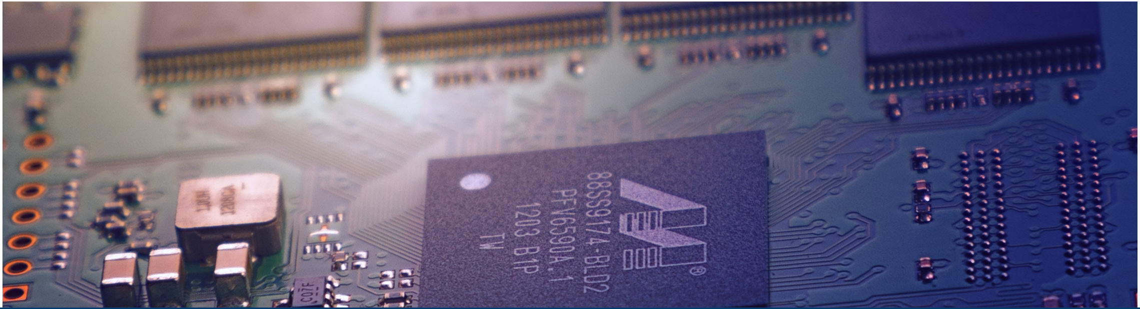


UNIFIED MEMORY

GSP GPU COURSE 2018

8 August 2018 | Andreas Herten | Forschungszentrum Jülich

Overview, Outline

Overview

- Unified Memory enables easy access to GPU development
- But some tuning might be needed for best performance

Contents

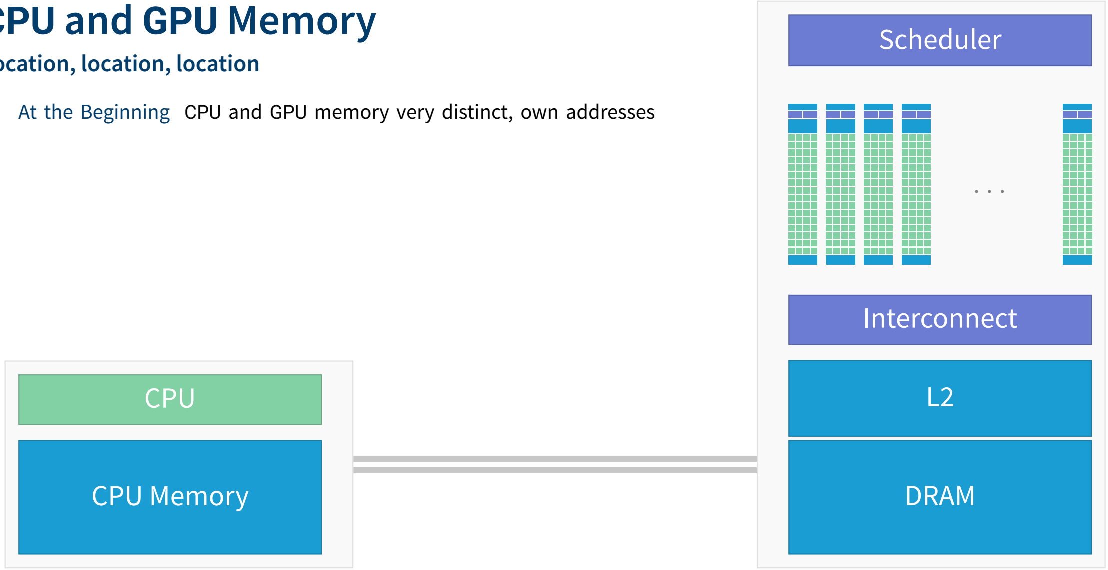
Background on Unified Memory

History of GPU Memory

CPU and GPU Memory

Location, location, location

At the Beginning CPU and GPU memory very distinct, own addresses

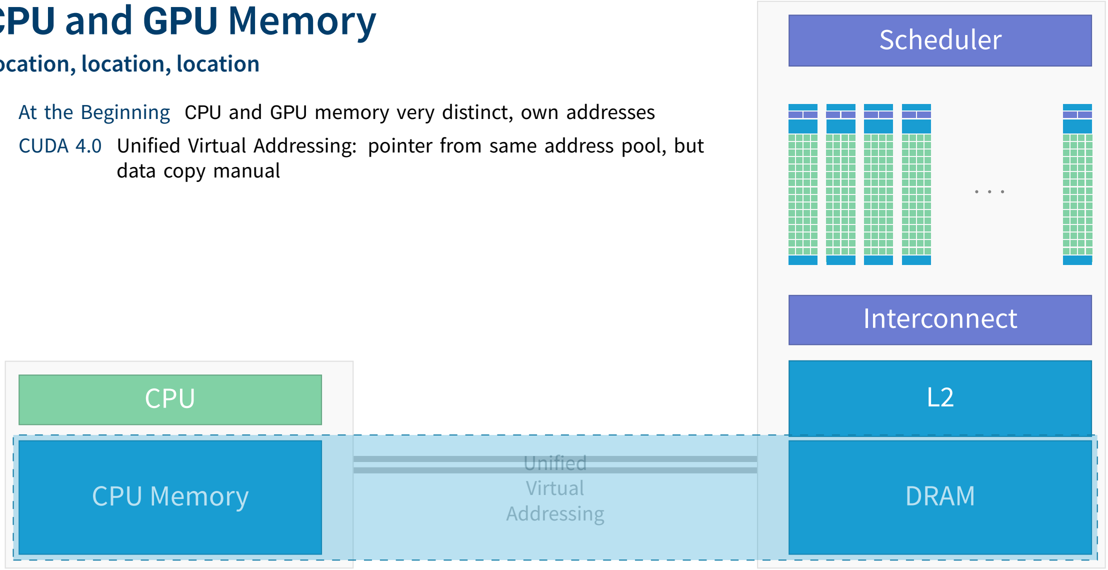


CPU and GPU Memory

Location, location, location

At the Beginning CPU and GPU memory very distinct, own addresses

CUDA 4.0 Unified Virtual Addressing: pointer from same address pool, but data copy manual



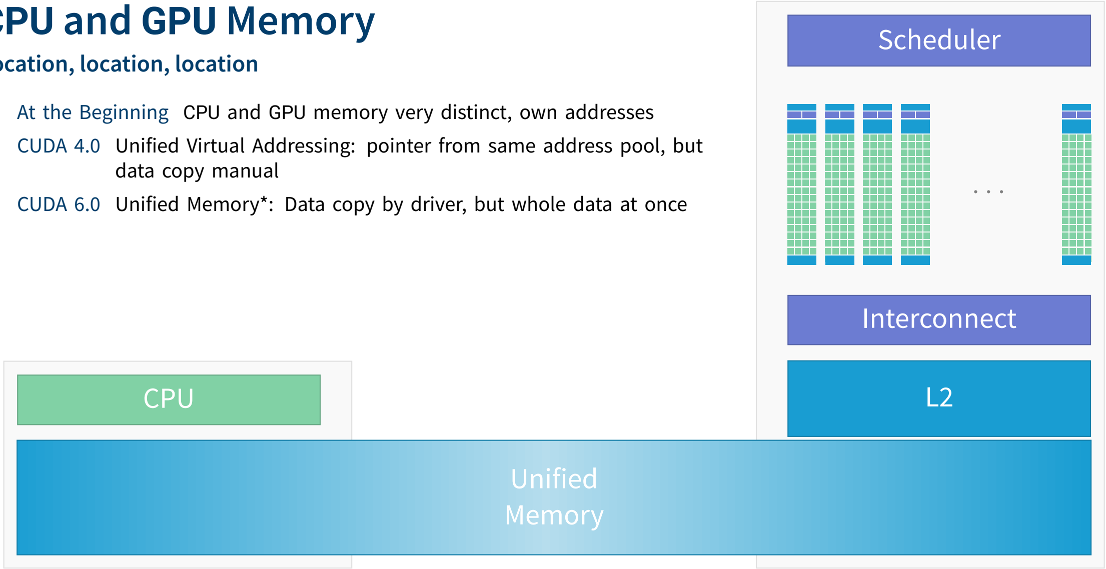
CPU and GPU Memory

Location, location, location

At the Beginning CPU and GPU memory very distinct, own addresses

CUDA 4.0 Unified Virtual Addressing: pointer from same address pool, but data copy manual

