Cache Efficient Functional Algorithms

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Machine Models

Traditionally, algorithm analysis is based on abstract machines.

- Classically, RAM or PRAM, with constant-time memory access.
- Low-level programming model, essentially assembly language.

Time complexity is measured by number of instruction steps.

- Robust across variations in model.
- Supports asymptotic time analysis.

Machine Models

RAM model is unreasonably low-level.

- Manual memory management.
- No abstraction or composition.
- Write higher-level code, reason about its compilation.

Basic RAM model ignores memory hierarchy.

- Memory access time is not constant.
- Cache effects are significant.

IO Model

Aggarwal and Vitter: I/O Model.

- Add cache of size $M = c \times B$ for some block size B.
- Memory traffic is in units of *B* words.
- Analyze cache complexity.

Obtained matching lower and upper bounds for sorting.

- eg, M/B-way merge sort: $O((n/B) \log_{M/B}(n/B))$.
- (Not cache oblivious.)

Language Models

We prefer to work with high-level linguistic models.

- Support abstraction and composition.
- Avoid low-level memory management and imperative mindset.

But can we understand their complexity?

- Avoid reasoning about compiled code.
- Account for implicit computation (esp., storage management).

Functional Models

Computation by transformation, not mutation.

- Persistent data structures by default.
- Naturally parallel: no artificial dependencies, no contention.
- Easily verified by inductive arguments.

(The basis for introductory CS at CMU since 2010.)

Functional Models

Functional mergesort: fun mergesort xs = if size(xs) <= 1 then xs else let (xsl,xsr) = split xs in merge (mergesort xsl, mergesort xsr) end

As natural as one could imagine!

Cost Semantics

Blelloch and Greiner pioneered a better way to go:

- Cost semantics: assign an abstract cost to a functional program.
- Provable implementation: transfer abstract costs to concrete costs.
- Cost of execution is a series-parallel graph.
 - Tracks dynamic data dependencies (no approximation).
 - Work = size of graph = sequential complexity.
 - Depth = span of graph = (idealized) parallel complexity.

Implicit Parallelism

Evaluation: $e \Downarrow^g v$.

$$\frac{e_1 \Downarrow^{g_1} \lambda x.e \quad e_2 \Downarrow^{g_2} v_2 \quad [v_2/x]e \Downarrow^g v}{e_1 e_2 \Downarrow^{(g_1 \otimes g_2) \oplus g \oplus 1} v}$$

Thm: If $e \Downarrow^g v$, where wk(g) = w and dp(g) = d, then e may be evaluated on a p-processor PRAM in time $O(\max(w/p, d))$.

The proof encodes the scheduling strategy (Brent's Principle).

Cache Complexity

Cost semantics for cache complexity is a bit more involved.

- Make reads and allocations explicit.
- In-cache computation costs 0; misses and evictions cost 1.
- Account for (implicit) control stack usage.

Provable implementation specifies:

- Stack management to control contention/interference (amortized analysis).
- Managing allocation and eviction (competitive analysis).

Main idea: ensure that temporal locality implies spatial locality.

Cost Semantics Overview

Storage model: $\sigma = (\mu, \rho, \nu)$ [Morrisett, Felleisen, and H.]

- μ is an unbounded memory partitioned into blocks of size *B*.
- ρ is a read cache of size *M* partitioned into blocks of size *B*.
- ν is a nursery of size M with a linear ordering $l_1 \prec_{\nu} l_2$.

Evaluation: $\sigma @ e \Downarrow_R^n \sigma' @ I$.

- All values are allocated in the store, σ , at a location, *I*.
- Root set *R* maintains liveness information.
- Abstract cost *n* represents cache complexity.

Cost Semantics Overview

Read: $\sigma @ I \downarrow^n \sigma' @ v$.

- Read location I from store σ to obtain value v.
- Abstract cost *n* represents cache loads and evictions.
- Store modification reflects cache effects.

