# Post-compiler Software Optimization for Reducing Energy

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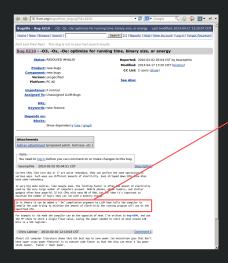
65 megawatts year

(nationalgeographic.com)

#### -Oe energy optimization flag



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-Oe ... trying to minimize the amount of energy the program will use

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 $\mathsf{Faster} = \mathsf{lower} \; \mathsf{energy}$ 

## Outline

Introduction

Technical Approach

**Experimental Evaluation** 

Conclusion

#### Problem Statement

#### Optimizing complex non-functional properties

 $properties \times hardware \times environment$ 

properties memory, network, energy, etc...

hardware architectures, processors, memory stack, etc... environment variables, load, etc...

#### Every program transformation requires

- a-priori reasoning
- manual implementation
- © guaranteed correctness

#### Our Solution

#### Genetic optimization algorithm

- empirically guided (guess and check)
- automated evolutionary search
- relaxed semantics

#### Applied to PARSEC benchmarks

- ► reduces energy consumption by 20% on average
- maintain functionality on withheld tests

#### Related Work

#### Extends combines and leverages

- profile guided optimization
- genetic programming
- superoptimization
- profiling
- testing

Post-compiler, test-driven, Genetic Optimization Algorithm

#### Post-compiler



Post-compiler, test-driven, Genetic Optimization Algorithm

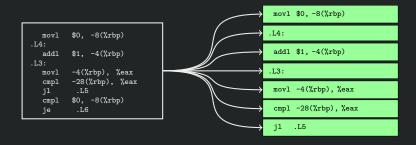
#### Test driven

Use test cases to exercise program

- evaluate functionality
- measure runtime properties

Post-compiler, test-driven, Genetic Optimization Algorithm

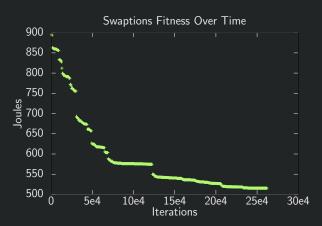
#### Genetic



Post-compiler, test-driven, Genetic Optimization Algorithm

#### Optimization algorithm

Iteratively improve performance (energy) over time



Post-compiler, test-driven, Genetic Optimization Algorithm

#### **Benefits**

- environment-specific adaptation
- hardware-specific adaptation
- exploit hidden HW complexities



(Mdf / CC-BY-SA-3.0)

