Programming GPUs for database applications

- outsourcing index search operations







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Why Search?

Honestly, how many times a day do you visit



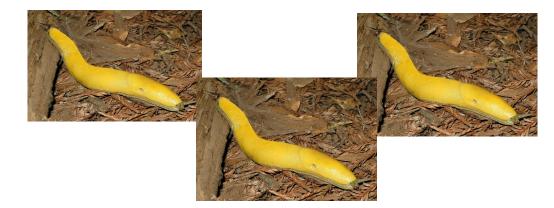


?

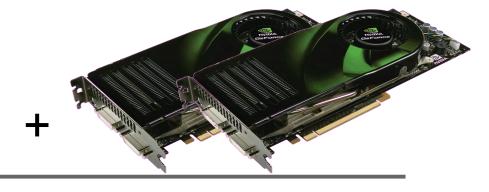








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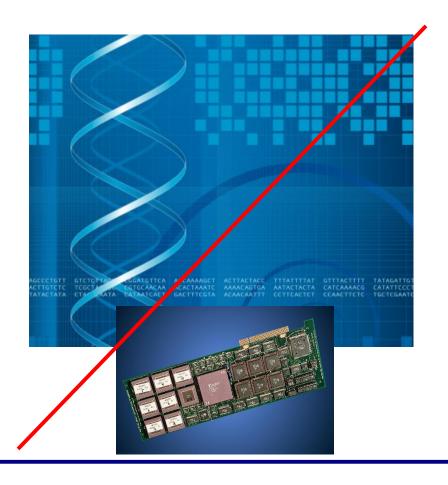
Agenda

- Introduction
 - GPU & DB (search)?
- GPU search
 - A first implementation binary search
 - Conventional search algorithms & GPUs a mismatch
 - Back to the drawing board:
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 - Experimental evaluation
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Database Workloads

- Data-intensive
- Processor performance is not a problem
- Sifting through large quantities of data fast enough is

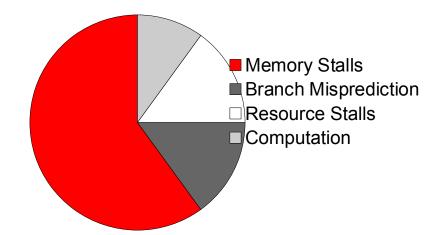






DB Performance – Where does Time Go

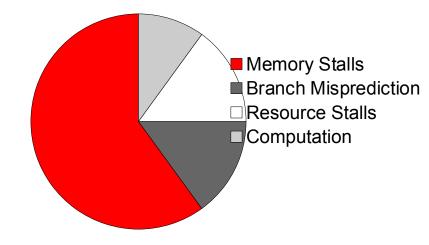
- CPU? I/O? Memory ? 1
 - 10% indexed range selection





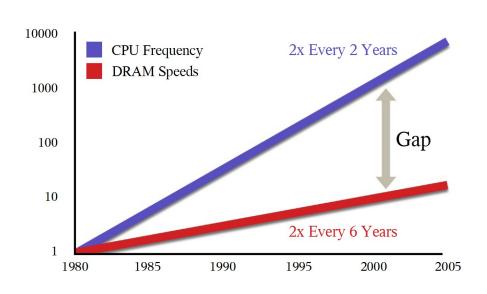
DB Performance – Where does Time Go

- CPU? I/O? Memory ? 1
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• It's getting worse ²



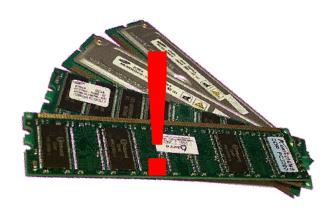


¹ A. Ailamaki, et al. DBMSs on a modern processor: Where does time go? VLDB'99

² David Yen. Opening Doors to the MultiCore Era. MultiCore Expo 2006



DB Performance – "It's the memory stupid!" ³

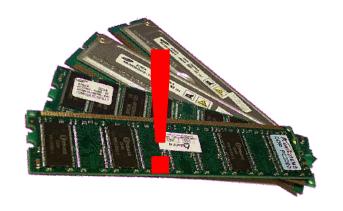




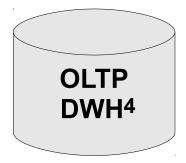
DB Performance – "It's the memory stupid!" 3

And worse:

- Growth rates of main memory size have outstripped the growth rates of structured data in the enterprise ⁴
- Multiple GB main memory DB ...





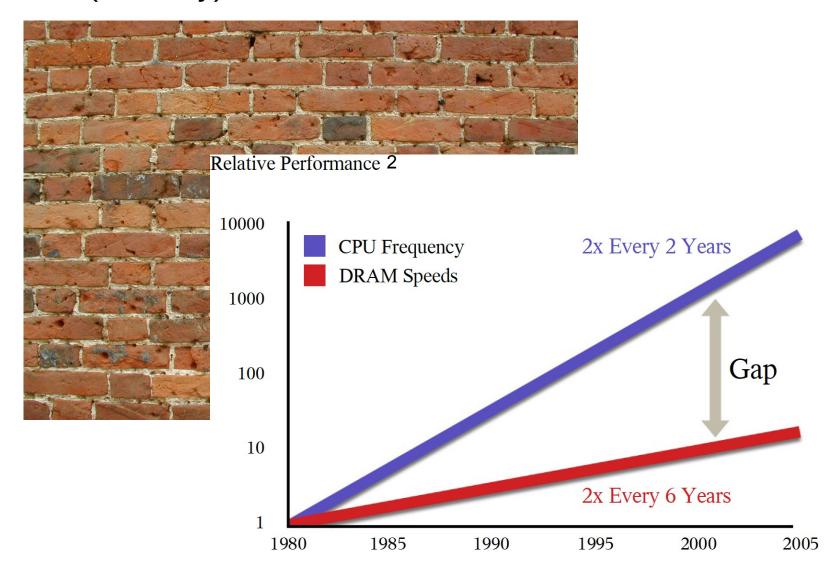


³ R. Sites. It's the memory, stupid! MicroprocessorReport, 10(10),1996

⁴ K. Schlegel. Emerging Technologies Will Drive Self-Service Business Intelligence. Garter Report 2/08



