



SAPIENZA
UNIVERSITÀ DI ROMA

Estimating the Empirical Cost Function of Routines with Dynamic Workloads

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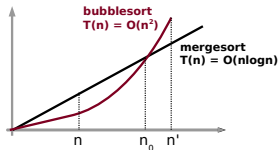
Romolo Marotta

February 18, 2014

Performance Scalability Analysis



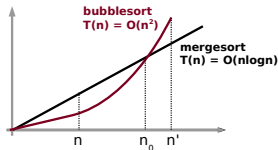
Theory: Asymptotic Analysis



Performance Scalability Analysis



Theory: Asymptotic Analysis



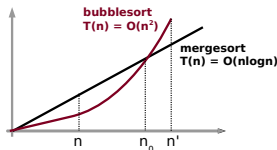
Practice: Performance Profiling

%time	%self	%children	function
99.9	2.00	16.29	main
52.2	5.82	3.70	foo
31.3	2.81	2.90	bar
20.3	3.70	0.00	foobar

Performance Scalability Analysis

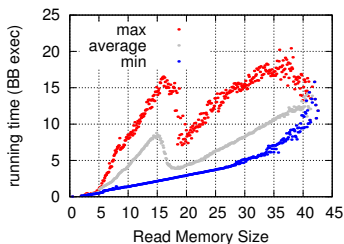


Theory: Asymptotic Analysis



Practice: Performance Profiling

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Our goal:
Predicting how code scales w.r.t.
its workload size

Analyzing the scalability of routines

A possible solution:

- 1 Choose workloads of increasing sizes



....

Analyzing the scalability of routines

A possible solution:

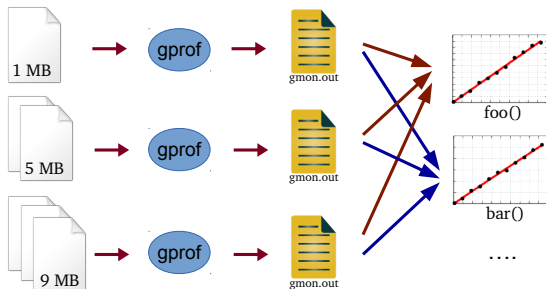
- 1 Choose workloads of increasing sizes
- 2 For each workload: run your application under gprof



Analyzing the scalability of routines

A possible solution:

- 1 Choose workloads of increasing sizes
- 2 For each workload: run your application under gprof
- 3 Plot and analyze the results



Drawbacks of gprof-like experiments

Need to have different workloads for different routines:
 application's workload \neq routine's workloads

Wrong assumptions can easily lead to misleading conclusions:



See case studies in [CDF12]

Workload-dependent profiling

Recent works investigate how an application's performance scales as a function of its input data:

Main sources of dynamic workloads

	Input Size Estimation	I/O & Syscall		Thread Intercom.
GAW07	Manual			
ZH12	Automatic	No	No	
CDF12	Automatic	No	No	

GAW07 Goldsmith, Aiken, and Wilkerson, Measuring empirical computational complexity, ESEC/FSE 2007

ZH12 Zaparanuks and Hauswirth, Algorithmic profiling, PLDI 2012

CDF12 Coppa, Demetrescu, and Finocchi, Input-Sensitive Profiling, PLDI 2012

Dynamic workloads are ubiquitous!

Many routines dynamically receive input values during their activations:

- Thread intercommunications: e.g., producer-consumer pattern
- I/O operations via syscalls: e.g., buffered read operations

If ignoring dynamic workloads,
then input size estimation may be wrong



analysis of profiling data may be misleading

Our contribution

Main sources of dynamic workloads

	Input Size Estimation	I/O & Syscall	Thread Intercom.
GAW07	Manual		
ZH12	Automatic	No	No
CDF12	Automatic	No	No
CDFM14	Automatic	Yes	Yes

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Estimating the input size: previous approaches

[ZH12] Input size \approx Size of (Java) Data Structures

Input size definition depends on the specific data structure (e.g., if array, then array size). Not suitable for low-level programming languages.

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[CDF12] Input size \approx Read memory size (RMS)

Read memory size of an execution of a routine r
 $=$
 number of distinct **memory cells**
first accessed by r (or by a descendant of r in the call tree)
 with a **read operation**

This work extends the RMS metric

RMS example

```

call f
  read x
  write y
  call g
    read x
    read y
    read z
    write w
  return
read w
return

```

Fn	Accessed cells (first-read green)	RMS

RMS example

```

→ call f
    read x
    write y
    call g
        read x
        read y
        read z
        write w
    return
read w
return

```

Fn	Accessed cells (first-read green)	RMS
f		

RMS example

```

→ call f
    read x
    write y
    call g
        read x
        read y
        read z
        write w
    return
read w
return
  
