BenchPress: A Deep Active Benchmark Generator

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ABSTRACT

Finding the right heuristics to optimize code has always been a difficult and mostly manual task for compiler engineers. Today this task is near-impossible as hardware-software complexity has scaled up exponentially. Predictive models for compilers have recently emerged which require little human effort but are far better than humans in finding near optimal heuristics. As any machine learning technique, they are only as good as the data they are trained on but there is a severe shortage of code for training compilers. Researchers have tried to remedy this with code generation but their synthetic benchmarks, although thousands, are small, repetitive and poor in features, therefore ineffective. This indicates the shortage is of feature quality more than corpus size. It is more important than ever to develop a directed program generation approach that will produce benchmarks with valuable features for training compiler heuristics.

We develop `BenchPress`, the first ML benchmark generator for compilers that is steerable within feature space representations of source code. `BenchPress` synthesizes compiling functions by adding new code in any part of an empty or existing sequence by jointly observing its left and right context, achieving excellent compilation rate. `BenchPress` steers benchmark generation towards desired target features that has been impossible for state of the art synthesizers (or indeed humans) to reach. It performs better in targeting the features of Rodinia benchmarks in 3 different feature spaces compared with (a) `CLgen` - a state of the art ML synthesizer, (b) `CLSmith` fuzzer, (c) `SRCIROR` mutator or even (d) human-written code from `GitHub`. `BenchPress` is the first generator to search the feature space with active learning in order to generate benchmarks that will improve a downstream task. We show how using `BenchPress`, Grewe's et al. CPU vs GPU heuristic model can obtain a higher speedup when trained on `BenchPress`'s

benchmarks compared to other techniques. `BenchPress` is a powerful code generator: Its generated samples compile at a rate of 86%, compared to `CLgen`'s 2.33%. Starting from an empty fixed input, `BenchPress` produces 10× more unique, compiling OpenCL benchmarks than `CLgen`, which are significantly larger and more feature diverse.

1 INTRODUCTION

Estimating compiler optimization heuristics through predictive modeling has been shown to outperform human experts and reduce development time in previous studies [7, 9]. However, designing effective predictive models requires extensive and diverse training data to help learn accurate compiler optimization heuristics. Training data typically take the form of static code features in benchmarks and their label for optimization heuristics [20]. Static code features are used to characterize the behaviour of programs and they are typically derived at the (1) Syntax level - by traversing the Abstract Syntax Tree (AST) (e.g. count number of operations in a function) or the (2) Intermediate Representation (IR) of a program - with the help of compiler passes (e.g. count of each LLVM-IR [27] instruction type). As shown in Figure 1, predictive models learn to infer optimal heuristics for a program based on program features and inputs.

Predictive models would be an elegant solution for generating compiler heuristics, if only we did not face an acute shortage of benchmarks, both in quantity and diversity [9, 38]. The average number of benchmarks used in performance tuning papers is 17 [2, 5–7, 16, 24, 38, 39]. Well established areas of machine learning meanwhile rely on orders of magnitude more data. ImageNet [11], for example, holds 1.3M images for training and 50k for validation. A shortage of benchmarks in training leads to poor feature space coverage that degrades the performance of predictive models [9, 18]. Cummins et al. [7] show that enhancing datasets with synthetic benchmarks, using their tool `CLgen`, can improve the
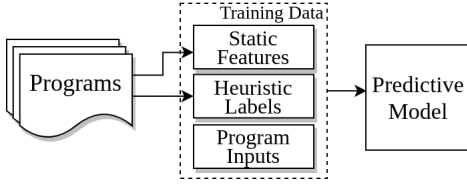
Figure 1: Training pipeline of a predictive model.

performance of the Grewe et al. [20] partitioning task by 1.27x. However, a case study by Goens et al. [18] shows that CLgen's synthetic benchmarks lack feature diversity with most generated benchmarks being small, repetitive and with little new features compared to existing benchmarks. We aim to address this with BenchPress, a targeted benchmark generator, that can generate compiler benchmarks with a desired set of features. In this work, we focus on generating OpenCL benchmarks, as predictive models for heterogeneous systems is a rapidly advancing field and training examples for them are very sparse.

We develop BenchPress [15], a BERT-based OpenCL benchmark generator [12, 36] that targets and synthesizes benchmarks in desired parts of the feature space. We use active learning to choose parts of the feature space and beam search to steer BenchPress's generated samples towards the requested features. We train BenchPress with OpenCL code samples that we collect by mining BigQuery [19] and GitHub directly using its API [17]. We support composite data types and calls to user-defined functions in our dataset and benchmark generation. BenchPress is a bidirectional generative model and learns to generate code in any part of a sequence by jointly considering left and right context. We achieve this with a new learnt token, the [HOLE], which hides a sequence from the input, whose length is unknown to BenchPress during training. BenchPress learns to fill [HOLE] by iteratively predicting an arbitrary number tokens that are likely to lead to a compiling function.

BenchPress outperforms CLgen in the task of undirected program generation from a fixed input feed, generating 10× more unique OpenCL kernels that are 7.5× longer on average, with a compilation rate of 86% compared to CLgen's 2.33%. BenchPress strongly outperforms benchmark synthesizers CLgen, CLSmith [1, 40], and human written code from GitHub in reaching close to the features of Rodinia benchmarks, developed by compiler experts. Finally, BenchPress uses active learning, specifically query by committee [34], to search the feature space and find missing features to improve Grewe's et al. [20] CPU vs GPU heuristic. Enhancing the heuristic's dataset with BenchPress's benchmarks improves the heuristic's speedup relative to the optimal static decision by 50%, increasing it from 4% to 6%, when the maximum possible speedup for this task is 12%.

In this paper, we present the following contributions:

(1) We are the first to develop a feature-space agnostic, steerable code generator towards desired program features.
(2) We develop an automated approach to rank the feature space of downstream tasks with active learning.

(3) We enable bidirectional source code generation by inserting [HOLE] tokens in any part of a sequence.