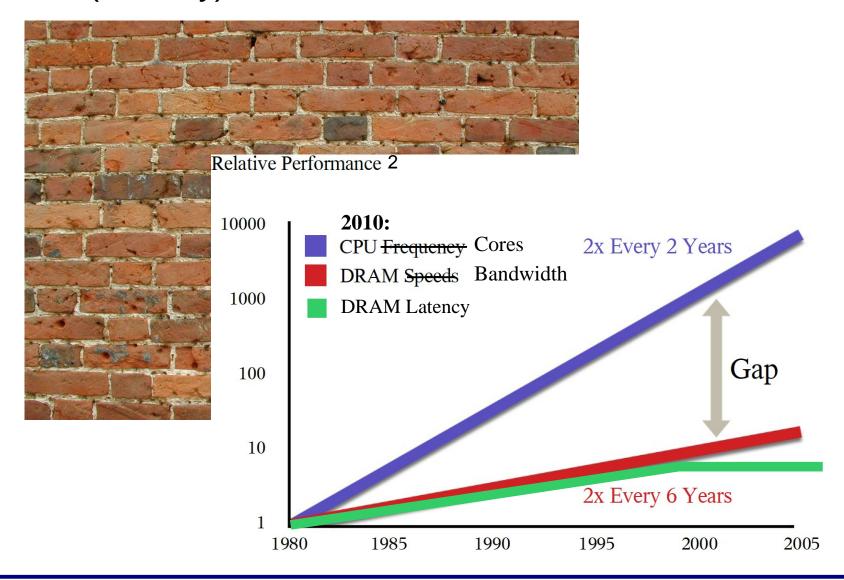
The (Memory) Wall ⁵



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The (Memory) Wall ⁵

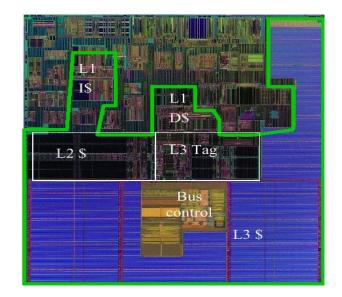


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Overcoming the Memory Wall

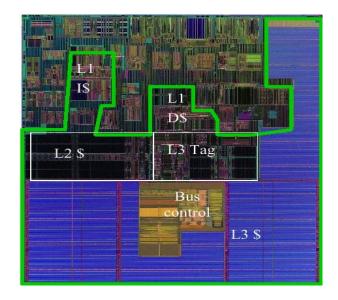
- Larger caches
 - Specialized processors
 - Top10 TPC-H 6/10 use Itanium





Overcoming the Memory Wall

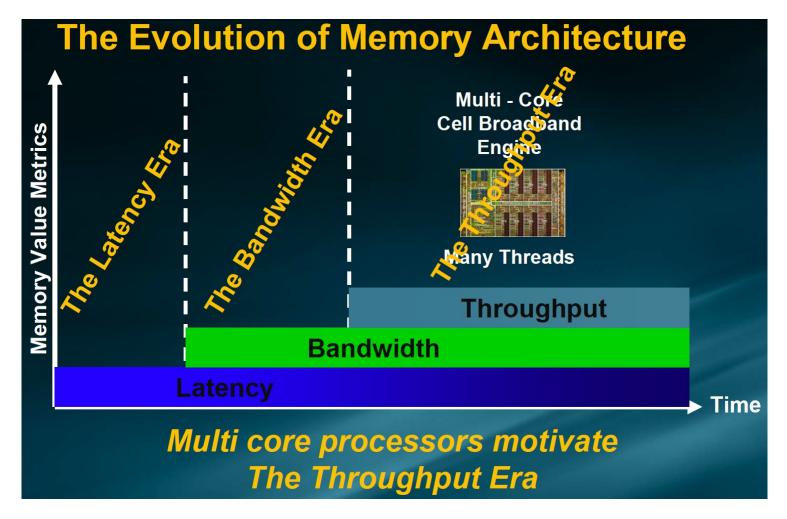
- Larger caches
 - Specialized processors
 - Top10 TPC-H 6/10 use Itanium
- Wait it out?







Parallel Memory Accesses → Throughput Computing



Source: Terabyte Bandwidth Initiative, Craig Hampel - Rambus, HotChips'08



GPUs as an example for highly parallel architectures

- Besides Teraflop(s) GPU's offer:
 - Massive Parallelism (240 cores)
 - 100+ GB/s memory bandwidth/throughput
 - Better performance per watt and per sqft. than CPUs





