CONTRASTIVE CODE REPRESENTATION LEARNING

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Paper under double-blind review

ABSTRACT

Machine-aided programming tools such as automated type predictors and autocomplete are increasingly learning-based. However, current approaches predominantly rely on supervised learning with task-specific datasets. We propose *Contrastive Code Representation Learning* (ContraCode), a self-supervised algorithm for learning task-agnostic semantic representations of programs via contrastive learning. Our approach uses no human-provided labels, only the raw text of programs. ContraCode optimizes for a representation that is invariant to semantic-preserving code transformations. We develop an automated source-to-source compiler that generates textually divergent variants of source programs. We then train a neural network to identify variants of anchor programs within a large batch of non-equivalent negatives. To solve this task, the network must extract features representing the functionality, not form, of the program. In experiments, we pre-train ContraCode with 1.8M unannotated JavaScript methods mined from GitHub, then transfer to downstream tasks by fine-tuning. Pre-training with ContraCode consistently improves the F1 score of baselines for code summarization by up to 8% and top-1 accuracy of type inference baselines by up to 13%. Overall, ContraCode achieves 9% higher top-1 and 40% higher top-5 accuracy than the current state-of-the-art static type analyzer for TypeScript.

1 INTRODUCTION

Programmers increasingly rely on machine-aided programming tools to aid software development (Kim et al., 2012). However, the wide diversity of programs encountered in practice limits the generalization of hand-written rules. Catching semantic bugs such as naming errors require deeper language understanding, motivating learning-based programming tools. Recent work uses machine learning for bug detection (Pradel & Sen, 2018) and optimization (Mendis et al., 2019). Consider predicting the type of the variable declaration "`var median = ...;`". Static analysis fails as the type is underspecified, but semantics of the variable name indicates the statement is a `float`.

Programming language datasets suffer from scarce annotations due to the time and expertise required for annotation. State-of-the-art approaches generally rely on either (1) synthetic supervised datasets or (2) self-supervised pre-training. Synthetic auto-generated labels have been used for method naming (Alon et al., 2019a;b) and bug detection (Ferenc et al., 2018; Benton et al., 2019; Pradel & Sen, 2018). However, synthetic code datasets suffer from duplication issues (Allamanis, 2019) and biases (Shin et al., 2019) which degrade generalization. Moreover, auto-generated data does not cover the diverse program behaviors encountered in the wild.

In contrast, self-supervised learning can leverage large open-source repositories such as GitHub with limited or no annotations. Inspired by the success of pre-training in natural language processing, recent work uses self-supervision to learn code representations. Authors have explored context-based token embeddings (Ben-Nun et al., 2018) and masked language modeling, where tokens are corrupted and reconstructed (Feng et al., 2020; Kanade et al., 2020) However, reconstruction focuses on superficial language reasoning and does not explicitly address the underlying program functionality. The resulting models attend to particularities of each program implementation such as variable names.

We hypothesize that *programs with the same functionality should have the same underlying representation* for downstream code understanding tasks, a principle illustrated in Figure 1. While it is time intensive to identify equivalent programs in a large corpus, it is cheap to leverage static compiler transformations to automatically generate many equivalent versions of a particular source program.

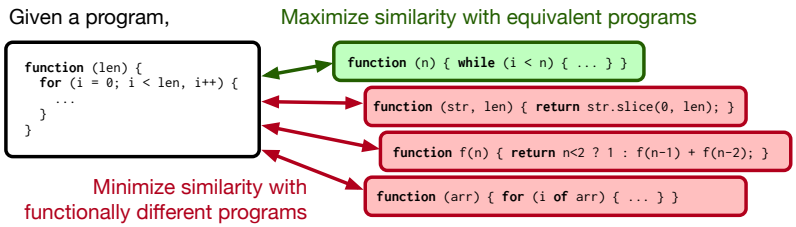

Figure 1: Programs with the same functionality should have the same underlying representation. ContraCode learns such representations with contrastive learning: the network is trained to find equivalent programs among many distractors, thereby distilling compiler invariants into the representation.

In this work, we develop ContraCode, a self-supervised representation learning algorithm that uses source-to-source compiler transformation techniques (e.g., dead code elimination, obfuscation and constant folding) to generate syntactically diverse but functionally equivalent programs. ContraCode uses these equivalent programs to construct a challenging *discriminative* pretext task that requires the model to identify equivalent programs out of a large dataset of distractors. In doing so, it has to embed the functionality, not the form, of the code. In essence, the domain knowledge from our code transformations induces the knowledge of the structure of programs onto learned representations. The contributions of our work include:

1. the novel use of compiler-inspired transformations as data augmentations for code,
2. the concept of program representation learning based on functional equivalence, and
3. a detailed analysis of architectures, code transformations and pre-training strategies, showing ContraCode improves the top-5 accuracy of static type inference baselines by up to 40%, learned type inference by 2% - 13%, and the F1 score of code summarization by up to 8%.

2 Related Work

Self-supervised learning (SSL) is a general representation learning strategy where some dimensions or attributes of a datapoint are predicted from the remaining parts. These methods are unsupervised in the sense that they do not rely on labels, but SSL tasks often adapt losses and architectures designed for supervised learning. Self-supervised pre-training has yielded large improvements in both NLP (Howard & Ruder, 2018; Devlin et al., 2018; Radford et al., 2018; 2019) and computer vision (Mahajan et al., 2018) by improving generalization (Erhan et al., 2010; Hao et al., 2019). Weak visual features, such as orientation (Gidaris et al., 2018), color (Zhang et al., 2016), and context (Pathak et al., 2016), are meaningful signals for representations (Mahajan et al., 2018).

Contrastive learning unifies many past SSL approaches that compare pairs or collections of similar and dissimilar items (Hadsell et al., 2006). Rather than training the network to predict labels or reconstruct data, contrastive methods minimize the distance between the representations of similar examples (positives) while maximizing the distance between dissimilar examples (negatives). Examples include Siamese networks (Bromley et al., 1994) and triplet losses (Schroff et al., 2015). Contrastive predictive coding (Oord et al., 2018; Hénaff et al., 2019) learns to encode chunks of sequential data to predict of future chunks with the InfoNCE loss, a variational lower bound on mutual information between views of the data (Tian et al., 2019; Wu et al., 2020) inspired by noise-constrastive estimation (Gutmann & Hyvärinen, 2010). In instance discrimination tasks (Wu et al., 2018), views and not pieces of an entire image are compared. SimCLR (Chen et al., 2020a) and Momentum Contrast (He et al., 2019; Chen et al., 2020b) recently made progress by using many negatives for dense loss signal. Beyond images, InfoNCE has been applied to NLP (Chuang et al., 2020; Giorgi et al., 2020), but may require supervision (Fang & Xie, 2020).