2 MOTIVATION

Figure 2 shows a two-dimensional slice of the Grewe's et al. [20] feature space: number of computational instructions vs number of memory instructions. Figure 2 also shows how the OpenCL benchmarks found in the Rodinia suite map into this plane, represented as purple diamonds. We find much of this two dimensional space is uncovered. 54 of the 58 Rodinia examples cluster in the lower left corner, the rest of the space having only four examples. Any optimization decision for programs in this area of the space would not be accurate due to lack of representative examples.
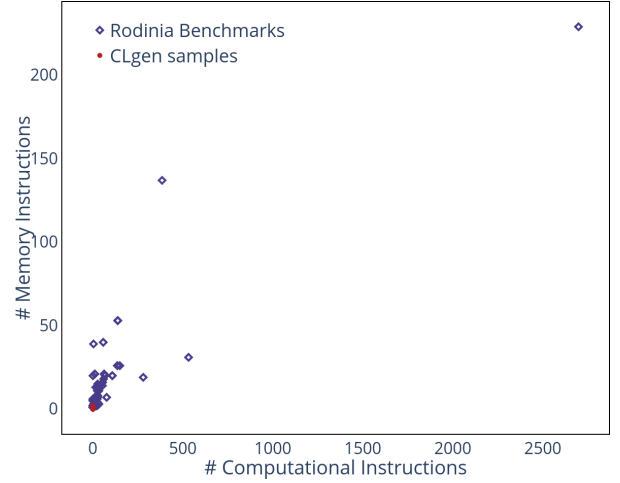

Figure 2: # Memory operations and # computational instructions for (a) Rodinia benchmarks in purple diamonds and (b) CLgen's samples in red dots. Generating samples with missing features is vital for predictive modeling's performance.

CLgen attempted to address this problem by automatically generating more training examples. However, the generated kernels lacked feature diversity and provided even poorer coverage of the feature space. Figure 2 represents their position in the 2D space as red dots. Almost all of them are concentrated in a corner covering a small percentage of the feature space. While CLgen can generate hundreds of millions of unique kernels, almost all of them will fail to compile. As the probability of having at least one illegal token in the kernel body increases with the number of tokens, only tiny kernels are valid. In our experiments in Section 5, the longest compiling CLgen kernel had 8 lines and 102 tokens. Given the small number of tokens in valid kernels, there is a high degree of repetitiveness in the generated corpus, not only in terms of features but also in terms of structure and functionality. As a result, this approach is not well suited to augmenting the training set with diverse feature benchmarks. There is a compelling need to generate training points for uncovered regions of the feature space and we attempt to address this need with BenchPress. In the following Sections, we discuss our approach and evaluation of BenchPress, comparing it to the existing state-of-the art for feature space coverage.

3 APPROACH

We present BenchPress, a deep learning model for directed compiler benchmark generation. BenchPress is the first steerable synthesizer that can synthesize compiling functions with target features. BenchPress steers its generation with a feature space-agnostic beam search algorithm to search the space and steer BenchPress's generation towards the target features. Given a downstream task, BenchPress learns what features to target in order to improve its performance by searching the space with active learning. BenchPress's language model is based on BERT [12], which we transform into a generative model.

The key feature in BenchPress that enables bidirectional code generation is a new token, namely, the [HOLE] token. We train BenchPress to learn and understand how to iteratively fill holes of unknown length that can be found in any part of an input sequence by conditioning it on the left and right context of the [HOLE]. Later, this approach enables us to use beam search and steer benchmark generation into the feature space iteratively as it can regress to previously generated benchmarks with new holes and produce newer samples with better features.

Figure 3 illustrates an overview of our approach. BenchPress consists of three main components:

(1) Learning corpus collection and processing.
(2) Source code language modeling.
(3) Feature space search and benchmark generation.
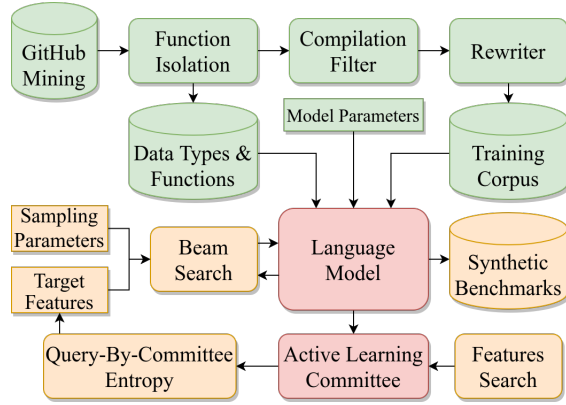
We discuss each step in the following subsections.

Figure 3: BenchPress's high-level approach.

3.1 Learning Corpus

Modeling source code accurately requires large amounts of data [28] similarly to other deep learning tasks. We develop a tool to collect data from BigQuery's GitHub dataset [19]. We also use GitHub's API [17] and mine directly extra repositories that are not included in BigQuery.

There are a few innovations in how we pre-process the code compared to previous works. First, we inline included header files recursively into source files to resolve type dependencies. Additionally, we automatically extract custom data types (e.g. struct, typedef) and utility functions found in the unprocessed corpus

and place them into header files that are accessible throughout BenchPress's pipeline. This way, we resolve most type dependencies by retaining the functionality and semantics of the original, human-written programs. These two steps enable us to increase significantly the amount of compiling kernels we end up with in our training dataset. Second, we isolate kernels into single instances because BenchPress is trained on complete functions. From the previous steps, the type dependencies of each kernel are known and we automatically provide them to the compiler, retaining their compilability. Finally, we compile all kernels with Clang and reject those that do not compile.

Next, we re-write identifiers by randomly sampling the alphabet, eliminating spurious naming patterns in the corpus. All kernels are padded to BenchPress's sequence length and kernels that are longer than this are truncated to fit. This helps BenchPress train its later indices' positional embeddings more effectively, for which we have less training information compared to earlier indices. Finally, we derive a tokenizer by parsing the AST of all source code. We reserve tokens for all OpenCL keywords and all intrinsic OpenCL function name identifiers found in the official OpenCL specifications [35]. We analyze the dataset and tokenize by word the most common function names and custom data type identifiers that we have collected. We encode all literals and infrequently used custom types and functions character by character to avoid exploding the size of the vocabulary. We define 5 meta tokens: [START], [END], [PAD], [HOLE], [ENDHOLE]. The derived tokenizer holds in total 2,201 unique tokens.

3.2 Language Modeling

BenchPress is based on BERT [12], a Transformer-based model originally designed for natural language modeling. BERT is trained to predict words that have been randomly hidden by [MASK] tokens. This way BERT learns fitting words with respect to their position in a sequence and also the left and right context, i.e., the text sequence before and after the masked token to be predicted. This type of training helps BERT learn what words mean within a given context, improving downstream tasks that rely on that knowledge.

While this is a useful property, it is not enough to turn BERT into a generative model. We also want to be able to extend a kernel by inserting an arbitrary number of tokens in arbitrary positions. We could iteratively add a [MASK] token to get one extra token at a time, until we have a full statement. This would be limiting. Each time the new token would be selected based on its probability of completing forming a plausible kernel. Every intermediate kernel in the iterative process would have to be plausible or almost plausible, which is not a general way for augmenting kernels.

