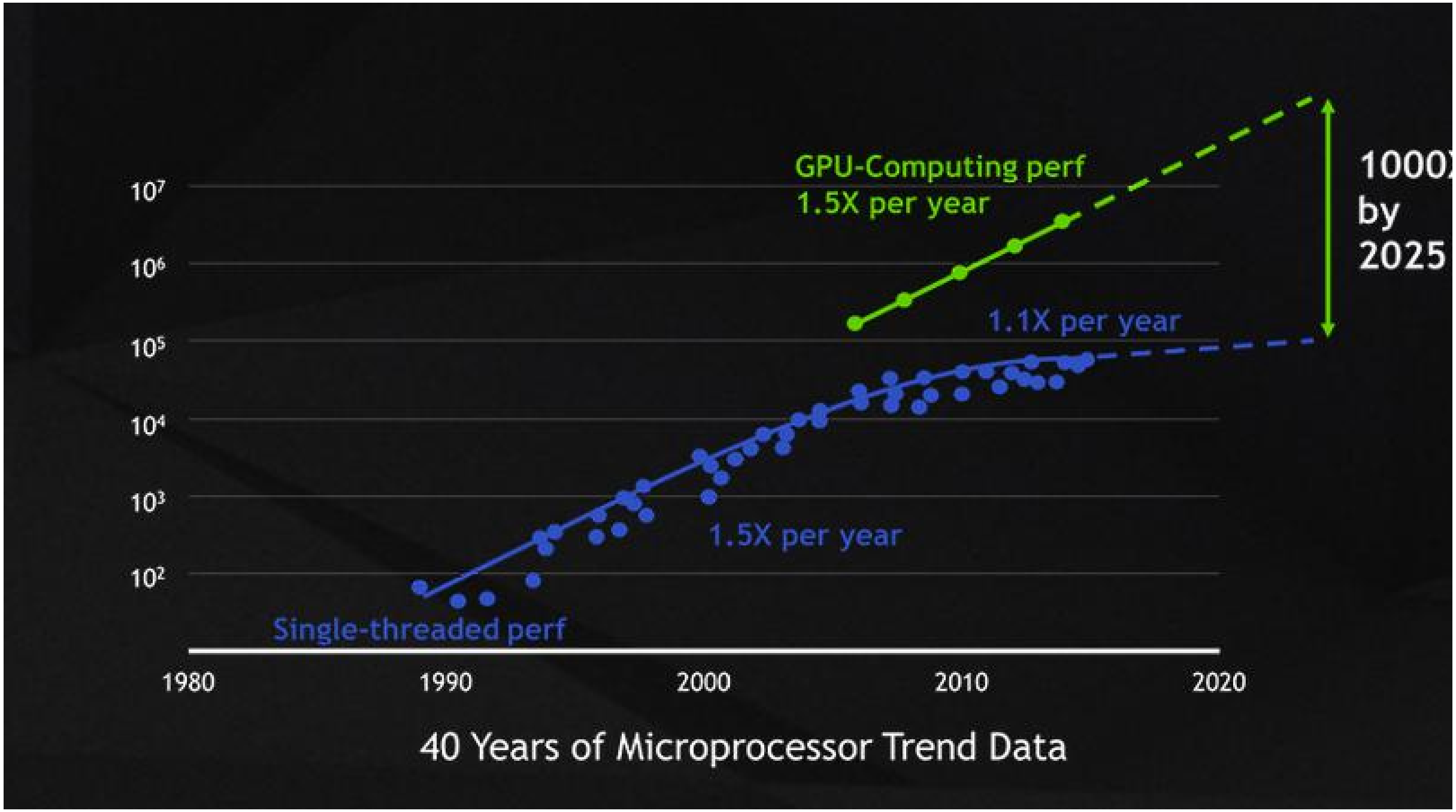
High Performance Computing on GPUs

Mark Silberstein
mark@ee.technion.ac.il

Why GPUs?



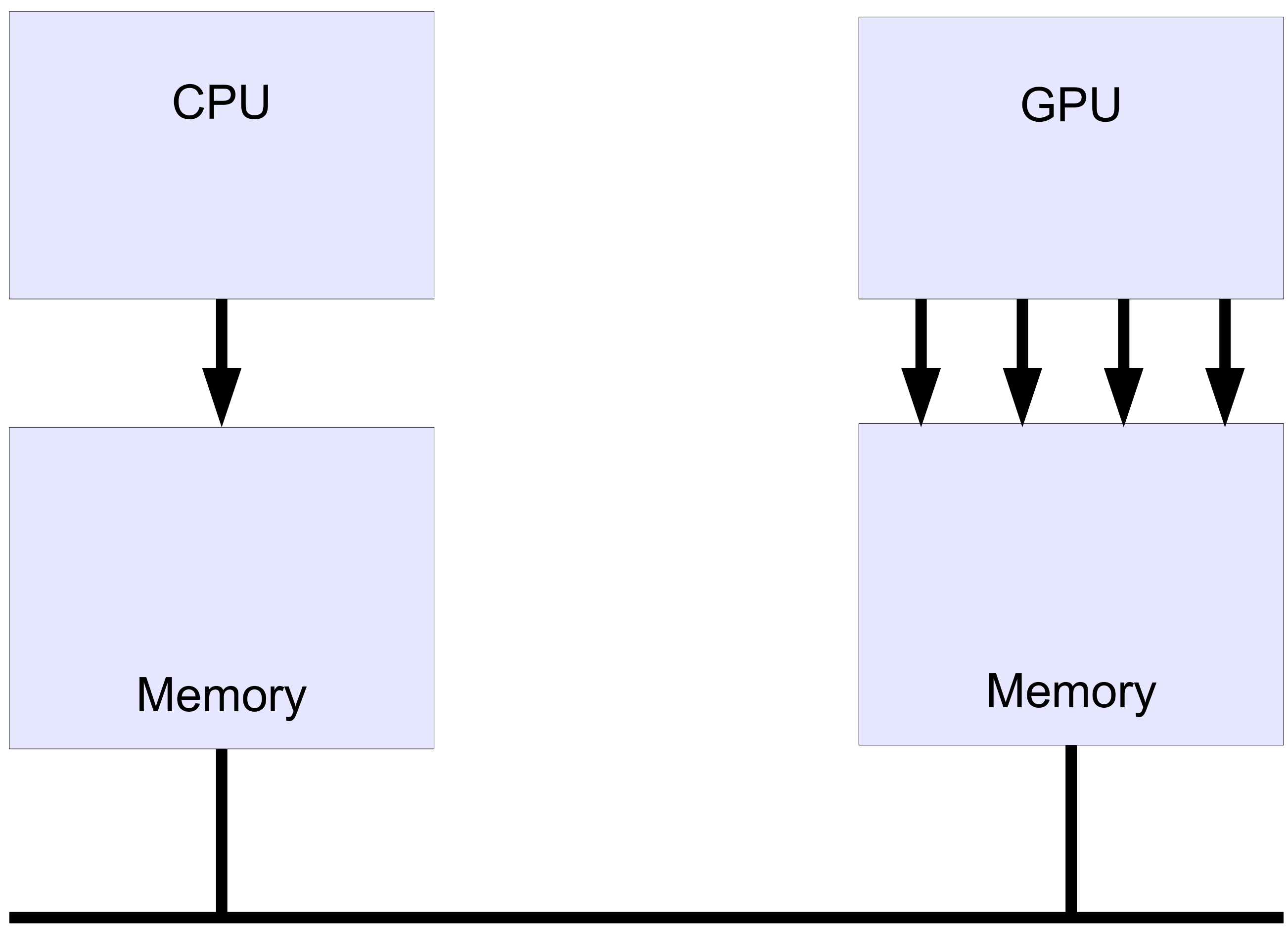
(from NVIDIA)

Is it a miracle? NO!

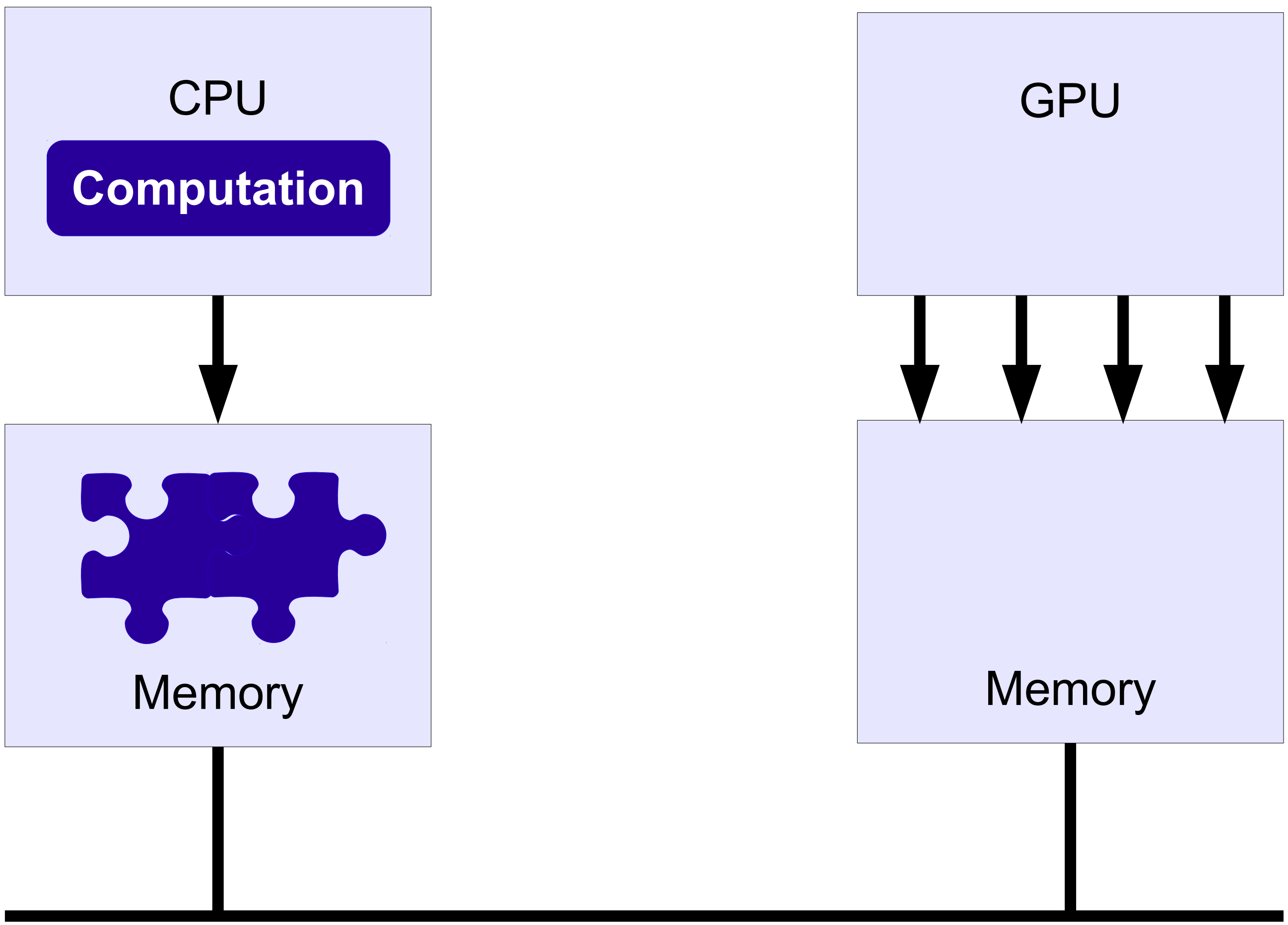
- Architectural solutions prefers parallelism!
- Example problem – I have 100 apples to eat
  1) “high performance”: finish one apple faster
  2) “high throughput”: finish **all apples** faster
- The 1st option is **unsustainable**
- Performance = parallel hardware + scalable parallel program!

Simplified GPU model

GPU 101



GPU is a co-processor



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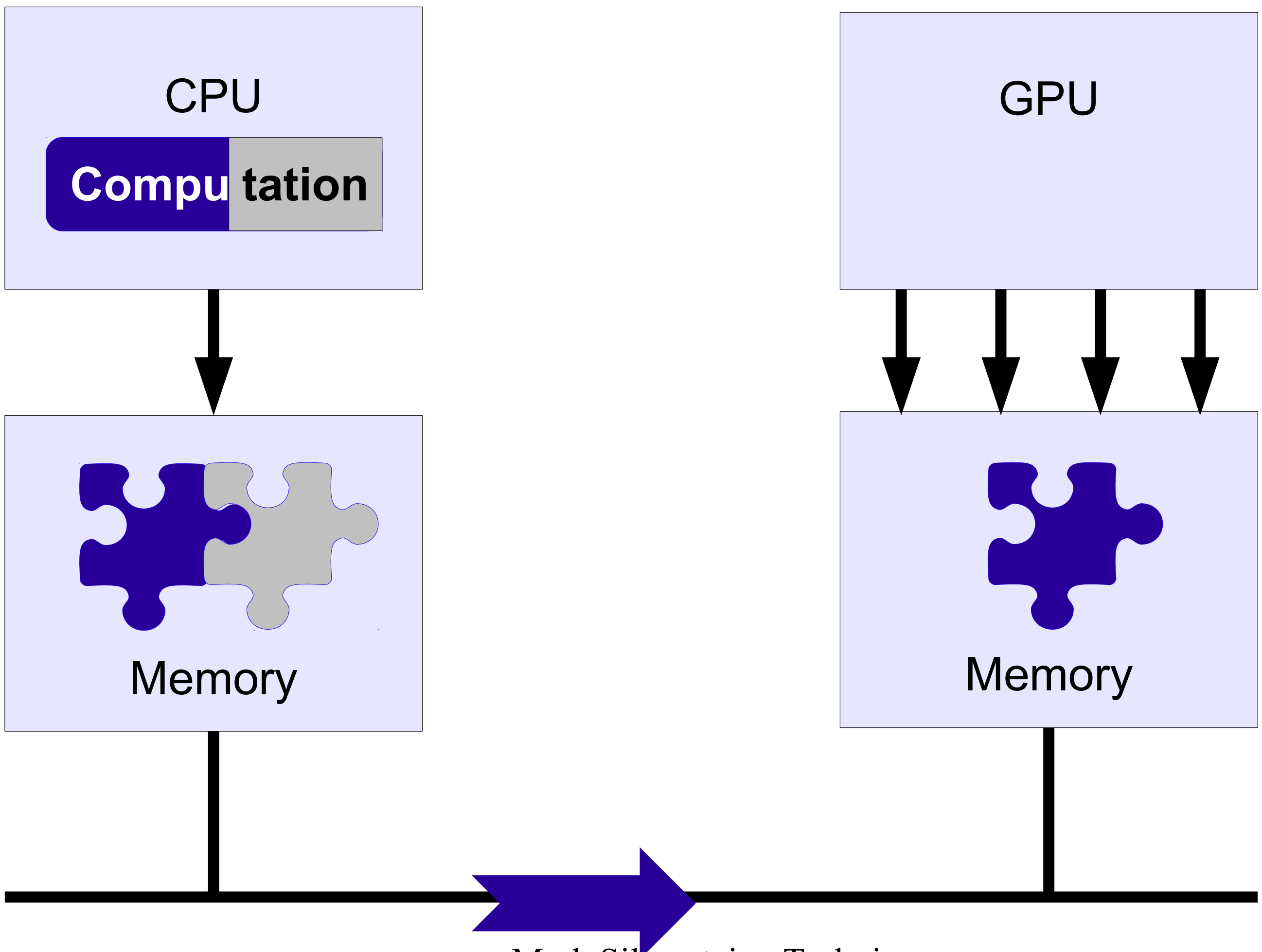

