Lecture 27 — Profiling

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Part I

Profiling

Basic Overview

General idea:

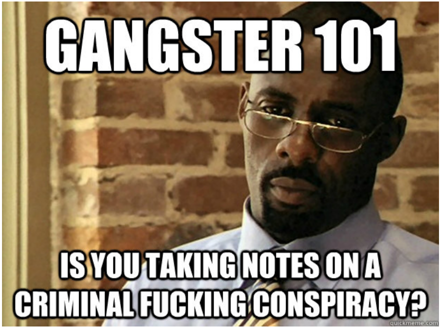
collect data on what parts of the code are taking up most of the time.

- What functions get called?
- How long do functions take?
- What's using memory?

There is always the “informal” way: “debug” by print statements.

On entry to `foo`, log “entering function foo”, plus timestamp.

On exit, log “exiting foo”, also with timestamp.



Console Profiling

Kind of works, and [JZ] has used it... But this approach is not necessarily good.

This is “invasive” profiling—change the source code of the program to add instrumentation (log statements).

Plus we have to do a lot of manual accounting.

Doesn’t really scale.

I ran the command `nvprof target/release/nbody-cuda`.

```
==20734== Profiling application: target/release/nbody-cuda
==20734== Profiling result:
            Type  Time(%)      Time     Calls       Avg       Min       Max  Name
 GPU activities:  100.00%  10.7599s         1  10.7599s  10.7599s  10.7599s  calculate_forces
                    0.00%  234.72us         2  117.36us  100.80us  133.92us  [CUDA memcpy HtoD]
                    0.00%  94.241us         1  94.241us  94.241us  94.241us  [CUDA memcpy DtoH]
      API calls:   97.48%  10.7599s         1  10.7599s  10.7599s  10.7599s  cuStreamSynchronize
                    1.92%  211.87ms         1  211.87ms  211.87ms  211.87ms  cuCtxCreate
                    0.54%  59.648ms         1  59.648ms  59.648ms  59.648ms  cuCtxDestroy
                    0.04%  4.8704ms         1  4.8704ms  4.8704ms  4.8704ms  cuModuleLoadData
                    0.00%  404.72us         2  202.36us  194.51us  210.21us  cuMemAlloc
                    0.00%  400.58us         2  200.29us  158.08us  242.50us  cuMemcpyHtoD
                    0.00%  299.30us         2  149.65us  121.42us  177.88us  cuMemFree
                    0.00%  243.86us         1  243.86us  243.86us  243.86us  cuMemcpyDtoH
                    0.00%  85.000us         1  85.000us  85.000us  85.000us  cuModuleUnload
                    0.00%  41.356us         1  41.356us  41.356us  41.356us  cuLaunchKernel
                    0.00%  18.483us         1  18.483us  18.483us  18.483us  cuStreamCreateWithPriority
                    0.00%  9.0780us         1  9.0780us  9.0780us  9.0780us  cuStreamDestroy
                    0.00%  2.2080us         2  1.1040us     215ns  1.9930us  cuDeviceGetCount
                    0.00%  1.4600us         1  1.4600us  1.4600us  1.4600us  cuModuleGetFunction
                    0.00%  1.1810us         2     590ns     214ns     967ns  cuDeviceGet
                    0.00%     929ns         3     309ns     230ns     469ns  cuDeviceGetAttribute
```

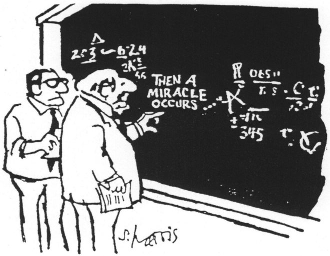
And the better version...

Oh, and for comparison, here's the one where I make much better use of the GPU's capabilities (with better grid and block settings):

```
=22619== Profiling result:
            Type  Time(%)      Time     Calls       Avg       Min       Max  Name
 GPU activities:   99.92%  417.53ms         1  417.53ms  417.53ms  417.53ms  calculate_forces
                    0.06%  236.03us         2  118.02us  101.44us  134.59us  [CUDA memcpy HtoD]
                    0.02%  93.057us         1  93.057us  93.057us  93.057us  [CUDA memcpy DtoH]
      API calls:   52.09%  417.54ms         1  417.54ms  417.54ms  417.54ms  cuStreamSynchronize
                   26.70%  214.00ms         1  214.00ms  214.00ms  214.00ms  cuCtxCreate
                   13.63%  109.26ms         1  109.26ms  109.26ms  109.26ms  cuModuleLoadData
                    7.42%  59.502ms         1  59.502ms  59.502ms  59.502ms  cuCtxDestroy
                    0.05%  364.08us         2  182.04us  147.65us  216.42us  cuMemcpyHtoD
                    0.04%  306.48us         2  153.24us  134.10us  172.37us  cuMemAlloc
                    0.04%  285.73us         2  142.86us  122.90us  162.83us  cuMemFree
                    0.03%  246.37us         1  246.37us  246.37us  246.37us  cuMemcpyDtoH
                    0.01%  61.916us         1  61.916us  61.916us  61.916us  cuModuleUnload
                    0.00%  26.218us         1  26.218us  26.218us  26.218us  cuLaunchKernel
                    0.00%  15.902us         1  15.902us  15.902us  15.902us  cuStreamCreateWithPriority
                    0.00%  9.0760us         1  9.0760us  9.0760us  9.0760us  cuStreamDestroy
                    0.00%  1.6720us         2     836ns     203ns  1.4690us  cuDeviceGetCount
                    0.00%  1.0950us         1  1.0950us  1.0950us  1.0950us  cuModuleGetFunction
                    0.00%     888ns         3     296ns     222ns     442ns  cuDeviceGetAttribute
                    0.00%     712ns         2     356ns     212ns     500ns  cuDeviceGet
```

