Part 2, course 3: Parallel External Memory and Cache Oblivious Algorithms

CR10: Data Aware Algorithms

September 23-24, 2020



Parallel External Memory

Cache Complexity of Multithreaded Computations

Experiments with Matrix Multiplication

Parallel External Memory

Model Prefix Sum Sorting List Ranking

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Multicore Memory Model Multithreaded Computations Parallel Scheduling of Multithreaded Computations Work Stealing Scheduler Conclusion

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Parallel External Memory Model

Prefix Sum Sorting List Ranking

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Parallel External Memory Model

Classical model of parallel computation: PRAM

- P processor
- Flat memory (RAM)
- Synchronous execution
- Concurrency models: Concurrent/Exclusive Read/Write (CRCW, CREW, EREW)

Extension to external memory:

- Each processor has its own (private) internal memory, size M
- Infinite external memory
- Data transfers between memories by blocks of size B

PEM I/O complexity: nb of parallel block transfers Other metrics: parallel computation time, total space

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Prefix Sum in PEM

Definition (All-Prefix-Sum).

Given an ordered set A of N elements, compute an ordered set B such that $B[i] = \sum_{k \leq i} A[i]$.

Theorem.

All-Prefix-Sum can be solved with optimal $O(N/PB + \log P)$ PEM I/O complexity.

Same algorithm as in PRAM:

- 1. Each processors sums N/P elements
- 2. Compute partial sums using pointer jumping
- 3. Each processor distributes (adds) the results to its $\ensuremath{\mathsf{N}}\xspace/\mathsf{P}$ elements

Analysis:

- ▶ Phases 1 and 3: linear scan of the data O(N/PB) I/Os
- ▶ Phase 2: at most O(1) I/O per step: $O(\log P) I/Os$

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Theorem (Mergesort in PEM).

We can sort *N* items in the CREW PEM model using $P \le N/B^2$ processors each having cache of size $M = B^{O(1)}$ in $O(N/P \log N)$ internal complexity with O(N) total memory and a parallel I/O complexity of:

$$O\left(\frac{N}{PB}\log_{\frac{M}{B}}\frac{N}{B}\right)$$

Proof: much more involved than the one for (sequential) external memory.

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List Ranking and its applications

List ranking:

- Very similar to All-Prefix-Sum: compute sum of previous elements
- But initial data stored as linked list
- Not contiguous in memory 🙁

Application:

- ► Euler tours for trees → Computation of depths, subtree sizes, pre-order/post-order indices, Lowest Common Ancestor, ...
- Many problems on graphs: minimum spanning tree, ear decomposition,...

List Ranking in PEM

In PRAM: pointer jumping, but very bad locality 🙁

Algorithm sketch for PEM:

- 1. Compute large independent set S
- 2. Remove node from S (add bridges)
- 3. Solve recursively on remaining nodes
- 4. Extend to nodes in S

NB: Operations on steps 2 and 4 require only neighbors.

Lemma.

An operation on items of a linked list which require access only to neighbors can be done in $O(\operatorname{sort}_P(N))$ PEM I/O complexity.

Computing an independent set 1/2

Objective:

- lndependant set of size $\Omega(N)$
- Or bound on distance between elements

Problem: *r*-ruling set:

There are at most r items in the list between two elements of the set

Randomized algorithm

- 1. Flip a coin for each item: $c_i \in \{0, 1\}$
- 2. Select items such that $c_i = 1$ and $c_{i+1} = 0$
- Two consecutive items are not selected.
- On average, N/4 items are selected

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Computing an independent set 2/2

Deterministic coin flipping

- 1. Choose unique item IDs
- **2**. Compute tag of each item: 2i + b
 - i: smallest index of different bits in item ID and successor ID
 - b: this bit in the current item
- 3. Select items with (local) minimum tags
- Successive items have different tags
- At most log N tag values
 - \Rightarrow distance between minimum tags $\leq 2 \log N$
- To decrease this value, re-apply step 2 on tags (tags of tags)
- Nb of steps to get constant size $k = log^*N$

PEM I/O complexity: $O(\operatorname{sort}_P(N) \cdot \log^* N)$

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Parallel Cache Oblivious Processing

In classical cache-oblivious setting:

- Cache and block sizes unknown to the algorithms
- Paging mechanism:

loads and evicts blocks (based on M and B)

When considering parallel systems:

- Same assumption on cache and block sizes
- Also unknown number of processors (or processing cores)
- Scheduler: (platform aware) places threads on processors
- Paging mechanism: as in sequential case

Focus on dynamically unrolled multithreaded computations.