GPU performance specs & measurements

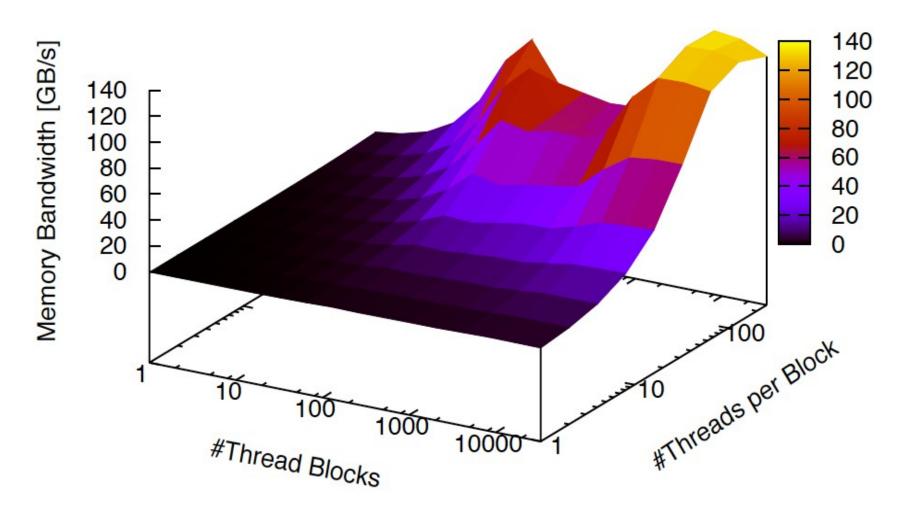




	GPU (GTX285)	CPU (i7-2600)
Power consumption	200 W	95 W
Peak Compute [Spec]	1063 GFLOP	109 GFLOP
Peak Memory Bandwidth [Spec]	160 GB/S	21 GB/s
Coalesced/Sequential Read [Measured]	140 GB/s	18 GB/s
Random Read [Measured]	8 GB/s	0.8 GB/s



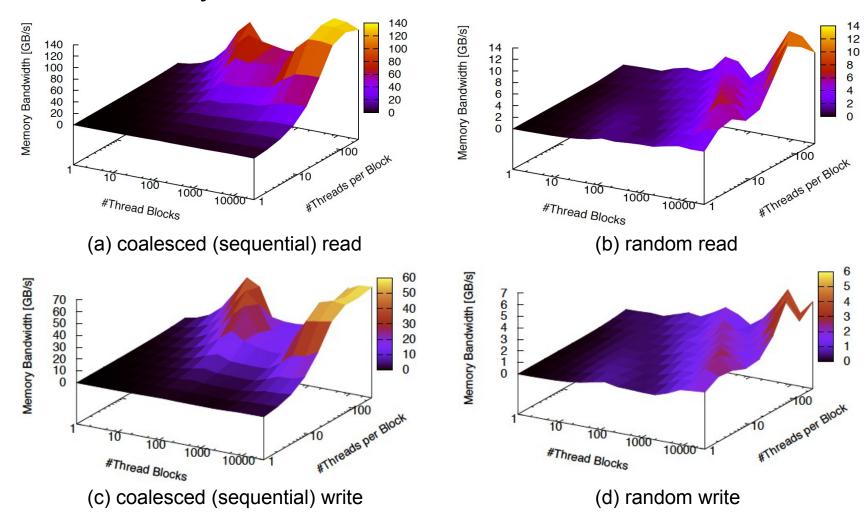
GPU memory bandwidth – it's a throughput machine



Bandwidth of sequential (coalesced) 32-bit read access for multiple thread configurations. Results for a nVidia GTX 285 1.5GHz, GDDR3 1.2GHZ.



GPU memory bandwidth



Parallel memory bandwidth for multiple thread configurations and access patterns. Results for a nVidia GTX 285 1.5GHz, GDDR3 1.2GHZ.



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Keyword

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



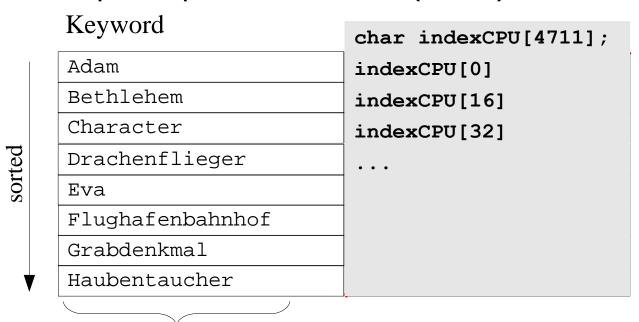
Keyword

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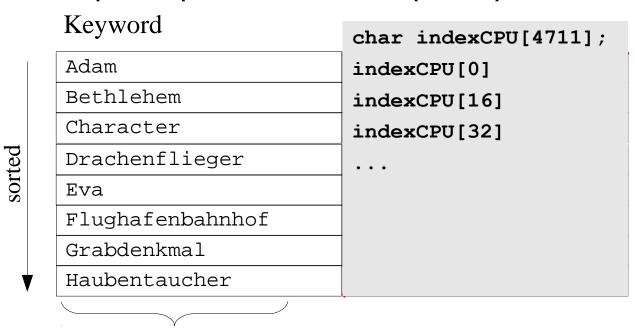
16 characters max.





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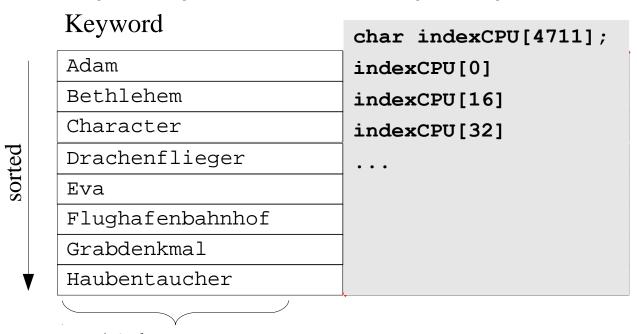




16 characters max.

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





16 characters max.

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

Can we just port a CPU implementation?



