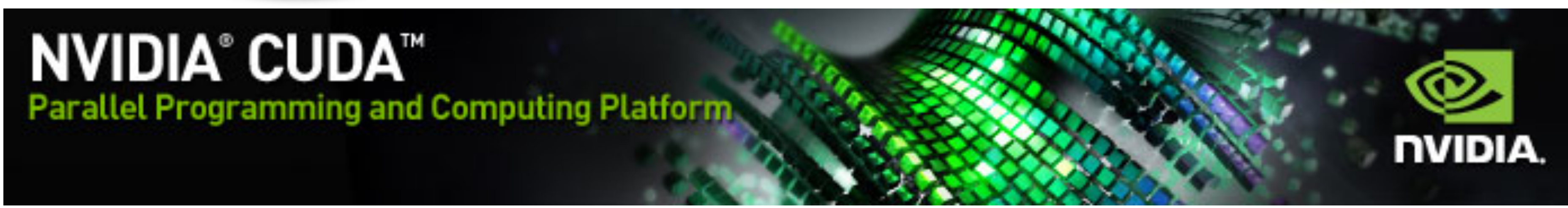
Tim Kaldewey

Apr 21 2014

Programming GPUs for non-graphics workloads
– from General Purpose GPU (GPGPU) to GPU compute



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Disclaimer

The author's views expressed in this presentation do not necessarily reflect the views of IBM.

Acknowledgements

I would like to thank all my co-authors from IBM and my prior positions at Oracle and UCSC whose work I am showing in this presentation.

I would also like to thank Patrick Cozzi for inviting me to teach in his classes multiple years in a row and for letting me re-use his introductory material.

Agenda

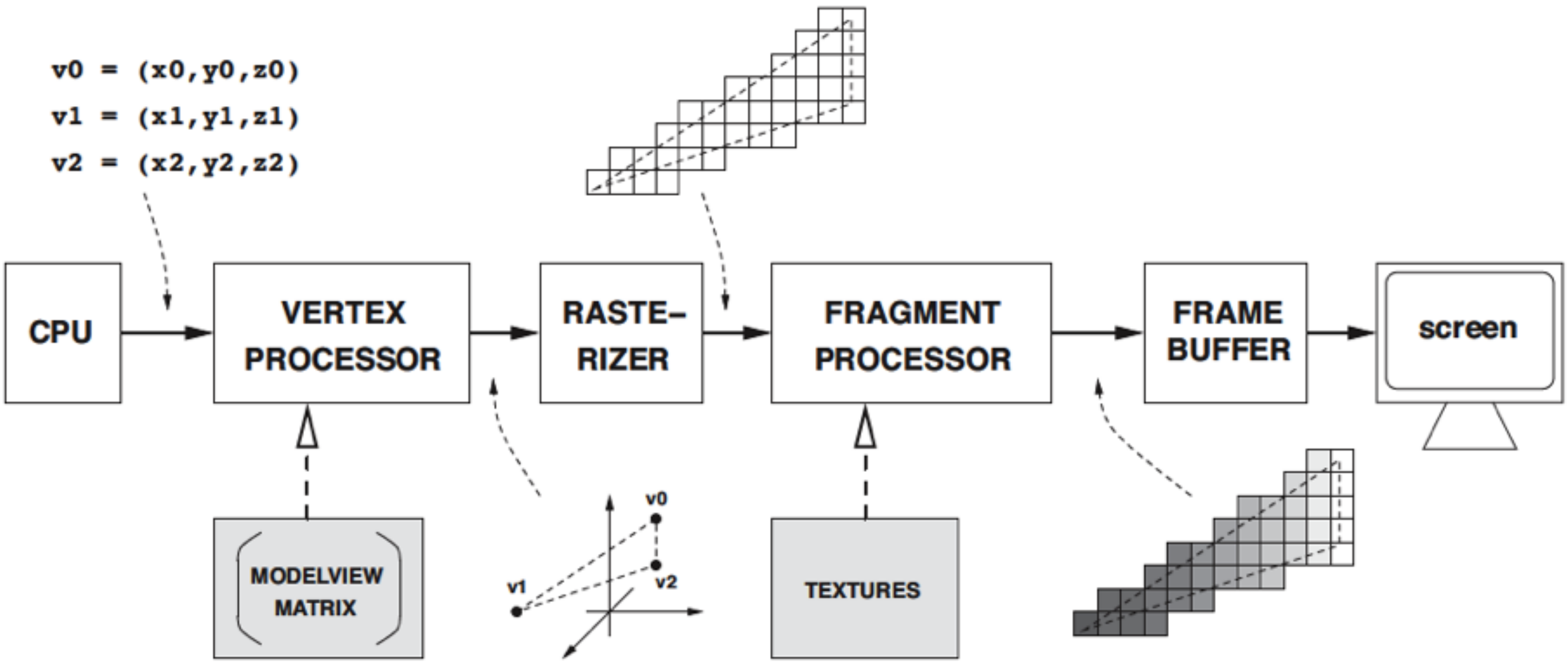
Programming GPUs for non-graphics workloads

- GPGPU
  - A brief introduction
  - Index Search implemented using openGL and Cg

- Modern GPU computing with CUDA
  - A very brief intro to CUDA
  - Index Search in CUDA
  - Performance optimizations
  - A new GPU-optimal (index) search algorithm

GPU Programming pre-CUDA

- The graphics pipeline



- Vertex Processor - geometric transformations of vertices in 3D space
- Rasterizer - transforms geometric primitives (triangles) into pixels
- Fragment Processor – colors the pixels
- Programmable were only vertex and fragment processors

GPGPU Programming

- GPGPU(.org)started in 2002 by Mark Harris
- Using Graphics APIs to solve non-graphics tasks
  - E.g. OpenGL & Cg
- Required use of graphics APIs
  - OpenGL for data transfers
  - Cg to “program”
  - Operations:
    - geometric transformations using the vertex processor (scatter)
    - coloring using the fragment processor (gather)
  - Vertices are stored as float4 (x,y,z,w)
  - Textures = 2D arrays of float4 vectors (r,g,b,a)
  - Compute = drawing

GPGPU Programming

Steps for GPGU compute:

1. Organize data in a screen size array
2. Set up a viewport with 1:1 pixel:texel ratio
3. Create and bind texture of the same size
4. Download input data into texture
5. Bind (load) fragment program (computational kernel)
6. Render a screen size quad to perform computation, i.e. run fragment program on each Pixel
7. Read back results

Let’s Pick a Simple, but Omnipresent Task … Search

- Why Search?
- Honestly, how many times a day do you visit:

Google™ YAHOO!® ?

Let's Pick a Simple, but Omnipresent Task … Search

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- How do you search (millions of) documents efficiently?
- Use an inverted index

sorted ↓

Keyword	DocID
Adam	1,2,3
Bethlehem	4,5
Character	1,2,3,301,5790
Drachenflieger	301,317,5790
Eva	1,2
Flughafenbahnhof	5790
Grabdenkmal	2,5790
Haubentaucher	300,5790

Searching an Index

- The task: search an inverted (document) index

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sorted

16 characters max.

Can be stored separately. Lookup by position.

Searching an Index

- The task: search an inverted (document) index

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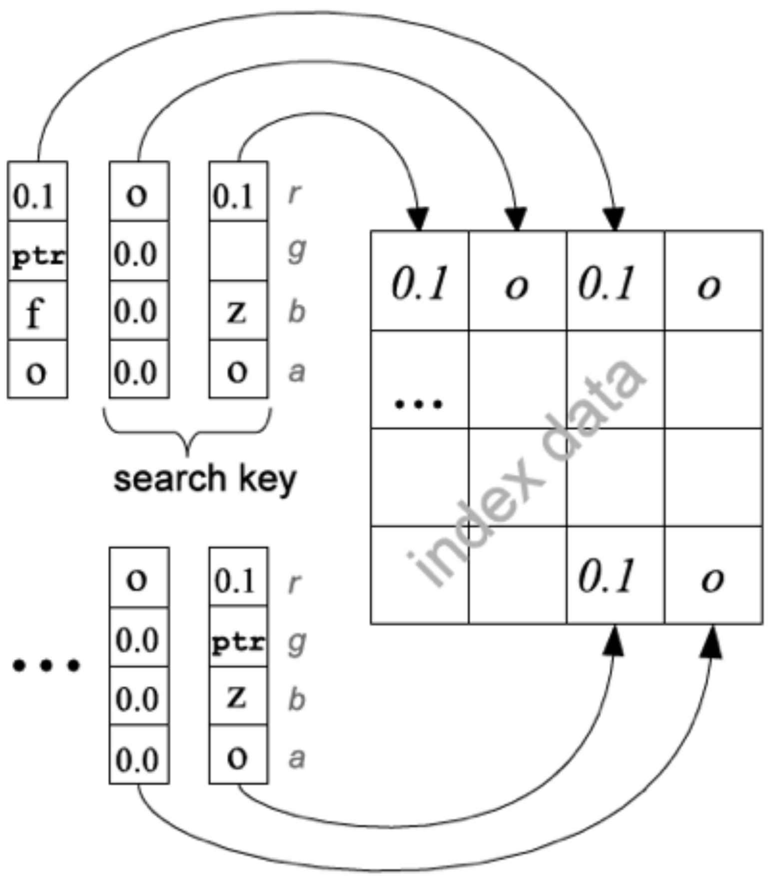
16 characters max.

- On the CPU we use a few library calls and we are done

```
char searchkey[16]= “Flughafenbahnhof”;
result = bsearch((void*)&searchkey,index,
                 numentries,sizeof(char)*16,
                 (int(*)(const void*,const void*)) strcmp);
```

GPGPU Search – Data Format

- Storing data
  - Obviously you want 1:1 pixel-to-texture element (texel) ratio *unless you would like to play Scrabble ;-)*



  - Ascii mapped to 0.0 to 255.0
  - 1 pixel stores 4 chars (better?)
  - Mark beginning of words with 0.1
  - Need to store pointer/position in document index ptr
  - Align word boundaries with r pixel boundaries r
  - Null-terminated strings 0.0

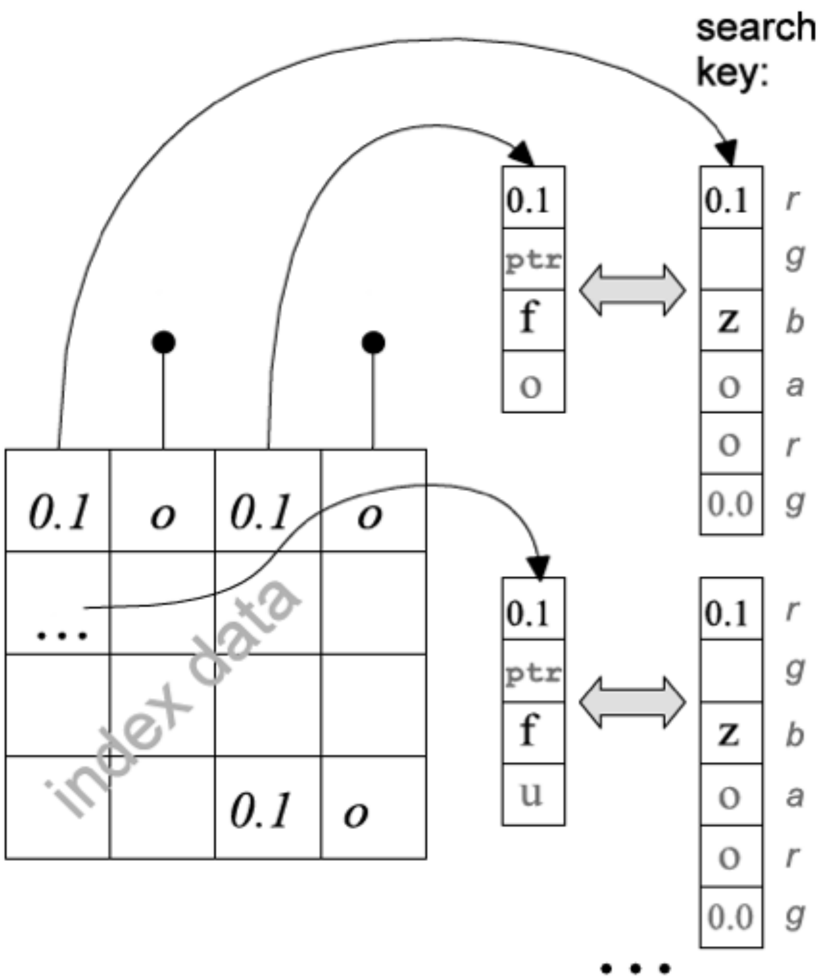
GPGPU Search – Data Storage

- Store data in texture

```
float* data = malloc(sizeof(float)*1200*1200*4);
...
data[pos++] = 0.1;
data[pos++] = *(float*)&docindex;
for (i=0;i<=strlen(currentString);i++) {
      data[pos++] = (float)currentString[i];
}
...
glTexSubImage2D(GL_TEXTURE_RECTANGLE_ARB,
                0,0,0, // detail level, x-, y- offset
                1200, 1200, // size
                GL_RGBA, // texture format
                GL_FLOAT, // data format
                data); // data pointer
```

GPGPU Search in Action

- Comparing search key with stored strings



- Simple test for equality
  – Compare floats directly
  – Color by color

GPGPU Search Code

```
float4 search(float2 coords: WPOS,
                    uniform samplerRECT texCgFrag) : COLOR {
      float2 data_coords = coords;
      float2 searchkey_coords = float2(0.5,0.5);
      float4 data = texRECT(texCgFrag, data_coords );
      float4 searchkey = texRECT(texCgFrag, searchkey_coords);
      float done =0.0;
      if (data.r == 0.1) {
         if (done == 0.0) {
            if (data.b != searchkey.b) done = -1.0;
            if (data.b == searchkey.b)
               if (data.b== 0.0) done = 1.0;
         }
         if (done == 0.0) {
            if (data.a != searchkey.a) done = -1.0;
            ...
```