#### Outline

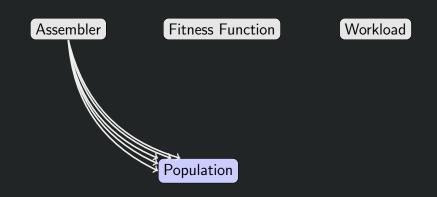
Introduction

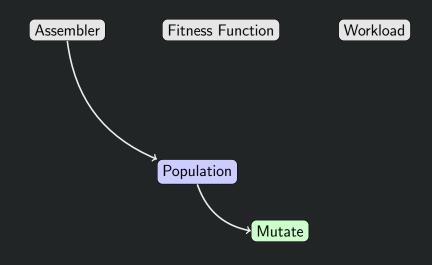
Technical Approach

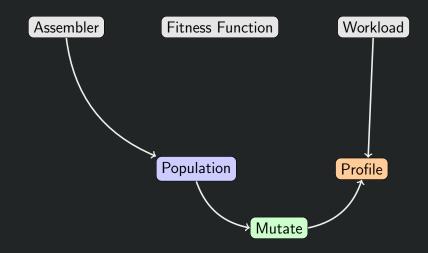
Experimental Evaluation

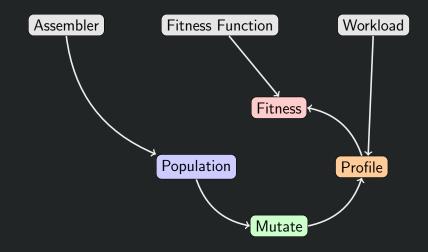
Conclusion

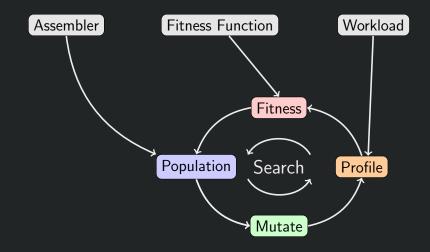
Assembler Fitness Function Workload

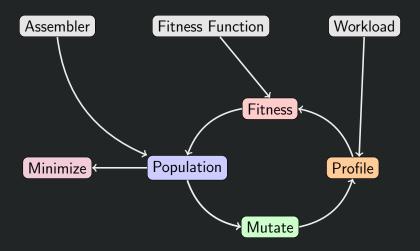


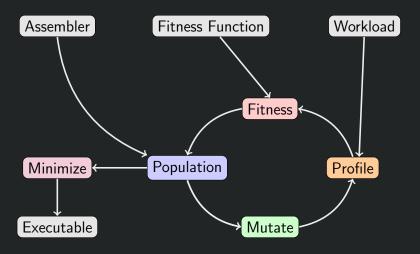








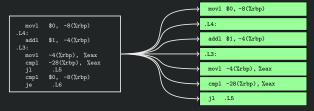




## Program Mutation



#### Software Representation

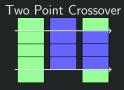


#### Mutation Operations









# Profiling





Hardware Performance Counters

## **Profiling**



\$ perf stat -- ./blackscholes 1 input /tmp/output

6,864,315,342 cycles 5,062,293,918 instructions

2,944,060,039 r533f00

1,113,084,780 cache-references 1,122,960 cache-misses

3.227585368 seconds time elapsed

#### Fitness Function



$$\frac{\textit{energy}}{\textit{time}} = \textit{C}_{\textit{const}} + \textit{C}_{\textit{ins}} \frac{\textit{ins}}{\textit{cycle}} + \textit{C}_{\textit{flops}} \frac{\textit{flops}}{\textit{cycle}} + \textit{C}_{\textit{tca}} \frac{\textit{tca}}{\textit{cycle}} + \textit{C}_{\textit{mem}} \frac{\textit{mem}}{\textit{cycle}}$$