Wizardry!

Like debugging: if you get to be a wizard you can maybe do it by code inspection.



I think you should be a little more specific, here in Step 2

But speculative execution inside your head is harder for perf than debugging.

So: we want to use tools
and do this in a methodical way.

So far we've been looking at small problems.

Must **profile** to see what's slow in a large program.

Two main outputs:

- flat;
- call-graph.

Two main data gathering methods:

- statistical;
- instrumentation.

Profiler Outputs

Flat Profiler:

- Only computes average time in a particular function.
- Does not include other (useful) information (callees).

Call-graph Profiler:

- Computes call times.
- Reports frequency of function calls.
- Gives a call graph: who called what function?

Statistical:

Mostly, take samples of the system state, that is:

- every 100ms, check the system state.
- will cause some slowdown, but not much.

Instrumentation:
Add instructions at specified program points:

- can do this at compile time or run time (expensive);
- can instrument either manually or automatically;
- like conditional breakpoints.

Guide to Profiling

When writing large software projects:

- First, write clear and concise code.
  Don't do premature optimizations—
  focus on correctness.
- Profile to get a baseline of your performance:
  - allows you to easily track any performance changes;
  - allows you to re-design your program before it's too late.

Focus your optimization efforts on the code that matters.

Things to Look For

Good signs:

- Time is spent in the right part of the system.
- Most time should not be spent handling errors; in non-critical code; or in exceptional cases.
- Time is not unnecessarily spent in OS.

Kitchener driver follows GPS directions right into Lake Huron...

Development vs Prod

You can always profile your systems in development, but that might not help with complexities in production.

The constraints on profiling production systems are that the profiling must not affect the system's performance or reliability.

Per-Process

We'll first talk about `perf`, the profiler recommended for use with Rust. This is Linux-specific, though.

The `perf` tool is an interface to the Linux kernel's built-in sample-based profiling using CPU counters.

Previous Offering Profiling

```
[plam@lynch nm-morph]$ perf stat ./test_harness

 Performance counter stats for './test_harness':

      6562.501429 task-clock                #    0.997 CPUs utilized
              666 context-switches          #    0.101 K/sec
                0 cpu-migrations            #    0.000 K/sec
            3,791 page-faults               #    0.578 K/sec
   24,874,267,078 cycles                    #    3.790 GHz
                                [83.32%]
   12,565,457,337 stalled-cycles-frontend   #   50.52% frontend cycles idle
        [83.31%]
    5,874,853,028 stalled-cycles-backend    #   23.62% backend  cycles idle
         [66.63%]
   33,787,408,650 instructions              #    1.36  insns per cycle
                                            #    0.37  stalled cycles per
                                                insn [83.32%]
    5,271,501,213 branches                  #  803.276 M/sec
                               [83.38%]
      155,568,356 branch-misses             #    2.95% of all branches
                      [83.36%]

      6.580225847 seconds time elapsed
```

The first thing to do is to compile with debugging info, go to your `Cargo.toml` file and add:

```
[profile.release]
debug = true
```

This means that `cargo build --release` will now compile the version with debug info.

I've got a Cunning Plan

Run the program using `perf record`, which will sample the execution of the program to produce a data set.

Then there are three ways we can look at the code: `perf report`, `perf annotate`, and a flamegraph.

During development of some of the code exercises, I used the CLion built-in profiler for this purpose.

It generates a flamegraph for you too, and I'll show that for how to create the flamegraph as well.

