Enabling Transformers to Understand Low-Level Programs

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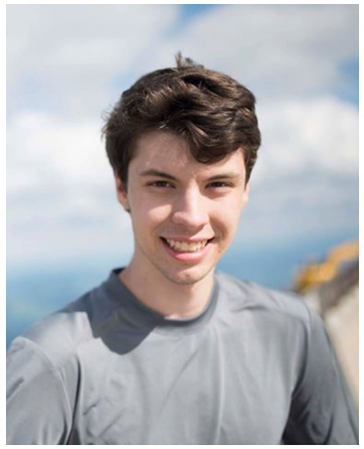

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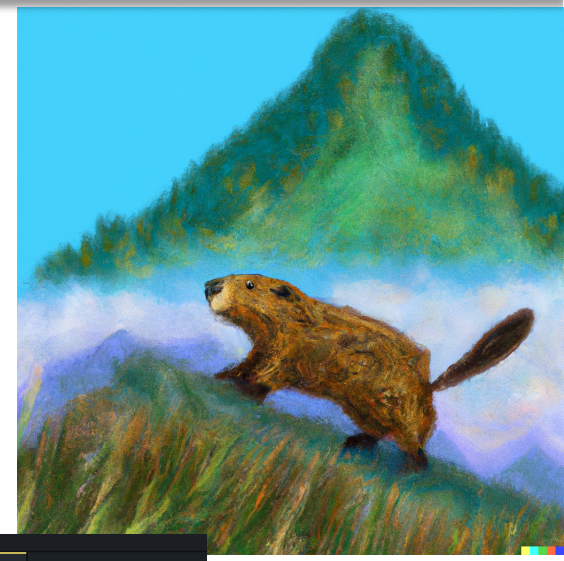
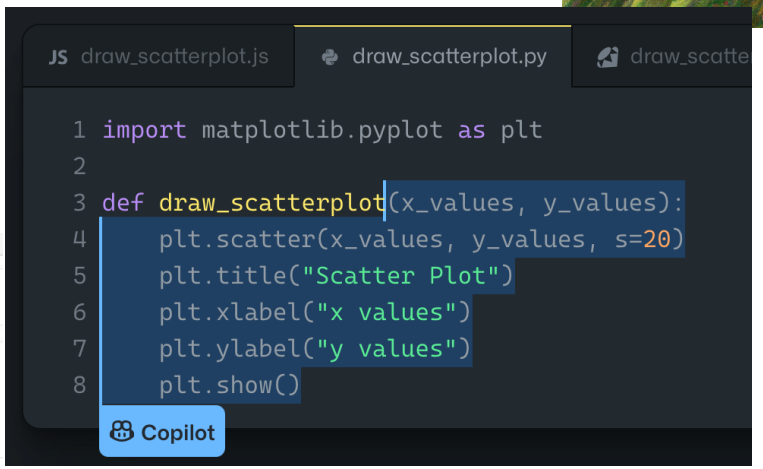
Advances in Modern Machine Learning

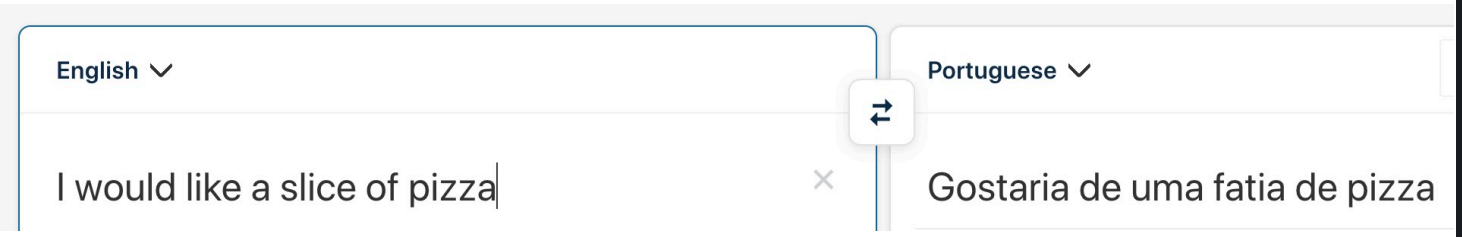
- ML breakthroughs in NLP thanks to Transformers
  - E.g. translation, code generation, image generation
- Larger amount of data + parameters = better outcomes (GPT-3)
- Successful on natural languages & high-level programs
- -> Can we use NLP advances to facilitate program ***optimization***?