GPGPU Search – Code Execution

- To execute the code:
  ```
  drawQuad(1200,1200);
  ```
- Result uses a magic number (not used for ASCII mapping) 0.9
- After completion Result is anywhere in the texture
- Copying whole texture back to main memory inefficient
- Reduction

GPGPU Search – Reduction

- To execute the code:
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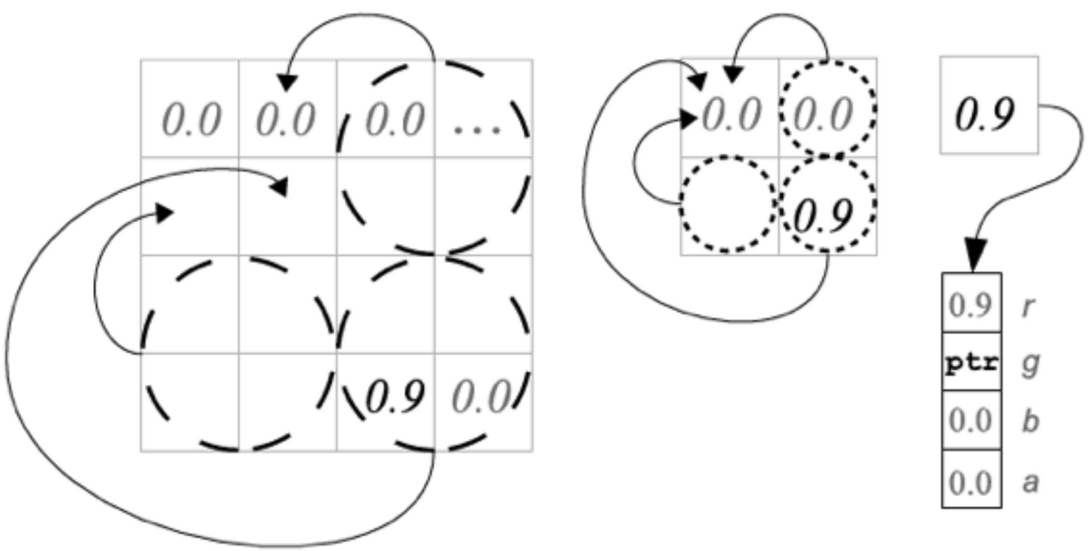


GPGPU Search – Reduction

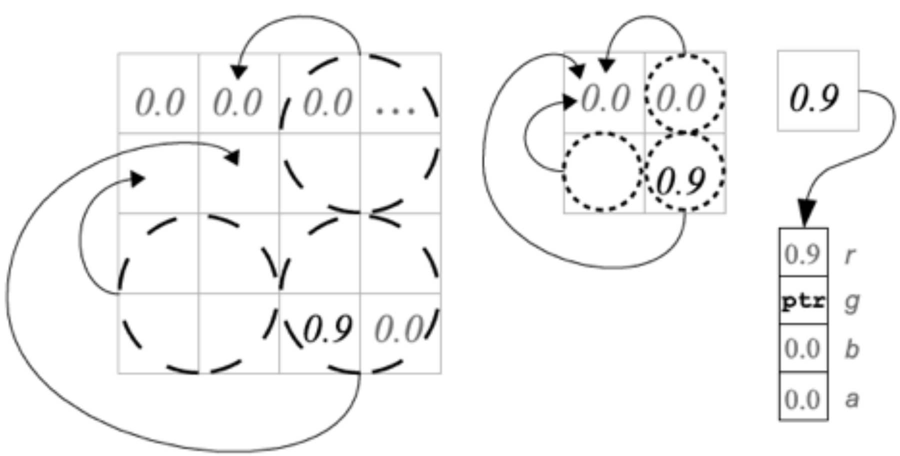
- Reduction means gathering "neighborhood" data

```
float4 reduce (float2 coords: WPOS,
                    uniform samplerRECT texCgFrag2) : COLOR {
      float2 topleft = ((coords-0.5)*2.0)+0.5;
      float4 val1 = texRECT(texCgFrag2, topleft);
      float4 val2 = texRECT(texCgFrag2, topleft+float2(1,0));
      float4 val3 = texRECT(texCgFrag2, topleft+float2(1,1));
      float4 val4 = texRECT(texCgFrag2, topleft+float2(0,1));
      float4 result = (0.0,0.0,0.0,0.0);
      if (val4.r == 0.9) result = val4;
      if (val3.r == 0.9) result = val3;
      if (val2.r == 0.9) result = val2;
      if (val1.r == 0.9) result = val1;
      return result;
}
```

GPGPU Search – Reduction

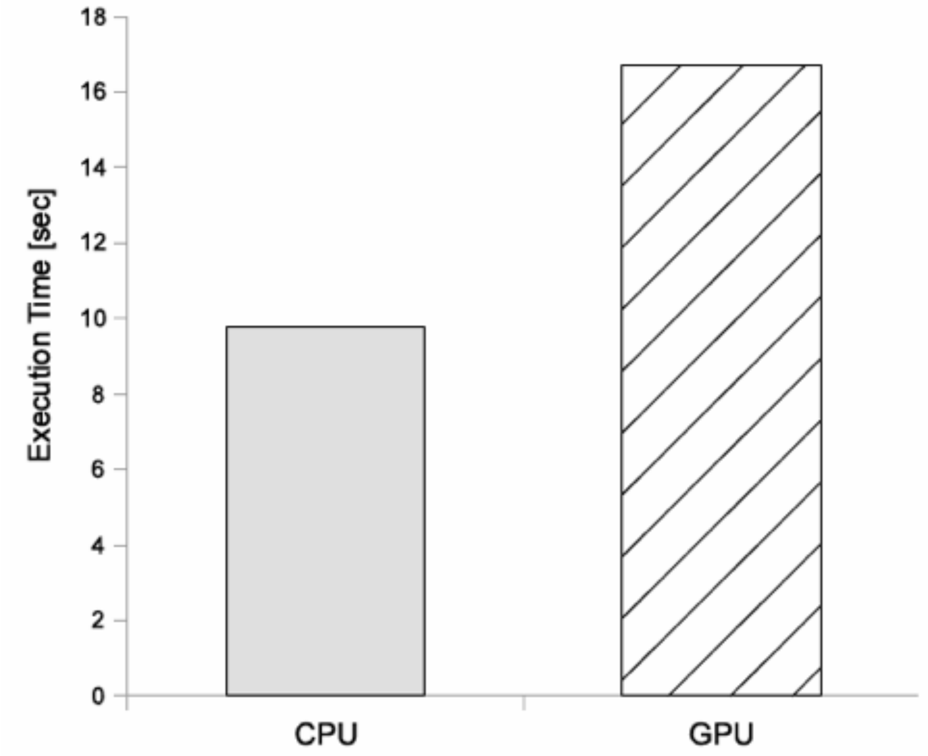
- Repeat until we end up with a single pixel
- Search result will be in top left pixel

```
numPasses = (int)(log((double)width)/log(2.0));
for (i=0; i<numPasses; i++) {
    ...
    outputWidth = outputWidth / 2;
    drawQuad(outputWidth,outputWidth);
    ...
```



GPGPU Search - Performance

- 10k Berkeley DB index operations (insert delete), all require searching the index first, Test001.tcl
- Berkley DB uses B-trees, which needed to be flattened for the GPU



Time required for 10k insert/delete operations using a dual-core 2.2ghz AMD Opteron vs. an nVidia 7900GS with 7 vertex and 20 fragment processors.

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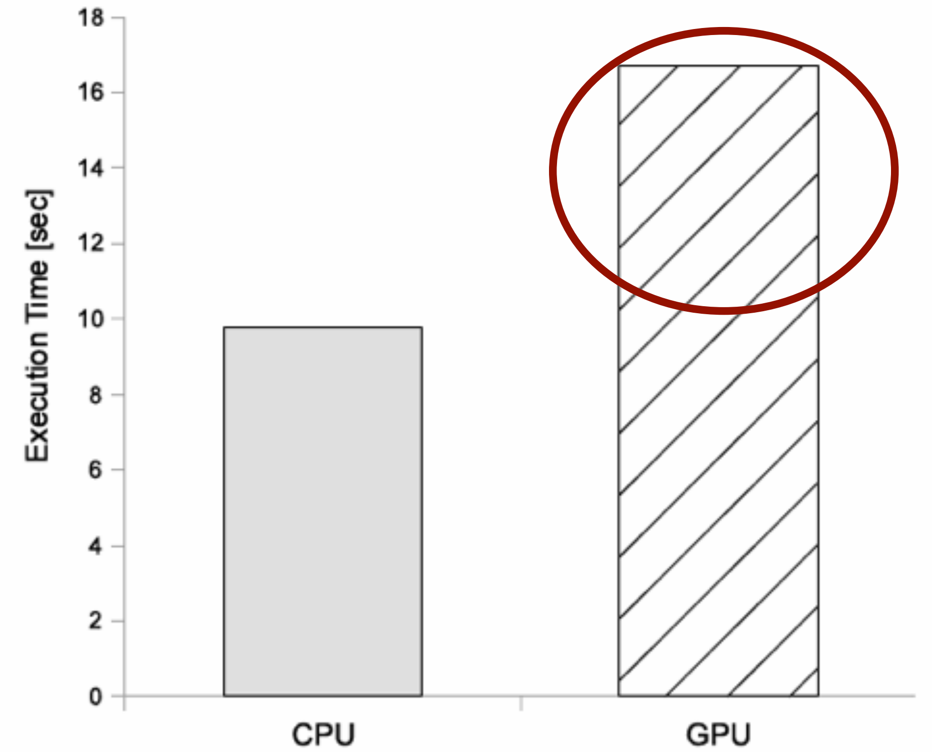

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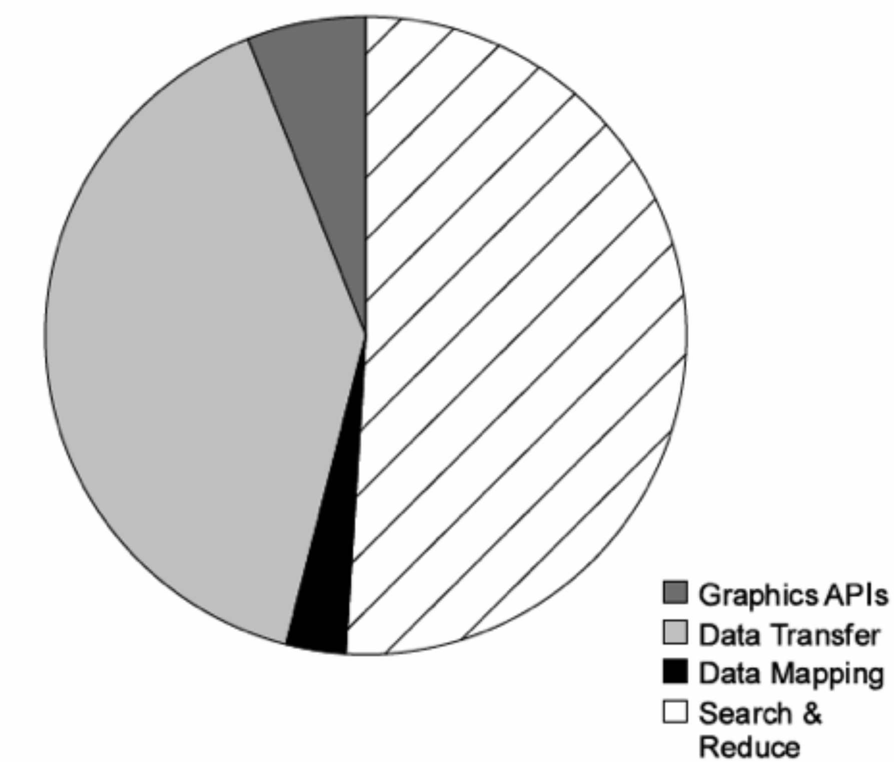
GPGPU Search – Where does time go ?



Time required for 10k insert/delete operations using a dual-core 2.2ghz AMD Opteron vs. an nVidia 7900GS with 7 vertex and 20 fragment processors.

- Data Transfer ~40%
  - More efficient data mapping, e.g. 4 char = 1 float   problematic?
- CUDA made GPGPU obsolete ...