Allocation: $\sigma \oslash v \uparrow_R^n \sigma' \oslash I$.

- Allocate value v in σ obtaining σ' and new location I.
- Root set *R* maintains liveness information.
- Abstract cost *n* represents migration of objects to memory.

Reading

In-cache and in-nursery reads are cost-free:

$$\frac{l \in \operatorname{dom}(\rho)}{(\mu, \rho, \nu) @ l \downarrow^{0} (\mu, \rho, \nu) @ \rho(l)}$$

$$\frac{l \in \operatorname{dom}(\nu)}{(\mu, \rho, \nu) @ l \downarrow^{0} (\mu, \rho, \nu) @ \nu(l)}$$

Out-of-cache reads load, and may evict, a block with cost 1/B:

$$\frac{l \notin \operatorname{dom}(\rho) \cup \operatorname{dom}(\nu) \quad |\operatorname{dom}(\rho)| \le M - B}{(\mu, \rho, \nu) \, \mathbb{O} \, l \downarrow^{1}(\mu, \rho \oplus \operatorname{nbhd}(\mu, l), \nu) \, \mathbb{O} \, \mu(l)}$$
$$\frac{l \notin \operatorname{dom}(\rho) \cup \operatorname{dom}(\nu) \quad |\operatorname{dom}(\rho)| = M \quad \beta \subseteq \rho}{(\mu, \rho, \nu) \, \mathbb{O} \, l \downarrow^{1}(\mu, \rho \ominus \beta \oplus \operatorname{nbhd}(\mu, l), \nu) \, \mathbb{O} \, \mu(l)}$$

Allocation

Nursery limited to *M* live objects:

$$\frac{|\operatorname{live}(R \cup \operatorname{locs}(o), \nu)| < M \quad l \notin \operatorname{dom}(\nu)}{(\mu, \rho, \nu) \, \mathbb{O} \circ \uparrow^{\mathbf{0}}_{R} (\mu, \rho, \nu[l \mapsto o]) \, \mathbb{O} \, l}$$

Migration blocks *B* oldest objects into memory:

 $\frac{|\operatorname{live}(R \cup \operatorname{locs}(o), \nu)| = M \quad \beta = \operatorname{scan}(R \cup \operatorname{locs}(o), \nu) \quad I \notin \operatorname{dom}(\nu)}{(\mu, \rho, \nu) \, \mathfrak{O} \circ \uparrow^{\mathbf{1}}_{R} (\mu \oplus \beta, \rho, (\nu \ominus \beta)[I \mapsto o]) \, \mathfrak{O} \, I}$

Evaluation

Functions are allocated in storage, represented by a "pointer":

 $\frac{\sigma @ \lambda x.e \uparrow_R^n \sigma' @ I}{\sigma @ \lambda x.e \Downarrow_R^n \sigma' @ I}$

Application chases pointers and allocates frames:

$$\left\{ \begin{array}{c} \sigma @ \operatorname{app}(-; e_2) \uparrow_{R \cup \operatorname{locs}(e_1)}^{n_1} \sigma_1 @ k_1 & \sigma_1 @ e_1 \Downarrow_{R \cup \{k_1\}}^{n'_1} \sigma'_1 @ l'_1 \\ \sigma'_1 @ l'_1 \downarrow^{n''_1} \sigma''_1 @ \lambda x. e & \sigma''_1 @ \operatorname{app}(l'_1; -) \uparrow_R^{n''_1} \sigma_2 @ k_2 \\ \sigma_2 @ e_2 \Downarrow_{R \cup \{k_2\}}^{n_2} \sigma'_2 @ l'_2 & \sigma'_2 @ [l'_2/x] e \Downarrow_R^{n'_2} \sigma' @ l' \\ \end{array} \right\}$$

Critical Invariants

Stack frames are allocated to account for implicit storage:

- Maintains correct ordering of allocated space.
- Maintains liveness information within cache.