Clusters of [MASK] tokens could allow us to insert multiple tokens in each iteration. This is still unsatisfactory. The number of [MASK] tokens in the cluster biases the kind of code that will be generated: if we ask such a generator to produce five tokens, it will give us a five token statement that could be expected to close this gap, not a five token sequence that could be the start of a much longer statement. We could place the left and right context to the edges of a sequence and fill intermediate positions with [MASK] tokens. BenchPress could predict a vocabulary or a stop token for a [MASK], allowing for arbitrary sequences. We test this

configuration and sample a trained model with a fixed input feed. BenchPress is unable to learn the [MASK]s' left and right context conditionally, when many [MASK]s are in a sequence, which leads to zero samples to compile or even resemble reasonable code.

What we do instead is to extend BERT's functionality with a new pair of learnt tokens, the [HOLE] and the [ENDHOLE]. [HOLE] follows the same logic with [MASK], however the number of tokens that have been hidden behind it is unknown to the model during training. The model only learns to predict the first token of an arbitrarily long missing sequence. At inference-time, we iteratively predict the first token of the remaining sequence and re-insert it just before the [HOLE]. This way BenchPress learns to generate arbitrarily large code sequences within any part of a sequence.
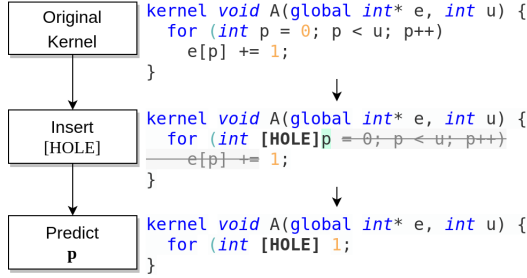

Figure 4: When a `[HOLE]` is inserted to a kernel at a random index, it hides a random number of tokens, unknown to `BenchPress`. On this example, `BenchPress` learns to predict the first hidden token, p.

Figure 4 shows how a [HOLE] is inserted into a function to create a datapoint. A random starting index and a random length are selected. The choice of index and length are only restricted by a potential overlap of the prospective hidden sequence with any of the other meta token or the maximum hole length that is defined as a training parameter for the architecture as a percentage of each function's length. When the specifications of a hole have been settled, the hidden sequence is discarded. Only the first token of it is kept as the target prediction for that hole. A hole can also represent an empty sequence, i.e. hiding 0 tokens. In this case, the target prediction during training is [ENDHOLE]. The training instances are randomly generated on demand, the entire space of possible instances is too large to be pre-generated. In this paper, we only insert 1 hole per training instance for BenchPress to learn. Multiple holes could be used during training, but this is not needed during BenchPress's current benchmark generation task.

3.3 Benchmark Generation

BenchPress's synthesizer operates as a generative model with the help of [HOLE] / [ENDHOLE] tokens. It receives an input with 1 or more [HOLE] tokens and returns a completed benchmark. For each [HOLE], BenchPress predicts one token that fits in the sequence at the [HOLE]'s index, with respect to its left and right context. If the predicted token is not [ENDHOLE], it moves the [HOLE] and all subsequent tokens one position to the right and inserts the predicted token to the initial target index. This intermediate kernel is iteratively provided as an input for the next token prediction and

the process is repeated until BenchPress predicts [ENDHOLE]. This marks a [HOLE] is complete and the final sample is returned, as shown in Figure 5.
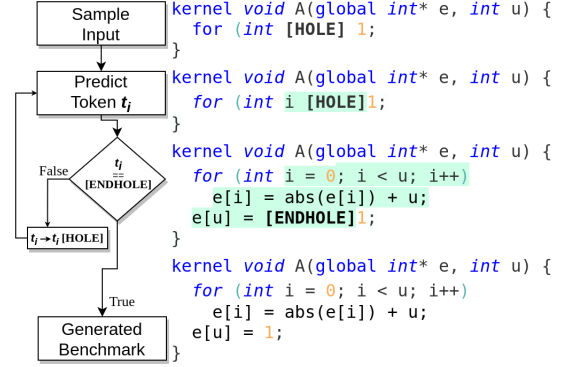

Figure 5: During sampling, `BenchPress` receives an input and predicts iteratively the fitting tokens. `BenchPress` predicts `[ENDHOLE]` to indicate a `[HOLE]` is complete.

On its own, this process only augments kernels. We also make it the first to target desired parts of a feature space by repeatedly generating kernels, selecting the ones closer to the target features, inserting new holes, and generating new augmented kernels. We use beam search to steer generation.

Given a target feature vector, BenchPress samples a starting, fixed input feed 'kernel void [HOLE]' and yields a collection of starting benchmarks. We reject benchmarks that do not compile and for the remaining we measure the Euclidean distance between their feature vectors and the target features. We select the *top-K* candidates that have the shortest distance from the target and we use them as inputs for the next generation. To improve diversity among promoted benchmarks we introduce randomness in the selection of *top-K* candidates: Each *top-K* sample, has a fixed probability $p = 0.15$ to be replaced by another random candidate of its generation. BenchPress lazily creates multiple different input instances for each selected candidate by placing a random [HOLE] of random length in order to synthesize a new sample. BenchPress generates a successive collection of benchmarks, of which K compiling ones with the shortest distance from the target again are selected with p-randomness and used as inputs. This search continues until a sample achieves a distance of 0 from the target, or until a threshold of generations (i.e. beam search depth) is exhausted. BenchPress returns the closest benchmark to the target's features along with all beam search's intermediate benchmarks that cover the model's traversal of the feature space starting from the origin and ending near the target features. For the benchmark synthesis process, we use categorical sampling with temperature to sample BenchPress's probabilities. The sampling temperature, beam search's width K and depth are defined as sampling parameters.

In the worst case, BenchPress's directed program generation is slow, ranging from a few seconds to one hour, as it typically requires thousands of language model inferences. However, BenchPressis the first program synthesizer that can target a set of desired program features.

3.4 Feature Space Search

A steerable synthesizer allows the generation of benchmarks with desired features. However, the automatic selection of those parts of the feature space that are worth targeting is challenging and depends on the downstream task.