Code representation learning There has been substantial work on architectures and tasks for machine learning on code (Allamanis et al., 2018). We adopt the summarization task of Alon et al. (2019a), and the variable type inference task of DeepTyper (Hellendoorn et al., 2018). Other authors have explored summarization (Movshovitz-Attias & Cohen, 2013; Allamanis et al., 2016; Iyer et al., 2016) and type inference (Pradel et al., 2019; Pandi et al., 2020; Wei et al., 2020; Allamanis et al.,

```
function x(maxLine) {
  const section = {
    text: '',
    data
  };

  for (; i < maxLine; i += 1) {
    section.text += `${lines[i]}\n`;
  }

  if (section) {
    parsingCtx.sections.push(section);
  }
}
```

Original JavaScript method

```
function x(t) {
  const n = {
    'text': '',
    'data': data
  };
  for (;i < t; i += 1) {
    n.text += lines[i] + '\n';
  }
  n && parsingCtx.sections.push(n);
}
```

Renamed variables, explicit object style, explicit concatenation, inline conditional

```
function x(t){const
n={'text':'','data':data};for(;i<t;i+=
1)n.text+=lines[i]
+'\n';n&&parsingCtx.sections.push(n)}
```

Mangled source with compressed whitespace

Figure 2: A JavaScript method from the unlabeled training set with two automatically generated semantically-equivalent programs. The original method is from the StackEdit Markdown editor.

2020; Bielik & Vechev, 2020) with different languages and datasets. The tree or graph structure of code can be exploited to encode invariances in the representation. Inst2vec (Ben-Nun et al., 2018) locally embeds individual statements in LLVM IR by processing a contextual flow graph with a context prediction objective (Mikolov et al., 2013). Tree-Based CNN embeds the Abstract Syntax Tree (AST) nodes of high-level source code. Code2seq (Alon et al., 2019a) embeds AST paths with an attention-based encoder and LSTM decoder for supervised sequence-to-sequence tasks. Kanade et al. (2020); Feng et al. (2020) pre-train the Transformer (Vaswani et al., 2017) on code using the masked language modeling objective (Devlin et al., 2018), an instance of the cloze task (Taylor, 1953) where the model reconstructs corrupted tokens. Recurrent networks have also been pre-trained on code (Hussain et al., 2020) as language models (Peters et al., 2018; Karampatsis & Sutton, 2020). Wang & Christodorescu (2019); Wang & Su (2019) assess the stability of program analyzers under semi-automated program transformations. Concurrent work by Rabin & Alipour (2020) found that code2vec and code2seq often change their classifications when statements are permuted, variables are renamed, or other-semantic preserving transformations are applied.

3 Method: Contrastive Code Representation Learning

Understanding program functionality and global structure is important for difficult tasks like summarizing code in natural language. For these problems, learned code representations should be similar for functionally equivalent programs and dissimilar for non-equivalent programs (Figure 1). The principle of contrastive learning offers a simple objective for learning such representations if data can be organized into pairs of *positives* and *negatives*. We use each pair to shape representation space, drawing positives together and pushing negatives apart. However, a major question remains: *given an unlabeled corpus of programs, how do we identify or generate similar programs?* We address this question in Sec. 3.1, then introduce our learning framework in Sec. 3.2.

3.1 Compilation as Data Augmentation

Modern programming languages afford great flexibility to software developers, allowing them to implement the same desired functionality through different implementation choices. Crowdsourced datasets mined from developers, such as GitHub repositories, have many near-duplicates in terms of textual similarity (Allamanis, 2019), and are bound to contain even more functional equivalences for common tasks. Satisfiability solvers can identify these equivalent programs (Joshi et al., 2002; Bansal & Aiken, 2006), but require formal documentation of semantics. Functional equivalence is also undecidable in general (Rice, 1953). Programs can instead be compared approximately using test-cases (Massalin, 1987), but this is also costly and requires executing untrusted code.

Instead of *searching for equivalences*, we propose *correct by construction data augmentation*. Our insight is to apply source-to-source compiler transformations to unlabeled code to generate many variants with the same functionality. For example, dead-code elimination (DCE) is a common compiler optimization that removes operations that leave the output of a function unchanged. While DCE preserves program functionality, Wang & Christodorescu (2019) find that up to 12.7% of the predictions of current algorithm classification models change after DCE—supervised datasets were not enough to acquire the domain knowledge that DCE does not matter.

	Code compression		**Identifier modification**
✓	Reformatting (R)	✓	Variable renaming (VR)
✓	Beautification (B)	✓	Identifier mangling (IM)
✓	Compression (C)		**Regularization**
✓	Dead-code elimination (DCE)	✓	Dead-code insertion (DCI)
✓	Type upconversion (T)	✓	Subword regularization (SW)
✓	Constant folding (CF)	✗	Line subsampling (LS)

✓ = semantics-preserving transformation ✗ = lossy transformation

Table 1: We augment programs with 11 automated source-to-source compiler transformations. 10 of the 11 transformations are correct-by-construction and do not modify operational semantics. More details are in Section A.3.

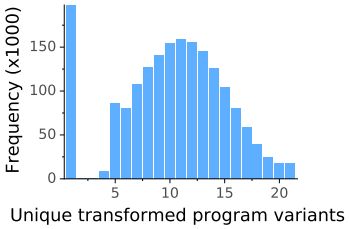

Figure 3: Histogram of the number of transformed variants per method during pre-training.

A particular source code sequence, e.g. "`W*x + b`" is parsed unambiguously into a tree-structured representation "`(+ (* W x) b)`". This tree is then transformed by automated traversal algorithms. A rich body of prior programming language work explores parsing then tranforming Abstract Syntax Trees to optimize a program prior to machine code generation. If source code is output rather than machine code, this is called source-to-source transformation. Source-to-source transformations are common for optimization and obfuscation purposes in dynamic languages like JavaScript. If each transformation maintains the function of the code, then their composition will also maintain its function. To achieve data diversity, we apply random subsets of the transformations to a given function. Figure 3 measures this diversity. 89% of the JavaScript functions in our dataset have more than one alternative after applying 20 random sequences of transformations.

We leverage the Babel and Terser compiler infrastructure tools for JavaScript (McKenzie et al., 2020; Santos et al., 2020) to parse code into an Abstract Syntax Tree (AST) and then perform correctness-preserving transformations on method bodies. Table 1 and Appendix A.3 list all transformations, but we broadly group program transformations into three categories. **Code compression** changes the syntactic structure of code and performs correct-by-construction transformations such as pre-computing constant expressions at compile time. **Identifier modification** substitutes method and variable names with random tokens, thereby masking part of the semantic information in programs. Finally, transformations for **Regularization** improve model generalization by reducing the number of trivial positive pairs with high text overlap; this group potentially modifies program semantics through the line subsampling pass. All transformations are fast. On a single CPU core, our compiler transforms 300 functions per second. Transformations are performed in a separate process from the training code, so the compiler can be implemented in the target language.

