
Contrastive Code Representation Learning

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Abstract

Machine-aided programming tools such as type predictors and code summarizers are increasingly learning-based. However, most code representation learning approaches rely on supervised learning with task-specific annotated 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, relying only on the raw text of programs. In particular, we design an unsupervised pretext task by generating textually divergent copies of source functions via automated source-to-source compiler transforms that preserve semantics. We train a neural model to identify variants of an anchor program within a large batch of negatives. To solve this task, the network must extract program features representing the functionality, not form, of the program. This is the first application of instance discrimination to code representation learning to our knowledge. We pre-train models over 1.8m unannotated JavaScript methods mined from GitHub. ContraCode pre-training improves code summarization accuracy by 7.9% over supervised approaches and 4.8% over RoBERTa pre-training. Moreover, our approach is agnostic to model architecture; for a type inference task, contrastive pre-training consistently improves the accuracy of existing baselines.

1 Introduction

Programmers increasingly rely on machine-aided programming tools such as automated refactoring and autocompletion [39]. However, the wide diversity of programs encountered in practice limits the generalization of handmade rules. Large classes of program behaviors, such as naming errors or semantic bugs, prove difficult to encode in rules and require deeper language understanding. As a consequence, learning based approaches are attractive. Recent work uses machine learning for bug detection [59], refactoring [42, 73], autocompletion [37, 63] and optimization [1, 38, 49, 51].

Due to the difficulty of annotating supervised training datasets over code, state-of-the-art approaches rely either on (1) synthetic supervised datasets or (2) self-supervised pre-training. Synthetic datasets with auto-generated labels have been applied to method naming [6, 7], documentation generation [71] and bug detection [10, 22]. However, auto-generated synthetic datasets suffer from subtle duplication issues [2] and biases [65] which degrade generalization performance. Moreover, autogenerated data is less diverse than real data and does not cover all program behaviors encountered in the wild.

In contrast, self-supervised pre-training enables the use of large open-source repositories such as GitHub with limited or no annotations without artificially generating labels. Prior work has explored context-based token embeddings [9], prediction of specific attributes [5], and masked language modeling [21, 35]. These efforts focus on reconstructing the textual content of a program given surrounding tokens. However, these pretext tasks focus on superficial language reasoning and do not

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Open-source model and code available at <https://github.com/parasj/contracode>
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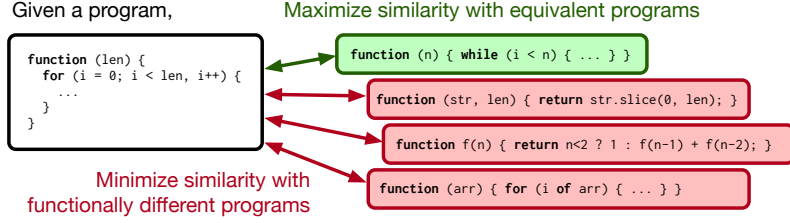


Figure 1: Programs with the same functionality should have the same underlying representation. ContraCode learns such representations with contrastive learning: the network is trained to find equivalent programs among many distractors, thereby distilling compiler invariants into the representation.

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.

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 concept of program representation learning based on functional equivalence, independent of the underlying encoder model architecture,
2. an instantiation of this based on a novel application of compiler transformations to generate equivalent, textually divergent batches of programs, and
3. an evaluation of several model architectures demonstrating that Contrastive Code Representation Learning results in a 10.2% relative accuracy improvement over supervised baselines for the code summarization task and up to 4.5% improvement for the type inference task.

2 Related Work

Self-supervised learning Self-supervised learning 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. However, self-supervised tasks are often solved using losses and architectures designed for supervised learning. Self-supervised pre-training has yielded large improvements in both natural-language processing [18, 29, 60, 61] and computer vision [46, 15, 14, 26, 28, 53] by improving generalization [19]. Early work in self-supervised learning for computer vision found that weak features, such as the orientation [23], color [74] and context [56] of an image, are meaningful signals for representation learning [46].