BenchPress attempts to solve this by searching the feature space with query by committee [34], a well-known active learning technique. We implement a committee of (a) 7 NN, (b) 7 k-NN and (c) 7 K-means models. We set their initial state by passively training on a small portion of the downstream task's data. We sample the committee with thousands of random points in the space, we collect the predicted labels and measure the entropy for each sample. The entropy shows the level of uncertainty among the committee about the predicted label of a given point and is defined as:

$$H = - \sum_{}^{l \epsilon L} (p(l) * \log(p(l))) \qquad (1)$$

where L is the set of all predicted labels and $p(l)$ the probability of label l in the committee's prediction set for a given input. The highest entropy point is an important feature vector to target and BenchPress steers benchmark generation towards it with the approach explained in 3.3. We collect the labels of generated benchmarks and we train incrementally the committee with them. Then, we sample it to find the next highest entropy point. We continue this process until we saturate the feature space. BenchPress's committee is agnostic to the downstream task or the feature space and its I/O dimensions are hyper-parameters selected with respect to the task's feature and prediction dimensions.

4 EXPERIMENTAL SETUP

We describe the configurations used in training BenchPress, and the parameters used in evaluation, namely (1) Feature Spaces - we use three different representations of program features, (2) Target Benchmarks - We use Rodinia benchmarks [5] and their features as the target for synthesis by BenchPress, (3) Comparison to SOTA - we compare BenchPress with code synthesizers and human written code in improving Grewe's et al. heuristic model.

4.1 Platforms

We train BenchPress and conduct all our experiments on two 64-bit systems each having one Intel Xeon E5-2620 16-core CPU, 2x Nvidia GeForce GTX 1080 GPU and 32 Gigabytes of RAM. We use Ubuntu 18.04, PyTorch 1.9.1 [31], CUDA version 11.4 and Nvidia driver version 510.47.03. We use Clang-10 as BenchPress's compiler and LLVM-10 to compile and execute InstCount and Autophase [22] extracting tools. For compatibility reasons, we are required to use Clang LibTooling from LLVM-6 to execute Grewe's et al. [20] feature extractor.

4.2 Language Modeling for source code

We collect OpenCL code from GitHub and split it into single function instances. We ensure no kernels that come from benchmarks suites used in the evaluation are included in our corpus. We pre-process text, re-write variables and reject OpenCL kernels that do not compile. In total we mine 63,918 OpenCL kernels across 12,860

GitHub repositories and we successfully compile 19,637 of them (31% compilation rate).

We train BenchPress on our OpenCL Corpus for 10M steps with a batch size of 32. For BenchPress's BERT model parameters, we select 2 hidden layers, 12 attention heads. We set intermediate size, hidden size and max position embeddings to 768. We set the maximum length of holes to be 90% of a kernel's token length, i.e. a hole can hide almost all tokens of a training instance. We optimize the model using Adam optimizer with a learning rate that reaches a maximum of $45x10^{-6}$ after 20,000 warmup steps and decays linearly over the remaining training steps. We train BenchPress's language model to a final loss value of 0.28.

4.3 Feature Spaces

Compiler predictive models use static code features to represent programs and learn optimisation heuristics. A vector of independent characteristics represent a single program. Each of them are typically an integer or float value. Features are extracted at the Syntax level by traversing the AST or at the IR level using the compiler's middle end (e.g. LLVM-IR). A feature space is the collection of all possible program feature vectors.

BenchPress is a generative model that can be steered to generate samples for a desired part of the feature space. We evaluate BenchPress on three source feature representations we find across the literature, (a) Syntax-level Grewe's et al. features [20], (b) IR-level LLVM-InstCount [27] and (c) IR-level Autophase [22].

Grewe's et al. features are extracted with Clang's LibTooling and used to train their predictive model on the CPU vs GPU task for OpenCL kernels. This feature space holds 8 dimensions. 4 dimensions describe the number of 1) computational, 2) relational, 3) atomic and 4) memory access instructions. The feature space also counts the different type of memory instructions, local memory or coalesced. Finally, the computational to memory and coalesced to memory ratios are defined.

InstCount is a standard pass provided by LLVM-IR framework and used in Compiler Gym by Cummins et al. [8]. InstCount holds 70 dimensions: 67 dimensions each counting all 67 LLVM-IR instruction types and total number of 1) instructions, 2) basic blocks and 3) functions. Autophase by Huang et al. [22] holds 56 dimensions. While many of the features used in Autophase are shared with InstCount, they introduce new ones such as number of input arguments to PHI Nodes or total number of memory instructions. On the other hand, they do not include the count of some LLVM instructions that are not considered to contribute to a program's representation, e.g. `CatchPad` instruction.

4.4 Analysis of BenchPress and CLgen language models

CLgen [7] is the current state of the art in OpenCL benchmark generation. Its synthetic benchmarks improve the accuracy of Grewe's et al. predictive model [20] by 1.27×. However, Goens et al. [18] perform a case study and show evidence that CLgen's synthetic benchmarks do not improve the quality of training data and, consequently, performance of predictive models. They show that a predictive model in fact performs worse with synthetic benchmarks as opposed to human written benchmarks or code from GitHub.

This study motivates us to perform an analysis of `BenchPress`'s language model, BERT, with `CLgen` in the task of undirected program generation. In this first experiment, we reproduce `CLgen` using the authors' artifacts and we sample it with a fixed input 'kernel void' to collect a dataset of unique OpenCL kernels. We use `BenchPress` on the same generative task and sample the model with the same fixed input 'kernel void [HOLE]' to obtain another dataset of unique benchmarks. In this experiment we focus on the language model's inference performance. We compare both generative models on their throughput, their ability to create compiling code, feature distribution and code size. In this experiment, we do not direct program generation. `BenchPress` generates compiling kernels in a single inference step.

4.5 Targeted Benchmark Generation

Next, we evaluate `BenchPress`'s ability to steer towards desired program features. We use well-established compiler benchmarks as our reference and target their features within this space. These benchmarks usually perform intensive operations, such as matrix multiplications or FFT analysis, they contain hundreds of computational and memory instructions and are specifically fine-tuned by experts to exercise compilers from different angles. As a result, we believe features in these benchmarks provide a good target to assess performance of `BenchPress`'s ability to target complex features.

We choose target benchmarks within the Rodinia suite [4, 5] as it is widely used in the literature [7, 9]. Similar to the training corpus, we collect the suite's source files, we inline header files and dependent OpenCL libraries into them, we split kernels into single source files and reject those that do not compile. In total, we collect 61 target Rodinia benchmarks out of which 58 compile. For the remaining benchmarks, we collect their features using the feature extractors for Grewe's et al., InstCount and Autophase feature spaces [20, 22, 27]. We target the feature vectors of these benchmarks and request `BenchPress` to generate at least one matching benchmark for each. We end up with three collective synthetic benchmark datasets, one for each feature space, that contain code with features matching Rodinia benchmarks. For each Rodinia benchmark's target feature vector, we measure the minimum Euclidean distance to it achieved between `BenchPress`, code from GitHub, `CLgen` and `CLSmith` [1, 40]. For GitHub's and CLSmith's kernels, we use `SRCIROR` [23] to apply code mutations exhaustively with beam search.

