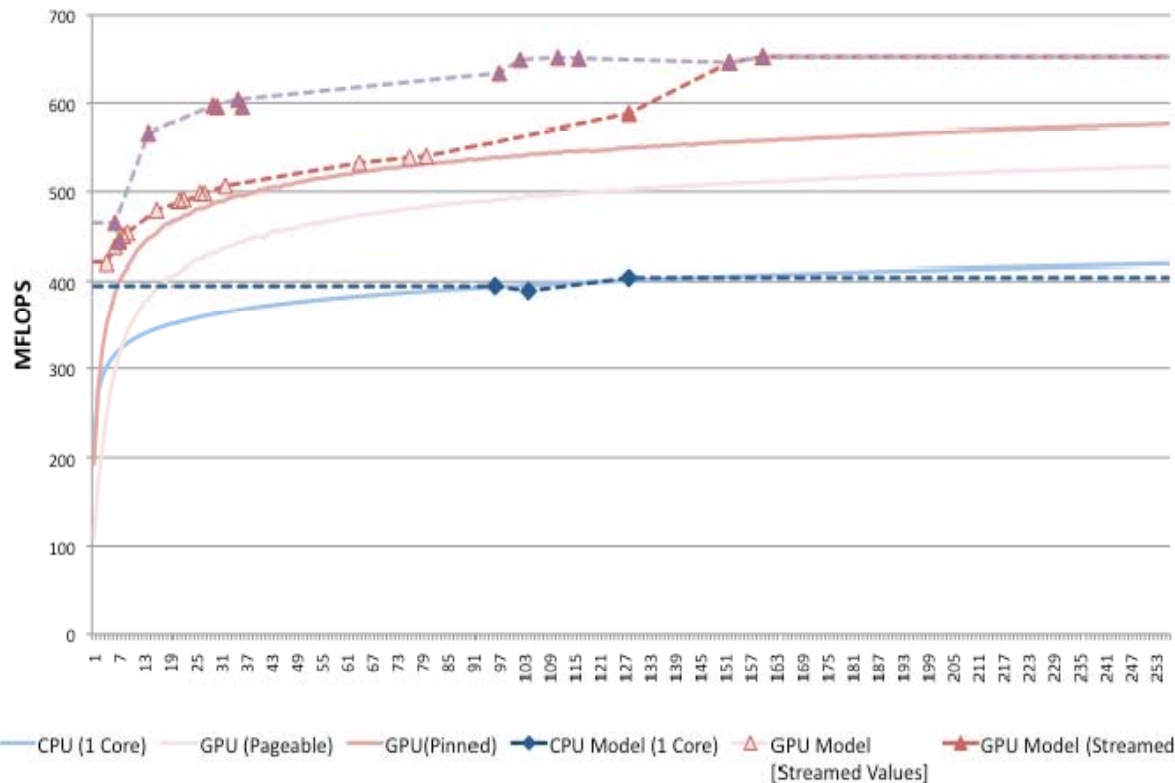
Initialization



Approximation



Iteration



- 1 Refine performance models with the newly obtained results
- ② GPU-specific Modeling: Using the obtained values from streaming execution
 - *HostToDevice* Bandwidth
 - *DeviceToHost* Bandwidth
 - GPU *Kernel* Performance
- ③ Incorporate streaming results
 - for each stream
 - for each stream restart
 - for every stream combination

COLLABORATIVE ENVIRONMENT FOR HETEROGENEOUS COMPUTERS

TRADITIONAL APPROACHES FOR PERFORMANCE MODELING

- Approximate the performance using number of points equal to the number of iterations
- In this case, **3 POINTS** per each device

PRESENTED APPROACH FOR PERFORMANCE MODELING

- Models the performance using **MORE THAN 30 POINTS**, in this case
- **COMMUNICATION-AWARE** – schedules in respect to limited and asymmetric interconnection bandwidth
- Employs **STREAMING STRATEGIES** to overlap communication with computation across devices
- **BUILDS SEVERAL PER-DEVICE MODELS AT THE SAME TIME**
 - OVERALL PERFORMANCE for each device + STREAMING GPU PERFORMANCE
 - HOSTTODEVICE BANDWIDTH Modeling
 - DEVICETOHOST BANDWIDTH Modeling
 - GPU KERNEL PERFORMANCE Modeling

Questions?

Thank you