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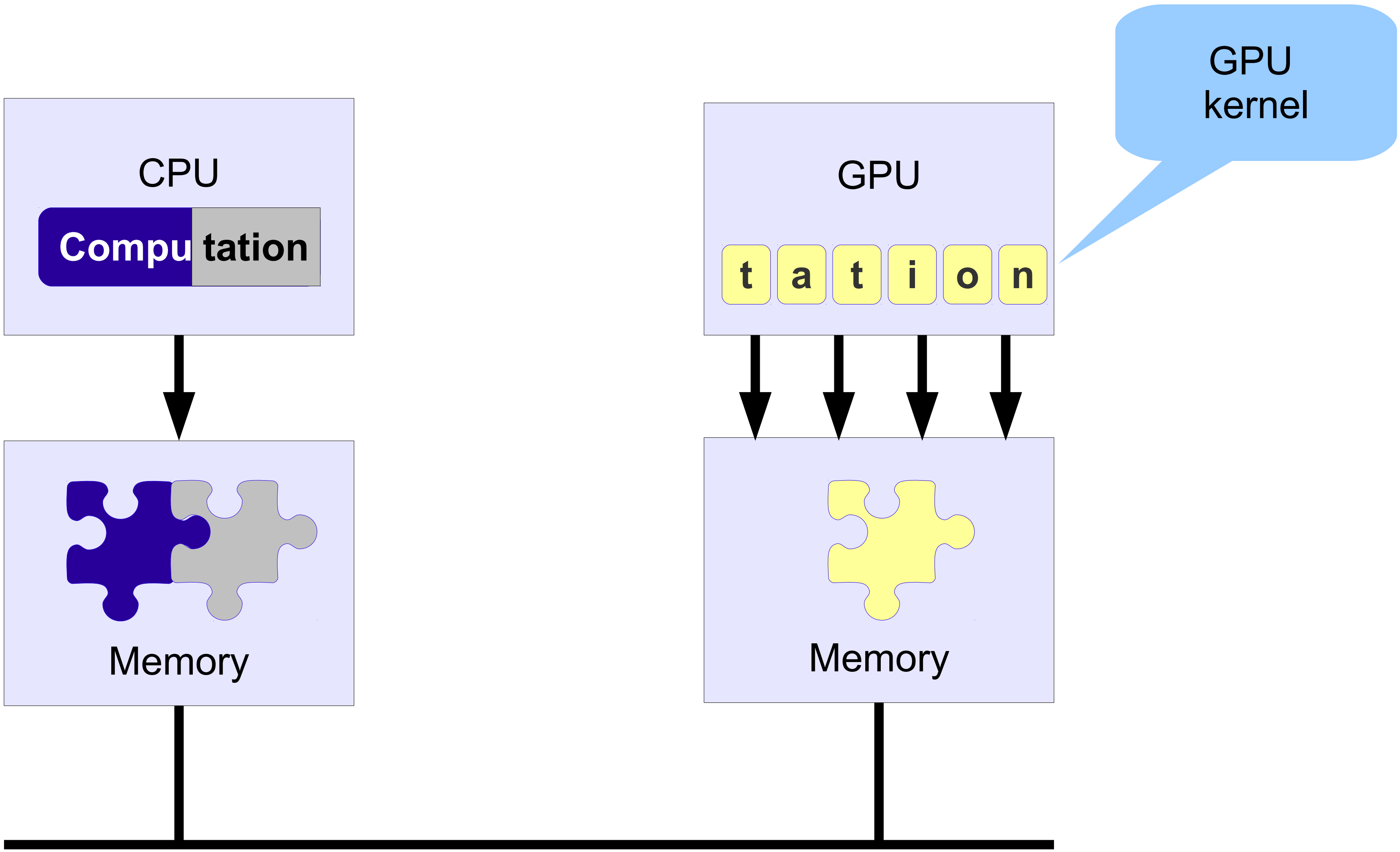

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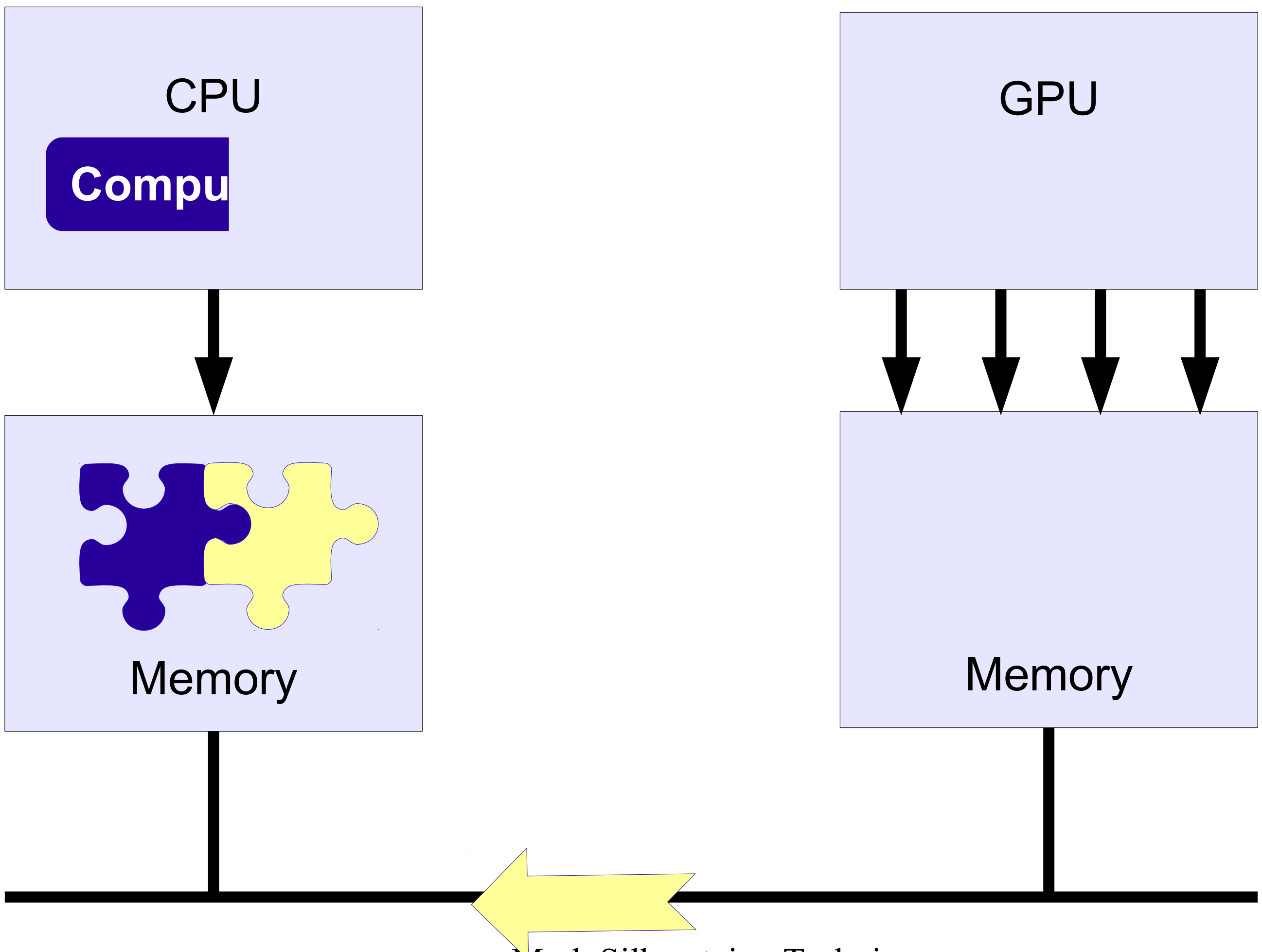
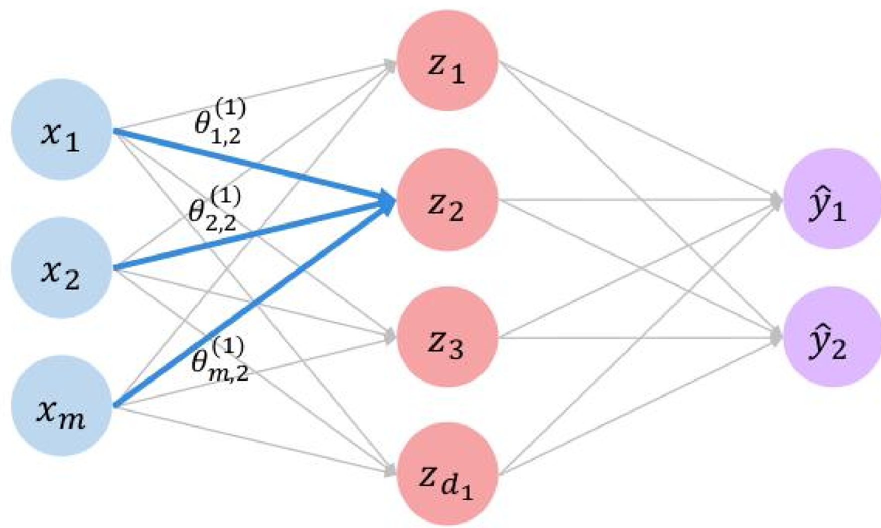


GPUs in ML – Linear Algebra Accelerators

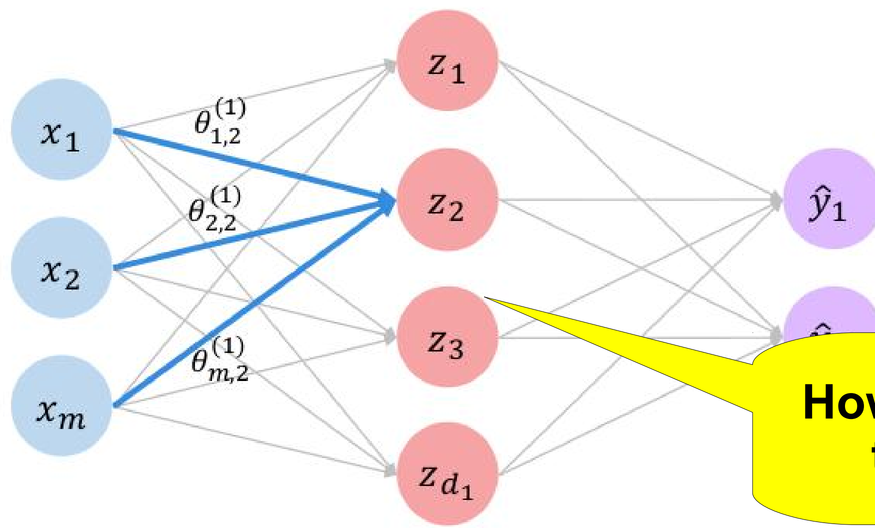


$$z_2 = \theta_{0,2}^{(1)} + \sum_{j=1}^{m} x_j \, \theta_{j,2}^{(1)}$$

$$= \theta_{0,2}^{(1)} + x_1 \, \theta_{1,2}^{(1)} + x_2 \, \theta_{2,2}^{(1)} + x_m \, \theta_{m,2}^{(1)}$$

Compute Matrix Product
ON GPU

GPUs in ML –
Linear Algebra Accelerators



How to program a GPU to compute this?

$$z_2 = \theta_{0,2}^{(1)} + \sum_{j=1}^{m} x_j\, \theta_{j,2}^{(1)}$$
$$= \theta_{0,2}^{(1)} + x_1\, \theta_{1,2}^{(1)} + x_2\, \theta_{2,2}^{(1)} + x_m\, \theta_{m,2}^{(1)}$$

Simple GPU program: exploiting data parallelism

- Idea: **same set** of operations is applied to different data chunks *in parallel*
- Algorithmic challenge – identify data-parallel tasks
- Implementation
  - Every *thread* runs the same code on different data chunks.
  - GPU concurrently runs thousands of parallel threads

Vector sum C=A+B

- Sequential algorithm

```
For every element i
    C[i]=A[i]+B[i]
```

Vector sum C=A+B

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For every i
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```

- Parallel algorithm

In parallel `For every i`

```
     C[i]=A[i]+B[i]
```

Implementation for a vector of length 1024

- GPU **kernel** (this program runs in every thread)

```
C[threadId]=A[threadId]+B[threadId]
```

Per-thread hardware-supplied ID

Implementation for a vector of length 1024

- GPU kernel

```
C[threadId]=A[threadId]+B[threadId]
```

- CPU

1. Allocate three arrays (in GPU memory)
2. Make data accessible to GPU (CPU->GPU copy)
3. Invoke kernel with 1024 threads
4. Wait until complete and make data accessible to CPU (GPU->CPU copy)

Complete example

```
CPU:
void vector_sum(float* A, float* B, float* C, int n)
{
    float* gA=GPU_get_reference(A);
    float* gB=GPU_get_reference(B);
    float* gC=GPU_allocate_mem(n);

   GPU_set_num_threads(n);
     // GPU will invoke n threads
   GPU_run(vector_sum_kernel(gA,gB,gC));
   GPU_retrieve(C,gC);
}

GPU:
void vector_sum_kernel(float* gA, float* gB, float*gC)
{
     int my=HardwareThreadID;
     gC[my]=gA[my]+gC[my];
}
```

Complete example

```
CPU:
void vector_sum(float* A, float* B, float* C, int n)
{
    float* gA=GPU_get_reference(A);
    float* gB=GPU_get_reference(B);
    float* gC=GPU_allocate_mem(n);

   GPU_set_num_threads(n);
     // GPU will invoke n threads
   GPU_run(vector_sum_kernel(gA,gB,gC));
   GPU_retrieve(C,gC);
}
```

GPU integration

```
GPU:
void vector_sum_kernel(float* gA, float*
{
     int my=HardwareThreadID;
     gC[my]=gA[my]+gC[my];
}
```

GPU programming

Complete example

```
CPU:
void vector_sum(float* A, float* B
{
    float* gA=GPU_get_reference(A)
    float* gB=GPU_get_reference(B);
    float* gC=GPU_allocate_mem(n);

   GPU_set_num_threads(n);
     // GPU will invoke n threads
   GPU_run(vector_sum_kernel(gA,gB,gC));
   GPU_retrieve(C,gC);
}

GPU:
void vector_sum_kernel(float*
{
     int my=HardwareThreadID;
     gC[my]=gA[my]+gC[my];
}
```

Many threads

Fine-grained parallelism (1 op per thread)

BUT!

