

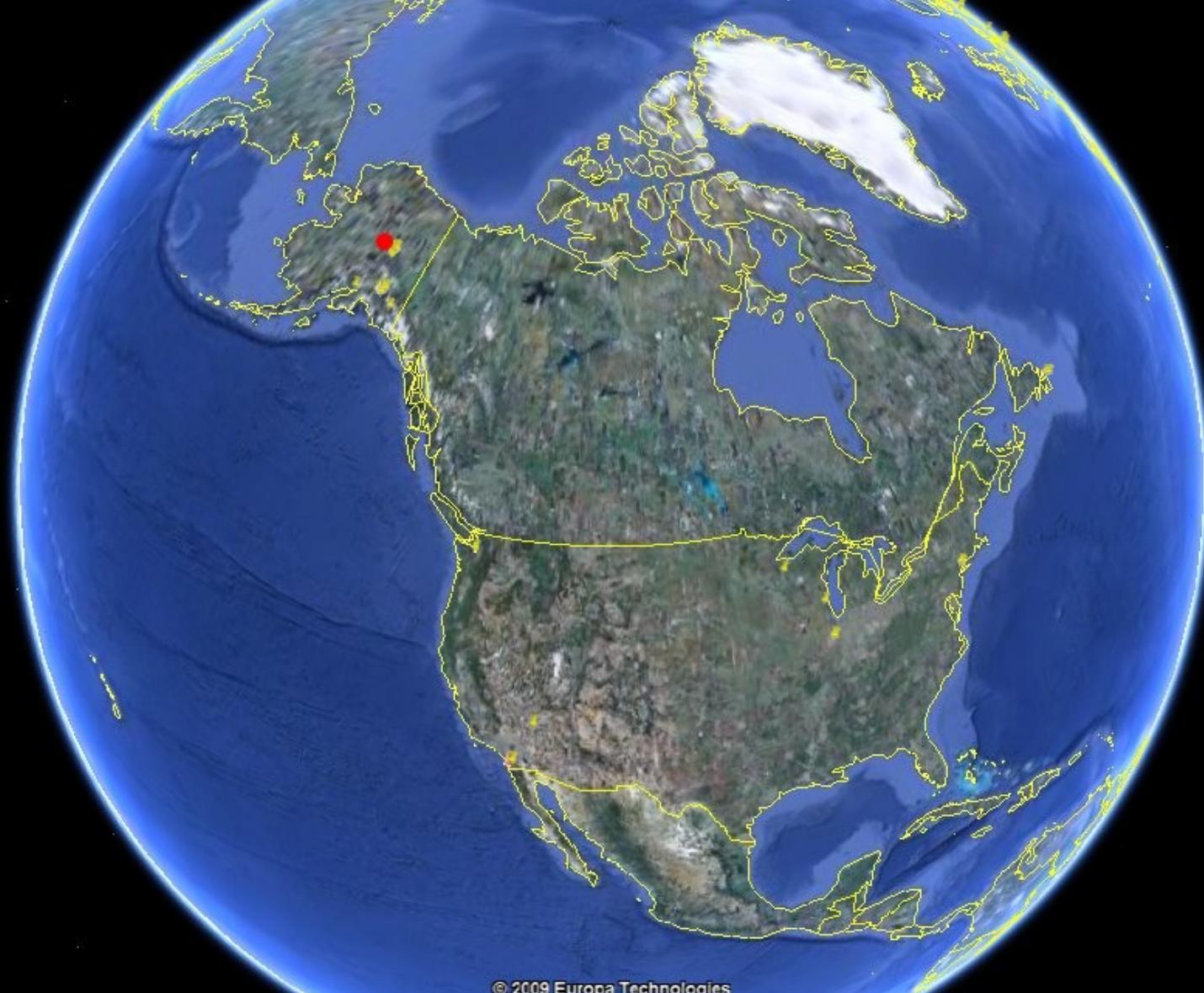
cudaMPI and glMPI: Message Passing for GPGPU Clusters

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Where is Fairbanks, Alaska?



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Talk Outline

- **Modern GPU Hardware**
- **Quantitative GPU Performance**
- **GPU-Network Interfacing**
- **cudaMPI and gIMPI Performance**
- **Conclusions & Future Work**

Modern GPU Hardware

Latency, or Bandwidth?

- **time=latency + size / bandwidth**
- **To minimize latency:**
 - Caching (memory)
 - Speculation (branches, memory)
- **To maximize bandwidth:**
 - Clockrate (since 1970)
 - Pipelining (since 1985)
 - Parallelism (since 2004)
- **For software, everything's transparent except parallelism!**

CPU vs GPU Design Targets

- Typical CPU optimizes for instruction execution latency
 - Millions of instructions / thread
 - Less than 100 software threads
 - Hardware caches, speculation
- Typical GPU optimizes for instruction execution bandwidth
 - Thousands of instructions / thread
 - Over 1 million software threads
 - Hardware pipelining, queuing, request merging

Modern GPUs: Good Things

- **Fully programmable**
 - Branches, loops, functions, etc
 - IEEE 32-bit Float Storage
- **Huge parallelism in hardware**
 - Typical card has 100 cores
 - Each core threaded 10-100 ways
 - Hardware thread switching (SMT)
- **E.g., \$250 GTX 280 has 240 cores, >900 gigaflops peak**
- **GPU is best in flops, flops/watt, flops/\$ [Datta ... Yelik 2008]**

Modern GPUs: Bad Things

- **Programming is really difficult**
 - Branch & load divergence penalties
 - Non-IEEE NaNs, 64-bit much slower
- **Huge parallelism in software**
 - Need millions of separate threads!
 - Usual problems: decomposition, synchronization, load balance
- **E.g., \$250 GTX 280 has *only* 1GB of storage, 4GB/s host RAM**
- **GPU is definitely a mixed blessing for real applications**

Modern GPU Programming Model

- “**Hybrid**” GPU-CPU model
 - GPU cranks out the flops
 - CPU does everything else
 - Run non-GPU legacy or sequential code
 - Disk, network I/O
 - Interface with OS and user
- Supported by CUDA, OpenCL, OpenGL, DirectX, ...
- Likely to be the dominant model for the foreseeable future
 - CPU may eventually “wither away”

GPU Programming Interfaces

- **OpenCL (2008)**
 - **Hardware independent (in theory)**
 - **SDK still difficult to find**
- **NVIDIA's CUDA (2007)**
 - **Mixed C++/GPU source files**
 - **Mature driver, widespread use**
- **OpenGL GLSL, DirectX HLSL (2004)**
 - **Supported on NVIDIA and ATI on wide range of hardware**
 - **Graphics-centric interface (pixels)**

NVIDIA CUDA

- Fully programmable (loops, etc)
- Read and write memory anywhere
 - Memory accesses must be “coalesced” for high performance
 - Zero protection against multithreaded race conditions
 - “texture cache” can only be accessed via restrictive CUDA arrays
- Manual control over a small shared memory region near the ALUs
- CPU calls a GPU “kernel” with a “block” of threads
- Only runs on new NVIDIA hardware

OpenGL: GL Shading Language

- Fully programmable (loops, etc)
- Can only read “textures”, only write to “framebuffer” (2D arrays)
 - Reads go through “texture cache”, so performance is good (iff locality)
 - Attach non-read texture to framebuffer
 - So cannot have synchronization bugs!
- Today, greyscale **GL_LUMINANCE** texture pixels store floats, not **GL_RGBA** 4-vectors (zero penalty!)
- Rich selection of texture filtering (array interpolation) modes
- **GLSL** runs on nearly every GPU

Modern GPU Fast Stuff

- **Divide, sqrt, rsqrt, exp, pow, sin, cos, tan, dot all sub-nanosecond**
 - Fast like arithmetic; not library call
- **Branches are fast iff:**
 - They're short (a few instructions)
 - Or they're coherent across threads
- **GPU memory accesses fast iff:**
 - They're satisfied by “texture cache”
 - Or they're coalesced across threads (contiguous and aligned)

GPU “coherent” \approx MPI “collective”

Modern GPU Slow Stuff

- Not enough work per kernel
 - >4us latency for kernel startup
 - Need >>1m flops / kernel!
- Divergence: costs up to 97%!
 - Noncoalesced memory accesses
 - Adjacent threads fetching distant regions of memory
 - Divergent branches
 - Adjacent threads running different long batches of code
- Copies to/from host
 - >10us latency, <4GB/s bandwidth¹⁶

