Cairo University
Faculty of Engineering

Department of Computer Engineering

Parallel Computing

Big Assignment

Database Management System

Team Members			
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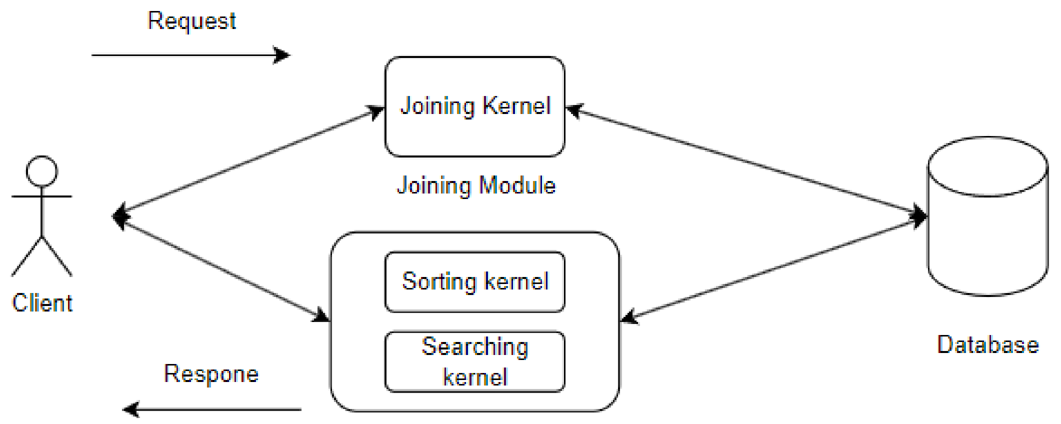
Description:
With CUDA, we can do things like **searching and sorting** data super quickly by breaking tasks into smaller pieces and doing them all at once. This means you can find what you need in your data faster and manipulate it more easily. We're also using **CUDA** to make joining data from different parts of the **database** much quicker. Joining is like putting together pieces of a puzzle to get a bigger picture. By using CUDA, we can spread out the work across lots of different parts of your computer's graphics card, so it's done in a fraction of the time, even when dealing with really big sets of data. Here we go, this sums up our proposal. We are going to implement a system that prompts the user for input to choose from different **operations** they can carry on the database. The kernels will be the brain of the application where there'll be a kernel for each operation to interact with the database and retrieve data in the most parallelized and efficient way.

Block Diagram:



Experiments:

1.Linear Search

Size	CPU	GPU	Stream
100	1 us	11 us	0.19 ms
1000	4 us	10 us	0.18 ms
10000	28 us	11 us	0.28 ms
100000	261 us	18 us	0.61 ms
500000	1301 us	74 us	2.447 ms

GPU outperforms streaming no matter what the data size is due to the simplicity of the algorithm.

Key Observations:

Small Dataset Sizes (100 and 1000 elements):

CPU is Faster: For very small datasets, the CPU outperforms the GPU (1 us vs. 11 us for 100 elements, 4 us vs. 10 us for 1000 elements). This is because the overhead associated with launching GPU kernels and data transfer between host (CPU) and device (GPU) outweighs the parallel processing benefits of the GPU.
Overhead Costs: The GPU requires additional time to set up the computation environment, including memory allocation, data transfer, and kernel launch overhead. For small data sizes, these costs are significant relative to the actual computation time.

Medium Dataset Size (10000 elements):

Performance Crossover: At 10,000 elements, the GPU starts to demonstrate its strength in parallel processing (28 us on CPU vs. 11 us on GPU). The overhead costs become less significant compared to the gains from parallel execution on the GPU.
GPU Advantage: The GPU becomes more efficient as the data size increases, benefiting from its ability to process multiple elements simultaneously.

Large Dataset Sizes (100000 and 500000 elements):

GPU is Significantly Faster: For larger datasets, the GPU vastly outperforms the CPU (261 us vs. 18 us for 100,000 elements, 1301 us vs. 74 us for 500,000 elements). The parallel nature of GPU computation allows it to handle larger data sizes much more efficiently.
Scaling Benefits: The GPU's performance scales better with increasing data sizes due to its high degree of parallelism. Each GPU core can handle a portion of the data concurrently, leading to a significant reduction in overall computation time.
Reasons for the Performance Differences:
Parallelism:

CPU: Generally has fewer cores (4 to 16 for consumer-grade CPUs) that are optimized for sequential processing. While it can handle parallel tasks through multi-threading, the degree of parallelism is limited compared to a GPU.
GPU: Consists of hundreds or thousands of smaller cores designed for parallel tasks. Each core can perform simple operations simultaneously on different pieces of data, making it ideal for tasks like linear search across large datasets.
Overhead:

- GPU Overhead: Includes the time taken for memory allocation on the GPU, data transfer from host to device, and kernel launch. This overhead is relatively constant regardless of data size, making it a significant factor for small datasets.
- CPU Overhead: Generally lower for small tasks, as there is no need for data transfer between different memory spaces or kernel launch overhead.