- Vector sum is simple – purely data parallel
- What if we need coordination between tasks

  Example: parallel dot product

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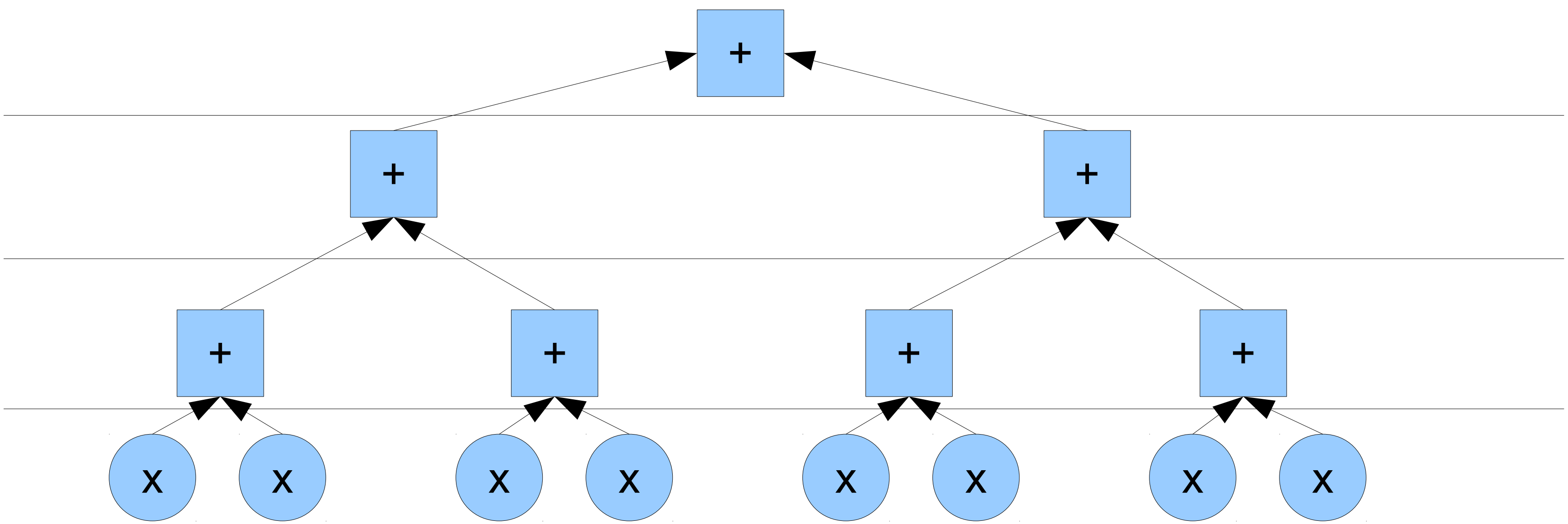
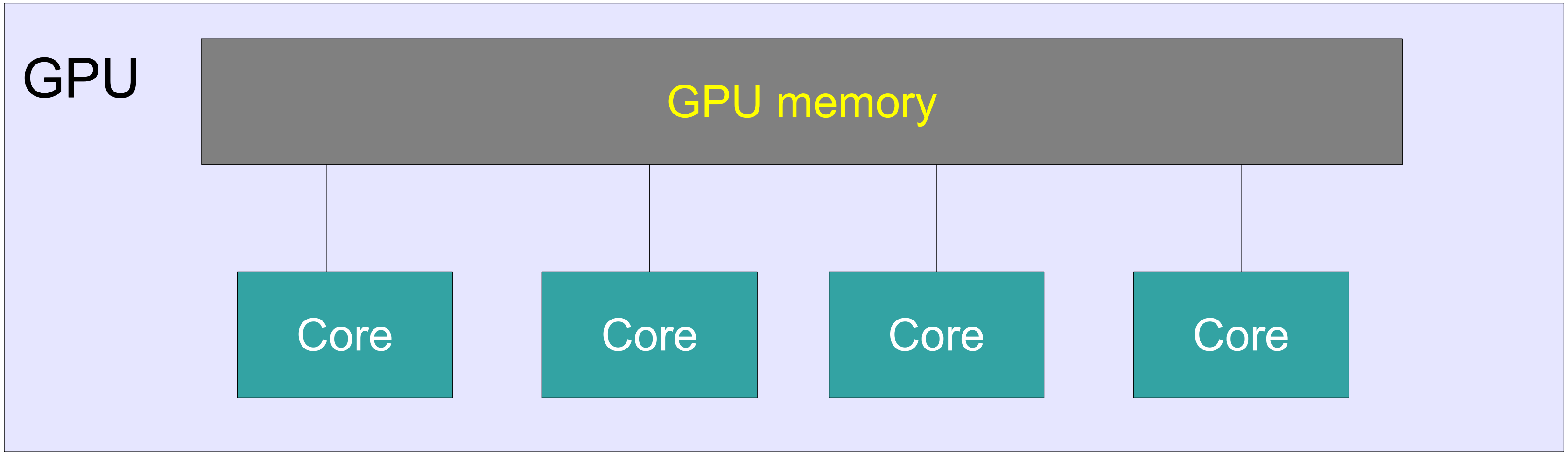
Example: parallel dot product