Quantitative GPU Performance

CUDA: Memory Output Bandwidth

- Build a trivial CUDA test harness:

```
__global__ void write_arr(float *arr) {  
    arr[threadIdx.x+blockDim.x*blockIdx.x]=0.0;  
}  
int main() { ... start timer  
    write_arr<<<nblocks,threadsPerBlock>>>(arr);  
    ... stop timer  
}
```

- Measure speed for various array sizes and number of threads per block

CUDA: Memory Output Bandwidth

Threads per Block	Number of Floats/Kernel					
	1K	10K	100K	1M	10M	
1	~1	~2	err	err	err	
2	~1	~2	~4	err	err	
4	~1	~4	~8	err	err	
8	~1	~6	~14	err	err	
16	~1	~6	~24	~32	err	
32	~1	~7	~37	~74	err	
64	~1	~7	~48	~117	err	
128	~1	~7	~64	~174	err	
256	~1	~7	~62	~172	~207	
512	~1	~7	~62	~172	~207	

Output Bandwidth (Gigafloats/second)

CUDA: Memory Output Bandwidth

Threads per Block	Number of Floats/Kernel				
	1K	10K	100K	1M	10M
1	0.1	0.2	err	err	err
2	0.1	0.3	0.4	err	err
4	0.1	0.4	0.8	err	err
8	0.1	0.5	1.4	err	err
16	0.1	0.6	2.4	3.3	err
32	0.1	0.7	3.6	6.4	err
64	0.1	0.7	4.8	11.7	err
128	0.1	0.7	5.4	16.4	err
256	0.1	0.7	5.3	16.4	20.7
512	0.1	0.7	5.2	16.3	20.7

Over 64K blocks needed

Output Bandwidth (Gigafloats/second)

CUDA: Memory Output Bandwidth

Kernel Startup Time		Number of Floats/Kernel				
Threads per Block	Dominates	1K	10K	100K	1M	10M
1	1	0.1	0.2	err	err	err
	2	0.1	0.3	0.4	err	err
	4	0.1	0.4	0.8	err	err
	8	0.1	0.5	1.4	err	err
	16	0.1	0.6	2.4	3.3	err
	32	0.1	0.7	3.6	6.4	err
	64	0.1	0.7	4.8	11.7	err
	128	0.1	0.7	5.4	16.4	err
	256	0.1	0.7	5.3	16.4	20.7
	512	0.1	0.7	5.2	16.3	20.7

CUDA: Memory Output Bandwidth

Block Startup Time	Threads per Block	Number of Floats/Kernel				
		1K	10K	100K	1M	10M
Dominates	1	0.1	0.2	err	err	err
	2	0.1	0.3	0.4	err	err
	4	0.1	0.4	0.8	err	err
	8	0.1	0.5	1.4	err	err
	16	0.1	0.6	2.4	3.3	err
	32	0.1	0.7	3.6	6.4	err
	64	0.1	0.7	4.8	11.7	err
	128	0.1	0.7	5.4	16.4	err
	256	0.1	0.7	5.3	16.4	20.7
	512	0.1	0.7	5.2	16.3	20.7
Output Bandwidth (Gigafloats/second)						

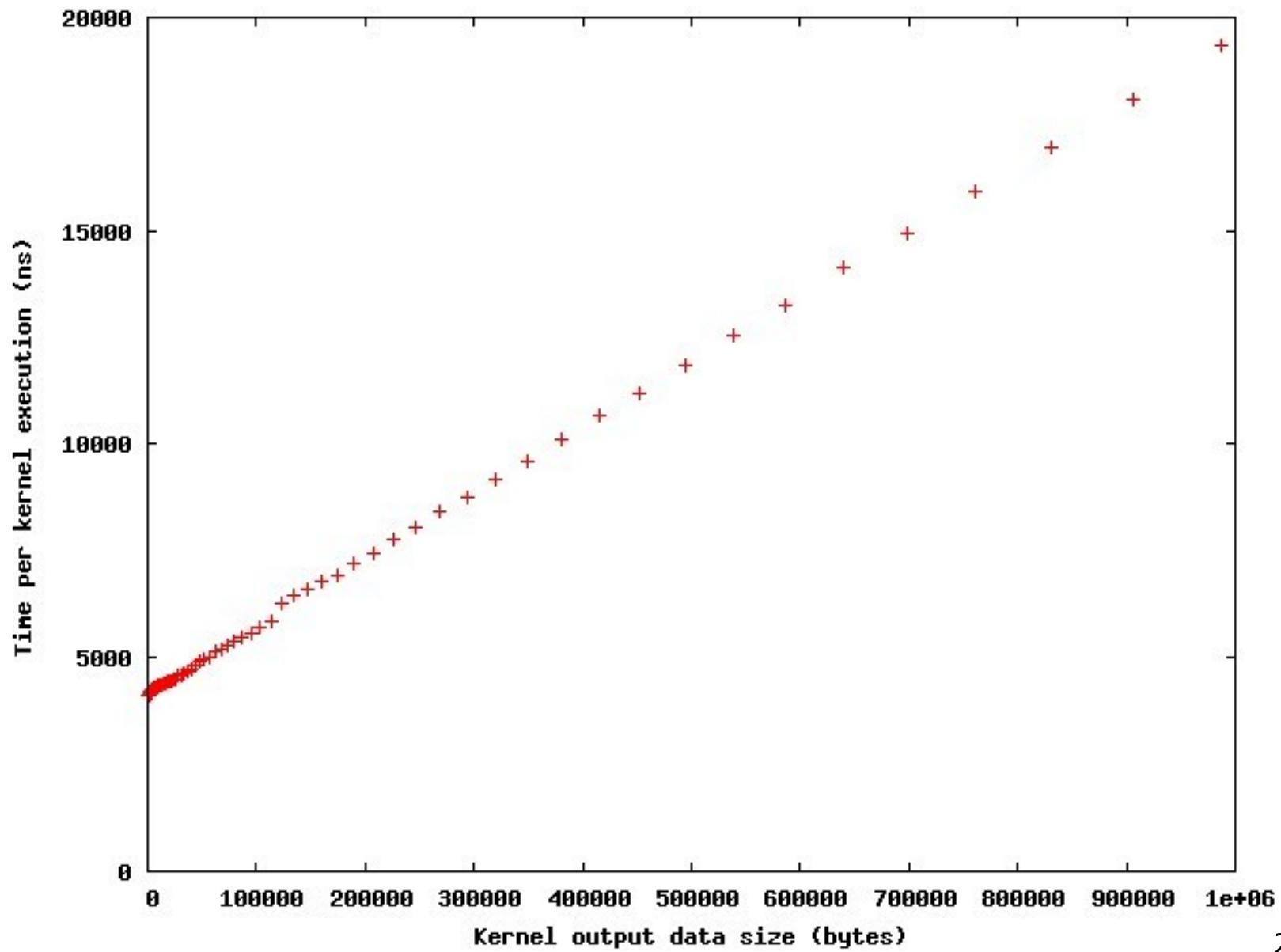
CUDA: Memory Output Bandwidth

Threads per Block	Number of Floats/Kernel				
	1K	10K	100K	1M	10M
1	0.1	0.2	err	err	err
2	0.1	0.3	0.4	err	err
4	0.1	0.4	0.8	err	err
8	0.1	0.5	1.4	err	err
16	0.1	0.6	2.4	3.3	err
32	0.1	0.7	3.6	6.4	err
64	0.1	0.7	4.8	11.7	err
128	0.1	0.7	5.4	16.4	err
256	0.1	0.7	5.3	16.4	20.7
512	0.1	0.7	5.2	16.3	20.7

Output Bandwidth (Gigafloats/second)

