Adapting to Memory Pressure from within Scientific Applications on Multiprogrammed Environments

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Research goals

Goal: Enable scientific codes to run efficiently in non-dedicated, shared resource environments:

- Loose networks of workstations (may share everything!)
- SMP machines (share memory, even w/ space-shared CPUs)
- Big buzzword: “Grid Computing”

Work has focused on two shared resources (CPU + RAM):

- CPU: Dynamic load balancing via algorithmic modifications
  - Specific class of inner-outer iterative methods
  - Simple *algorithmic* modifications
  - Very low overhead

- RAM: Dynamic adaptation to memory pressure
Memory pressure in shared environments

Over-committing memory can cause severe performance penalties! E.g.:
- Multigrid, no memory pressure: 14 seconds per iteration
- With Matlab QR factorization: 472 seconds per iteration

System response to memory shortage:
- The system may move a process to wait queue

Synchronous parallel programs stall, despite load balancing!
Memory pressure in shared environments

Over-committing memory can cause severe performance penalties! E.g.:
- Multigrid, no memory pressure: 14 seconds per iteration
- With Matlab QR calculation: 472 seconds per iteration

System response to memory shortage:
- The system may move a process to wait queue.
- Or, all jobs run, resulting in thrashing.
- Either case is disastrous, especially for synchronous parallel programs!

Many CPU cycles wasted!
Avoiding/coping with memory pressure

Many approaches exist at OS, compiler, middleware levels:
- Adaptive schedulers, VM modifications, compiler support, middleware memory managers, ....

We explore an **application-level** memory adaptation framework.

Why? Application has full knowledge of
- Granularity
- Communication pattern
- Memory access pattern
- Dynamic memory size requirements

**Goal:** Applications exploit this knowledge to adapt memory requirements to memory availability.
Target scientific apps, where large, repetitive data access typical.

Many scientific apps use blocked access pattern:

\[
\text{for } i = 1:P \\
\quad \text{Get panel } p_i \text{ from lower memory level} \\
\quad \text{Work on } p_i \\
\quad \text{Write results and evict } p_i \text{ to lower level}
\]

Suggests an adaptation framework:

- Use named mmap() to access data set
- Cache (mmap) as many panels as possible in-core
- Control RSS by varying number of panels cached
- User-defined replacement policy
- Encapsulate caching decisions within \text{get\_panel()}
Detecting memory shortage/surplus

OS provides no accurate estimate of available memory!

- We infer shortage if RSS decreases w/o unmapping by us.

- Detecting surplus is more complicated:
  - Periodically probe for more memory
    - Map new panel w/o unmapping another
      (increase panels_in)
    - If memory available, RSS grows by one panel
    - Otherwise, RSS stays constant or decreases
  - Note: Don’t probe if RSS < dRSS = panels_in * panel_size

- Simplest policy: Probe when RSS = dRSS = panels_in * panel_size
Simplest policy too aggressive

- Safe RSS/dRSS is 30-35 MB; regularly exceeded!
- Unsuccessful probes drop RSS dramatically.

70 MB adaptive job vs. 70MB dummy job; 128 MB system RAM.
Use dynamic delay to reduce aggressiveness

We must reduce frequency of probes for surplus memory:
After a detected shortage, delay probing for some time.

Choice of delay must consider two penalties:
- Probe too often → VM system takes memory (“incursion penalty”)
  penalty: \( \frac{\text{maxRSS}}{B_w} \)
- Probe too infrequently → Wasteful reads from disk (“inaction penalty”)
  penalty: \( \frac{\text{maxRSS} - \text{RSS}}{B_w} \)

Can balance two penalties by scaling some base delay by their ratio.
- After shortage, must touch panels to re-load lost pages.
  → Use time for sweep through all panels as base delay.

\[
\text{Delay} = (\text{Time for last full sweep}) \times \left( \frac{\text{maxRSS}}{\text{maxRSS} - \text{RSS}} \right)
\]
Dynamic delay improves performance

- dRSS quickly finds safe value.
- Fluctuations in RSS greatly reduced.
- Time per matvec reduced from 17.5 sec to 4.4 sec.

RSS (solid line) and desired RSS (dashed line) for dynamic delay with ratio

Average iteration time: 4.4 sec

70 MB adaptive job vs. 70MB dummy job; 128 MB system RAM.
Graceful performance degradation in CG

Average CG iteration time vs. memory pressure

- **Memory-adaptive**
- **panel_in fixed at optimal value**
- **In-core**
Modified Gram-Schmidt; Ising via Metropolis

Average time for MGS to add last 10 vectors vs. memory pressure

- Memory-adaptive
- panels_in fixed at optimal value
- In-core

Average Ising sweep time vs. memory pressure

- Memory-adaptive
- panels_in fixed at optimal value
- In-core
Application-level memory-adaptation framework:
- Enables graceful performance degradation under memory pressure (order of magnitude speedups not atypical)
- Minimal reliance on OS-provided information
- Requires minimal code changes to many scientific kernels
- Suited to non-centrally administered, open systems

Key contributions:
- Algorithm judges memory availability with single metric
- Demonstrated in three application kernels
- Modular, flexible supporting library
PFLOW: Multiphase subsurface flow

- Parallel, multiphase, fully-implicit subsurface flow
- Object-oriented Fortran 90 code: uses derived types, modules to provide encapsulation
- Uses PETSc iterative solvers, communication constructs
Comparison of different CG implementations

Compared memory adaptive CG (mema) with other CG codes:

- Conventional in-core (incore)
- Conventional out-of-core (ooc)
- Memory-mapped I/O (mmap)

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Modified Gram-Schmidt

From vectors $W$, generate orthonormal vector basis $V$:

- Orthogonalize $w_2$ against $v_1$: $v_2 = w_2 - (v_1 * w_2)v_1$
- Orthogonalize $w_3$ against $v_1$ and $v_2$
- Orthogonalize $w_i$ against $v_1, v_2, ..., v_{i-1}$

- Working set increases as vectors added to basis.
- Once added to basis, vector not written again.

- Our test code:
  - Generates random vector, orthonormalizes, adds to basis.
  - Restarts (discards vectors) when max basis size reached.
  - Note: Like GMRES, but doesn’t build Krylov space.
  - Can specify min basis size to guarantee memory pressure.
Modified Gram-Schmidt

Average time to add last 10 vectors vs. memory pressure

- Memory-adaptive
- panels_in fixed at optimal value
- In-core

Average time (seconds) to process last 10 vectors vs. Size of locked region (MB)
Ising Model via Metropolis

- Ferromagnet modeled as rectangular lattice.
- Sites possess only spin up (+1) or down (-1).
- Interaction with four nearest-neighbors only.
- Similar to a wide range of physics models.

- Monte-Carlo simulation:
  - Generate configurations that represent equilibrium.
  - Sweep through the lattice, making trial spin flips.
    - Accept new spin if $\Delta E < 0$ OR
    - Accept with probability $\exp(-\Delta E/kT)$ otherwise.

- Partition lattice row-wise into panels.
- At panel boundaries, need both panels for $\Delta E$ calc.
Metropolis Ising model simulation

Average Ising sweep time vs. memory pressure

- Memory-adaptive
- panels_in fixed at optimal value
- In-core

Average time (seconds) per Ising sweep

Size of locked region (MB)