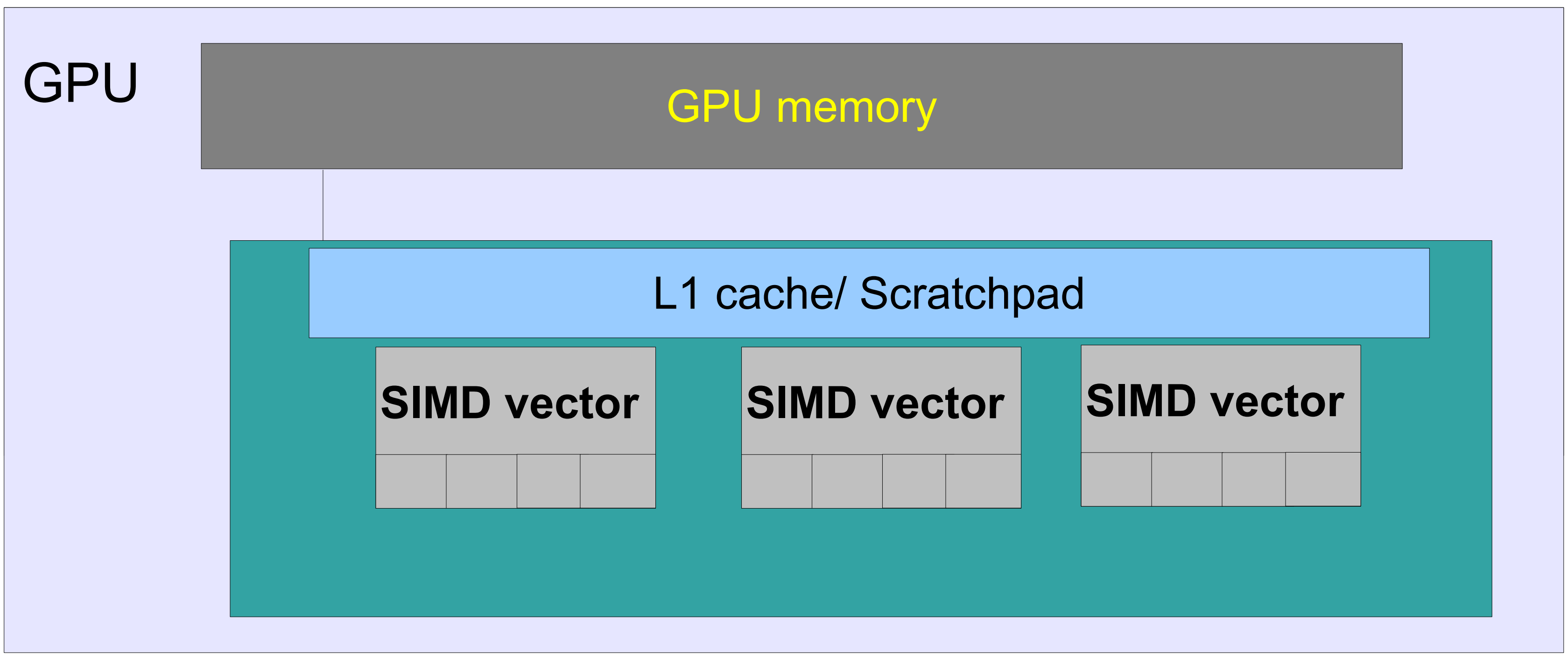


GPU hardware

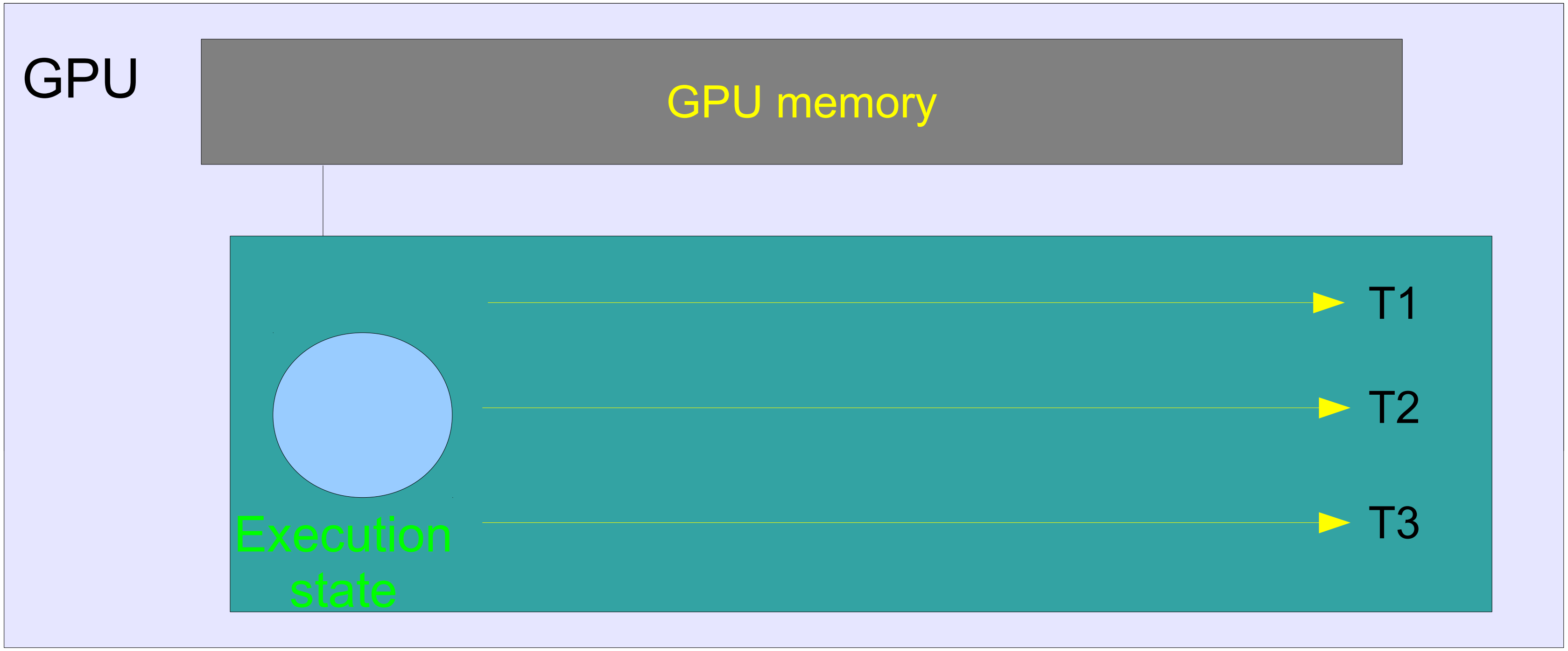
GPU hardware parallelism
1. Multi-core



GPU hardware parallelism
2. SIMD



GPU hardware parallelism
3. Hardware multithreading



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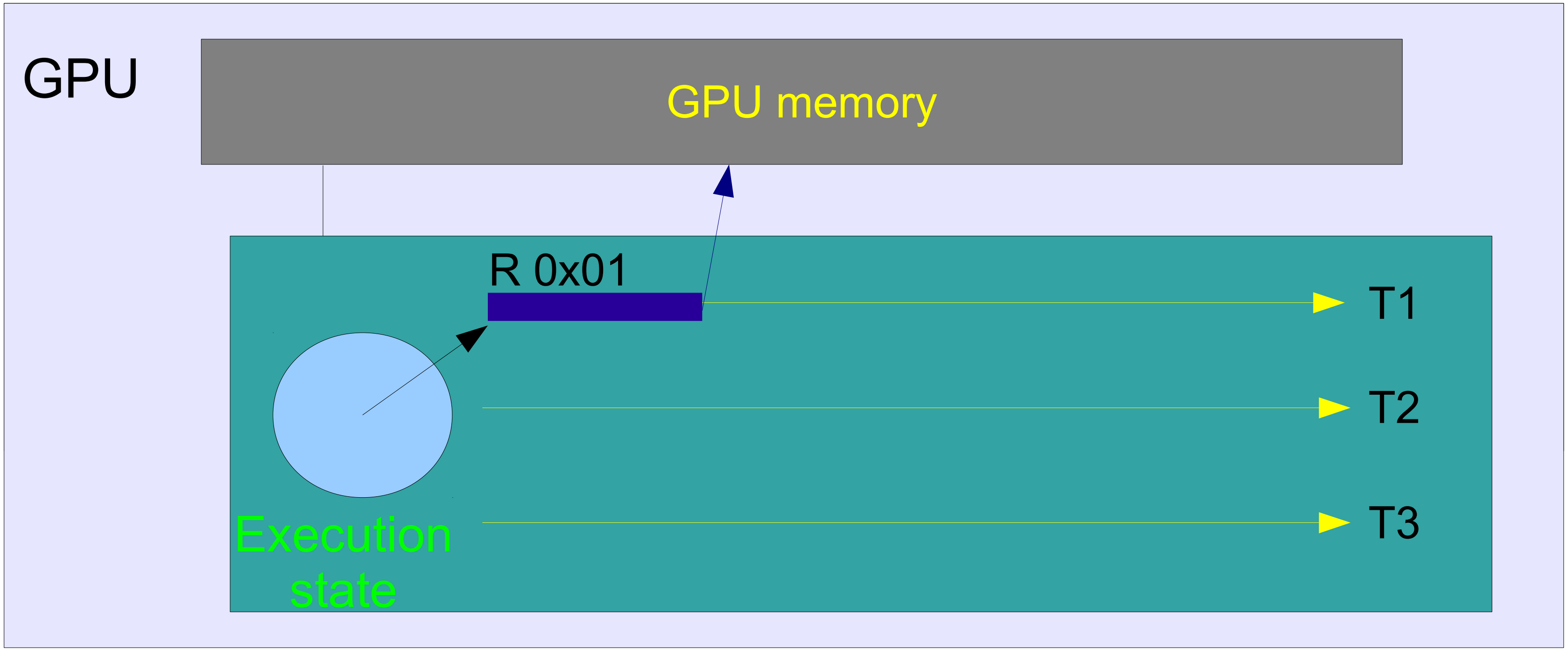

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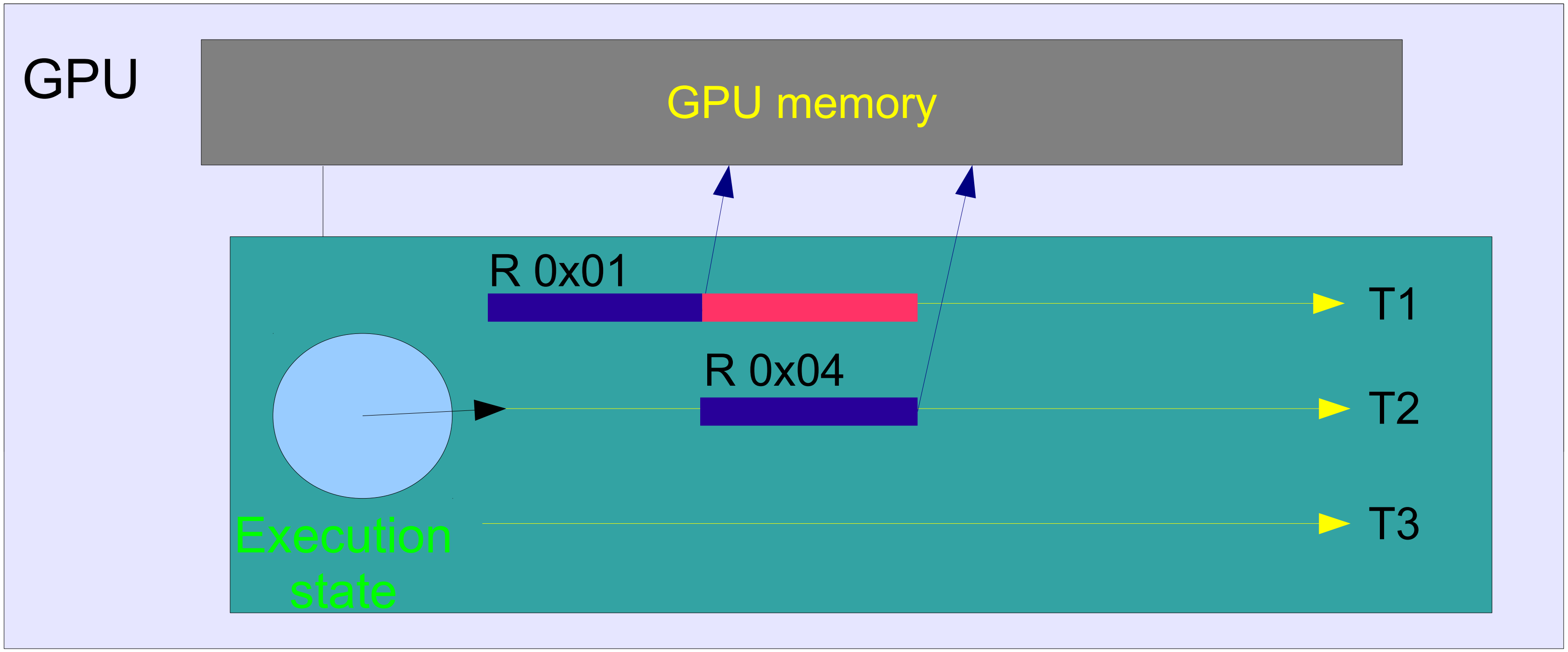

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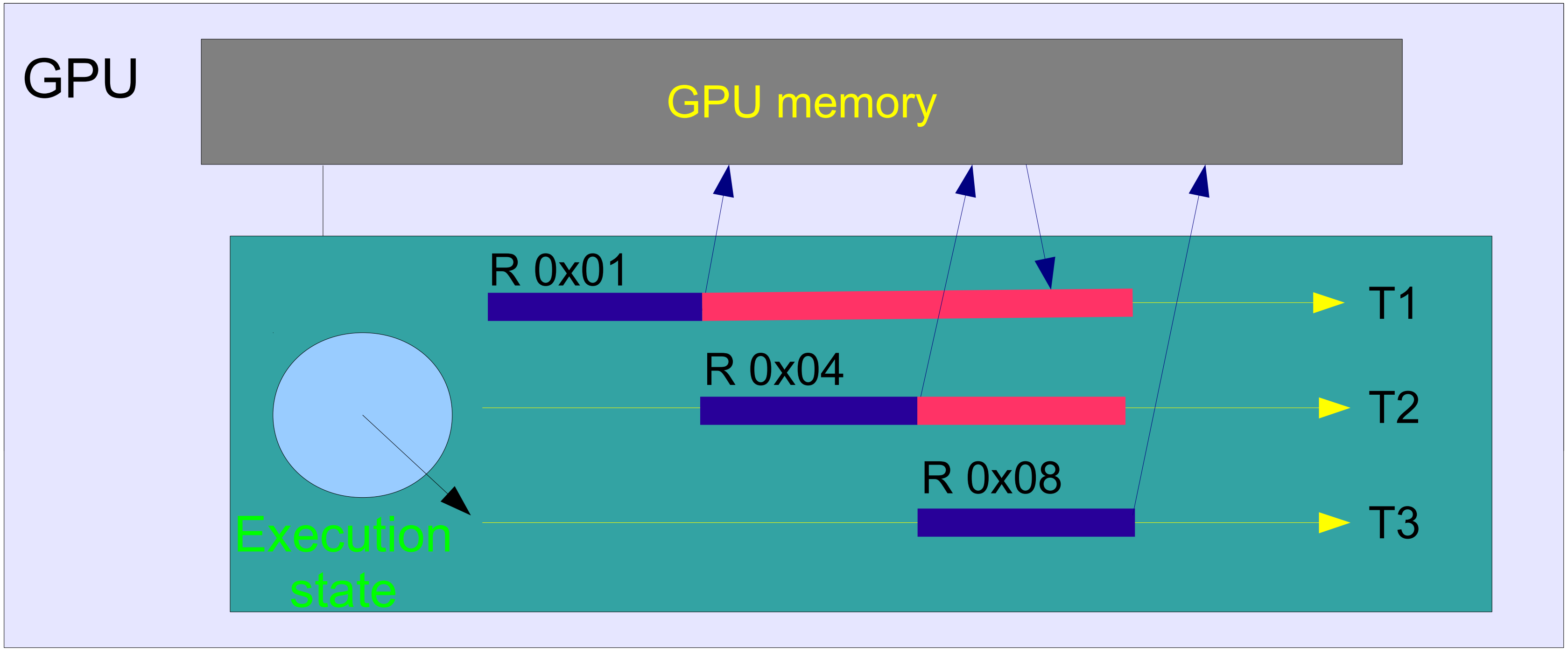

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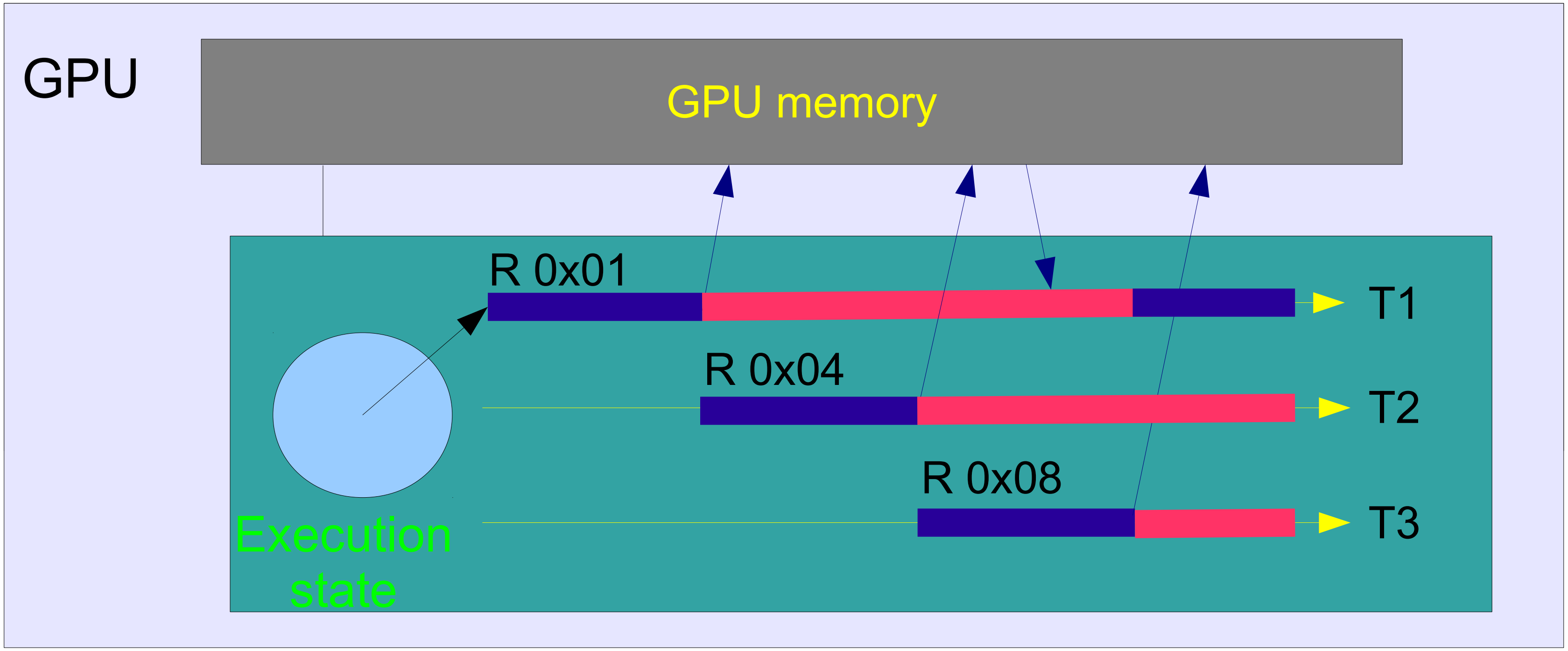
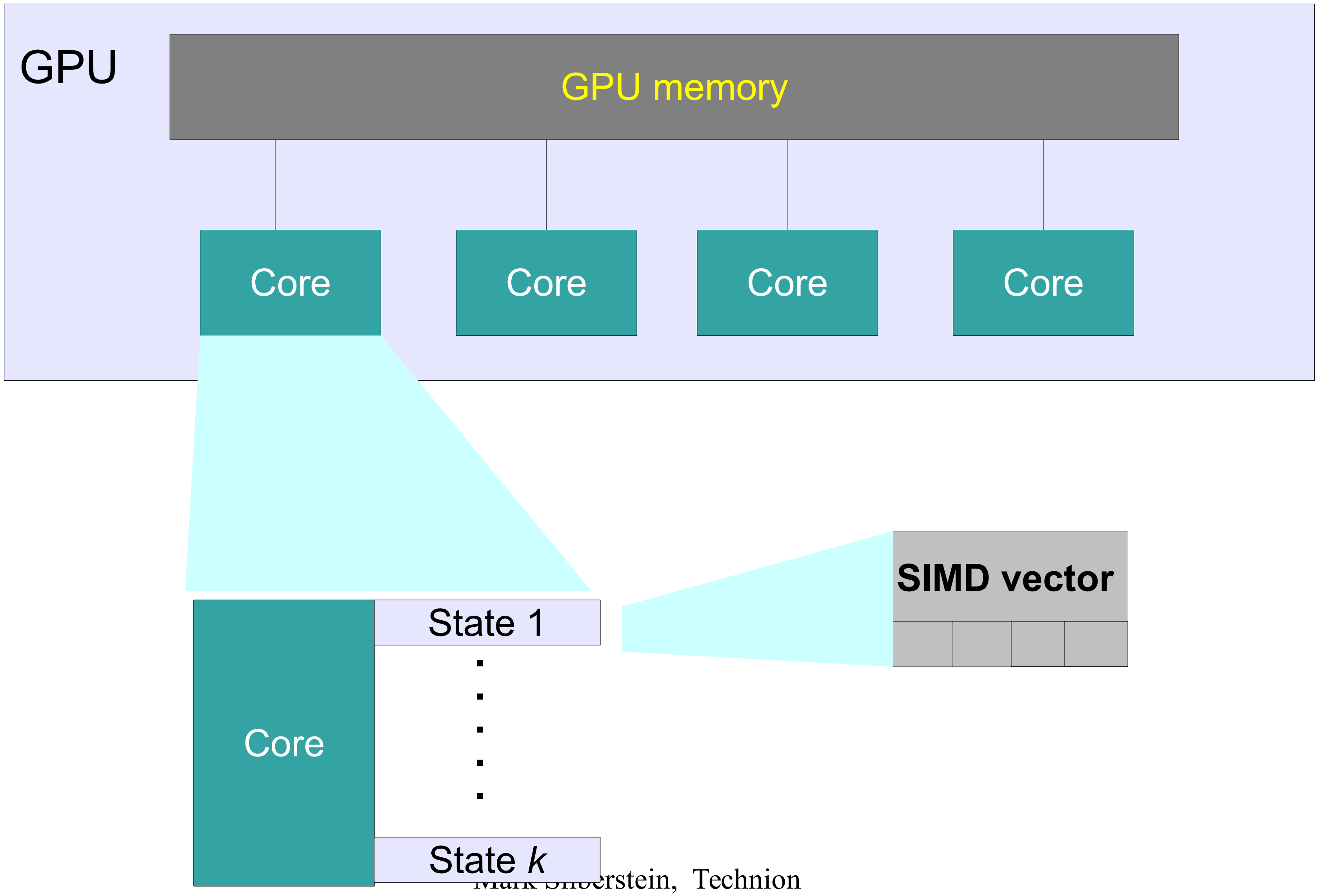
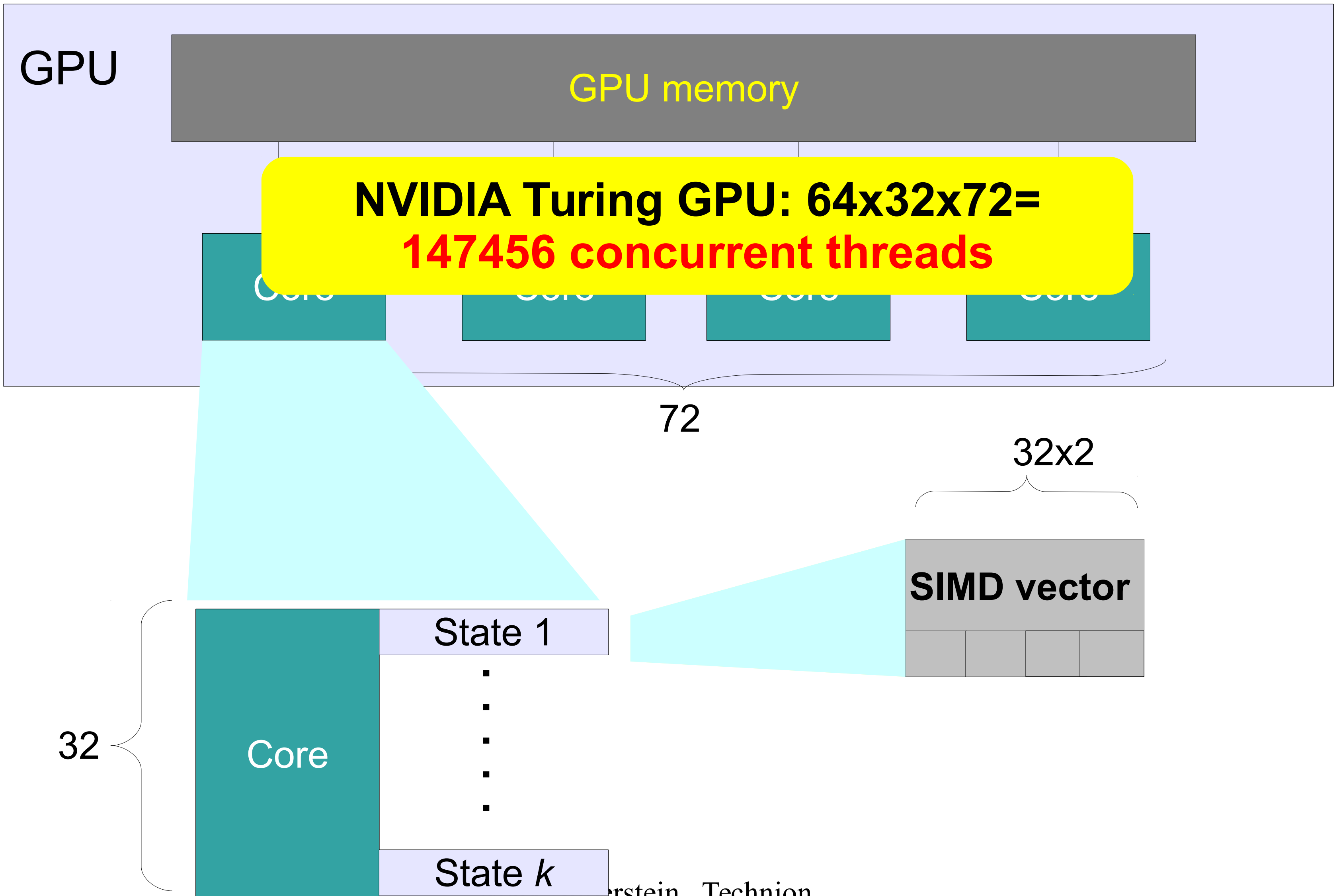