Part II

Profiler Guided Optimization

Profiler Guided Optimization

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

Example: branch prediction.

```
fn which_branch(a: i32, b: i32) {
    if a < b {
        println!("Case one.");
    } else {
        println!("Case two.");
    }
}
```

A Virtual Call to Devirtualize

```
trait Polite {
    fn greet(&self) -> String;
}

struct Kenobi {
    /* Stuff */
}
impl Polite for Kenobi {
    fn greet(&self) -> String {
        return String::from("Hello
            there!");
    }
}
```

```
struct Grievous {
    /* Things */
}
impl Polite for Grievous {
    fn greet(&self) -> String {
        return String::from("General
            Kenobi.");
    }
}

fn devirtualization(thing: &Polite) {
    println!("{}", thing.greet());
}
```

```
fn match_thing(x: i32) -> i32 {
    match x {
        0..10 => 1,
        11..100 => 2,
        _ => 0
    }
}
```

Same thing with x: what is its typical value? If we know that, it is our prediction.

Actually, in a match block with many options, could we rank them in descending order of likelihood?

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.

Profiling Mitigates Uncertainty

Rust: 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.

Step One: Measure

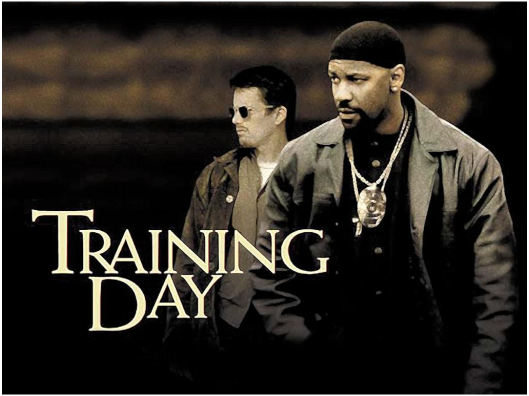
First, generate an executable with instrumentation.

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).

Step Two: Training Day



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.

Step Two: Training Day

Don't exercise every part of the program (not SE 465/ECE 453 here!)

That would be counterproductive.

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

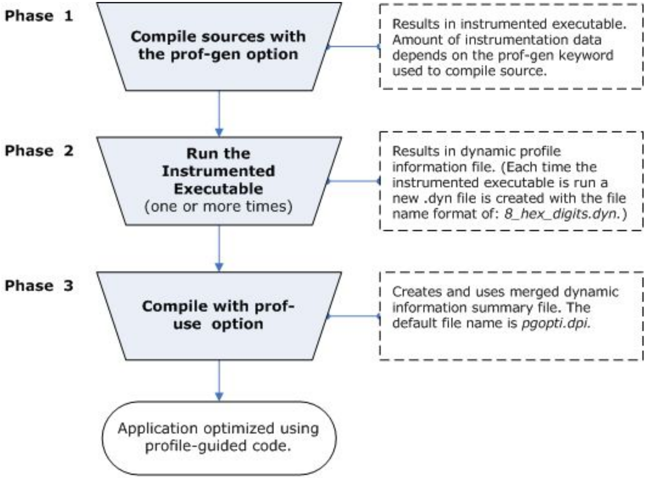
Or you might end up teaching it that almost nothing is important... ("everything's on the exam!")

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.


Phase 1
Compile sources with the prof-gen option
Results in instrumented executable. Amount of instrumentation data depends on the prof-gen keyword used to compile source.
Phase 2
Run the Instrumented Executable
(one or more times)
Results in dynamic profile information file. (Each time the instrumented executable is run a new .dyn file is created with the file name format of: 8_hex_digits.dyn.)
Phase 3
Compile with prof-use option
Creates and uses merged dynamic information summary file. The default file name is pgopti.dpi.
Application optimized using profile-guided code.

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.

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.

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.

Full Test Scenario

```
# STEP 1: Compile the binary with instrumentation
rustc -Cprofile-generate=/tmp/pgo-data -O ./main.rs

# STEP 2: Run the binary a few times, maybe with common sets of args.
#         Each run will create or update '.profraw' files in /tmp/pgo-data
./main mydata1.csv
./main mydata2.csv
./main mydata3.csv

# STEP 3: Merge and post-process all the '.profraw' files in /tmp/pgo-data
llvm-profdata merge -o ./merged.profdata /tmp/pgo-data

# STEP 4: Use the merged '.profdata' file during optimization. All 'rustc'
#         flags have to be the same.
rustc -Cprofile-use=./merged.profdata -O ./main.rs
```

Behind the Scenes

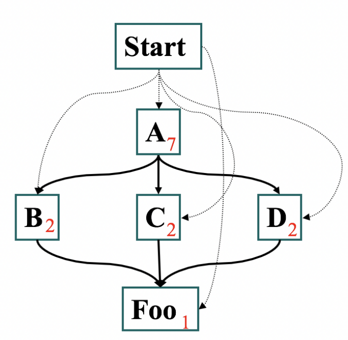
In the optimize phase, compiler uses the training data for:

1. Full and partial inlining
2. Function layout
3. Speed and size decision
4. Basic block layout
5. Code separation
6. Virtual call speculation
7. Switch expansion
8. Data separation
9. Loop unrolling