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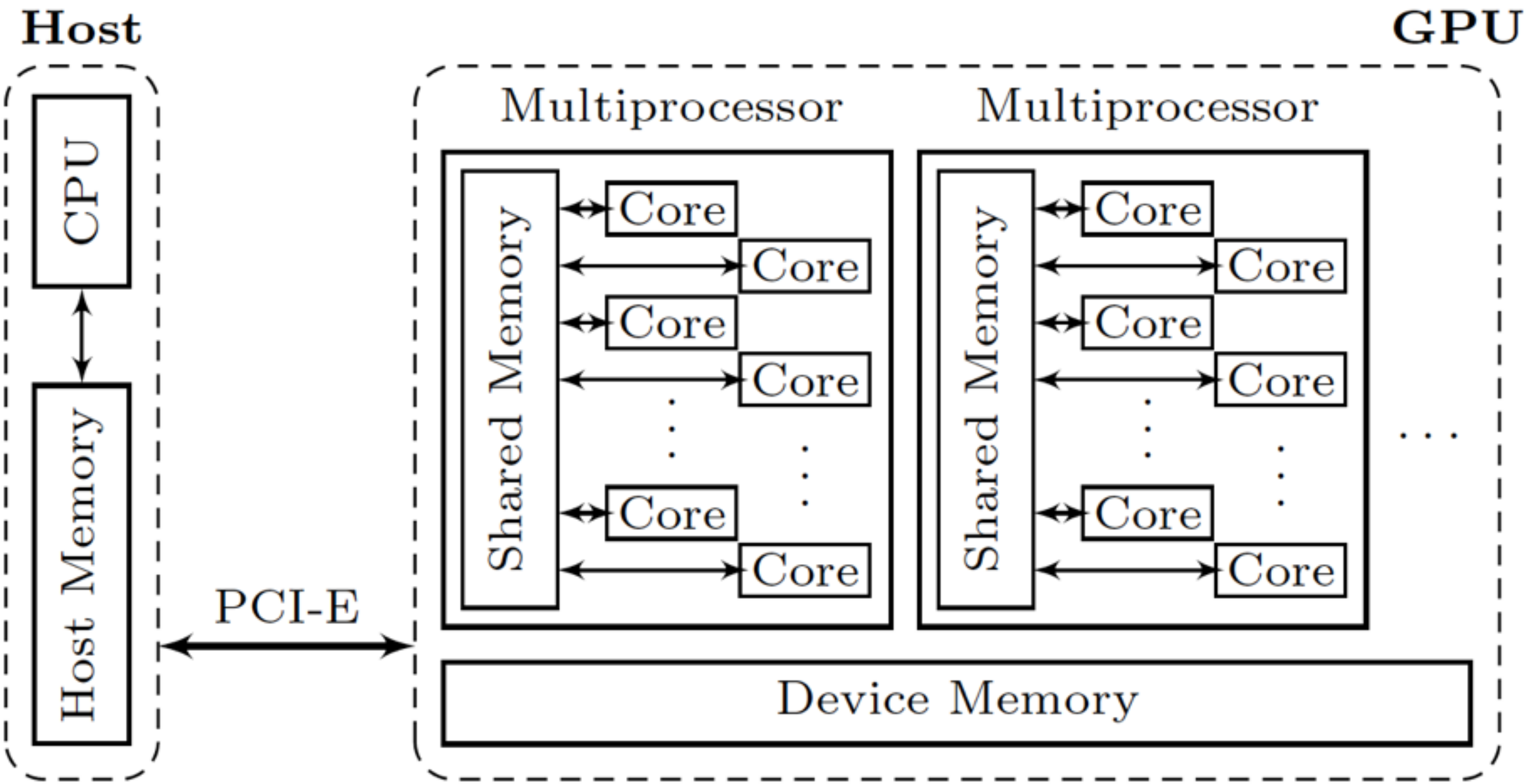
CUDA Key Concepts – Architecture



CUDA Key Concepts – Function Classifiers

- `__global__`
  - callable from host
  - must return void
- `__device__`
  - callable only from device
  - function inlined by default (newer CUDA versions)
- Global and device functions
  - No recursion (except Fermi)
  - No static variables
  - No malloc()
  - Careful with function calls through pointers (Fermi)
  - Cannot access host memory “directly”

CUDA Key Concepts – Memory address spaces

- Host (CPU) and Device (GPU) have separate (memory) address spaces
  - Data needs to be “transferred” to/from the GPU
  - Simplest way is to explicitly copy data to/from device memory
  - Data copy always initiated by host

```
cudaMemcpy(void* dst,
           const void* src,
           size_t count,
           cudaMemcopyHostToDevice | cudaMemcopyDeviceToHost
)
```

  - Specify direction of data copy
  - `ToDevice` for input data
  - `ToHost` for results
- When calling `__global__` function pass `dst` pointer

CUDA Key concepts – Vector types

- `char[1-4]`, `uchar[1-4]`, `short[1-4]`, `ushort[1-4]`, `int[1-4]`, `uint[1-4]`, `long[1-4]`, `ulong[1-4]`, `longlong[1-2]`, `ulonglong[1-2]`
- `float[1-4]`, `double[1-2]`
- `dim3`
- Available in host and device code
- Construct with `make_<type name>`

```
int2 i2 = make_int2(1, 2);
float4 f4 = make_float4(
  1.0f, 2.0f, 3.0f, 4.0f);
```

- Access with `.x, .y, .z, and .w`

```
int2 i2 = make_int2(1, 2);
int x = i2.x;
int y = i2.y
```

- No `.r, .g, .b, .a, etc.` like OpenGL, Cg

CUDA Key Concepts – Invoking GPU Functions (Kernels)

```
__global__ void gpu_Kernel(int a, ...){
...
}
...


dim3 grid(14,0,0);
Dim3 block(192,0,0);
gpu_Kernel<<<grid,block>>>(42,...);
```

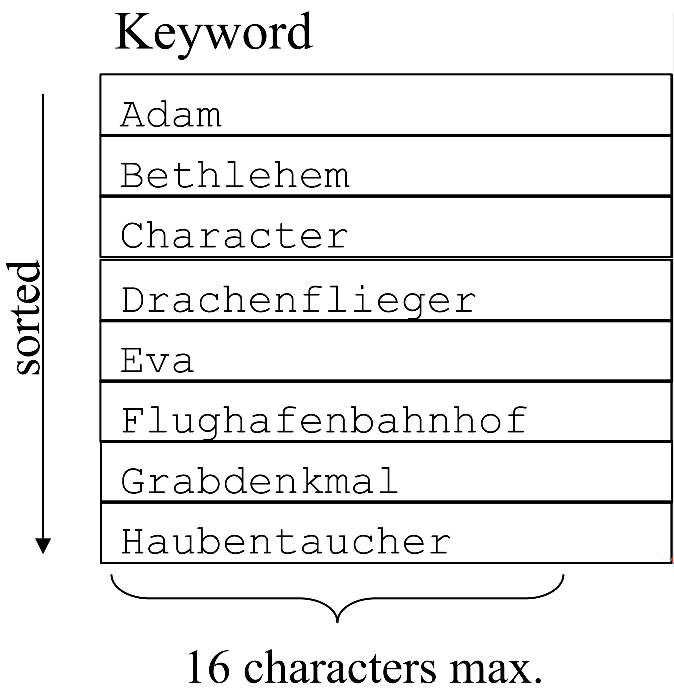
- Calling GPU (`__global__`) function requires to specify
  - grid dimensions – How many blocks of threads to launch
    - 1 block executes on 1 streaming multiprocessor to completion
  - block dimensions – How many threads are in a block
    - threads execute in groups of 32 (warps) in SIM[T/D] fashion
    - #threads > warp can be synchronized with `__synchthreads()`

CUDA Key Concepts – “Global” Variables

```
__device__ int a_dev;
...
__shared__ int a_smem;
```

- `__device__` variables
  - stored in device memory
  - accessible from all blocks
- `__shared__` variables
  - stored in shared on-chip memory (space constraints?)
  - accessible only within a block

Index search on the CPU

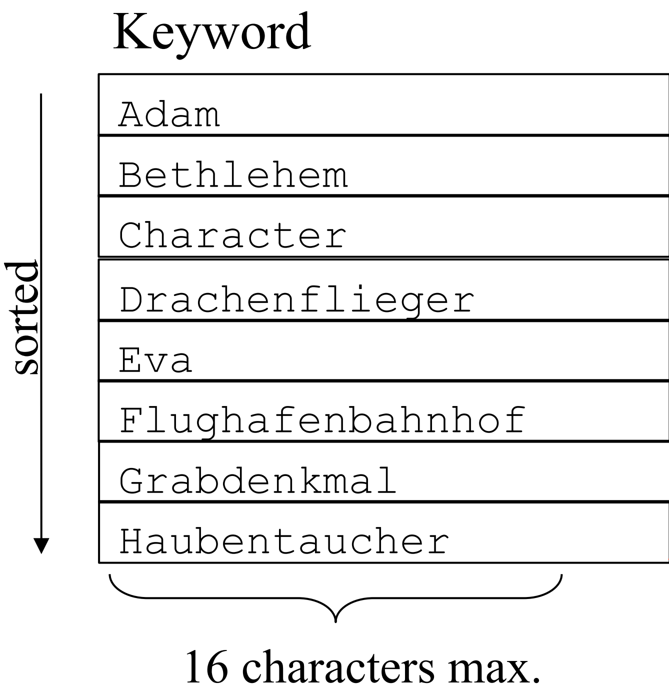



```
char indexCPU[4711];
indexCPU[0]
indexCPU[16]
indexCPU[32]
...
```

- On the CPU we use a few library calls and we are done

```
char searchkey[16]= "Flughafenbahnhof";
result = bsearch((void*)searchkey,indexCPU,
                  numentries,sizeof(char)*16,
                  (int(*)(const void*,const void*)) strcmp);
```

A Simple implementation of (index) search

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result = bsearch((void*)searchkey,indexCPU,
                  numentries,sizeof(char)*16,
                  (int(*)(const void*,const void*)) strcmp);
```

- Can we just port a CPU implementation?

Index search on the CPU

- Get the data to the GPU

```
char* indexGPU;
char* searchkeysGPU;
char* resultsGPU;
// copy the data
cudaMalloc((void**)&indexGPU, sizeof(char)*wordlength*entries);
cudaMemcpy(indexGPU, indexCPU, sizeof(char)*wordlength*entries,
           CudaMemcpyHostToDevice);
// copy the searchkey(s)
cudaMalloc((void**)&searchkeysGPU, …
cudaMemcpy(searchkeysGPU, searchkeysCPU,
           sizeof(char)*wordlength*numsearches,
           CudaMemcpyHostToDevice);
// make room for the results
cudaMalloc((void**)&resultsGPU, …
```

A Simple GPU implementation

- Get the data to the GPU

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           sizeof(char)*wordlength*numsearches,
           CudaMemcpyHostToDevice);
// make room for the results
cudaMalloc((void**)&resultsGPU, …
```

- Know your hardware (GTX 285, 30 SMs, 8 cores each, 240 cores)
  - Set up an execution configuration & call global function

```
dim3 Dg = dim3(30,0,0);
dim3 Db = dim3(8,0,0);
searchGPU< < < Dg,Db > > >(indexGPU, entries...
```

A Simple GPU implementation

- The GPU kernel

```
__global__ void searchGPU(char* index, int entries, int wordlength,
                          char* search_keys, int* results) {
   char* res;
   // use block and thread numbers for indexing
   res = bsearch(&search_keys[((blockIdx.x*BLOCK_SIZE)+threadIdx.x)
                                    *wordlength],
                 index,
                 entries,
                 wordlength);
   // use block and thread numbers for indexing
   results[(blockIdx.x*BLOCK_SIZE)+threadIdx.x] = (res-data)/
                                                   MAX_WORD_LENGTH;
}
```

A Simple GPU implementation

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                 index,
                 entries,
                 wordlength);
   // use block and thread numbers for indexing
   results[(blockIdx.x*BLOCK_SIZE)+threadIdx.x] = (res-data)/
                                                  MAX_WORD_LENGTH;
}
```

- There is no libc on the GPU =(
- Just stick __device__ in front of the libc code?
- “bsearch” is recursive, but there is no recursion on the GPU

➔ Write a iterative one ...

A Simple GPU binary search

```
__device__  char* bsearchGPU(char *key, char *base, int n, int size){
    char *mid_point;
    int  cmp;

    while (n > 0) {
        mid_point = (char *)base + size * (n >> 1);
        if ((cmp = strcmpGPU(key, mid_point)) == 0)
            return (char *)mid_point;
        if (cmp > 0) {
            base  = (char *)mid_point + size;
            n     = (n - 1) >> 1;
        } // cmp < 0
        else n >>= 1;
    }
    return (char *)NULL;
}
```

- Still need strcmp

A Simple GPU binary search

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        } // cmp < 0
        else n >>= 1;
    }
    return (char *)NULL;
}
```
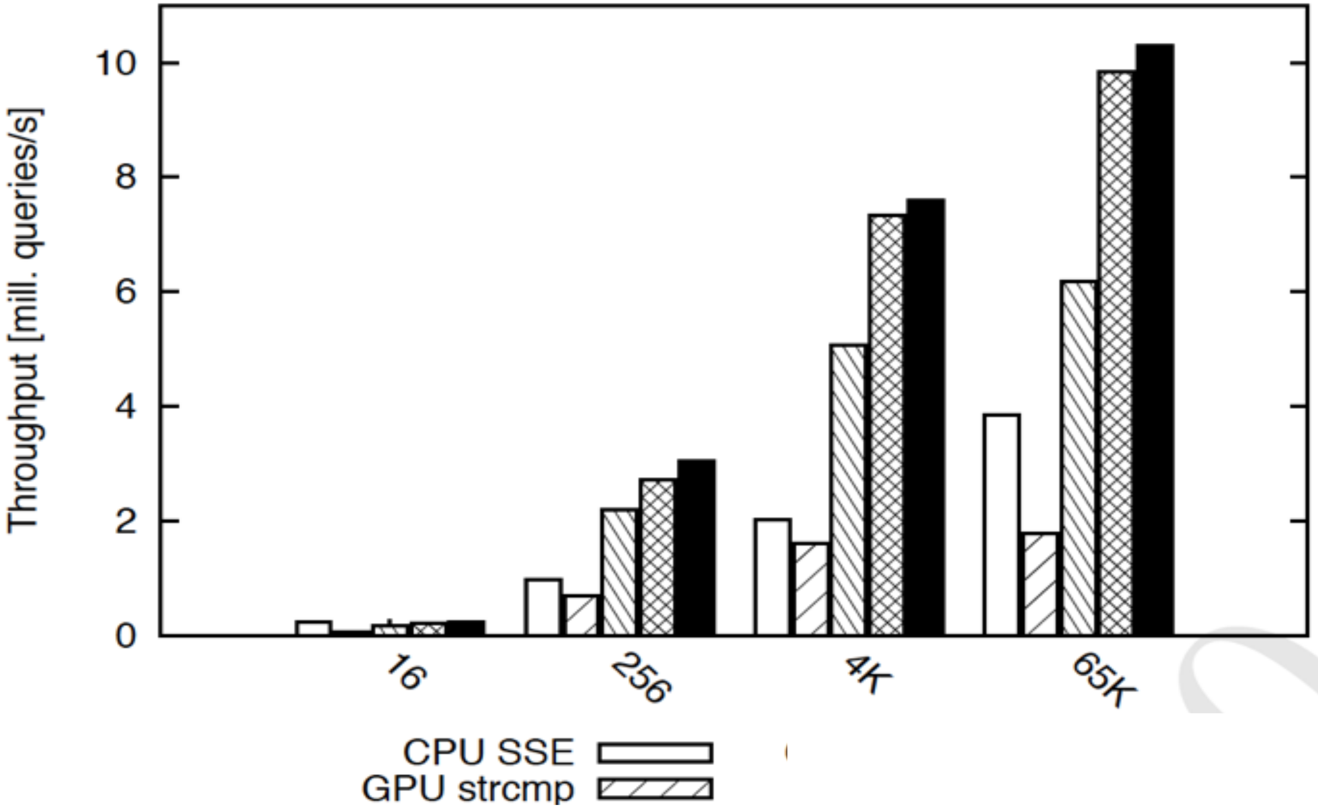

- Still need strcmp
- Again, stick __device__ in front of the libc code

```
__device__  int strcmpGPU(char* s1, char* s2){
   while (*s1 == *s2++)
       if (*s1++ == 0) return 0;
   return (*s1 - *(s2 - 1));
}
```

Binary Search on the GPU

- Searching a large data set (512MB) with 33 million (225) 16-character strings



Binary Search on the GPU – Why is it slow?