Contrastive learning Recently, contrastive learning has emerged as a simple framework unifying many past approaches to self-supervised learning based on comparing pairs or collections of similar and dissimilar items [25]. Rather than training the network to predict labels or generate data, contrastive methods directly minimize a distance between the representations of similar data (positives) and maximize the distance between dissimilar data (negatives). Approaches that use few negatives include Siamese networks [13] and triplet losses [4, 62]. Contrastive predictive coding [54, 28] learns to encode pieces of sequential data such as audio so that the representations are predictive of representations of future pieces of the data using the InfoNCE loss [53], a variational lower bound on mutual information between views of the data [72] inspired by noise-contrastive estimation [24].

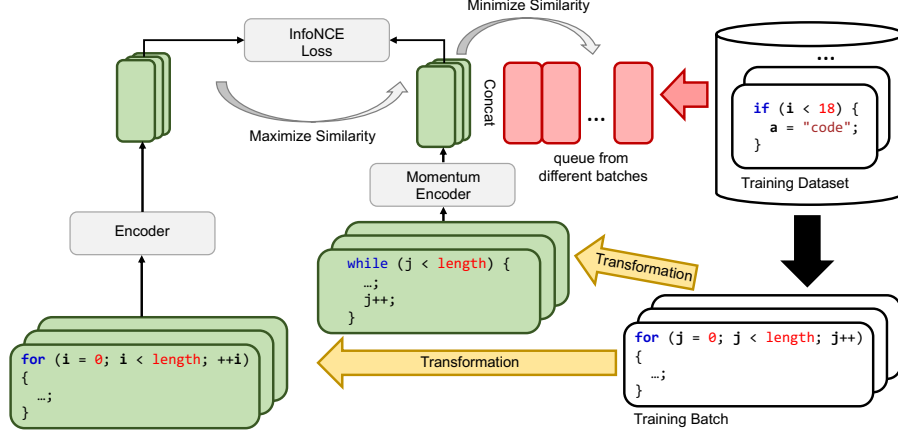


Figure 2: ContraCode extends the MoCo training framework [26] to learn an encoder of programs using a database of unlabeled programs and a suite of semantics-preserving transformations.

By framing the problem as classification, the model need not generate all the fine details of the data, but must extract its identity. In instance discrimination tasks, rather than comparing pieces of data such as timeslices, variants (data augmentations) of an entire image are compared to different images. Momentum Contrast [26] is a memory-efficient method for contrastive learning that caches representations of negative samples and only computes gradients for the positive query encoder. SimCLR [14] evaluated an InfoNCE-like loss over exceptionally large batch sizes, thereby providing a dense loss signal between positive and negative pairs. SimCLR demonstrated state-of-the-art results without the momentum queue in MoCo. However, it requires considerable computational resources to train over such large batch sizes. A recent extension of MoCo [15] added the projection head and additional augmentations from SimCLR. In computer vision, simple augmentations such as rotating, cropping, blurring or jittering an image can generate diverse variants of a base image. However, text-based domains like code lack such simple transformations. The InfoNCE pre-training objective has been applied to natural language [54, 16], but is outperformed by baselines or requires auxiliary supervised models for data augmentation [20].