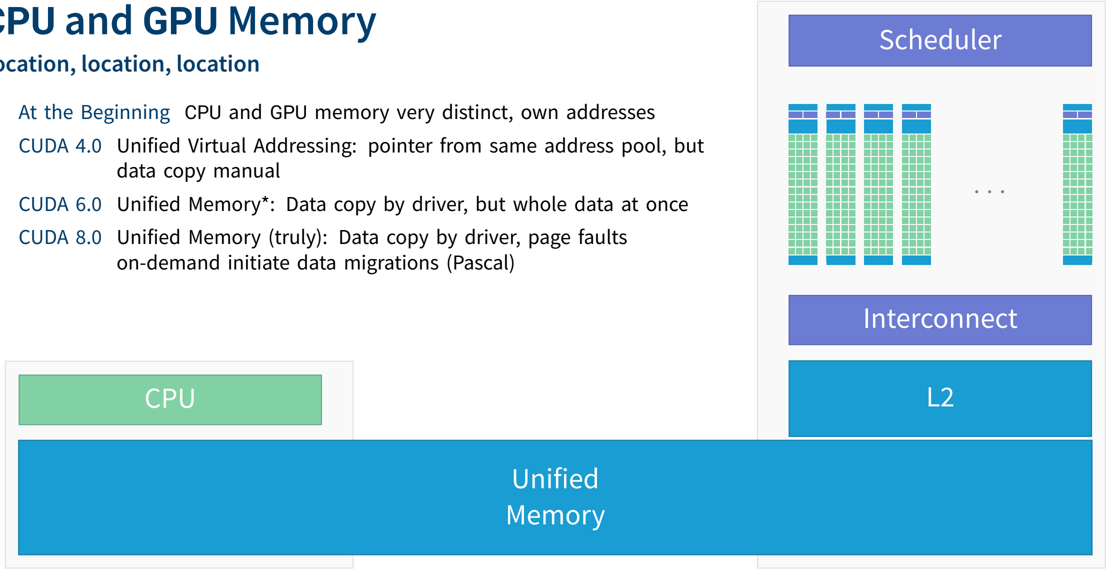
CUDA 6.0 Unified Memory*: Data copy by driver, but whole data at once



CPU and GPU Memory

Location, location, location

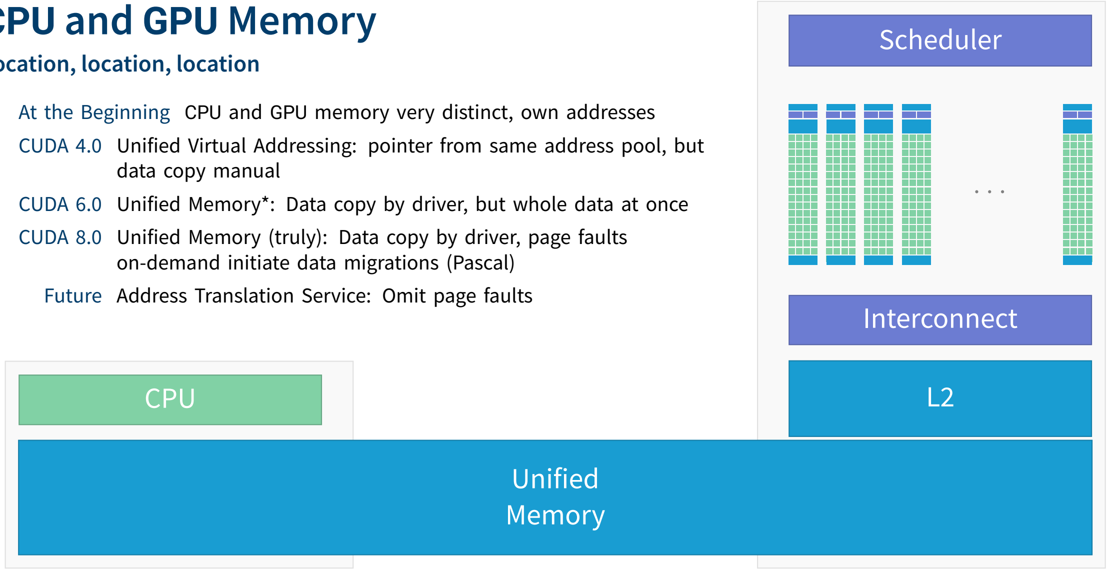
- At the Beginning — CPU and GPU memory very distinct, own addresses
- CUDA 4.0 — Unified Virtual Addressing: pointer from same address pool, but data copy manual
- CUDA 6.0 — Unified Memory*: Data copy by driver, but whole data at once
- CUDA 8.0 — Unified Memory (truly): Data copy by driver, page faults on-demand initiate data migrations (Pascal)



CPU and GPU Memory

Location, location, location

At the Beginning	CPU and GPU memory very distinct, own addresses
CUDA 4.0	Unified Virtual Addressing: pointer from same address pool, but data copy manual
CUDA 6.0	Unified Memory*: Data copy by driver, but whole data at once
CUDA 8.0	Unified Memory (truly): Data copy by driver, page faults on-demand initiate data migrations (Pascal)
Future	Address Translation Service: Omit page faults



Unified Memory in Code

Vojgjfe Nfnpsz

```
void sortfile(FILE *fp, int N) {
    char *data;
    char *data_d;

    data = (char *)malloc(N);
    cudaMalloc(&data_d, N);

    fread(data, 1, N, fp);

    cudaMemcpy(data_d, data, N,
    ↪  cudaMemcpyHostToDevice);
    kernel<<<...>>>(data, N);

    cudaMemcpy(data, data_d, N,
    ↪  cudaMemcpyDeviceToHost);
    host_func(data);
    cudaFree(data_d); free(data); }
```

```
void sortfile(FILE *fp, int N) {
    char *data;


    cudaMallocManaged(&data, N);


    fread(data, 1, N, fp);




    kernel<<<...>>>(data, N);
    cudaDeviceSynchronize();



    host_func(data);
    cudaFree(data); }
```


JÜLICH Forschungszentrum | JÜLICH SUPERCOMPUTING CENTRE

Implementation Details (on Pascal)

Under the hood

```
cudaMallocManaged(&ptr, ...);


*ptr = 1;


kernel<<<...>>>(ptr);
```

Implementation Details (on Pascal)

Under the hood

```
cudaMallocManaged(&ptr, ...);
```
Empty! No pages anywhere yet (like `malloc()`)

```
*ptr = 1;
```

```
kernel<<<...>>>(ptr);
```

Implementation Details (on Pascal)

Under the hood

```
cudaMallocManaged(&ptr, ...);
```
Empty! No pages anywhere yet (like `malloc()`)

```
*ptr = 1;
```
CPU page fault: data allocates on CPU

```
kernel<<<...>>>(ptr);
```

Implementation Details (on Pascal)

Under the hood

`cudaMallocManaged(&ptr, ...);` ← Empty! No pages anywhere yet (like `malloc()`)

`*ptr = 1;` ← CPU page fault: data allocates on CPU

`kernel<<<...>>>(ptr);` ← GPU page fault: data migrates to GPU

Implementation Details (on Pascal)

Under the hood

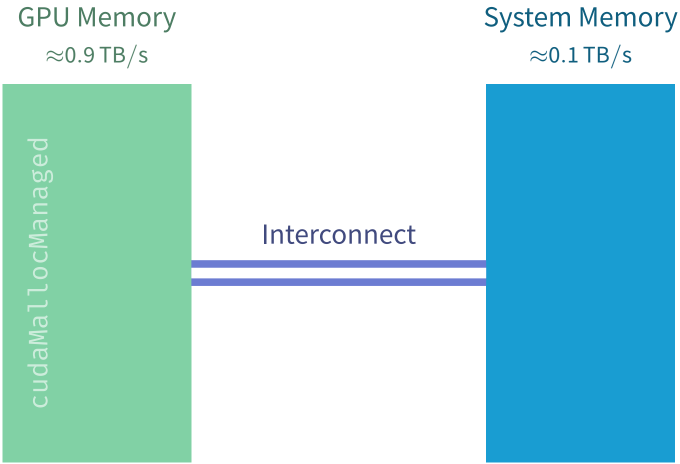
`cudaMallocManaged(&ptr, ...);` ← Empty! No pages anywhere yet (like `malloc()`)

`*ptr = 1;` ← CPU page fault: data allocates on CPU

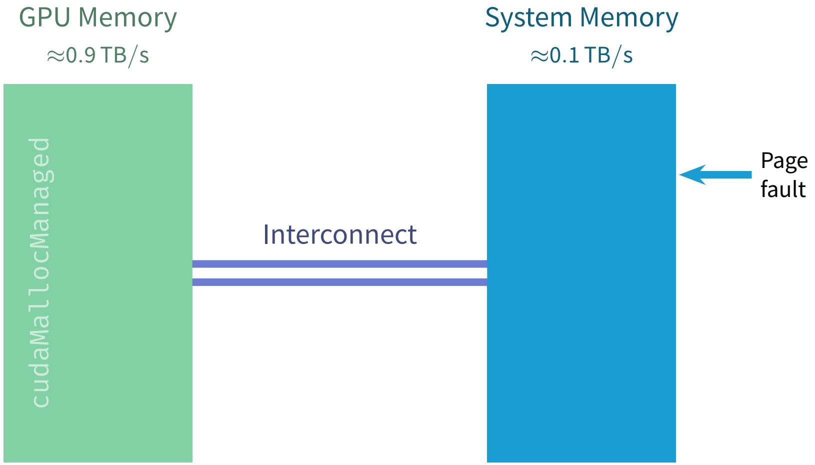
`kernel<<<...>>>(ptr);` ← GPU page fault: data migrates to GPU

