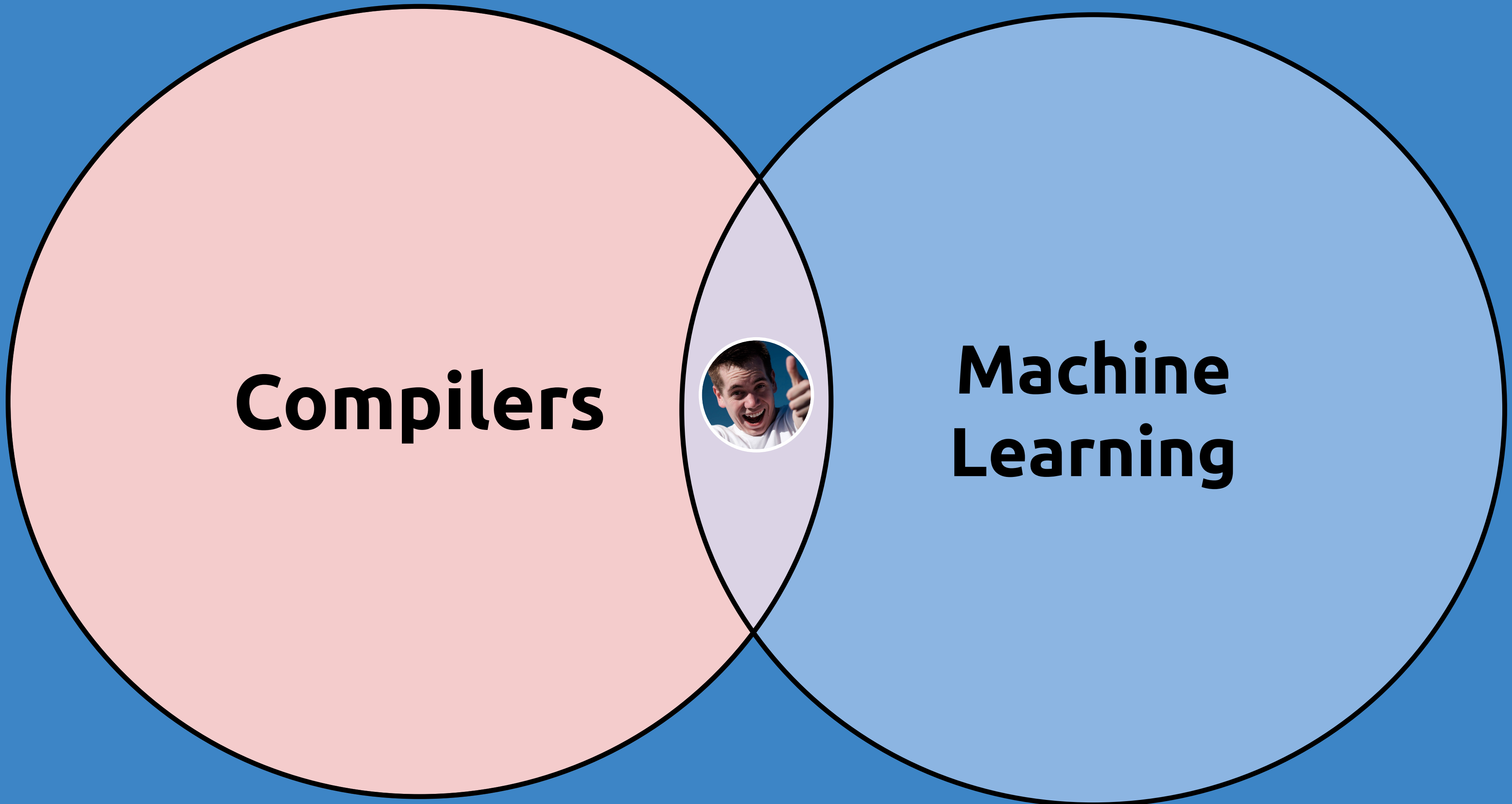
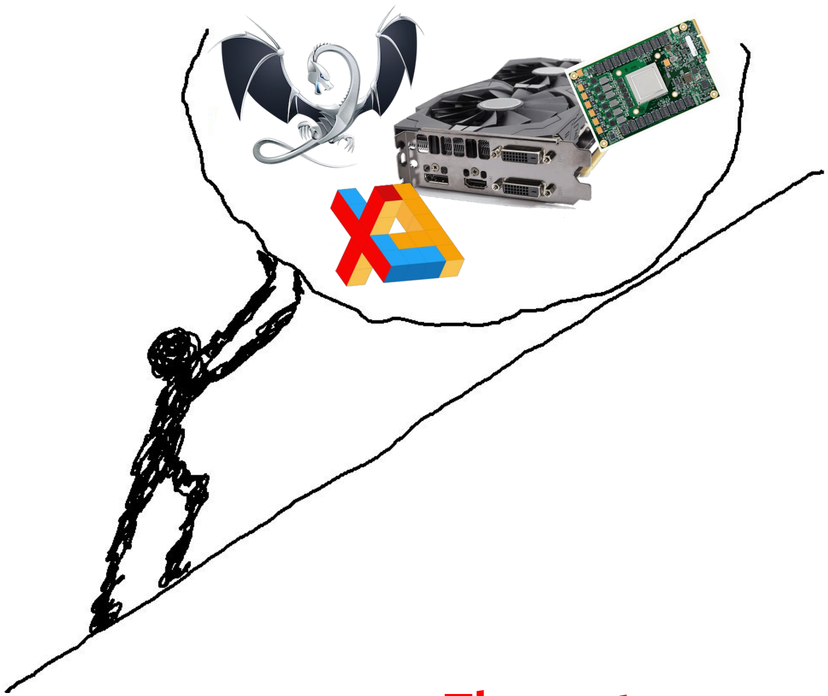
ProGraML: Graph-based Deep Learning for Program Optimization and Analysis.

Chris Cummins
Facebook AI Research

"machine learning for compilers for machine learning"



Tuning optimizing compilers...