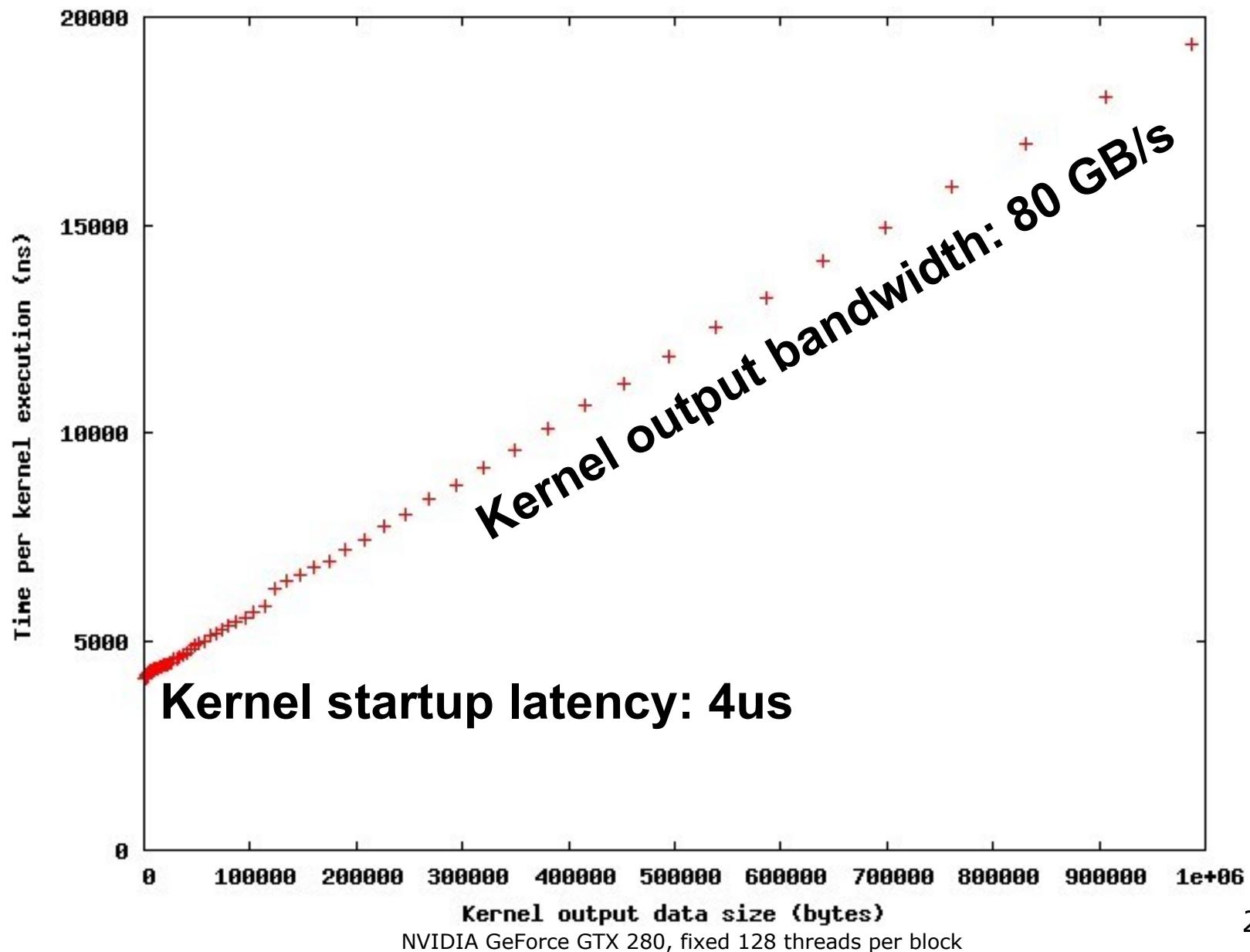
Good Performance

CUDA: Memory Output Bandwidth

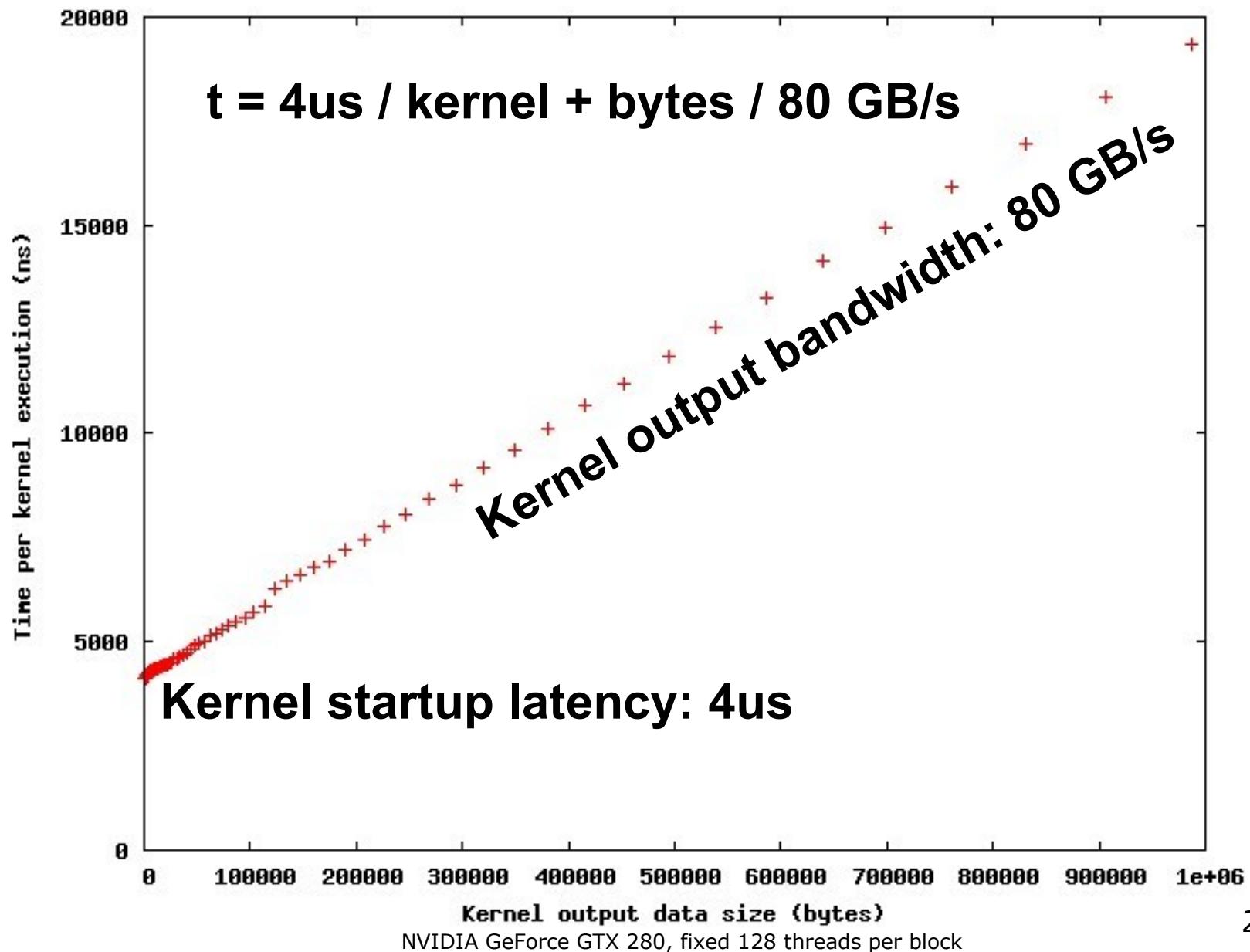


NVIDIA GeForce GTX 280, fixed 128 threads per block

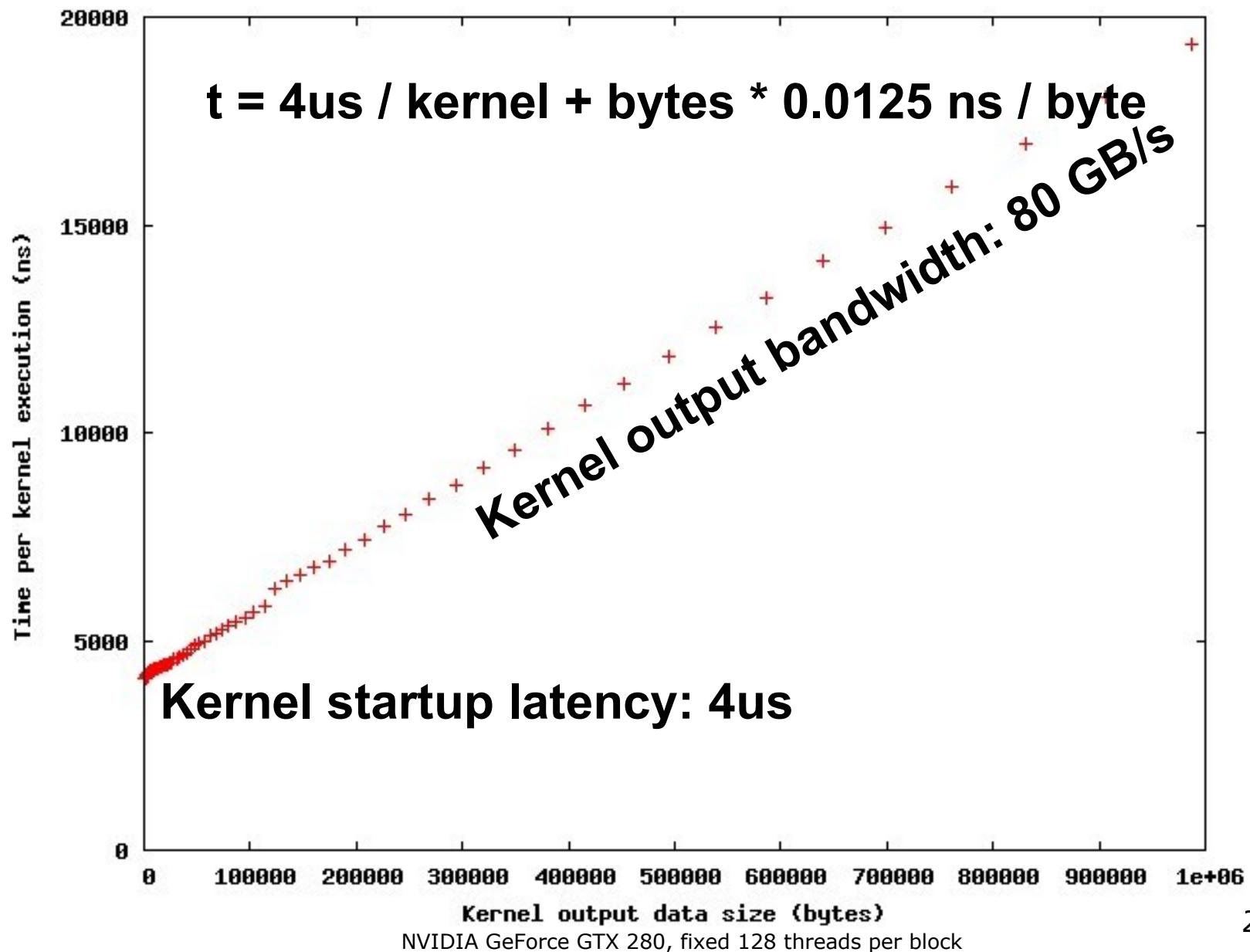