```

Fn	Accessed cells (first-read green)	RMS
f	x	1

RMS example

```

call f
  read x
  → write y
  call g
    read x
    read y
    read z
    write w
    return
  read w
  return

```

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→

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f	x y	1
g		

RMS example

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  call g
    →   read x
        read y
        read z
        write w
        return
  read w
  return

```

Fn	Accessed cells (first-read green)	RMS
f	x y	1
g	x	1

RMS example

```

call f
  read x
  write y
  call g
    read x
    read y
    read z
    write w
  return
read w
return

```



Fn	Accessed cells (first-read green)	RMS
f	x y	1
g	x y	2

RMS example

```

call f
  read x
  write y
  call g
    read x
    read y
    read z
    write w
  return
read w
return

```



Fn	Accessed cells (first-read green)	RMS
f	x y z	2
g	x y z	3

RMS example

```

call f
  read x
  write y
  call g
    read x
    read y
    read z
    write w
  return
read w
return

```



Fn	Accessed cells (first-read green)	RMS
f	x y z w	2
g	x y z w	3

RMS example

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call f
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    write w
    return
  → read w
  return

```

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RMS example

```

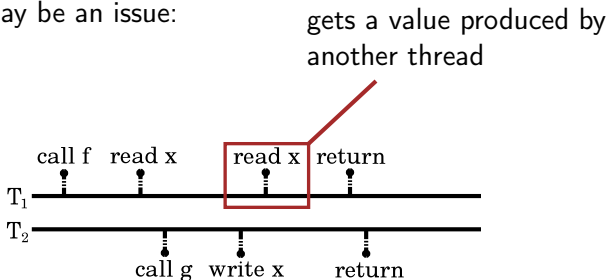
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  read w
→ return

```

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When RMS does not work: an example

Multithreading may be an issue:



$\text{RMS}_f = 1$, but actual input size is 2!

RMS fails to properly characterize the input size of routine activations under **dynamic workloads**

From RMS to Dynamic Read Memory Size (DRMS)

r = routine activation

t = thread

ℓ = memory location

A read operation on ℓ is:

First-read

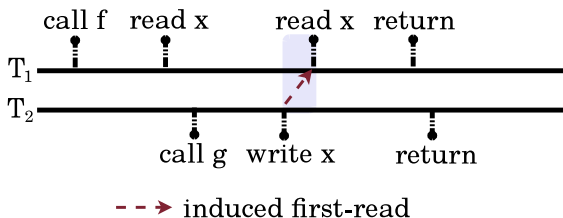
if ℓ has never been accessed before by r or by any of its descendants in the call tree of thread t .

Induced first-read

if no previous access to ℓ has been made by t since the latest write to ℓ performed by a thread different from t , if any.

Induced first-read example

T_1 did not access location x since the latest write to x performed by T_2



The second read x is an induced first-read

Dynamic Read Memory Size (DRMS)

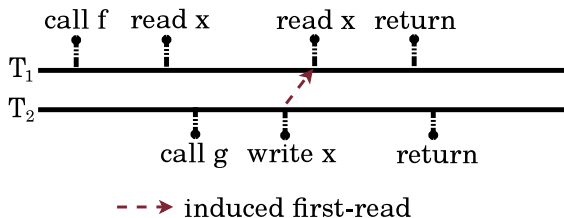
Input size \approx Dynamic Read Memory Size

$\text{DRMS}_{r,t} :=$ # of first-reads or **induced first-reads**

Notice that:

$\text{RMS}_{r,t} :=$ # of first-reads

DRMS example



First read x : first-read

Second read x : induced first-read



$$\text{DRMS}_{f, T_1} = 2$$

These kinds of patterns occur frequently in real applications

Pattern 1: producer-consumer

procedure producer()

```

1: while (1) do
2:   wait(empty)
3:   wait(mutex)
4:   x = produceData()
5:   signal(mutex)
6:   signal(full)
  
```

procedure consumer()

```

1: while (1) do
2:   wait(full)
3:   wait(mutex)
4:   consumeData (x)
5:   signal(mutex)
6:   signal(empty)
  
```

always the same
memory location
across iterations!

When producer has generated n values:

$$\text{RMS}_{\text{consumer}} = 1$$



while

$$\text{DRMS}_{\text{consumer}} = n$$



Pattern 2: data streaming

procedure streamReader()

1: **for** $i = 1$ to n **do**

2: fill x with external data from the network

3: consumeData (x)

always the same memory
location across iterations!