3.2 CONTRASTIVE PRE-TRAINING

Augmentations discussed in Section 3.1 can be used to adapt several contrastive learning objectives and frameworks to code representation learning. We adapt the Momentum Contrast (He et al., 2019) method that was designed for efficient image representation learning. Our training procedure is depicted in Figure 4. Each transformation is a function $\tau : F \rightarrow F$, where F denotes the space of programs. At the beginning of an iteration, a batch of programs is sampled from a large database. Each program f_i in the batch is transformed twice using two different, random subsets of transformations $\{\tau_i\}$ to derive textually different *query programs* and *key programs* according to Algorithm 1. That is,

$$x_i^q = \tau_{q_1} \circ \tau_{q_2} \circ \cdots \circ \tau_{q_m}(x_i), \qquad x_i^k = \tau_{k_1} \circ \tau_{k_2} \circ \cdots \circ \tau_{k_n}(x_i).$$

Query and key programs generated by transforming the same x_i define a positive pair. In effect, we encode each query program to retrieve its matching key program from a dictionary. We exploit previously encoded programs to generate a very large set of negatives by storing key embeddings in a queue across iterations. As there are relatively few identical programs in a varied dataset, these programs will largely be functionally different from the positives. Following He et al. (2019), the query programs are embedded with an encoder trained via gradient descent, as is standard in code representation learning, while key programs are embedded with an architecturally identical momentum encoder trained slowly via an exponential moving average (EMA) of the query encoder parameters. EMA is important so that the precomputed key embeddings do not shift across training iterations, making the dictionary lookup a more stable training task. Since keys are only embedded once per

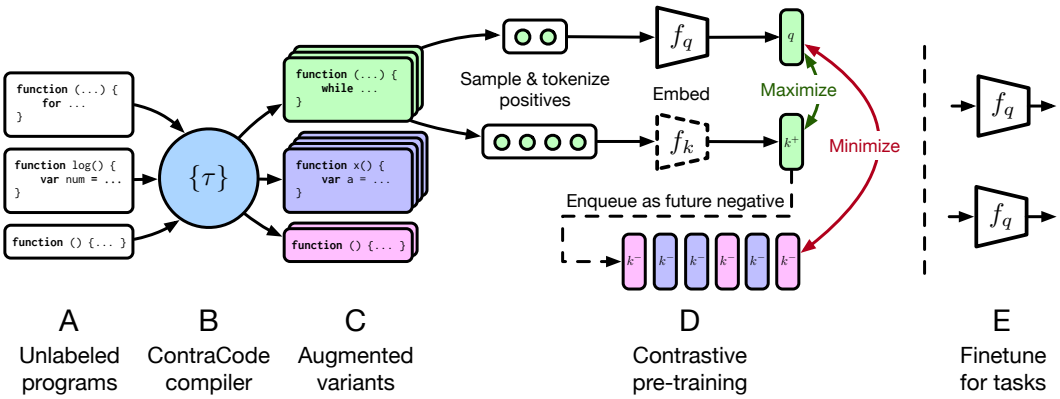

Figure 4: ContraCode pre-trains a neural program encoder f_q and transfers it to downstream tasks. **A-B.** Unlabeled programs are transformed, **C.** producing augmented variants. **D.** We pre-train f_q by maximizing similarity of embeddings of *positive* program pairs–variants of the same program–and minimizing similarity with queue of cached negatives. **E.** f_q is fine-tuned on smaller labeled datasets.

epoch, we use a very large set of negatives, over 100K, with minimal additional computational cost and no explicit hard negative mining. While we could re-embed all negatives each iteration, NLP architectures like the Transformer are memory and compute intensive.

Our method is independent of the choice of underlying encoder architecture. We evaluate contrastive pre-training of Transformer (Vaswani et al., 2017) and BiLSTM (Schuster & Paliwal, 1997; Huang et al., 2015) architectures, with specific details in Section 4.

Pre-training objective Our contrastive objective should maximize similarity for positives without collapsing onto a single representation. InfoNCE (Oord et al., 2018) is a tractable objective that frames contrastive learning as a classification task: can the positives be identified among a batch of sampled negatives? So far, we have addressed the negative sampling problem through code transformation. InfoNCE computes classification probabilities by taking softmax of representation similarities. Equation (1) shows our version of the InfoNCE loss for instance discrimination, a function whose value is low when q is similar to the positive key embedding k^+ and dissimilar to negative key embeddings k^-. t is a temperature hyperparameter proposed by Wu et al. (2018).

$$\mathcal{L}_{q,k^+,k^-} = -\log \frac{\exp(q \cdot k^+/t)}{\exp(q \cdot k^+/t) + \sum_{k^-} \exp(q \cdot k^-/t)} \tag{1}$$

The query representation $q = f_q(x^q)$ is computed by the encoder network f_q and x^q is a query program. Likewise, $k = f_k(x^k)$ using the EMA key encoder f_k. Views x^q, x^k depend on the specific domain and pretext task. In our case, the views are tokenized representations of the augmented programs, and the summation $\sum_{k^-}$ in the normalizing denominator is taken over the queue of pre-computed negatives as well as other non-matching keys in the batch.

Transfer learning After pre-training converges, the encoder f_q is transferred to downstream tasks. As the output space of the task can differ from the encoder, we add a task-specific MLP or Transformer decoder after f_q, then train the resulting network end-to-end on task data.

4 Experiments

We evaluate whether self-supervised pre-training with ContraCode improves the accuracy of code analysis in JavaScript and TypeScript. Specifically, we benchmark on the (1) extreme code summarization task from Allamanis et al. (2016) and the (2) TypeScript type inference task from Hellendoorn et al. (2018). Our evaluation demonstrates that ContraCode improves accuracy on both tasks. Contrastive pre-training with our compiler-based augmentations outperforms both baseline supervised learning methods as well as RoBERTa pre-training. Furthermore, we find it is better to augment the large set of unlabeled programs during pre-training rather than augmenting smaller supervised

Table 2: Type inference accuracy on TypeScript programs in the Hellendoorn et al. (2018) dataset. ContraCode (BiLSTM) outperforms baseline top-1 accuracies by 2.28% to 13.16%. As ContraCode does not modify model architecture, contrastive pre-training can be combined with each baseline. Compared with TypeScript's built-in type inference, ContraCode improves top-5 accuracy by 40.4%.