- Searching a large data set (512MB) with 33 million (225)
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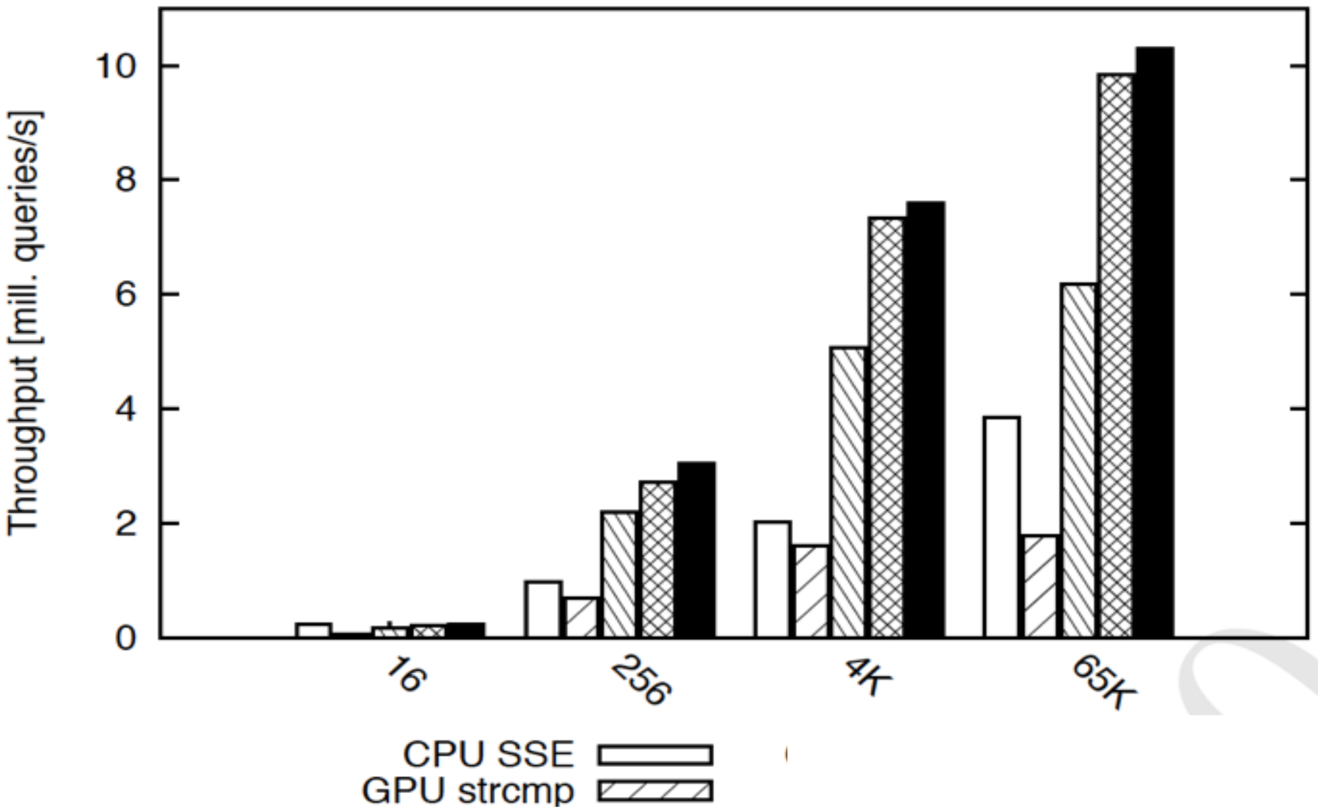
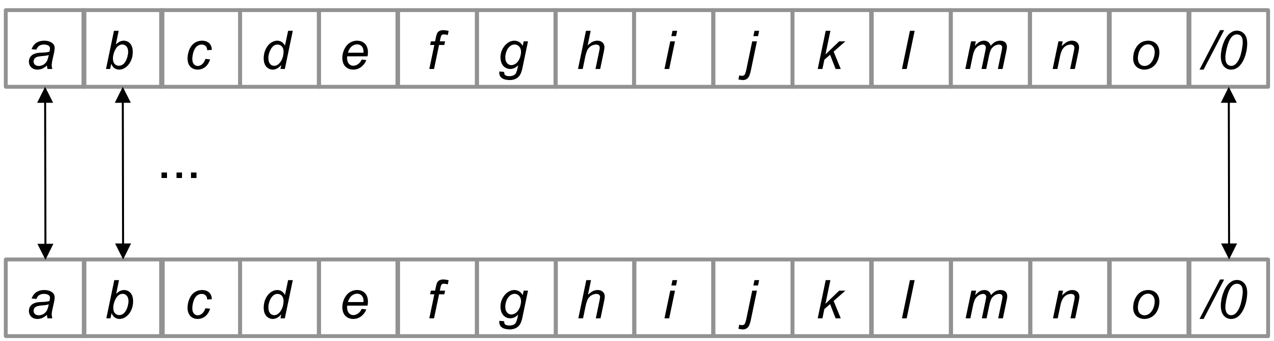


- It's slower than a CPU implementation for all data set sizes!
  - Let's try some optimizations ...

Search requires to compare

- Search naturally requires MANY comparisons
- The strcmp() library function:

```
int strcmp(const char* s1, const char* s2){
        while (*s1 == *s2++)
                if (*s1++ == 0)return 0;
        return (*s1 - *(s2 - 1));
}
```



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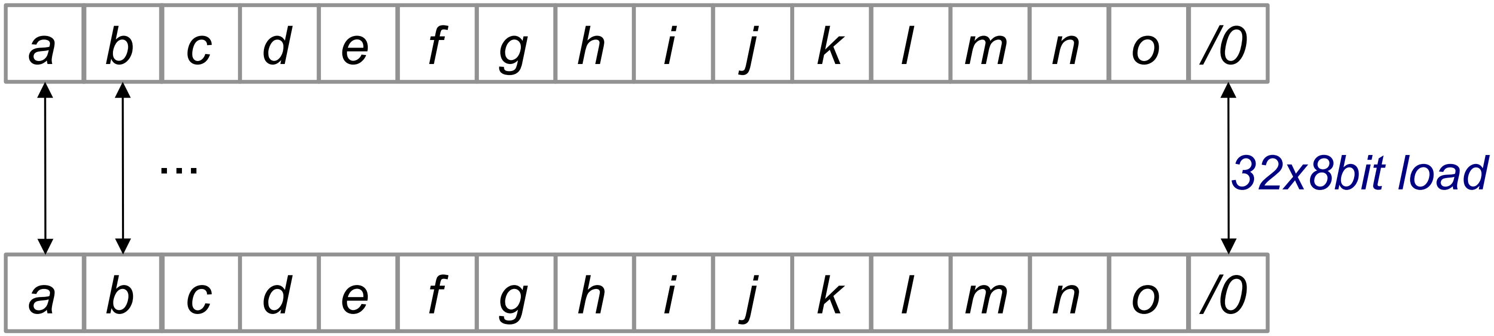
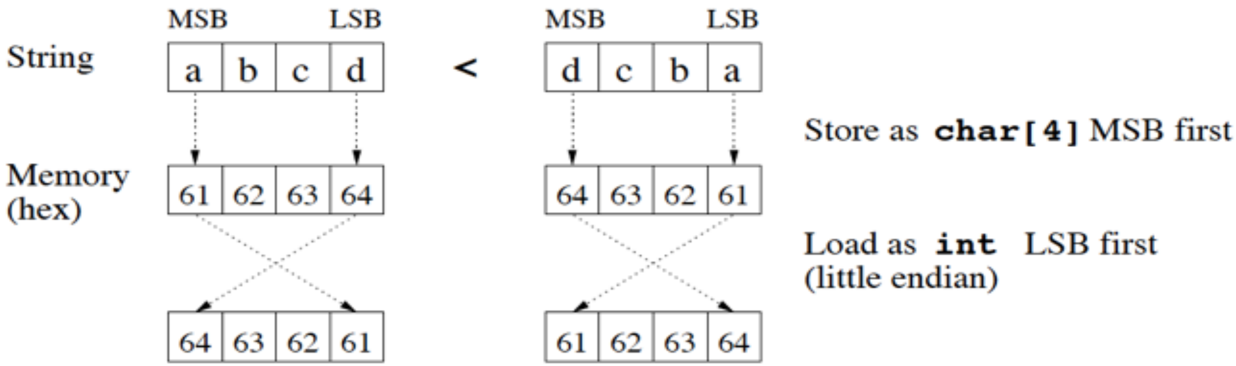


- Byte-wise memory access is known to be slow

Optimizing compare operations

- How about vector string comparison, a la SSE?
- No Byte vectors on the GPU … but Integer vectors



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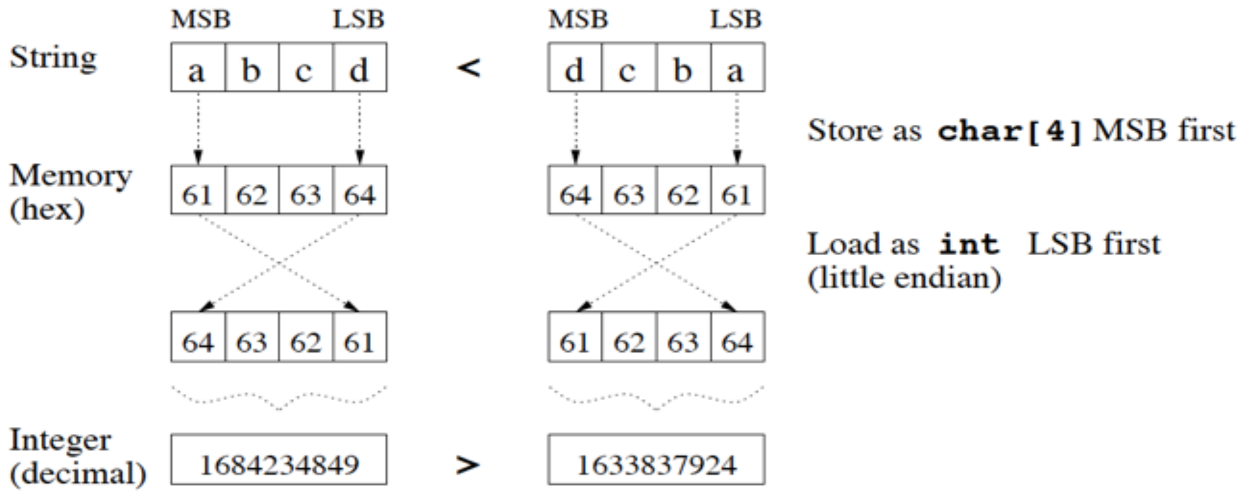

Optimizing compare operations

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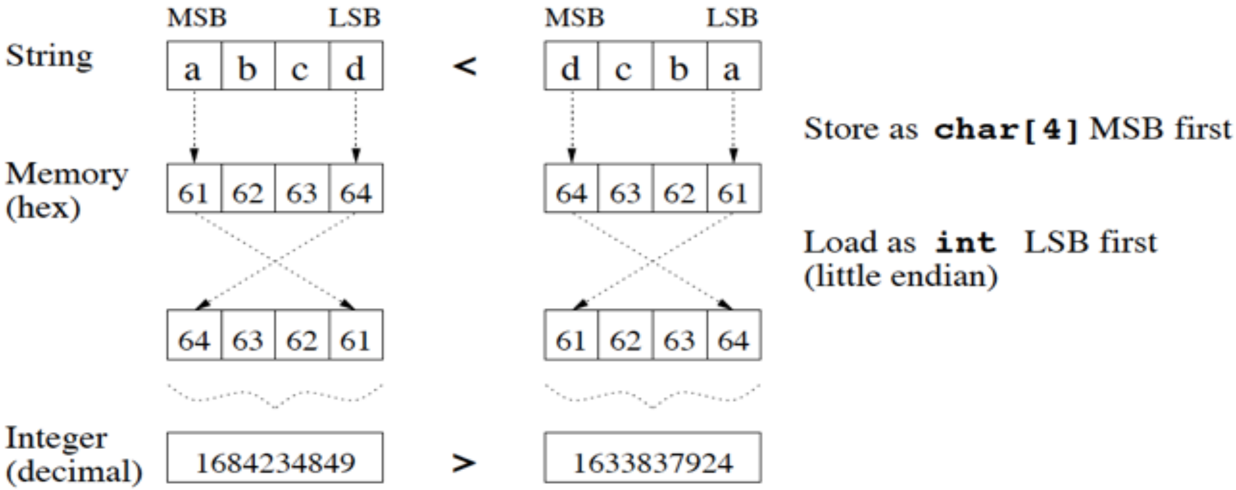

- Loading character strings as int changes endianness
- CPU has bswap, on the GPU we have to write it:

```
#define BSWP( x ) ; \
temp = ( x ) << 24 ; \
temp = temp | ( ( ( x ) << 8) & 0x00FF0000 ) ; \
temp = temp | ( ( ( unsigned ) ( x ) >> 8) & 0x0000FF00 ) ; \
x = temp | ( ( unsigned ) ( x ) >> 24 ) ;
```

Optimizing compare operations

- Comparing integer vectors (bswap for <> skipped for clarity)

```
__device__ int intcmp(uint4* a, uint4* b){

   int r =1;
   if ((*a).x < (*b).x)
      r=-1;
   else if ((*a).x == (*b).x) {
        if ((*a).y  < (*b).y)
           r=-1;
        else if ((*a).y == (*b).y) {
             if ((*a).z  < (*b).z)
                r=-1;
             else if ((*a).z == (*b).z) {
                  if ((*a).w < (*b).w)
                     r=-1;
                  else if ((*a).w == (*b).w)
                     r=0;
            }
        }
   }
   return r;
}
```

- Still dereferencing 16 memory pointers ...