CUDA: Memory Output Bandwidth



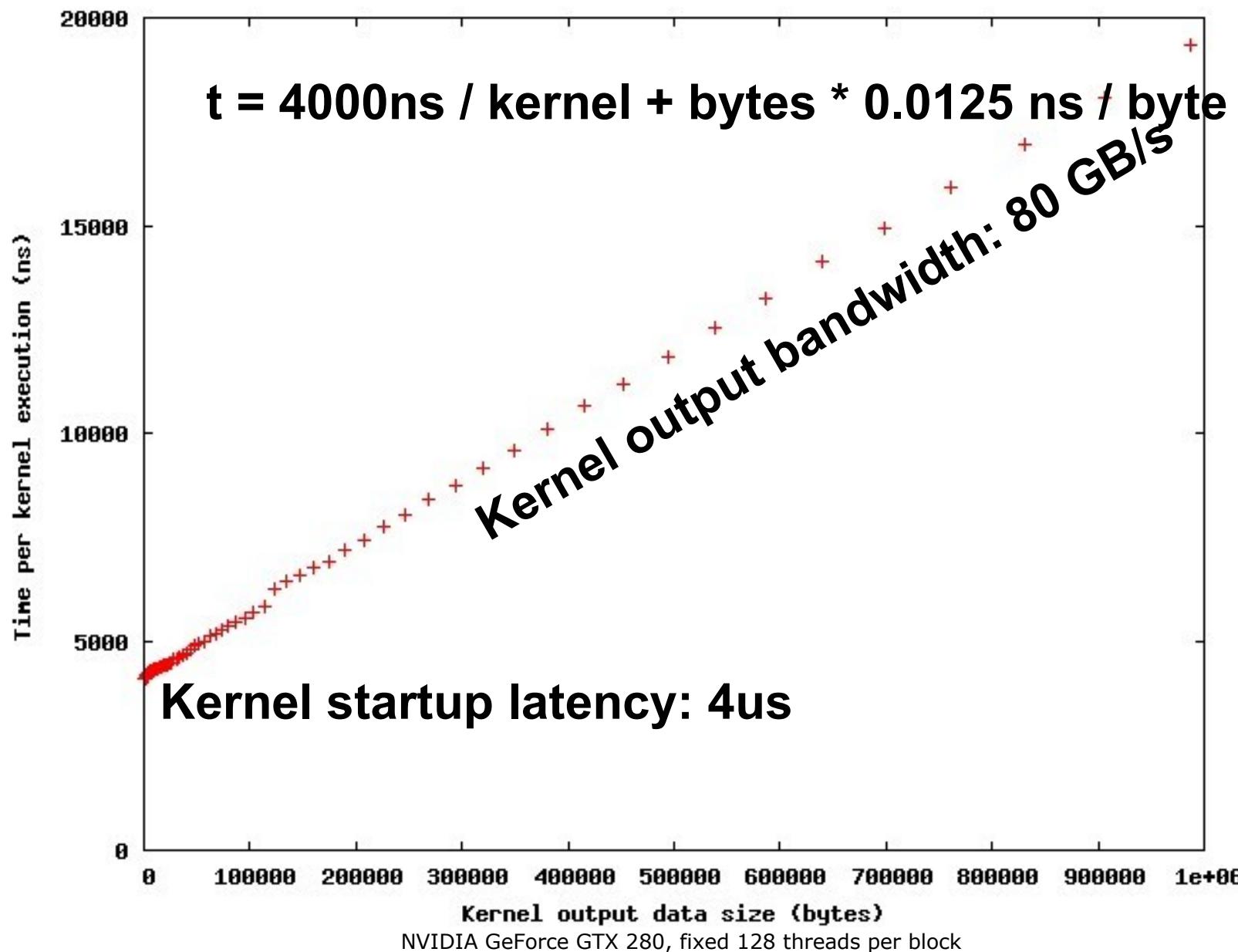
CUDA: Memory Output Bandwidth



CUDA: Memory Output Bandwidth



CUDA: Memory Output Bandwidth



CUDA: Memory Output Bandwidth

