Cost Modelling for Register Allocation and Beyond
COST MODELLING FOR REGISTER ALLOCATION AND BEYOND

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WHY FAST, ACCURATE, AND STATIC COST MODELS?

» Benchmarking is expensive and noisy.

» Cost models might be called millions of times during training.

» Having deterministic results can make ML training easier.

» The better the accuracy, the more "deterministic" model training can be.

» Higher accuracy leads to better deployed models.
Currently, we’re using a linear model, implemented in \texttt{llvm/lib/CodeGen/RegAllocScore.cpp}

- Counts the number of a couple memory specific instructions, weights by latencies and MBB frequency.
- Does produce some signal.
- Leaves a lot to be desired in terms of "determinism" in training.
- Still can produce performant heuristic-replacing models. One is currently deployed in Google Search.
EVALUATING COST MODELS - PROCESS

Source Code → Clang/LLVM

PGO Data → Score → Evaluation

Fuzzed Regalloc Eviction Decisions → Executable → Benchmarking
EVALUATING COST MODELS - METRICS

» Polarity correct - polarity prediction around an arbitrary pivot point.
» Mean difference
» Ordering (tau coefficient)
LINEAR MODEL PERFORMANCE

» Does not perform particularly well.
» Polarity correct metric hovers around the 50-60% mark.
» Average difference is a little under 5%.
» Tau coefficient for standard benchmarks hovers around 0.
» Fitting new weights greatly improves performance but offers no generalization.
USING SOA BB COST MODELS

» New BB cost models are quite accurate\(^1\) and reasonably fast.
» Models many more properties than the simple linear model (like instruction ordering).
» Learned models are also highly performant\(^2\).

\(^1\)Abel and Reineke, “uiCA”.
\(^2\)Sykora et al., GRANITE.
BB COST MODELS - PROCESS

Source Code → Clang/LLVM → PGO Data → BB Frequencies → Executable → BB Cost Model
Significantly better than the linear model on all metrics.
Percent error drops by up to 50%.
Polarity accuracy increases even in hard to model cases.
Actual accuracy of ordering is about the same.
LIMITATIONS OF THIS WORK

» The current evaluation framework only works on small benchmarks.
» Only a small variety of benchmarks have been tested.
» Achieving ideal execution conditions while running non-trivial benchmarks is difficult.
» Only fuzzed part of the register allocator.
WHERE/WHY DO THESE MODELS FAIL

» These models all assume ideal execution environments.
» Ideal conditions are rare and non-ideal conditions can change results by multiple orders of magnitude.
» Presence of L1 cache misses significantly impacts the performance of the linear model.
» Anything beyond the stream of instructions in a BB is not modelled (i.e., branching, function call overhead).
FUTURE DIRECTIONS - BETTER LEARNED BB MODELS

» Learned cost models are more adaptable to new (micro)architectures.

» Ground truth data has a lot of collection nuances.\(^3\)

» Should be landing changes soon in \texttt{llvm-exegesis} to alleviate this problem.

» Assembly fuzzing might alleviate models learning false patterns\(^5\).

\(^3\)Abel and Reineke, “uiCA”.
\(^4\)Chen et al., “BHive”.
\(^5\)Ritter and Hack, “AnICA”.
Modelling non-ideal execution completely statically is essentially impossible.

Collecting profile information and tagging specific instructions should massively increase accuracy.

Building data collection pipelines and integrating this data into LCMs is an open scientific/engineering problem.
» Artifacts available at https://github.com/boomanaiden154/regalloc-cost-model-evaluation

» Questions?