- Pages populate on **first touch**
- Pages migrate on-demand
- GPU memory over-subscription possible
- Concurrent access from CPU and GPU to memory (page-level)

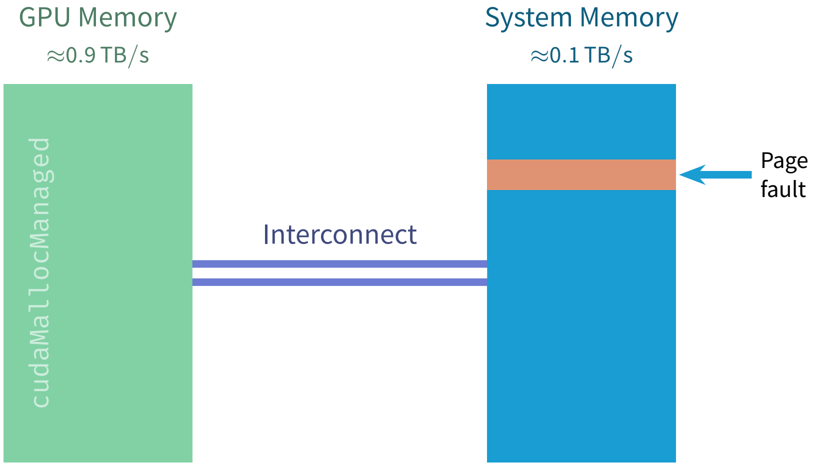
On-Demand Migration Flow (Pascal, Volta)



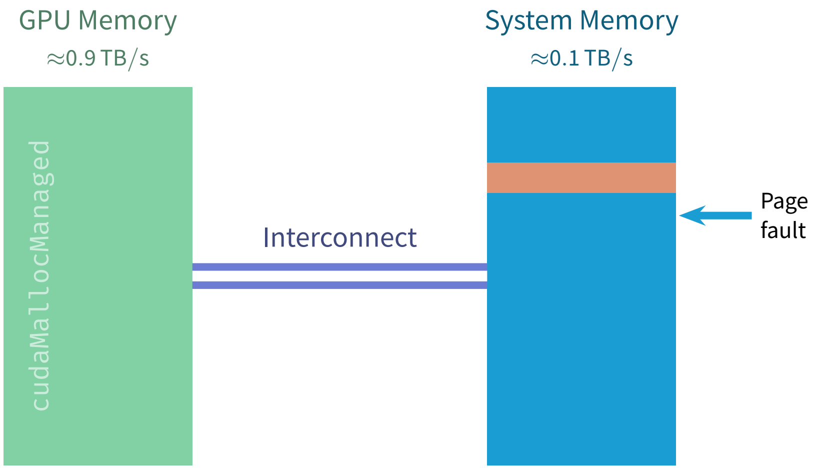
On-Demand Migration Flow (Pascal, Volta)



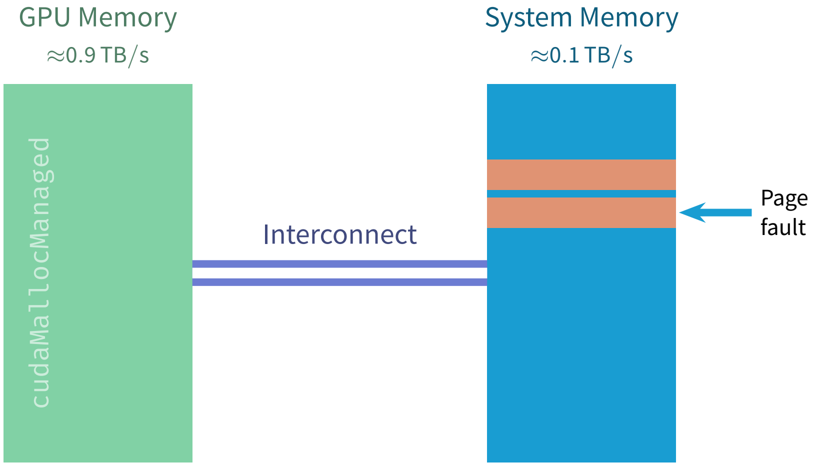
On-Demand Migration Flow (Pascal, Volta)



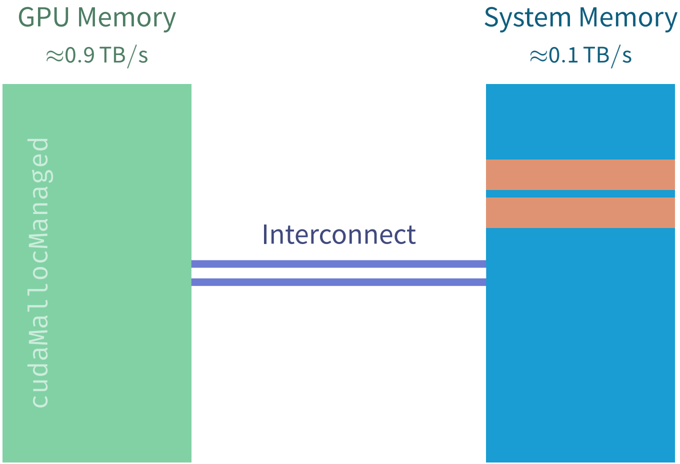
On-Demand Migration Flow (Pascal, Volta)



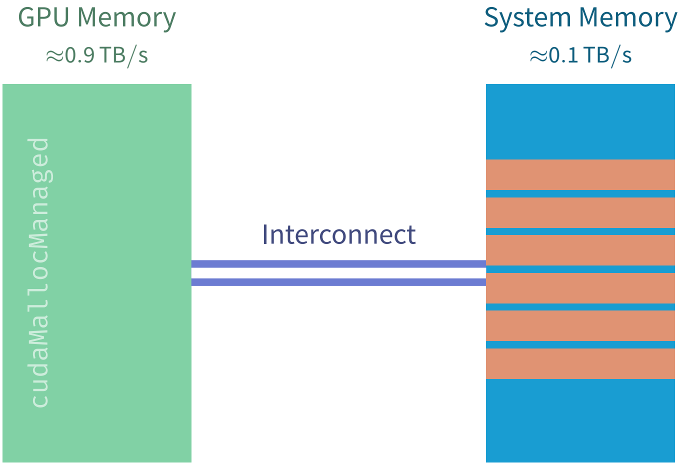
On-Demand Migration Flow (Pascal, Volta)



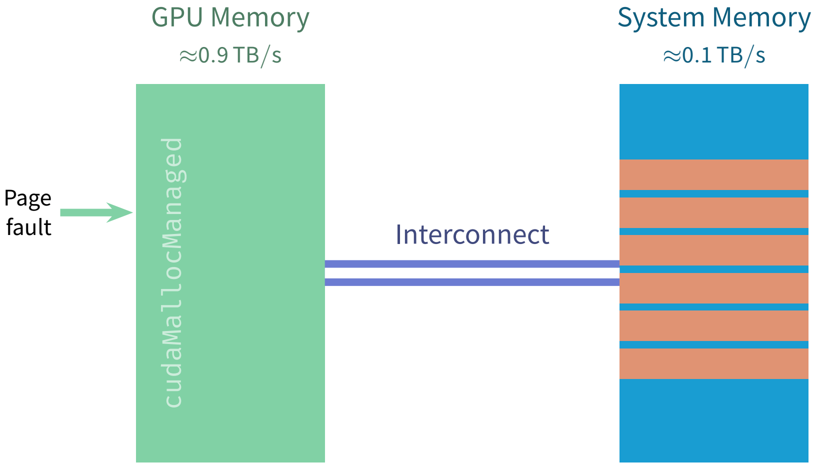
On-Demand Migration Flow (Pascal, Volta)



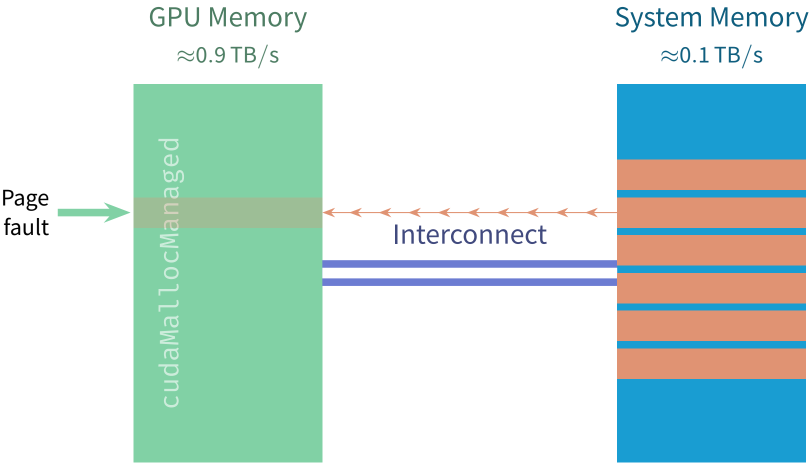
On-Demand Migration Flow (Pascal, Volta)