Code representation learning There has been substantial work on architectures and tasks for machine learning on code [3]. The tree or graph structure of code can be exploited to encode invariances into the representation learning method. Inst2vec [9] locally embeds individual statements in LLVM IR by processing a contextual flow graph with a context prediction objective [50]. Tree-Based CNN embeds the Abstract Syntax Tree (AST) nodes of high-level source code. Code2seq [6] embeds paths in the AST with a specialized attention-based encoder and an LSTM decoder for supervised sequence-to-sequence tasks. These architectures are orthogonal to the training objective. Transformer [67] architectures have been pre-trained on unlabeled code [35, 21] using the masked language modeling objective [18, 44], an instance of the cloze task [66] where hidden tokens predicted by the model. Recurrent networks have also been pre-trained for code tasks [32] e.g. through language modeling [57, 36]. These models do not use contrastive learning, though semi-automated program transformations have been used to assess the stability of the predictions of program classifiers under refactoring and optimization [68, 69]. Our framework differs from previous work in that it learns contextual embeddings of program tokens in an unsupervised fashion via contrastive learning and transfers knowledge to tasks. We adopt the extreme code summarization (method naming) task from [6] to verify the performance and the semantic meaning of the representation learned by the encoder, and the variable type inference task of DeepTyper [27]. Other authors have explored summarization [52, 5, 33] and type inference [11, 55, 70, 4, 58] with different languages and datasets.

3 Method: Contrastive Code Representation Learning

Learned code representations should be similar for functionally equivalent programs and dissimilar for non-equivalent programs (Figure 1). Program structure encodes the global information about programs necessary for code understanding tasks such as code summarization [5] and algorithm

<pre>function x(maxLine) { const section = { text: '', data }; for (; i < maxLine; i += 1) { section.text += `\${lines[i]}\n`; } if (section) { parsingCtx.sections.push(section); } }</pre>	<pre>function x(t) { const n = { 'text': '', 'data': data }; for (; i < t; i += 1) { n.text += lines[i] + '\n'; } n && parsingCtx.sections.push(n); }</pre>	<pre>function x(t){const n={'text':'','data':data};for(;i<t;i+= 1)n.text+=lines[i] +'\n';n&&parsingCtx.sections.push(n)}</pre>
Original JavaScript method	Renamed variables, explicit object style, explicit concatenation, inline conditional	Mangled source with compressed whitespace

Figure 3: A JavaScript method from the unlabeled training set with two automatically generated semantically-equivalent programs. The original method from the StackEdit Markdown editor.

classification [68]. The principle of contrastive learning offers a simple objective for learning such representations if data can be organized into pairs of *positives* and *negatives*. The objective uses 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 equivalent programs?* We address this question in Sec. 3.1, then introduce the learning framework in Sec. 3.2.

3.1 Equivalence by construction

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 [2], and are bound to contain even more functional equivalences for common tasks. Satisfiability solvers can identify these equivalent programs [34, 8], though are slow and require formal documentation of semantics. Programs can instead be compared using test-cases [47], but this is also costly and requires dependencies and execution environments to run the code.

Instead of *searching for equivalences*, we propose *equivalent by construction* data generation. 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 the functionality of the program is the same after DCE, [68] finds that up to 12.7% of the predictions of current code understanding models change after the transformation.

A particular source code sequence, e.g. “`W*x + b`” can be parsed unambiguously into a tree-structured representation “`(+ (* W x) b)`”. This structure opens the possibility of performing automated code transformations. A rich body of prior programming language work explores transformations of Abstract Syntax Trees that parse and optimize a program prior to machine code generation. We leverage compiler infrastructure tools for JavaScript [48, 17] and perform the following source-to-source transformations on JavaScript method bodies:

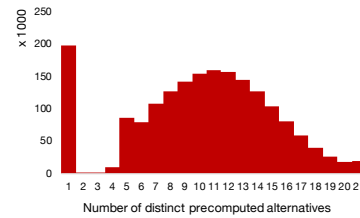


Figure 4: Per-example variants

Variable renaming, identifier mangling: Arguments can be renamed with random word sequences and identifiers can be replaced with short tokens to learn naming invariance. Program behavior is preserved despite obfuscation.

Reformatting, beautification, compression: Personal coding conventions do not affect the semantics of code; autoformatting normalizes style conventions.

Dead-code insertion: Commonly used no-ops such as comments and log statements that do not affect program behavior are inserted.