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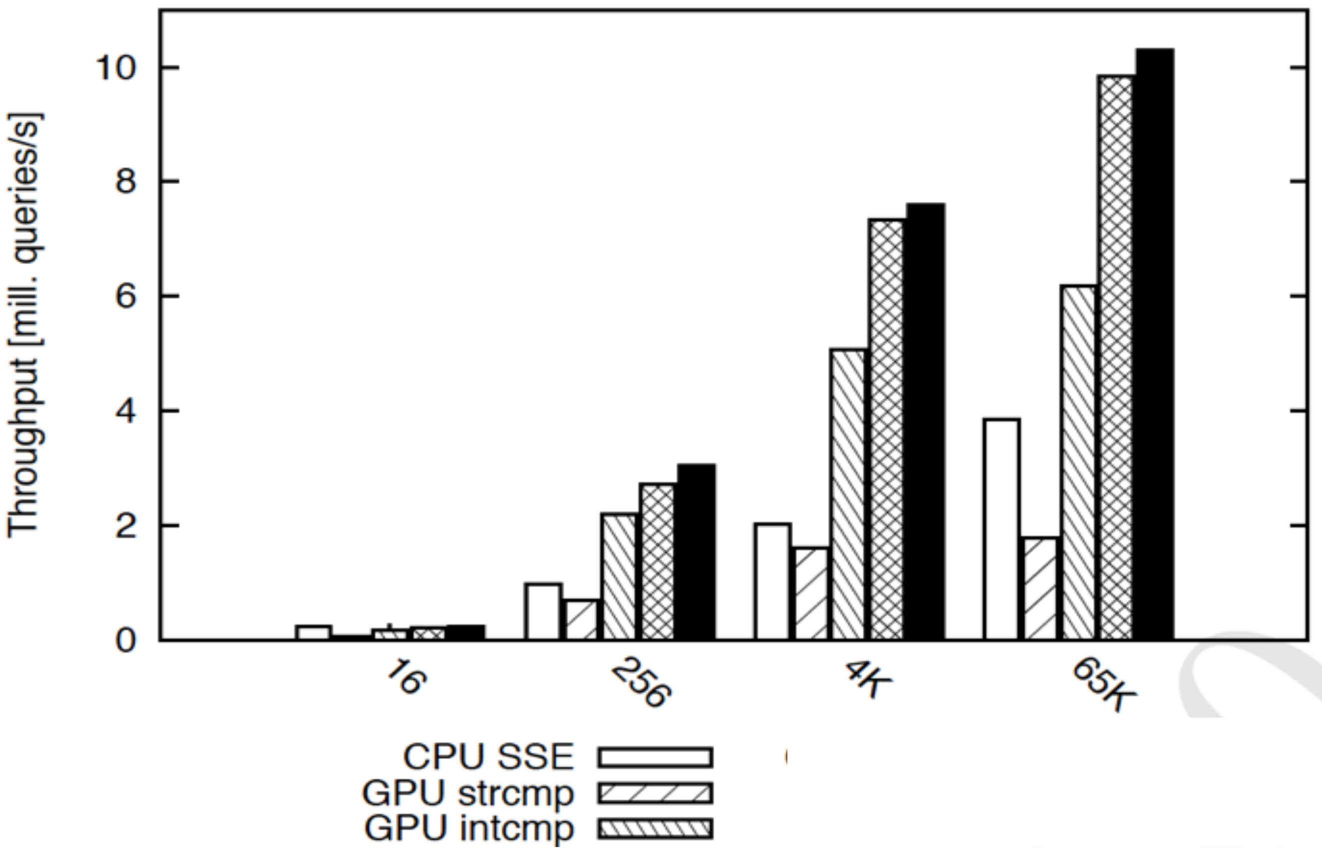

- With intcmp it's only marginally faster than a CPU implementation
- We still do pointer chasing, i.e. roundtrips to memory ...

Reducing global memory access

- Intcmp is memory latency sensitive

Processor	L1 [cyc]	L2 [cyc]	L3 [cyc]	mem [cyc]
Intel Core i7 2.6GHz	4	10	40	350
nVidia GT200b 1.5 GHz	4	n/a	n/a	500

x 16 for each comparison !!!

- We can use shared memory like L1

Reducing global memory access

- Intcmp is memory latency sensitive

Processor	L1 [cyc]	L2 [cyc]	L3 [cyc]	mem [cyc]
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x 16 for each comparison !!!

- We can use shared memory like L1

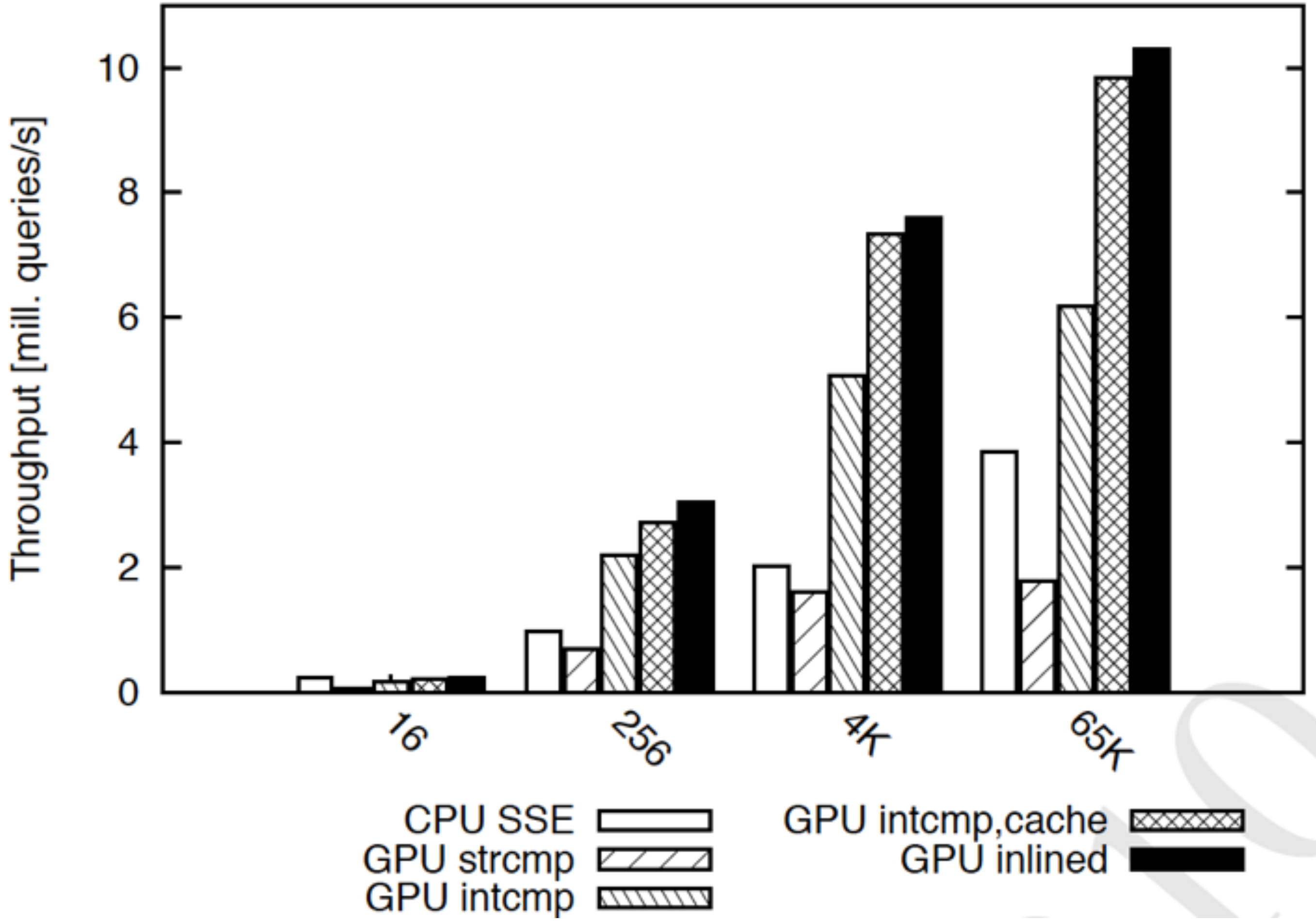
```
__shared__ uint4 cache[NUM_THREADS*2];

__device__ uint4* bsearchGPU( uint4 *key,  uint4 *base,
          size_t nmemb,  size_t size)
{
   uint4 *mid_point;
   int  cmp;
   cache[threadIdx.x*2]= *key;

   while (nmemb > 0) {
      mid_point = (uint4 *)base + size * (nmemb >> 1);
      cache[threadIdx.x*2+1]= *mid_point;
      if ((cmp = intcmp(&cache[threadIdx.x*2],
                  &cache[threadIdx.x*2+1]))== 0)
          return (uint4 *)mid_point;
```

Binary Search on the GPU – optimized

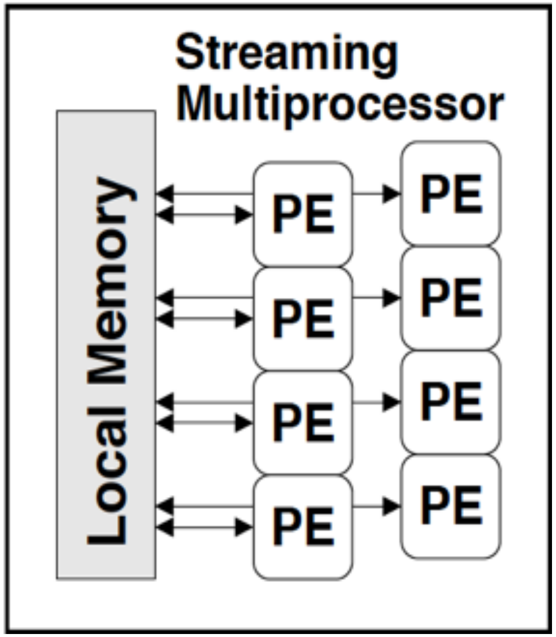
- Searching a large data set (512MB) with 33 million (225) 16-character strings



Is binary search optimal for a SIM[D/T] architecture ?

GPU architecture reminder – SIMD/SIMT

- Inside Streaming Mulitprocessor
  - Single Instruction Multiple Threads/Data (SIMT/SIMD)
  - All PEs in 1SM execute same instruction or no-op (SIMD threads)
  - Warps of 32 threads (or more to hide memory latency)



What happens during Multi-threaded Binary Search ?

- Index: a sorted char array 32 entries
- 4 queries: t , 8 , f , r
- 4 processor cores: P1-P4
- 1 processor core – 1 search: P0:t , P1:8 , P2:f , P3:r
- Theoretical worst-case execution time: $\log_2(32)=5$

4	5	6	7	8	9	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y	z

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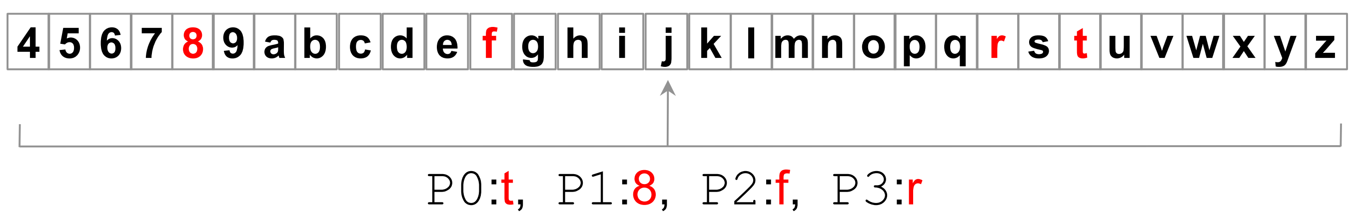
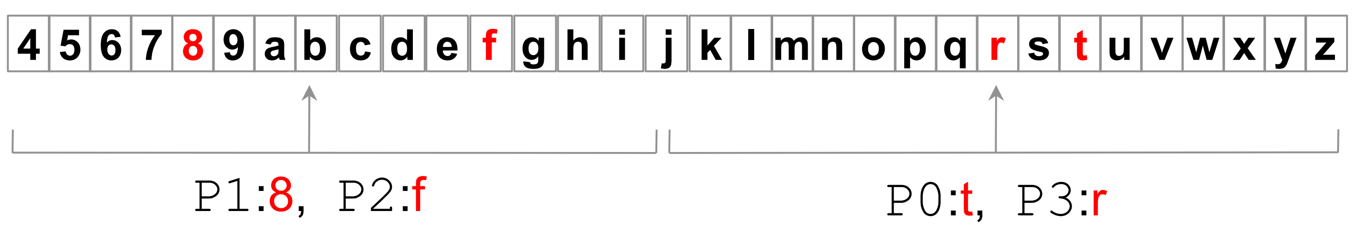
Iter. 1)



Iter. 2)



