Google

Accurate Runtime Performance Estimation for Predictably Training ML Guided Register Eviction Policies

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Why do this in the first place?

Rewards are critical for training learned heuristics.

Trace-based Cost Modeling

Agenda

01 Trace Based Cost Modeling for Register Allocation

02 (Distributed) Training of Models

03 Further Improvements

Traces vs PGO Data

PGO-Based

```
.loop:
        add     eax, dword ptr [rdi + 4*rdx]
        inc     rdx
        cmp     rcx, rdx
        jne     .loop
```

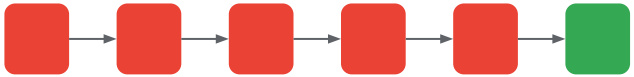
X5

```
.exit:
        add     eax, 5
        ret
```

X1

- Reward is a linear combination of instruction types multiplied by their block frequency.

Trace-Based



- Reward is some operation (typically cycles) over the sequence of instructions. We have several options to choose from:
  - Analytical CPU pipeline models.
  - ML based CPU models.
  - Raw Instruction Counting.

Sourcing Trace Data

- Previous work, llvm-mcad (EuroLLVM 2022 mshockwave@), (https://youtu.be/ZGEP7JEIKNo) that guided us down this direction used a QEMU plugin.
- Use DynamoRIO to produce traces due to good internal support.

Basic Block Trace Modeling

We need to be able to collect a single trace and apply it to many variants of the same binary as rerunning each time defeats the point.

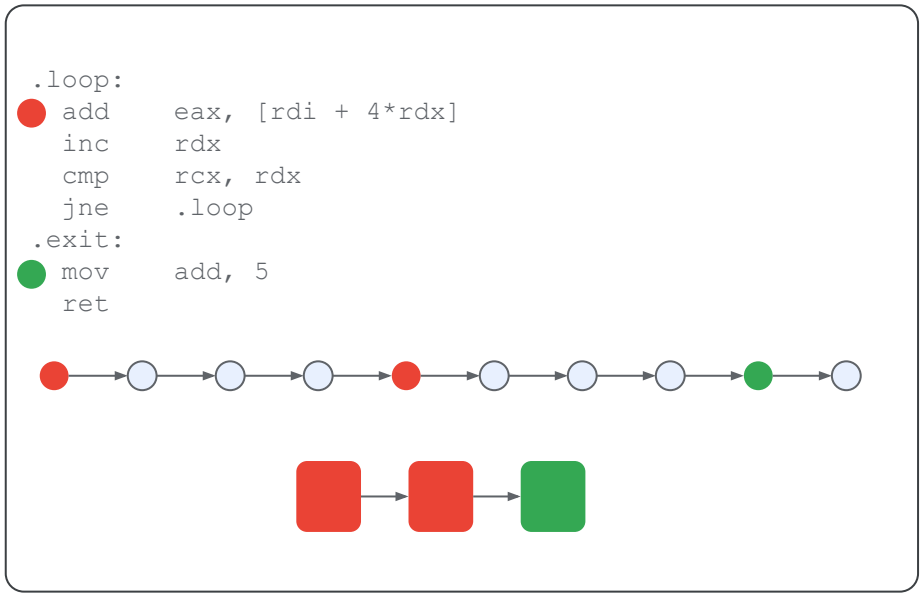
Sourcing Basic Block Information

Take Advantage of some of the Propeller Infrastructure (Basic Block Address Maps).

BB Trace Extraction

How to turn an instruction stream into a BB stream that can be replayed.

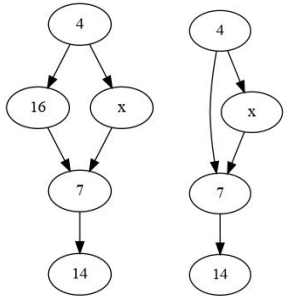
- Add a basic basic block to the trace every time we encounter an instruction with a PC starting at the beginning of a BB.
- Sometimes we need to split BBs.
  - Call Instructions
  - TCMalloc RSeq
  - Inline Assembly

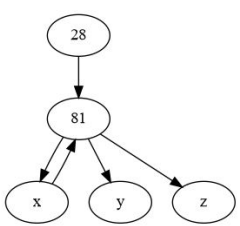


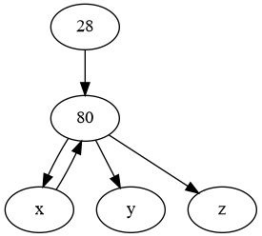
Basic Block Trace Modelling

Becomes as simple as loading BBs from the binary/compiled corpus.