On-Demand Migration Flow (Pascal, Volta)

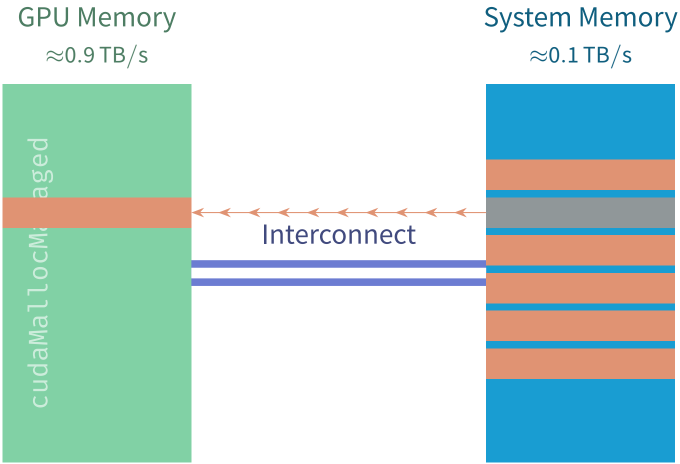


On-Demand Migration Flow (Pascal, Volta)



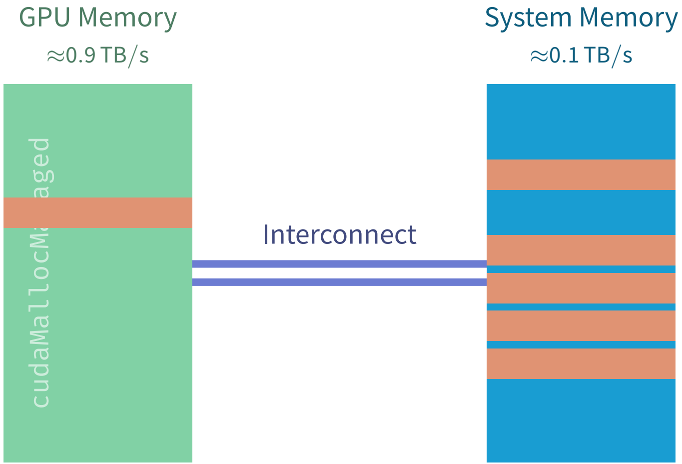
JÜLICH Forschungszentrum JÜLICH SUPERCOMPUTING CENTRE

On-Demand Migration Flow (Pascal, Volta)

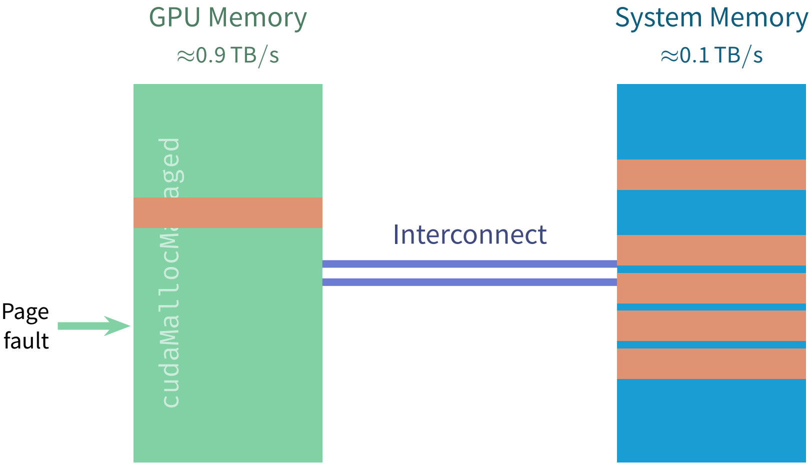


JÜLICH Forschungszentrum JÜLICH SUPERCOMPUTING CENTRE

On-Demand Migration Flow (Pascal, Volta)

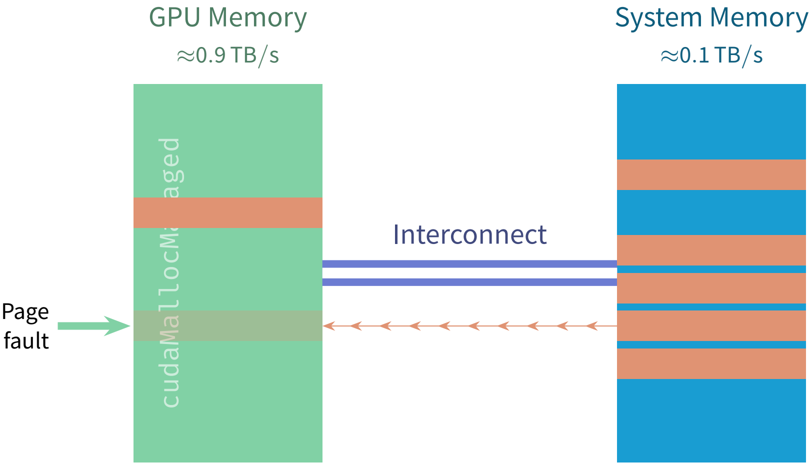


On-Demand Migration Flow (Pascal, Volta)

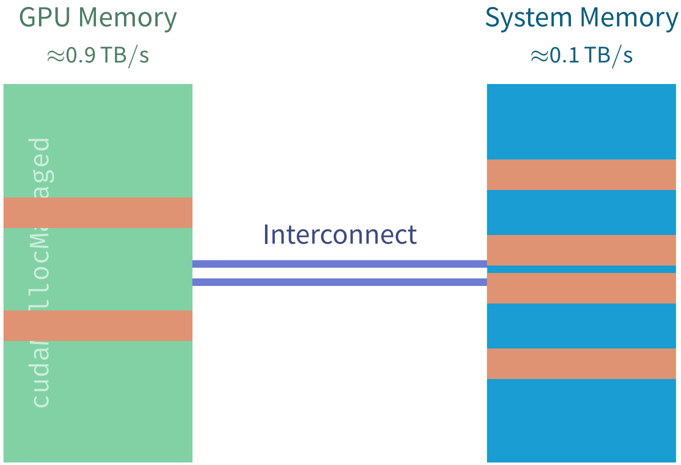


JÜLICH Forschungszentrum | JÜLICH SUPERCOMPUTING CENTRE

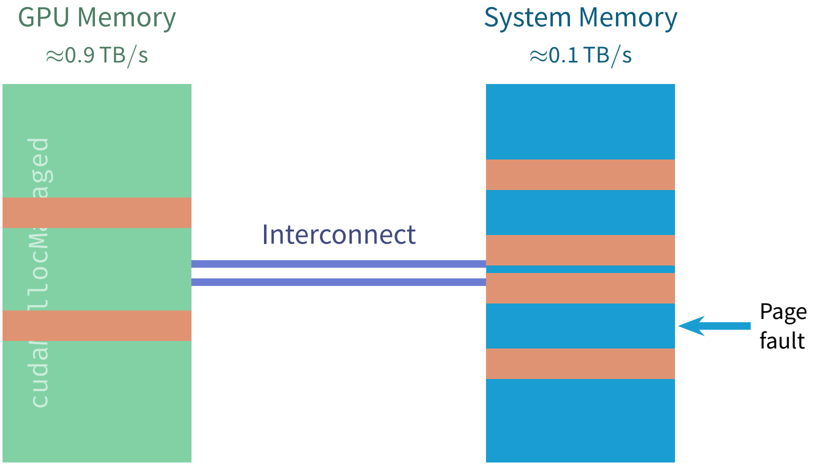
On-Demand Migration Flow (Pascal, Volta)



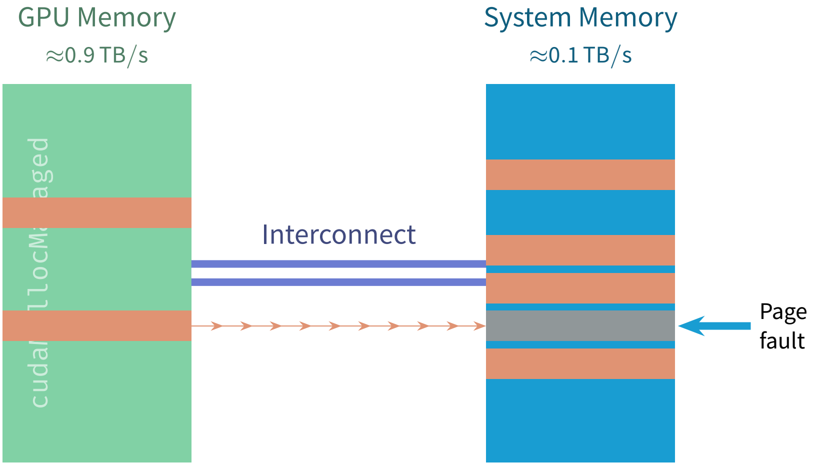
On-Demand Migration Flow (Pascal, Volta)



On-Demand Migration Flow (Pascal, Volta)