DALL-E



GitHub Copilot



DeepL Translator

How Are Optimizations Applied Presently

```
float sq(float x) {
  return x * x;
}
```

High Level Program

Lower

Optimization

Low Level Program

CodeGen

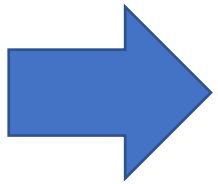
Executable

Why ML on Low-Level Code Is Hard

```
//Compute magnitude in O(n)
double mag(double[] x) ) { … }

//Compute norm in O(n^2)
void norm(double[] out, double[] in) {

  for (int i=0; i<n; i++) {
    out[i] = in[i] / mag(in);
  }
}
```



```
declare double @mag(double* readonly) argmemonly

define void @norm(double* noalias %0, double* noalias %1)
  br label %loop

%5 = phi i64 [ 0, %2 ], [ %11, %4 ]
%6 = getelementptr inbounds double, double* %1, i64 %5
%7 = load double, double* %6, align 8, !tbaa !4
%8 = call double @mag(double* noundef %1) #2
%9 = fdiv double %7, %8
%10 = getelementptr inbounds double, double* %0, i64 %5
store double %9, double* %10, align 8, !tbaa !4
%11 = add nuw nsw i64 %5, 1
%12 = icmp eq i64 %11, 100
br i1 %12, label %end, label %loop

ret void
```

Loop invariant code motion (LICM)

- More verbose and precise semantics
- -> Ensures that optimizations can be performed (moving `mag` outside loop requires `mag` to be readonly)

Previous Approaches

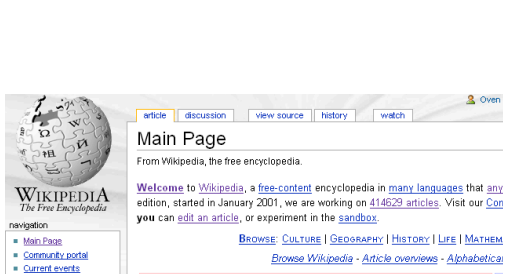
- Focus on smaller objectives=> training on specific objectives like optimizing inlining-for-size or register-allocation (MLGO)
- More supervised ML than unsupervised
- Unsupervised approaches are just starting to be applied to code and tend to be applied to either high level programs or very specific objectives (e.g. superoptimization)

Our Paper: Enabling Transformers to Understand Low-Level Programs (IEEE HPEC ’22)

- ***Goal: Determine effectiveness of end-to-end optimization / generation of low level programs***
- Whole program analysis with Transformers
- Leverage autogenerated and unlabeled training data from compiler (clang)
- Build novel low-level specific optimizations

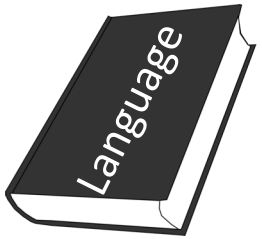
- Paper Link: https://ieeexplore.ieee.org/abstract/document/9926313

Transformers (Vaswani et al. 2017)



Unlabeled Data

Pretraining

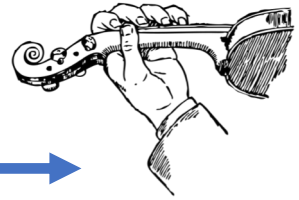


General Model

+

Translate English to French

Task



Fine Tuning

Fine-tune Model

- Train on a large corpus of unlabeled data & fine-tune on a small dataset
- Cross-lingual model of both high-level and low-level programs => provide information that compensates each other
- Better inform us where and how to apply compiler optimization considering whole program context