Baseline	Method	Acc@1 (all types)	Acc@5 (all types)
Static analysis	TypeScript CheckJS (Bierman et al., 2014)	45.11%	45.11%
	Name only (Hellendoorn et al., 2018)	28.94%	70.07%
Transformer	Transformer (supervised)	45.66%	80.08%
	with ContraCode pre-training	**46.86%**	**81.85%**
RoBERTa	Transformer (RoBERTa MLM pre-training)	40.85%	75.76%
	with ContraCode pre-training	**47.16%**	**81.44%**
DeepTyper (BiLSTM)	DeepTyper (supervised)	51.73%	82.71%
	with RoBERTa MLM pre-training (10K steps)	50.24%	82.85%
	with ContraCode pre-training	52.65%	84.60%
	with ContraCode pre-training (w/ subword reg. ft.)	**54.01%**	**85.55%**

datasets. As ContraCode makes no modifications to model architecture, we find that contrastive pre-training can transparently extend diverse baselines and improve end-to-end accuracy.

Pre-training dataset We pre-train over a large corpus of methods extracted from popular GitHub repositories. The CodeSearchNet dataset collected by Husain et al. (2019) contains 1,843,099 JavaScript programs. Only 81,487 methods have both a documentation string and a method name. The asymmetry between labeled and unlabeled programs stems from JavaScript coding practices where anonymous functions are widespread. The augmented pre-training datatset is pre-computed by applying random subsets of the transformations to each program using ContraCode's compiler. We sample up to 20 unique transformed variants per program' Figure 3 shows pre-training dataset statistics. 10.8% of the methods have no syntactically distinct alternatives after our compiler transforms, such as one-line functions that are obfuscated. We apply subword regularization (Kudo, 2018) as a final transform to derive different tokenizations every batch, so pairs will still differ.

4.1 Result: Impact of ContraCode pre-training on Type Inference

Type inference tools predict variable types from context, which can help programmers find bugs and document code. To learn to infer types, we use the same annotated dataset of TypeScript programs from DeepTyper (Hellendoorn et al., 2018), without GitHub repos that were made private or deleted since publication. The training set consists of 15,570 TypeScript files from 187 projects with 6,902,642 total tokens. Validation and test sets are from held-out repositories. For additional supervision during training, additional types are inferred by static analysis to augment user-defined types as targets. All type annotations are removed from the input to the model. We evaluate a 2-layer Bidirectional LSTM, as used by DeepTyper, and a 6-layer Transformer, modified from RoBERTa to have a comparable parameter count. A 2-layer MLP head predicts types from the model's embedding of each token. We perform early stopping based on validation set top-1 accuracy.

This task is challenging because it requires cross-language knowledge transfer. Our models are pre-trained on JavaScript, not TypeScript. TypeScript adds unseen syntactic sugar in addition to type annotations that must be learned during fine-tuning. Table 2 summarizes results. Contrastive pre-training outperforms all baseline learned methods. Our best-performing model (bottom row) achieves +8.3% higher top-1 accuracy than a supervised Transformer model trained from scratch, +13.2% higher than a pre-trained RoBERTa model and +2.3% higher than DeepTyper.

ContraCode can also be applied in a drop-in fashion to each of the baselines without modifying model architecture. Simply pre-training each baseline with our contrastive objective and data augmentations yields absolute accuracy improvements of +1.2%, +6.3%, +2.3% top-1 and +1.8%, +5.7%, +2.8% top-5 over the Transformer, RoBERTa, and DeepTyper, respectively. The RoBERTa baseline may perform poorly since the masked language modeling objective focuses on token reconstruction that is

Table 3: Results for different settings of the **code summarization task**: supervised training with 81k functions, masked language model pre-training and contrastive pre-training with fine-tuning.

Method	Precision	Recall	F1
code2vec (Alon et al., 2019b)	10.78%	8.24%	9.34%
code2seq (Alon et al., 2019a)	12.17%	7.65%	9.39%
RoBERTa MLM (Liu et al., 2019)	15.13%	11.47%	12.45%
Transformer (Vaswani et al., 2017)	18.11%	15.78%	16.86%
Transformer + ContraCode + augmentation	**20.34%**	**14.96%**	**17.24%**

overly sensitive to local syntactic structure. To combine the approaches, we minimized our loss in addition to MLM as a hybrid local-global objective during pre-training.

Learning outperforms static analysis by a large margin. Overall, ContraCode achieves +8.9% higher top-1 accuracy than the best static type inference system, the built-in TypeScript CheckJS system. As learned approaches can rank multiple candidate types, ContraCode achieves *+8.90% higher top-1 accuracy and +40.44% higher top-5 accuracy*, showing the promise of learned code analysis tools.

4.2 Result: Impact of ContraCode pre-training on Extreme Code Summarization

The extreme code summarization task asks a model to predict the name of a method given its body (Allamanis et al., 2016). Tokenized method names often contain a short summary of functionality, such as `reverseString(...)`. Summarization models could be used to explain obfuscated or poorly documented code. We create a JavaScript summarization dataset using the 81,487 labeled methods in the CodeSearchNet dataset. The method name is masked in the declaration of the function and then predicted by a sequence-to-sequence model with an autoregressive decoder trained to maximize log likelihood of the ground-truth name, a form of abstractive summarization. All models overfit, so we use early stopping according to validation loss. As proposed by Allamanis et al. (2016), we evaluate model predictions by precision, recall and F1 scores over the set of tokens in the method name.

Table 3 shows code summarization results in four settings: (1) supervised training using baseline tree-structured architectures that analyze the AST (code2vec, code2seq), (2) pre-training on all 1.84M programs using masked language modeling followed by fine-tuning on the labeled programs (RoBERTa), (3) supervised training from scratch with a Transformer architecture and (4) contrastive pre-training with all 1.84M programs followed by fine-tuning (ContraCode).

Contrastive pre-training with fine-tuning outperforms the prior code2seq model, a competitive supervised baseline, by 8.2% in test precision, 7.3% in recall, and 7.9% in F1 score. The tree-based code2seq architecture is a way to encode code-specific invariances into the model, while contrastive pre-training induces domain invariances through data augmentation; reduced inductive biases in the Transformer model architecture leads to better performance. ContraCode outperforms self-supervised pre-training with RoBERTa by 4.8% F1, showing that code token reconstruction is not an effective pre-training strategy for code summarization. ContraCode also achieves higher performance than the Transformer with the same network architecture.

4.3 Understanding the importance of data augmentation

In this section, we first analyze the effect of our proposed augmentations on supervised training without contrastive pre-training. We then perform an ablation to study the importance of particular augmentations during pre-training.

Supervised learning with data augmentation As a baseline, we re-train models from scratch with compiler transformations during *supervised learning* rather than during pre-training. Data augmentation artificially expands the size of labeled training sets. For the sequence-to-sequence summarization model, a variety of augmentations are applied without changing ground-truth labels.