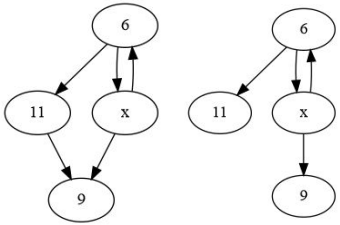
Reconciling CFG Differences - The Problem

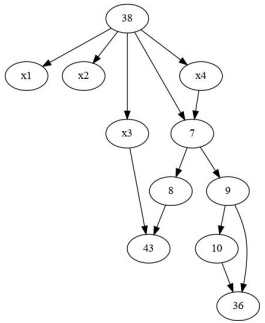


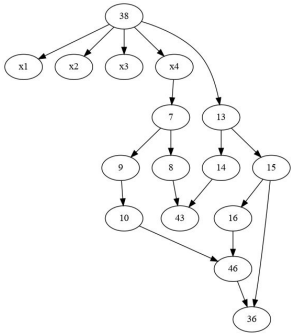




- Most cases are trivially reconcilable.
- Some cases are impossible to reconcile without additional information.







Reconciling CFG Differences - The Side Step

Disabling 3.5 Passes eliminates all CFG Differences

Findings

1. Disabling three (believed to be) non-regalloc-coupled passes eliminates all CFG differences.
2. Disable one option on another pass (the half a pass).
3. Simple trick allows for much simpler BB trace modelling design.

BB Traces are Reasonably Close to Source Traces

0.5% missing instructions

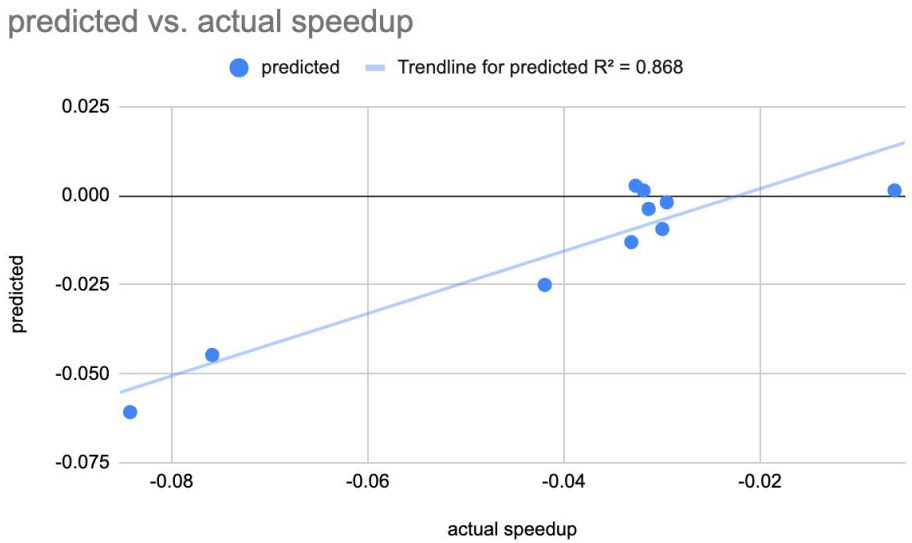
On traces upwards of 10M instructions.

Some cases we are not handling currently like interrupted restartable sequences and symbols from assembly files. No theoretical obstacles to completely fixing the gap.

It Even Works With PGO+CSPGO+ThinLTO!

For skylake, measuring runtime in cycles. Albeit with a large constant offset.