Get the data to the GPU



Get the data to the GPU

- Know your hardware (GTX 285, 32 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...
```



The GPU kernel



The GPU kernel

- 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



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```

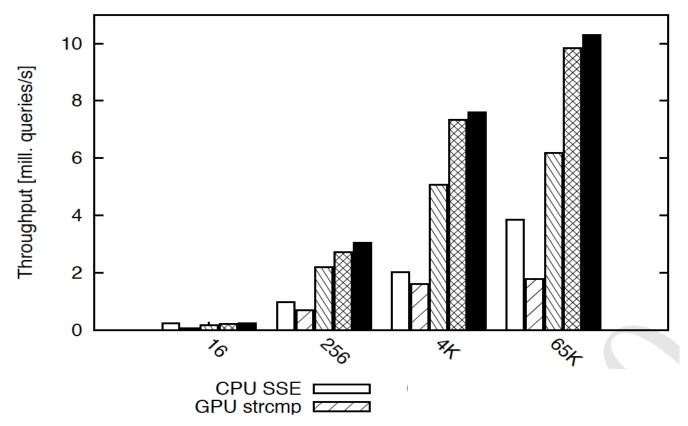
- Still need strcmp
- Again, stick __device__ in front of the libc code

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



Binary Search on the GPU

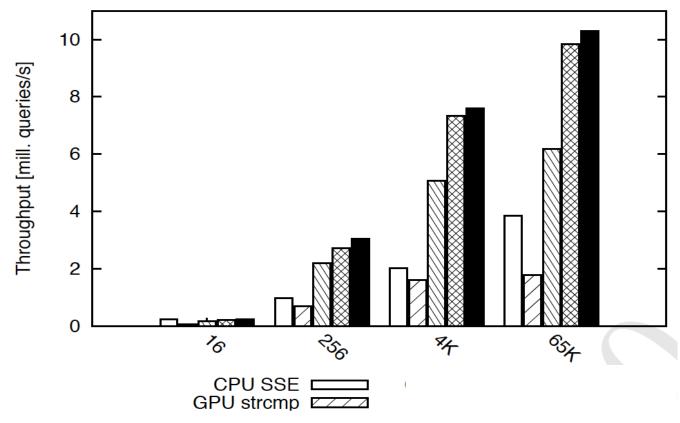
Searching a large data set (512MB) with 33 million (225)
 16-character strings





Binary Search on the GPU – Why is it slow?

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



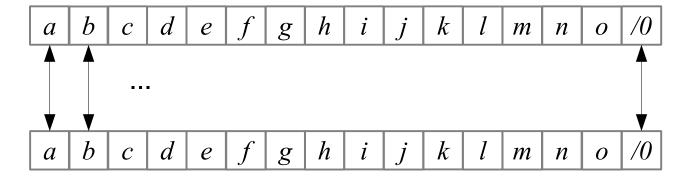
- It's slower than a CPU implementation for all data set sizes!
 - Let's try some optimizations ...



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));
}
```

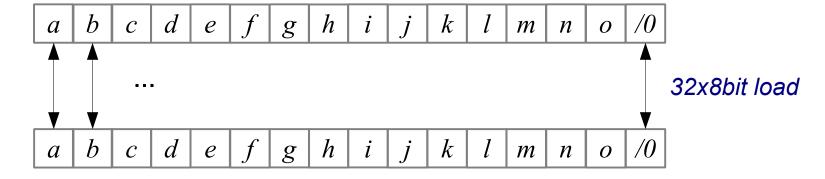




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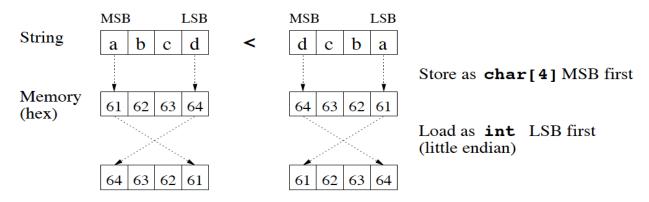
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        if (*s1++ == 0)return 0;
    return (*s1 - *(s2 - 1));
}
```



Byte-wise memory access is known to be slow

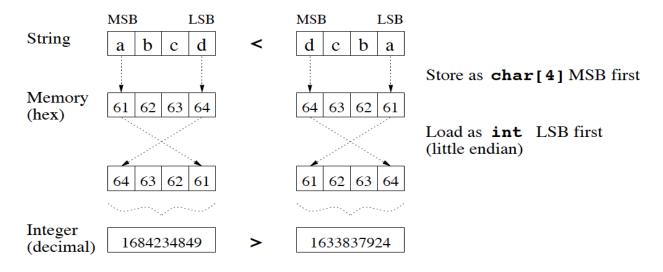


- How about vector string comparison, a la SSE?
- No Byte vectors on the GPU ... but Integer vectors



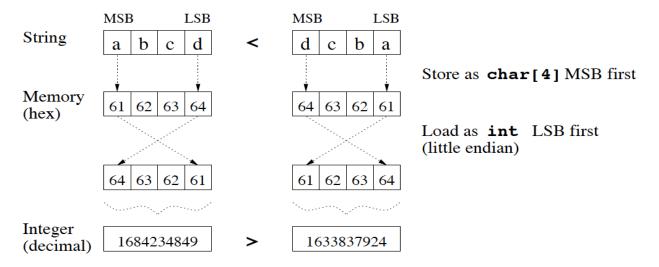


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- How about vector string comparison, a la SSE?
- No Byte vectors on the GPU ... but Integer vectors



- 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) & 0x00FF00000 ) ; \
temp = temp | ( ( unsigned ) ( x ) >> 8) & 0x000FF00 ) ; \
x = temp | ( unsigned ) ( x ) >> 24 ) ;
```