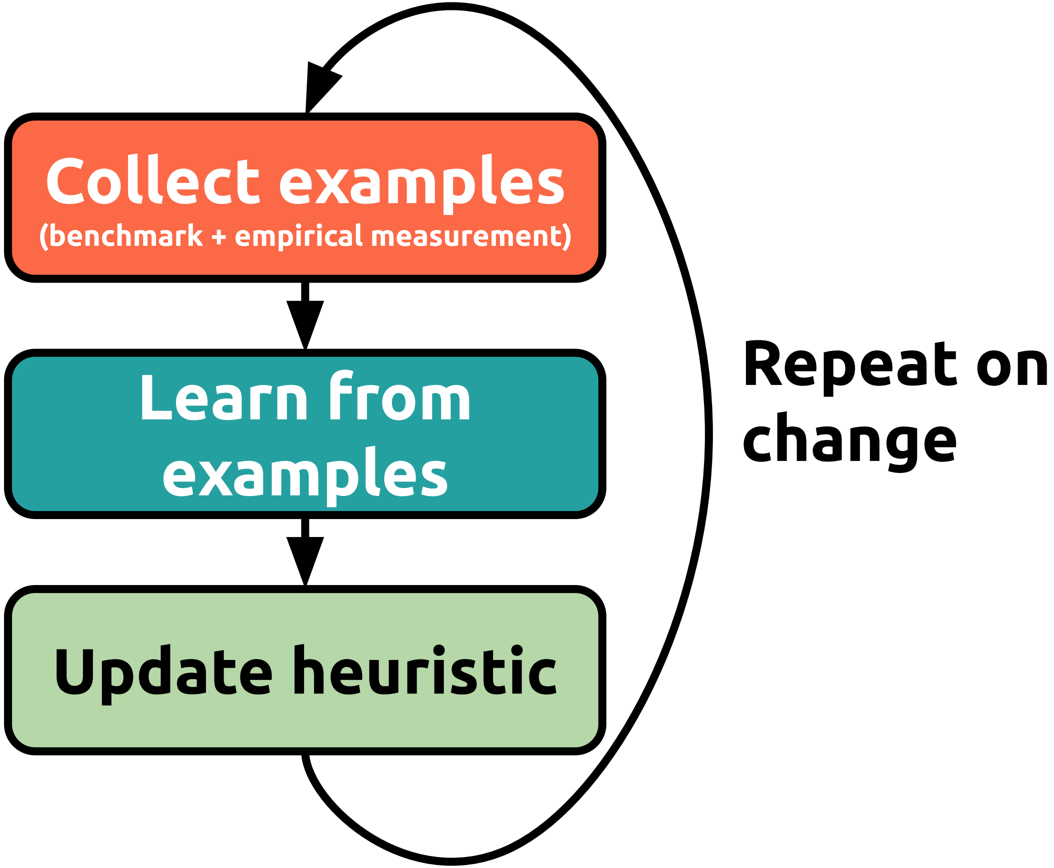
The problem

- 1000s of variables
- Limited by domain expertise
- Compiler / HW keeps changing

The cost

- Bad heuristics
- Wasted energy, $$$
- Widening performance gap

"**Build** an optimizing compiler, your code will be fast for a day.
Teach a compiler to optimize ... "

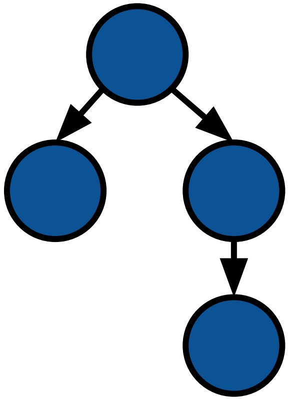


Summarize the program

Program

```
void LinearAlgebraOp<InputScalar,
OutputScalar>::AnalyzeInputs(
    OpKernelContext* context, TensorInputs* inputs,
    TensorShapes* input_matrix_shapes, TensorShape*
batch_shape) {
  int input_rank = -1;
  for (int i = 0; i < NumMatrixInputs(context); ++i) {
    const Tensor& in = context->input(i);
    if (i == 0) {
      input_rank = in.dims();
      OP_REQUIRES(
          context, input_rank >= 2,
          errors::InvalidArgument(
                   "Input tensor ", i,
                   " must have rank >= 2"));
```

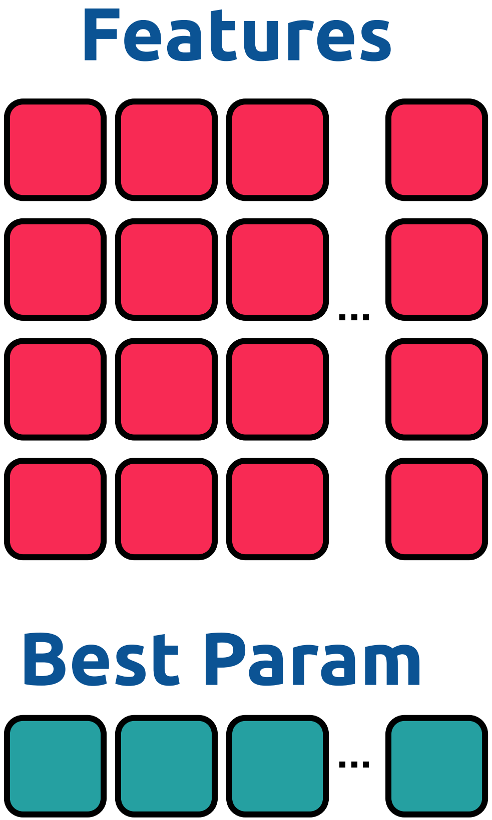
IR
(CFG, DFG, AST,...)