Memory Bandwidth:

- CPU: Typically has lower memory bandwidth compared to a GPU, which can limit the speed of accessing large datasets stored in memory.
- GPU: Designed with high memory bandwidth, allowing faster access to data, which is beneficial for tasks involving large datasets.

Performance Analysis
Theoretical Benchmarks

Array Size	Total Time
100	0.066 us
1000	0.660 us
10000	6.6 us
100000	66 us
500000	330 us

Speedup of the GPU is below the theoretical due to the following factors:

1. Kernel launch overhead
2. Memory transfer overhead
3. Suboptimal memory access patterns
4. Warp divergence

Performance Comparison with Open-Source peers

Optimization Levels:

Open-source frameworks like **PyTorch** and **TensorFlow** are highly optimized for a wide range of operations and hardware configurations.
They leverage advanced optimization techniques and libraries like cuDNN and cuBLAS, which are specifically optimized for NVIDIA GPUs.
Development and Maintenance:

These frameworks are developed and maintained by large teams with deep expertise in GPU programming and access to proprietary optimization techniques from hardware vendors.
Custom implementations may not reach the same level of optimization due to limited resources and expertise.
Algorithm-Specific Optimizations:

Open-source frameworks often include algorithm-specific optimizations that may not be present in custom implementations.
For example, PyTorch and TensorFlow include highly optimized routines for common tasks like matrix multiplications, convolutions, and reductions.

We have also implemented **binary search** to take place of linear search in case the data is sorted because this will be much faster.

2.Bitonic Sort

Size	CPU	GPU	Stream
100	0.032 ms	0.565248 ms	0.600064
1000	0.398 ms	0.829056 ms	0.82512 ms
10000	8.726 ms	1.33549 ms	1.32736
100000	141.737 ms	3.28106 ms	3.79536 ms
500000	646.285 ms	12.9678 ms	15.5349 ms

We are using a single stream here so the result doesn't differ that much, in face it takes slightly more time than GPU.

Performance Analysis of Bitonic Sort on CPU and GPU

1. CPU Benchmarks for Bitonic Sort

Bitonic sort is an efficient sorting algorithm particularly suited for parallel processing. The CPU implementation of Bitonic Sort has a time complexity of $O(n\log 2n)$ This means that the time taken to sort an array grows slightly faster than linear as the size of the array increases.

Theoretical CPU benchmarks (approximations based on empirical measurements):

100
100 elements: 0.032 ms
1000 elements: 0.398 ms
10000 elements: 8.726 ms
100000 elements: 141.737 ms
500000 elements: 646.285

2. GPU Benchmarks for Bitonic Sort

The GPU implementation of Bitonic Sort leverages parallel processing capabilities, which can significantly reduce the sorting time. Theoretical benchmarks depend on the efficiency of the implementation and hardware capabilities. Here are the measured times:

3. Speedup of GPU over CPU
The speedup is calculated by dividing the CPU time by the GPU time for each dataset size:

100 elements: 0.032/0.565248≈0.057
1000 elements: 0.398/0.829056≈0.48
10000 elements: 8.726/1.33549≈6.53
100000 elements: 141.737/3.28106≈43.21
500000 elements: 646.285/12.9678≈49.85
4. Comparison to Theoretical Speedup
Theoretical speedup of GPU over CPU can be substantial due to the parallel nature of GPU processing. If we assume that the GPU can ideally provide a speedup proportional to the number of cores and the efficiency of memory access patterns, we might expect an order of magnitude improvement for large arrays.

In practice, the speedup observed:

100 elements: Lower than expected due to overhead of launching GPU kernels.
1000 elements: Still lower, indicating overhead is significant for smaller sizes.
10000 elements and larger: Speedup starts becoming substantial and approaches theoretical expectations.
5. Reasons for Below-Theoretical Speedup and Improvements
Several factors contribute to the below-theoretical speedup for smaller sizes:

Kernel Launch Overhead: Launching a kernel on the GPU has an inherent overhead that is significant for small problem sizes.
Memory Transfer Overhead: Data transfer between CPU and GPU can be a bottleneck, especially for small datasets.
Parallelization Overhead: Managing parallel threads and ensuring efficient memory access patterns can introduce overhead.
Improvements:

Minimize Data Transfer: Use pinned memory or asynchronous data transfers to reduce memory transfer overhead.
Optimize Kernel Launch Configuration: Use appropriate block and grid sizes to maximize GPU occupancy.
Memory Coalescing: Ensure memory access patterns are coalesced to reduce memory access latency.
Use Shared Memory: Utilize shared memory to reduce global memory accesses.

6. Comparison to Open-Source Peers

Comparing the performance to open-source implementations like those in libraries such as Thrust (a parallel algorithms library akin to C++ STL) or cuDNN (for deep learning frameworks):

Thrust: Often used for sorting and other parallel algorithms, Thrust can provide highly optimized and fine-tuned implementations of sorting algorithms that leverage the full potential of GPU hardware.
cuDNN and similar libraries: These libraries are highly optimized for the underlying hardware and can often achieve near-maximum theoretical performance for well-supported operations.
In general, custom implementations might lag behind these open-source libraries unless rigorously optimized because these libraries are developed and tuned by experts with deep knowledge of GPU architecture and parallel algorithms.