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

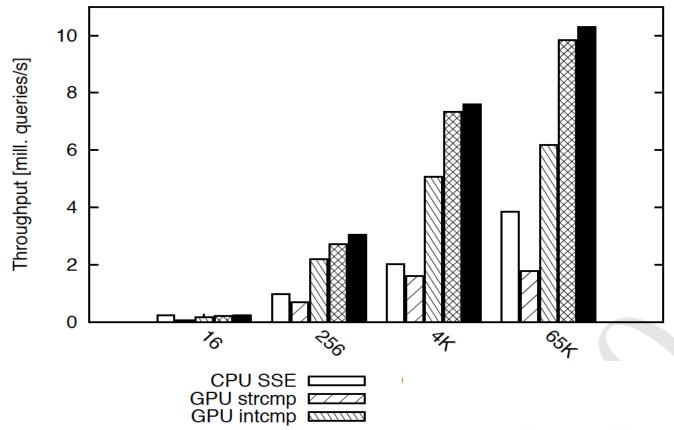
```
device int intcmp(uint4* a, uint4* b) {
  int r = 1;
  if ((*a).x < (*b).x)
     r=-1;
  else if ((*a).x == (*b).x) {
       if ((*a).y < (*b).y)
          r=-1;
       else if ((*a).y == (*b).y) {
            if ((*a).z < (*b).z)
               r=-1;
            else if ((*a).z == (*b).z) {
                 if ((*a).w < (*b).w)
                    r=-1;
                 else if ((*a).w == (*b).w)
                    r=0;
  return r;
```

Still dereferencing 16 memory pointers ...



Binary Search on the GPU – Why is it slow?

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



- With intemp 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

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

We can use shared memory like L1

x 16 for each comparison !!!



Reducing global memory access

Intemp is memory latency sensitive

	L1	L2	L3	mem
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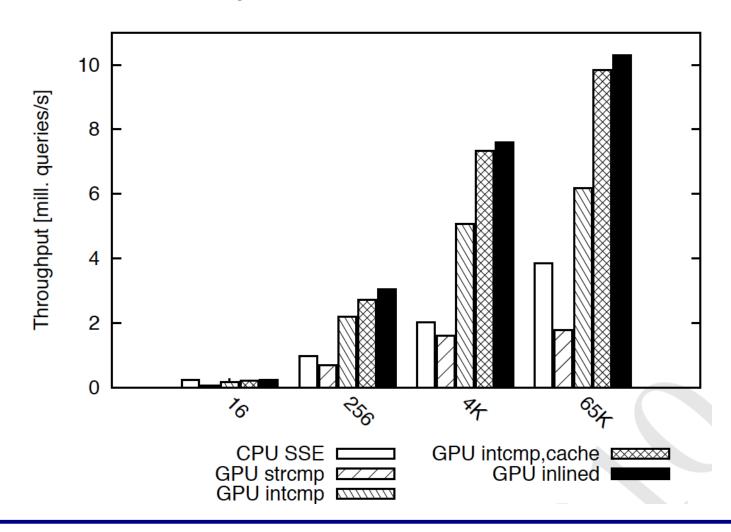
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Binary Search on the GPU – optimized

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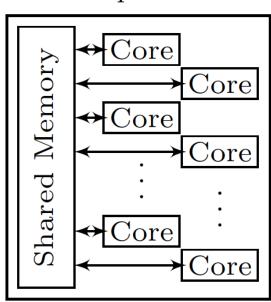




GPU architecture reminder – SIMD/SIMT

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

Multiprocessor







Multi-threaded Binary Search – Example

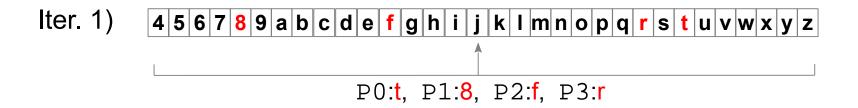
- 1 Index: a sorted char array 32 entries
- 4 queries: t, 8, f, r
- 4 processor cores: P1-P4
- 1 processor core 1 search: P0:t, P1:8, P2:f, P3:r
- Theoretical worst-case execution time: log₂(32)=5

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



Multi-threaded Binary Search – Example

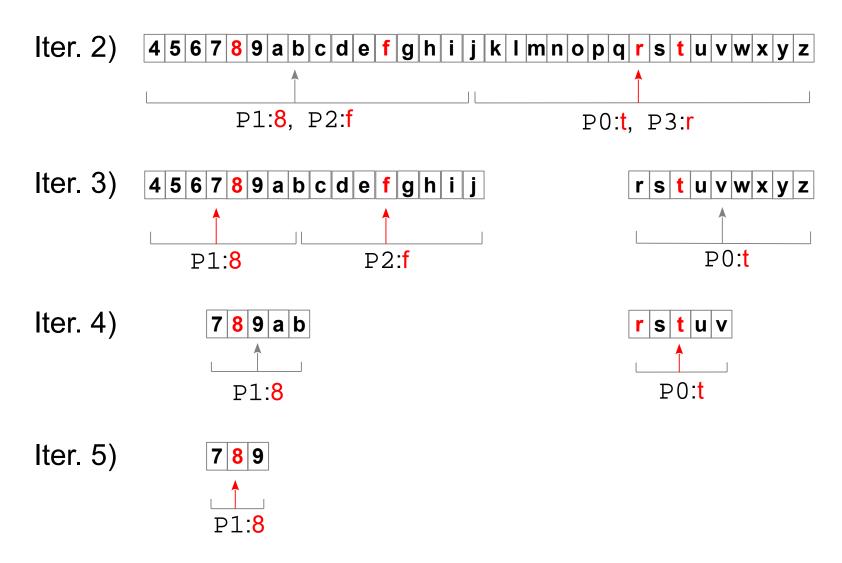
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Multi-threaded Binary Search – Example





Conventional multi-threading – Analysis

- 100% utilization requires #cores concurrent queries
- Queries finishing early
 - → utilization < 100%
- Memory access collisions
 - → serialized memory access
- #memory accesses log₂(n)
- More threads
 - → more results
 - → response time likely to be worst case: log₂(n)



Can we improve the worst case?



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- Porting search to the GPU using CUDA
 - Conventional search and GPU architecture a mismatch
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Our Goal

• Improve response time (latency) of core database functions like search in the era of throughput oriented (parallel) computing.