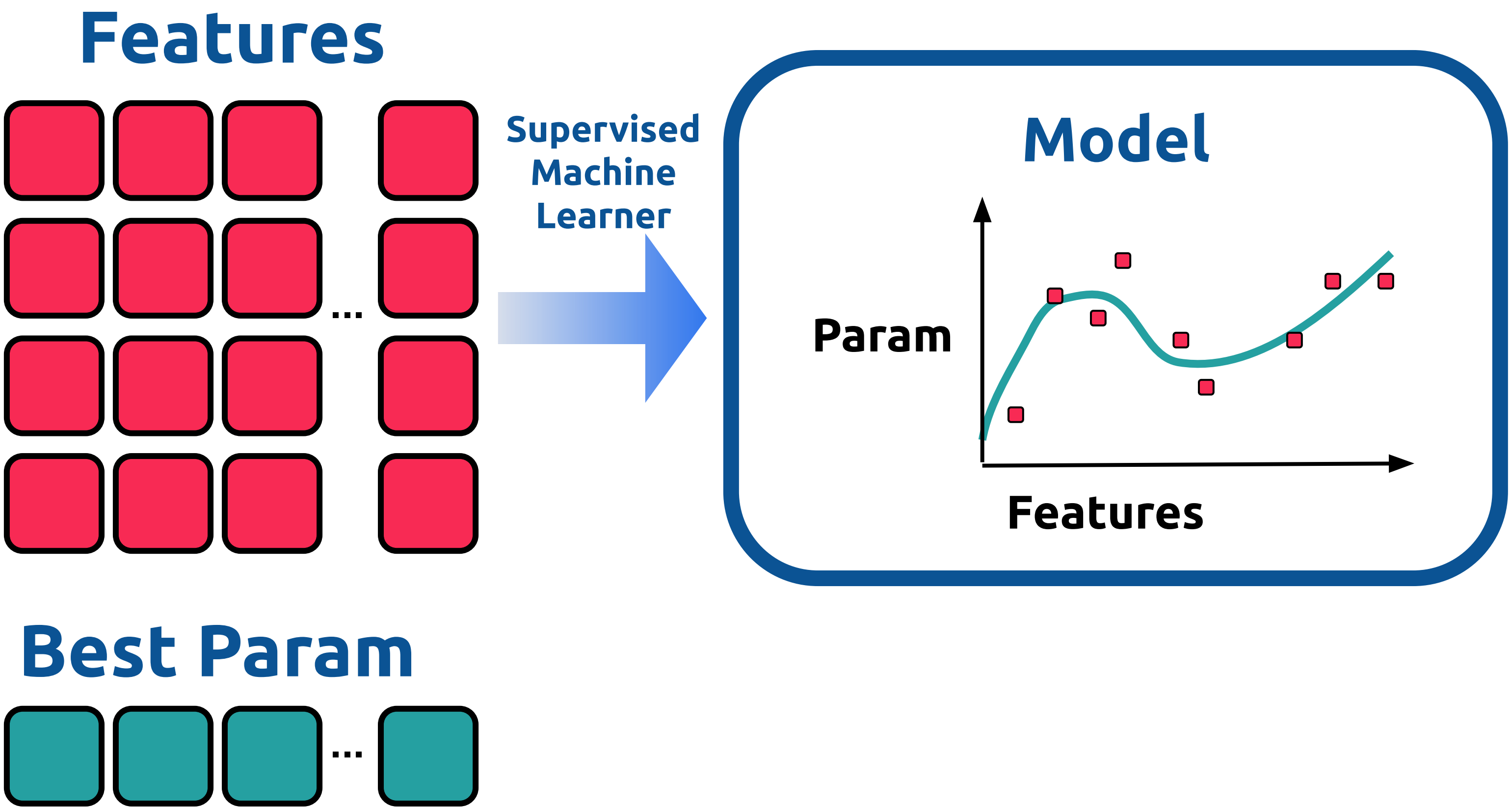
Features

- #. instructions
- loop nest level
- arithmetic density
- trip counts

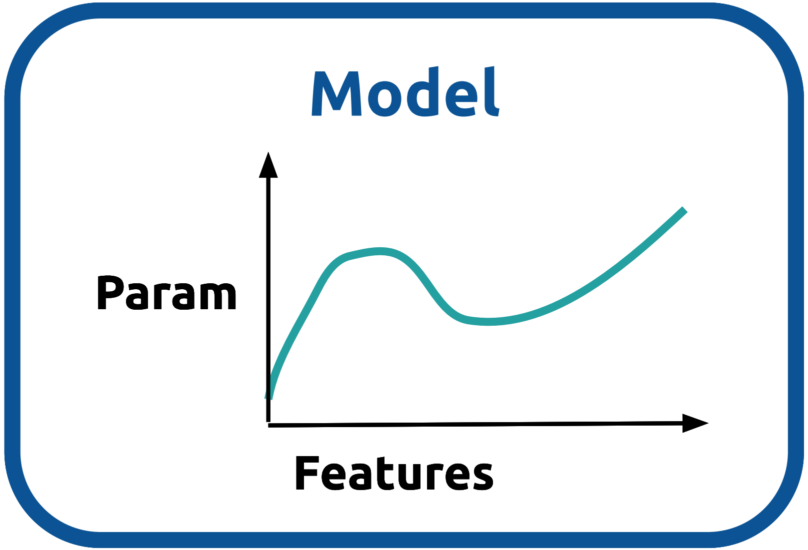
Collect examples



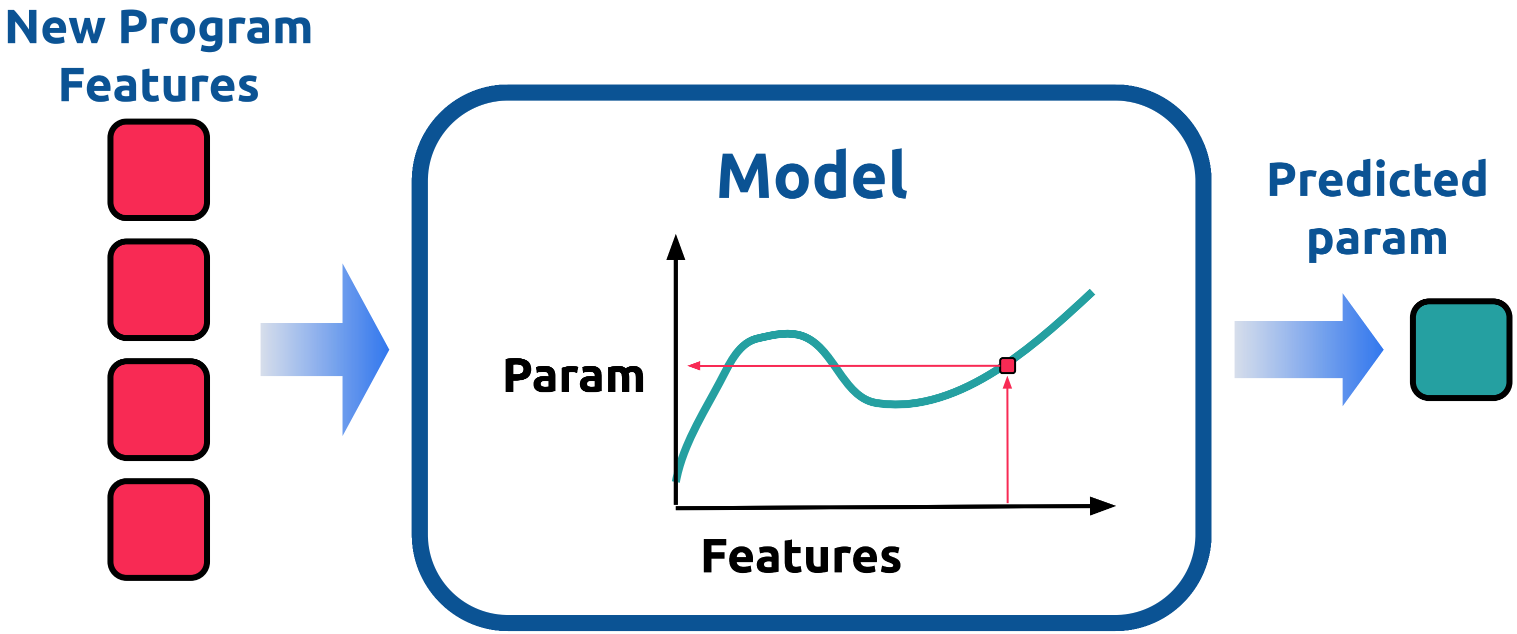
Learn from examples



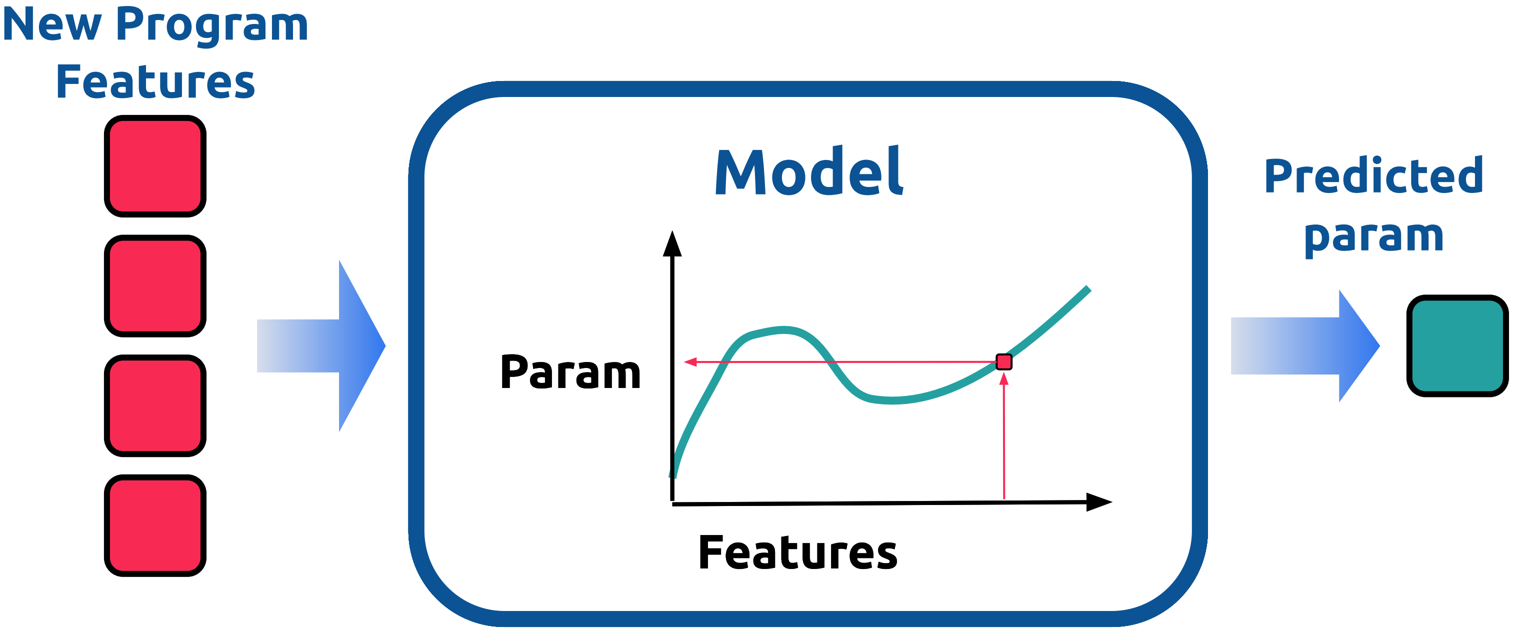
The model is the heuristic



The model is the heuristic



The model is the heuristic

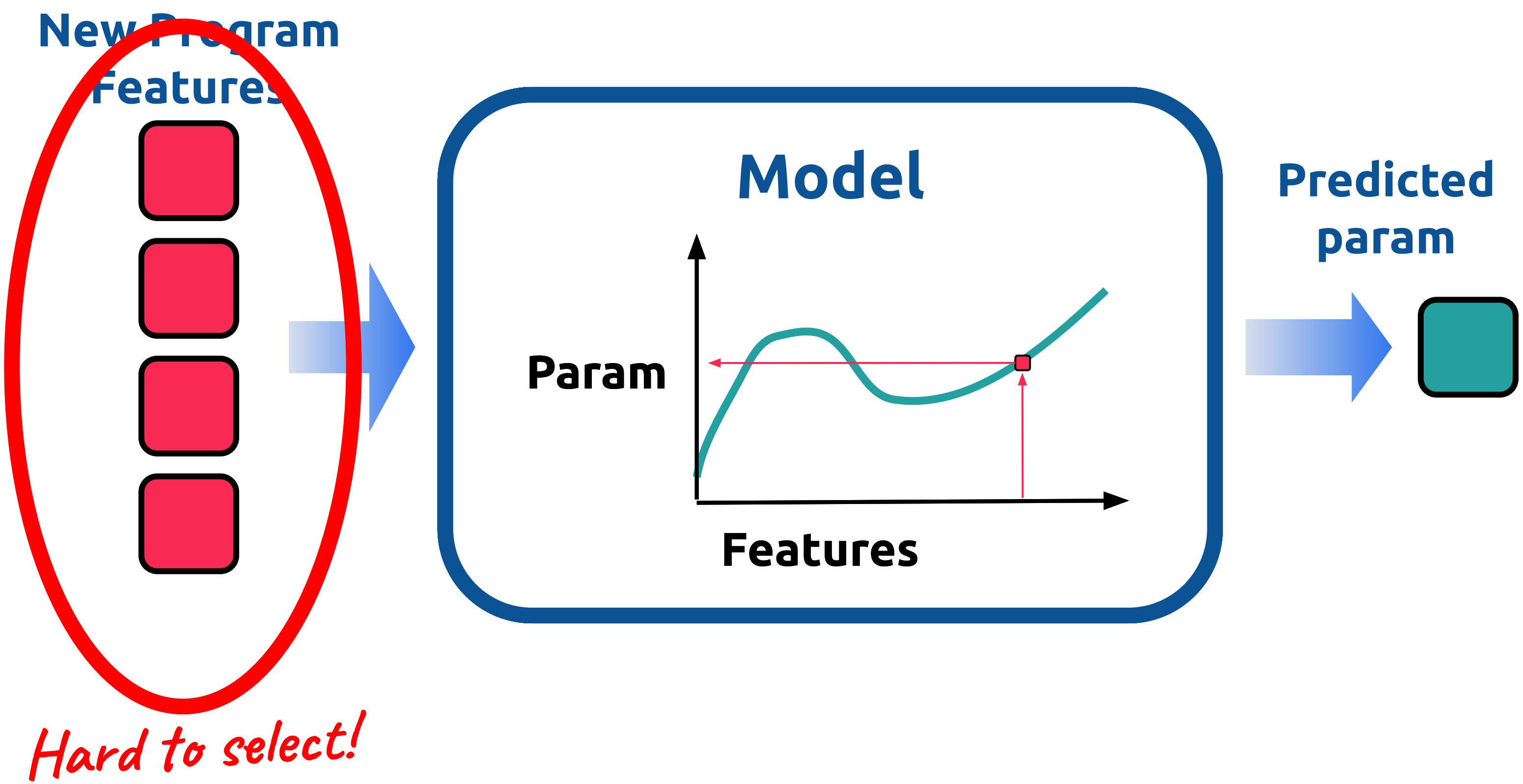


Very successful!

Huge performance gains to be had. Typically outperforms human expert. [Wang et. al. 2018]

Why aren't our compilers full of ML?

The model is the heuristic



Learning without features

(Cummins et al., PACT 17)
"End-to-end Deep Learning of Optimization Heuristics"

1. Input

```
kernel void A(global float* a, const float b) {
  a[get_global_id(0)] *= 3.14 + b;
}
```

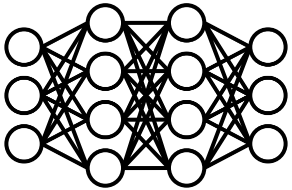
