## Lecture 28 — Profiler Guided Optimization

Jeff Zarnett & Patrick Lam {jzarnett, patrick.lam}@uwaterloo.ca

Department of Electrical and Computer Engineering University of Waterloo

January 4, 2019

ECE 459 Winter 2019 1/26

## **Profiler Guided Optimization**

Using static analysis, the compiler makes its best predictions about runtime behaviour.

Example: branch prediction.

ECE 459 Winter 2019 2/26

#### A Branch To Predict

```
void whichBranchIsTaken(int a, int b)
{
    if (a < b) {
        puts("a_is_less_than_b.");
    } else {
        puts("b_is_>=_a.");
    }
}
```

ECE 459 Winter 2019 3 / 26

#### A Virtual Call to Devirtualize

ECE 459 Winter 2019 4 / 26

```
void switchCaseExpansion(int i)
    switch (i)
    case 1:
        puts("I_took_case_1.");
        break:
    case 2:
        puts("I_took_case_2.");
        break;
```

ECE 459 Winter 2019 5 / 26

## Adapting to an Uncertain World

How can we know where we go?

■ could provide hints...

Java HotSpot virtual machine: updates predictions on the fly.

So, just guess.
If wrong, the Just-in-Time compiler adjusts & recompiles.

The compiler runs and it does its job and that's it; the program is never updated with newer predictions if more data becomes known.

ECE 459 Winter 2019 6 / 26

# **Profiling Mitigates Uncertainty**

C: usually no adaptive runtime system.

#### POGO:

- observe actual runs;
- predict the future.

So, we need multi-step compilation:

- compile with profiling;
- run to collect data;
- recompile with profiling data to optimize.

ECE 459 Winter 2019 7/26

Step One: Measure

First, generate an executable with instrumentation.

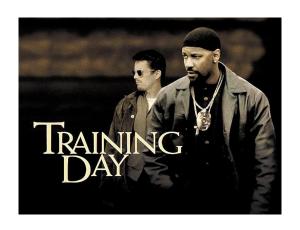
The compiler inserts a bunch of probes into the generated code to record data.

- Function entry probes;
- Edge probes;
- Value probes.

Result: instrumented executable plus empty database file (for profiling data).

ECE 459 Winter 2019 8/26

# Step Two: Training Day



ECE 459 Winter 2019 9 / 26

## **Step Two: Training Day**

Second, run the instrumented executable.

Real-world scenarios are best.

Ideally, spend training time on perf-critical sections.

Use as many runs as you can stand.

ECE 459 Winter 2019 10/26

## **Step Two: Training Day**

Don't exercise every part of the program (ain't SE 465 here!)

That would be counterproductive.

Usage data must match real world scenarios, or compiler gets misfacts about what's important.

Or you might end up teaching it that almost nothing is important... ("everything's on the exam!")

ECE 459 Winter 2019 11/26

#### Step Three: Recompile

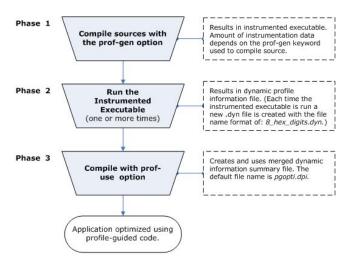
Finally, compile the program again.

Inputs: source plus training data.

Outputs: (you hope) a better output executable than from static analysis alone.

ECE 459 Winter 2019 12 / 26

#### **Summary Graphic**



ECE 459 Winter 2019 13/26

## Save Some Steps

Not necessary to do all three steps for every build.

Re-use training data while it's still valid.

Recommended dev workflow:

- dev A performs these steps, checks the training data into source control
- whole team can use profiling information for their compiles.

ECE 459 Winter 2019 14 / 26

## Not fixing all the problems in the world

What does it mean for it to be better?

The algorithms will aim for speed in areas that are "hot".

The algorithms will aim for minimal code size in areas that are "cold".

Less than 5% of methods compiled for speed.

