Pre-Training Representations of Binary Code Using Contrastive Learning

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Abstract—Binary code analysis and comprehension is critical to applications in reverse engineering and computer security tasks where source code is not available. Unfortunately, unlike source code, binary code lacks semantics and is more difficult for human engineers to understand and analyze. Limited work has explored incorporating multiple program representations. In this paper, we present CONTRABIN, a contrastive learning technique that integrates source code and comment information along with binaries to create an embedding capable of aiding binary analysis and comprehension tasks. Specifically, we present three components in CONTRABIN: (1) a primary contrastive learning method for initial pre-training, (2) a simplex interpolation method to integrate source code, comments, and binary code, and (3) an intermediate representation learning algorithm to train a binary code embedding. We evaluate the effectiveness of CONTRABIN through four indicative downstream tasks related to binary code: algorithmic functionality classification, function name recovery, code summarization, and reverse engineering. The results show that CONTRABIN considerably improves performance on all four tasks, measured by accuracy, mean of average precision, and BLEU scores as appropriate. CONTRABIN is the first language representation model to incorporate source code, binary code, and comments into contrastive code representation learning and is intended to contribute to the field of binary code analysis. The dataset used in this study is available for further research.

Index Terms—Technical articles in SE, artificial intelligence, binary code analysis, contrastive learning

1 INTRODUCTION

Binary code provides valuable information about a program’s content and behavior and is often the only available representation of a program in certain cases, such as legacy systems, proprietary software, and penetration testing [1]. Binary code analysis is critical to many software related tasks, and understanding binary code can serve as a critical source of information about program content and behavior, and thus a foundation of many applications [2]–[5]. However, while understanding and analyzing binary code is essential for various tasks, there exists no practical, generalizable strategy for comprehending binary code due to inherent characteristics: compared to source code and natural languages, binary code has very limited semantics, is substantially more difficult for humans to understand, and is much more difficult to analyze automatically.

Currently, binary code analysis is approached through two methods: (1) traditional static and dynamic analysis and (2) AI-based methods. Traditional methods use manual techniques and specific algorithms (e.g., dataflow analysis), but are limited in their ability to be used across different platforms and applications [6]–[8]. AI-based methods use machine learning to capture both program structure and semantics, and have combined syntax, semantics, and structure to create embeddings for specific tasks [9]–[11]. However, few focus on large-scale pre-trained representations for binary code, which is a largely unexplored area [9], [12], instead focusing primarily on source code or related syntactic structures like abstract syntax trees.

Considering the critical challenges needed to assist binary code analysis, in this paper, we present CONTRABIN, a novel contrastive learning model that combines simplex interpolation to approximate human gradual learning, and intermediate contrastive learning to produce a high quality embedding for binary code. Large corpora of source code and documentation can be combined with corresponding compiled binary code to serve as a basis for an effective contrasting learning approach.

CONTRABIN consists of three components and an evaluation, illustrated in Figure 2. First, we leverage comments...
Fig. 1: Illustration of the software compilation and human documentation process. Expert programmers can analyze source code to write comments or produce code based on comments. Compilers can compile source code and obtain binary code, whereas decompilers can decompile binary code and get source code.

within the source code and the corresponding binary code (which can be obtained from compiling the source code), and randomly choose two of the three representations (i.e., source code, comments, and binary code) to conduct primary contrastive learning. Then, we design linear and non-linear simplex interpolation methods to interpolate two data embeddings and obtain an intermediate representation. Next, we introduce an intermediate contrastive learning approach to incorporate source code and comment information into binary code. Lastly, we evaluate the trained binary code embedding on three downstream tasks for binary code analysis to validate our model. We elaborate upon the design of CONTRA Bin in Section 2.

The design of CONTRA Bin is based on three key insights derived from multi-view learning, human translation and code compilation, and contrastive learning: (1) source code, corresponding human-written comments, and compiled binary code can flexibly represent the same semantics of a given program but just in different modalities. (2) Human documentation (e.g., comments within source code, written in natural languages) and compilation (or decompilation) by the compiler share similar gradual learning properties, as shown in Figure 1. With this insight, we design simplex interpolation among source code, binary code, and comments to imitate a unified learning process. (3) While source code, binary code, comments, and their intermediate representations correspond to the same program semantics, they are dissimilar to other source code, binary code, comments, intermediate representations. We show how these insights can be combined to form an effective multi-modal contrastive learning embedding capable of aiding the analysis of binaries.

We evaluate CONTRA Bin’s pre-trained embeddings against state-of-the-art large-scale pre-trained models [9], [12]–[14]. We evaluate CONTRA Bin in four indicative downstream tasks and corresponding datasets that entail binary code analysis: (1) binary functional algorithm analysis, (2) binary function name recovery, (3) binary code summarization, and (4) binary reverse engineering, using POJ-104 [15], DIRE [10], and two subsets of AnghaBench [16], respectively. We choose these tasks and datasets because they also permit a fair comparison with state-of-the-art models that make use of source code. Our results show that CONTRA Bin substantially outperforms current code analysis models on the vast majority of task-relevant metrics and achieves comparable performance on others. In conclusion, we claim the following contributions:

- We present CONTRA Bin, a novel contrastive learning-based framework leveraging simplex interpolation on source code, comments, and binary code to learn an effective representation (i.e., a pre-trained embedding) of binary code.
- We design a new simplex interpolation approach to capture the inherent process of gradual learning of humans to assist contrastive learning.
- We derive a novel intermediate contrastive learning algorithm to incorporate external knowledge and semantics in source code and comments into binary code.
- To the best of our knowledge, this is the first study to derive intermediate contrastive learning for binary code analysis to improve representation model performance.
- We conduct extensive experiments on indicative datasets in evaluation, demonstrating that CONTRA Bin outperforms other state-of-the-art models in all four downstream tasks on binary code analysis with respect to task-relevant metrics such as BLEU-4 for summarization and accuracy for algorithmic classification.