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

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

Type upconversion: 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`.

Subword regularization [41]: With an appropriate vocabulary, text can be tokenized in several different ways, with a single word (`_function`) versus many subtokens sequences (`_func tion`).

Line subsampling: We randomly select a subset ($p = 0.9$) of lines from a method body. This transformation is not semantics-preserving. However, it serves as a valuable regularization.

3.2 Contrastive pre-training

Augmentations discussed in Section 3.1 can be used to adapt several contrastive learning frameworks to code representation learning. We adapt the Momentum Contrast [26] method that was designed for vision model pre-training. Our training procedure is depicted in Figure 2. In each iteration of training, a batch of programs is sampled from a large database of programs. Each program in the batch is transformed in two different ways using a random subset of transformations to derive functionally equivalent *query programs* and *key programs*. The query programs are embedded with an encoder trained via SGD, while key programs are embedded with an architecturally identical momentum encoder trained slowly via an exponential moving average (EMA) of the query encoder parameters.

While equivalent query and key programs define positive pairs, we exploit past programs to generate a very large set of negatives. Past embeddings of the key programs are stored in a queue. As there are few identical programs in a varied dataset, these programs will largely be functionally different from the positives and define the negatives. This approach allows us to use a very large set of negatives, over 100K, with minimal additional computational cost.

Our method is independent to the choice of underlying encoder architecture. We evaluate contrastive pre-training over a Transformer [67] and BiLSTM [30] architecture, with specific details in Sec. 4.1.

Pre-training objective To pre-train, we minimize the InfoNCE loss by formulating a contrastive objective that measures similarity between programs by the inner product of their embeddings. Equation (1) shows the InfoNCE loss for instance discrimination, a function whose value is low when q is similar to its positive key k^+ and dissimilar to all other keys (considered negative keys for q):

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

In general, the query representation is $q = f_q(x^q)$ where f_q is an encoder network and x^q is a query sample (likewise, $k = f_k(x^k)$ using the EMA key encoder). Views x^q, x^k depend on the specific domain and pretext task. In our case, the views are tokenized representations of the program with appropriate data augmentation via code transformation. This loss can be seen as pre-training f_q to classify the positive x^{k^+} among all x^k , using the normalizing denominator to define possible labels.

Transfer 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, LSTM or Transformer decoder after f_q , then train the resulting network end-to-end on task data.

4 Experiments

In this section, we explore the following experimental questions: (1) *Can neural network text encoders learn program representations that are predictive of equivalent programs?* and (2) *Does contrastive pre-training improve downstream task performance?* We also perform ablations to understand partial transfer of the model. To answer these questions, we compare models from the extreme code summarization and type inference literature to versions pre-trained with ContraCode.

4.1 Dataset and tasks

For pre-training, we use the CodeSearchNet dataset [31], a large corpus of methods extracted from popular Github repositories across 6 programming languages. We train models on the JavaScript

programming language. CodeSearchNet includes 1,843,099 JavaScript training programs, 81,487 of which have an extracted documentation string and method name. The asymmetry in labeled and unlabeled dataset sizes stems from JavaScript coding practices: anonymous functions with no name and often no documentation are widespread. These labeled programs are used for a downstream extreme code summarization task, method prediction [5, 7, 6]. In addition, we use the Github dataset from DeepTyper [27] for a type inference task. Some repositories used by DeepTyper have been deleted or made private since publication, so we regenerate a subset of the dataset using the same procedure. Dataset statistics are included in the supplement. We precompute up to 21 equivalent forms of each training method by applying 20 random subsets of the transformations from Section 3.1, keeping the original method, and removing exact duplicates. The statistics are shown in Figure 4. 11% of the methods have no alternatives after our compiler transforms, such as one-line functions that are already obfuscated. However, we apply subword regularization [41] during pre-training to derive random, different tokenizations for each batch, so pairs will still differ. After pre-training, we fine-tune the network’s encoder for downstream tasks.