To make our experiment more intuitive we use two datasets for `GitHub`: a) GitHub consisting of all OpenCL kernels we collected and b) `GitHub-768`, a proper subset of `GitHub` which contains only the kernels that do not exceed `BenchPress`'s sequence length of 768 tokens. Since `BenchPress` benchmarks' size are restricted to the architecture's sequence length, we feel it is important to make this distinction in order to present a view of `BenchPress`'s actual performance on features that may be unreachable within the current sequence length. For example, it may be impossible to generate 2,000 computational instructions within 768 tokens. For such cases, we believe `GitHub-768` with its equally restricted sequence length would allow for a fairer comparison.

For all three feature spaces, we weed out the Rodinia benchmarks that have an exact matching sample (i.e. a Euclidean distance of

0) in `GitHub-768`. Since we already have matching samples for them, we do not need to target them with `BenchPress` or any other generative model. However, we do not skip benchmarks whose features exist only in `GitHub`'s full dataset as we wanted to explore the feasibility of using `BenchPress` to generate a sample with the same features but smaller sequence length. Applying this restriction we end up with 22 Rodinia benchmarks for Grewe's et al., 52 for InstCount and 36 for Autophase feature spaces.

4.6 Active Learning for Feature Selection

`BenchPress`'s steerable generation is vital for searching the feature space while also finding useful features to target with active learning. In this experiment, we evaluate `BenchPress` in the downstream task of training the predictive model proposed by Grewe et al. [20], a well-tested problem used by many baseline models.

Grewe et al. train a decision tree model to predict the optimal device to execute a benchmark, choosing between a CPU and a GPU. They measure their model's performance as speedup achieved with using the predicted device for execution versus statically executing all benchmarks on the GPU. To train the predictive model, they use OpenCL benchmarks from 7 well-known benchmarks suites [7, 20]. In this experiment, we reproduce Grewe's et al. heuristic using their artifact and we also retrain it with datasets enriched with executable benchmarks from `BenchPress` using active learning and passive learning (i.e. targeting random parts of the feature space instead of searching it), `CLgen` and `GitHub`. We measure the speedup over static mapping for each of them.

To collect our evaluated datasets, we execute OpenCL benchmarks with `CLDrive` [7] by Cummins et al. `CLDrive` automatically generates inputs and drives kernels to the hardware. It measures the execution time per device across thousands of runs and it rejects kernels that produce runtime errors, do not modify any of the inputs (no output) or modify them differently for each run (not deterministic). For (a) the 7 human-written benchmarks suites, (b) `BenchPress`, (c) `CLgen` and (d) `GitHub`, we execute their kernel on `CLDrive` using a range of different *local* and *global size* configurations. We label each instance with the fastest measured device (the CPU or the GPU), in the same way Cummins et al. [7] and Grewe et al. [20] performed their evaluation.

5 RESULTS AND ANALYSIS

In this section, we show our experiments' results and compare `BenchPress` with state of the art techniques in OpenCL benchmark synthesis. We present case studies of (a) `BenchPress`'s throughput as a generative model compared to `CLgen`, (b) its ability to steer benchmark generation towards desired features and (c) its performance in searching the feature space to enhance a downstream task's performance.

5.1 Analysis of `BenchPress` and `CLgen` language models

We perform an analysis of `BenchPress` and `CLgen` as language models and compare them in generating a collection of benchmarks from a fixed input feed, 'kernel void [HOLE]' and 'kernel void' respectively. We compare the two approaches measuring (a) the generative models' throughput and (b) the quality of their

	# unique benchmarks	# compiling benchmarks	compilation rate	max tokens	max inst (LLVM-IR)	time per sample (ms)
BenchPress	190,460	142,607	86%	750	161	162
CLgen	1,564,011	13,035	2.33%	102	32	103

Table 1: Throughput comparison between `BenchPress` and `CLgen` on generated OpenCL benchmarks when `BenchPress` does not use feature-directed program generation.

generated benchmarks in terms of code size and features. In this experiment, we do not use any directed search or iterative approach for BenchPress's generation. We perform this evaluation to measure how BERT, BenchPress's underlying language model, compares with CLgen as a generative model. Table 1 presents the aggregate measurements for the generated benchmarks using both approaches.
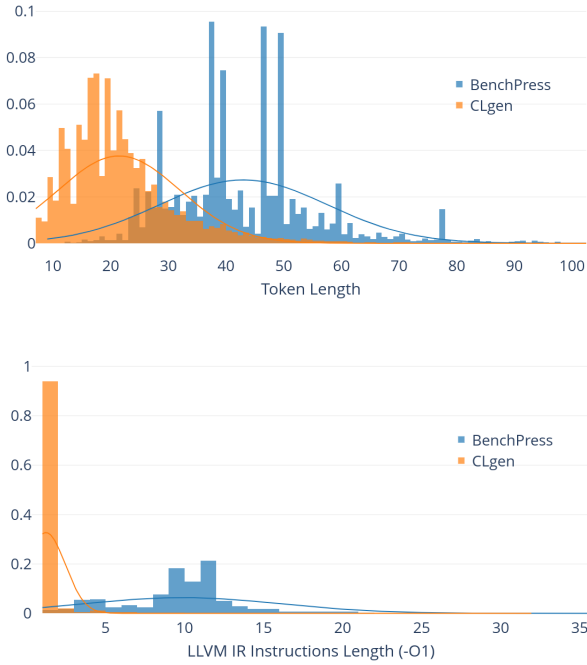

Figure 6: Probability distribution of (a) token length and (b) LLVM-IR Instruction count among `BenchPress`'s and `CLgen`'s generated benchmarks. `BenchPress`'s benchmarks presented here are generated at a single inference step without iteratively directing program synthesis.

Compilation rate and code quality. BenchPress generates over 10× more unique compiling benchmarks than CLgen. This result is observed despite BenchPress generating 8× fewer unique benchmarks than CLgen. The compilation rate with BenchPress is 86% while CLgen has an exceedingly small rate of 2.3%. BenchPress's largest sample is 750 tokens compiling to 161 LLVM-IR instructions. This is a 7.5× and 5× increase in number of tokens and

number of LLVM-IR instructions compared to CLgen's largest kernel. The only drawback of BenchPress compared to CLgen is that it is considerably slower in generating candidates. This is because the transformer-based architecture in BenchPress is significantly larger in number of parameters than CLgen's LSTM. Additionally, BenchPress tends to generate longer kernels than CLgen, necessitating more inference steps and longer generation time.