# Steady State Genetic Algorithm



#### **Details**

- ▶ population size: 2<sup>10</sup>
- ▶ 2<sup>18</sup> fitness evaluations
- $ightharpoonup \sim 16$  hour runtime per optimization

```
5358c5358
< .L808:
> addl %ebx, %ecx
5416c5416
< addl %ebx, %ecx
> .L808:
5463 - 5463
< .L970:
> .bvte 0x33
565145650
< .loc 1 457 0 is_stmt 0 discriminator 2
5841 d 5839
< addg %rdx, %r14
6309c6307
< xorpd %xmm1, %xmm7
> cmpq %r13, %rdi
6413a6412
> cmpl %ecx, %esi
```



```
5358c5358
< .L808:
> addl %ebx, %ecx
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5463 - 5463
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565145650
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5841 d 5839
< addg %rdx, %r14
```



```
5463c5463
< .L970:
> .byte 0x33
565145650
< .loc 1 457 0 is_stmt 0 discriminator 2
5841 d 5839
< addg %rdx, %r14
```



```
5463c5463
< .L970:
> .bvte 0x33
5841 d 5839
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```



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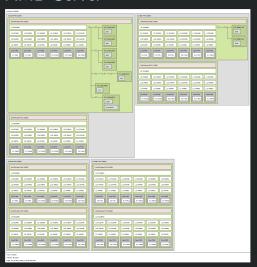
## Benchmark Applications

	C/C++	ASM	
Program	Lines	of Code	Description
blackscholes	510	7,932	Finance modeling
bodytrack	14,513	955,888	Human video tracking
facesim			no alternate inputs
ferret	15,188	288,981	Image search engine
fluidanimate	11,424	44,681	Fluid dynamics animation
freqmine	2,710	104,722	Frequent itemset mining
raytrace			no testable output
swaptions	1,649	61,134	Portfolio pricing
vips	142,019	132,012	Image transformation
×264	37,454	111,718	MPEG-4 video encoder
total	225,467	1,707,068	

Table : PARSEC benchmark applications.

#### Hardware Platforms

#### **AMD** Server



#### Intel Desktop



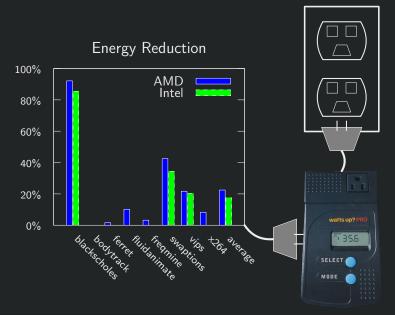
# **Energy Model**

$$\frac{\textit{energy}}{\textit{time}} = \textit{C}_{\textit{const}} + \textit{C}_{\textit{ins}} \frac{\textit{ins}}{\textit{cycle}} + \textit{C}_{\textit{flops}} \frac{\textit{flops}}{\textit{cycle}} + \textit{C}_{\textit{tca}} \frac{\textit{tca}}{\textit{cycle}} + \textit{C}_{\textit{mem}} \frac{\textit{mem}}{\textit{cycle}}$$

		Intel	AMD
Coefficient	Description	(4-core)	(48-core)
$C_{const}$	constant power draw	31.530	394.74
$C_{ins}$	instructions	20.490	-83.68
$C_{flops}$	floating point ops.	9.838	60.23
$C_tca$	cache accesses	-4.102	-16.38
$C_{mem}$	cache misses	2962.678	-4209.09

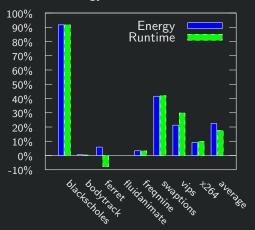
Table: Energy model coefficients.

# Results: Energy Reduction



# Results: Runtime and Energy Reduction

#### AMD Energy and Runtime Reduction



# Functionality on Withheld Tests

Program	AMD	Intel
blackscholes	100%	100%
bodytrack	92%	100%
ferret	100%	100%
fluidanimate	6%	31%
freqmine	100%	100%
swaptions	100%	100%
vips	100%	100%
×264	27%	100%

### **Anecdotes**

#### Blackscholes

- ▶ 90% less energy
- removed redundant outer loop
- modified semantics

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## **Swaptions**

- ▶ 42% less energy
- improved branch prediction
- hardware specific

### **Anecdotes**

#### **Blackscholes**

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- removed redundant outer loop
- modified semantics

## Swaptions

- ▶ 42% less energy
- improved branch prediction
- hardware specific

# Vips

- ▶ 20% less energy
- substitution of memory access for calculation
- resource trade-off

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### Caveats

# Limitations and Generality

- experimental evaluation
  - energy reduction
  - GCC-produced assembler
  - PARSEC benchmarks
- some benchmarks show no improvement
- requires high-quality test cases
- may change program behavior

## Conclusion

- 1. optimize complex runtime properties (energy)
- 2. leverages particulars of hardware, and environment
- 3. reveal compiler inefficiencies
- 4. find efficiencies, e.g., loop elimination
- 5. transformations presented as ASM diff

### Resources

# Genetic Optimization Algorithm

GOA tooling

https://github.com/eschulte/goa

reproduce results

https://github.com/eschulte/goa/tree/asplos2014

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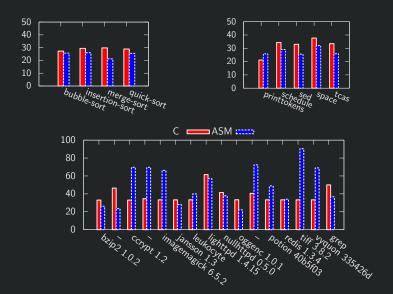
# Backup Slides

# Genetic Algorithm

#### **Parameters**

Parameter	Genprog	GOA
population size	40	2 <sup>10</sup>
evaluations	400	$2^{18}$
selection	fitness proportionate	tournament of 2
runtime	minutes	hours

# Software Mutational Robustness



# Program Syntactic Space