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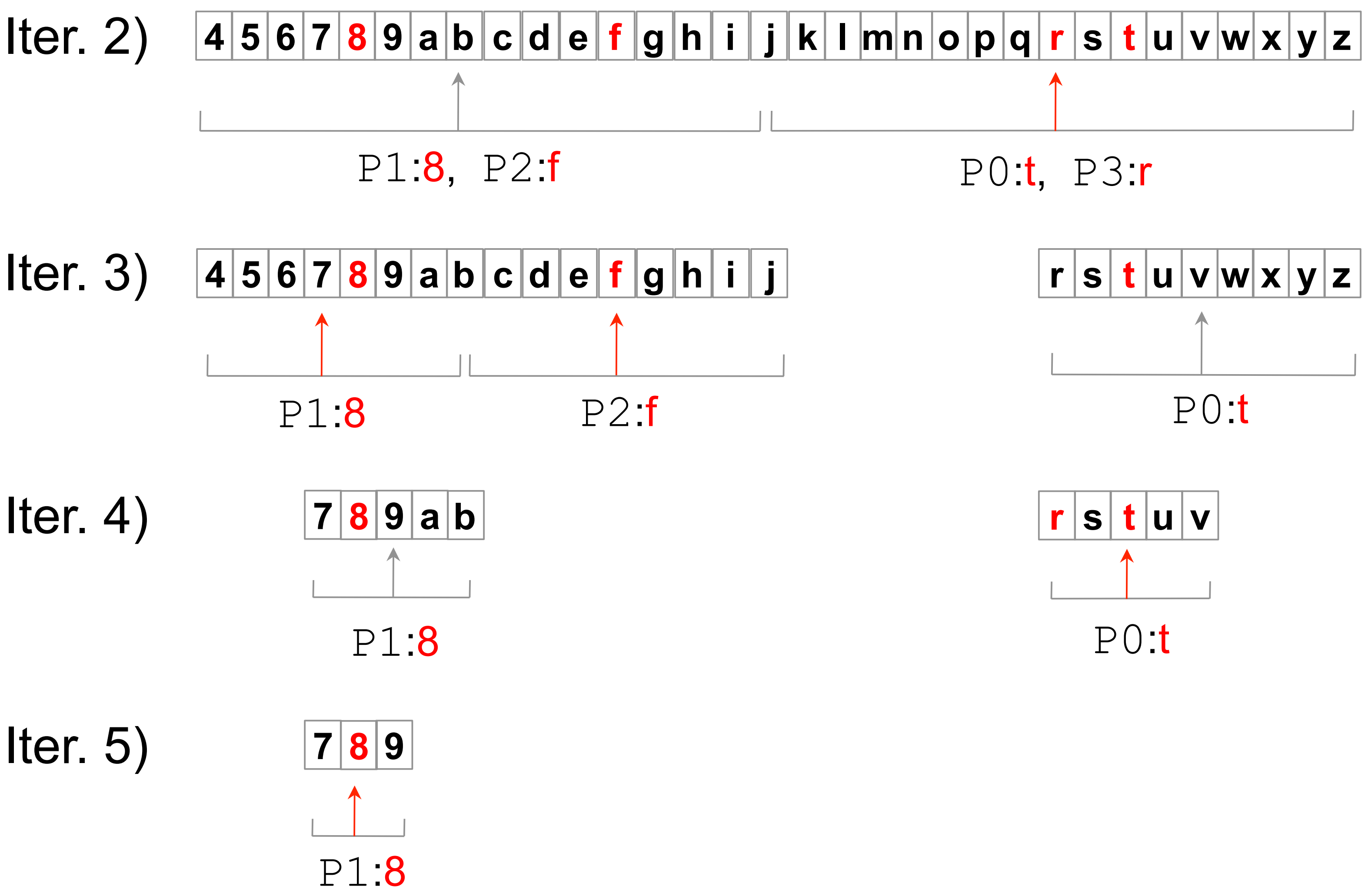


Multi-threaded Binary Search - Analysis

- 100% utilization requires #cores concurrent queries
- Queries finishing early

  ➔ utilization < 100%
- Memory access collisions

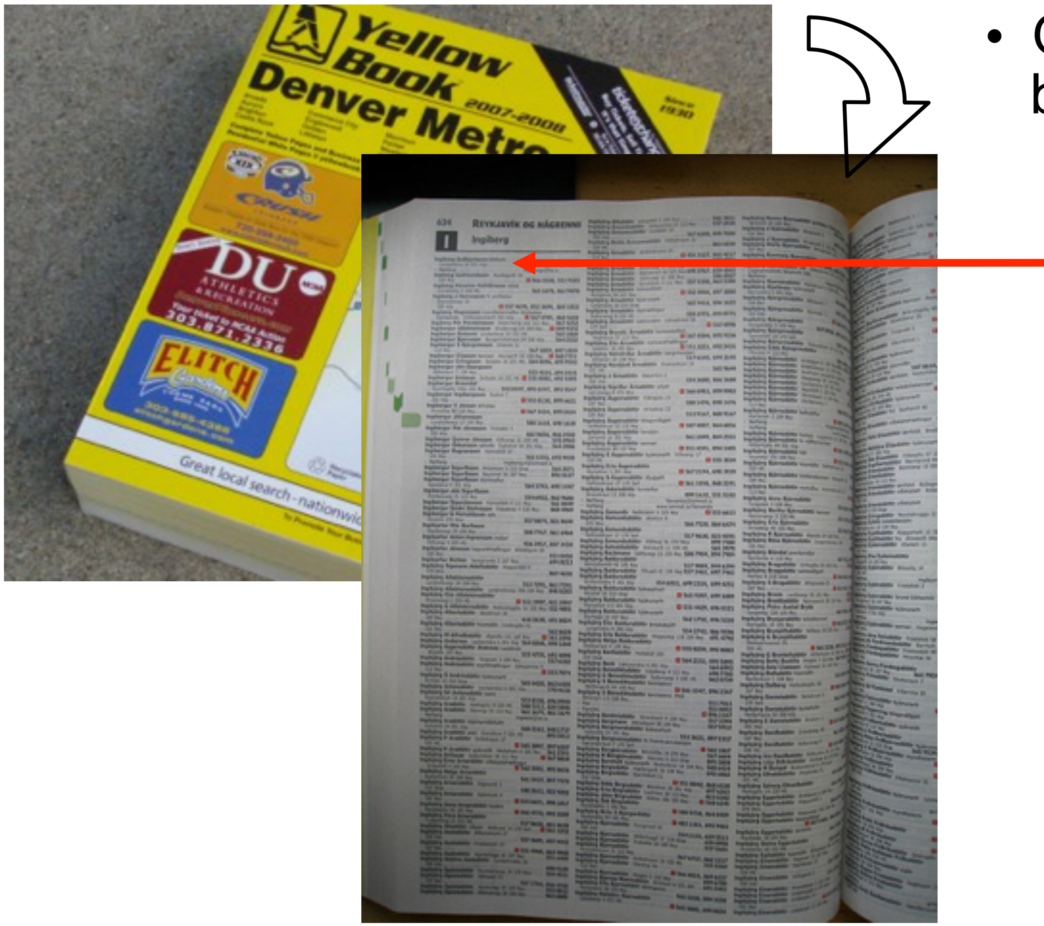
  ➔ serialized memory access
- #memory accesses $\log_2(n)$
- More threads
  ➔ more results

  ➔ response time likely to be worst case: $\log_2(n)$

Can we improve the worst case?

Binary Search

- How Do you (efficiently) search an index?



- Open phone book ~middle
- 1st name = whom you are looking for?
- < , > ?
- Iterate
  – Each iteration: #entries/2 (n/2)
  – Total time: ➔ $\log_2(n)$

Parallel (Binary) Search

- What if you have some friends (3) to help you ?

- Divide et impera !
- Give each of them ¼ *
  - Each is using binary search takes $\log_2(n/4)$
  - All can work in parallel ➔ faster: $\log_2(n/4) < \log_2(n)$

* You probably want to tear it a little more intelligent than that, e.g. at the binding ;-)

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  - 3 of you are wasting time !

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P-ary Search

- Divide et impera !!

- How do we know who has the right piece ?

P-ary Search

- Divide et impera !!

- How do we know who has the right piece ?

- It's a sorted list:
  - Look at first and last entry of a subset
  - If first entry < searched name < last entry
    - Redistribute
    - Otherwise … throw it away
  - Iterate

P-ary Search

- What do we get?

+

- Each iteration: n/4
  ➔ $\log_4(n)$
- Assuming redistribution time is negligible:
  $\log_4(n) < \log_2(n/4) < \log_2(n)$
- But each does 2 lookups !
- How time consuming are lookup and redistribution ?

P-ary Search

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memory access	synchronization

P-ary Search

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  $\log_4(n) < \log_2(n/4) < \log_2(n)$
- But each does 2 lookups !
- How time consuming are lookup and redistribution ?

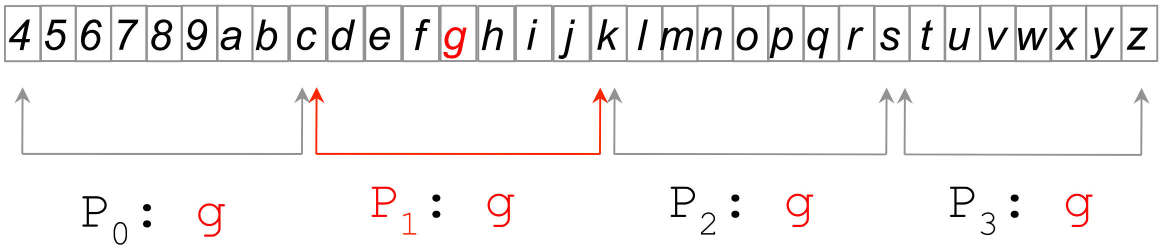
=	=
memory access	synchronization

- Searching a database index can be implemented the same way
  – Friends = Processor cores (threads)
  – Without destroying anything ;-)

P-ary Search - Implementation

- Strongly relies on fast synchronization
  - friends = threads / vector elements

Iteration 1)



P-ary Search - Implementation

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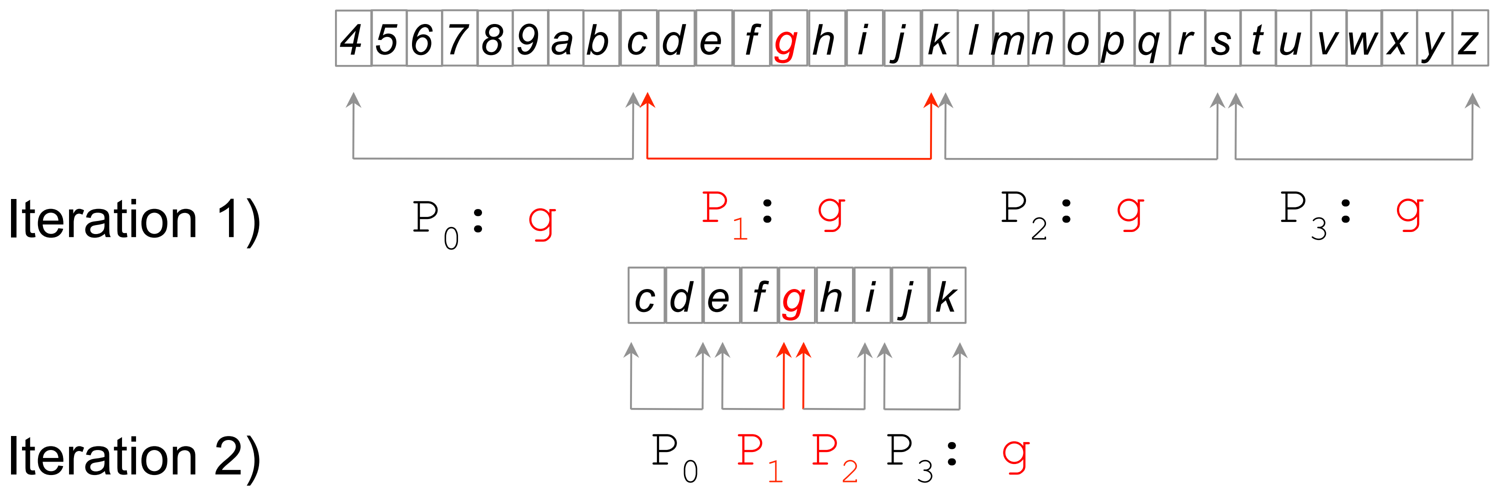