In Figures 6a and 6b, we show the frequency distribution of the number of tokens and number of LLVM-IR instructions for compiling kernels for both datasets. To visualize our results better, we focus on synthesized kernels with token lengths ≤ 100 and instructions lengths ≤ 25 where the vast majority of benchmarks are found. Most of BenchPress's benchmarks are found to have 20 to 80 tokens and 3 to 16 LLVM-IR instructions. The majority of CLgen's benchmarks are found to have 5 to 45 tokens and only up to 4 LLVM-IR instructions. 94% of CLgen's generated benchmarks have only 1 instruction when compiled to LLVM-IR. We analyze the dataset to explain this phenomenon and find CLgen generates a lot of comments, repeated dead statements and awkward non-human-like code such as multiple semi-colons. These results agree with the case study by Goens et al. [18] that shows the AST depth distribution of CLgen's code is significantly narrower compared to code from GitHub or standard benchmarks.

Feature space coverage. To further enhance our comparison, we perform an analysis on the feature space coverage of BenchPress's and CLgen's synthesized programs in all three feature spaces. Feature coverage is the most critical metric when evaluating the effectiveness of a benchmark synthesizer for predictive modeling. We use Principal Component Analysis (PCA-2) to represent the feature spaces in an easy to visualize 2-dimensional space. In Figures 7a, 7b and 7c we show the extent of feature space covered by candidates in the two approaches. CLgen's samples are clustered around the origin, while there is one outlier for Autophase and two for Grewe's et al. and InstCount features. Candidates generated by BenchPress are more scattered achieving a much wider coverage of the feature space.

5.2 Targeted Benchmark Generation

We use beam search to generate samples that target desired parts of the feature space. We compare BenchPress with human-written benchmarks from GitHub and synthetic benchmarks from CLgen and CLSmith in targeting the features of Rodinia benchmarks on three feature spaces. We use SRCIROR code mutator with beam search to collect GitHub and CLSmith benchmarks with closer features. For each target benchmark, we gather one OpenCL kernel per evaluated dataset whose features have the minimum available Euclidean distance from the target features. Figures 8a, 8b and 8c show the relative proximity of each benchmark to the target. This
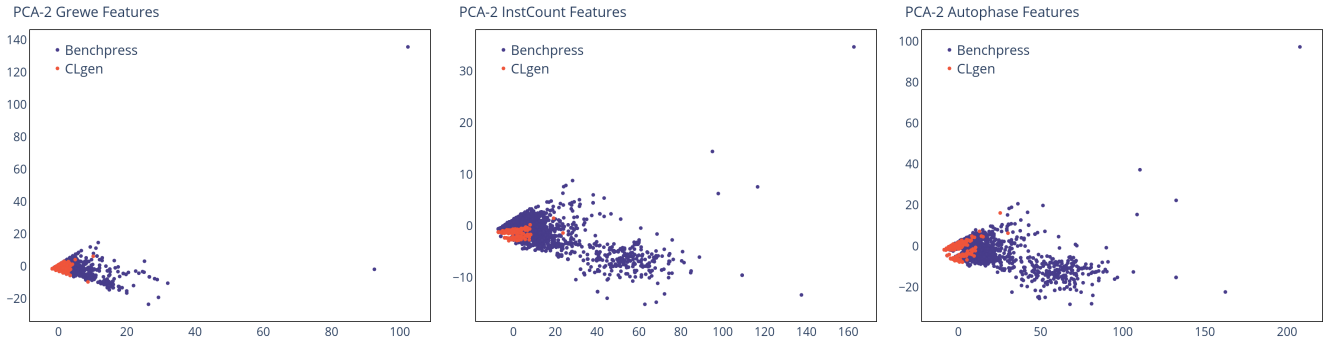
Figure 7: PCA-2 representation of feature space coverage of `BenchPress` and `CLgen` for (a) Grewe's et al., (b) InstCount and (c) Autophase feature spaces. In this experiment, `BenchPress`'s generation is undirected and no iterative space search is performed.

proximity is the complement of the relative distance of the two kernels, i.e, 1 minus the distance between the two kernels in the feature space relative to the distance of the Rodinia kernel from the axes origin. This allows us to express the quality of the match with an intuitive 0% to 100% scale: 100% means the two kernels have the same features, 0% means the best kernel is as close to the target as an empty kernel. We mark perfect matches with a white asterisk (*).

Performance on syntactic features. On Grewe's et al. feature space, `BenchPress` generates kernels that are the closest ones in features for all 22 Rodinia Benchmarks compared to `CLgen` and `CLSmith`, and 20 out of 22 compared to `GitHub` and `GitHub-768`. `BenchPress` synthesizes an exact match (100% relative proximity) for 14 target benchmarks.

We pick out and discuss a few examples from our results. The absolute distance achieved for 'nw-1' and 'ellipse_opt', is 1.0. For both targets, almost all features match except for one missing instruction (`coalesced mem access` and `atomic inst` respectively). For 'hotspot' `GitHub` and `BenchPress` produce a candidate kernel with exact matching features. However, `BenchPress` generates the matching candidate kernel in 421 tokens, unlike `GitHub`'s closest benchmark that has 798 tokens. For the two target benchmarks that `BenchPress`'s candidates were not closest to, we found only `GitHub` contains better samples for 'com_dwt-3' and and 'gpu-1', while `BenchPress` does not. We find both benchmarks to be fairly large (901 and 5,200 tokens respectively) and `BenchPress` cannot reach these features within 768 tokens. For the same reason, `GitHub-768`, `CLgen` and `CLSmith` does worse than `BenchPress` on these targets.

Performance on LLVM IR features. Autophase and InstCount features are extracted from the LLVM-IR of a program that has been compiled with `-01` flag to apply basic optimisations such as dead code elimination. `BenchPress` occasionally generates repeating operations that a compiler will remove or numerical operations that may be reduced to simple assignments. Owing to these optimisations, we find targeting benchmarks on these two feature spaces is more challenging than Grewe's et al. syntax-level features. With InstCount features, `BenchPress` generates candidates whose features completely match 2 out of the 52 Rodinia benchmarks. Among the remaining 50, `BenchPress` outperforms

`CLgen`, `CLSmith`, `GitHub` and `GitHub-768` for all target benchmarks, achieving higher proximity. SRCIROR significantly improves `GitHub` leading to `GitHub+SRCIROR` to achieve better proximity for 18 out of 52 Rodinia benchmarks compared to `BenchPress`. On Autophase features, `BenchPress` generates candidates matching the same 2 target benchmarks, while outperforming `CLgen`, `CLSmith` and `GitHub` on 30 out of 36 Rodinia benchmarks in total. `GitHub+SRCIROR` performs better than `BenchPress` for 8 out of 36 target benchmarks and produces an exact match for 'hotspotKernel'.