2. Vocab

Token	Index	Token	Index
kernel	0	,	9
[space]	1	const	10
void	2	b	11
A	3	)	12
(	4	{	13
global	5	\n	14
float	6	[	15
*	7	get_global_id	16
a	8	0	17

181 tokens

3. Encoded

0 1 2 1 3 4 5 1



LSTM

Optimization Decision

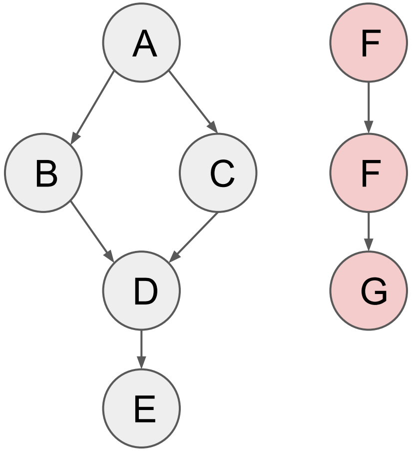
✓

The problem with code representations

Source code is ***highly structured***

It isn't a vector of numbers

Feature vectors are easy to fool (e.g. insert dead code).



It isn't a sequence of tokens

Sequential representations fail on non-linear relations, long-range deps.

```
void A(int a) {
  int b = init();
  //
  // ... 1000 lines
  //
  //
  return b - a;
}
```

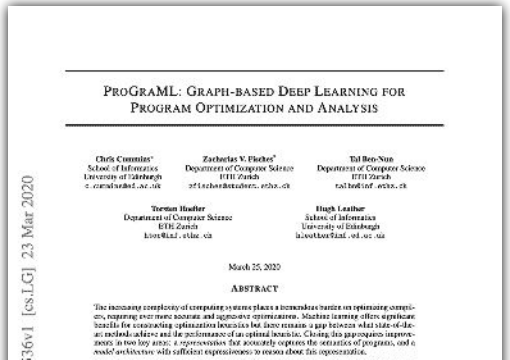
Can we make ML think like a compiler?

Program Graphs for Machine Learning

General-purpose representation of programs for optimization tasks.