2 Approach

In this section, we describe CONTRA Bin, our approach to obtain high quality representation for binary code that can be used for a swath of binary analysis and comprehension tasks. In practice, our goal is to augment stripped, semantics-dearth binaries with rich contextual information provided by comments and source code. At a high level, we use a large-scale pre-training task along with downstream tasks related to binary code. CONTRA Bin leverages tuples of (source code, binary code, comments) from many different programs scraped from GitHub, which form the basis of a contrastive learning task. The architecture of CONTRA Bin is summarized in Figure 2, which consists of three components. Given source code, we first generate comments using pre-trained models, compile each code snippet to emit binary code, and randomly choose two of the three code representations in each batch of triplets to conduct primary contrastive learning. Then, we derive embeddings for the triplets from our encoder as a simplex projection, and generate an intermediate representation based on random and learnable interpolation. Next, we train our encoder by intermediate contrastive learning using anchored representation and intermediate representation (i.e., one of the three representations is anchored while the other two are not). Finally, we apply the trained binary code embedding to four downstream tasks to evaluate its performance.
Pre-training binary code representation

Triplet Data Preparation

Simplex Interpolation for Gradual Learning

Intermediate Representation Learning

Binary Code Downstream Tasks

(a) Comment

(b) Source Code

(c) Binary Code

Fine-tuning for downstream tasks after pre-training

Fig. 2: Diagram of simplex interpolation and intermediate representation learning in CONTRABIN. It consists of four main components: (a) triplet data preparation, (b) simplex interpolation for gradual learning 2.2, (c) intermediate contrastive learning 2.3, and (d) task-specific fine-tuning 2.5. After pre-training an embedding, the trainable encoder for binary code will be applied to the task-specific fine-tuning stage. In CONTRABIN, we use assembly code lifted from executable binary code. In (b), two encoded representations are randomly selected for interpolation to obtain an intermediate representation.

**Background** In recent years, pre-trained representations have become a powerful tool in code analysis, offering the ability to leverage vast amounts of existing knowledge to improve the performance and generalization of models. By pre-training on large datasets of source code and natural language comments, these representations capture essential patterns and semantics that are difficult to learn from binary code alone. In our approach, we utilize these pre-trained models to bridge the gap between the rich, high-level information available in source code and comments, and the lower-level, more abstract nature of binary code. This strategy allows our model to develop a deeper understanding of binary code by learning from multiple modalities, ultimately enhancing its ability to perform complex tasks in code analysis.

To achieve this, our approach is structured in several key stages, each building on the previous one to refine and improve the model’s understanding of binary code. We begin by aligning the representations of source code, comments, and binary code through a series of pre-training steps designed to capture the nuances of each modality. By progressively refining these embeddings, our model learns to effectively transfer knowledge between different forms of code representation, ensuring that the final binary code embedding is robust and semantically rich. The following sections detail each of these stages, illustrating how they contribute to the overall effectiveness of our methodology.

### 2.1 Primary Contrastive Learning

This subsection introduces the primary contrastive learning approach for the simplex interpolation. Recall that the conversion process between two representations can involve complex analyses (e.g., compilation) or creative human processes (e.g., code comprehension). At the same time, no generalizable models have been trained on datasets containing binary code. This can lead to the cold start problem in representation learning [17] when a new data representation (e.g., a novel program never seen before) emerges in a system. Therefore, it is challenging to capture their features — the same scenario applies to binary code representation.

**Comparison** The initial phase of CONTRABIN reflects the early learning stages individuals go through when encountering a new concept, emulating it using straightforward comparisons.

To mitigate this cold start problem, we adopt primary contrastive learning in the first step of model training. Specifically, we use three representations of a program: comments (i.e., documentation written by human experts), source code (i.e., as written by developers), and binary code (i.e., as emitted from a compiler), and randomly choose two of them to conduct contrastive learning, as shown in Figure 2. During this step, the simplex interpolation module is disabled: this approach is inspired by multi-view learning [18] in computer vision, in which an object can have \( k \) views, and all of the views are exactly from the same object. In our model, either source code, binary code, or comment can represent the same program, so we treat the three representations (also denoted as modalities or views) of a program to enrich the information in binary code. There are two steps in primary contrastive learning: manifold projection and batch-wise similarity comparison.

**Manifold projection** To perform primary contrastive learning, the vector representation for each input string (i.e., of instructions, source code, or comments) is obtained by an encoding function \( f_M \) that projects an instance \( x \) into a manifold space \( M \) with dimension \( d \). In this paper, \( x_s, x_b \) and \( x_c \) denote input string of source code tokens, binary code (assembly or IR lifted from a binary), and comment of one program, while \( h_s, h_b, h_c \in \mathbb{R}^d \) are their corresponding vector representations. The batch-wise manifold projection
Learnable Simplex Interpolation Module is designed to address the inherent differences between starting point for subsequent steps. The model will then back propagate the loss and update the parameters.

**Explanation of the loss function** The loss function is designed to address the inherent differences between binary code and higher-level code or comments. By minimizing this loss, the model learns to position related concepts—whether from binary code, source code, or comments—closely together in a unified embedding space. This approach enhances the model’s ability to transfer knowledge across these diverse representations, leading to improved performance in downstream tasks. Although inspired by the contrastive loss used in CLIP, this function is tailored to the specific needs of binary code representation, ensuring that similar embeddings are aligned while distinct ones are separated. This loss function can then help to align the binary code embedding closer to the representations of comments and binary code in the manifold $\mathcal{M}$, thereby providing a well-trained binary code embedding as the starting point for subsequent steps. The model will then back propagate the loss and update the parameters.

**2.2 Simplex Interpolation for Gradual Learning**

After completing primary contrastive learning, we use simplex interpolation for gradual learning among the three representations, as shown in Figure 2 (a). Simplex interpolation is inspired by human translation (e.g., from source code to comment or vice versa) and the code compilation (or decompilation) process, in which conversion from one representation to the other involves intermediate thinking or analysis. While we acknowledge that the manifold assumption is a common tool in understanding deep learning phenomena, its application here serves primarily to align with our color boxes discussed from Section 2.1 to Section 2.4. This assumption provides a simplified framework to conceptualize the interpolation process, aiding in the explanation of our model’s behavior in binary code representation learning.

Analogy and extrapolation The subsequent portion suggests that CONTRABIN compares representations of the same program to learn differences and similarities among programs.