We previously explain the importance of having diverse features in compiler benchmarks and we show, in Figure 2, how sparse Rodinia benchmarks are on Grewe's et al. reduced feature space and how `CLgen` fails to provide any additional features. Now we introduce into this 2-dimensional space all `BenchPress`'s kernels that are generated while performing directed space search to target Rodinia benchmarks and we present them in Figure 9. `BenchPress` densely populates the space around the target benchmarks that are clustered around the lower left corner. We find `BenchPress`'s samples progressively converge to the target benchmark features with successive generations. For example, `BenchPress` targets 'com_dwt-3' at 385 computational and 137 memory instructions, starting from the axes origin and attempting to reach its features from different directions. One of the directions prevail but does not manage to exactly reach the target. The same happens for the top right point, 'gpu-1'. `BenchPress`'s samples get closer developing a straight line from the origin to 1,000 computational and 100 memory instructions. At this point `BenchPress` is restricted by its sequence length and cannot augment further its samples. This is depicted by its attempt to reduce the distance by swapping the two instruction types within the same token length, forming a perpendicular line with a negative slope. We argue the area of Grewe's et al. feature space that `BenchPress` can cover within 768 tokens to be the area of the triangle formed by the intersections of the axes with the extension of the negative slope line developed by `BenchPress`'s samples.

Summary - `BenchPress` vs GitHub vs CLgen vs CLSmith. 6 of the targeted Rodinia benchmarks exceed `BenchPress`'s maximum sequence length of 768 tokens. In LLVM-IR feature spaces, care must be taken to generate code that will not be removed by compiler

Figure 8: Relative proximity to each Rodinia benchmark of the candidate kernel with the closest features. We report the best match for seven datasets (`BenchPress`'s, `CLgen`'s, `GitHub`'s and `GitHub-768`'s datasets also combined with exhaustive mutations with `SRCIROR`) over three feature spaces ((a) Grewe's et al., (b) InstCount and (c) Autophase). Relative proximity is 1 minus the distance of the two kernels in the feature space relative to the distance of the Rodinia benchmark from the axes origin. 100% means an exact match in features and is highlighted with a white asterisk (*). A score towards 0% indicates the closest match is closer to the axes origin than the benchmark, i.e., a very small or empty kernel.
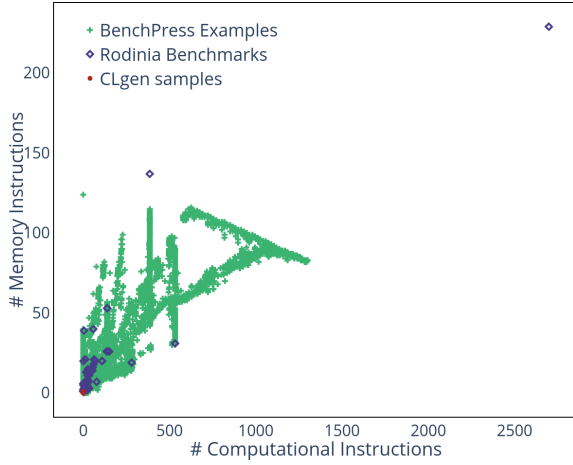
Figure 9: # Memory operations and # computational instructions for (a) Rodinia benchmarks in purple diamonds, (b) `CLgen`'s samples in red dots and `BenchPress`'s benchmarks in green crosses after performing directed search for all Rodinia benchmarks.

	Speedup %	Precision	Recall	Specificity
Benchmarks	+4%	0.81	0.86	0.61
BenchPress-AL	+6%	0.84	0.86	0.64
BenchPress-P	+1%	0.84	0.85	0.48
CLgen	-1%	0.52	0.86	0.43
GitHub	+1%	0.85	0.83	0.61

Table 2: Grewe et al. heuristic model's performance, precision, recall, and specificity when trained on each technique. Speedup is the geometrical mean of speedups over all benchmarks relative to the optimal static decision, i.e. running on the GPU. Precision, recall, and specificity treat GPU labels as positive and CPU labels as negative.
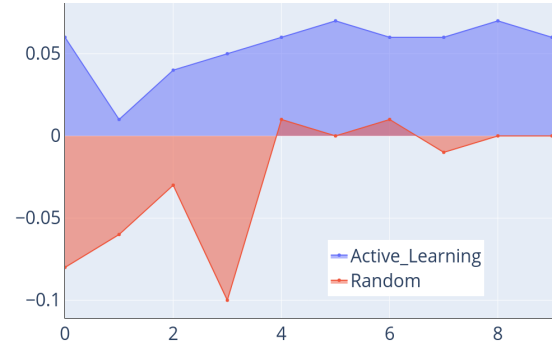

Figure 10: `BenchPress`'s performance enhancement of Grewe et al. heuristic model when using active learning compared to passively targeting random parts of the feature space over the course of 10 sampling epochs.

optimisations. This is a difficult challenge for source code generative models. However, our results demonstrate that `BenchPress` can generate OpenCL kernels that approach target human-written benchmarks compared to `GitHub` code and CLgen candidates. Our experiments also show `BenchPress` is dramatically better in all cases than `CLgen`, the current state of the art in OpenCL synthetic benchmark generation. We further elaborate on `BenchPress`'s performance in the next subsections.

5.3 Active Learning for Feature Selection

We combine `BenchPress`'s ability to generate benchmarks targeting desired features with active learning in order to generate benchmarks that improve the training of the Grewe et al. heuristic. We evaluate this against passive training with `CLgen`, `GitHub` code, and `BenchPress` with randomly selected target features. All approaches augment the same baseline training set that is taken from [7], containing 7 benchmark suites[1]. Table 2 shows the effect of each approach on the predictive power of the heuristic. Training only on human written benchmarks improves the heuristic's performance by 4%, as shown in Table 2's first row. To understand the maximum achievable improvement in the heuristic, we compute the best speedup (= 12%) that is achieved if the model chooses the optimal device as opposed to always picking the GPU. For 71% of the benchmarks, GPU is the optimal device, so no speedup improvement is possible. For the remaining 29% benchmarks, predicting the 'CPU' label correctly with Grewe et al. will result in a speedup improvement.