Task independent - capture structured relations fundamental to program reasoning (i.e. data flow analysis)

Language independent - derived from compiler IRs



PROGRAML: GRAPH-BASED DEEP LEARNING FOR PROGRAM OPTIMIZATION AND ANALYSIS

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ABSTRACT

The increasing complexity of computing systems places a tremendous burden on optimizing compilers, requiring ever more accurate and aggressive optimizations. Machine learning offers significant benefits for constructing optimization heuristics but there remains a gap between what state-of-the-art methods achieve and the performance of an optimal heuristic. Closing this gap requires improvements in two key areas: a representation that accurately captures the semantics of programs, and a model architecture with sufficient expressiveness to reason about this representation.

Building ProGraML: IR

Derive **IR** from input program (here, LLVM)

Why IR?

Language **agnostic**
(e.g. C, C++, OpenCL, Swift, Haskell, Java for LLVM)

We want to improve compiler decisions, so use a **compiler's eye** view.

```
int Fib(int x) {
 switch (x) {
  case 0:
   return 0;
  case 1:
   return 1;
  default:
   return Fib(x - 1)
        + Fib(x - 2);
 }
}
```

```
define i32 @Fib(i32) #0 {
 switch i32 %0, label %3 [
   i32 0, label %9
   i32 1, label %2
 ]

; <label>:2:
 br label %9

; <label>:3:
 %4 = add nsw i32 %0, -1
 %5 = tail call i32 @Fib(i32 %4)
 %6 = add nsw i32 %0, -2
 %7 = tail call i32 @Fib(i32 %6)
 %8 = add nsw i32 %7, %5
 ret i32 %8

; <label>:9:
 %10 = phi i32 [ 1, %2 ], [ %0, %1 ]
 ret i32 %10
}
```

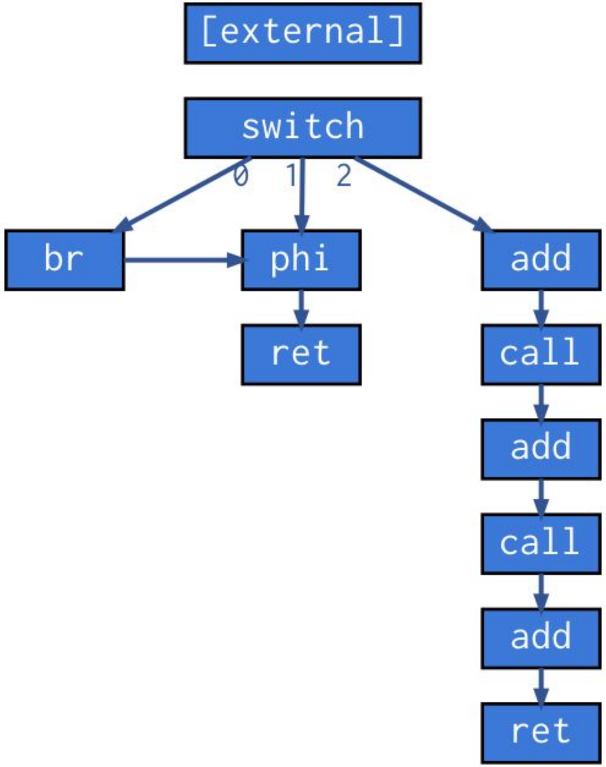
Building ProGraML: Control-flow

Full-flow-graph: represent
each instruction as a vertex.

Vertex label is the **instruction name**.

Edges are **control-flow**.

Edge position attribute for
branching control-flow.

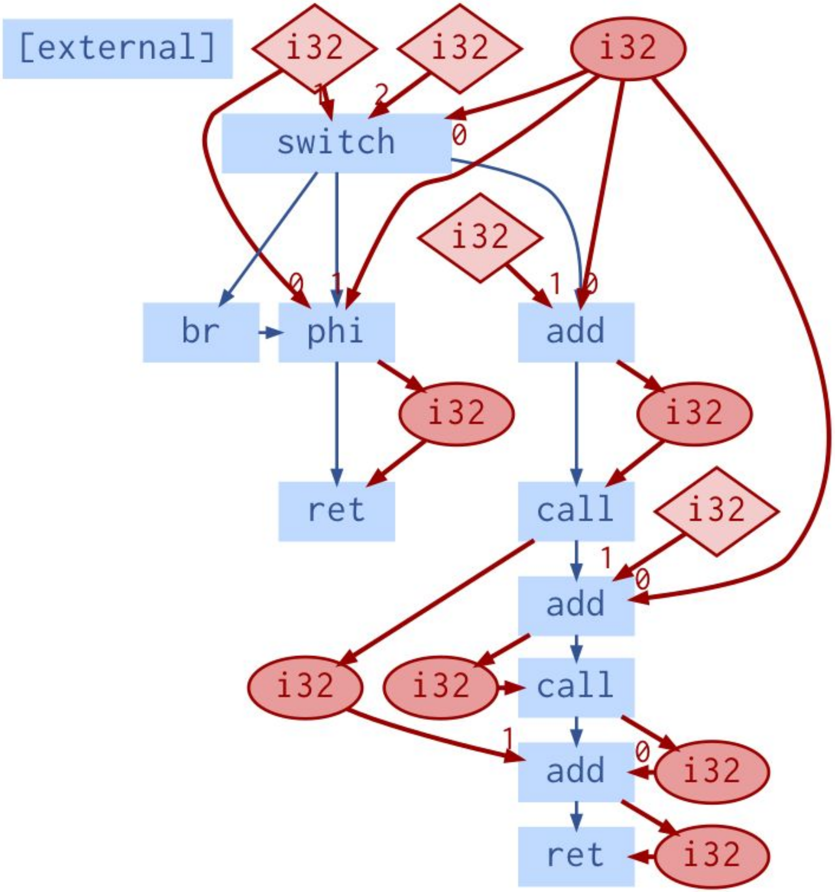


Building ProGraML: Data-flow

Add graph vertices for
constants (diamonds) and
variables (oblongs).

Edges are **data-flow.**

Edge position attribute for
operand order.