We use both linear and non-linear simplex interpolation as part of a gradual learning approach to obtain increasingly expressive embeddings. Based on simplex interpolation theories [21], we presume the intermediate representations...
between any of the two in source code, binary code, and comments can be a different view of the same program. The detailed steps are shown as follows:

**Linear interpolation for direct learning** We create two interpolation methods to generate inputs for contrastive learning: linear interpolation and non-linear interpolation, as shown in a unified Figure 3. Both interpolation methods follow the same interpolation function \( \Gamma(a, b; \lambda) \) defined as

\[
\Gamma(A, B; \lambda) = \lambda \odot A + (1 - \lambda) \odot B,
\]

where \( A \) and \( B \) are batch data representations, \( \lambda \in [0, 1] \) denotes the interpolation index, and \( \odot \) indicates element-wise product. In CONTRABIN, we have \( H_1 = \Gamma(H_1, H_2; \lambda_1) \) and \( H_n = \Gamma(H_1, H_2; \lambda_n) \) for linear and non-linear interpolation, respectively. Linear interpolation imitates the learning process between one thing to another, in which people make overall progress towards all knowledge points for a given task. In practice, we regard the interpolation index as a trainable parameter, learned by a neural network, denoted as

\[
\lambda_i = f^i_{\text{interp}}(H_1 \odot H_2),
\]

where \( f^i_{\text{interp}} \) denotes the interp NN function that learn the optimal interpolation index for both \( H_1 \) and \( H_2 \), and \( \lambda_i \) denotes a linear interpolation index ranging from 0 to 1. Note that the Interp NN blocks in Figure 3 is just one of the possible implementations. Then, we apply linear interpolation onto the manifold vectors of source code and binary code, using

\[
H_i = \lambda_i \odot H_1 + (1 - \lambda_i) \odot H_2,
\]

where \( H_i \) denotes batch-wise intermediate representation generated by the linear interpolation. Here, we adopt the broadcast property in computation so the index number \( \lambda_i \) will be expanded to the shape of \( H_1 \) and \( H_2 \) and become an item in vector multiplication.

**Non-linear interpolation for customized learning** We further consider a non-linear interpolation to capture complex semantics and enhance the model performance. Specifically, instead of regarding the interpolation index as a real number, we allow it to be a matrix with the identical shape of \( H_1 \) and \( H_2 \). In this case, we are able to capture the feature-wise and finer-grained information. Formally, \( \lambda_n = f^n_{\text{interp}}(H_1 \odot H_2) \) and \( H_n = \lambda_n \odot H_1 + (1 - \lambda_n) \odot H_2 \). Both interpolated embedding \( H_i \) and \( H_n \) serve as input to the intermediate contrastive learning.

### 2.3 Intermediate Contrastive Learning

After obtaining the anchored and intermediate representation, we use an intermediate contrastive learning method to learn binary code embeddings. This is inspired by a continuation of Subsection 2.2.2, in which we obtain intermediate representations that contains an alternative view of the semantics of the same program. We treat these intermediate representations as unseen but reasonable information about the program.

**Learn smartly** The last component of CONTRABIN facilitates the learning process for analogy and extrapolation. It helps to decide the optimal way to combine knowledge.

As shown in Figure 4, we use each interpolated program representation \( h_i \) (interpolation between source code projection \( h_a \) and comment projection \( h_c \) in the Figure) to compare with the other program representation (binary code projection \( h_b \) in the Figure) in manifold \( M \). For simplicity, \( h' \) denotes all dissimilar projections (including intermediate and the other representations not from the same program in a batch).

We adopt a similar training process in Subsection 2.1, replacing two of the representations with intermediate and anchored representations to conduct intermediate contrastive learning.

### 2.4 Gradual Learning

Following the gradual learning literature, models learn most effectively when they follow a natural, progressive order as humans do [22], [23]. Specifically, models learn high-level data abstracts initially, then progress to more complicated embeddings. Following this intuition, we train our model via primary contrastive learning during cold start. After several epochs (10 epochs in our implementation), we switch the training pattern to contrastive learning based on linear simplex interpolation and non-linear simplex interpolation to further improve the generalizability of our model and finalize the training process, shown in Algorithm 1.

By integrating all three parts, CONTRABIN follows a natural learning curve (i.e., from simple to complex) to better understand the meaning of binary code.

### 2.5 Task-Specific Fine-tuning

For evaluating the performance of our pre-trained binary code embedding, we select four downstream tasks: (1) algorithmic functionality classification from binaries, (2) binary code function name recover, (3) binary code summarization, and (4) binary reverse engineering. We choose these four to cover two binary code analysis tasks (1 and 2) and two binary code comprehension tasks (3 and 4). Detailed descriptions are as follows:

**Algorithmic functionality classification from binaries** For this task, we classify a binary code input according...
to its functionality (i.e., “quicksort” is different from “md5 hash”). Categorizing the functionality of binary code blocks enables developers to isolate code blocks of interest, which improves readability, saves development time, and aids in reverse engineering [24]. Here, we classify a given binary into a specific category (e.g., sorting vs. hashing vs. search). We hypothesize that our approach will enable accurate functionality classification because we incorporate information from multiple representations of many programs.

**Function name recovery** In this task, we recover function names from sequences of binary code. In legacy systems, malware analysis, or in cases where source is unavailable, researchers and engineers must work with binary code directly or use tools to analyze binaries. However, stripped binary executables lack meaningful names and debugging information. Hence, automatic classification of the function names in binary code can substantially reduce the manual effort required for binary code analysis.

**Code summarization** In this task, we aim to translate binary code into an English summary. Summarizing the functionality of binary code can improve the comprehension of software and the effectiveness of software analyses, while offering the potential to carry out important security and vulnerability assessment, reverse engineering, and software maintenance tasks.

**Reverse Engineering** In this task, we aim to decompile binary code back into source code, providing the ability to conduct further analysis. While decompilation is currently supported by tools like Hex-Rays and Ghidra, decompiled code typically lacks valuable symbol names and differs substantially from canonical code written by developers. Transforming binaries to canonical source code plays a crucial role in comprehending binary code as it facilitates the examination of previously created software. By reversing the code, researchers gain insight into how it operates, identify problems, and make improvements to its functionality. This reverse engineering of binary to source facilitates security.