   `BenchPress` using active learning (`BenchPress-AL`) clearly outperforms all other approaches in terms of average speedup, improving it by 6%. When trained on `BenchPress` with passive/random feature selection (`BenchPress-P`), the speedup achieved is only 1%. To our surprise, the same speedup is achieved with `GitHub`,

which is worse compared with training only on the original benchmark suites. We further analyze the dataset collected from `GitHub` code and we find it to be imbalanced with 90% of its training instances are labelled as 'GPU'. This leads the model having a higher precision of 0.85, i.e. predicting correctly that a kernel should execute on the GPU, but falling short when it comes to correctly predicting the 'CPU' label. Training the heuristic with `CLgen` actually leads to a slowdown: it is 1% slower to execute kernels on the predicted devices compared to statically executing everything on the GPU, the baseline device. We analyze `CLgen`'s dataset and observe the opposite pattern found in `GitHub`'s dataset. 63% of its training data execute faster on the CPU than on the GPU. This is a direct consequence of `CLgen` generating small benchmarks that are poor in features, as the CPU may be slower than the GPU but the large overhead of transferring data to the GPU makes the CPU a better choice for small workloads. `CLgen` containing too many CPU-labeled kernel explains the heuristic's low precision and specificity, as it becomes biased to select the CPU very often leading to a slowdown.

   Our main motivation behind using active learning is that it gives `BenchPress` the ability to target directly those parts of the feature space that will maximize a downstream task's performance. To assess the active learner's performance, we compare the Grewe

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[1]The benchmarks have been updated with a wider range of `global` and `local` sizes.

et al. heuristic's speedup when trained on `BenchPress`'s benchmarks that target areas of the feature space selected by the active learner versus benchmarks that target random features. In both cases, we execute `BenchPress` for the same amount of time, 10 sampling epochs (i.e., performing steered generation for 10 target feature vectors). In Figure 10, we show the speedup achieved by the heuristic when trained on the data collected at that step. Using active learning to target features, `BenchPress`'s dataset improves the heuristic's speedup by 50% after 5 sampling steps, from 4% to 6%. Targeting random features never leads to a speedup higher than 1%. `BenchPress` can still develop the same speedup by targeting random features if infinite amount of time was available. Our active learner ensures that missing features are going to be quickly targeted, improving the state of the art within 5 sampling epochs.

6 CONCLUSION

Predictive models for compilers have been shown to outperform compiler experts but they are restricted by the amount and quality of training data they are exposed to. What is needed is an approach that can synthesize benchmarks and enhance datasets with missing features. In this paper we propose `BenchPress`, a powerful code generator that uses active learning to search the feature space and steers generation towards desired features. `BenchPress` generates 10× more and 7.5× larger undirected benchmarks with 37× greater compilation rate than `CLgen` - a state of the art compiler benchmark generator - from a fixed input feed. `BenchPress` outperforms `CLgen`, `CLSmith`, code from `GitHub` and applied mutations with `SRCIROR` in generating OpenCL kernels that target the features of Rodinia benchmarks developed by human experts. `BenchPress` applies active learning to enhance Grewe's et al. dataset with benchmarks with missing features and leads to improving the heuristic's speedup by 50%. We hope this work to demonstrate a sustainable method to direct feature space search of program generation and that `BenchPress`'s release to researchers will enable research in related domains.

7 RELATED WORK

`BenchPress` is inspired by BERT, a representation model by Devlin et al. [12]. Contrary to previous techniques [32, 33], BERT learns on unlabeled text data by jointly conditioning on both left and right context. BERT enables multiple applications of this architecture to a wide variety of difficult machine learning tasks, including programming languages. In CuBERT [26], Kanade et al. apply BERT over Python programs and evaluate it on finding typical mutation faults. In CodeBERT [14], Feng et al. fine-tune BERT to perform NL-PL and PL-NL transformations. In this work, we extend BERT to a bidirectional generative model, with the help of `[HOLE]` token.

Cummins et al. [7] develop `CLgen`, a deep learning generator based on LSTM [25] for OpenCL programs. They try to tackle the compiler benchmark shortage by providing synthetic benchmarks as training data for compiler heuristics. The authors present the Grewe et al. [20] heuristic model improved its performance by 1.27× when trained on their synthetic benchmarks. However, Goens et al. [18] show that training with `CLgen`'s synthetic samples lead to a slowdown compared to training on human-written benchmarks only. To explain this, they measure the AST depth of

`CLgen`'s samples and show it is 3× smaller compared to human-written benchmarks and code from `GitHub` and poor in features, therefore unrealistic. This motivates us to develop `BenchPress`, which produces 10× more unique kernels that are 7.5× larger on average.

In 2019, Nye et al. develop SketchAdapt [30], which uses a generator-synthesizer [3, 13] to generate program sketches given I/O specifications. The synthesizer samples sketches and the generator fills <HOLE> tokens with statements. SketchAdapt performs better than other architectures [3, 13], however it samples only a pre-defined pool of operations, which restricts its diversity. Bruen et al. [10], propose a Tree2Tree approach for code generation using VAE. They encode AST nodes using Tree-LSTMs (Tai et al. [37]) and train their model on C++ functions. They test their approach against a VAE with an LSTM Seq2Seq model. They use their model as a synthesizer by sampling random AST representations which they extend to new programs. Their Seq2Seq model achieves a compilation rate of up to 67% with greedy search, however this happens because the model greedily selects the most probable labels, leading to repetitive samples. When sampling with temperature, their Tree2Tree architecture is able to generate a wider variety of samples, but only achieves a compilation rate of 22%, which translates to a few functions.

Gupta et al. [21] develop SED, a two-stage generator. A synthesizer receives I/O specifications and generates programs likely to satisfy them and a neural debugger applies program repair to reform them into functions that match specifications. Gupta et al. evaluate three synthesizer architectures and measure (a) the correctness of generated programs across tests and (b) the accuracy of their debugger to repair code. While SED is an innovative work, Karel is a small-scale language and SED's generative performance on a complex programming language is not evaluated. Faustino et al. develop Anghabench [9] to tackle the benchmark shortage [7, 38]. Anghabench is a collection of C programs mined from `GitHub`. In order to make it compilable, they use Psyche-C [29] type inference engine to apply type reconstruction and resolve dependencies. Structs, unions and other composite data types are omitted or re-declared with primitive types. Their benchmarks are compiling, but cannot be executed. Compared to AnghaBench, `BenchPress` resolves type dependencies of composite types and user-defined functions without changing the functionality or semantics of programs.

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