Predicted Speedup vs. Actual Speedup

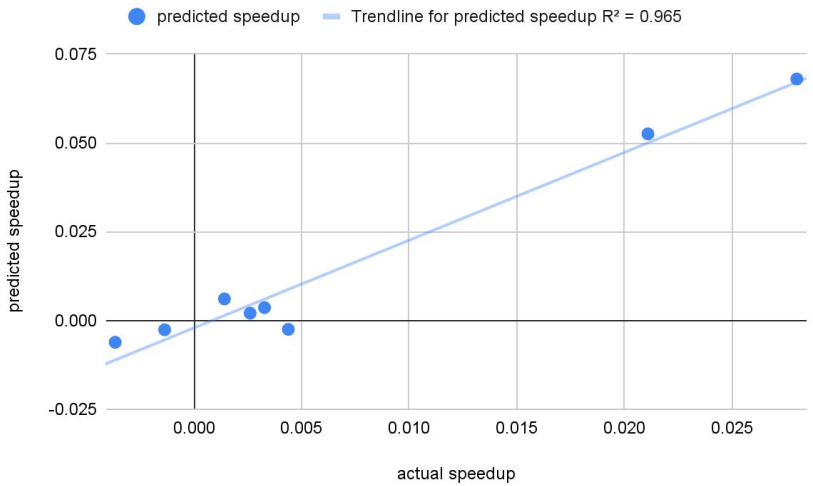


Results from LLVM opt.

The Non-PGO case works as well:

`opt -passes="default<O3>" -disable-output` on StructuralHash.cpp from LLVM. ~10M retired instructions.

Predicted Speedup vs. Actual Speedup



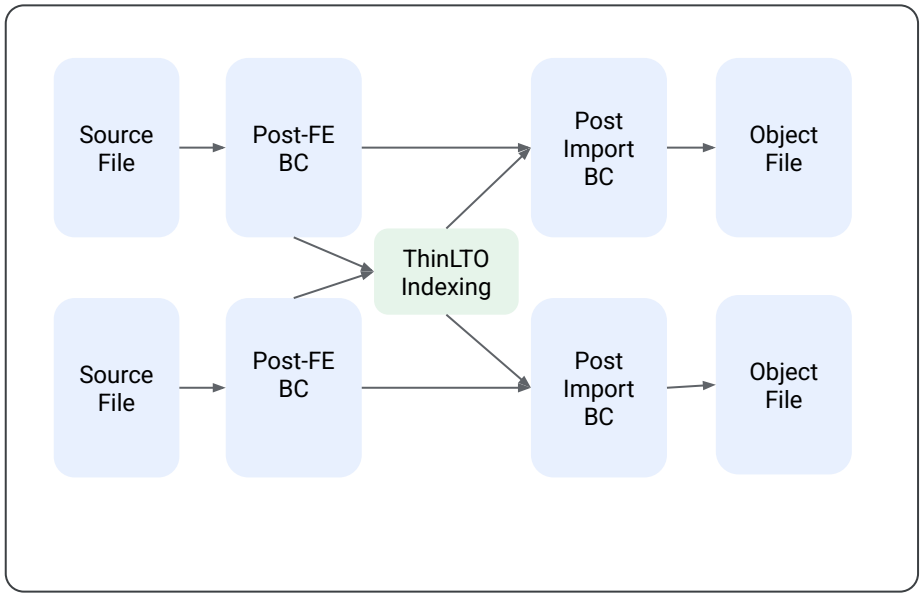
Results from LLVM opt.

Training with Reinforcement Learning

Background - The Corpus

How should we efficiently collect training data?

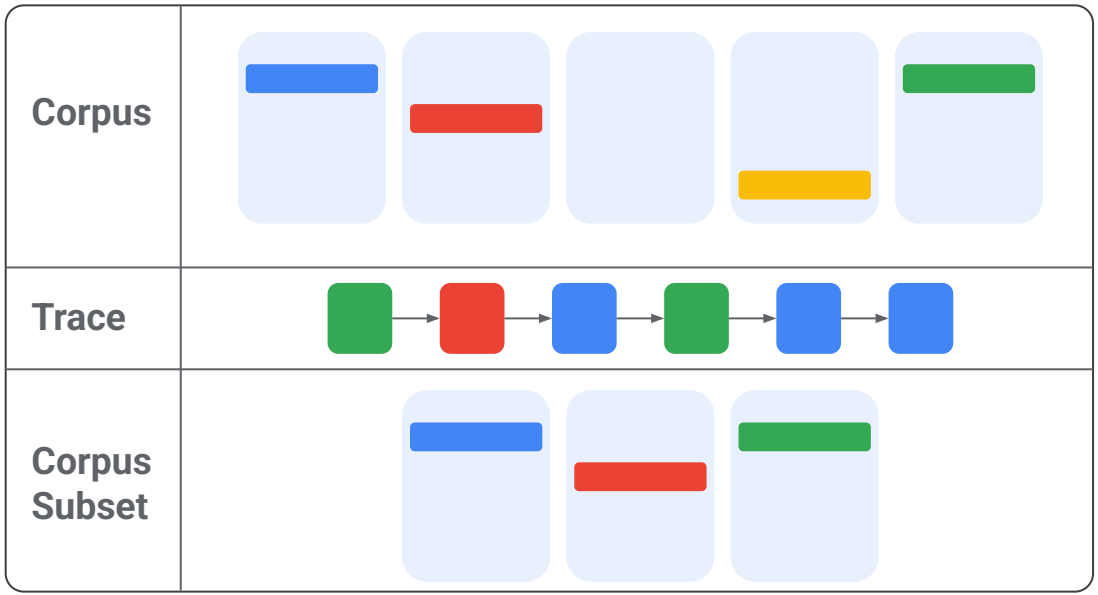
We collect LLVM Bitcode for all translation units involved in the final link.