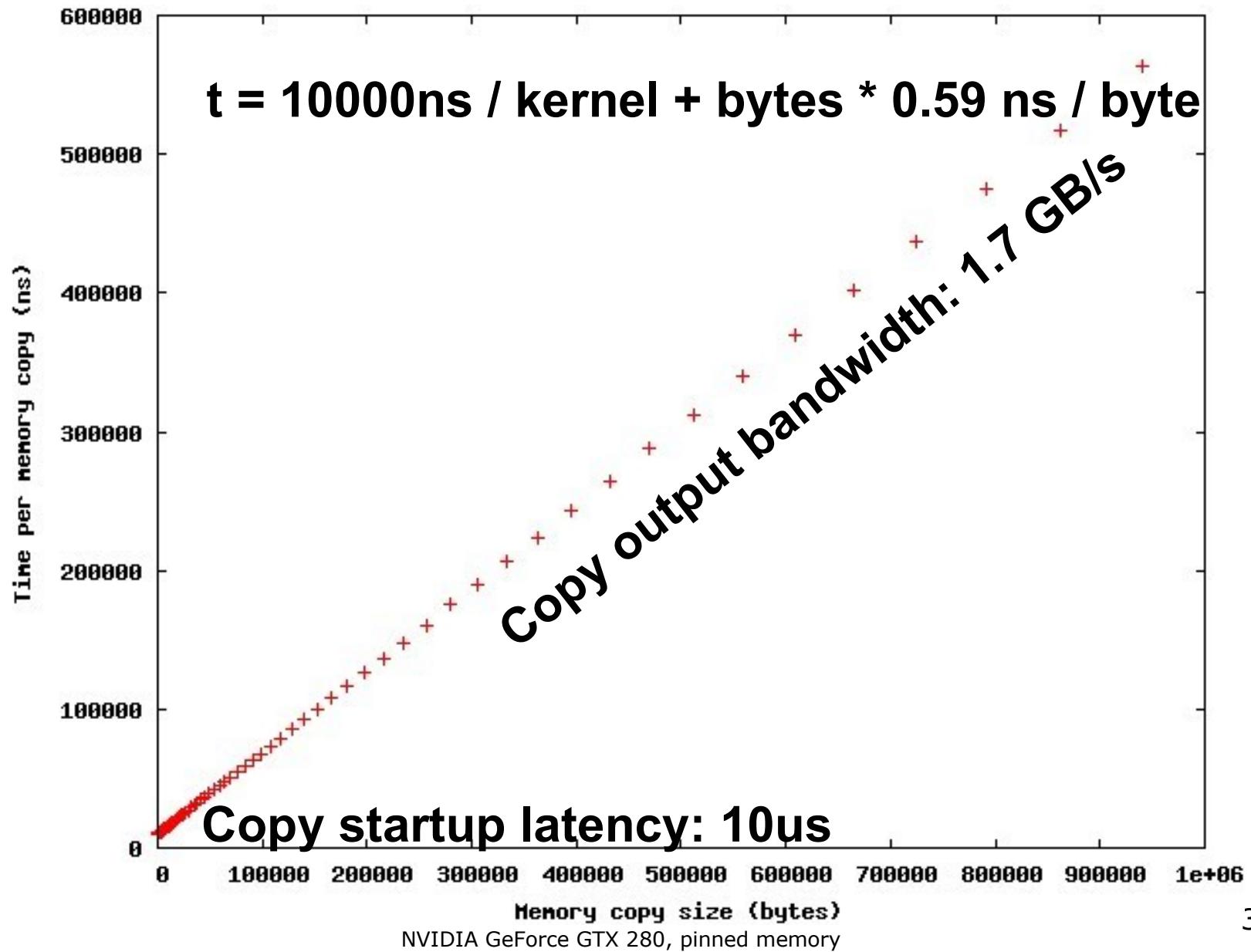
$$t = 4000\text{ns} / \text{kernel} + \text{bytes} * 0.0125 \text{ ns} / \text{byte}$$



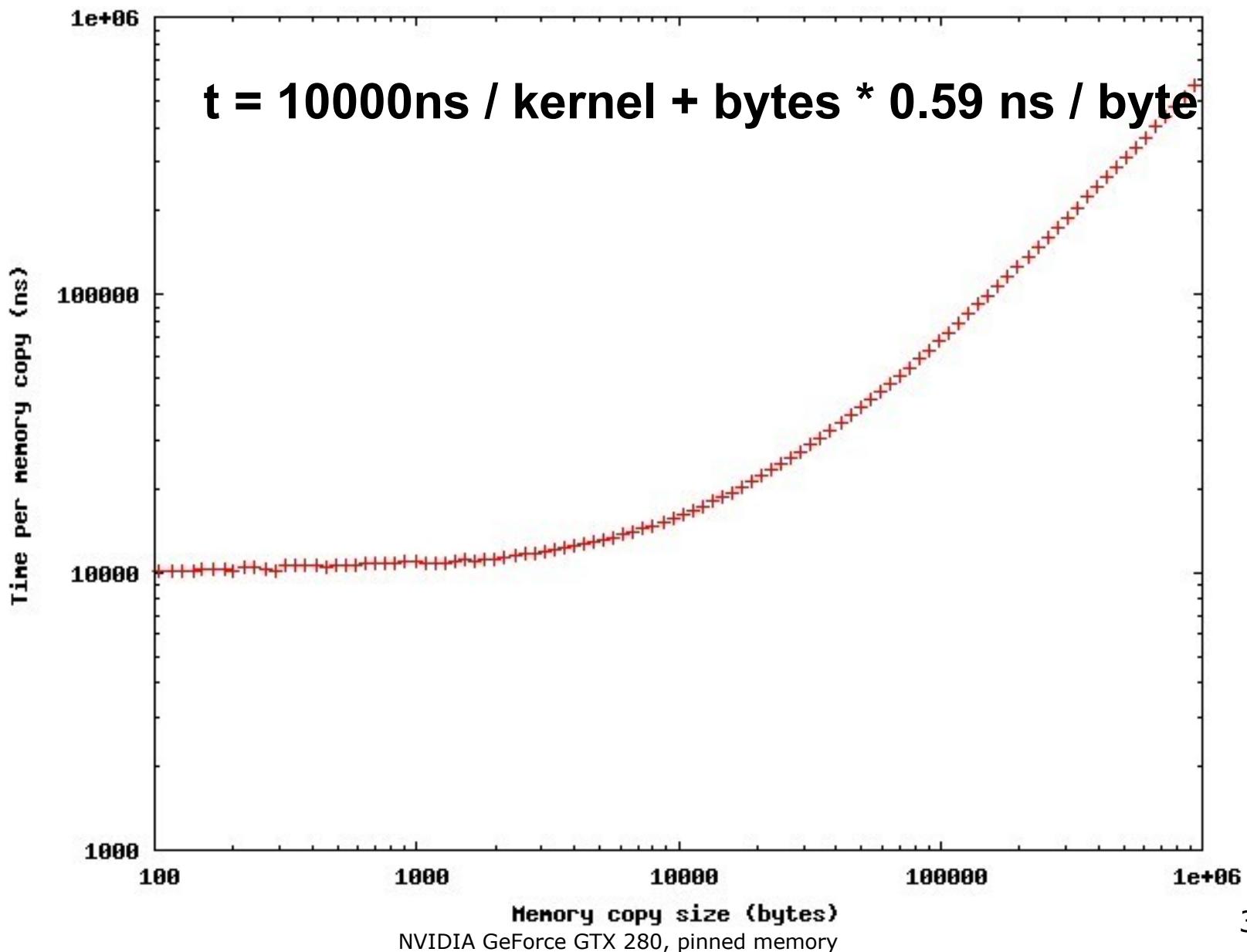
WHAT!?

time/kernel = 320,000 x time/byte!?