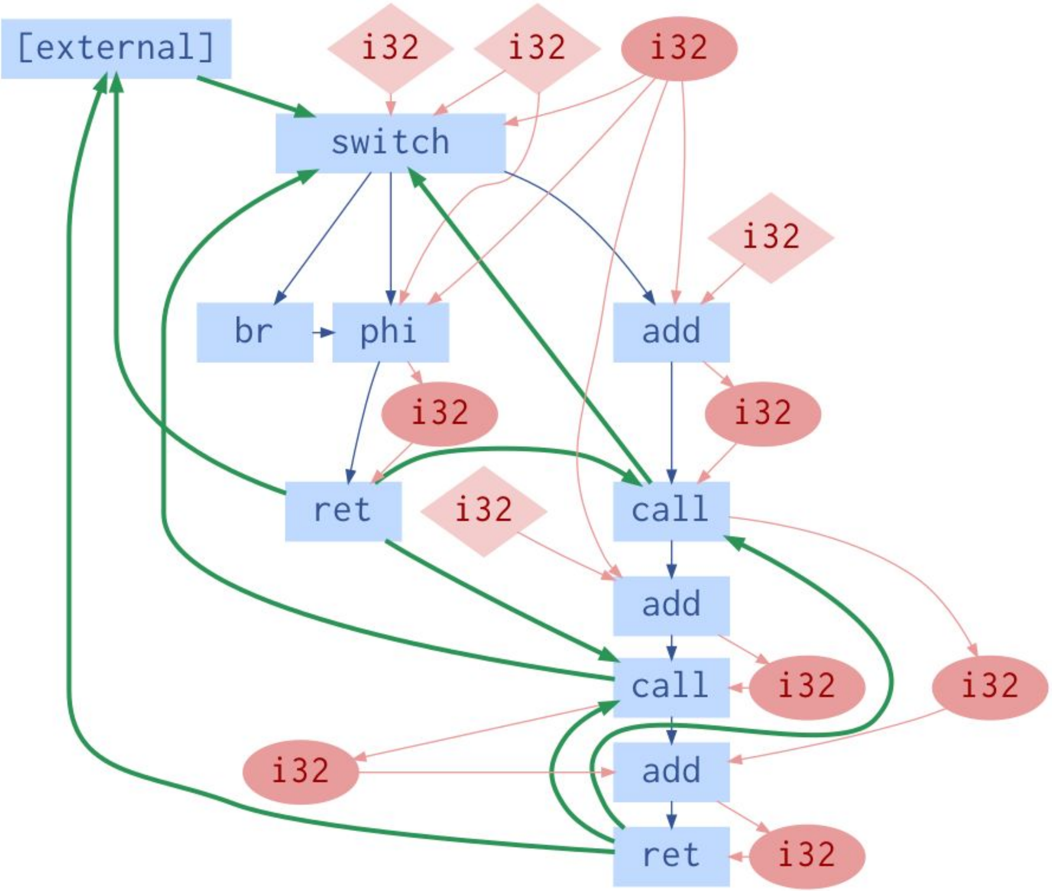


Building ProGraML: Call-flow

Edges are **call-flow.**

Inbound edge to
function entry instruction.

Outbound edge from
(all) **function exit** instruction(s).

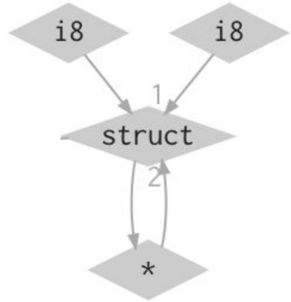


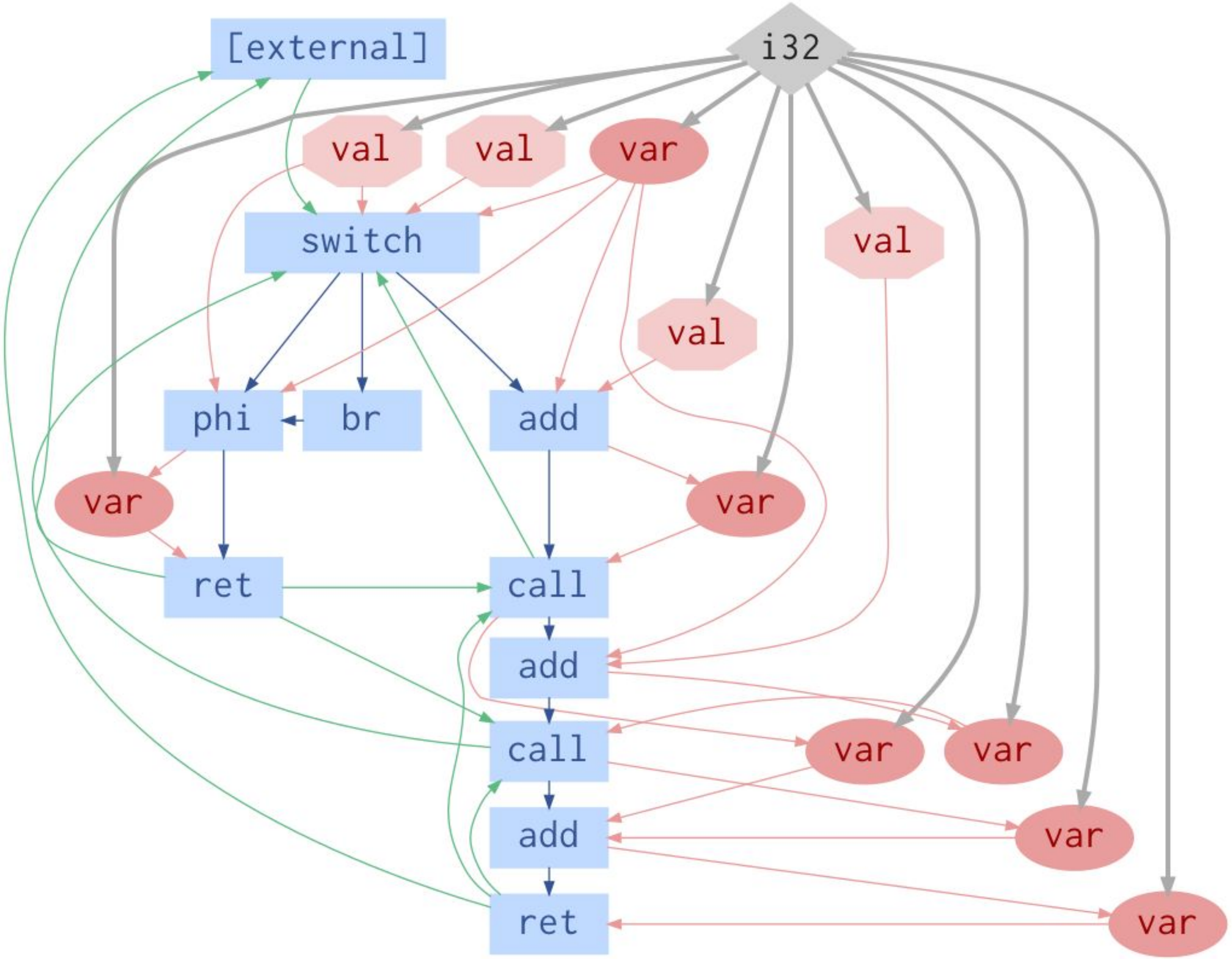
Building ProGraML: Types

Nodes represent **types**,
Edges are **instances**.

Types are **composable.**
Edge position per field.

```
struct S {
  char a;
  char b;
  struct S* c;
};
```





Learning with ProGraML: Node Embeddings

Use vertex labels as embedding keys br → 0 add → 1 i32 → 2

Derive vocab from set of unique vertex labels on **training graphs**.

Separate type/instruction nodes leads to **compact vocab**, excellent coverage on unseen programs compared to prior approaches:

	Vocabulary size	Test coverage
inst2vec [12]	8,565	34.0%
CDFG [14]	75	47.5%
PROGRAML	2,230	**98.3%** *without types

inst2vec: combined instruction+operands

```
i32 <id> = a<id> <int8>
```

CDFG: uses only instructions for vocab, ignores data

Learning with ProGraML: GGNNs

Message Passing

$$M(h_w^{t-1}, e_{wv}) = W_{\text{type}(e_{wv})}\left(h_w^{t-1} \odot p(e_{wv})\right) + b_{\text{type}(e_{wv})}$$