Research Question

- How can we (algorithmically) exploit parallelism to improve response time (of search)?
 - Can we trade-off throughput for latency?
 - Do we have to trade?



Binary Search

How Do you (efficiently) search an index?



Open phone book ~middle

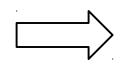
- 1st name = whom you are looking for?
- < , > ?
- Iterate
 - Each iteration:#entries/2 (n/2)
 - Total time:
 - $\rightarrow \log_2(n)$



Parallel (Binary) Search

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







Divide et impera!

- Give each of them 1/4 *
- Each is using binary search takes log₂(n/4)
- All can work in parallel → faster: log₂(n/4) < log₂(n)

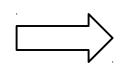
^{*} You probably want to tear it a little more intelligent than that, e.g. at the binding ;-)



Parallel (Binary) Search

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Divide et impera!

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- Each is using binary search takes log₂(n/4)
- All can work in parallel → faster: log₂(n/4) < log₂(n)
- 3 of you are wasting time!



• Divide et impera !!



How do we know who has the right piece?



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</p>
 - Redistribute
 - Otherwise ... throw it away
 - Iterate



What do we get?

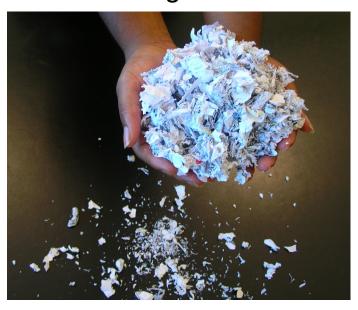


- Each iteration: n/4
 - $\rightarrow \log_4(n)$
- Assuming redistribution time is negligible: log₄(n) < log₂(n/4) < log₂(n)
- But each does 2 lookups!
- How time consuming are lookup and redistribution?





What do we get?



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 → log₄(n)
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II II memory synchronization access



What do we get



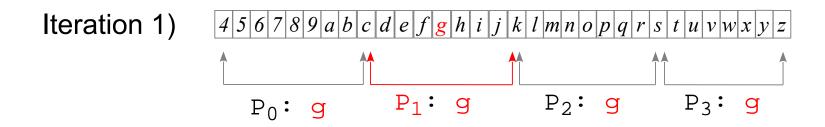
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- How time consuming are lookup and redistribution?

II II memory synchronization access

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

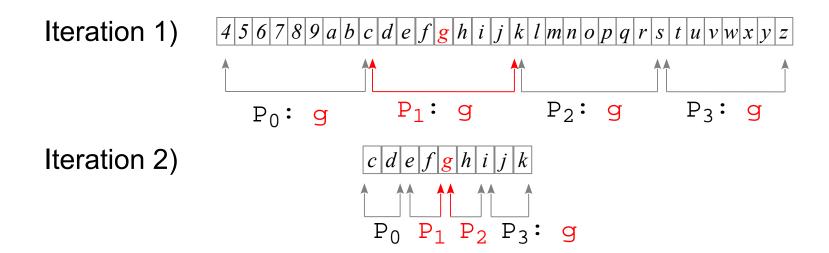


- Strongly relies on fast synchronization
 - friends = threads / processor cores / vector elements



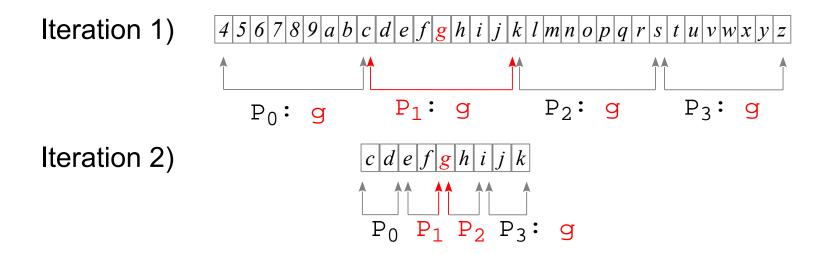


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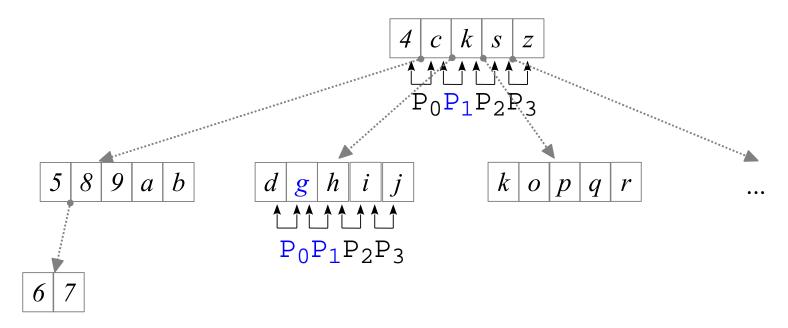
- Strongly relies on fast synchronization
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- Synchronization ~ repartition cost
 pthreads (\$\$), cmpxchng(\$),
 SIMD {SSE-vector, GPU threads via shared memory} (~0)
- Implementation using a B-tree is similar and (obviously) faster



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)



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

```
global void parySearchGPU(int* data , int range length , int*
                            search keys , int* results)
 int sk , old range length=range length, range start ;
 // initialize search range starting with the whole data set
 // this is done by one thread
 if (threadIdx.x==0) {
    range offset=0;
    // cache search key and upper bound in shared memory
    cache[BLOCKSIZE]=0x7FFFFFFF;
    cache[BLOCKSIZE+1] = searchkeys[blockIdx.x];
 // require a sync, since each thread is going to
 // read the above now
 Syncthreads();
 sk = cache[BLOCKSIZE+1];
```