At the end of the execution:

$\text{RMS}_{\text{streamReader},t} = 1$



while

$\text{DRMS}_{\text{streamReader},t} = n$



Computing DRMS: a simple-minded approach

r = routine activation

ℓ = memory location

t = thread

$L_{r,t}$ = set of locations accessed by r

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t = thread

ℓ = memory location

$L_{r,t}$ = set of locations accessed by r

$\text{read}_t(\ell)$	if $\ell \notin L_{r,t}$ then $\text{DRMS}_{r,t}++$ $L_{r,t} \leftarrow L_{r,t} \cup \{\ell\}$
$\text{write}_t(\ell)$	$L_{r,t} \leftarrow L_{r,t} \cup \{\ell\}$
$\text{write}_{t'}(\ell), t' \neq t$	$L_{r,t} \leftarrow L_{r,t} \setminus \{\ell\}$

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● Repeat for all pending rtn activations in the call stack

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- Repeat for all pending rtn activations in the call stack
- Repeat for all rtn activations in any stack

Computing DRMS: a simple-minded approach

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- Repeat for all pending rtn activations in the call stack
- Repeat for all rtn activations in any stack (on a write)

$$O\left(\sum_{t \in \text{Threads}} |\text{Stack}_t|\right)$$

time per access

$$O\left(\sum_{t \in \text{Threads}} \cdot \sum_{r \in \text{Stack}_t} |L_{r,t}|\right)$$

current memory footprint

Computing DRMS efficiently

Our solution based on:

- a timestamp algorithm
- a global shadow memory
- thread-private shadow memory for each thread
- periodic global renumbering algorithm

time per access:

$$O(\log |S_{currentThread}|)$$

memory footprint:

$$O\left(\sum_{t \in Threads} |\text{accessed locations by } t|\right)$$

Details in the paper

Implementation

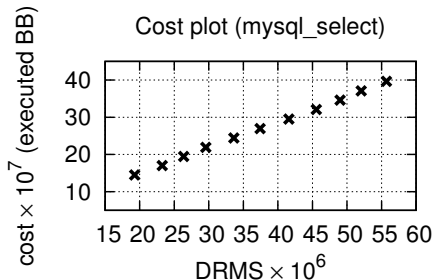
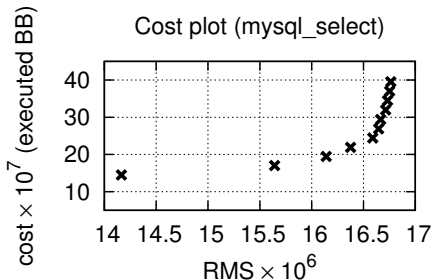


aprof-drms is based on the Valgrind framework, a dynamic instrumentation infrastructure that translates the binary code into an architecture-neutral intermediate representation (VEX)

Events	Instrumentation	Data structures
memory accesses	easy	shadow memory
threads	easy	thread state
function calls/returns	hard	shadow stack
system calls	easy	shadow memory

A case study on MySQL

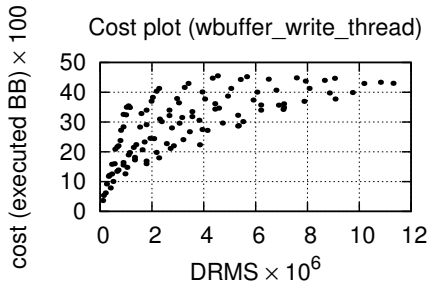
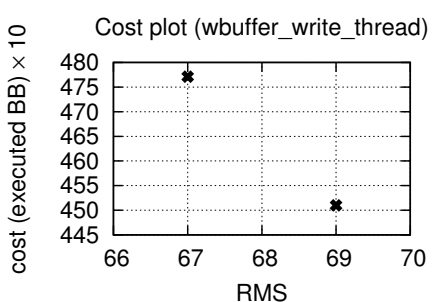
Repeating a select query on tables of increasing sizes:



RMS may be misleading with I/O bound or multithreaded applications!

A case study on vips

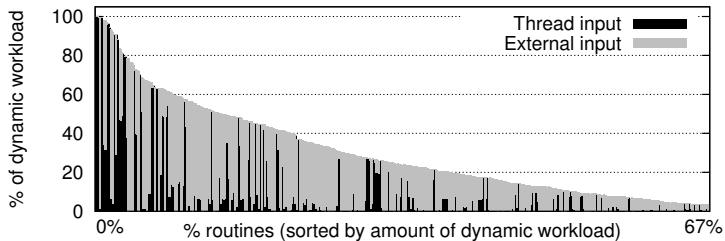
Processing some images of increasing sizes:



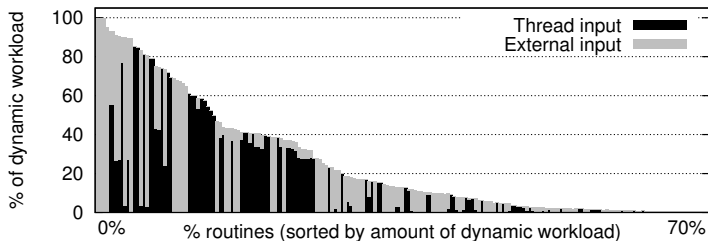
DRMS typically yields richer profiles than RMS