6 typed weight matrices for
{forwards,backwards} {control,data,call}
edge types

Position gating to differentiate
control branches and operand order

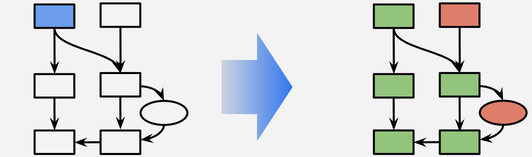
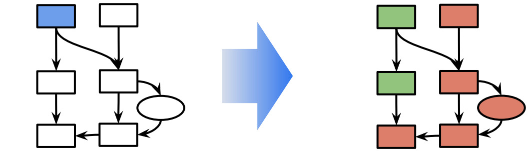
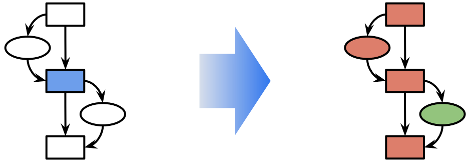
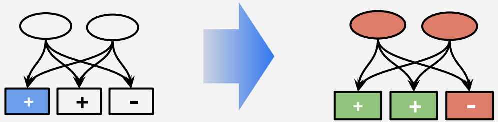
Readout Head

$$R\ (h_v^T, h_v^0) = \sigma\left(f(h_v^T, h_v^0)\right) \cdot g(h_v^T)$$

per-vertex prediction after *T*
message-passing steps

Deep Data Flow

Dataset: 450k LLVM-IRs covering 5 programming languages

		F1 scores		
		inst2vec	**CDFG**	**ProGraML**
Reachability Trivial forwards control-flow E.g. dead code elimination		0.012	**0.998**	**0.998**
Dominance Forwards control-flow E.g. global code motion		0.004	0.999	**1.000**
Data Dependencies Forwards data-flow E.g. instruction selection		-	-	**0.997**
Live-out Variables Backwards control- and data-flow E.g. register allocation		-	-	**0.937**
Global Common Subexpressions Instruction/operand sensitive E.g. GCS Elimination		0.000	0.009	**0.996**

Deep Data Flow

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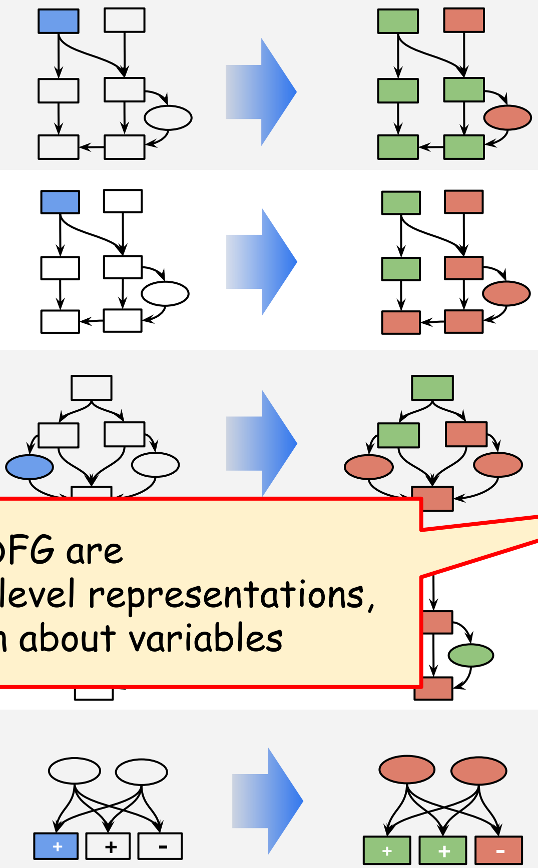

	F1 scores		
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Live-out V Backwards control- ar E.g. regist	-	-	**0.937**
Global Common Subexpressions Instruction/operand sensitive E.g. GCS Elimination	0.000	0.009	**0.996**

inst2vec/CDFG are instruction-level representations, can't reason about variables

Caveat: limited problem size

Data flow analyses iterate until a fixed point is reached.

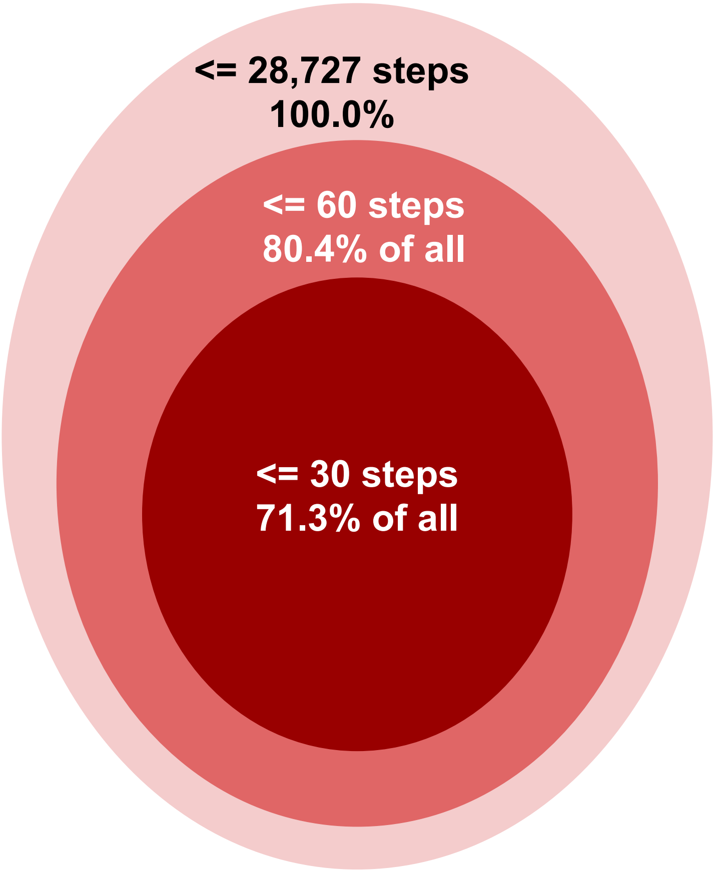
GGNNs iterate for a fixed number of timesteps **T**.

For each example in the train/test sets, we count the number of steps required for an iterative analysis to solve.

We then filter the train/test set to include only examples which the iterative analysis required **<= T** steps to solve.

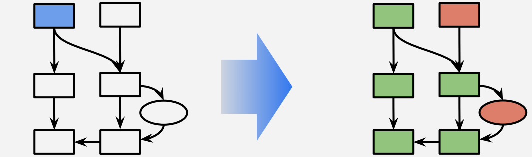
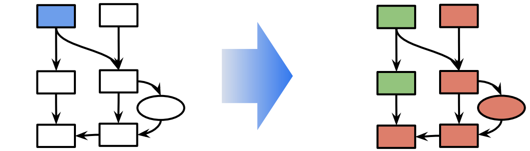
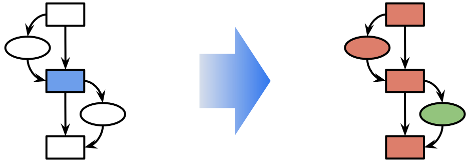
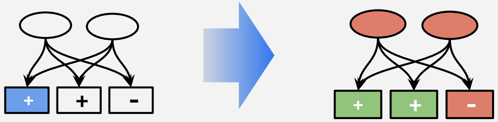
Previous slide was **T=30**, excluding 28.7% of examples.

Next slide shows performance models, trained on **T=30**, with different inference steps (**T=60**, **T=200**).