**Algorithm 1 CONTRABIN pre-training framework**

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Algorithm 1 CONTRABIN pre-training framework

Require: Source code set S, with paired binary code set \( S_b \) and comment set \( S_c \), split into train \( S_{train} \) and validation \( S_{val} \).
Ensure: Minimization of loss on \( S_{val} \).
1: if Primary contrastive learning then
2: for batch = 1, \ldots, k \_start do
3: Project \( S_c, X_s \) and \( S_b \) to \( M \) with encoders \( f_a \) and \( f_b \).
4: Compute batch-wise similarity loss between two representations in \( M \) and train the predictors and encoder
5: end for
6: end if
7: if Contrastive learning by linear or non-linear simplex interpolation then
8: for batch = 1, \ldots, k \_interp do
9: Project \( S_c, X_s \) and \( S_b \) to \( M \) with encoder \( f_a \) and \( f_b \).
10: Choose two of the encoded representations and compute the index \( \lambda_i \) or \( \lambda_a \) by the interpolation NN and get intermediate representations
11: Compute batch-wise similarity loss between intermediate and the other representation in \( M \) and train the binary encoder and interp NN
12: end for
13: end if
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3 EXPERIMENTAL DESIGN

In this section, we introduce the experimental design for the evaluation of CONTRABIN. Specifically, we design and conduct four experiments in total: one assessment of the pre-training of CONTRABIN, and three others for evaluating the performance of CONTRABIN’s embeddings using indicative downstream tasks relating to binary code analysis. We introduce these experiments to answer the following research questions:

- **RQ1**: How accurately can the embeddings provided by CONTRABIN perform in the tasks of binary code analysis? Does CONTRABIN outperform state-of-the-art pre-trained language representation models evaluated by classification metrics?
- **RQ2**: How well do the embeddings provided by CONTRABIN in the task of binary code comprehension? Is it better than state-of-the-art pre-trained language representation models evaluated by NLP metrics and human perception?
- **RQ3**: How effective is the linear and non-linear intermediate contrastive learning in CONTRABIN, and what are the advantages and areas for improvement?

Before we evaluate each RQ in turn, we first introduce the experimental configuration, including the dataset for training and evaluation, as well as the experimental procedures and settings.

### 3.1 Training Design

To train CONTRABIN, we must build a dataset consisting of three program representations: source code, compiled
binary code, and source code comments or summaries, and train CONTRABIN to generate improved embeddings for downstream tasks. We obtain each program representation as follows:

**Source code:** To obtain source code, we use a widely-used public dataset called AnghaBench [16] as our source data for training CONTRABIN. Specifically, we adopt the benchmark dataset that contains 1 million single-function C files extracted from programs and mined from popular GitHub repositories. This dataset serves as the source code representation in our method to incorporate semantic variability into the training process.

**Binary code:** After obtaining the source code from AnghaBench, we compile the code snippets in AnghaBench using Clang (specifically, LLVM[^4]) to generate the corresponding assembly code. We choose LLVM assembly for platform transparency — many static and dynamic analyses exist for LLVM, and the Clang infrastructure supports many language backends from LLVM bitcode. However, in practice, any straight-line assembly language could fit the requirements of CONTRABIN (i.e., the contrastive learning framework).

**Comments:** During pre-analysis, we found most comments in real-world source code are not globally informative. Specifically, human-written comments can be random in content (e.g., they may contain copyright notifications, random snippets of old code, or unstructured explanations), or contain partial information about the current location of code statements — source code comments in general are not always descriptions of semantics of a program’s complete source code. Therefore, we adopt an Encoder-Decoder CodeT5 [25] model to automatically generate a single comment for each snippet of source code in our dataset.

Figure 5 shows the length distribution of the processed dataset derived from AnghaBench. The overall comment length distribution is quite different from both source and binary code since comments are considered a high-level abstraction of information using natural languages (as opposed to structured programming or assembly languages). We also compute the 90th percentile of length and find the results for source code, binary code, and comments to be 422, 2853, and 63, respectively.

We use two Nvidia A40 GPUs during model pre-training and follow the parameter settings of SimpleCLIP [26]. We set the random seed as 42 in the pre-training for reproduction. To better evaluate the performance and robustness, we also train two versions of our model, CONTRABIN-PCL and CONTRABIN. For CONTRABIN-PCL, we set 10 epochs for primary contrastive learning only. For CONTRABIN, we use 10, 10, and 10 to improve the overall model efficiency on binary code analysis, and 10, 30, 30 to enhance the general model performance on binary code comprehension.

### 3.2 Evaluation Design

Our evaluation of each research question considers different tasks and perspectives. For each of our three downstream tasks, we choose a publicly available dataset (and corresponding reference in the literature). We preprocess each dataset so that they can leverage the pre-trained embeddings from CONTRABIN. The evaluation datasets include different source code and their compiled assembly. We describe each task and associated dataset in detail below.

**POJ-104** For the binary functional algorithm classification task (RQ1: Downstream Task 1), we adopt POJ-104 from the CodeXGLUE dataset [27]. In an Open Judge (OJ) system, students submit their solutions to a programming problem, and the OJ system judges whether the code can run successfully on all available test suites. In this way, the OJ system aims to improve the programming skills of users. From this dataset, we can find other programs that perform the same task as an input program (e.g., programs can be classified as bubble sort vs. heap sort vs. Fibonacci sequence, etc.). The dataset includes programming problems and verified source code solutions. There are 104 programming problems in POJ-104, with 500 examples each. The dataset is categorized into train/development/test sets with non-overlapping program problem labels. Thus, we can view this dataset as containing 104 different classes in which to classify an input program. While the original POJ-104 dataset used source code structural information, we adapt it for classifying input binaries.

In our experiments, we compile each solution in POJ-104 to LLVM assembly code, keeping the functionality label unchanged, as shown in Table 2. This change transforms POJ-104 into an assembly code dataset, allowing our binary analysis interests. We fine-tune each model with 2 epochs and a block size of 400. We use training and validation batch sizes of 32 and 8, respectively, and choose learning rate to be 2e-5 and maximal gradient normalization to be 1. In all fine-tuning processes, we use the default random seed of 123456.