ECE 459 Winter 2019 15 / 26

## **Combining Training Runs**

Can combine multiple training runs and manually give suggestions about important scenarios.

The more a scenario runs in the training data, the more important it will be, from POGO's point of view.

Can merge multiple runs with user-assigned weightings.

ECE 459 Winter 2019 16 / 26

## Show, Don't Tell

With the theory behind us, perhaps a demonstration about how it works is in order.

Let us consider an example using the N-Body problem.

You could look at the video https://www.youtube.com/watch?v=zEsdBcu4R00&t=21m45s (from 21:45 to 34:23).

ECE 459 Winter 2019 17/26

#### **Behind the Scenes**

In the optimize phase, compiler uses the training data for:

- Full and partial inlining
- Function layout
- Speed and size decision
- Basic block layout
- **5** Code separation
- Virtual call speculation
- Switch expansion
- Data separation
- Loop unrolling

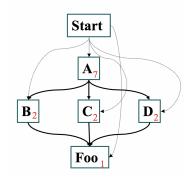
ECE 459 Winter 2019 18 / 26

#### Muh Gainz

Most performance gains from inlining.

Decisions based on the call graph path profiling.

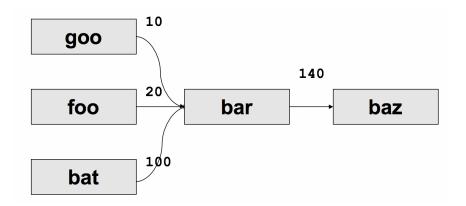
But: behaviour of function foo may be very different when called from B than when called from D.



ECE 459 Winter 2019 19 / 26

## **Another Call Graph**

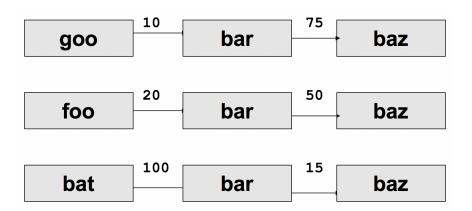
Example 2 of relationships between functions. Numbers on edges represent the number of invocations:



ECE 459 Winter 2019 20 / 26

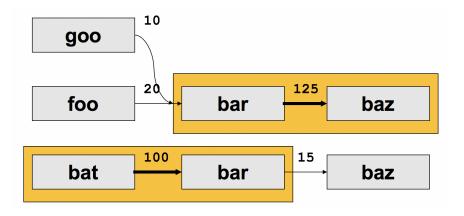
#### The POGO View of the World

When considering what to do here, POGO takes the view like this:



ECE 459 Winter 2019 21 / 26

#### The POGO View of the World



ECE 459 Winter 2019 22 / 26

## Page Locality

Call graph profiling data also good for packing blocks.

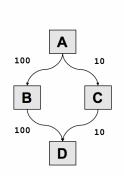
Put most common cases nearby.
Put successors after their predecessors.

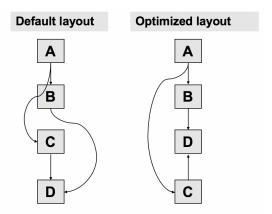
Packing related code = fewer page faults (cache misses).

Calling a function in same page as caller = "page locality".

ECE 459 Winter 2019 23 / 26

# **Block Layout**





ECE 459 Winter 2019 24 / 26

According to the author, "dead" code goes in its own special block.

Probably not truly dead code (compile-time unreachable).

Instead: code that never gets invoked in training.

ECE 459 Winter 2019 25 / 26

#### **Benchmark Results**

OK, how well does POGO work?

The application under test is a standard benchmark suite (Spec2K):

Spec2k:	sjeng	gobmk	perl	povray	gcc
App Size:	Small	Medium	Medium	Medium	Large
<b>Inlined Edge Count</b>	50%	53%	25%	79%	65%
Page Locality	97%	75%	85%	98%	80%
Speed Gain	8.5%	6.6%	14.9%	36.9%	7.9%

We can speculate about how well synthetic benchmarks results translate to real-world application performance...

ECE 459 Winter 2019 26 / 26