Table 4: Ablating compiler transformations used during contrastive pre-training. The DeepTyper BiLSTM is pre-trained with constrastive learning for 20K steps, then fine-tuned for type inference. Augmentations are only used during pre-training. Each transformation contributes to accuracy.

Augmentations used during pre-training	Acc@1	Acc@5
All augmentations (Table 2)	**52.65%**	**84.60%**
without identifier modification (-VR, -IM)	51.94%	84.43%
without line subsampling (-LS)	51.05%	81.63%
without code compression (-T,C,DCE,CF)	50.69%	81.95%

Since type labels are aligned to input tokens, labels must be corresponded with the transformed program. We apply all transformations that correspond token locations.

Table 5 shows the results. On both benchmarks, compiler-based data augmentations degrade supervised models, perhaps by creating a training distribution not reflective of evaluation programs. Augmentations during ContraCode pre-training results in a more robust model. Our contrastive learning framework also allows learning large numbers of unlabeled programs that supervised learning alone cannot leverage. The ablation indicates that augmentations do not suffice, and contrastive learning is important.

Table 5: Compiler-based data augmentations degrade performance when training supervised models from scratch.

Code summarization	F1
Transformer (Table 3)	**16.86**
w/ LS,SW,VR,DCI aug.	15.65
Type Inference	**Acc@1**
Transformer (Table 2)	**45.66**
w/ SW reg.	43.96
w/ LS,SW aug.	44.14
DeepTyper (Table 2)	**51.73**
w/ SW reg.	49.93
w/ LS,SW aug.	50.93
w/ stronger LS,SW aug.	50.33

Ablating data pre-training augmentations Some data augmentations may be more valuable than others for learning a representation via instance discrimination. Empirically, pre-training converges faster with a smaller set of augmentations since the positives are syntactically more similar, but this hurts downstream performance. Table 4 shows that type inference accuracy degrades when different groups of augmentations are removed. Semantics-preserving code compression passes that require code analysis are the most important, improving top-1 accuracy by 1.95% when included. Line subsampling serves as a regularizer, but change program semantics. LS is relatively less important, but does help accuracy. Identifier modification passes preserve semantics, but remove potentially useful naming information. Removing these hurts accuracy the least.

Additional results We perform extensive ablations in Sec. A.1 by transferring different parts of the network to downstream tasks, computing the contrastive objective with representations taken from different encoder layers, varying architecture, and tuning the pre-training procedure. These experiments suggest that as many parameters as possible should be transferred to the downstream task. Details of the pre-training strategy are also important. Computing the contrastive objective using a "global" representation q summarizing the whole input sequence outperforms more a "local" representation based on aggregating token representations. Further, a large diversity of programs and large batch size are helpful to stabilize pre-training. Sec. A.2 includes qualitative results.

5 Conclusions

Large-scale unannotated repositories of code like GitHub are a powerful resource for learning-based machine-aided programming tools. However, most current approaches to code representation learning do not leverage unannotated data. We propose ContraCode, a contrastive self-supervised algorithm that learns representations that are invariant to semantics-preserving code transformations. Our method induces invariances between automated semantics-preserving code transformations via novel augmentations for code. ContraCode significantly improves the accuracy of extreme code summarization baselines (+2.3% to +13.2%) and TypeScript type inference models (up to +7.9% F1). ContraCode outperforms self-supervised RoBERTa pre-training. Moreover, contrastive pre-training outperforms supervised training with our augmentations. As ContraCode makes no modifications to model architecture, it consistently improves accuracies when applied to diverse baselines.

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A APPENDIX

A.1 ADDITIONAL ABLATIONS

Which part of the model should be transferred? SimCLR (Chen et al., 2020a) proposed using a small MLP head to reduce the dimensionality of the representation used in the InfoNCE loss during pre-training, and did not transfer the MLP to the downstream image-classification task. In contrast, we find it beneficial to transfer part of the contrastive MLP head to type inference, showing a 2% improvement in top-5 accuracy over transferring the encoder only (Table 6). We believe the improvement stems from fine-tuning both the encoder and MLP which allows feature adaptation, while SimCLR trained a linear model on top of frozen features. We only transferred the MLP when contrasting the mean of token embeddings during pre-training, not the terminal hidden states, as the dimensionality of the MLP head differs. These representations are compared next.

Should we pre-train global or local representations? We compare pre-training DeepTyper with two variants of ContraCode. We either use the mean of token hidden states across the program (averaging local features), or the terminal hidden states as input to the MLP used to extract the contrastive representation $q = f_q(x)$ (global features). Token-level features might capture more syntactic details, but averaging pooling ignores order. Table 7 shows the accuracy of a BiLSTM pre-trained with each strategy. Using the global features for pre-training yields significantly improved performance, +2.38% acc@1 after 10K iterations of pre-training (not converged for the purposes of ablation). The global pre-training strategy achieves the best results in Table 2.

Do pre-trained encoders help more with shallow decoders? For the sequence-to-sequence code summarization task, ContraCode only pre-trains the encoder of the Transformer. In Table 8, we ablate the depth of the decoder to understand how much shallow decoders benefit from contrastive pre-training of the encoder. Similar experiments were performed in a vision context by Erhan et al. (2010), where different numbers of layers of a classifier are pretrained. After 45k pre-training steps, the 4-layer decoder achieves 0.50% higher precision, 0.64% higher recall and 0.77% higher F1 score

Table 6: If local representations are learned, transferring part of the Contrastive MLP head improves type inference. The encoder is a 2-layer BiLSTM (d=512), with a 2-layer MLP head for both pre-training purposes and type inference. The mean hidden state representation is optimized for 10K iterations for the purposes of this ablation.

Transferred from pre-training	Acc@1	Acc@5
Transfer BiLSTM	**49.32%**	80.03%
Transfer BiLSTM, 1 layer of MLP	49.15%	**82.58%**

Table 7: Contrasting global, sequence-level representations outperforms contrasting local representations. We compare using the terminal (global) hidden states of the DeepTyper BiLSTM and the average token-level (local) hidden states.

Representation	Optimization	Acc@1	Acc@5
Global	InfoNCE with terminal hidden state, 20K steps (Table 2)	**52.65%**	**84.60%**
	InfoNCE with terminal hidden state, 10K steps	51.70%	83.03%
Local	InfoNCE with mean token rep., 10K steps	49.32%	80.03%

Table 8: Training time and decoder depth ablation on the method name prediction task. Longer pre-training significantly improves downstream performance when a shallow, 1 layer decoder is used.