**DIRT** For the binary function name recovery task (RQ2), we chose the DIRT dataset used to train DIRTY [10], a recent machine learning model augmenting decompiler outputs with variable type and name predictions. The full dataset contains around 1 million functions spread across 75,656 binaries that were mined from public GitHub repositories using GHCC[^5]. With the help of a decompiler, each binary is lifted into equivalent C pseudocode and processed into a list of lexemes and an implementation-defined format for enumerating source-level variable information. Because the DIRT dataset is a preprocessed dataset that does not conform with CONTRABIN’s expected inputs, we instead obtained the list of GitHub repositories that were used to construct the DIRT dataset and compiled each project ourselves. We modified GHCC to save the intermediate LLVM bitcode objects produced during compilation and disassemble each bitcode object into readable LLVM assembly using the LLVM disassembler.

In our experiments, we select function names with number of functions larger than 200, and remove some function names that are not specific to a type of function (i.e., main, __ and __list_add) to make sure the model is trained on meaningful data. We further strip all LLVM files of their original function names (i.e., @TESTFUN0 as the name of

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3. AnghaBench: [http://cuda.dcc.ufmg.br/angha/home](http://cuda.dcc.ufmg.br/angha/home)
4. LLVM Compiler Infrastructure: [https://LLVM.org/](https://LLVM.org/)
5. GHCC: [https://github.com/huzecong/ghcc](https://github.com/huzecong/ghcc)
the first function in an LLVM file) and measure CONTRABIN’s ability to classify these function names. The dataset statistics are shown in Table 2. We fine-tune each model with 5 epochs and a block size of 256. We use training and validation batch sizes of 8 and 16, respectively, and choose learning rate to be 2e-5 and maximal gradient normalization to be 1. In all fine-tuning processes, we use the default random seed as 123456.

**AnghaBench** For the binary code summarization and reverse engineering tasks, we use the AnghaBench test set [16] during pre-training, which includes code never been seen by the model. Specifically, we only select the main function in LLVM code and its paired source code for fine-tuning the code summarization and reverse engineering tasks. To better fit the capacity of pre-trained language models, we further truncate the length of binary code by only selecting the first 512 instructions. The dataset statistics are displayed in Table 2. In this paper, we evaluate the model’s ability to translate and summarize binary code using the validation set and analyze its embedding using the test set.

In our experiments, we defined the input length for both the summarization and reverse engineering tasks as 512, and the output length for summarization and translation as 32 and 512, respectively. We use training and evaluation batch size of 16 and beam size of 5. We set the number of epochs for the summarization task to 5 and the batch number for the reverse engineering task to 20000. For reproducibility, the random seed is set to 42 for both tasks.

### 4 Experimental Results

In this section, we present the results of our evaluation, addressing each of our research questions. We provide a detailed analysis of the data, discussing how it supports or challenges our hypotheses. Specifically, we examine the effectiveness of our proposed approach in integrating binary code into large-scale pre-training models and incorporating rich information from source code and comments into binary code. We also evaluate the generalizability of our model across different downstream tasks in binary code analysis.

#### 4.1 Embedding Analysis

We perform an embedding analysis to understand the changes in binary code embedding after pre-training our model. The visualization presented in Figure 6 serves as an intuitive case study to illustrate the distribution of embeddings generated by our model. This rough visualization is intended to provide an initial, qualitative glimpse into how distinct functions are scattered across the embedding space, reflecting the model’s ability to differentiate various functionalities. It should be noted that this is not the sole evidence of the model’s effectiveness; comprehensive qualitative and quantitative analyses are presented in subsequent sections to substantiate our claims with robust empirical data. As shown in Figure 6, the five models generated different embeddings for the binary code of the AnghaBench test set. Since the original embedding dimension was 768, we used T-SNE [28] to reduce the dimensionality to two for visualization. As a contrast model, we refer to the model trained solely with primary contrastive learning for 10 epochs as CONTRABIN (PCL).

**General embedding analysis** The comparison models, including RoBERTa, CodeBERT, and GraphCodeBERT, showed some clustering of binary code embedding in the two-dimensional space. However, according to the dataset statistics, all binary code in the AnghaBench test set is unique, and therefore should not show any clustering. Thus, we can conclude that the binary code could not be correctly embedded into the manifold by the comparison models. On the other hand, CONTRABIN (PCL) and CONTRABIN-generated binary code embeddings showed more distinct properties. The embedding generated by CONTRABIN (PCL) showed only two natural clusters, while there was only one in CONTRABIN-generated embedding. The visualization of the embedding proves that our model can improve embedding quality.

**Case study** To investigate how our model projects binary code into the manifold, we selected two binary codes whose paired source codes had similar semantics. Specifically, we used two source codes called process_record_keymap and process_record_user, respectively, as shown in Figure 6. Both codes had similar input sets and functionality. When we used RoBERTa, CodeBERT, and GraphCodeBERT to project their compiled binary code into the manifold and visualize them, we observed that the two programs were separated by a certain distance, as indicated by the circled red and orange dots. In contrast, our model, which included CONTRABIN (PCL) and CONTRABIN, was able to project them into much closer positions in the manifold. In comparison with the embedding generated by CONTRABIN (PCL), CONTRABIN was able to further reduce the distance between them, demonstrating an improvement in performance in binary code representation learning by utilizing intermediate contrastive learning.

#### 4.2 RQ1: Binary Code Analysis

After analyzing embedding of binary code using all pre-trained models, we start qualitative binary code analysis of...
Fig. 6: Embedding analysis of pre-trained models for binary code. In each subfigure, the red and orange dots represent the embeddings of the keymap function and key record function binary codes, respectively. The lower part shows their source code.

Table 4: Quantitative evaluation of CONTRABin and multiple pre-trained methods on binary function name recovery of DIRE using accuracy, mean of average precision (MAP), mean of average recall (MAR), and mean of average F1 score (MAF) as four key criteria.

| Approaches       | Accuracy | MAP   | MAR   | MAF   |
|------------------|----------|-------|-------|-------|
| RoBERTa [13]     | 29.41    | 28.41 | 25.00 | 26.59 |
| CodeBERT [12]    | 24.94 (+15.20%) | 23.25 (+18.15%) | 20.82 (+16.70%) | 21.97 (+13.79%) |
| GraphCodeBERT [9] | 25.95 (-11.76%) | 27.59 (-2.87%) | 22.52 (-9.91%) | 24.80 (-6.74%) |
| CONTRABin (PCL)  | 28.83 (+1.96%) | 28.65 (-0.85%) | 25.83 (-3.35%) | 27.17 (+2.16%) |
| CONTRABin (Ours) | 33.41 (+13.60%) | 30.79 (+8.39%) | 28.14 (+12.58%) | 29.41 (+10.58%) |

Contr ativ e learning over three different modalities, which can result in the binary code embedding becoming overfitted to the exact embedding of either source code or comments, making the model less effective.