Putting it all together: 3 levels of hardware parallelism



Takeaway 1:
100,000-s of concurrent threads!



Requirements for allowing fast GPU execution

- We have enough parallelism
- We have enough space to store state per thread
- We have enough bandwidth to memory
- We have efficient *scheduler* to manage threads

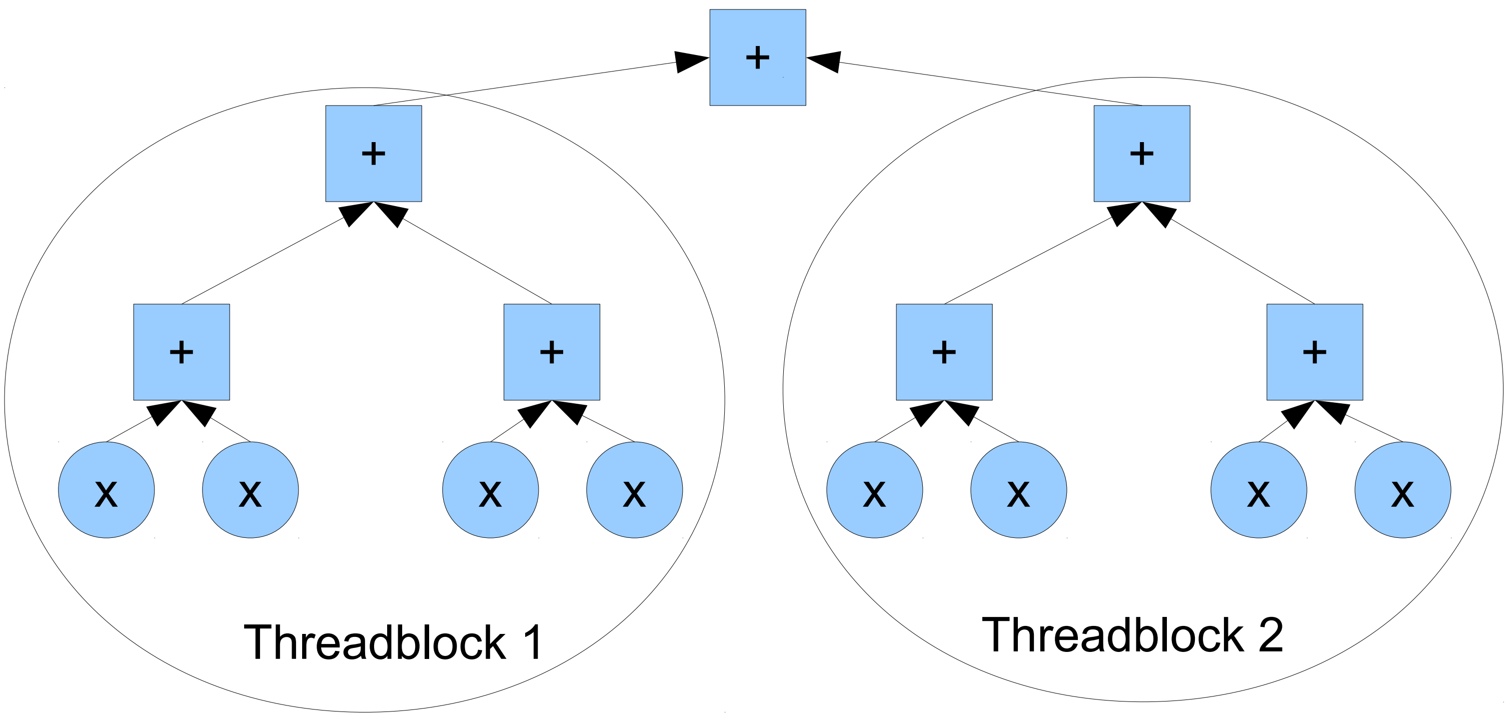
How GPU manages threads?

- Application threads are grouped into threadblocks
- Programmer defines the number of threads / threadblocks for each run

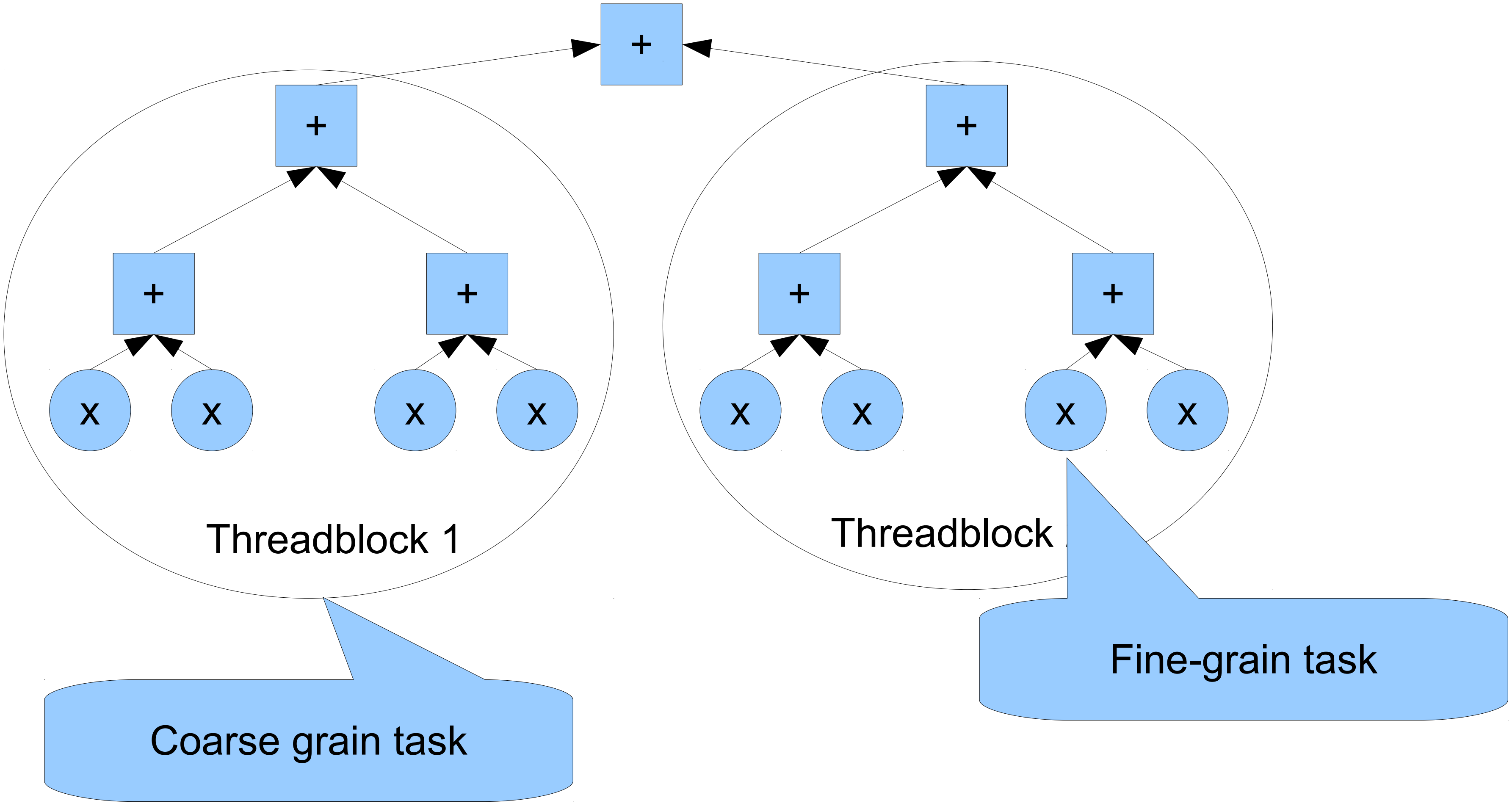
Threadblock is a building block of GPU algorithms

- Threads inside a threadblock can communicate efficiently!
  - Share a small fast scratchpad memory
  - Can be synchronized via barriers
- Threadblocks are independent
- A program consists of many threadblocks