Decoder	Pre-training (1.8M programs)	Supervision (81k programs)	Precision	Recall	F1
Transformer, 1 layer	MoCo, 10k steps	Original set	11.91%	5.96%	7.49%
Transformer, 1 layer	MoCo, 45k steps	Original set	**17.71%**	**12.57%**	**13.79%**
Transformer, 4 layers	MoCo, 45k steps	Original set	**18.21%**	**13.21%**	**14.56%**

```javascript
function x(url, callback, error) {
  var img = new Image();
  img.src = url;
  if(img.complete){
    return callback(img);
  }
  img.onload = function(){
    img.onload = null;
    callback(img);
  };
  img.onerror = function(e){
    img.onerror = null;
    error(e);
  };
}
```

Ground truth: `loadImage`
Prediction: `loadImage`

Other predictions:

1. `getImageItem`
2. `createImage`
3. `loadImageForBreakpoint`
4. `getImageSrcCSS`

Figure 5: A JavaScript program from the CodeSearchNet dataset not seen during training and the predicted method names from a Transformer pre-trained with ContraCode. ContraCode predicts the correct method name as its most likely decoding.

than the 1-layer model, so additional decoder depth is helpful for the downstream task. The 1-layer decoder model also benefits significantly from longer pre-training, with a 6.3% increase in F1 from 10k to 45k iterations. This large of an improvement indicates that ContraCode could be more helpful for pre-training when the number of randomly initialized parameters at the start of fine-tuning is small. For larger decoders, more parameters must be optimized during-finetuning, and the value of pre-training is diminished.

Contrastive representation learning strategies In Figure 8, we compare two strategies of refreshing the MoCo queue of key embeddings (the dictionary of negative program representations assumed to be non-equivalent to the batch of positives). In the first strategy, we add 8 items out of the batch to the queue ($1\times$), while in the second we add 96 items ($12\times$). In addition, we use a larger queue (65k versus 125k keys) and a slightly larger batch size (64 versus 96). We observe that for the baseline queue fill rate, the accuracy decreases for the first 8125 iterations as the queue fills. This decrease in accuracy is expected as the task becomes more difficult due to the increasing number of negatives during queue warmup. However, it is surprising that accuracy grows so slowly once the queue is filled. We suspect this is because the key encoder changes significantly over thousands of iterations: with a momentum term $m = 0.999$, the original key encoder parameters are decayed by a factor of 2.9×10^{-4} by the moving average. If the queue is rapidly refreshed, queue embeddings are predicted by recent key encoders, not old parameters. This also indicates that a large diversity of negative, non-equivalent programs are helpful for rapid convergence of ContraCode pre-training.

A.2 Qualitative results

We qualitatively inspect the quality of learned representations by visualizing ContraCode representations using t-SNE (Maaten & Hinton, 2008) over 8 programs with respective program variants. We annotate each method with the source program ID before semantics-preserving transformations. Variants of the source program closely cluster together. Indeed, contrastive learning learns representations that are invariant to a wide class of automated compiler-based transformations. We found that the representations learned by BERT showed more overlap between different algorithm tags; contrastive features may therefore learn better global representations of programs.

Figure 5 shows a qualitative example of predictions for the code summarization task. The JavaScript method is not seen during training. A Transformer pretrained with ContraCode predicts the correct method name as the most likely decoding through beam search. The next four predictions are reasonable, capturing that the method processes an image. The 2nd and 3rd most likely decodings, `getImageItem` and `createImage`, use `get` and `create` as synonyms for `load`, though the final two unlikely decodings include terms not mentioned in the method body.

We can also visualize outputs of the type inference model. Figure 6 shows two TypeScript programs from the held-out test set. User-provided type annotations are removed from the programs, and the

```
import {
  write,
  categories,
  messageType
} from "s";
export const animationsTraceCategory = "s";
export const rendererTraceCategory = "s";
export const viewUtilCategory = "s";
export const routerTraceCategory = "s";
export const routeReuseStrategyTraceCategory = "s";
export const listViewTraceCategory = "s";
export function animationsLog ( message: string 100.0% ): void 99.9% {
  write(message, animationsTraceCategory);
}
export function rendererLog (msg): void 53.7% {
  write(msg, rendererTraceCategory);
}
export function rendererError ( message: string 99.5% ): void 99.7% {
  write(message, rendererTraceCategory, messageType.error);
}
export function viewUtilLog (msg): void 100.0% {
  write(msg, viewUtilCategory);
}
export function routerLog ( message: string 99.9% ): void 100.0% {
  write(message, routerTraceCategory);
}
export function routeReuseStrategyLog ( message: string 99.8% ): void 99.98% {
  write(message, routeReuseStrategyTraceCategory);
}
export function styleError ( message: string 99.97% ): void 100.0% {
  write(message, categories.Style, messageType.error);
}
export function listViewLog ( message: string 100.0% ): void 100.0% {
  write(message, listViewTraceCategory);
}
export function listViewError ( message: string 99.93% ): void 100.0% ...
```

```
import {
  ComponentRef,
  ComponentFactory,
  ViewContainerRef,
  Component,
  Type,
  ComponentFactoryResolver,
  ChangeDetectorRef
} from "s";
import {
  write
} from "s";
export const CATEGORY = "s";

function log( message: string 56.95 ) {
  write(message, CATEGORY);
}
@ Component({
  selector: "s",
  template: `template`
}) export class DetachedLoader {
  constructor(private resolver: ViewContainerRef 63.85% (GT: ComponentFactoryResolver) ,
              private changeDetector: ChangeDetectorRef 100.0% ,
              private containerRef: ViewContainerRef 100.0% ) {}
  private loadInLocation (
      componentType<any>: TemplateRef 99.6% (GT: Type)) <ComponentRef<any>>: Promise 100.0% {
    const factory = this.resolver.resolveComponentFactory(componentType);
    const componentRef = this.containerRef.createComponent(
      factory, this.containerRef.length, this.containerRef.parentInjector);
    log("s");
    return Promise.resolve(componentRef);
  }
  public detectChanges() {
    this.changeDetector.markForCheck();
  }
  public loadComponent (
      componentType<any>: TemplateRef 99.9% (GT: Type)) <ComponentRef<any>>: Promise 100.0% {
    log("s");
    return this.loadInLocation(componentType);
  } ...
```

Figure 6: Our model, a variant of DeepTyper pretrained with ContraCode, generates type annotations for two programs in the held-out set. The model consistently predicts the correct return type of functions, and even predicts project-specific types imported at the top of the file. The model corresponds to the top row of Table 7, though is not our best performing model.

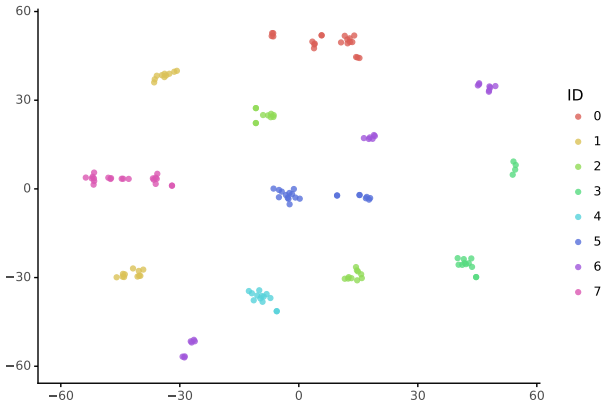


Figure 7: t-SNE (Maaten & Hinton, 2008) plot of ContraCode representations, colored by source program ID.