Scaling to larger problems

Dataset: 450k LLVM-IRs covering 5 programming languages

		F1 scores		
		30 timesteps	60 timesteps	200 timesteps
Reachability Trivial forwards control-flow E.g. dead code elimination		**0.998**	0.997	0.943
Dominance Forwards control-flow E.g. global code motion		**1.000**	0.991	0.123
Data Dependencies Forwards data-flow E.g. instruction selection		**0.997**	0.993	0.965
Live-out Variables Backwards control- and data-flow E.g. register allocation		0.937	**0.939**	0.625
Global Common Subexpressions Instruction/operand sensitive E.g. GCS Elimination		**0.996**	0.967	0.959

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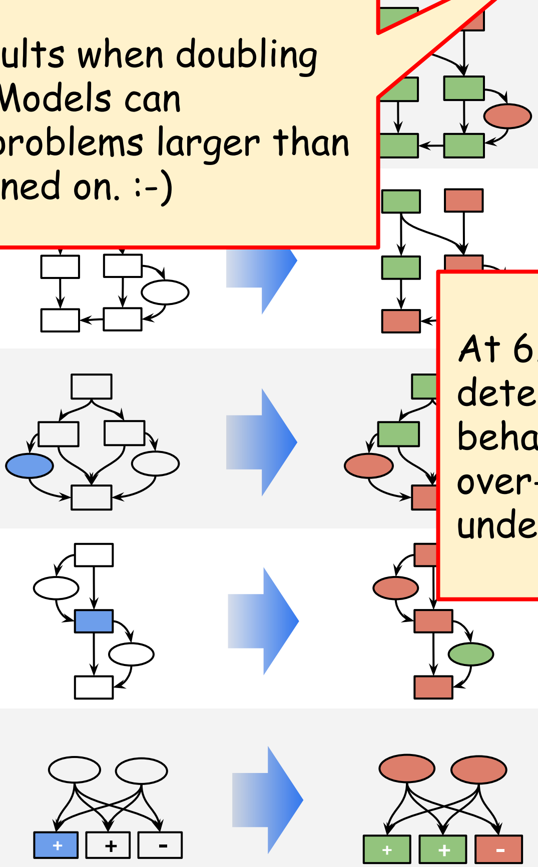
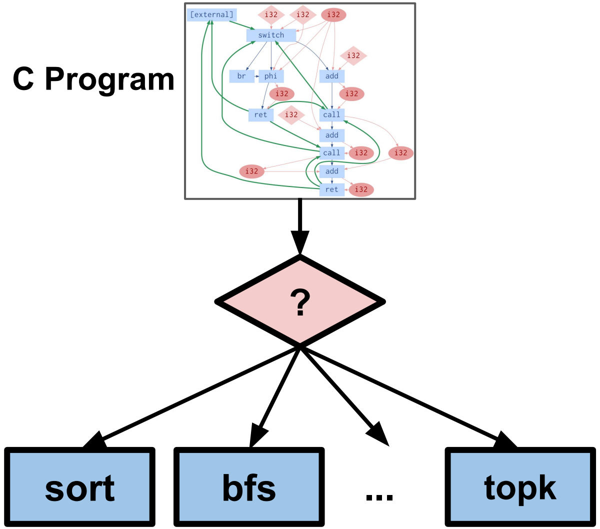


Consistent results when doubling problem size. Models can generalize to problems larger than they were trained on. :-)

At 6.6x training step count, inference deteriorates significantly. :-(No longer behaving like fixed point - model over-approximates on some problems and under-approximates on others.

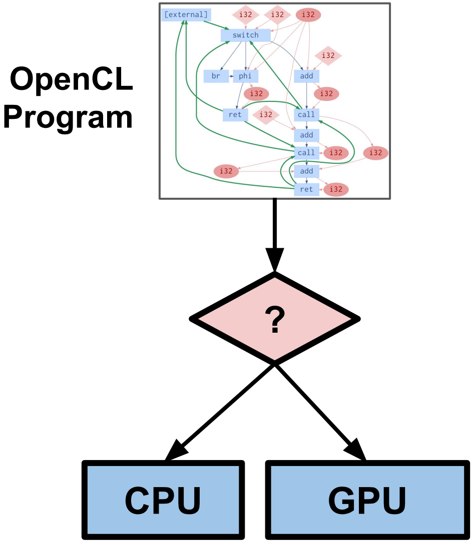
Downstream tasks

1. Algorithm Classification



1.35× improvement over state-of-art

2. Heterogeneous Device Mapping

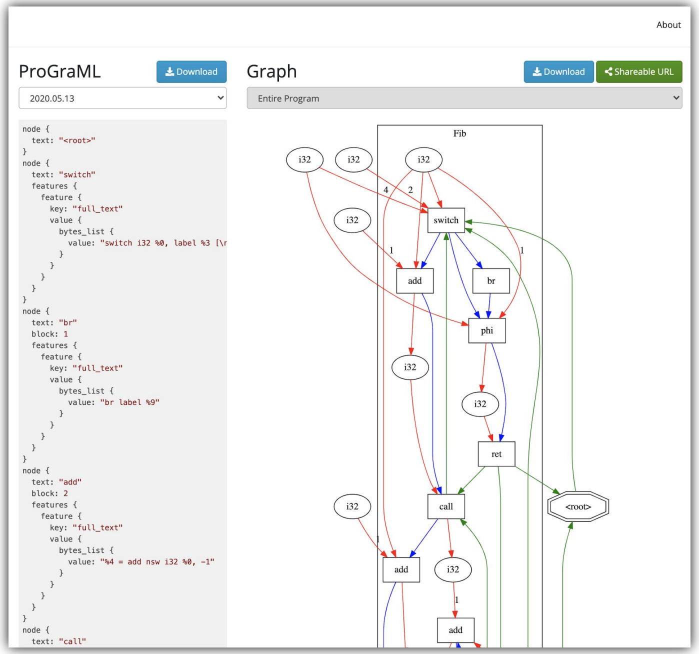


1.20× improvement over state-of-art

Further Reading

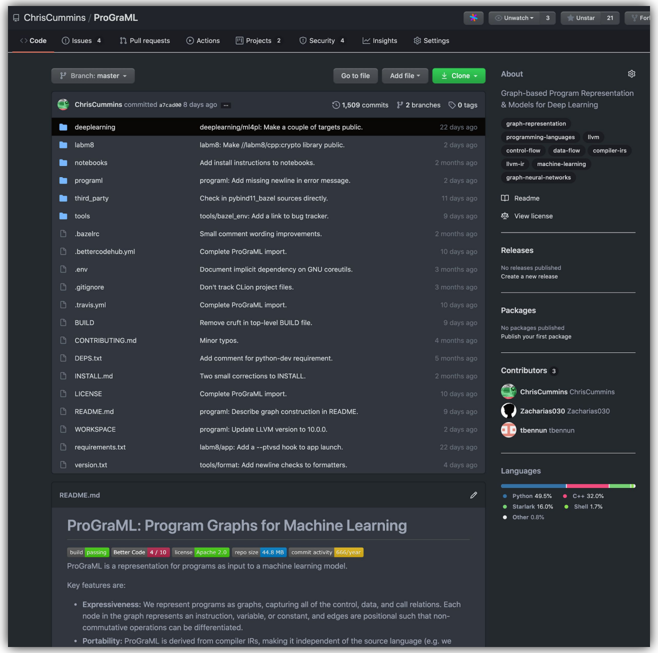
Preprint

https://arxiv.org/abs/2003.10536



In-browser demo

https://chriscummins.cc/s/program_explorer



Source code + datasets

https://github.com/ChrisCummins/ProGraML

Apache 2.0

Conclusions

Reasoning about programs requires the right combination of representation + model.

ProGraML: combines control-, data-, call-, and type-graphs to model programs at IR level.

When processed with GGNNs, significantly outperforms prior approaches.

Interesting challenges

1. Processing **arbitrary sized** graphs.
   Idea: Structure the MPNN like an iterative DF solver, self-terminating.
2. Handling **unbounded vocabularies**, e.g. compound types or MLIR dialects.
   Idea: decompose types into tree structure in graph.
3. Representing **literal values**.
   Requires new vocabulary encoding.