Corpus Subsetting

How do we efficiently evaluate models?

- Find the minimum set of translation units covering the entire set of functions in the trace.
- Pull them to the side.



Background - Training Setup

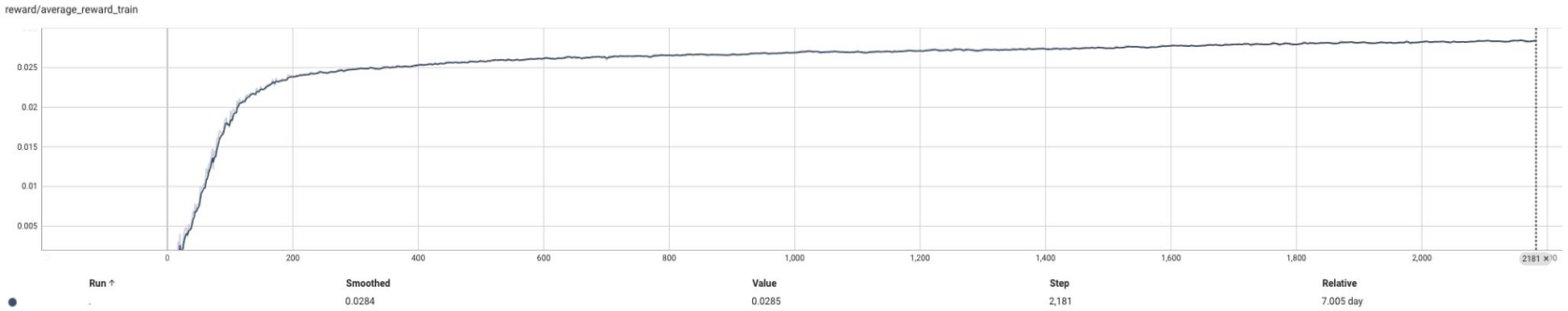
How do the requirements on the ML side interface with the cost model/compiler side?

- We use ES (Evolutionary Strategies) as our training algorithm.
  - Simple math, relatively easy to understand.
  - Enables long trajectories - We can give feedback on many individual decisions and the algorithm will still adjust the policies appropriately.
  - Has a set of perturbations for each iteration.
- Utilize existing training infrastructure
  - But scaled given now we need to compile an entire corpus subset to get a signal rather than a handful of modules.
- First experiments were performed with the same opt invocation from earlier. ~10M retired instructions.

Training Results

It trains! Somewhat slowly… (for LLVM opt)

Reward (Predicted speedup over baseline)



- 100 Machine Slices (1600 Threads)
- 100 Perturbations per iteration
- ~800 Modules
- ~7 Days of training time
- 0.5% Real World Performance Improvement over an already peak optimized (PGO+CSPGO+ThinLTO) binary.

So Why Does This Matter?

We have a validated, predictive cost model for real applications.

Distributed Training

Distributing the Training Process

Using more machines will at least help.

01

Parallelize individual workers

We use a threadpool within each worker to enable parallel compilation with the modelling component already being parallelized.

02

Spawn a bunch of distributed workers.

We use XM to manage experiments, with each worker being given about 32CPU cores, giving us reasonable scalability.