Case study: Translating C to LLVM-IR

```c
double relu3(double x) {
  double result;
  if (x > 0)
    result = pow(x, 3);
  else
    result = 0;
  return result;
}
```

```
define double @relu3(double %0) {
   %2 = fcmp ogt double %0, 0
   br %2, label %3 , label %5
3:
   %4 = tail call double @pow (%0, double
   3)
   br label %5
5:
   %6 = phi [%4, %3], [0, %1]
   ret %6
}
```

- Preprocessing
  - Use TransCoder tokenizer for C tokenizer and build our own LLVM-IR tokenizer based on Clang
  - Performed Byte-Pair Encoding (BPE)
- Transfer Learning:
  - Pretrained first with Masked Language Modeling (MLM) on all data
  - Fine-tuned with Machine Translation instead of Back Translation on functions only

Preprocessing Modification & Optimizations

- Expanding preprocessing directives with clang –E such as pasting the definition of imported libraries, compile-time constants, and more.

```
#ifdef AARCH64
#define size_t int64_t
#else
#define size_t int32_t
#endif
size_t getsize();
```

```
int64_t getsize();
```

- Reduce redundancies in program grammar while making sure to faithfully restore the original

```
%4 = load i32**, i32*** %2
```

```
%4 = load i32** %2
```

Preprocessing Modification, cont.

- Prefix Notation
  - A * B + C / D => + * A B / C D
  - Prefix notation previously shown effective for mathematics (Griffith & Kalita, 2019)

```
{ [4 x i8], i32, { i8, i32 }}
```

```
STRUCT 5 ARR 3 4 x i8 i32 STRUCT 2 i8 i32
```

- Writing out definitions of global variables so they can be recoverable on the function level, which makes the programs more complex

```
%struct.1 = type { i32, i32, i64 }
...
%2 = alloca %struct.1, i64 %1
```

```
%struct.1 = type { i32, i32, i64 }
...
%2 = alloca { i32, i32, i64 }, i64 %1
```

Data & Results

- Csmith (randomly generated compilable C programs) (Yang et al., 2011)
- Project CodeNet (web scrape of competitive programming online judging websites) (Puri et al., 2021)
- AnghaBench (1 million selected and cleaned compilable GitHub C programs) (de Silva et al., 2021)

Model evaluation result on the 3 datasets

	Csmith	Project CodeNet	AnghaBench
Training Accuracy	90.73%	93.66%	99.03%
Reference Match	N/A	5.76	13.33%
BLEU Score (0~100)	43.39	51.01	69.21

Ablation Analysis

Ablation studies of model evaluation result on AnghaBench dataset

	Original	Cleaned	Prefix	Prefix & Global	-O1
Training Accuracy	99.03%	97.84%	99.60%	99.36%	97.87%
Reference Match	13.33%	21.15%	**49.57%**	38.61%	38.73%
BLEU Score (0~100)	69.21	72.48	**87.68**	82.55	77.03
Compilation Acc.	14.97%	N/A	N/A	**43.07%**	N/A

- The various cleanup simplifies LLVM IR programs and boosts accuracy, while the expansion of global variables ensures compilation but reduces accuracy

Summary

- We explore how effectively ML can analyze/optimize low-level programs
- Case study: translate C to unoptimized and optimized LLVM IR
- A 49.57% verbatim match and BLEU score of 87.68 against Clang -O0 38.73% verbatim match and BLEU score of 77.03 against Clang -O1
- Preprocessing transformations (e.g. prefix notation, type sugaring) improves BLEU score from 72.48 to 87.68
- Tradeoff between ability to be compiled and accuracy
- Opens up possibilities for whole program optimization

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