Extreme code summarization by method name prediction The CodeSearchNet dataset used for pre-training includes method name labels where available. We extract 81,487 methods that have a documentation string and method name. The asymmetry in labeled and unlabeled dataset sizes stems from JavaScript coding practices; anonymous functions with no name nor docstring are widespread. These labeled programs are used for a downstream extreme code summarization task, where the method name is masked in the input function and predicted by the neural network [5, 7, 6]. Method names are generally informative and summarize the method when tokenized, such as `reverseString`.

Our downstream method name prediction task is a sequence-to-sequence generation problem, so we implement a Transformer model [67] with 6 encoder layers and 4 decoder layers. The encoder and decoder share the same token embedding, which is weight-tied with the output projection in the decoder. We use subword tokenization based on fitting a unigram language model, with a top-down EM procedure to iteratively reduce the size of the vocabulary to 8,000 tokens following [41]. Unlike bottom-up byte-pair encoding [64], the unigram LM allows multiple decodings to be sampled. While the dataset has a long-tail of rare symbols, the vocabulary covers 99.95% of characters in the text.

Type inference Type inference or hinting tools can generate type annotations for untyped JavaScript programs, which can help programmers find bugs and serve as documentation. We regenerate the DeepTyper dataset using the subset that is still available on GitHub using the original procedure. The training set consists of 15,570 TypeScript files from 187 projects with 6,902,642 total tokens, and the validation and test sets are from held-out repositories. For training, additional types are inferred by static analysis to augment user-defined types; all types are removed from the input to the model. We generate contextual embeddings of each token using a 2-layer Bidirectional LSTM, as used by DeepTyper, and a 6-layer Transformer, modified from RoBERTa to be parameter equivalent to the LSTM. A 2-layer MLP head is used to predict types from the predicted embedding of each token.

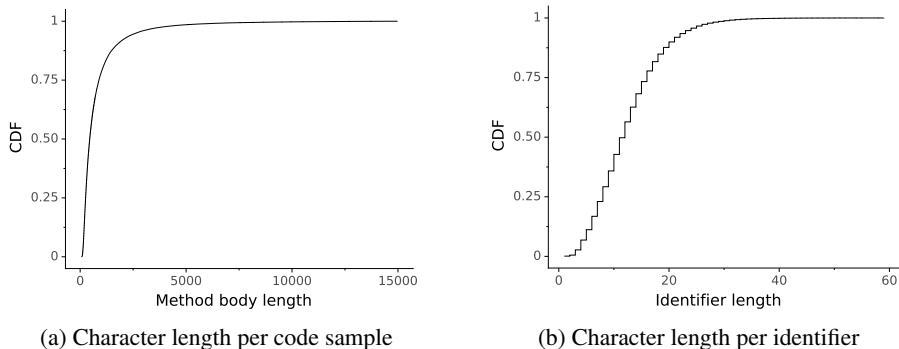


Figure 5: CodeSearchNet code summarization dataset statistics: (a) The majority of code sequences are under 2000 characters, but there is long tail of programs that span up to 15000 characters long, (b) JavaScript identifiers are relatively short compared to languages like C# and Java.