Table 5: Quantitative evaluation of CONTRABin and multiple pre-trained methods on binary code summarization of AnghaBench using BLEU-4, GLUE-4, ROUGE-2, METERO and exact match (xMatch).

| Approaches       | BLEU-4 | GLUE-4 | ROUGE-2 | xMatch       |
|------------------|--------|--------|---------|--------------|
| RoBERTa [13]     | 24.30  | 25.55  | 30.16   | 4.95         |
| CodeBERT [12]    | 32.07 (+31.98%) | 32.80 (+28.39%) | 38.83 (+28.75%) | 7.91 (+60.00%) |
| GraphCodeBERT [9] | 32.43 (+33.44%) | 32.94 (+28.92%) | 39.45 (+30.80%) | 7.91 (+60.00%) |
| CONTRABin (PCL)  | 30.89 (+27.13%) | 31.33 (+21.84%) | 37.02 (+22.76%) | 6.70 (+35.56%) |
| CONTRABin (Ours) | 34.36 (+41.39%) | 34.82 (+36.28%) | 41.20 (+36.60%) | 9.34 (+88.89%) |

Contr ativ e learning over three different modalities, which can result in the binary code embedding becoming overfitted to the exact embedding of either source code or comments, making the model less effective.

Result for POJ-104 Our first downstream task is algorithmic functionality classification for binary code. Recall that, in this setting, we use pre-trained embeddings from CONTRABin to aid classifying an input binary snippet into one of 104 classes of algorithms (e.g., bubble sort vs. heap sort vs. Fibonacci, etc.). To evaluate the performance of CONTRABin in this downstream task, we adopt mean of average precision (MAP), mean of average recall (MAR), and mean of average F1 score (MAF) as three key criteria. We consider only C code that can be compiled to binaries — while most programs compiled successfully, we exclude those that could not be compiled, and report MAP, MAR, and MAF across all 104 classes. For this task and the three subsequent tasks, we used the results of RoBERTa as a baseline for comparison.

Table 3 presents the quantitative evaluation of CONTRABin against several pre-trained methods. CodeBERT and GraphCodeBERT shows comparable performance to RoBERTa on all three metrics, with a performance improvement of less than 5%. However, CONTRABin demonstrates a substantial improvement in MAP, MAR, and MAF by 14.34%, 18.55%, and 16.71%, respectively. We note that the performance of CONTRABin (PCL) is lower than that of RoBERTa. This can be partially attributed to the use of contrastive learning over three different modalities, which can result in the binary code embedding becoming overfitted to the exact embedding of either source code or comments, making the model less effective.

Result for DIRE Our second task for binary code analysis is function name recovery, which is transformed into a function name classification task where the models are required to classify binary code into one of the 91 function names based on the settings. To evaluate the model performance, we used the same metric set as in POJ-104, with an additional accuracy metric, and applied all models to compiled LLVM code of the DIRE dataset.

The overall performance, as shown in Table 4, revealed that fine-tuning CodeBERT and GraphCodeBERT resulted in a decrease in performance, making them less effective than the baseline RoBERTa model in all metrics by up to approximately 20%. This demonstrated that current models are unable to generalize when the domain of downstream applications for binary code analysis shifts and may even become ineffective. On the other hand, CONTRABin still demonstrated considerable improvement over all three metrics by 13.6%, 8.39%, and 10.58%, respectively, demonstrating the generalizability of our pretrained model on different downstream tasks.

4.3 RQ2: Binary Code Comprehension

We further analyze CONTRABin’s ability in binary code comprehension by evaluating its performance on two ad-
other models in all metrics, achieving substantial improvements of 41.39% for BLEU-4, 36.82% for GLUE, 36.6% for ROUGE, and 88.89% for xMatch over the baseline method.

We further demonstrate the effectiveness of CONTRABIN through a case study shown in Figure 7. In the first case, CONTRABIN accurately captures the functionality of the program in summarizing binary code, whereas the summarization of other models have diverged to different objectives, such as cpu, file, lock, etc. In the second case, other models encountered issues in summarizing long binary code. For instance, CONTRABIN (PCL) generates incomplete sentences, while RoBERTa, CodeBERT, and GraphCodeBERT generate wrong summarization and overly general summaries, respectively. This showcases the long-term semantic consistency and robustness of binary code summarization achieved through the use of binary embeddings generated by CONTRABIN.

**Result for AnghaBench (Reverse Engineering)** For the binary code reverse engineering task, we use similar metrics, except ROUGE, which is designed for summarization.

**TABLE 6: Quantitative evaluation of CONTRABIN on binary reverse engineering of AnghaBench using BLEU-4, GLUE-4 and exact match (xMatch).**

| Approaches          | BLEU-4 | GLUE-4 | xMatch |
|---------------------|--------|--------|--------|
| RoBERTa [13]        | 69.72  | 68.29  | 23.52  |
| CodeBERT [12]       | 70.37 (+0.94%) | 67.27 (-1.50%) | 23.41 (+0.47%) |
| GraphCodeBERT [9]   | 71.56 (+2.64%) | 69.88 (+2.32%) | 24.73 (+5.14%) |
| CONTRABIN (PCL)     | 69.73 (+0.02%) | 69.41 (+1.64%) | 23.41 (+0.47%) |
| CONTRABIN (Ours)    | 71.14 (+2.04%) | 70.41 (+3.10%) | 25.16 (+7.01%) |

**Fig. 7: A positive case study on binary code summarization. The first case demonstrates CONTRABIN’s ability for semantic completion, while the second showcases its long-term semantic reconstruction capability.**

**Fig. 8: A positive case study on binary reverse engineering. The first case demonstrates CONTRABIN’s ability to control generated content, while the second showcases its ability to maintain semantic consistency.**

additional downstream tasks: binary code summarization and binary code reverse engineering. We used the test set of AnghaBench to perform in-domain analysis to assess the effectiveness of our proposed approach.

