Cache- and IO-Efficient Functional Algorithms

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- Space = number of cells of storage.

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Machine-based approaches suffer some important weaknesses:

- Relies on pseudo-code and compilation strategy.
- Not very realistic, eg with respect to memory hierarchies.
- No concept of composition of programs.

Our goal is to promote functional language models for algorithms.

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- Analyze the code you actually run.
- Independent of a compilation method.

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Obtain end-to-end asymptotics for realistic functional languages.

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- Records true data dependencies (no approximation).
- Exposes inherent parallelism and sequentiality.

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Two measures of a cost graph g:

- Work, or sequential complexity: size of g.
- Span, or parallel complexity: diameter of g.

Example: function application.

$$\frac{e_1 \Downarrow \lambda x.e \quad e_2 \Downarrow \quad v_2 \quad [v_2/x]e \Downarrow \quad v}{e_1(e_2) \Downarrow \qquad v}$$

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

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Cost Graphs g_1 g2 g

Work = $w_1 + w_2 + w + 1$, Span = max(s_1, s_2) + 1 + s.

Provable Implementation

Brent's Theorem: A computation with work w and span s can be implemented on a p-processor PRAM in time O(w/p + s).

- Work in chunks of *p* as much as possible.
- Proof is constructive: exhibits a scheduler.

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Validates prediction given by high-level asymptotics.

- Transfers from high-level to low-level model.
- Provable cost bounds on a PRAM.

IO Model [Aggarwal & Vitter 88]

RAM-based IO model:

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Example results:

- Matrix multiply without blocking: $O(n^3/B)$.
- ... with blocking: $O(n^3/(B\sqrt{M}))$.
- 2-way merge sort: $O((n/B) \log_2(n/B))$.
- ... M/B-way: $O((n/B) \log_{(M/B)} (n/B))$

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Memory allocation and layout done by hand!

Replicate A&V results in a purely functional language model.

- Automatic storage management.
- Natural functional code, not pseudo-code.

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Confirms that automatic storage management is cache-friendly.

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Storage model: $\sigma = (\mu, \rho, \nu)$ [Morrisett, Felleisen, & H. 95]

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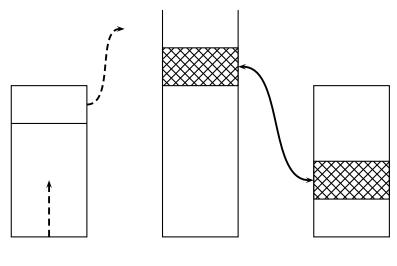
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- μ : unbounded secondary memory with blocks of size *B*.
- ρ : bounded primary memory of size $M = k \times B$.
- ν : nursery of size M with a linear ordering on its domain.

Simplified Memory Model



Nursery

Secondary

Primary

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

- Read location I from store σ to obtain value v.
- Cost accounts for loads to and evictions from primary.
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Allocate: $\sigma @ v \uparrow^n \sigma' @ I$.

- Allocate value v in σ obtaining σ' and I.
- Cost *n* accounts for migration to secondary.
- Live objects are blocked on migration to secondary.

Functions are allocated in memory:

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Application follows pointers:

$$\left\{ \begin{array}{ccc} \sigma_1 \otimes e_1 \Downarrow^{n'_1} & \sigma'_1 \otimes l'_1 \\ & & \end{array} \right\}$$

$$\sigma \otimes \operatorname{app}(e_1; e_2) \Downarrow^{n'_1 + n''_1 + \dots + n'_2} \sigma' \otimes l'$$

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Theorem If l is compact and f is simple, then map f l is compact and has IO cost O(n/B).

Example: Merge

Nearly standard implementation:

```
fun merge nil ys = ys
| merge xs nil = xs
| merge (xs as x::xs') (ys as y::ys') =
   case compare x y of
    LESS ⇒ !x::merge xs' ys
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The notations !x and !x denote deep copy to ensure compactness.

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Theorem For compact input of size *n*, sort xs has cost $O((n/B) \log_{(M/B)}(n/B))$.

(Matches A&V bound in IO model.)

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Proof sketch:

• Copying GC with semispaces for nursery: $2 \times M$.

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However, the "theorem" is not quite correct as stated

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But consider non-tail recursive factorial:

Simplified semantics predicts O(1) cost, but true cost is O(n/B)!

$$\left\{ \begin{array}{l} \sigma @ \operatorname{app}(-; e_2) \uparrow_{R \cup \operatorname{locs}(e_1)}^{n_1} \sigma_1 @ k_1 \end{array} \right.$$

$$\sigma @ \operatorname{app}(e_1; e_2) \Downarrow_R^{n_1 + n'_1 + n''_1 + n'''_1 + n_2 + n'_2} \sigma' @ l'$$

$$\left\{ \begin{array}{l} \sigma @ \operatorname{app}(-; e_2) \uparrow_{R \cup \operatorname{locs}(e_1)}^{n_1} \sigma_1 @ k_1 \quad \sigma_1 @ e_1 \Downarrow_{R \cup \{k_1\}}^{n'_1} \sigma'_1 @ l'_1 \\ \end{array} \right\}$$

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The cost semantics must be enhanced to allocate frames:

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

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Modifications:

- Frames are never read! Allocation cost suffices.
- Root set *R* records live data in the (implicit) control stack.

Provable Implementation (Corrected)

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Theorem If $\sigma @ e \Downarrow_R^n \sigma' @ I$, then e can be executed in the IO model in time $k \times n$ using a primary cache of size $4 \times M + B$.

Proof given in two major steps:

- Implement cost semantics on a stack machine.
- Implement stack machine on A&V IO model.

Stack frames are allocated in the nursery.

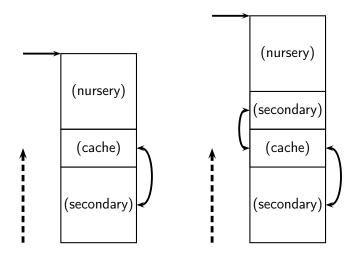
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Dedicate a cache block of *B* frames in primary memory.

- Not influenced by frames in nursery.
- Specially managed read cache for stack frames.



Typical Stack

Deep Recursion

Stack cache block may be evicted up to *B* times.

- Newer frames may overflow nursery.
- Reading evicted frames replaces stack cache.

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Amortize cost of eviction over allocation of newer frames.

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

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Aggarwal & Vitter's results can be matched using natural functional code.

- Must consider compactness of data structures.
- End-to-end comparable to machine-level implementation.

Open Questions

Can we sort IO optimally with a cache oblivious algorithm?

- Merge sort uses M/B-way split.
- Frigo, et al. 99 give a cache-oblivious sorting algorithm.

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Can the IO model be extended to account for parallelism?