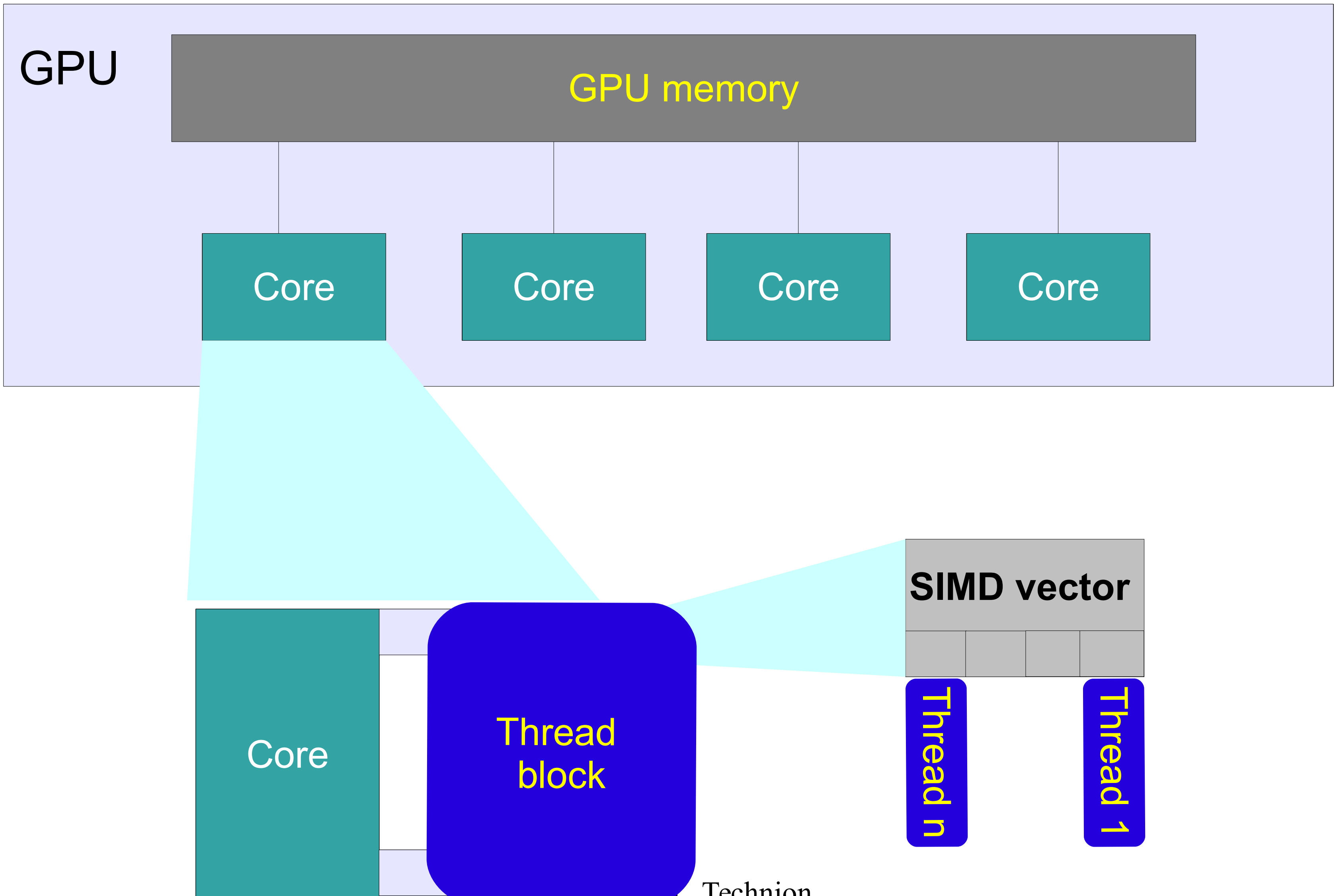
Dot-product: hierarchical parallelization Decomposing into threadblocks



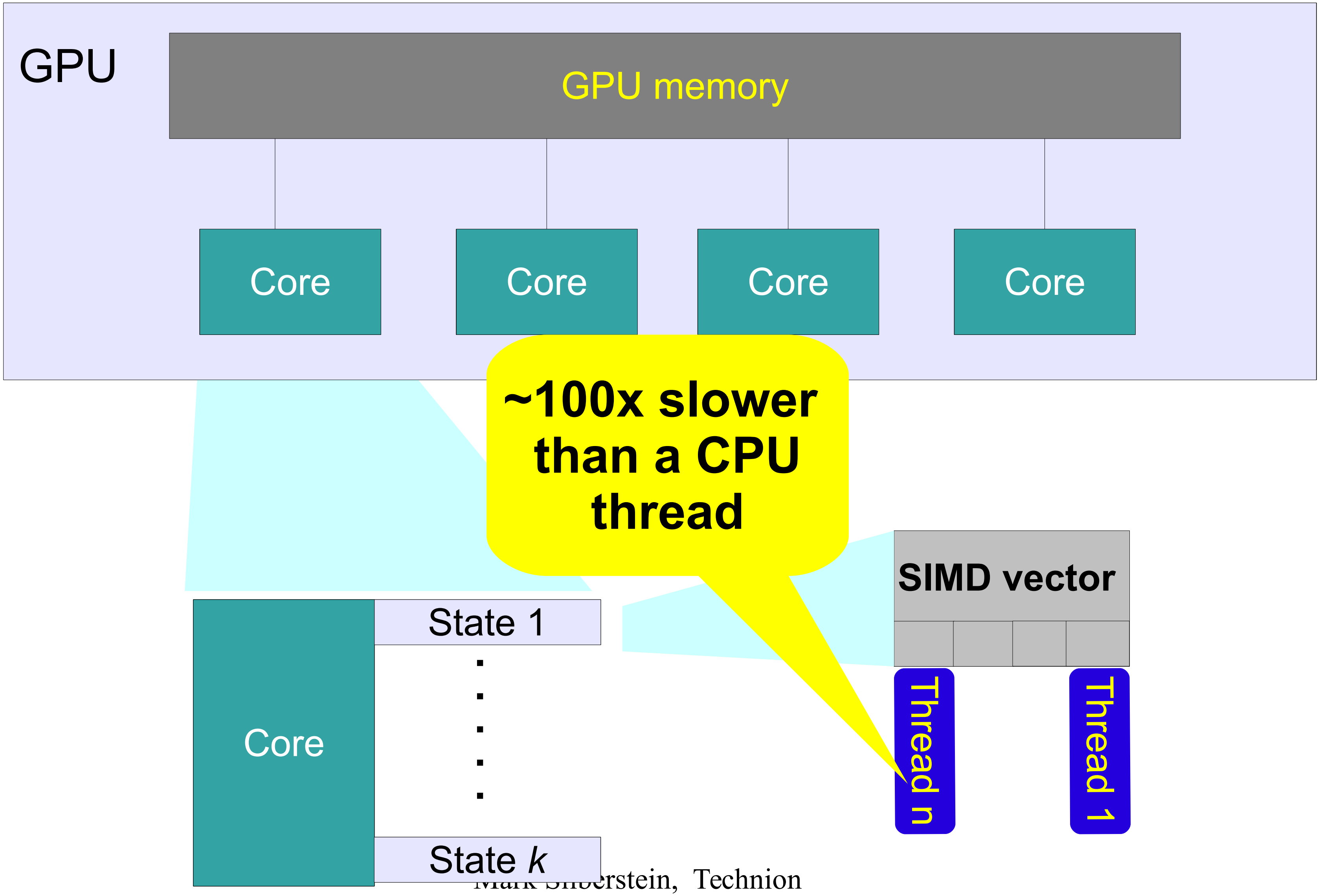
Takeaway: parallelism hierarchy



Software-Hardware mapping



Takeaway 2: One thread is slow



Dot product

```
void vector_dotproduct_kernel(float* gA, float* gB, float* gOut)
{
     _local_ float l_res[TB_SIZE]; //local core memory

     int thid=LocalThreadID;
     int tbid=ThreadBlockID;

   int offset=tbid*WG_SIZE+thid;

   l_res[tid]=gA[offset]*gB[offset];

     BARRIER(); // wait for all products

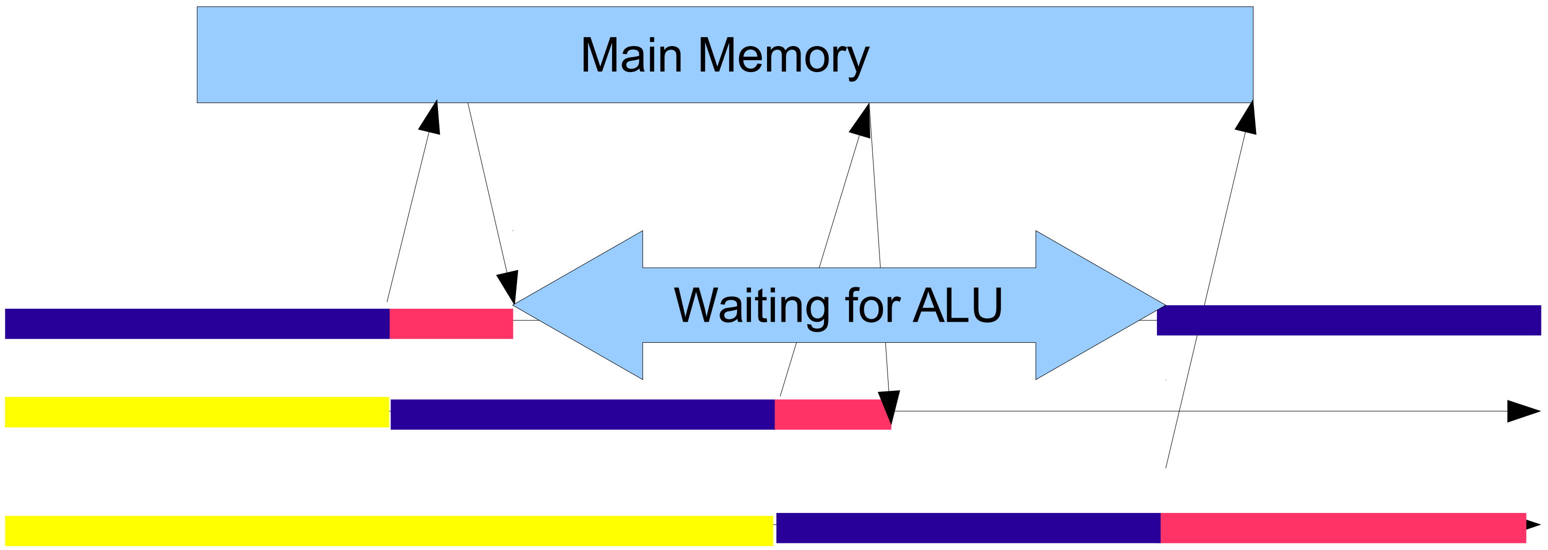
     for(int i=TB_SIZE/2; i>0;i/=2)
     {
       if (thid<i) l_res[thid]=l_res[thid]+l_res[i+thid];
           BARRIER(); // wait for all partial sums
     }
   if (thid==0) gOut[tbid]=l_res[0];
}
```

Parallelism structure of GPU programs

- Having many independent tasks is not enough
- Parallel structure should map well on hardware hierarchy

Estimating application performance on high-throughput processors

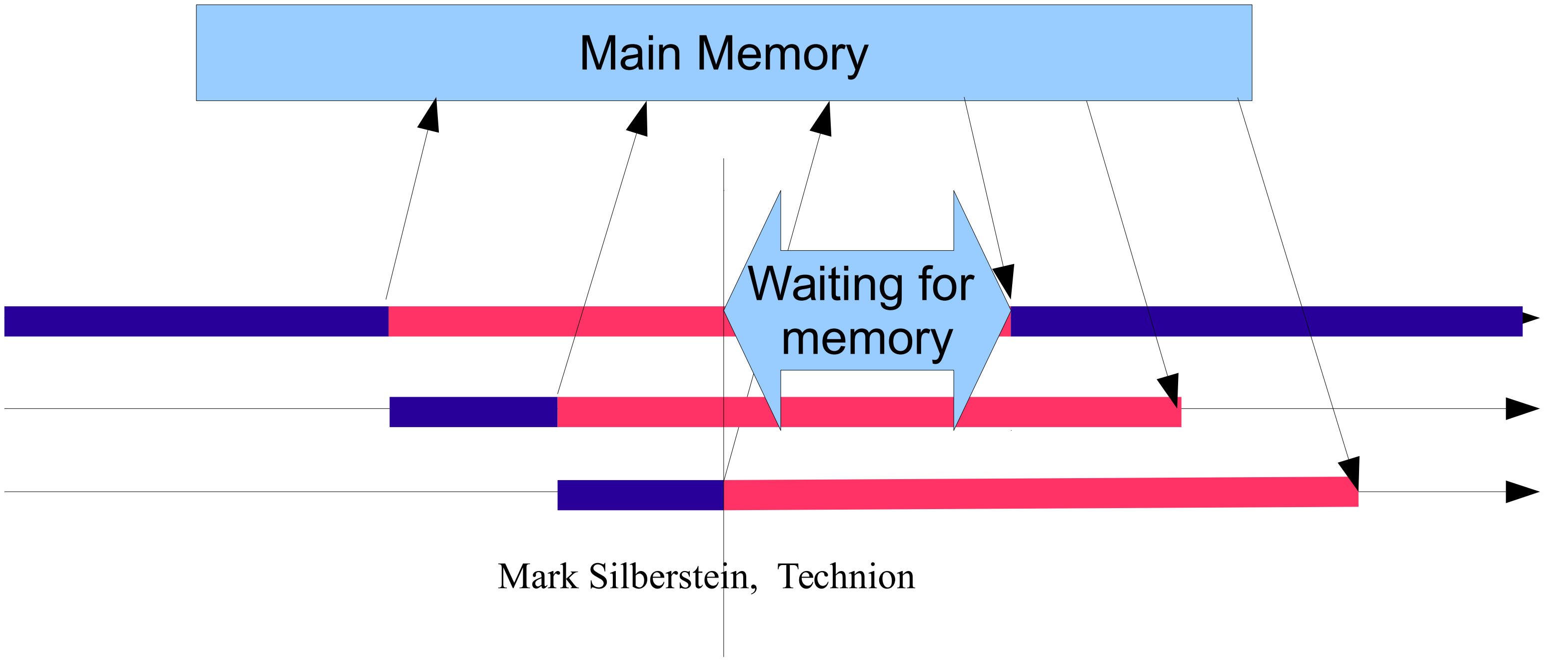
Compute-bound tasks



Performance bounded by maximum ALU capacity

Memory-bound tasks

- We can fully utilize a processor only if data is available in an ALU on time
- How fast can the data be made available?
  - Assume infinite number of threads, ideal parallelization



Measure of ALU/memory ratio: Arithmetic intensity

- Number of OPs per **memory(**)** access
  - Vector sum: 1 operation per 3 accesses. A=1/3

Upper bound on performance

- For memory bound algorithms only

  (why?)