**Result for AnghaBench (Summarization)** For the binary code summarization task, we use four commonly used metrics, including BLEU-4 [29], GLUE-4 [30], ROUGE-2 [31], and Exact Match (xMatch) to evaluate the performance of all models. As shown in Table 5, CONTRABIN outperforms all
only, to evaluate the performance of CONTRA on direct code translation between source code and binary code. As shown in Table 6, CONTRA improves the baseline method by 2.04% in BLEU, 3.10% in GLEU, and 7.01% in xMatch. Compared with GraphCodeBERT, which outperforms CONTRA in BLEU, CONTRA outperforms on the other two metrics (GLUE and xMatch).

We also show a case study in Figure 8. In the first case, CONTRA can maintain the consistency of variable names in the generated source code, while the other methods have issues such as changing variable names and adding incorrect statements. In the second case, the other methods also generate more redundant information. This highlights the ability of CONTRA to generate semantically consistent binary code translations.

### 5.1 Ablation Studies

We assess each component of our model through ablation studies. Specifically, we remove three conditions to test the efficiency of each design element: (1) We remove comments as one of the modalities during training, (2) we replace the anchored encoder with a learnable one so that it can be updated during training, and (3) we eliminate both linear and non-linear interpolation from our model design. For the pretraining process, we adhere to the original hyperparameters, training the first and second ablations for 30 epochs and the third ablation for 10 epochs. For the third ablation, we ensure that the model is converged by the end of pretraining. We test the pretrained models on the binary functional algorithm classification of POJ140, using the same hyperparameters. The results are shown in Figure 7.

From the figure, it is evident that removing comments, stopping gradients, and eliminating interpolation decrease the MAF1 scores by 2.07%, 7.46%, and 18.25%, respectively. This demonstrates the effectiveness of each component in our model design. The baseline performance observed in these ablation studies is as follows: MAP of 43.78, MAR of 33.87, and MAF1 of 38.19. We will use these baseline performance metrics as a reference in the following subanalysis to further dissect the contributions of individual components.

### 5.2 Comparison of Human-Written and LLM-Generated Comments in Pretraining

In our study, we explored the impact of using human-written versus LLM-generated comments during the pretraining phase of ContraBin. The objective was to evaluate how each type of comment influences the model's ability to comprehend and process binary code. While human-written comments provide a diverse range of insights, they are often inconsistent in length and detail, which may limit their effectiveness in large-scale pretraining scenarios. On the other hand, LLM-generated comments tend to be more consistent and focused, potentially offering a more structured learning experience for the model. The following analysis compares the length distributions and performance outcomes associated with both types of comments.

**Comment length distribution analysis** The analysis of comment length distributions, as depicted in Figure 9, reveals a significant difference between human-written and LLM-generated comments. Human-written comments display a broader spread and variability in length, suggesting diverse approaches to code documentation by developers. On the other hand, LLM-generated comments tend to be shorter and more consistent in length, indicating a more standardized generation process by the model. These distinctions in comment length and variability may impact the pretraining effectiveness of ContraBin. To explore this further, we conducted a series of experiments to compare the performance of ContraBin when pre-trained using human-written versus LLM-generated comments.

**Performance comparison** The experiments reveal a striking decrease in performance when ContraBin is trained with human-written comments compared to LLM-generated comments. Specifically, the use of human-written comments led to a reduction of 40.67% in MAP, 30.86% in MAR,

### Table 7: Ablation studies of CONTRA on binary functional algorithm classification of POJ104 using mean of average precision (MAP), recall (MAR) and F1 score (MAF1).

| Ablations       | MAP    | MAR    | MAF1   |
|-----------------|--------|--------|--------|
| None (CONTRA)   | 43.78  | 33.87  | 38.19  |
| Comment         | 42.76  | 33.23  | 37.40  |
| Anchor          | 40.96  | 31.07  | 35.34  |
| Interpolations  | 37.03  | 26.99  | 31.22  |

- The analysis of comment length distributions, as depicted in Figure 9, reveals a significant difference between human-written and LLM-generated comments. Human-written comments display a broader spread and variability in length, suggesting diverse approaches to code documentation by developers. On the other hand, LLM-generated comments tend to be shorter and more consistent in length, indicating a more standardized generation process by the model. These distinctions in comment length and variability may impact the pretraining effectiveness of ContraBin. To explore this further, we conducted a series of experiments to compare the performance of ContraBin when pre-trained using human-written versus LLM-generated comments.

**Performance comparison** The experiments reveal a striking decrease in performance when ContraBin is trained with human-written comments compared to LLM-generated comments. Specifically, the use of human-written comments led to a reduction of 40.67% in MAP, 30.86% in MAR,
5.4 Negative Cases

In this negative case study, we examine a scenario involving function classification in binary code, as illustrated in Fig.

5.5 Extensibility to Contemporary LLMs

The evolving landscape of LLMs necessitates the adaptation of existing methodologies to newer, more advanced architectures. As LLMs like T5 [7], CodeT5 [25] and its derivatives become increasingly prominent, it is crucial to ensure that techniques initially developed for models like RoBERTa can be effectively extended to these contemporary frameworks. This section outlines the key adaptations required to transition from RoBERTa’s encoder-only architecture to T5’s encoder-decoder structure.

- Model Architecture Adaptation: Adapting from RoBERTa to T5 requires handling the transition from an encoder-only architecture to an encoder-decoder framework. This involves modifying the model structure to ensure that the input is properly processed through both the encoder and decoder layers of T5. Specifically, tasks previously handled by RoBERTa’s single encoder must now be split between T5’s encoder and decoder to fully leverage T5’s capacity for generating meaningful output sequences.

- Tokenizer and Data Processing: The transition also involves switching from RoBERTa’s Byte-Pair Encoding (BPE) tokenizer to T5’s SentencePiece tokenizer. This change necessitates revisiting the data preprocessing steps to accommodate the differences in how tokens are generated, including adjustments in token length, padding, and special token handling to ensure compatibility with T5’s tokenization requirements.