Object migration is oldest first:

- Migrate only live objects.
- Nursery is implicitly garbage-collected to free dead objects.
- Neighborhood is fixed at the moment of migration.

Provable Implementation

Three main ingredients:

- Manage the memory traffic engendered by the control stack.
- Read cache eviction policy.
- Liveness analysis and compression for migration.

Stack Management

Reserve a block of size *B*, the stack cache, for the top of the stack.

- Stack frames originate in the nursery, then migrate to memory as necessary.
- Stack frames are loaded into the stack cache as a block from main memory.
- Loading the stack cache evicts its current contents.

Must ensure that one block in the read cache is always available for the top of the control stack.

Stack Management

Amortized analysis bounds cost of stack management:

- Accessing frames in the nursery is free.
- The first load of a frame must previously have been migrated to memory.
- Only newer frames can evict older frames from stack cache.
- Every frame must eventually be read and used exactly once.

Upshot: the traffic arising from stack frames may be attributed to their allocation.

Stack Management

Associate the cost of the load and reload with the frames that force the eviction.

- Put \$3 on each frame block as it is migrated.
- Use \$1 for migration.
- Use \$1 for initial load.
- Use \$1 for reload.

Thm A computation with abstract cache complexity *n* can be implemented on a stack machine with cache complexity at most $3 \times n$.

Allocation Management

Read and allocate may be implemented within a small constant, given a cache of size $4 \times M + B$ objects.

Storage assumptions:

- Object sizes are bounded by the size of the program.
- Must assume sufficient word size to hold a pointer.

Read cache evicts least-recently-used block.

- 2-competitive with ICM [Sleator, et al.]
- Standard, easily implemented.

Allocation Management

Copying garbage collection manages liveness and compaction:

- Allocation of frames ensures that liveness can be determined without memory traffic.
- Require $2 \times M$ nursery size to allow for copying GC.
- Copying collection is constant-time per object (amortized across allocations).

Must double-load blocks to ensure that neighborhood is loaded even when GC is performed.

Analysis Methods

A data structure of size *n* is compact if it can be traversed in time O(n/B) in the model.

- Intuitively, the components are allocated "adjacently."
- Robust under change of traversal order.
- Defined in the semantics, not the implementation.

A function is hereditarily finite (HF) if it maps hereditarily finite inputs to hereditarily finite outputs using only constant space.

- Used to analyze higher-order functions such as map.
- Standard notion in semantics.

Example: Map

The map function transforms compact lists into compact lists.

- Temporal locality implies spatial locality.
- Assuming function mapped is hereditarily finite.

For HF f, map f xs has cache complexity O(n/B), where n is the length of xs.

Example: Merge

Almost entirely standard implementation:

```
fun merge nil bs = bs
  | merge as nil = as
  | merge (as as a::as') (bs as b::bs') =
    case compare a b of
    LESS ⇒ !a::merge as' bs
    | GTEQ ⇒ !b::merge as bs'
```

Proviso: !a and !b specify copying of element to ensure compactness.

Example: Merge

For HF less and compact as and bs, the function merge as bs has cache complexity O(n/B), where n is the sum of the sizes of as and bs.

Main points:

- Recurs down lists allocating only stack *n* frames: O(n/B).
- Returns allocating *n* list cells: O(n/B).
- Temporal locality ensures spatial locality.

Example: Merge Sort

A similar analysis for binary merge sort yields $O(n/B \log n/M)$ cache complexity.

- Same bound as for manual allocation.
- Cache oblivious: no use of cache parameters.

Aggarwal and Vitter's results on k-way merge are attained by the functional program.

- $O(n/B \log_{M/B} n/B)$.
- Not cache-oblivious: k is M/B.

Summary

Cost semantics mediates between analysis and implementation.

- High-level programming model: complexity analysis at the level of the code itself.
- Low-level implementation: transfer asymptotics to machine level.

The cache complexity of an algorithm may be expressed using a cost semantics for a purely functional language.

Can match bounds on cache complexity given for low-level models.