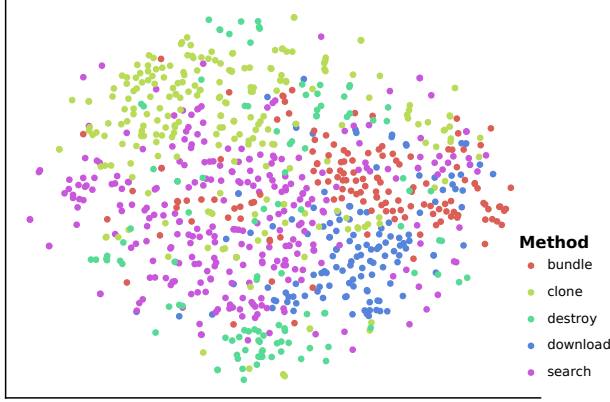


Figure 6: t-SNE [45] plot of ContraCode representations

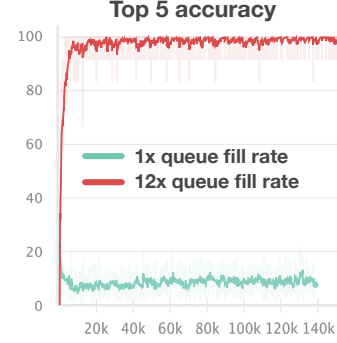


Figure 7: Pre-training quickly converges if non-equivalent programs frequently change.

4.2 Can ContraCode program representations match equivalent programs?

In Figure 7, we compare two strategies of refreshing the MoCo queue of key embeddings (i.e., the set of negative, non-equivalent programs). 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 the ContraCode pre-training task.

We qualitatively inspect the quality of learned representations by visualizing ContraCode representations using t-SNE [45]. We annotate each method with a tag derived from the method name. While there is some overlap, each method class is clustered with other similarly tagged methods. 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.

4.3 Does contrastive pre-training improve downstream task performance?

After contrastive pre-training, we fine-tune the model on the downstream task of code summarization (method name prediction). In Table 1, we tested 3 different settings: (1) supervised training with the 81k labeled programs using baseline AST-based architectures (code2vec, code2seq), (2) pre-training on all 1.84M programs using the masked language model objective followed by fine-tuning on the labeled programs (RoBERTa [44]), (3) supervised training with a Transformer architecture using ContraCode augmentations and (4) contrastive pre-training with all 1.84M programs followed by pre-training (ContraCode). We find that all models overfit during supervised training, so we use early stopping according to the validation loss.

Contrastive pre-training with fine-tuning outperforms the prior code2seq model, a competitive supervised baseline, by 8.2% in test precision and 7.9% in test F1 score. ContraCode outperforms a model fine-tuned after RoBERTa pre-training by 4.8% F1. Representations learned via masked language modeling appear to learn poor structural representations of code. Surprisingly, ContraCode augmentations improve supervised learning performance; a simple Transformer model with our augmentations (described in Sec. 3.1) obtains a higher F1 score than RoBERTa pre-training.

Table 2 shows the improvements that ContraCode offers on the type inference task in terms of accuracy averaged over all typed variables and averaged over all typed variables with a type other than the catch-all any type. We use early stopping based on validation set top-1 accuracy across all types. All learning-based approaches outperform static-analysis baselines. In addition, learned

Table 1: 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	Pre-training (1.8M programs)	Precision	Recall	F1
code2vec [7]	-	10.78%	8.24%	9.34%
code2seq [6]	-	12.17%	7.65%	9.39%
RoBERTa-6 [44]	MLM [18], 90k	15.13%	11.47%	12.45%
Transformer [67] + ContraCode augmentations	-	18.01%	13.84%	15.65%
Transformer [67] + ContraCode pre-training	MoCo, 20k steps	20.34%	14.96%	17.24%

Table 2: Results for different settings of the **type inference task**, supervised with 15.6k files.