03

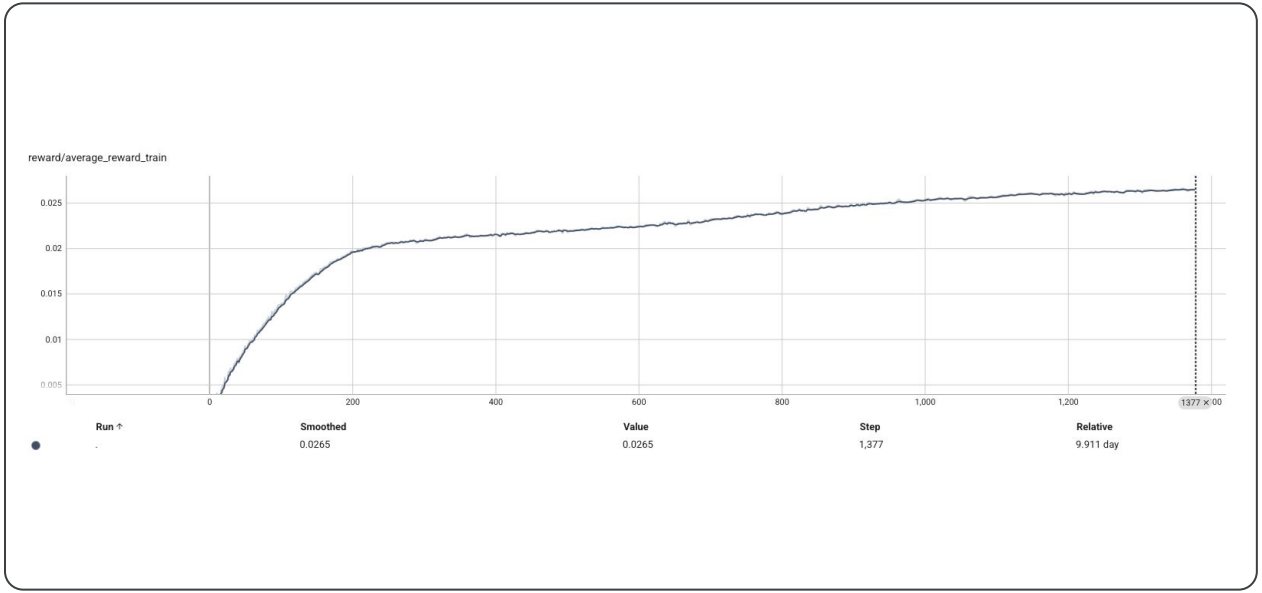
Profit (Somewhat)

This dropped iterations times to about five minutes. The latency of an individual model evaluation precludes us from going faster. We can evaluate many perturbations in parallel.

Shipping a Model

Training - Training Hyperparameter Tuning/RL

RL training started to go significantly faster when we realized the learning rate could be increased 10x with no ill-effect. More experimentation is still needed.



Some Reasonable Initial Performance Improvements

This is from a new model trained on a single workload. It ends up generalizing reasonably well.

Internal Server App 1

- 0.34ms latency on action 1
- 0.24ms latency on action 2

Internal Search App 1

```
Benchmark Setup 1:
---- total:qps ----
diff: +0.32% ±0.088%
---- <workload1 cpu kcycles> ----
diff: -0.75% ±0.198%
Benchmark Setup 2:
---- <workload2 cpu kcycles> ----
diff: -0.46% ±0.268%
```

Internal Search App 2

```
-- <round trip latency> --
diff: -0.64% ±0.372%
```

Current and Future Work

During training, only compiling functions with regalloc decisions causes compile time drops from 3-4 minutes to 5-10s.

Modeling time remains about the same as it is bottlenecked by MCA. We have some ideas on how to fix that...

Reducing Modeling Costs

Now that compile times have been drastically reduced, modeling costs dominate. It would be good to reduce them too.

- Only modeling changing functions might provide significant benefits.
  - Benefits depends upon how many functions they call.
  - Needs empirical validation.
  - Natural extensions (like excluding blocks from functions that get called) also need separate validation.
- Trace subsetting - Only evaluate a subset of the traces on each invocation.

Future Work

Future Work

Understanding Constant Offsets

- Understand why our model is producing large constant offsets.
- Hopefully leads to better models.
- Experiment with other modelling techniques (ML based, etc.)

Ship Better Models

- Utilize more efficient training techniques, train better models and ship them.

What do we need to do to Generalize for other Optimizations?

- Control flow graph reconciliation?
- Keep track of data/inputs to interpret (M)IR?
- Something else?
- Better cost modelling techniques?

Thank You!

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Thank You!

(Questions?)

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