Routine-by-routine thread and external input

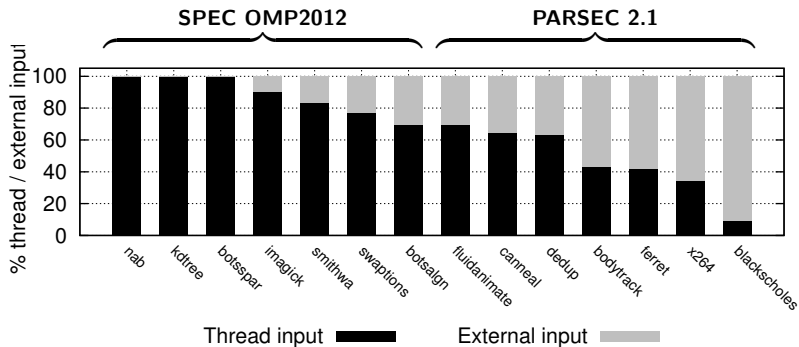
MySQL



vips

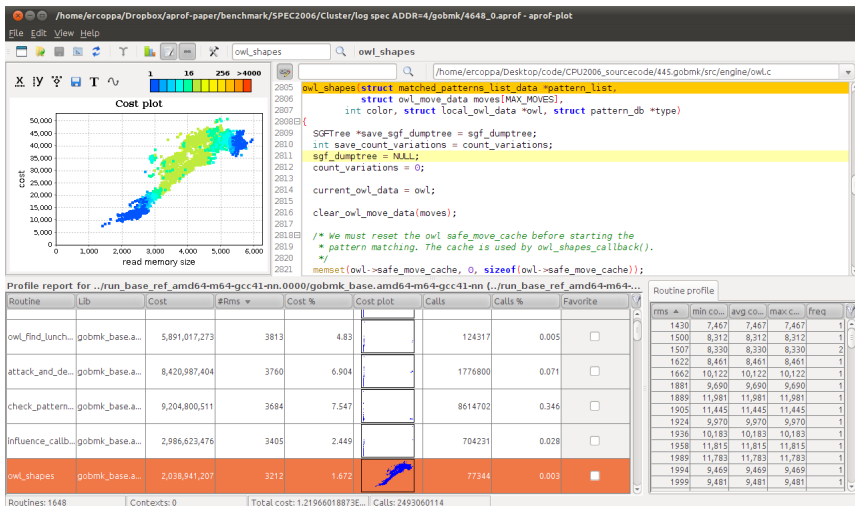


Characterization of induced first-reads



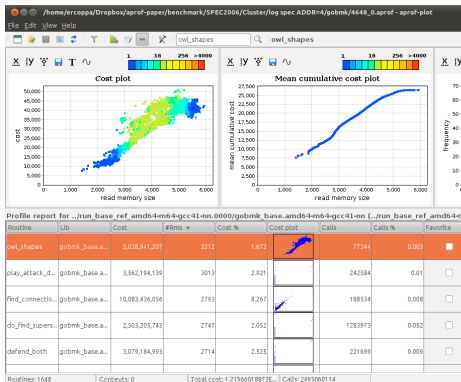
Advertisement 😊

aprof-plot: interactive graphical viewer for aprof profiles



Thanks!

Download aprof at:
<http://code.google.com/p/aprof/>



```

ercoppa@macbook: ~/Desktop/code/aprof
File Edit View Search Terminal Help

ercoppa@macbook:~/Desktop/code/aprof$ aprof ls
==2741== aprof-0.1, Input-sensitive Profiler - http://code.google
==2741== By Emilio Coppa, Camil Demetrescu, Irene Finocchi
==2741== Using Valgrind-3.8.0.SVN and LibVEX; rerun with -h for o
==2741== Command: ls

aprof-bin    callgrind-bin  log           paper2        tags
aprofplot    CDAPSP_DE_res ls.aprof      PIN           tf-bin
benchmark    gcc-instrument paper         pintool       valgrind
==2741==

ercoppa@macbook:~/Desktop/code/aprof$

```

Slowdown & space overhead

Both benchmark suites were set up for running 4 threads:

	memcheck	helgrind	aprof	aprof-drms
Slowdown (Geom. Mean)				
SPEC OMP	94.1×	179.4×	101.5×	140.8×
PARSEC 2.1	51.8×	153.3×	57.1×	68.2×
Space overhead (Geom. Mean)				
SPEC OMP	2.0×	4.5×	2.8×	3.3×
PARSEC 2.1	2.9×	8.4×	4.6×	6.1×

- All tools suffer Valgrind serialization
- aprof-drms delivers comparable performance wrt other Valgrind tools