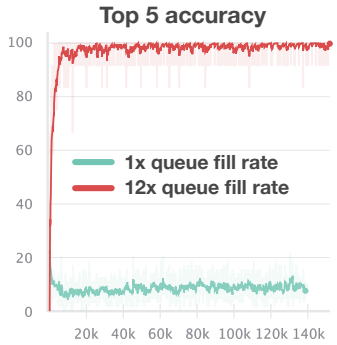


Figure 8: Pre-training quickly converges if non-equivalent programs frequently change.

model is provided with a tokenized form without access to dependencies. We visualize predictions from a variant of DeepTyper pretrained with ContraCode, the best-performing model in Table 7. In the first program, our model consistently predicts the correct return and parameter type. While a tool based on static analysis could infer the `void` return types, the type of the `message` argument is ambiguous without access to the imported `write` method signature. Still, the model correctly predicts with high confidence that the variable `message` is a string.

In the second program, ContraCode correctly predicts 4 of 8 types including the `ViewContainerRef` and `ChangeDetectorRef` types, each imported from the AngularJS library. As this sample is held-out from the training set, these predictions show generalization from other repositories using AngularJS.

A.3 Program transformation details

We use the Babel compiler infrastructure (McKenzie et al., 2020) and the `terser` JavaScript library for AST-based program transformations. We perform variable renaming and dead code insertion (variable declaration insertion) using custom Babel transforms, subword regularization with `sentencepiece` Python tokenization library, line subsampling using JavaScript string manipulation primatives and other transformations with `terser`. Terser has two high-level transformation modes, mangling and compression, each with finer grained controls such as formatting, comment and log removal, and dead code elimination. We show an example merge sort with example equivalent variants in Figure 9.

Reformatting, beautification, compression (R, B, C): Personal coding conventions do not affect the semantics of code; auto-formatting normalizes according to a style convention.

Dead-code elimination (DCE): In this pass, all unused code with no side effects are removed. Various statements can be inlined or removed as stale or unneeded functionality.

Type upconversion (T): In JavaScript, some types are polymorphic and can be converted between each other. As an example, booleans can be represented as `true` or as `1`.

Constant folding (CF): During constant folding, all expressions that can be pre-computed at compilation time can be inlined. For example, the expression `(2 + 3) * 4` is replaced with `20`.

Variable renaming, identifier mangling (VR, IM): Arguments can be renamed with random word sequences and identifiers can be replaced with short tokens to make the model robust to naming choices. Program behavior is preserved despite obfuscation.

Dead-code insertion (DCI): Commonly used no-ops such as comments and logging are inserted.

Subword regularization (SW): From Kudo (2018), text is tokenized in several different ways, with a single word (`_function`) or subtokens (`_func tion`).

Line subsampling (LS): We randomly sample ($p = 0.9$) lines from a method body. While not semantics-preserving, line subsampling serves as a regularizer.

```
// Split the array into halves and merge them recursively
function mergeSort (arr) {
  if (arr.length === 1) {
    // return once we hit an array with a single item
    return arr
  }
  const middle = Math.floor(arr.length / 2)
  // get the middle item of the array rounded down
  const left = arr.slice(0, middle)
  // items on the left side
  const right = arr.slice(middle)
  // items on the right side
  return merge(
    mergeSort(left),
    mergeSort(right)
  )
}
```

Original merge sort program

```
function mergeSort(e) {
  if (e.length === 1) {
    return e;
  }
  const t = Math.floor(e.length / 2);
  const l = e.slice(0, t);
  const n = e.slice(t);
  return merge(mergeSort(l), mergeSort(n));
}
```

After variable renaming, comment removal, reformatting (mangling)

```
function mergeSort(e) {
  if (1 === e.length) return e;
  const t = Math.floor(e.length / 2), r = e.slice(0, t), n = e.slice(t);
  return merge(mergeSort(r), mergeSort(n));
}
```

After combining variable declarations, inlining conditional (mangling and compression)

Figure 9: Given a JavaScript code snippet implementing the merge sort algorithm, we apply semantics-preserving transformations to produce functionally-equivalent yet textually distinct code sequences. Compression eliminates unnecessary characters such as redundant variable declarations and brackets.

While compilers are generally deterministic, we require a variety of alternatives to each program for contrastive representation learning. Algorithm 1 samples N augmented variants of a source program x using a set of deterministic compiler transformations τ_i. Stochasticity is introduced by randomly toggling each transformation according to Bernoulli samples with probabilities p_i. When adding a program to the set of variants $\mathcal{V}$, uniqueness is determined by string comparison.

A.4 Experimental setup

Architectures The Transformer has 6 encoder layers (23M parameters) in all experiments, and 4 decoder layers for method name prediction in Table 3. We leverage the default positional embedding function ($\sin$, $\cos$) as used in the original Transformer architecture. The network originally proposed in DeepTyper (Hellendoorn et al., 2018) had 11M parameters with a 300 dimensional hidden state. We increase the hidden state size to 512 to increase model capacity, so our BiLSTM for type prediction has 17.5M parameters. During fine-tuning, across all experiments, we optimize parameters using Adam with linear learning rate warmup and decay. For the Transformer, the learning rate is linearly increased for 5,000 steps from 0 to a maximum of 10^{-4}. For the bidirectional LSTM, the learning rate is increased for between 2,500 and 10,000 steps to a maximum of 10^{-3}. Type inference hyperparameters are selected by validation top-1 accuracy.