Method	Pretraining (1.8M programs)	Acc@1 (all types)	Acc@5 (all types)	Acc@1 (- any)	Acc@5 (- any)
any type	-	41.82%	41.82%	0.00%	0.00%
TypeScript CheckJS [12]	-	45.11%	45.11%	16.32%	16.32%
Name only [27]	-	28.94%	70.07%	-	-
Transformer [67]	-	45.66%	80.08%	51.87%	71.95%
Transformer + ContraCode	MoCo, 240k steps	46.86%	81.85%	52.54%	71.56%
RoBERTa-6 [44]	MLM, 90k steps [18]	40.85%	75.76%	48.37%	68.00%
RoBERTa-6 + ContraCode	MLM + MoCo, 240k steps	47.16%	81.44%	51.32%	71.93%
DeepTyper [27] (d=512)	-	51.73%	82.71%	60.60%	78.20%
DeepTyper (d=512) + RoBERTa-6	MLM, 10k steps [18]	50.24%	82.85%	59.45%	78.42%
DeepTyper (d=512) + ContraCode	MoCo (mean) + MLP, 10k	49.15%	82.58%	60.88%	79.41%
DeepTyper (d=512) + ContraCode	MoCo (hidden), 10k	51.70%	83.03%	62.16%	79.56%
DeepTyper (d=512) + ContraCode	MoCo (hidden), 20k	52.65%	84.60%	63.35%	79.69%

models rank multiple type annotations that can be displayed to users, allowing us to compute top-5 accuracy. ContraCode significantly improves accuracy across three representative baseline models: Transformer, pre-trained RoBERTa with a masked language modeling objective, and the BiLSTM used by DeepTyper. In particular, we outperform the supervised Transformer by up to 1.77% in top-5 accuracy and the supervised DeepTyper model by up to 2.75% in top-1 accuracy (4.5% relative increase), simply by pre-training for global representations with ContraCode. The model pretrained with masked language modeling performs poorly due to the superficial local reconstruction objective. We enrich the MLM objective with ContraCode via an auxiliary loss. This hybrid local-global representation achieves between 2.95% and 6.31% increases in top-1 accuracy over RoBERTa.

4.4 Qualitative results

Figure 9 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, getItem 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 8 shows two TypeScript programs from the held-out test set. User-provided type annotations are removed from the programs, and the model is provided with a tokenized form without access to dependencies. We visualize predictions from a variant of DeepTyper (a bidirectional LSTM) pretrained with ContraCode, the best-performing model in Table 2. 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.


```

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 8: 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 bottom row of Table 2.

Figure 9: 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.

```
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

Table 3: 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%

Table 4: 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.

Method	Pre-training (1.8M programs)	Acc@1 (all)	Acc@5 (all)	Acc@1 (- any)	Acc@5 (- any)
Transfer BiLSTM	MoCo (mean), 10k steps	49.32%	80.03%	59.75%	77.98%
Transfer BiLSTM, 1 layer of MLP	MoCo (mean), 10k steps	49.15%	82.58%	60.88%	79.41%

4.5 Ablations

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). Using the global features for pre-training yields significantly improved performance (bottom two rows, Table 2).

Do pre-trained encoders help more with shallow decoders? In Table 3, we ablate the size of the decoder [19] to understand whether large untrained decoders limit the improvements from contrastive encoder pre-training. We tested 1-layer and 4-layer Transformers. We can conclude that 4-layer Transformer achieves higher performance using all 3 criteria. With 45k pre-training steps, the 4-layer decoder achieves 0.50% higher precision, 0.64% higher recall and 0.77% higher F1 score than the 1-layer model. The 1-layer decoder models benefit significantly from longer pre-training, with a 6.3% increase in F1 from 10k to 45k iterations. We hope to see similarly large gains in downstream tasks with small decoders like code classification, the setting considered by self-supervised vision models.

Which part of the model should be transferred? SimCLR [14] 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 4). We believe the improvement stems

from fine-tuning both the encoder and MLP, while SimCLR did not fine-tune. We only transferred the MLP when pre-training with the mean of token embeddings, not the terminal hidden states, as the dimensionality of the MLP head differs.

5 Conclusions

A key challenge when applying machine learning to machine-aided programming tools is how to leverage large-scale unannotated repositories of code like GitHub. We propose ContraCode, a pre-training task that learns global representations of the functionality of code based on the hypothesis that good representations of functionally equivalent programs should be similar. We leverage contrastive learning to induce this invariance via automatically applying equivalence preserving transformations to the source code. We find application of ContraCode pre-training significantly improves accuracy on two downstream tasks. Our approach is complementary to model architecture and consistently improves performance when combined with baseline approaches.