Model of computation:

- P processing cores (=processors)
- Infinite memory
- ► Shared L2 cache of size C₂
- Private L1 caches of size C_1 , with $C_2 \ge P \cdot C_1$
- ▶ When a processor reads the data:
 - ▶ if in its own L1 cache: no i/O
 - otherwise, if in L2 cache, or in other L1 cache: L1 miss
 - otherwise: L2 miss
- When a processor writes a data: Stored in its L1 cache, invalidated in other caches (thanks to cache coherency protocol)
- Two I/O metrics:
 - Shared cache complexity: number of L2 misses
 - Distributed cache complexity: total number of L1 misses (sum)

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Multithreaded computations 1/2

Threads:

- Sequential execution of instructions
- Each thread has its own activation frame (memory)
- May launch (spawn) other threads (children)
- Can wait for completion or messages from other threads
- DAG of instructions
 - Continue edges: within same thread
 - Spawn edges: to create new thread
 - Join edges: message to other threads/completion
- Dynamic behavior: may depends on the data (execution graph unknown before the computation)

Constraints:

- Strict computation: Join edges only directed to ancestors in the activation tree
- ► Fully strict computation: Join edges only directed to parent in the activation tree → Series-Parallel graph of instructions

Multithreaded computations 1/2

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Classical bound on total duration:

- Work $W = T_1$: total (weighted) number of instructions
- Critical path (or span) T_{∞} : length of longest path
- Greedy scheduling: running time (makespan) bounded by $T_1/P + T_\infty$
- Tight bound (no better schedule) for some computations

In the sequential case:

- Natural order: Depth-First traversal (1DF)
- Queue (stack) of threads
- Whenever a thread is spawned:
 - Current thread put in the queue
 - Newly created thread executed

<u>Outline</u>

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Parallel Depth First Scheduling (PDF)

Parallel adaptation of 1DF, targeting shared memory

- Global pool of ready threads
- Same behavior as 1DF when spawning threads
- When a processor is idle (current threads stalls or dies): it starts working on the next thread that would be activated by the 1DF sequential scheduler
- ▶ When thread enabled (unlocked from stall), put in the pool

Theorem (Shared cache complexity).

Let C_1 (resp. C_P) be the size of the cache for 1DF (resp. PDF). If $C_P \ge C_1 + PT_{\infty}$, then PDF does at most as many shared cache misses as 1DF.

Corollary (Memory Usage)

Assuming unlimited memory, if the sequential depth first schedule uses a memory of M_1 , the work stealing execution uses at most a memory of $M_1 + PT_{\infty}$.

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Scheduler for Multicore Memory Hierarchy

Contradictory objectives:

- Re-use data as much as possible in shared cache
- Work on disjoint datasets in private caches
- Focus: divide-and-conquer algorithms

Simple recurrence relations:

T(n) = t(n) + aT(n/b) (seq. time complexity)

Q(M, n) = q(M, n) + qQ(M, n/b) (seq. cache complexity)

Hierarchical recurrence relations:

$$T_k(n) = t_k(n) + a_k T_k(n/b_k) + \sum_{i < k} a_{k,i} T_i(n/b_i)$$

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Sequential space complexity: S(n)
 r: ratio between parallel and sequential space complexity

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Controlled Parallel Depth-First

- L1-supernodes: of size $n_1 = S^{-1}(C_1)$
- L2-supernodes: of size $n_2 = S^{-1}(C_2/r)$
- Split recursion tree into L2 supernodes, executed one after the others
- Within a L2-supernode, distribute L1-supernodes to cores
- Optimal parallel speedup if enough L1-supernodes within one L2-supernode

Theorem (Cache complexities).

Asymptotically optimal L1 and L2 cache complexities:

 $Q_{L1}(n) = O(Q_k(C_1, n))$ and $Q_{L2}(n) = O(Q_k(C_2, n))$

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Work Stealing Scheduler

First ideas in the 1980s, formalised in the 1990s, now implemented in several thread schedulers (CILK, Java fork/join, Kaapi, etc.)

Distributed and dynamic scheduler:

- Each processor has its own local queue of ready threads
- Local queue stored as a deque (double-ended queue)
- When spawning a thread:
 - Current thread placed at the bottom of the local queue
 - Newly created thread executed
- When a processor is idle:
 - If work in the local queue: pick thread at the bottom
 - Otherwise, steal thread from the top of a random remote queue
- Thread enabled: put at the bottom of the local queue

NB: Dot not rely on platform characteristics.

Work Stealing: Running Time Analysis

(Similar results for many platform/computation models)

Theorem (Running time).