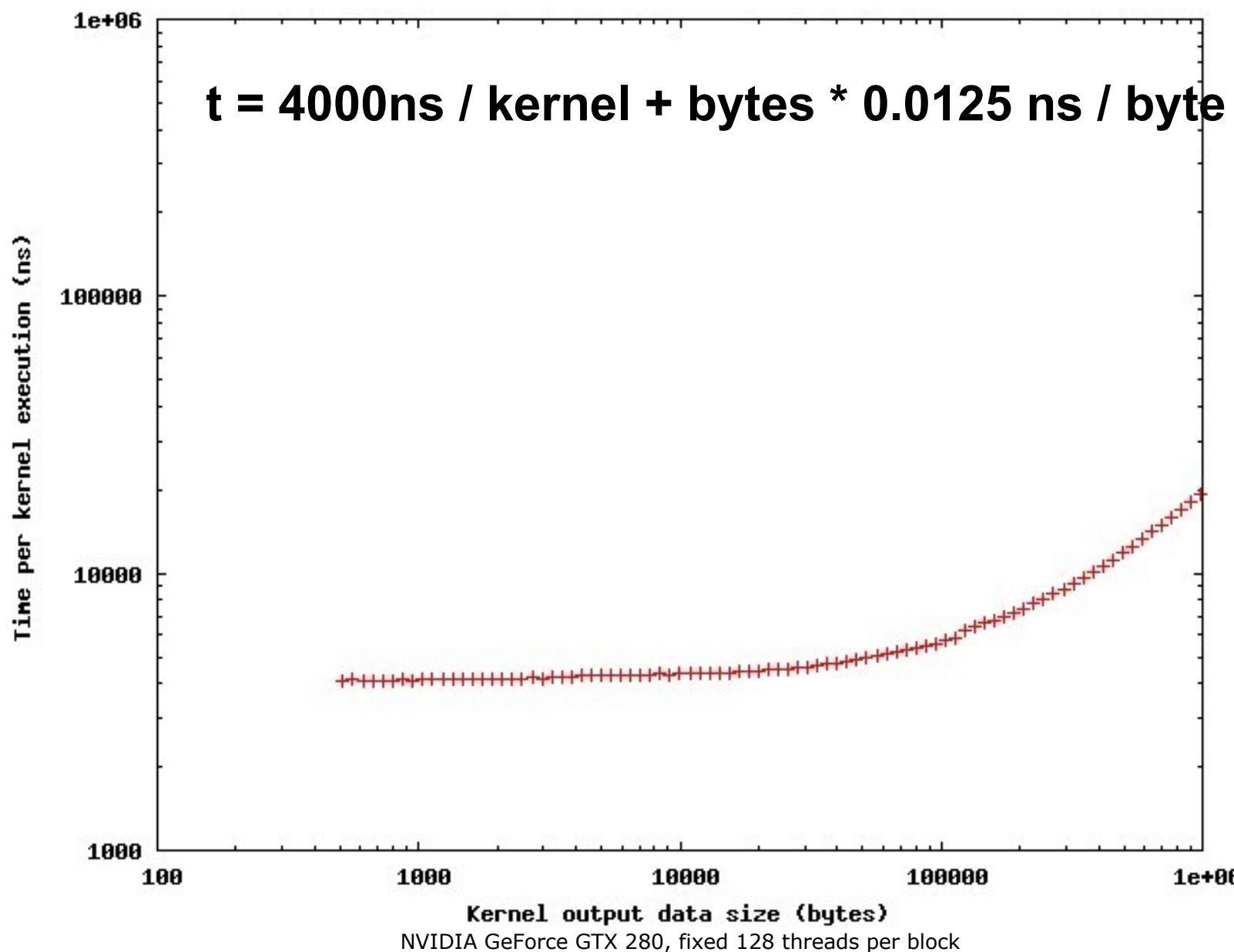
CUDA: Device-to-Host Memcopy



CUDA: Device-to-Host Memcopy



CUDA: Memory Output Bandwidth



Performance Analysis Take-Home

- **GPU Kernels: high latency, and high bandwidth**
- **GPU-CPU copy: high latency, but low bandwidth**
- **High latency means use big batches (not many small ones)**
- **Low copy bandwidth means you MUST leave most of your data on the GPU (can't copy it all out)**
- **Similar lessons as network tuning! (Message combining, local storage.)**

Why GPGPU clusters?

Parallel GPU Advantages

- **Multiple GPUs: more compute & storage bandwidth**

# GPUs	Output Rate	Computation	Network	Efficiency
1	6.1 Gpix/s	7.81 ms	- ms	100%
2	11.3 Gpix/s	3.91 ms	0.35 ms	92%
3	16.2 Gpix/s	2.62 ms	0.35 ms	88%
4	20.7 Gpix/s	1.97 ms	0.36 ms	84%
5	25.0 Gpix/s	1.58 ms	0.35 ms	81%
6	28.5 Gpix/s	1.32 ms	0.37 ms	77%
7	32.4 Gpix/s	1.13 ms	0.36 ms	75%
8	35.3 Gpix/s	1.00 ms	0.37 ms	71%
9	38.2 Gpix/s	0.91 ms	0.39 ms	67%
10	40.7 Gpix/s	0.80 ms	0.39 ms	66%

Parallel GPU Communication

- **Shared memory, or messages?**
 - **History:** on the CPU, shared memory won for small machines; messages won for big machines
 - **Shared memory GPUs:** Tesla
 - **Message-passing GPUs:** clusters
 - Easy to make in small department
 - E.g., \$2,500 for ten GTX 280's (8 TF!)
 - Or both, like NCSA Lincoln
- **Messages are lowest common denominator:** run easily on shared memory (not vice versa!)¹⁶

Parallel GPU Application Interface

- On the CPU, for message passing the Message Passing Interface (MPI) is standard and good
 - Design by committee means if you need it, it's already in there!
 - E.g., noncontiguous derived datatypes, communicator splitting, buffer mgmt
- So let's steal that!
 - Explicit send and receive calls to communicate GPU data on network

Parallel GPU Implementation

- Should we send and receive from GPU code, or CPU code?
 - GPU code seems more natural for GPGPU (data is on GPU already)
 - CPU code makes it easy to call MPI
- Network and GPU-CPU data copy have high latency, so message combining is crucial!
 - Hard to combine efficiently on GPU (atomic list addition?) [Owens]
 - But easy to combine data on CPU

Parallel GPU Send and Receives

- **cudaMPI_Send** is called on CPU with a pointer to GPU memory
 - cudaMemcpy into (pinned) CPU communication buffer
 - MPI_Send communication buffer
- **cudaMPI_Recv** is similar
 - MPI_Recv to (pinned) CPU buffer
 - cudaMemcpy off to GPU memory
- **cudaMPI_Bcast, Reduce, Allreduce, etc** all similar
 - Copy data to CPU, call MPI (easy!)

Asynchronous Send and Receives

- **cudaMemcpy, MPI_Send, and MPI_Recv** all block the CPU
- **cudaMemcpyAsync, MPI_Isend, and MPI_Irecv** don't
 - They return a handle you occasionally poll instead
- Sadly, **cudaMemcpyAsync** has much higher latency than blocking version (40us vs 10us)
- **cudaMPI_Isend and Irecv** exist
 - But usually are not worth using!

OpenGL Communication

- It's easy to write corresponding `glMPI_Send` and `glMPI_Recv`
 - `glMPI_Send`: `glReadPixels`, `MPI_Send`
 - `glMPI_Recv`: `MPI_Recv`, `glDrawPixels`
- Sadly, `glDrawPixels` is very slow: only 250MB/s!
 - `glReadPixels` is over 1GB/s
 - `glTexSubImage2D` from a pixel buffer object is much faster (>1GB/s)

CUDA or OpenGL?

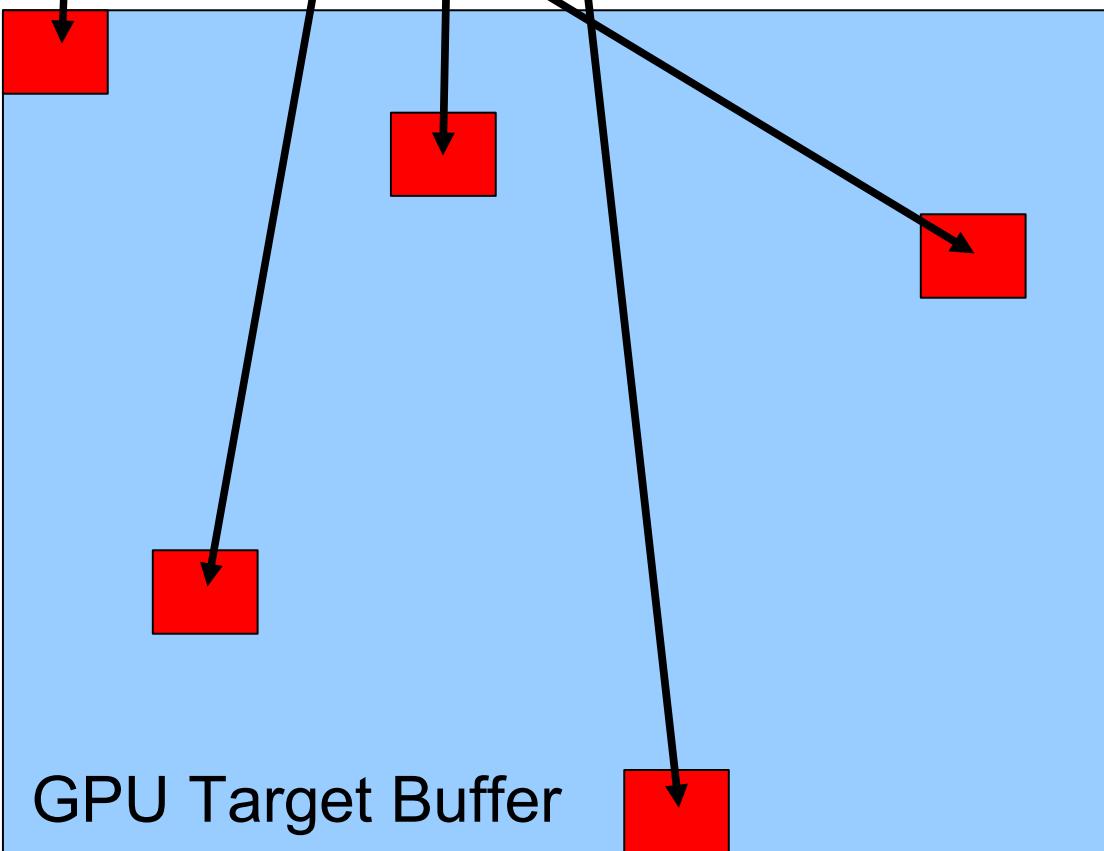
- **cudaMemcpy requires contiguous memory buffer**
- **glReadPixels takes an arbitrary rectangle of texture data**
 - **Rows, columns, squares all equally fast!**
- **Still, there's no way to simulate MPI's rich noncontiguous derived data types**

Noncontiguous Communication

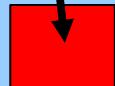
Network Data Buffer



- Scatter kernel?
- Fold into read?