P-ary Search - Implementation

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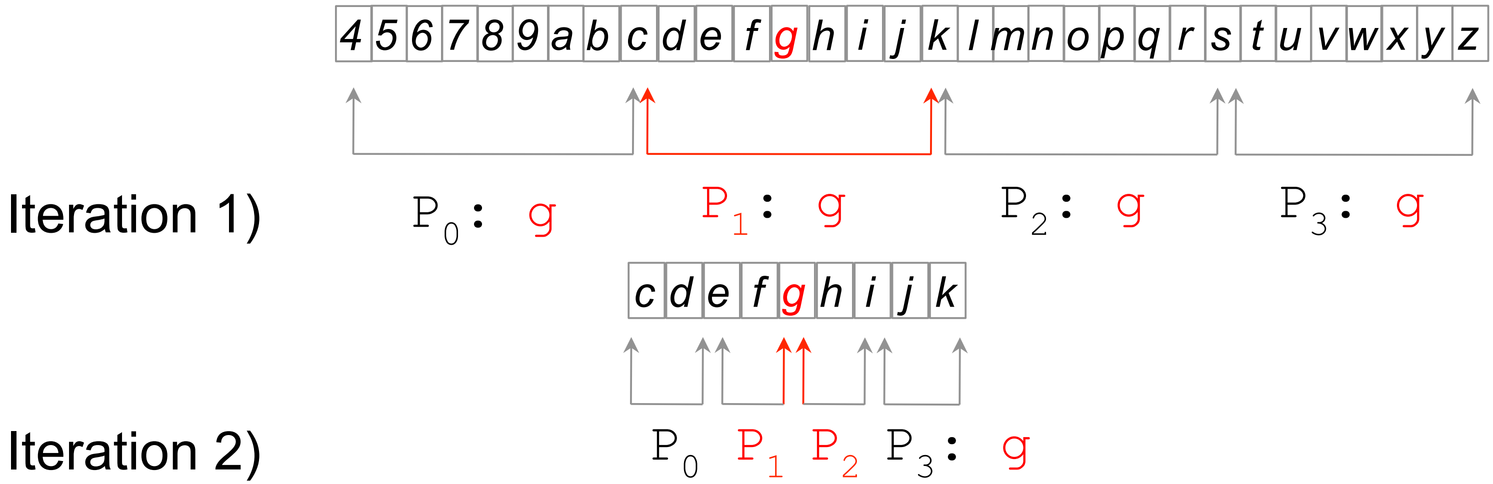
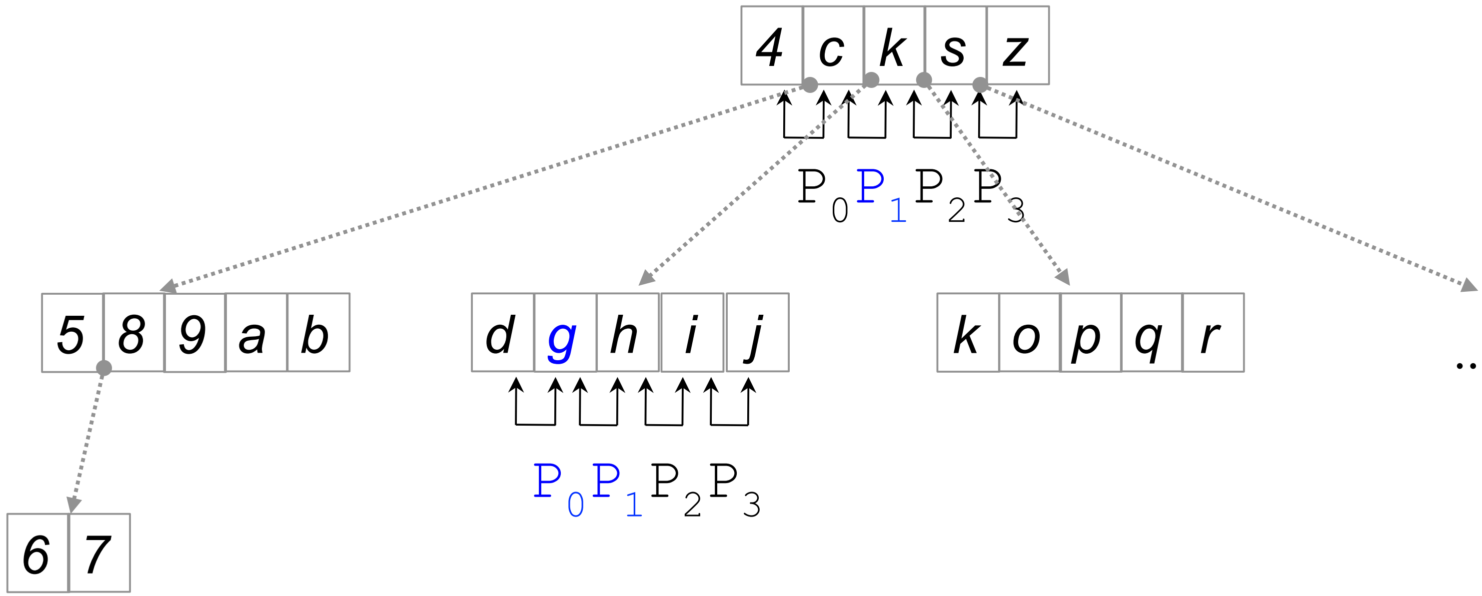


  - Synchronization ~ repartition cost
  - pthreads ($$), **`cmpxchng`**($)
  - SIMD SSE-vector, GPU threads via shared memory (~0)
- Implementation using a B-tree is similar and (obviously) faster

P-ary Search - Implementation

- B-trees group pivot elements into nodes



- Access to pivot elements is coalesced instead of a gather
- Nodes can also be mapped to
  - Cache Lines (CSB+ trees)
  - Vectors (SSE)
  - #Threads per block

P-ary Search on a sorted integer list – Implementation (1)

```
__shared__ int offset;
__shared__ int cache[BLOCKSIZE+2]

__global__ void parySearchGPU(int* data, int length,
                              int* list_of_search_keys, int* results)

   int start, sk;
   int old_length = length;
// initialize search range starting with the whole data set
   if (threadIdx.x ==0 ) {
      offset = 0;
      // cache search key and upper bound in shared memory
      cache[BLOCKSIZE] = 0x7FFFFFFF;
      cache[BLOCKSIZE+1] = list_of_search_keys[blockIdx.x];
      results[blockIdx.x] = -1;
   }
   __syncthreads();
   //
   sk = cache[BLOCKSIZE+1];
```

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   }
   __syncthreads();
   //
   sk = cache[BLOCKSIZE+1];
```

Why?

P-ary Search on a sorted list – Implementation (2)

```
// repeat until the #keys in the search range < #threads
while (length > BLOCKSIZE){
    // calculate search range for this thread
    length = length/BLOCKSIZE;
    if (length * BLOCKSIZE < old_length) length += 1;
    old_length = length;
    // why don't we just use floating point?
    start = offset + threadIdx.x * length;
    // cache the boundary keys
    cache[threadIdx.x] = data[start];
    __syncthreads();
    // if the searched key is within this thread's subset,
    // make it the one for the next iteration
    if (sk >= cache[threadIdx.x] && sk < cache[threadIdx.x+1]){
        offset = start;
    }
    __syncthreads();
    // all threads start next iteration with the new subset
}
```

P-ary Search on a sorted list – Implementation (2)

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        offset = start;
    }
    __syncthreads();
    // all threads start next iteration with the new subset
}
```

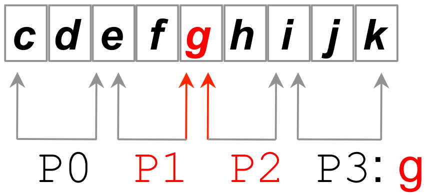
Why?

P-ary Search on a sorted list – Implementation (3)

```
    // last iteration
    start = offset + threadIdx.x;
    if (sk == data[start])
        results[blockIdx.x] = start;
}
```

P-ary Search – Analysis

- 100% processor utilization for each query
- Multiple threads can find a result
  - How does this impact correctness?



IBM

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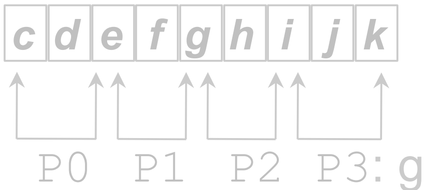
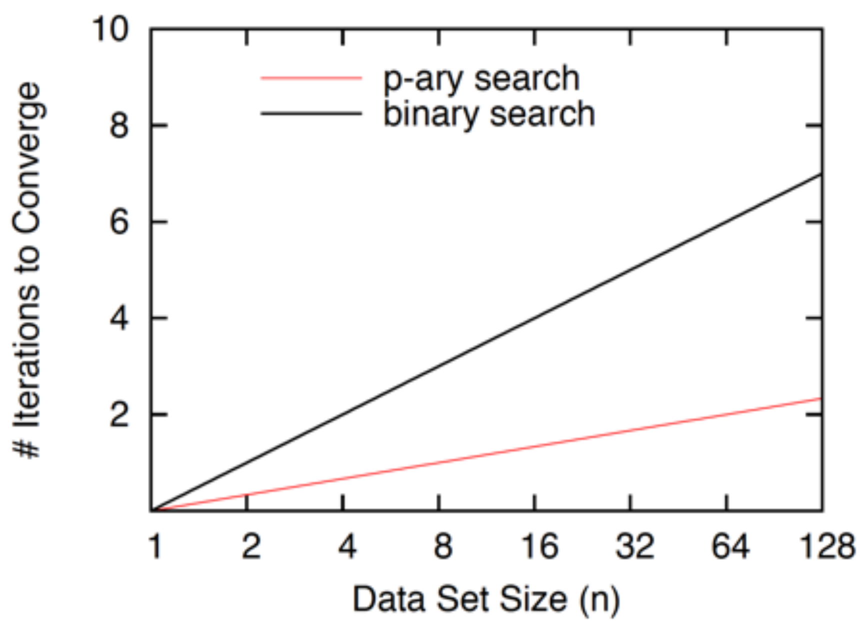


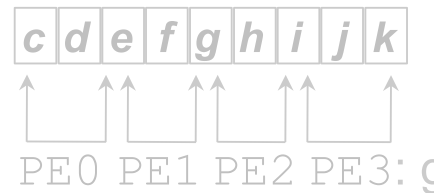
- Convergence depends on #threads
- GTX285: 1 SM, 8 cores(threads) → p=8
- Better Response time
  - $\log_p(n)$ vs $\log_2(n)$



P-ary Search – Analysis

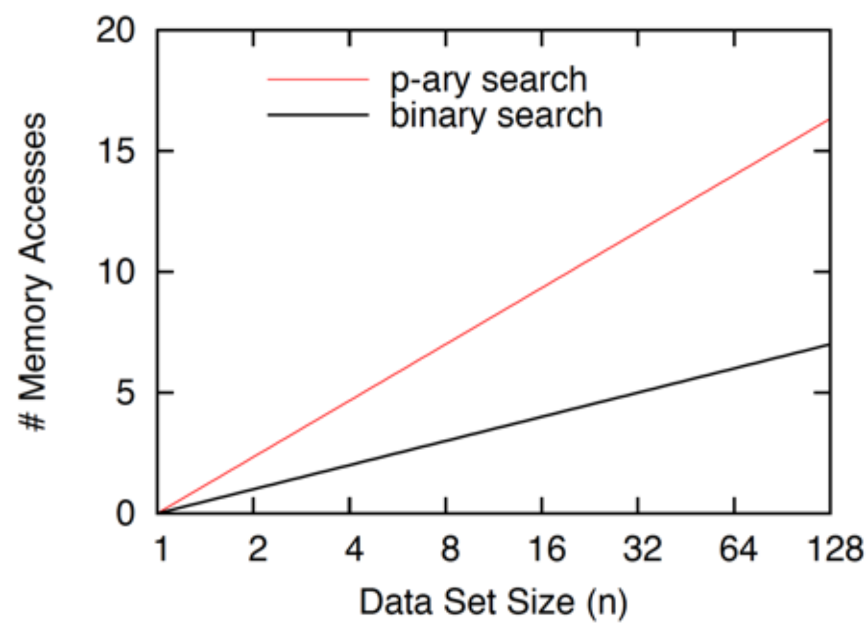
- 100% processor utilization for each query
- Multiple threads can find a result
  - Does not change correctness
- Convergence depends on #threads

GTX285: 1 SM, 8 cores(threads) → p=8



- Better Response time
  - $\log_p(n)$ vs $\log_2(n)$
- More memory access
  - (p*2 per iteration) * $\log_p(n)$
  - Caching

  (p-1) * $\log_p(n)$ vs. $\log_2(n)$



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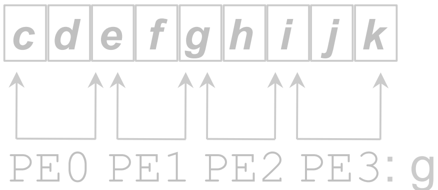