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

```
// repeat until the #keys in the search range is
// smaller than the number of threads
while (range length>BLOCKSIZE) {
    // calculate search range for this thread
    // avoiding floating point operations
    range length = range length/BLOCKSIZE;
    if (range length * BLOCKSIZE < old range length)</pre>
        range length+=1;
    old range length=range length;
    range start = range offset + threadIdx.x * range length;
    // cache the boundary keys
    cache[threadIdx.x]=data[range start];
      syncthreads();
    // if the seached 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]){</pre>
        range offset = range start;
    // all threads need to start next iteration
    // with the new subset
    syncthreads();
```

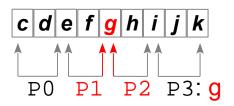


P-ary Search on a sorted list – Implementation (3)

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

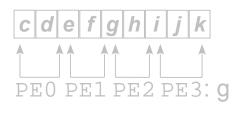


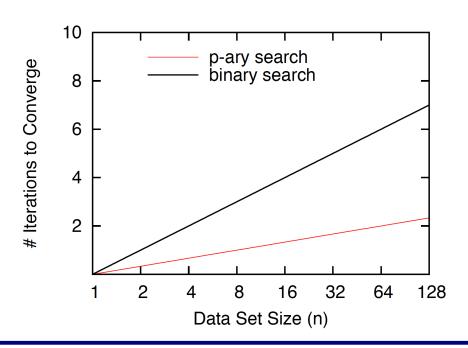
- 100% processor utilization for each query
- Multiple threads can find a result
 - Does not change correctness





- 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 $\log_2(n)$



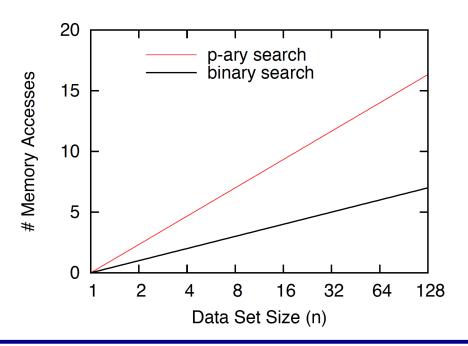




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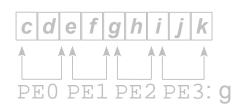


- Better Response time
 - $-\log_p(n)$ vs $\log_2(n)$
- More memory access
 - (p*2 per iteration) * log_p(n)
 - Caching(p-1) * log_p(n) vs. log₂(n)

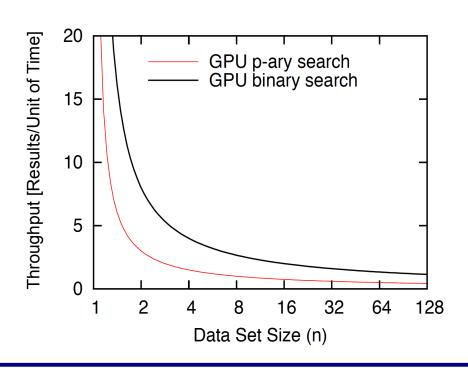




- 100% processor utilization for each query
- Multiple threads can find a result
 - Does not change correctness
- Convergence depends on #threads
 GTX285: 1 SM, 8 cores(threads) → p=8



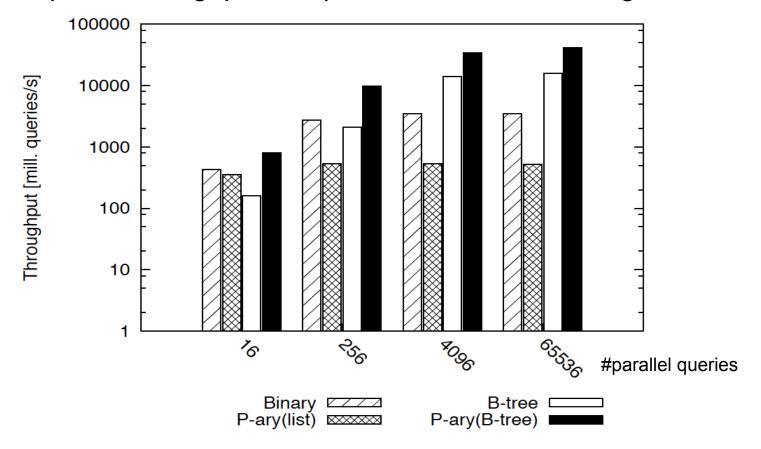
- Better Response time
 - $-\log_p(n)$ vs $\log_2(n)$
- More memory access
 - p*2 per iteration * log_p(n)
 - Caching $(p-1) * log_p(n) vs. log_2(n)$
- Lower Throughput
 - $-1/log_p(n)$ vs $p/log_2(n)$





P-ary Search (GPU) – Throughput

Superior throughput compared to conventional algorithms

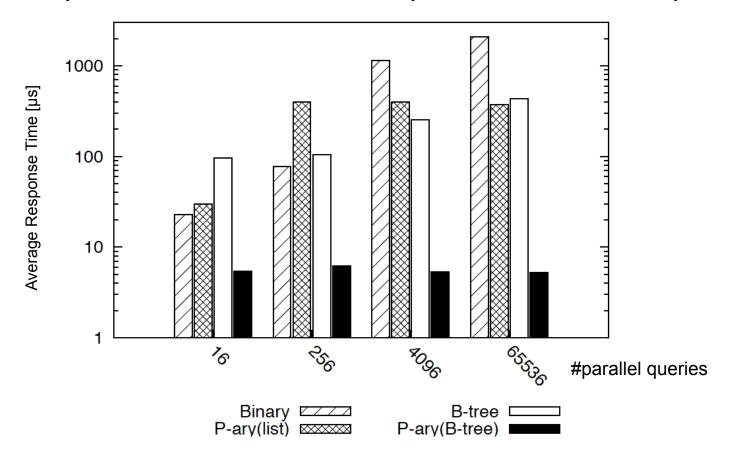


Searching a 512MB data set with 134mill. 4-byte integer entries, Results for a nVidia GT200b, 1.5GHz, GDDR3 1.2GHz.