Broader Impact

Complex software systems are deployed in safety-critical applications. Software bugs impact end-user safety; tragic examples include unintended acceleration [40] and radiation therapy overdoses [43]. Machine-aided programming tools such as type checkers have improved end-user safety by preventing bugs before code deployment.

We believe these tools also improve the equity of programming by making it more accessible to novice programmers. Developer tools have significantly improved developer productivity by providing insights on large code bases during development. Machine learning methods like ContraCode have the potential to further these benefits through summarization and semantic code understanding.

Still, machine-aided programming tools have the potential to introduce software bugs via false positives or miss bugs via false negatives that a user may not notice. Such errors should be characterized prior to deploying a tool pre-trained by ContraCode, and may be mitigated by surfacing several possible predictions to the user with associated confidence scores. It is important that learned machine-aided programming tools do not provide a false sense of security.

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A Appendix

A.1 Experimental setup

Architectures Within an experimental results table, we use the same hyperparameters across runs. 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 the first 5,000 steps from 0 to a maximum of 10^{-4} . For the bidirectional LSTM, the learning rate is increased for 10,000 steps to a maximum of 10^{-3} . The Transformer has 6 encoder layers (23M parameters) in all experiments, and 4 decoder layers for method name prediction in Table 1. We leverage the default positional embedding function (\sin , \cos) as used in the original Transformer architecture. The BiLSTM originally proposed in DeepTyper [27] had 11M parameters with a 200 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.

ContraCode pretraining 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 (hidden) and the sequence averaging configuration as (mean) in Table 2. We pretrain the BiLSTM with batch size 512 and weight decay.

Type prediction Following DeepTyper [27], 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, but we used the same commit hashes for available projects so our splits are a subset of the original. To select the number of training epochs before evaluation, we perform early stopping. 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.

Extreme code summarization As described in Section 4.1, we train method prediction models using the labeled subset of CodeSearchNet. Method names and docstrings are not 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 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 distribution of programs in 5.

A.2 Baselines

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

AST-based models The authors of code2vec [7] and code2seq [6], 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 well-documented in prior work; F1 scores for code2vec [7] vary between 19 [6] and 43 [7] depending on the dataset used. Therefore, we reimplement the same dataset generation procedure for fair comparison. We first parse the source functions using the Babel compiler infrastructure. 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.

```
// 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 program (merge sort)

```
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 Mangling (variable renaming, comment removal, reformatting)

```
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 Mangling and Compression (combined variable declarations, inline conditional)

Figure 10: Given a JavaScript code snippet (merge sort), we apply semantics preserving transformations to produce functionally-equivalent yet textually-distinct code sequences. We demonstrate *mangling* which replaces named variables and identifiers with a short replacement and *compression* which eliminates unnecessary characters such as redundant variable declarations and brackets.

DeepTyper [27] DeepTyper leverages 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 and leverage subword tokenization via Byte Pair Encodings [64].

RoBERTa We pre-trained an encoder using RoBERTa [44] on the CodeSearchNet datasets. Unlike the original BERT paper [18] which cuBERT [35] is based on, hyperparameters from RoBERTa [44] 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. Following RoBERTa, we did not utilize the Next Sentence Prediction (NSP) loss which RoBERTa finds to be redundant with MLM. We normalize baseline parameter count by reducing the number of Transformer layers from 24 to 6 for a total of 23M parameters.

A.3 Code transformations

We use the Babel compiler infrastructure and the [48] `terser` JavaScript library to generate equivalent programs, and the `sentencepiece` Python library for tokenization. We perform variable renaming, dead code insertion (variable declaration insertion) and line subsampling using custom Babel transforms, subword regularization with `sentencepiece` 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 and its corresponding equivalent version after mangling and compression in Fig. 10.