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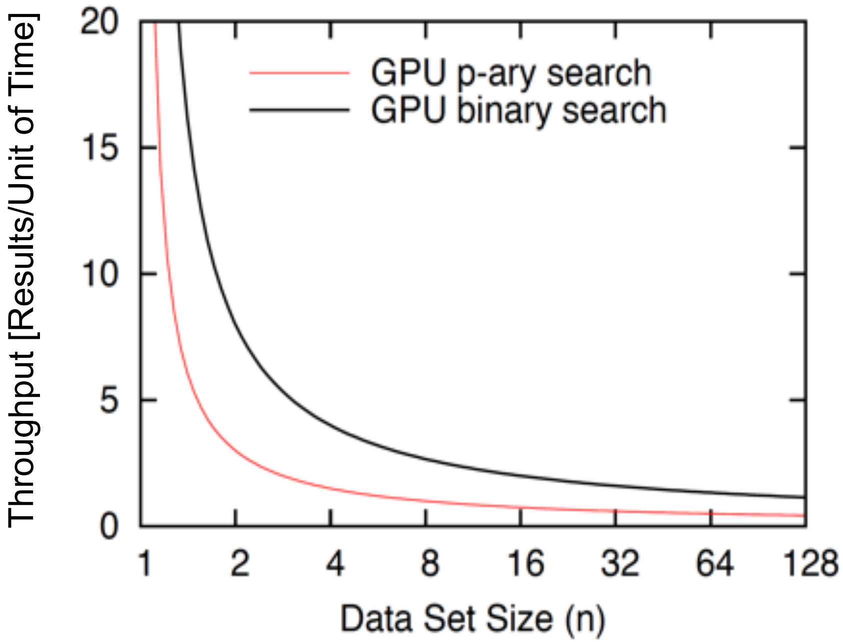
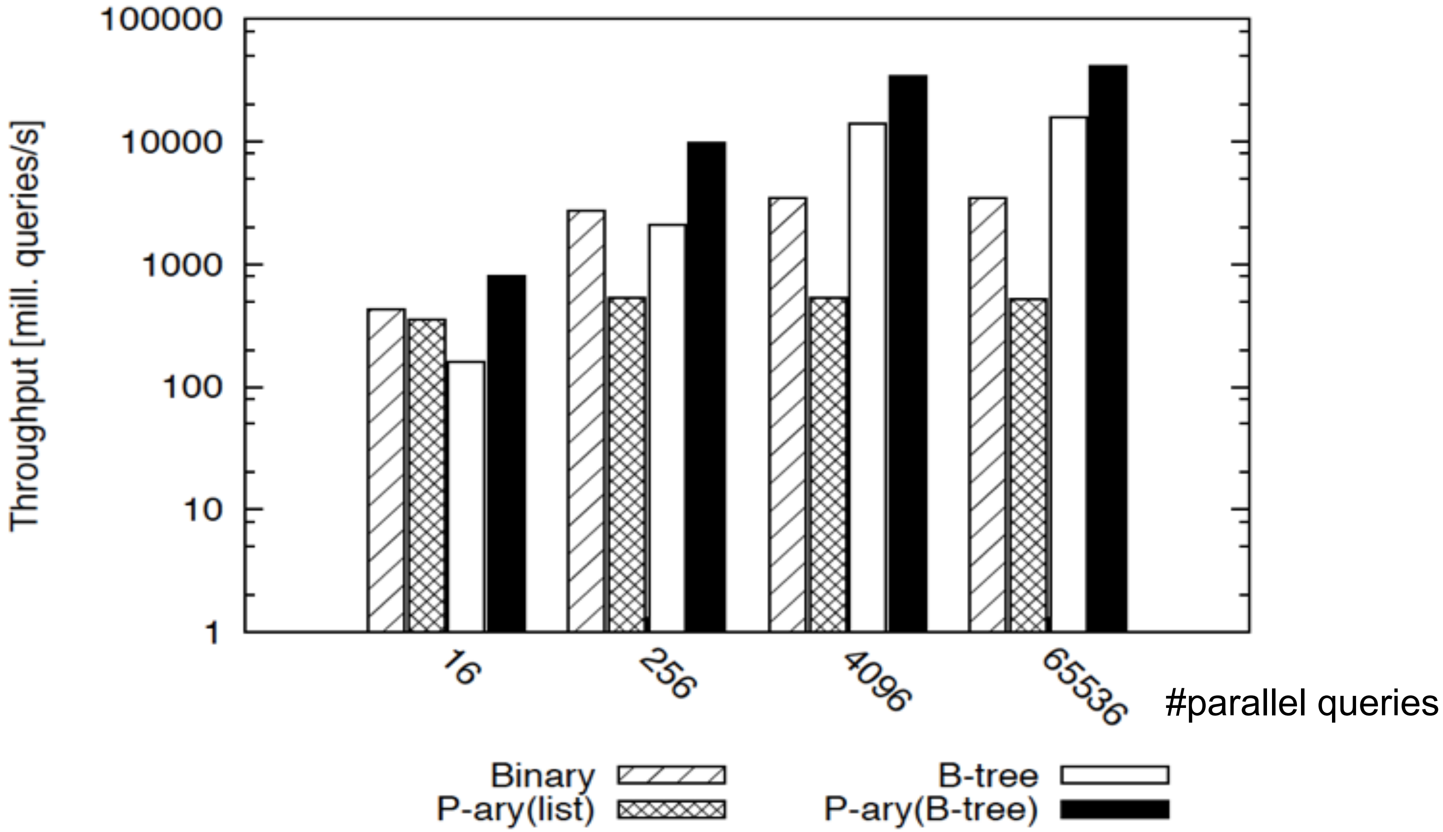
  $(p-1) * \log_p(n)$ vs. $\log_2(n)$
- Lower Throughput
  - $1/\log_p(n)$ vs $p/\log_2(n)$



P-ary Search (GPU) – Throughput

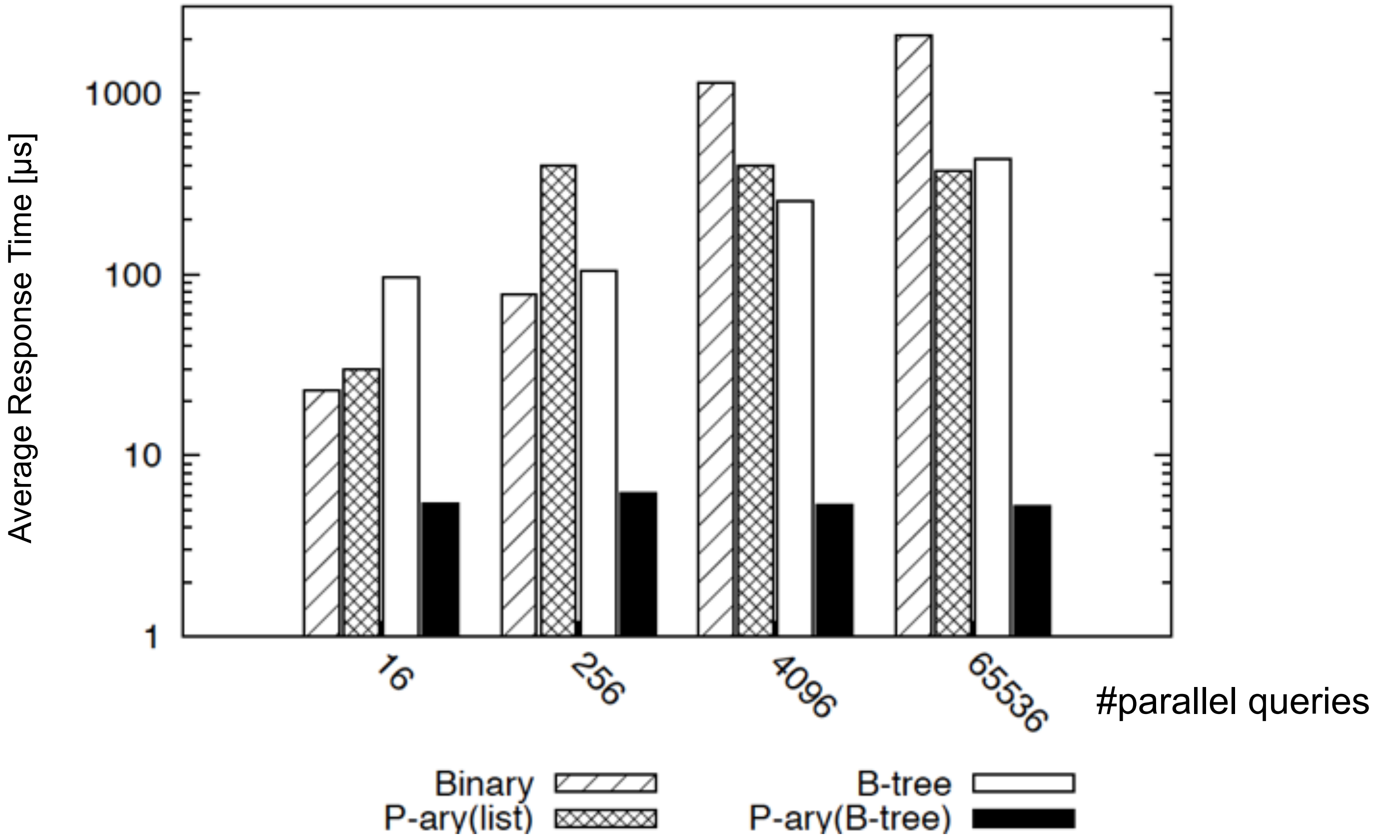
- Superior throughput compared to conventional algorithms



Searching a 512MB data set with 134mill. 4-byte integer entries,
Results for a nVidia GT200b, 1.5GHz, GDDR3 1.2GHz.

P-ary Search (GPU) – Response Time

- Response time is workload independent for B-tree implementation



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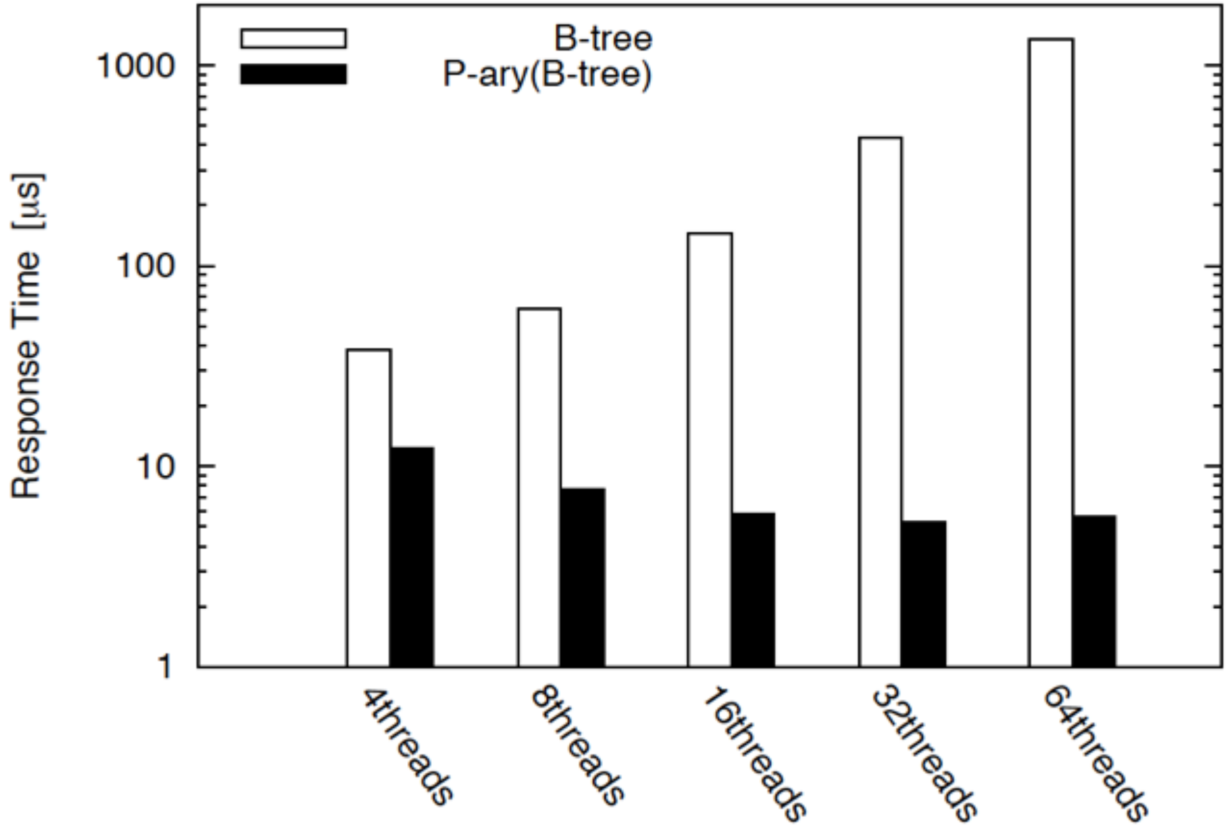
P-ary Search (GPU) – Scalability

- GPU Implementation using SIMT (SIMD threads)
- Scalability with increasing #threads (P)



64K search queries against a 512MB data set with 134mill. 4-byte integer entries,
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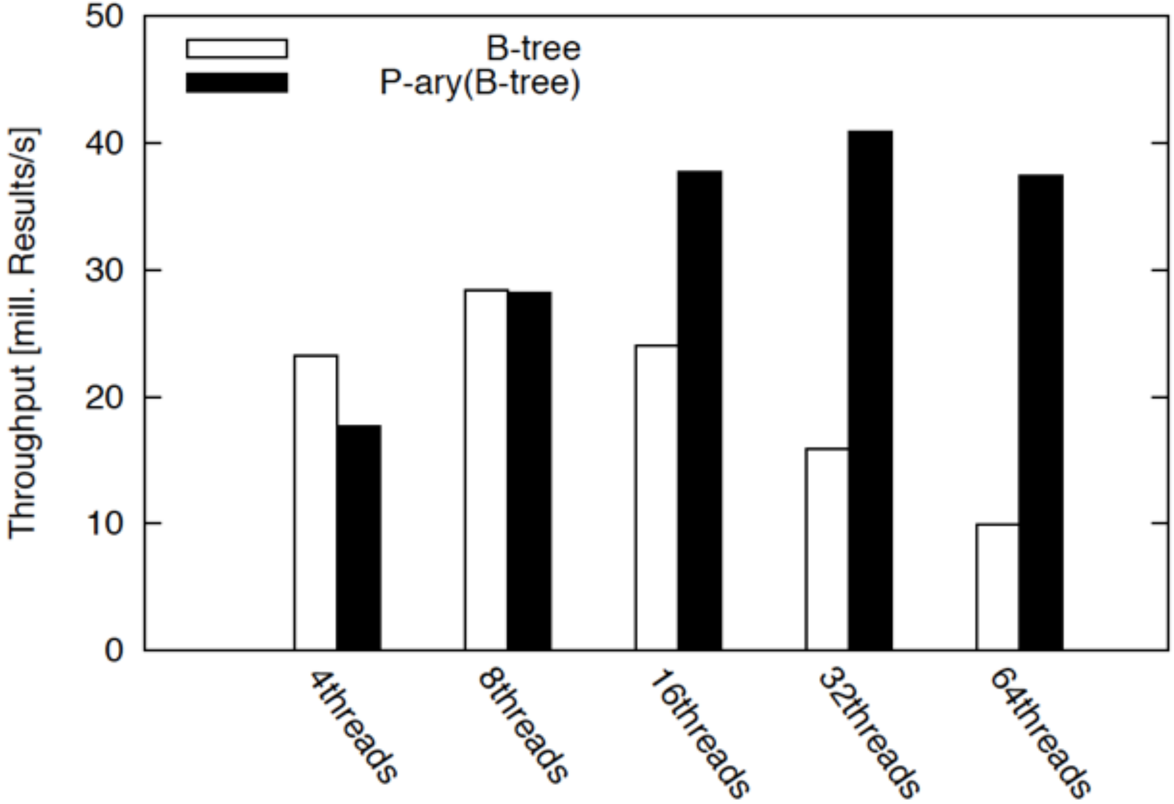

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Questions?