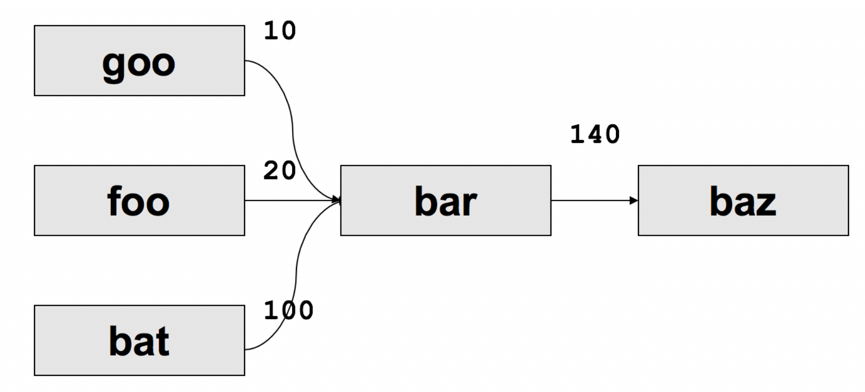
Most performance gains from inlining.

Decisions based on the call graph path profiling.

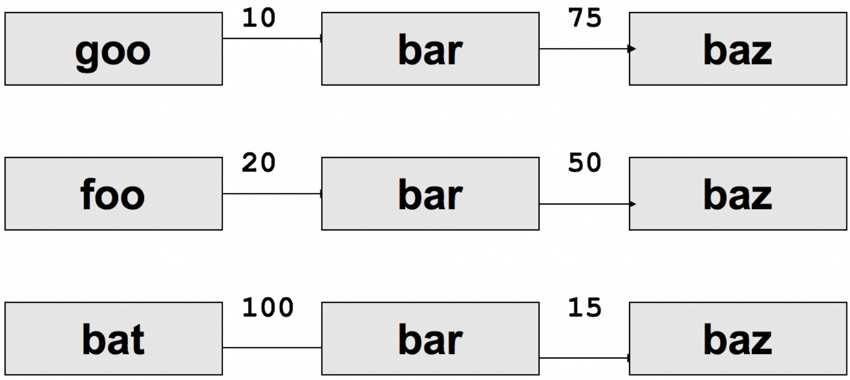
But: behaviour of function `foo` may be very different when called from `B` than when called from `D`.

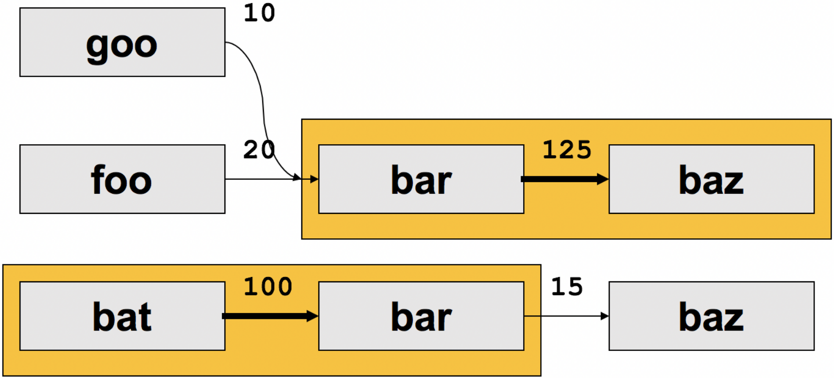


Example 2 of relationships between functions.
Numbers on edges represent the number of invocations:



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




goo
10
foo
20
bar
125
baz
bat
100
bar
15
baz

Page Locality

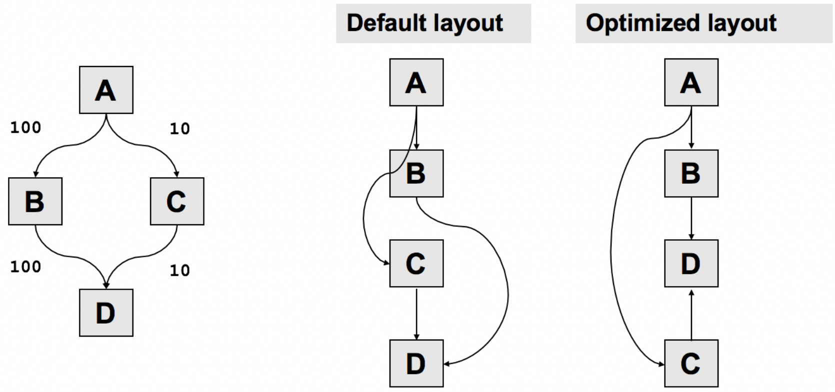
Call graph profiling data also good for packing blocks.

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".

Block Layout



Dead Code?

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.

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
Inlined Edge Count	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…