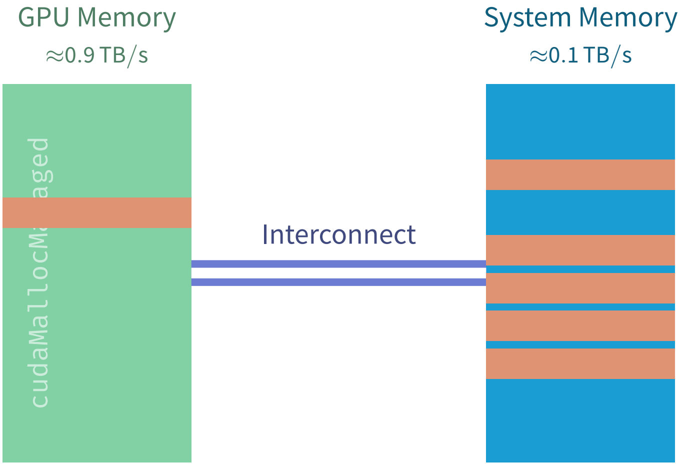


On-Demand Migration Flow (Pascal, Volta)

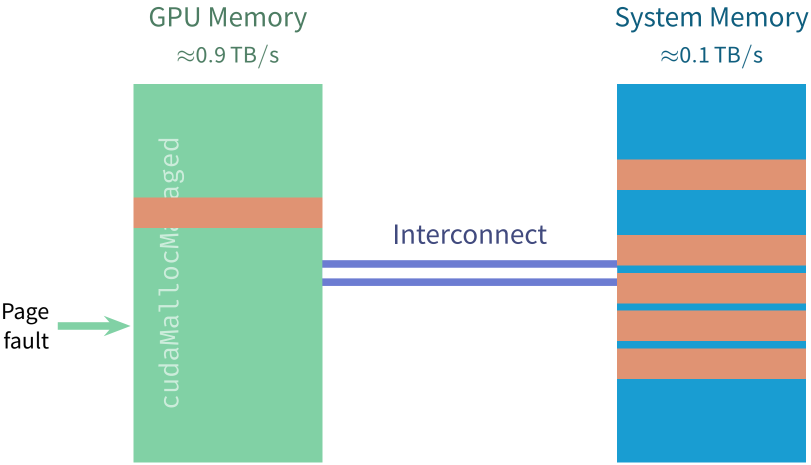


JÜLICH Forschungszentrum
JÜLICH SUPERCOMPUTING CENTRE

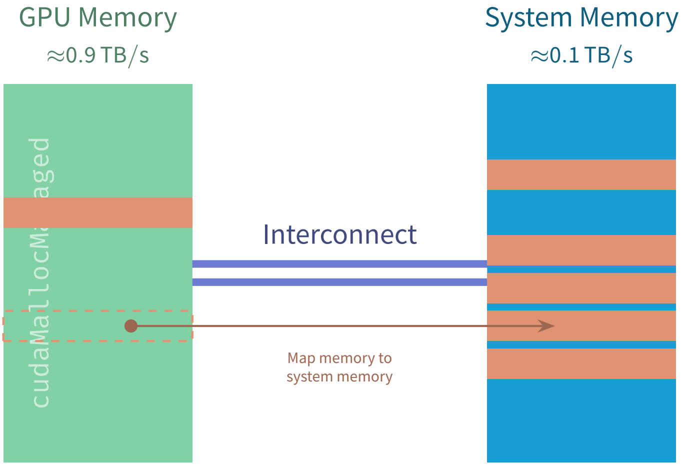
On-Demand Migration Flow (Pascal, Volta)



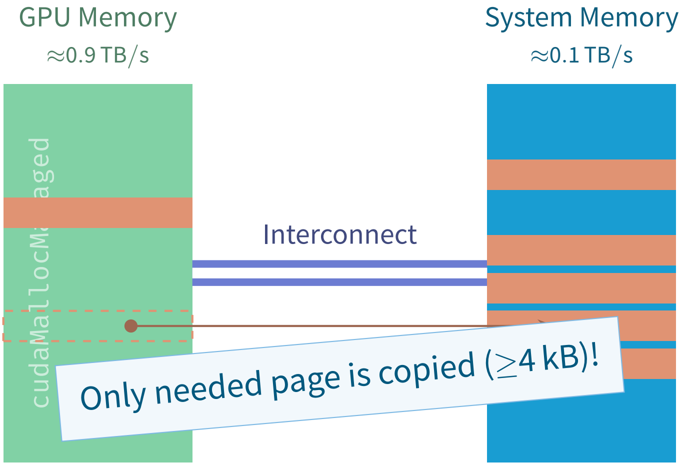
On-Demand Migration Flow (Pascal, Volta)



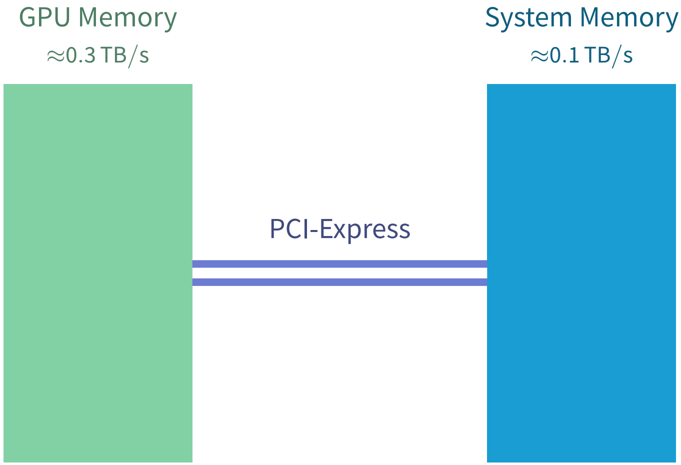
On-Demand Migration Flow (Pascal, Volta)



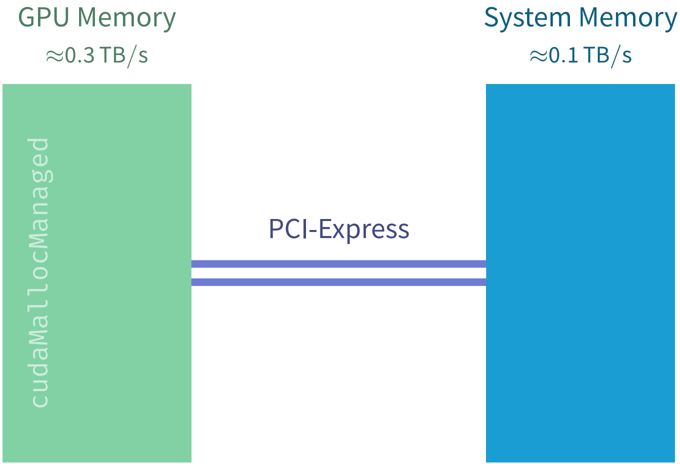
On-Demand Migration Flow (Pascal, Volta)