- Attention Mechanisms and Loss Function: The difference in attention mechanisms between RoBERTa
and T5 requires revising the attention computation, especially in the forward pass. Additionally, because T5 is designed for sequence-to-sequence tasks, the loss function and output processing need adjustments to align with T5’s architecture, ensuring that the model optimizes effectively during training.

For this task, we utilized 8 Nvidia A100 GPUs for CONTRABIN (CodeT5) model pre-training, with the random seed set to 42 to ensure reproducibility. Since the focus was exclusively on binary code analysis rather than comprehension, we adjusted our training strategy accordingly. We reduced the training duration to 40% of the previous rounds to concentrate the model’s efforts on this specific task. This reduction was intentionally implemented to optimize the model’s performance in binary code analysis, ensuring precision and efficiency without unnecessary overextension.

As shown in Table 8, the CONTRABIN (CodeT5) model with our pretraining method achieves significant improvements over CodeT5. Specifically, our model achieves a MAP of 30.1, which is a 4.45% improvement over CodeT5, a MAR of 22.16 (+2.07%), and a MAF1 of 25.53 (+3.11%). These results underscore the effectiveness of our training methodology in enhancing the model’s ability to comprehend and process binary code, demonstrating the adaptability and strength of the T5 architecture.

By addressing the challenges in model architecture, tokenization, and attention mechanisms, we have demonstrated how our approach not only maintains but also enhances its effectiveness in processing binary code across different LLM architectures. This adaptability underscores the flexibility and robustness of our methodology, particularly when applied to state-of-the-art models like T5.

### 6 RELATED WORK

In this section, we highlight key areas of related work, including traditional program analysis and neural models for program analysis related to binary code. Furthermore, we also introduce the background and related work that inspire the design of CONTRABIN, namely large-scale pre-trained embeddings, simplex interpolation, contrastive learning and graph representation learning.

**Binary code analysis** Binary code analysis plays an important role in the bigger domain of software analysis and maintenance. For example, tracing execution can help the analysis of the functionality algorithms from binaries [3], reusing profile information can speed up the similarity comparison of frequently executed core code [2], incorporating sequences of system calls can help detect software vulnerabilities [5], and combining machine and binary-interface descriptions can assist software reverse engineering [4]. Traditionally, in programming language and software engineering, researchers have presented various work based on static and dynamic program analysis techniques. For instance, BYTEWEIGHT [6] automatically classifies algorithms by functionality from binaries, BINSEC [7], [32] formalizes low-level regions of code to extract semantics on the programs, and BinSide [8] uses intermediate representations to conduct cross-platform static analysis.

**Neural code models** In recent years, neural code models have attracted the attention of researchers in software engineering and security. With the assistance of AI [33], it can improve many source code analysis tasks, such as neural clone detection, neural code similarity comparison, neural code search, etc [34]–[38]. For example, SySeVR combines syntax, semantics, and neural vector representation to

![Fig. 10: A negative case study on POJ function classification in binary code. The second example shows CodeT5’s success in maintaining functional integrity, while the third example highlights a misclassification by CONTRABIN, which overfit to the source and comment information due to contrastive learning.](image)

| Model         | MAP         | MAR         | MAF1        |
|---------------|-------------|-------------|-------------|
| T5 [2]        | 23.35       | 17.34       | 19.90       |
| CodeT5 [25]   | 28.82 (+23.42%) | 21.71 (+25.21%) | 24.76 (+28.34%) |
| CONTRABIN (CodeT5) | 30.1 (+28.91%) | 22.16 (+27.79%) | 25.53 (+28.34%) |

**Choice of CodeT5**

```c
#define _GLIBCXX_USE_CXX11_ABI 0

void work(int var1) {
    int main() {
        int var1 = 0;
        var1 = read();
        scanf("%d", &var2);
        work(var2);
        return 0;
    }
}
```

**Choice of CONTRABIN**

```c
#include <stdio.h>
int read();
void work(int var1);

int main() {
    int var1 = 0;
    var1 = read();
    scanf("%d", &var2);
    work(var2);
    return 0;
}
```
detect software vulnerabilities [39], InnerEye adopts techniques in Natural Language Processing (NLP) to compare between samples of binary code [40], GNN-BPE [41] applies Graph Neural Networks (GNN) on binary code by fusing the semantics of Control Flow Graphs (CFG), Data Flow Graphs (DFG), and call graphs, and Bin2Vec [42] learns binary code representation via Graph Convolutional Networks (GCN). However, these methods involve complex aggregation of additional binary code representations and have limited generalizability across tasks.

**Large-scale pre-trained embeddings** With the recent success of large-scale pre-trained embedding in AI, research has been conducted on applying similar approaches to code analysis [34], [43]–[45]. In particular, RoBERTa [13] serves as the baseline, CodeBERT [12] incorporates code generation and identification into training process, GraphCodeBERT [9] combines Abstract Syntax Tree (AST) to further improve embedding quality. There are also many recent models designed for source code understanding, including CodeTrans [46] and CoTTeX [47] that incorporate different language modalities and multi-sub tasks for better code representation learning, and CodeT5 [25] which proposes an identifier-aware pre-training task to improve embedding distinction. CONTRABIN aims similar goals with these large-scale language representation models but focuses on a more effective and efficient representation for binary code in terms of better semantics.

**Contrastive learning** As a recent emerging research direction, contrastive learning can enhance the performance of many computer vision tasks by contrasting samples against each other to learn common properties [48], [49]. For example, MoCo [50] proposes a dynamic dictionary to facilitate contrastive learning, SimSiam [51] introduces a Siamese network and stop gradient scheme to prevent collapsing in optimization, and CLIP [19] integrates visual concepts and raw text about images to provide much better semantics. However, these methods involve complex aggregation of additional binary code representations and have limited generalizability across tasks.

**7 Conclusion** To summarize, we propose a novel approach that fully integrates binary code into the large-scale pre-training model framework and incorporates rich information from source code and comments into binary code. Our experiments demonstrate that our proposed components outperform other approaches in four downstream tasks in binary code analysis and comprehension. We believe that our research work can inspire the AI, software engineering, and security communities to develop new methods that can further improve binary code analysis and comprehension and facilitate binary code applications from various perspectives.

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