$$\text{Perf}=\text{GPUMemBandwidth}*A$$

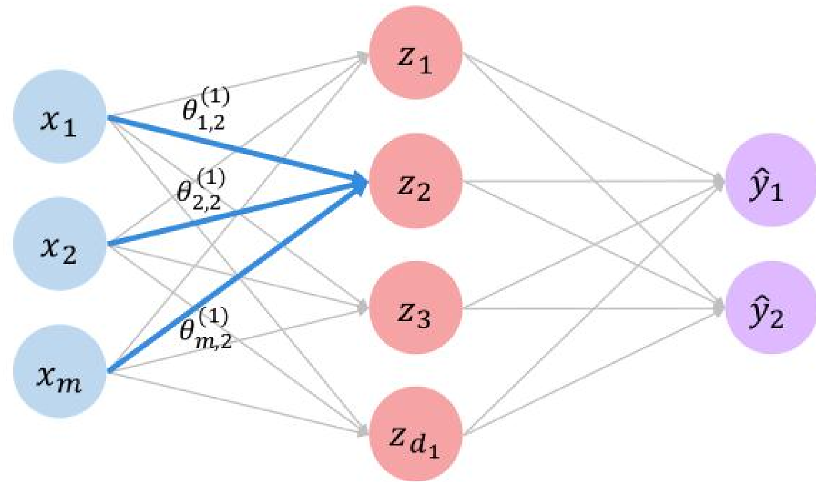
Bytes/sec*Ops/Bytes=Ops/sec

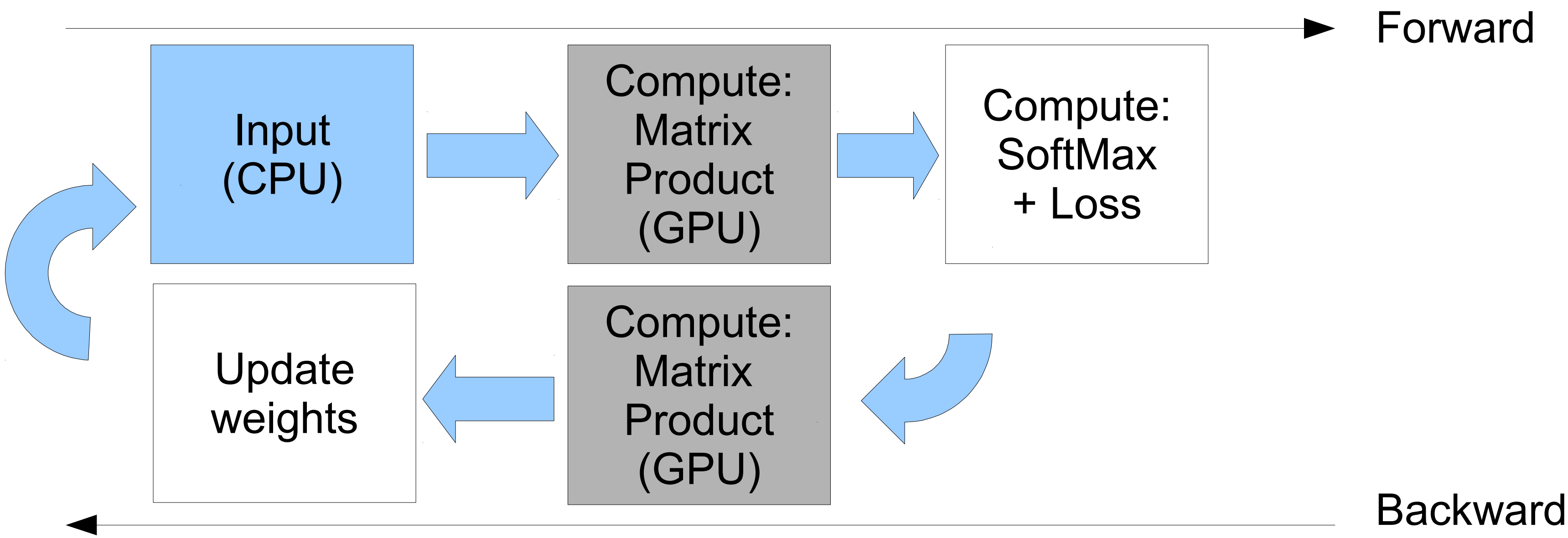
Vector sum performance estimate

- Example: sum of vectors, GPU GTX Titan
- A=1/(3*(4 bytes)), MemBW=~70GFloat/s: Performance= ~23GFLOP/s
- For comparison: raw capacity: 4.5 TFLOPs
- **Only 0.5% of computing capacity utilized!!**

