Leveraging Artificial Intelligence on Binary Code Comprehension

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ABSTRACT
Understanding binary code is an essential but complex software engineering task for reverse engineering, malware analysis, and compiler optimization. Unlike source code, binary code has limited semantic information, which makes it challenging for human comprehension. At the same time, compiling source to binary code, or transpiling among different programming languages (PLs) can provide a way to introduce external knowledge into binary comprehension. We propose to develop Artificial Intelligence (AI) models that aid human comprehension of binary code. Specifically, we propose to incorporate domain knowledge from large corpora of source code (e.g., variable names, comments) to build AI models that capture a generalizable representation of binary code. Lastly, we will investigate metrics to assess the performance of models that apply to binary code by using human studies of comprehension.

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1 INTRODUCTION
Artificial Intelligence for Software Engineering (AI4SE) is an emerging direction aiming to leverage AI-based approaches to assist software engineering tasks [8, 15]. In particular, binary code comprehension is among the most challenging tasks due to the complexity and lack of semantics in binary code [23]. Meanwhile, understanding binary code is an essential step in critical tasks such as reverse engineering [6], malware analysis [2], and compiler optimization [25]. In addition, AI is highly effective in revealing complex patterns from large corpora. For example, AI has been used for code search [12], malware classification [18], and code summarization [1]. Thus, leveraging AI for binary code comprehension can help address complex problems while paving the way for new research directions in both the SE and AI communities.

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Existing research in code comprehension includes both SE and AI approaches. Traditional SE practices depend on the generalizability of inherent code structure and fixed properties to make complex decisions. For example, researchers use various compilation methods and consistent structural information for code clone detection [3, 19], or adopt dynamic and static analysis to automatically extract statistical features from assembly functions or binary code [5, 16]. However, these techniques have not reliably applied to binary code because it contains less useful structural and semantic statistical information. Meanwhile, research has shown that AI-based models can facilitate human comprehension of source code [4, 26, 27]. Related studies apply state-of-the-art neural networks to extract code information from scratch [11, 22], or adopting large-scale pretrained models [9, 13, 14] to transfer knowledge learned from corpora of Natural Languages (NLs).

However, there has been limited work assisting binary code comprehension using AI-based approaches. There are two key challenges for this direction: (1) binary code does not capture valuable, abstract semantics, and (2) there is a dearth of infrastructure and literature to support large scale training of binary code (e.g., there is no public dataset for binary code comprehension tasks). In this thesis, we propose to leverage AI to facilitate the comprehension of binary code via four research thrusts:

1. We will transfer knowledge contained in AI models for source code to apply to binary code with a particular focus on stable knowledge that generalizes across software application domains (Section 3.1).
2. We will apply contrastive learning to integrate the semantic information learned from Thrust 1 to develop an enhanced embedding for binary code. This thrust will enable transferring rich knowledge from source code to binary code (Section 3.2).
3. We will investigate the generalizability of our binary embedding from Thrust 2 across multiple programming languages. This thrust will strengthen the stability of our binary code comprehension model (Section 3.3).
4. We will systematically investigate effective metrics for evaluating the applicability of our AI models for binary code comprehension through human studies. This final research thrust will incorporate critical feedback from human engineers (see Section 3.4).

This dissertation will result in new AI models and associated representations of programs that will aid in the comprehension of binary code.
2 RELATED WORK

Various approaches exploit machine learning techniques to analyze myriad representations of code fragments to guide the comprehension of source code, such as code summarization, clone detection, or program generation. One approach is to adopt the structure of abstract syntax trees (ASTs) to build models [20]. For instance, ASTNN [33] incorporates AST fragments into a bidirectional RNN model to build a vector representation of programs; TECCD [10] captures an AST embedding using a lightweight neural method.

In addition, compiling source to binary code can be used to assist program comprehension. For example, jTrans [31] learns representations of binary code using the Transformer neural architecture, and BugGraph [17] uses a graph triplet-loss network on the control flow graph to produce a similarity ranking.