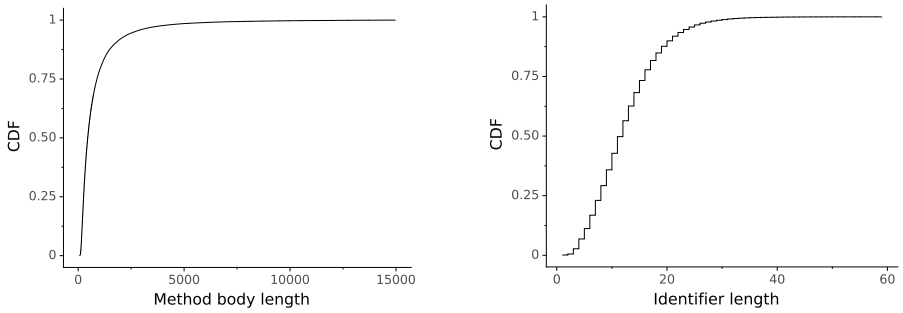
Algorithm 1 Stochastic program transformation

Input: Source code string x, transformation functions $\tau_1, \dots \tau_k$, application probabilities $p_1, \dots p_k$, sample count N
Initialize a set of program variants $\mathcal{V} := \{x\}$
for SAMPLE from 1 to N **do**
  Let $x' := x$ be a copy of the input program to mutate
  Let ISAST := false be a flag tracking the program representation
  for transform index t from 1 to k **do**
    if transform $\tau_t(\cdot)$ expects an AST and ISAST is false **then**
      $x' = \text{PARSE}(x')$
    else if transform $\tau_t(\cdot)$ expects source code and ISAST **then**
      $x' = \text{GENERATECODE}(x')$
    end if
    With probability p_t, let $x' = \tau_t(x')$ and update ISAST flag based on returned data structure
  end for
  if ISAST **then**
    $x' = \text{GENERATECODE}(x')$
  end if
  Add x' to variant set $\mathcal{V}$
end for
return $\mathcal{V}$

ContraCode pretraining The InfoNCE objective (1) is minimized with temperature $t = 0.07$ following He et al. (2019). Also following He et al. (2019), the key encoder's parameters are computed with the momentum update equation $\theta_k \leftarrow m\theta_k + (1 - m)\theta_q$, equivalent to an EMA of the query encoder parameters θ_q. To pretrain a Transformer using the ContraCode objective, we first embed each token in the program using the Transformer. However, the InfoNCE objective is defined in terms of a single embedding for the full program. Our model averages the 512-dimensional token embeddings across the sequence, then applies a two-layer MLP with 512 hidden units and a ReLU activation to extract a 128-dimensional program embedding for the loss. The ContraCode Transformer is pretrained with a batch size of 96. The DeepTyper bidirectional LSTM architecture offers two choices for extracting a global program representation. We aggregate a 1024-dimensional global representation of the program by concatenating its four terminal hidden states (from two sequence processing directions and two stacked LSTM layers), then apply the same MLP architecture as before to extract a 128-dimensional program representation. Alternatively, we can average the hidden state concatenated from each direction across the tokens in the sequence before applying the MLP head. We refer to the hidden-state configuration as a global representation and the sequence averaging configuration as a local representation in Table 7. We pre-train the BiLSTM with large batch size of 512 and apply weight decay.

Type prediction Following DeepTyper (Hellendoorn et al., 2018), our regenerated dataset for type prediction has 187 training projects with 15,570 TypeScript files, totaling 6,902,642 tokens. We tune hyperparameters on a validation set of 23 distinct projects with 1,803 files and 490,335 tokens, and evaluate on a held-out test set of 24 projects with 2,206 files and 958,821. The training set is smaller than originally used in DeepTyper as several projects were made private or deleted from GitHub before May 2020 when we downloaded the data, but we used the same commit hashes for available projects so our splits are a subset of the original. We have released the data with our open-source code to facilitate further work on a stable benchmark as more repositories are deleted over time. We perform early stopping to select the number of training epochs. We train each model for 100 epochs and select the checkpoint with the minimum accuracy@1 metric (all types, including `any`) on the validation set. Except for the model learned from scratch, the Transformer architectures are pre-trained for 240K steps. Models with the DeepTyper architecture converge faster on the pre-training tasks and are pre-trained for 20K iterations (unless otherwise noted).

Extreme code summarization by method name prediction We train method prediction models using the labeled subset of CodeSearchNet. Neither method names nor docstrings are provided as input to the model: the docstring is deleted, and the method name is replaced with the token '`x`'. Thus, the task is to predict the method name using the method body and comments alone. To decode method



(a) Character length per code sample

(b) Character length per method name

Figure 10: CodeSearchNet code summarization dataset statistics: (a) The majority of code sequences are under 2000 characters, but there is long tail of programs that span up to 15000 characters long, (b) JavaScript method names are relatively short compared to languages like C♯ and Java.

names from all models except the code2vec and code2seq baselines which implement their own decoding procedures, we use a beam search with a beam of size 5 and a maximum target sequence length of 20 subword tokens. We detail the cumulative distribution of program lengths in Figure 10. The ContraCode summarization Transformer only needed to be pre-trained for 20K iterations, with substantially faster convergence than RoBERTa (240K iterations). During fine-tuning, we apply the LS,SW,VR,DCI augmentations to ContraCode.

A.5 BASELINES

Baselines for code summarization and type prediction trained their models on an inconsistent set of programming languages and datasets. In order to normalize the effect of datasets, we selected several diverse state-of-the-art baselines and reimplemented them on the JavaScript dataset.

AST-based models The authors of code2vec (Alon et al., 2019b) and code2seq (Alon et al., 2019a), AST-based code understanding models, made both data and code available, but train their model on the Java programming language. In order to extend the results in their paper to JavaScript for comparison with our approach, we generated an AST path dataset for the CodeSearchNet dataset. The sensitivity of path-mining embeddings to different datasets is documented in prior work, so published F1 scores are not directly comparable; F1 scores for code2vec (Alon et al., 2019b) vary between 19 (Alon et al., 2019a) and 43 (Alon et al., 2019b) depending on the dataset used. Therefore, we use the same dataset generation code as the authors for fair comparison. We first parse the source functions using the Babel compiler infrastructure. Using the original code on these ASTs, up to 300 token-to-token (leaf-to-leaf) paths are extracted from each function's AST as a precomputed dataset. Then, we generate a token and AST node vocabulary using the same author-provided code, and train the models for 20 epochs, using early stopping for code2seq. We observed that code2vec overfits after 20 epochs, and longer training was not beneficial.

DeepTyper (Hellendoorn et al., 2018) DeepTyper uses a two layer GRU with a projection over possible classes, with an embedding size of 300 and hidden dimension of 650. However, we found improved performance by replacing the GRU with a bidirectional LSTM (BiLSTM). We normalize the LSTM parameter count to match our model, and therefore use a hidden dimension size of 512. We also use subword tokenization rather than space delimited tokens according to Kudo (2018), as subword tokenization is a key part of state-of-the-art models for NLP (Sennrich et al., 2015).

RoBERTa We pre-trained an encoder using RoBERTa on the CodeSearchNet dataset. Unlike the original BERT paper which cuBERT (Kanade et al., 2020) is based on, hyperparameters from RoBERTa have been found to produce better results during pre-training. RoBERTa pre-trains using a masked language modeling (MLM) objective, where 15% of tokens in a sentence are masked or replaced and are reconstructed by the model. We did not use the BERT Next Sentence Prediction (NSP) loss which RoBERTa finds to be unnecessary. We normalize baseline parameter count by reducing the number of Transformer layers from 24 to 6 for a total of 23M parameters.