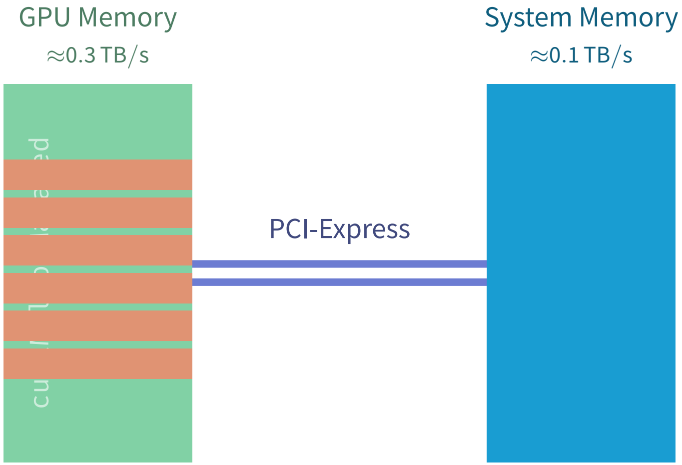
Migration on Kepler



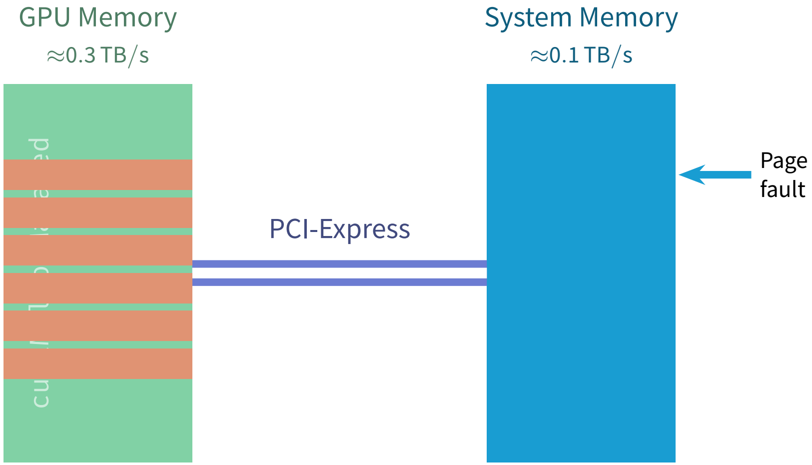
Migration on Kepler



Migration on Kepler

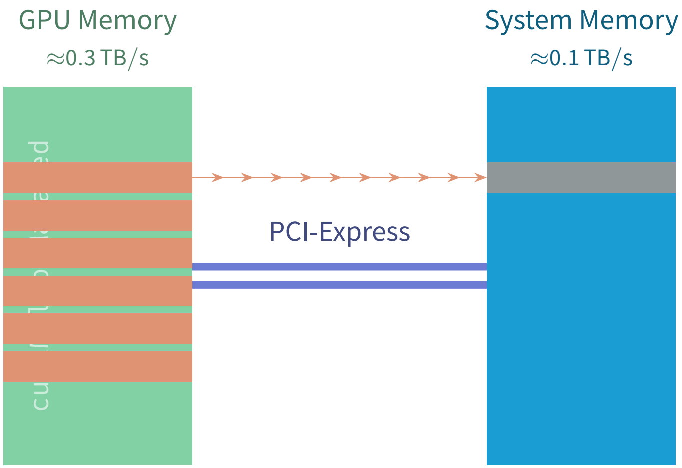


Migration on Kepler

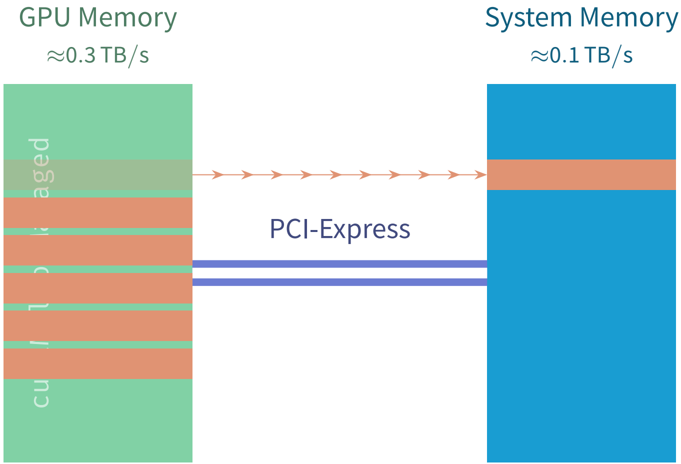


JÜLICH Forschungszentrum | JÜLICH SUPERCOMPUTING CENTRE

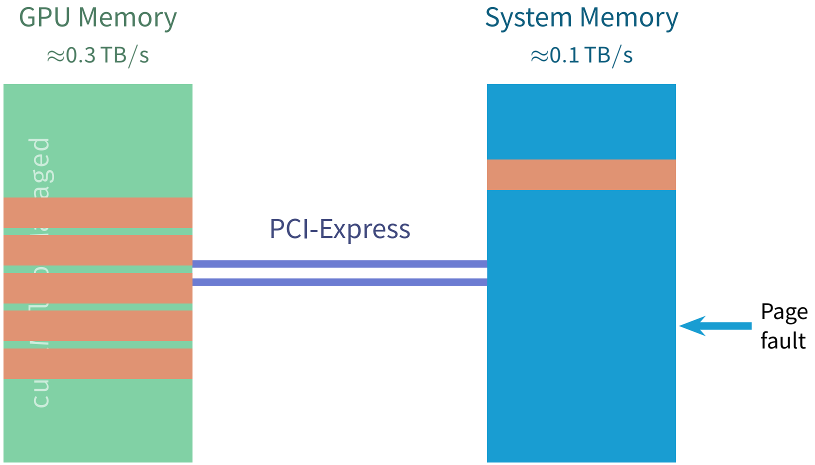
Migration on Kepler



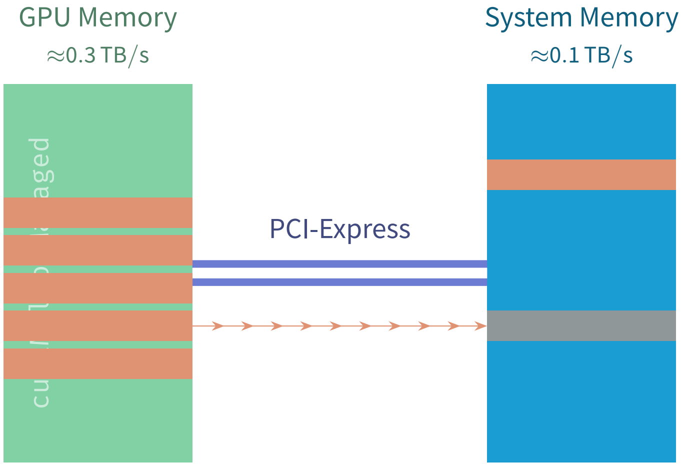
Migration on Kepler



Migration on Kepler

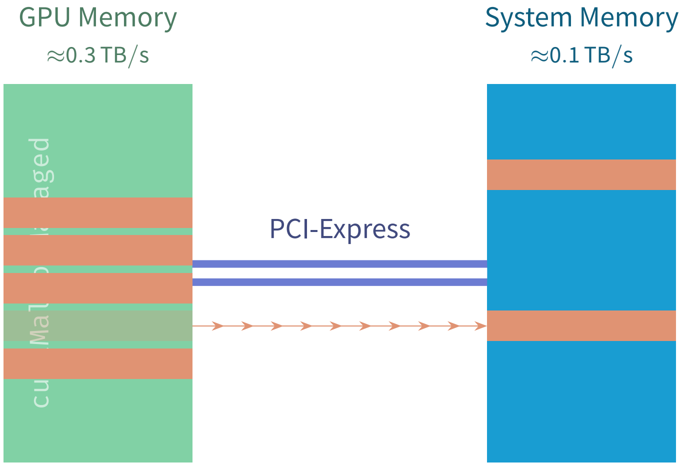


Migration on Kepler

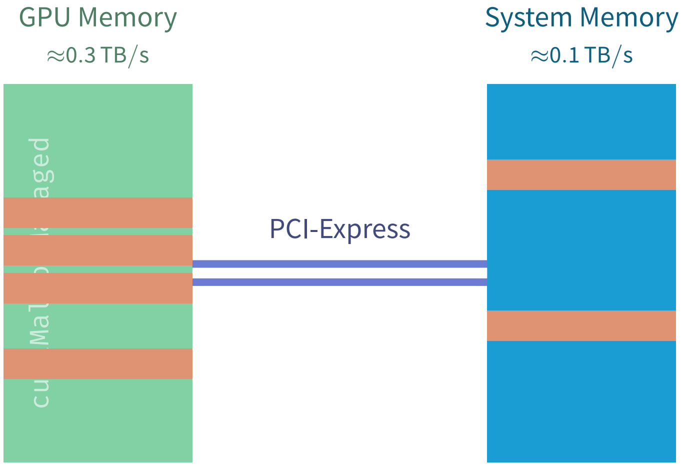


JÜLICH Forschungszentrum JÜLICH SUPERCOMPUTING CENTRE

Migration on Kepler

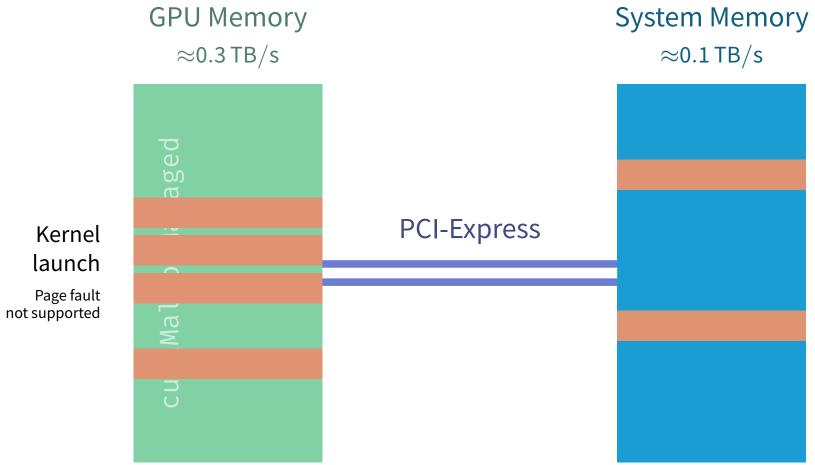


Migration on Kepler

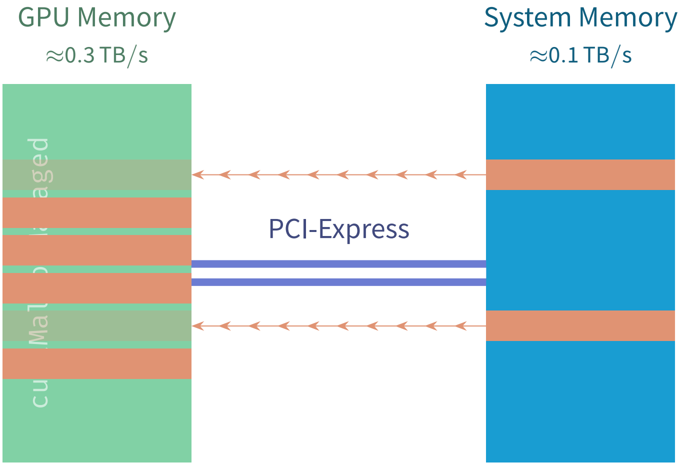


JÜLICH Forschungszentrum | JÜLICH SUPERCOMPUTING CENTRE

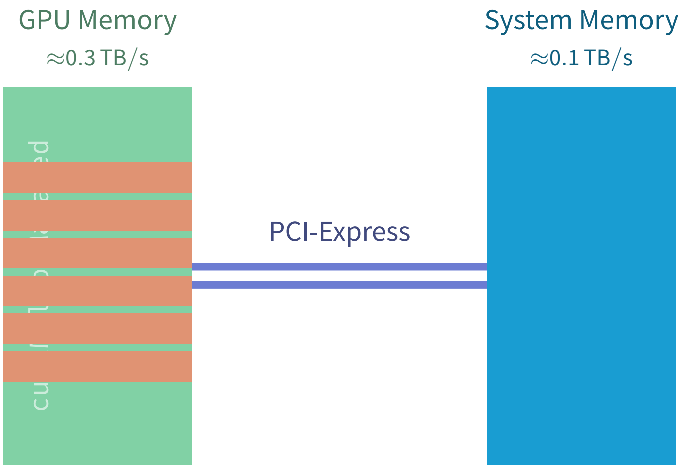
Migration on Kepler



Migration on Kepler



Migration on Kepler



Implementation before Pascal

Kepler (JURECA), Maxwell, ...

- Pages populate on GPU with `cudaMallocManaged()`

→ Might migrate to CPU if touched there first

- Pages migrate <u>in bulk</u> to GPU on kernel launch
- No over-subscription possible

Practical Differences

Revisiting `scale_vector_um` Example

Comparing UM on Pascal & Kepler

Different `scales`

Comparing `scale_vector_um` on JURON (JUWELS) and JURECA

Comparing UM on Pascal & Kepler

Different `scales`

Comparing `scale_vector_um` on JURON (JUWELS) and JURECA

JUWELS

```
==109924== Profiling result:
Time(%)      Time     Calls       Avg       Min       Max  Name
100.00%  4.9247ms         1  4.9247ms  4.9247ms  4.9247ms  scale(float, float*, float*, int)
```

JURECA

```
==12922== Profiling result:
Time(%)      Time     Calls       Avg       Min       Max  Name
100.00%  136.03us         1  136.03us  136.03us  136.03us  scale(float, float*, float*, int)
```

Comparing UM on Pascal & Kepler

Different `scales`

Comparing `scale_vector_um` on JURON (JUWELS) and JURECA

JURON

```
==109924== Profiling result:
Time(%)      Time     Calls       Avg       Min       Max  Name
100.00%  1.8203ms         1  1.8203ms  1.8203ms  1.8203ms  scale(float, float*, float*, int)
```

JURECA

```
==12922== Profiling result:
Time(%)      Time     Calls       Avg       Min       Max  Name
100.00%  136.03us         1  136.03us  136.03us  136.03us  scale(float, float*, float*, int)
```

Comparing UM on Pascal & Kepler

Different `scales`

Comparing `scale_vector_um` on JURON (JUWELS) and JURECA

JURON

```
==109924== Profiling result:
Time(%)      Time     Calls       Avg       Min       Max  Name
100.00%  1.8203ms         1  1.8203ms  1.8203ms  1.8203ms  scale(float, float*, float*, int)
```

Why?!

Shouldn't P100 and V100 be much faster than K80?

JURECA

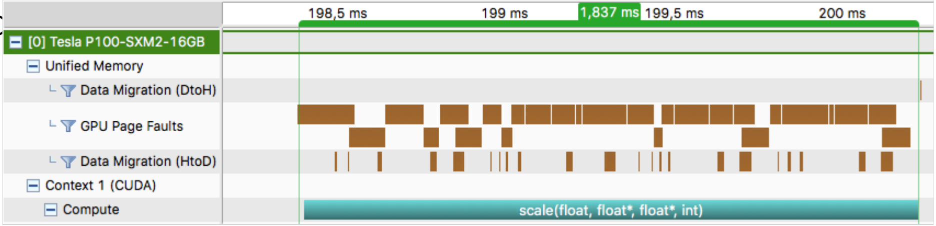
```
==12922== Profiling result:
Time(%)      Time     Calls       Avg       Min       Max  Name
100.00%  136.03us         1  136.03us  136.03us  136.03us  scale(float, float*, float*, int)