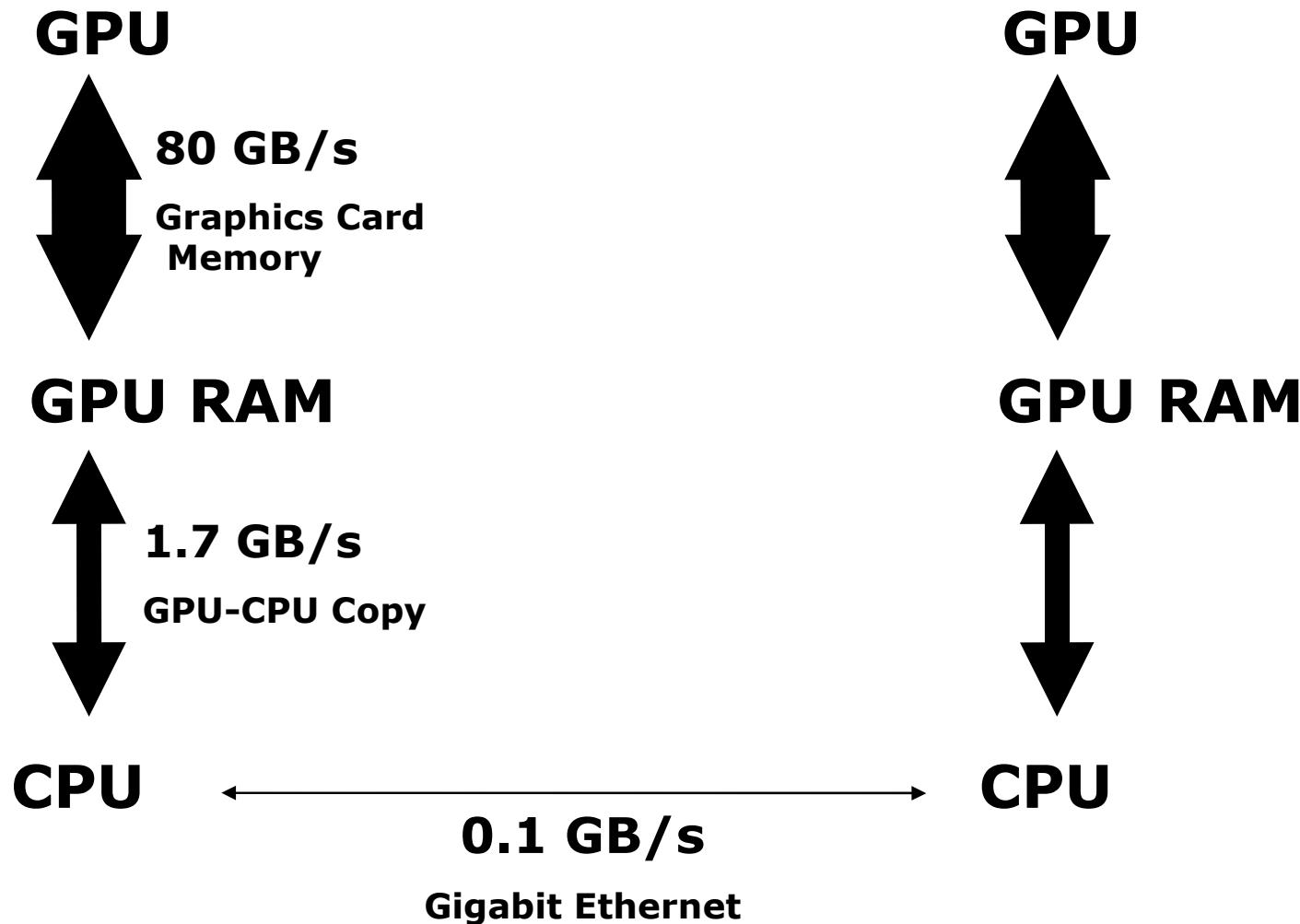
GPU Target Buffer



cudaMPI and gMPI Performance

Parallel GPU Performance

- Networks are really low bandwidth!



Parallel GPU Performance: CUDA

# GPUs	Output Rate	Computation	Network	Efficiency
1	6.1 Gpix/s	7.81 ms	- ms	100%
2	11.3 Gpix/s	3.91 ms	0.35 ms	92%
3	16.2 Gpix/s	2.62 ms	0.35 ms	88%
4	20.7 Gpix/s	1.97 ms	0.36 ms	84%
5	25.0 Gpix/s	1.58 ms	0.35 ms	81%
6	28.5 Gpix/s	1.32 ms	0.37 ms	77%
7	32.4 Gpix/s	1.13 ms	0.36 ms	75%
8	35.3 Gpix/s	1.00 ms	0.37 ms	71%
9	38.2 Gpix/s	0.91 ms	0.39 ms	67%
10	40.7 Gpix/s	0.80 ms	0.39 ms	66%

Ten GTX 280 GPUs over gigabit Ethernet; CUDA

Parallel GPU Performance: OpenGL

# GPUs	Output Rate	Computation	Network	Efficiency
1	-	-	-	-
2	20.4 Gpix/s	2.01 ms	0.34 ms	85%
3	27.8 Gpix/s	1.36 ms	0.36 ms	78%
4	34.2 Gpix/s	1.06 ms	0.35 ms	72%
5	39.2 Gpix/s	0.85 ms	0.37 ms	66%
6	43.7 Gpix/s	0.72 ms	0.38 ms	61%
7	47.9 Gpix/s	0.63 ms	0.37 ms	57%
8	51.3 Gpix/s	0.55 ms	0.38 ms	54%
9	53.3 Gpix/s	0.51 ms	0.39 ms	50%
10	55.3 Gpix/s	0.47 ms	0.40 ms	46%

Ten GTX 280 GPUs over gigabit Ethernet; OpenGL

Conclusions

Conclusions

- Consider OpenGL or DirectX instead of CUDA or OpenCL
- Watch out for latency on GPU!
 - Combine data for kernels & copies
- Use cudaMPI and glMPI for free:
 - <http://www.cs.uaf.edu/sw/>
- Future work:
 - More real applications!
 - GPU-JPEG network compression
 - Load balancing by migrating pixels
 - DirectXMPI? cudaSMP?