Moreover, program comprehension can be improved through transpilation of a program from one language to another. While there is no single perfect technique for transpilation, several works have investigated transpilation under specific circumstances. For example, NOSTT2 [21] leverages neural-guided synthesis to convert imperative code to functional, and HeteroGen [34] converts C/C++ code to support High-Level Synthesis.

Last, because both NLs and PLs are based on English characters and words, researchers often adopt contemporary metrics from Natural Language Processing (NLP) to evaluate AI models in code comprehension, such as the BLEU score [24]. Most such work aim to improve such metrics using by sequential neural network models [30, 32] and large-scale pretrained model [9, 14]. Researchers have demonstrated that direct application of metrics in NLP cannot help AI models to achieve satisfactory performance in SE tasks [28].

3 HYPOTHESES AND METHODOLOGY

Our research methodology comprises four stages. First, we will incorporate domain knowledge of PLs to improve the stability and generalizability of source code comprehension. Second, we will transfer domain knowledge from source to binary code via contrastive learning. Third, we will develop a general representation across multiple PLs to enhance the performance of AI models. Last, we will define unified metrics for better evaluate our AI models for binary code comprehension. The planned works at each stage are shown below:

3.1 Source Code Comprehension

Many studies have already incorporated properties of source code to build AI models, but often directly use the source code or an associated intermediate representation without an in-depth understanding of the domain knowledge contained within. Therefore, we define our first hypothesis as:

| Hypothesis 1: Program source code contains critical domain knowledge relevant to program comprehension. Incorporating this knowledge can improve the stability and generalizability of AI models. |

To validate this hypothesis, we will design domain knowledge-guided source code comprehension on program generation, clone detection, and code summarization to test the performance of our source code comprehension model in cross-domain tasks.

3.2 Knowledge Transfer from Source Code to Binary Code Comprehension

Next, we will use contrastive learning to transfer valuable domain knowledge from source code to binary code. Most recent research adopts state-of-the-art AI models to learn properties of binary code without considering the connection between source code and binary code. Therefore, we define our second hypothesis as:

| Hypothesis 2: Binary code shares similar properties to source code, but the representation precludes extracting such properties. By compiling source code, we can develop AI models that associate source code with corresponding binary code. This will provide generalizable models for tasks involving binary code when the original source code is unavailable. |

To validate this hypothesis, we will develop and evaluate models that apply to source code and corresponding binary code for reverse engineering and vulnerability detection.

3.3 Generalizability Across Different PLs

Third, we will combine research outputs in the previous two steps to develop a general representation across multiple PLs. General approaches in this task still rely on a case-by-case analysis and are not well-studied from the perspective of domain generalization. Therefore, we define our third hypothesis as:

| Hypothesis 3: We can extract common semantic information for a given program written in several programming languages that can aid binary code comprehension. |

To validate this hypothesis, we will apply transpilation knowledge-guided domain generalization methods to extract common features from programs written in multiple languages, and use dimensionality reduction skills (e.g., PCA [7], T-SNE [29]) to further visualize them and justify its effectiveness.

3.4 Unified Metrics for Evaluation of Binary Code Comprehension Models

Finally, we will define unified metrics for evaluating our AI models for binary code comprehension. Researchers have demonstrated that directly applying the metrics from NLP to SE tasks can be ineffective or even problematic in comprehending code and assisting programmers. Therefore, we define our fourth hypothesis as:

| Hypothesis 4: PLs and NLs have syntactic and semantic differences. New metrics can improve the general performance of AI models in binary code comprehension by helping models learn which is the better direction in optimization of AI models. |

To validate this hypothesis, we will test our new metrics on several binary code datasets for multiple tasks, including binary code similarity comparison, vulnerability detection, reverse engineering. We will investigate how models tailored to these binary comprehension tasks are affected by our new metrics.

4 EXPECTED CONTRIBUTION

This thesis will investigate how to leverage AI for binary code comprehension. The expected contributions of the thesis are:
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