```

Comparing UM on Pascal & Kepler

Different scales

C

JURON



JURECA

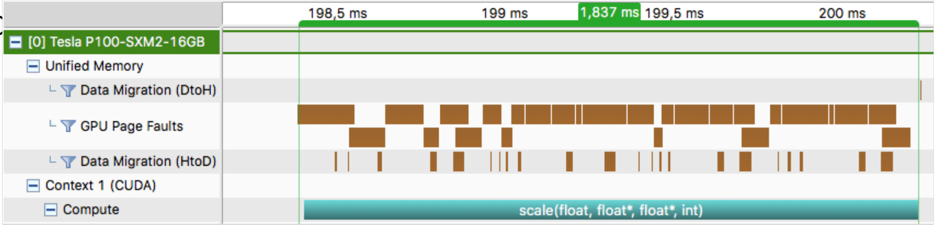
```
==12922== Profiling result:
Time(%)      Time     Calls       Avg       Min       Max  Name
100.00%  136.03us         1  136.03us  136.03us  136.03us  scale(float, float*, float*, int)
```

Comparing UM on Pascal & Kepler

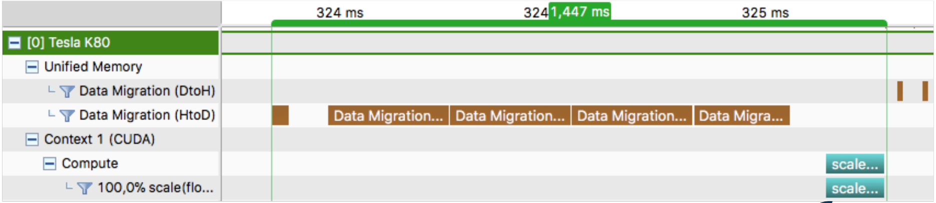
Different `scales`

C

JURON



JURECA



Comparing UM on Pascal & Kepler

What happens?

JURON Kernel is launched, data is needed by kernel, data migrates host$\rightarrow$device
$\Rightarrow$ Run time of kernel **incorporates** time for data transfers

JURECA Data will be needed by kernel – so data migrates host$\rightarrow$device **before** kernel launch
$\Rightarrow$ Run time of **kernel** without any transfers

Comparing UM on Pascal & Kepler

What happens?

JURON Kernel is launched, data is needed by kernel, data migrates host$\rightarrow$device
$\Rightarrow$ Run time of kernel **incorporates** time for data transfers

JURECA Data will be needed by kernel – so data migrates host$\rightarrow$device **before** kernel launch
$\Rightarrow$ Run time of **kernel** without any transfers

- Implementation on Pascal is the more convenient one
- Total run time of whole program does not principally change
  Except it gets shorter because of faster architecture
- But data transfers sometimes sorted to kernel launch

Comparing UM on Pascal & Kepler

What happens?

JURON Kernel is launched, data is needed by kernel, data migrates host$\rightarrow$device
$\Rightarrow$ Run time of kernel **incorporates** time for data transfers

JURECA Data will be needed by kernel – so data migrates host$\rightarrow$device **before** kernel launch
$\Rightarrow$ Run time of **kernel** without any transfers

- Implementation on Pascal is the more convenient one
- Total run time of whole program does not principally change
  Except it gets shorter because of faster architecture
- But data transfers sometimes sorted to kernel launch

$\Rightarrow$ *What can we do about this?*

Performance Hints for UM

General hints

- **Keep data local**
  Prevent migrations at all if data is processed by close processor

Performance Hints for UM

General hints

- **Keep data local**
  Prevent migrations at all if data is processed by close processor
- **Minimize thrashing**
  Constant migrations hurt performance

Performance Hints for UM

General hints

- **Keep data local**
  Prevent migrations at all if data is processed by close processor
- **Minimize thrashing**
  Constant migrations hurt performance
- **Minimize page fault overhead**
  Fault handling costs $\mathcal{O}(10\,\mu s)$, stalls execution

Performance Hints for UM

New API routines

API calls to augment data location knowledge of runtime

- `cudaMemPrefetchAsync(data, length, device, stream)`
  Prefetches data to `device` (on `stream`) asynchronously