For a computation with work T_1 and critical path T_{∞} , the schedule obtained by work stealing has an expected duration of $T_1/P + O(T_{\infty})$. Furthermore, the duration is bounded by $T_1/P + O(T_{\infty} + \log P + \log 1/\epsilon)$ with probability at least $1 - \epsilon$.

Theorem (Number of steals).

The number of steal attempts is bounded by $O(PT_{\infty})$.

Theorem (Communication time).

The time spent in sending data among processor is bounded by $O(PT_{\infty}(1 + n_d)M_{\max})$ where:



- M_{max} : maximal memory on a processor
- n_d: maximum number of join edges to parent

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Working Stealing: Cache Complexity and Memory

Theorem (Shared Cache Complexity).

If the memory for the sequential depth first schedule is M_1 and work stealing is given a memory of PM_1 , its shared cache complexity is in $O(Q_1)$, where Q_1 is the cache complexity of the sequential schedule.

Corollary (Memory usage)

Assuming unlimited memory, if the sequential schedule uses a memory of M_1 , the work stealing execution uses a memory of PM_1 .

Theorem (Distributed Cache Complexity).

For series-parallel computations, the distributed cache complexity of work stealing is bounded by $Q_1(Z) + O(ZPT_{\infty})$ where Z is the size of each distributed cache and Q_1 is the sequential cache complexity.

NB: for non SP computations, unbounded dist. cache complexity 30 / 41

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Conclusion on Schedulers

Parallel-Depth First:

- Bound for shared memory
- Adaptation to memory hierarchies: Controlled PDF

Work-Stealing:

- ► Very simple: amenable both to analysis and implementation
 - Bounds on running time, number of steals, communications, etc. in various models
 - Present in several real-world thread schedulers
- Bounds on shared and distributed cache complexities
- Data-locality problem for distributed platforms (clusters)
- Trade-off between:
 - Fixed data distribution for (load balance and) locality
 - Dynamic work-stealing for real-time load balance

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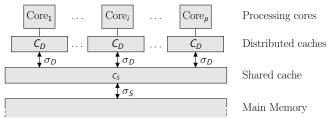
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Model and Metric

Algorithm and Data Layout Results

Platform Model



- Multicore with p cores
- Different cache bandwidths

New metric: data access time

$$T_{\text{data}} = rac{M_S}{\sigma_S} + rac{M_D}{\sigma_D}$$

 M_S : nb of shared cache misses M_D : nb of distributed cache misses

- Largest block size in shared cache: $\lambda \times \lambda$
- Largest block size in distributed cache: $\mu \times \mu$

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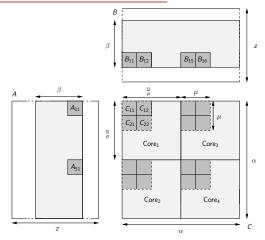
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Minimizing Data Access Time



• when $\alpha = \lambda$, we optimize for shared-memory

• when $\alpha^2 = p \times \lambda^2$, we optimize for distributed-memory

• Constraint:
$$2\alpha \times \beta + \alpha^2 \leq C_S$$

• Minimize $T_{data} = \frac{1}{\sigma_S}(mn + \frac{2mnz}{\alpha}) + \frac{1}{\sigma_D}(\frac{mnz}{p\beta} + \frac{2mnz}{p\mu})$

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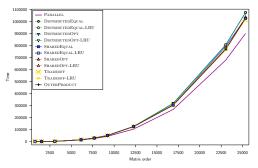
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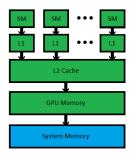
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Results on multicore CPU



- ▶ Intel Xeon E5520 processor (quad-core) running at 2.26 GHz.
- Shared L3 of 8MB (16-way associative)
- Distributed L2 256KB (8-way associative)
- All variants reach about 89% of GotoBlas2 (same for MKL)
- Our strategy perform less cache misses
- ► GotoBlas2: more regular memory accesses
 - \Rightarrow automatic prefetch is much more efficient

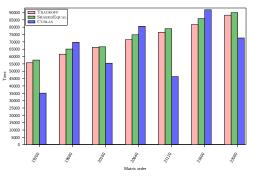
Results on GPUs



GPU architecture: similar tradeoff

- Several Streaming Multiprocessor (many simple cores, SIMD)
- ▶ Limited GPU memory (at this time) ~ shared cache
- \blacktriangleright L1 \sim distributed cache

Results on GPUs



- Running times on GeForce GTX285 with 240 cores and 2GB global memory
- Results: depend on the matrix size
- Cublas uses different kernels depending on size
 Some kernels use GPU-specific features (texture units)
- On average Cublas performs 40% more shared cache misses and 90%–240% more distributed cache misses