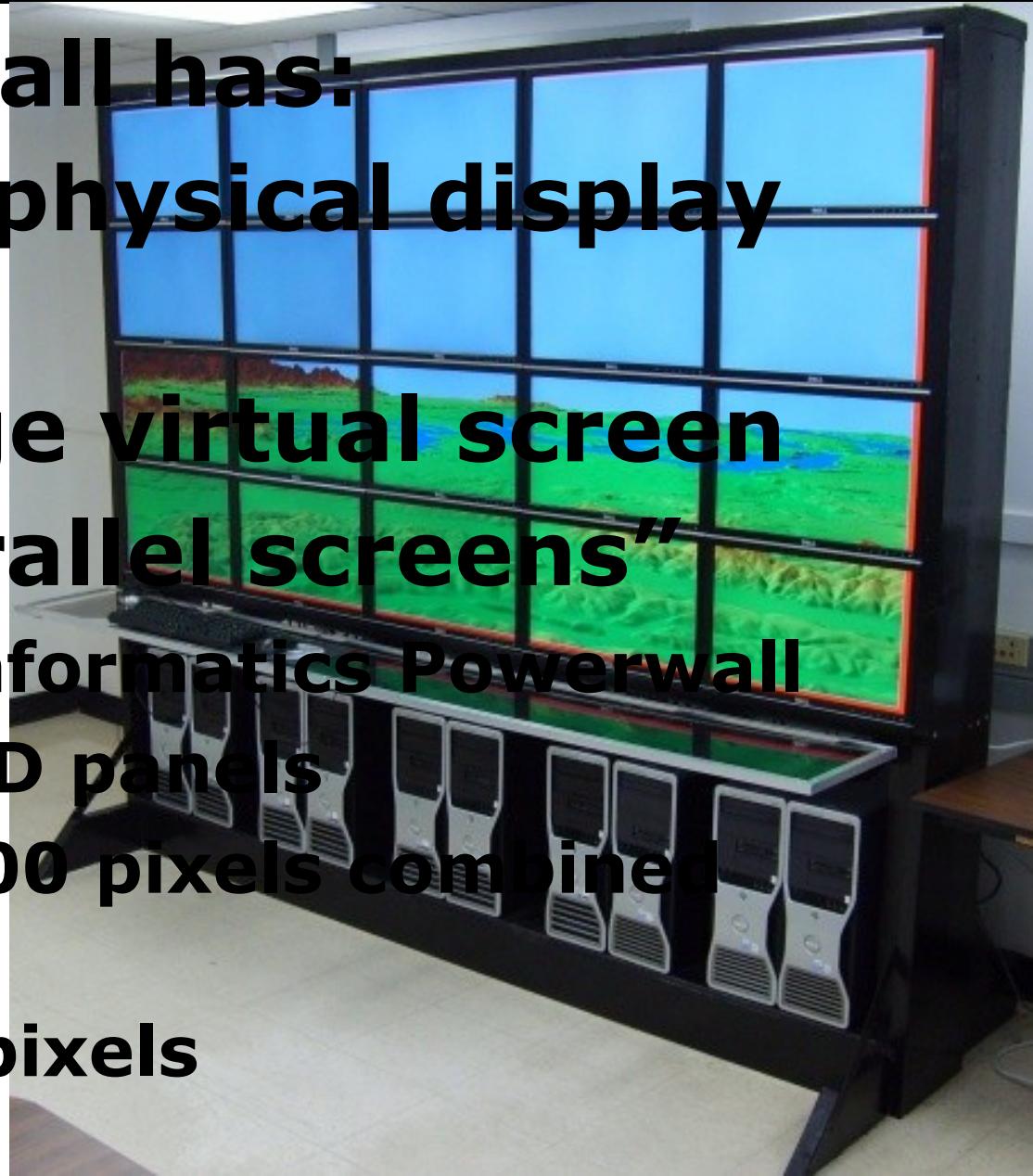
Related work:
MPIglut

MPIglut: Motivation

- All modern computing is parallel
 - Multi-Core CPUs, Clusters
 - Athlon 64 X₂, Intel Core2 Duo
 - Multiple Multi-Unit GPUs
 - nVidia SLI, ATI CrossFire
 - Multiple Displays, Disks, ...
- But languages and many existing applications are sequential
 - Software problem: run existing serial code on a parallel machine
 - Related: easily write parallel code

What is a “Powerwall”?

- A powerwall has:
 - Several physical display devices
 - One large virtual screen
 - I.E. “parallel screens”
- UAF CS/Bioinformatics Powerwall
 - Twenty LCD panels
 - 9000 x 4500 pixels combined resolution
 - 35+ Megapixels







MPIglut: The basic idea

- Users compile their OpenGL/glut application using MPIglut, and it “just works” on the powerwall
- MPIglut's version of glutInit runs a separate copy of the application for each powerwall screen
- MPIglut intercepts glutInit, glViewport, and broadcasts user events over the network
- MPIglut's glViewport shifts to render only the local screen

MPIglut Conversion: Original Code

```
#include <GL/glut.h>
void display(void) {
    glBegin(GL_TRIANGLES); ... glEnd();
    glutSwapBuffers();
}
void reshape(int x_size,int y_size) {
    glViewport(0,0,x_size,y_size);
    glLoadIdentity();
    gluLookAt(...);
}
...
int main(int argc,char *argv[]) {
    glutInit(&argc,argv);
    glutCreateWindow("Hello!");
    glutMouseFunc(...);
    ...
}
```

MPIGlut: Required Code Changes

```
#include <GL/mpiglut.h>
void display(void) {
    glBegin(GL_TRIANGLES); ... glEnd();
    glutSwapBuffers();
}
void
glutDisplay(void)
{
    glClear(GL_COLOR_BUFFER_BIT);
    gluLookAt(...);
}
...
int main(int argc,char *argv[])
{
    glutInit(&argc,argv);
    glutCreateWindow("Hello!");
    glutMouseFunc(...);
}
}
```

**This is the only source change.
Or, you can just copy mpiglut.h
over your old glut.h header!**

MPIglut Runtime Changes: Init

```
#include <GL/mpiglut.h>
void display(void) {
    glBegin(GL_TRIANGLES); ... glEnd();
    glutSwapBuffers();
}
void reshape(int x_size,int y_size) {
    glViewport(0,0,x_size,y_size);
    glLoadIdentity();
    gluLookAt(...,0,0,0,1,0,0);
}
...
int main(int argc,char *argv[]) {
    glutInit(&argc,argv);
    glutCreateWindow("Hello!");
    glutMouseFunc(...);
    ...
}
```

**MPIglut starts a separate copy
of the program (a “backend”)
to drive each powerwall screen**

MPIglut Runtime Changes: Events

```
#include <GL/mpiglut.h>
void display(void) {
    glBegin(GL_TRIANGLES); ... glEnd();
    glutSwapBuffers();
}
void reshape(int x_size,int y_size) {
    glViewport(0,0,x_size,y_size);
    glLo
    glut
}
...
int mai
    glut
    glutCreateWindow("TITLE");
    glutMouseFunc ...);
    ...
}
```

Mouse and other user input events are collected and sent across the network.

Each backend gets identical user events (collective delivery)

MPIGlut Runtime Changes: Sync

```
#include <GL/mpiglut.h>
void display(void) {
    glBegin(GL_TRIANGLES); ... glEnd();
    glutSwapBuffers();
}
void reshape(int x_size,int y_size) {
    glViewport(0,0,x_size,y_size);
    glLo
    gluL
}
...
int main(int argc,char *argv[]) {
    glutInit(&argc,argv);
    glutCreateWindow("Hello!");
    glutMouseFunc(...);
}
}
```

**Frame display is (optionally)
synchronized across the cluster**

MPIglut Runtime Changes: Coords

```
#include <GL/mpiglut.h>
void display(void) {
    glBegin(GL_TRIANGLES); ... glEnd();
    glutSwapBuffers();
}
void reshape(int x_size,int y_size) {
    glViewport(0,0,x_size,y_size);
    glLoadIdentity();
    gluLookAt(...);
}
...
int main()
{
    glutInit(...);
    glutCreateWindow(...);
    glutDisplayFunc(display);
    glutReshapeFunc(reshape);
    ...
}
```

User code works only in global coordinates, but MPIglut adjusts OpenGL's projection matrix to render only the local screen

MPIglut Runtime Non-Changes

```
#include <GL/mpiglut.h>
void display(void) {
    glBegin(GL_TRIANGLES); ... glEnd();
    glutSwapBuffers();
}
void re...
glVi...
glLo...
glul...
}
...
int ma...
glut...
glutCreateWindow("Hello!");
glutMouseFunc(...);
...
}
```

MPIglut does NOT intercept or interfere with rendering calls, so programmable shaders, vertex buffer objects, framebuffer objects, etc all run at full performance

MPIglut Assumptions/Limitations

- Each backend app must be able to render its part of its screen
 - Does not automatically imply a replicated database, if application uses matrix-based view culling
- Backend GUI events (redraws, window changes) are collective
 - All backends must stay in synch
 - Automatic for applications that are deterministic function of events
 - Non-synchronized: files, network, time

MPIGlut: Bottom Line

- **Tiny source code change**
- **Parallelism hidden inside MPIGlut**
 - Application still “feels” sequential
- **Fairly major runtime changes**
 - Serial code now runs in parallel (!)
 - Multiple synchronized backends running in parallel
 - User input events go across network
 - OpenGL rendering coordinate system adjusted per-backend
 - But rendering calls are left alone

Load Balancing a Powerwall

- **Problem:**



- **Solution: Move the rendering for load balance, but you've got to move the finished pixels back for display!**

Future Work: Load Balancing

- **AMPIglut: principle of persistence should still apply**
- **But need cheap way to ship back finished pixels every frame**
- **Exploring GPU JPEG compression**
 - DCT + quantize: really easy
 - Huffman/entropy: really hard
 - Probably need a CPU/GPU split
 - 10000+ MB/s inside GPU
 - 1000+ MB/s on CPU
 - 100+ MB/s on network