Performance Hints for UM

New API routines

API calls to augment data location knowledge of runtime

- `cudaMemPrefetchAsync(data, length, device, stream)`
  Prefetches data to `device` (on `stream`) asynchronously
- `cudaMemAdvise(data, length, advice, device)`
  Advise about usage of given data, `advice`:

Performance Hints for UM

New API routines

API calls to augment data location knowledge of runtime

- `cudaMemPrefetchAsync(data, length, device, stream)`
  Prefetches data to `device` (on `stream`) asynchronously
- `cudaMemAdvise(data, length, advice, device)`
  Advise about usage of given data, `advice`:
  - `cudaMemAdviseSetReadMostly`: Data is mostly read and occasionally written to

Performance Hints for UM

New API routines

API calls to augment data location knowledge of runtime

- `cudaMemPrefetchAsync(data, length, device, stream)`
  Prefetches data to `device` (on `stream`) asynchronously
- `cudaMemAdvise(data, length, advice, device)`
  Advise about usage of given data, `advice`:
  - `cudaMemAdviseSetReadMostly`: Data is mostly read and occasionally written to
  - `cudaMemAdviseSetPreferredLocation`: Set preferred location to avoid migrations; first access will establish mapping

Performance Hints for UM

New API routines

API calls to augment data location knowledge of runtime

- `cudaMemPrefetchAsync(data, length, device, stream)`
  Prefetches data to `device` (on `stream`) asynchronously
- `cudaMemAdvise(data, length, advice, device)`
  Advise about usage of given data, `advice`:
  - `cudaMemAdviseSetReadMostly`: Data is mostly read and occasionally written to
  - `cudaMemAdviseSetPreferredLocation`: Set preferred location to avoid migrations; first access will establish mapping
  - `cudaMemAdviseSetAccessedBy`: Data is accessed by *this* device; will pre-map data to avoid page fault

Performance Hints for UM

New API routines

API calls to augment data location knowledge of runtime

- `cudaMemPrefetchAsync(data, length, device, stream)`
  Prefetches data to `device` (on `stream`) asynchronously
- `cudaMemAdvise(data, length, advice, device)`
  Advise about usage of given data, `advice`:
  - `cudaMemAdviseSetReadMostly`: Data is mostly read and occasionally written to
  - `cudaMemAdviseSetPreferredLocation`: Set preferred location to avoid migrations; first access will establish mapping
  - `cudaMemAdviseSetAccessedBy`: Data is accessed by *this* device; will pre-map data to avoid page fault
- Use `cudaCpuDeviceId` for `device` CPU, or use `cudaGetDevice()` as usual to retrieve current GPU device id (default: 0)

Hints in Code

```
void sortfile(FILE *fp, int N) {
    char *data;
    // ...
    cudaMallocManaged(&data, N);

    fread(data, 1, N, fp);


    cudaMemPrefetchAsync(data, N, device);
    kernel<<<...>>>(data, N);
    cudaDeviceSynchronize();

    host_func(data);
    cudaFree(data); }
```

Hints in Code

```
void sortfile(FILE *fp, int N) {
    char *data;
    // ...
    cudaMallocManaged(&data, N);

    fread(data, 1, N, fp);


    cudaMemPrefetchAsync(data, N, device);
    kernel<<<...>>>(data, N);
    cudaDeviceSynchronize();

    host_func(data);
    cudaFree(data); }
```

Prefetch data to avoid expensive GPU page faults

Hints in Code

```
void sortfile(FILE *fp, int N) {
    char *data;
    // ...
    cudaMallocManaged(&data, N);

    fread(data, 1, N, fp);

    cudaMemAdvise(data, N, cudaMemAdviseSetReadMostly, device);
    cudaMemPrefetchAsync(data, N, device);
    kernel<<<...>>>(data, N);
    cudaDeviceSynchronize();

    host_func(data);
    cudaFree(data); }
```

Read-only copy of data is created on GPU during prefetch
→ CPU and GPU reads will not fault

Prefetch data to avoid expensive GPU page faults

Tuning `scale_vector_um`

TASK

Express data movement

- Location of code: `3-Unified-Memory/exercises/tasks/scale/`
- Look at `Instructions.md` for instructions
  1. Show runtime that data should be migrated to GPU before kernel call
  2. Build with `make`
  3. Run with `make run`

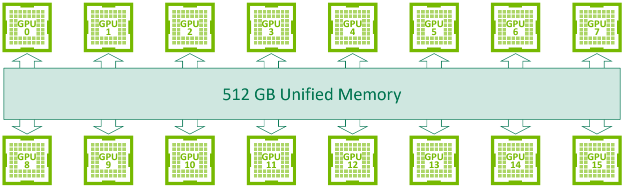
     Or `srun --gres=gpu -p gpus ./scale_vector_um`
  4. Generate profile to study your progress – see `make profile`
- See also CUDA C programming guide for details on data usage

Finished early? There's one more task in the appendix!

Conclusions

What we've learned

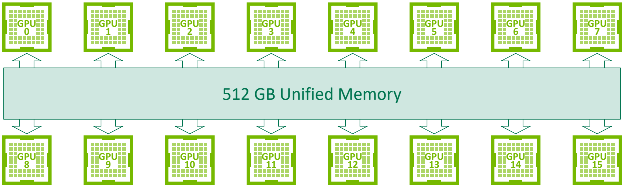
- **Unified Memory** is *productive* feature for GPU programming
- Unified Memory is implemented differently on Pascal (JURON) and Kepler (JURECA)
- With CUDA 8.0, there are new API calls to express **data locality**
- CUDA 9.x and DGX-2: `cudaMalloc()` across all GPUs, then `cudaMemAdviseSetPreferredHome`



Conclusions

What we've learned

- **Unified Memory** is *productive* feature for GPU programming
- Unified Memory is implemented differently on Pascal (JURON) and Kepler (JURECA)
- With CUDA 8.0, there are new API calls to express **data locality**
- CUDA 9.x and DGX-2: `cudaMalloc()` across all GPUs, then `cudaMemAdviseSetPreferredHome`



Thank you for your attention!

a.herten@fz-juelich.de

JÜLICH Forschungszentrum | JÜLICH SUPERCOMPUTING CENTRE

Appendix

Jacobi Task

Glossary

Jacobi Task

TASK

One more time…

- Location of code: `3-Unified-Memory/exercises/tasks/jacobi/`
- See Jiri Kraus' slides on Unified Memory from 2016 at `3-Unified-Memory/exercises/slides/jkraus-unified_memory-2016.pdf`
- Short instructions
  - Avoid data migrations in while loop of Jacobi solver: apply boundary conditions with provided GPU kernel; try to avoid remaining migrations
  - Build with `make` (CUDA needs to be loaded!)
  - Run with `make run`
  - Look at profile – see `make profile`

Glossary I

CUDA Computing platform for GPUs from NVIDIA. Provides, among others, CUDA C/C++. 4, 5, 6, 7, 8, 71, 72, 73

JSC Jülich Supercomputing Centre, the supercomputing institute of Forschungszentrum Jülich, Germany. 76

JURECA A multi-purpose supercomputer with 1800 nodes at JSC. 56, 57, 58, 72, 73

JURON One of the two HBP pilot system in Jülich; name derived from Juelich and Neuron. 50, 51, 52, 53, 54, 55, 56, 57, 58, 72, 73

JUWELS Jülich's new supercomputer, the successor of JUQUEEN. 50, 51, 52, 53, 54, 55

NVIDIA US technology company creating GPUs. 76, 77

Glossary II

NVLink NVIDIA's communication protocol connecting CPU $\leftrightarrow$ GPU and GPU $\leftrightarrow$ GPU with high bandwidth. 77

P100 A large GPU with the Pascal architecture from NVIDIA. It employs NVLink as its interconnect and has fast *HBM2* memory. 53

Pascal GPU architecture from NVIDIA (announced 2016). 4, 5, 6, 7, 8, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 56, 57, 58, 77

V100 A large GPU with the Volta architecture from NVIDIA. It employs NVLink 2 as its interconnect and has fast *HBM2* memory. Additionally, it features *Tensorcores* for Deep Learning and Independent Thread Scheduling. 53

Volta GPU architecture from NVIDIA (announced 2017). 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 77

Glossary III

CPU Central Processing Unit. 4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 48, 62, 63, 64, 65, 66, 67, 70, 77

GPU Graphics Processing Unit. 2, 3, 4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 48, 62, 63, 64, 65, 66, 67, 69, 70, 71, 72, 73, 75, 76, 77

HBP Human Brain Project. 76

References: Images, Graphics I

[1] Martin Oslic. *Bug*. Freely available at Unsplash. URL: https://unsplash.com/photos/Qi93Pl5vDRw.

[2] Glenn Dearth and Vyes Venkataraman. *Picture: DGX-2 Memory Layout*. GTC18 Talk: S8688 – INSIDE DGX-2. 2018. URL: http://on-demand.gputechconf.com/gtc/2018/presentation/s8688-extending-the-connectivity-and-reach-of-the-gpu.pdf.

JÜLICH Forschungszentrum | JÜLICH SUPERCOMPUTING CENTRE