P-ary Search (GPU) – Response Time

Response time is workload independent for B-tree implementation

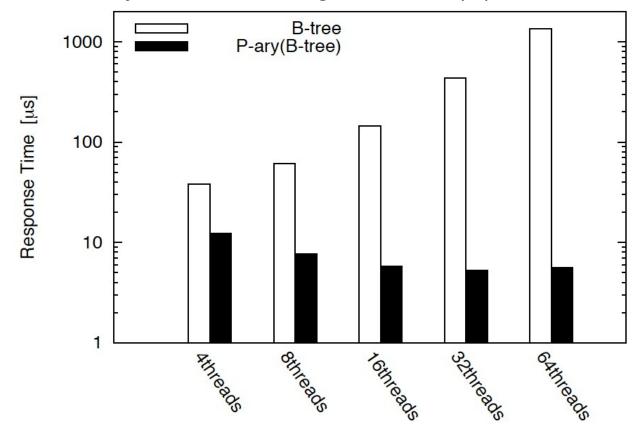


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P-ary Search (GPU) – Scalability

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

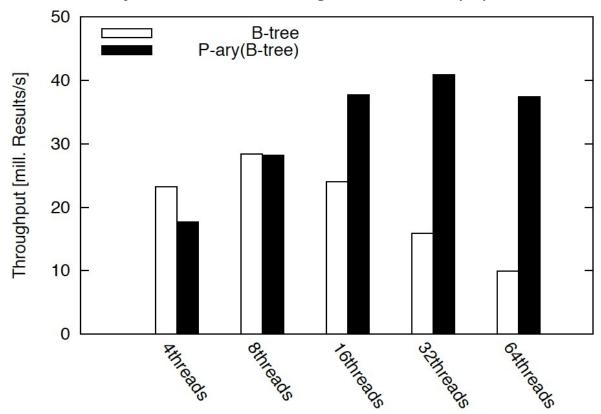


64K search queries against a 512MB data set with 134mill. 4-byte integer entries, Results for a nVidia GT200b, 1.5GHz, GDDR3 1.2GHz.



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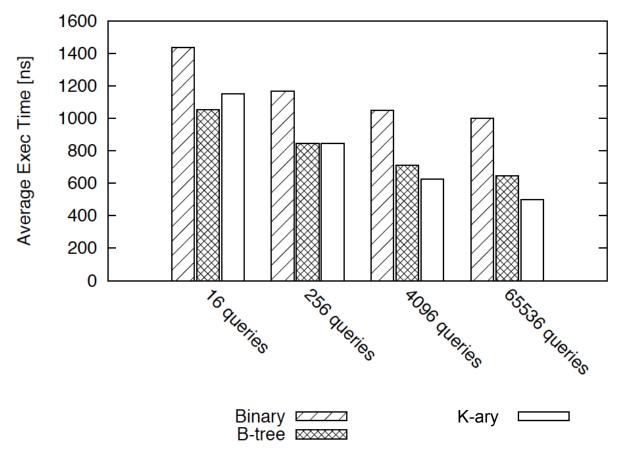


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P-ary Search(CPU) = K-ary Search

 K-ary¹ search is the same algorithm ported to the CPU using SSE vectors (int4) → convergence rate log4(n)

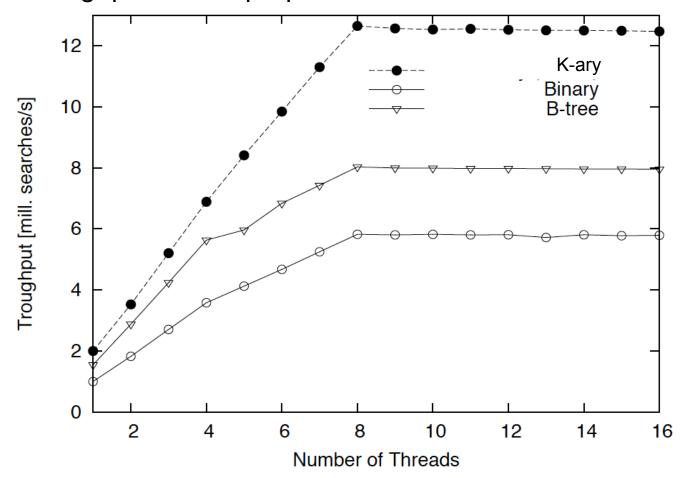


Searching a 512MB data set with 134mill. 4-byte integer entries, Core i7 2.66GHz, DDR3 1666.



P-ary Search(CPU) = K-ary Search

Throughput scales proportional to #threads



64K search queries against a 512MB data set with 134mill. 4-byte integer entries, Core i7 2.66GHz, DDR3 1666.



P-ary search - an architecture perspective

- Architecture trends
 - Memory latency has bottomed out more than a decade ago
 - Parallel memory bandwidth keeps increasing
 - e.g. Core 2 8GB/s, Core i7 24GB/s (10GB/s per core)
 - Multi-core is just the beginning, many-core is the future
 - Cache per core keeps decreasing (GPU, no caches)
 - Linear (coalesced) memory accesses take its place
 - Core/ thread synchronization costs keep decreasing
- → Only thing to hope for are increases in parallel memory bandwidth



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- → Only thing to hope for are increases in parallel memory bandwidth
- P-ary search was designed under this premises and provides
 - Scalable performance fast thread synchronization
 - Reduced query response time parallel memory access
 - Increased throughput coalesced memory access
 - Workload independent constant query execution time