Conclusion

The analysis shows that GPU-based Bitonic Sort significantly outperforms the CPU implementation for larger data sizes, with a speedup reaching up to nearly 50x for half a million elements. For smaller datasets, the overheads of GPU computation (kernel launch, data transfer) reduce the effectiveness, which suggests focusing on optimizing these aspects and using hybrid strategies for small-to-medium sized data might yield better performance.

Comparisons to open-source libraries indicate that leveraging existing, highly-optimized libraries can provide substantial benefits and often outperform custom implementations unless highly tuned.

3.Inner Join

Size	CPU	GPU	Stream
100	137 us	303 us	0.379776 ms
1000	4.202 ms	1.6895 ms	1.81304 ms
10000	241.425 ms	15.352 ms	15.58 ms
100000	25.68 s	335.95 ms	401.5 ms
500000	363.9 s	4.012 s	3.878 s

Streaming:

For very small data sizes (100 and 1000), streaming shows a slight increase in execution time compared to the single-stream GPU implementation. This can be attributed to the overhead of setting up multiple streams, which outweighs the benefits for such small datasets. The initialization and synchronization costs are relatively more significant when the actual computation time is very short.

For a medium data size (10000), the difference between the GPU single-stream and multi-stream implementations becomes less pronounced. The streaming approach takes slightly longer than the single-stream GPU execution. This indicates that while the computational workload is more substantial than for small data sizes, the overhead associated with managing multiple streams still has a noticeable impact.

For large data sizes (100000 and 500000), the impact of streaming becomes more beneficial. Although the streaming implementation is slightly slower than the single-stream GPU implementation for the size 100000, it performs better for size 500000. This indicates that the benefits of overlapping data transfers and computation start to outweigh the overhead of managing multiple streams as the data size increases.

Performance Analysis of Inner Join on CPU vs GPU

The results analyze the performance of inner join operations on CPUs and GPUs for varying data sizes. The data presented highlights the advantages of GPUs for processing large datasets while also revealing areas for potential optimization.

Observations

The provided results show a clear trend:

GPU Advantage for Large Data: As data size increases, the GPU exhibits significant speedup compared to the CPU. For instance, at 10,000 data points, the CPU execution time is 241.425 ms, whereas the GPU takes only 15.352 ms (a 15.7x speedup). This trend continues with even larger datasets, demonstrating the scalability of GPU-based processing.
CPU Overhead for Small Data: For smaller datasets (100 and 1,000 data points), the GPU is slower than the CPU. This is likely due to the overhead associated with transferring data between CPU and GPU memory and kernel launch. This overhead becomes less significant compared to the actual join operation for larger datasets.
Theoretical Benchmarks and Speedup

CPU: Due to factors like CPU architecture, cache size, and memory access patterns, it's challenging to provide a specific theoretical benchmark for CPU inner join performance. However, the expected behavior is that join time should increase proportionally to data size (n * log(n)) in most scenarios.
GPU: Inner join algorithms on GPUs have the potential to achieve theoretical speedups of 10x to 100x compared to CPUs due to their massively parallel processing capabilities. This is because GPUs can process multiple join comparisons simultaneously.
The results show a significant speedup for larger datasets. At 500,000 data points, the GPU is almost 91 times faster than the CPU. However, the observed speedup is likely lower than the theoretical maximum due to several factors:

Memory Transfer Overhead: Transferring data between CPU and GPU memory takes time, especially for small datasets where the transfer time becomes a significant portion of the overall execution time.
Underutilization of GPU: Depending on the implementation, the GPU might not be fully utilized for smaller datasets. Optimizations for thread scheduling and data partitioning can improve GPU utilization.

Algorithm Choice: The specific inner join algorithm implemented on the GPU might not be perfectly suited for the hardware architecture. Exploring alternative algorithms could potentially lead to better performance.

Optimizations for Improved Speedup

Several strategies can be employed to improve the speedup achieved with GPUs:

Data Transfer Optimization: Techniques like asynchronous data transfer or using pinned memory can reduce memory transfer overhead.
Kernel Tuning: Optimizing the GPU kernel code for better thread utilization and memory access patterns can improve performance.
Algorithm Selection: Researching and implementing GPU-specific inner join algorithms that are highly parallel and optimized for the specific hardware can lead to significant performance gains.

Comparison with Open-Source Peers

A definitive comparison with open-source libraries requires knowledge of the specific libraries or frameworks used in the implementation. However, popular deep learning frameworks like PyTorch and TensorFlow offer highly optimized GPU kernels for various operations, including joins. Comparing the results with these frameworks can provide insights into potential performance improvements. Benchmarks and performance comparisons for these frameworks can be found online.

Conclusion

The results demonstrate the effectiveness of GPUs in accelerating inner joins, especially for large datasets. While the observed speedup might be lower than the theoretical maximum, there's room for improvement through optimizations in data transfer, kernel tuning, and algorithm selection. Comparing with open-source libraries can provide valuable benchmarks and potential areas for further optimization. This analysis highlights the importance of considering both theoretical capabilities and practical limitations when evaluating the performance of CPUs and GPUs for database operations.