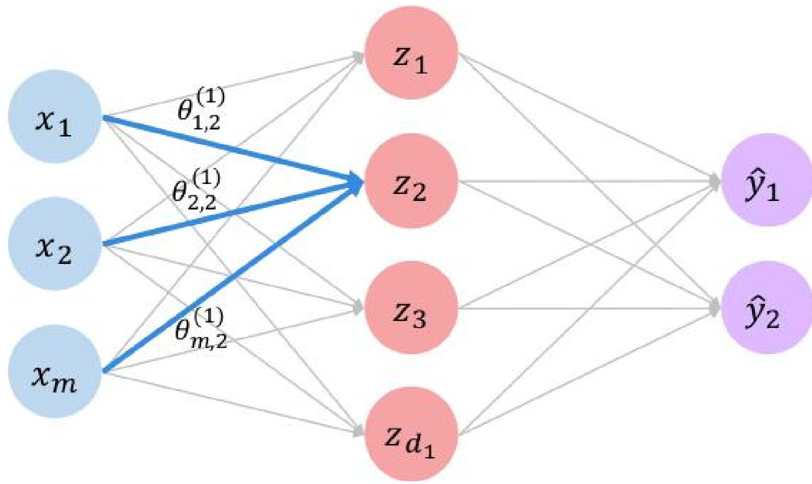
Integrating GPUs with applications

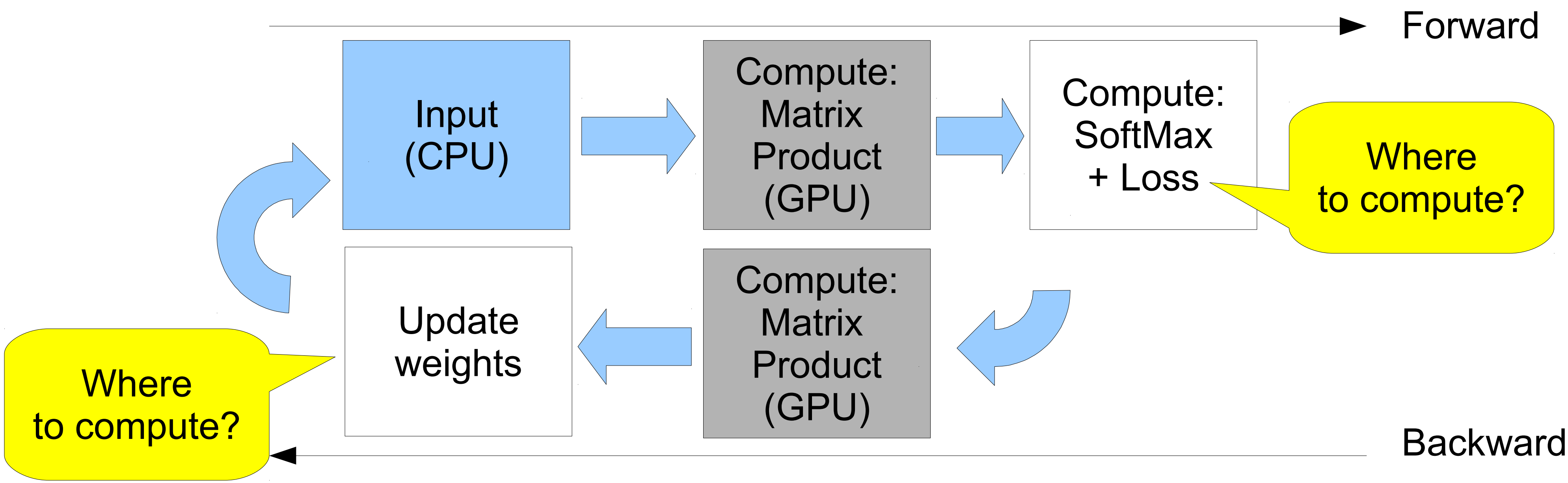
GPUs and data locality



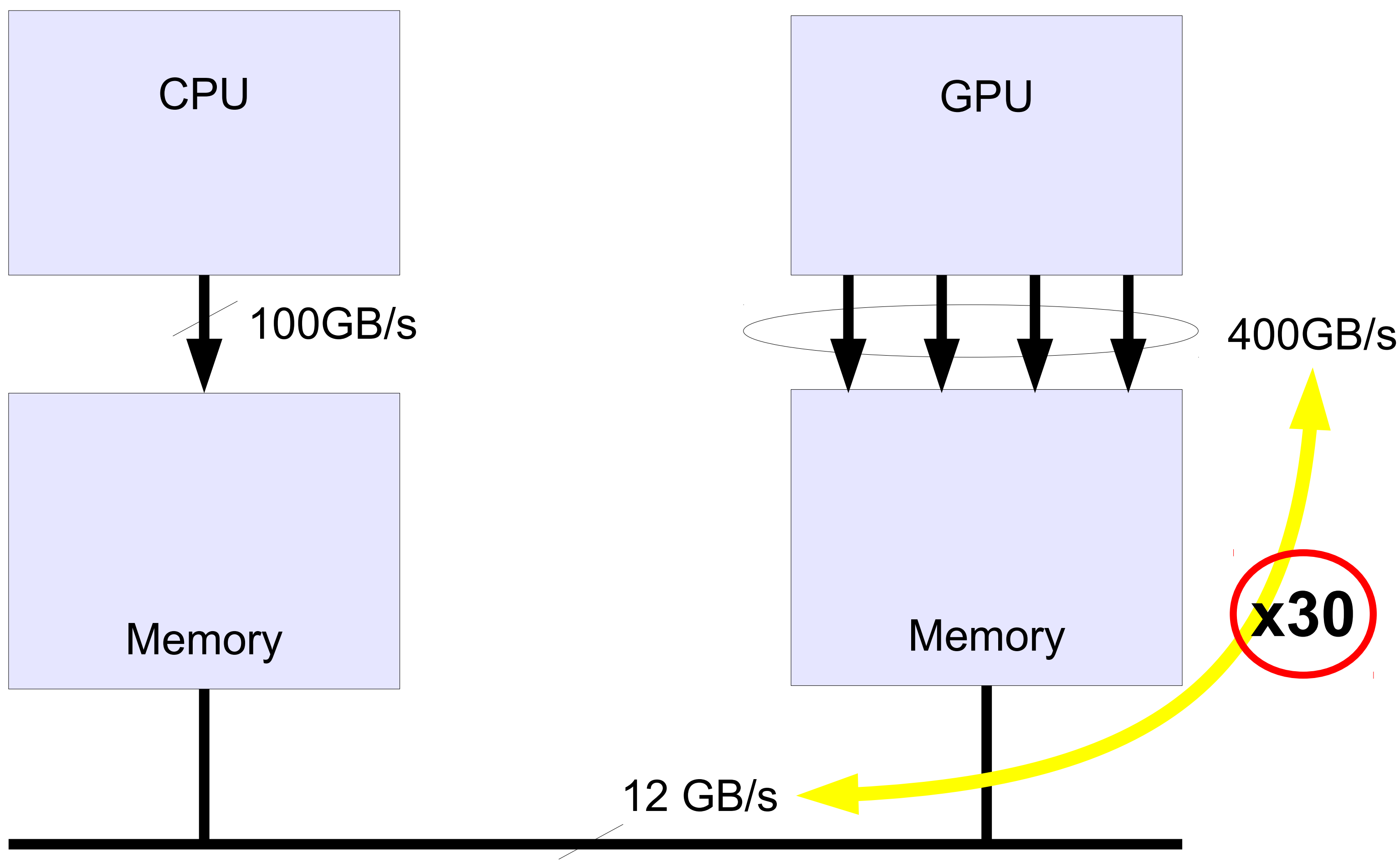


GPUs and data locality

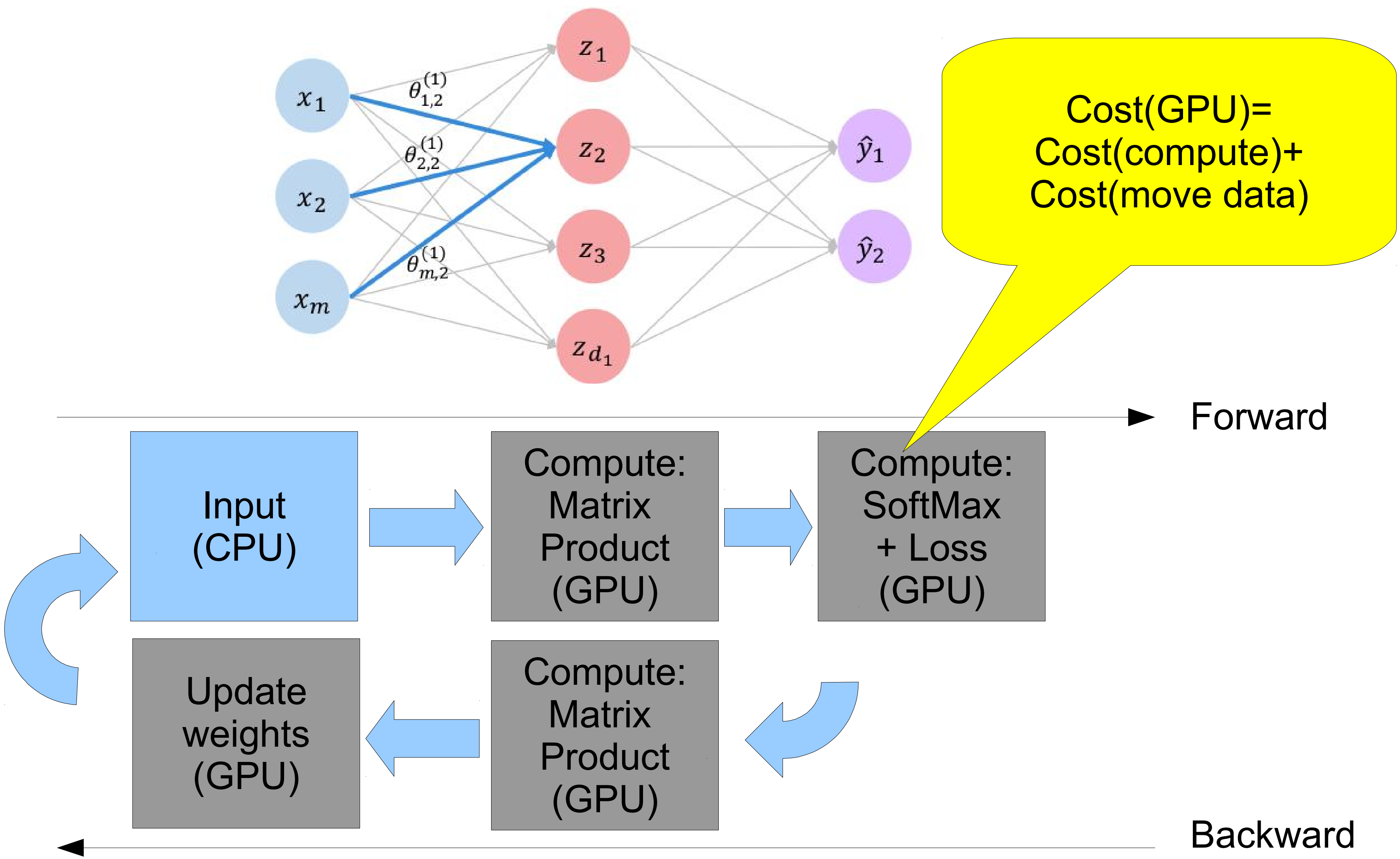




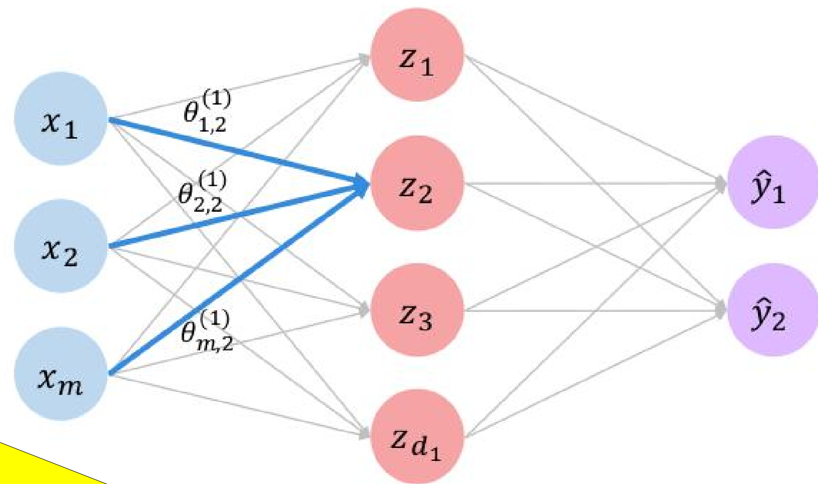
Problem: separate GPU memory



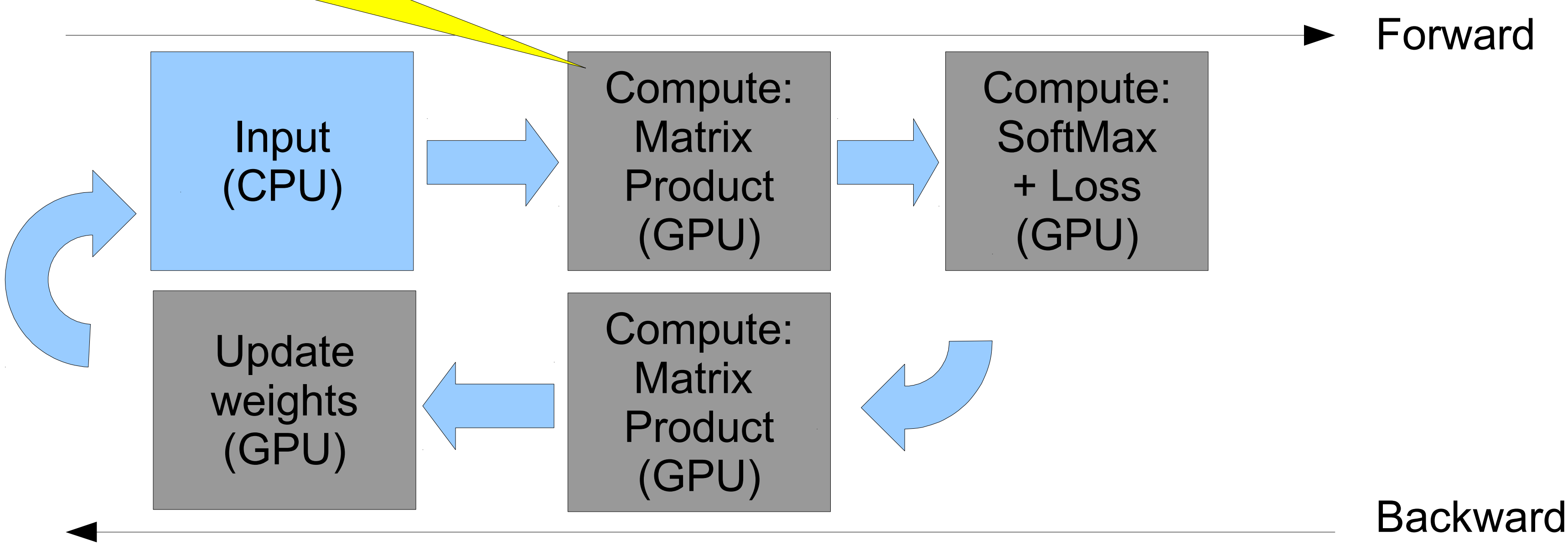
Data must be on a GPU



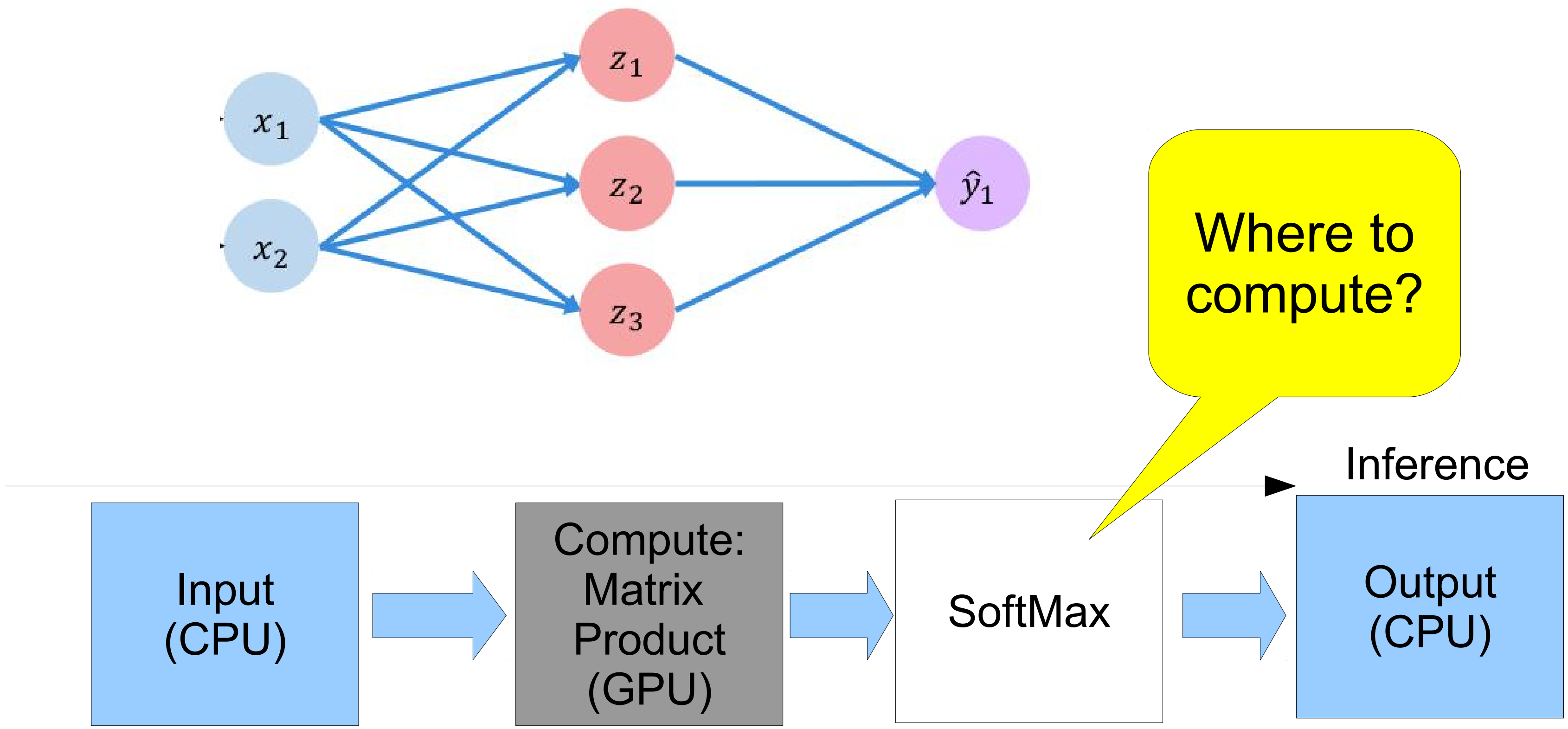
Data must stay on a GPU



And what if data does not fit?



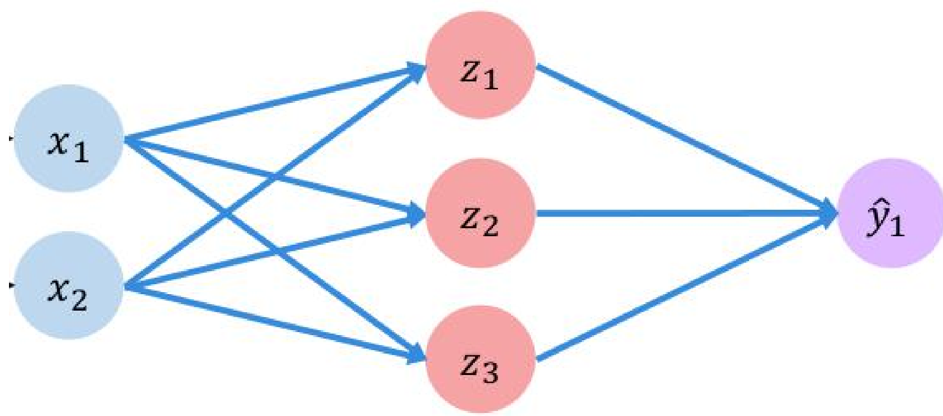
GPUs and invocation cost

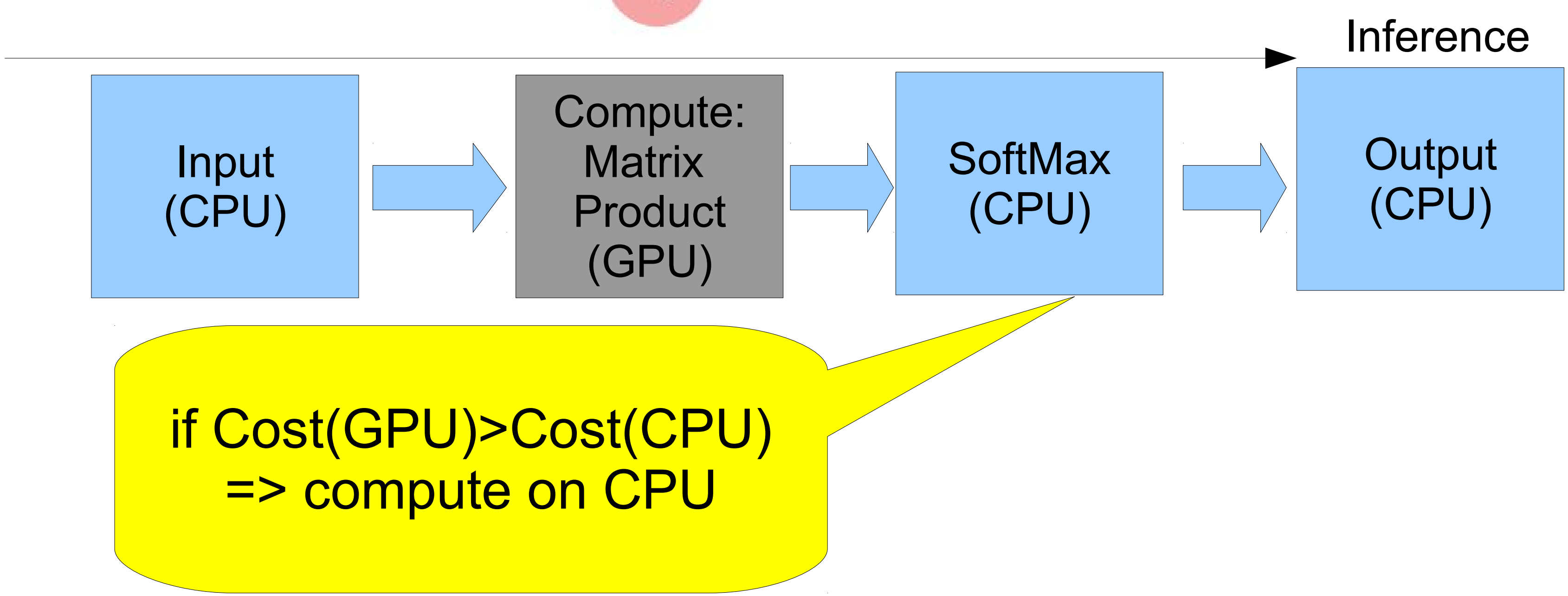


Management overhead

- GPU invocation takes at least 30,000 single CPU core cycles
- Short GPU invocations do not pay off
  - Batch multiple invocations

Sometimes CPU is faster even when it's slower





GPUs are used automatically, but..

- cuBLAS, cuDNN,cuFFD
  - provide powerful GPU-accelerated functions
- TensorFlow, MxNet, Caffe,...
  - run on GPUs
- So why learn how to use GPUs?

Other interesting projects in my lab

- GPU networking
- GPU access to storage
- GPU security
- GPU interaction with Smart NICs and other accelerators

Want to hear more?

- Accelerators and accelerated systems: 236278
- Undergraduate/master projects @ Accelerated Computing Systems Lab (ACSL)

mark@ee.technion.ac.il

Fishbach 408, TCE