Variable Name Recovery in Decompiled Binary Code using Constrained Masked Language Modeling

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1 INTRODUCTION

Despite the recent progress in the software open source movement, source code is oftentimes unavailable to security researchers, analysts, and even software vendors. This makes software reverse engineering, a family of techniques that aim at understanding the behavior of software without accessing its original source code, irreplaceable [12]. Reverse engineering techniques are essential to accomplishing a set of security-critical tasks, including malware analysis, vulnerability discovery, software defect diagnosis, and software repairing [2].

With the rapid development of modern decompilers (e.g., Hex-Rays Decompiler [11, 21] and Ghidra [15]), decompilation, or reverse compilation, is gradually becoming an essential technique for software reverse engineering tasks. Built atop advanced program analysis techniques and sophisticated heuristics, these decompilers can identify much information that is lost during compilation and binary stripping, such as function boundaries, function prototypes, variable locations, variable types, etc. Names of variables in a program usually embed much semantic information that is crucial for understanding the behaviors and logic of the program. Nevertheless, the state-of-the-art decompilers are all limited to recovering structural information and cannot recover meaningful variable names. Therefore, the usual first step taken by a decomplier user is painfully interpreting the decompiled code and renaming the unnamed variables one by one. This is, unfortunately, an insurmountable obstacle for reverse engineering stripped binary programs.

While researchers have taken steps in predicting variable names in high-level programming languages [1, 3, 4, 26, 41, 45], it is worth noting that inferring variable names in decompiled binary code poses a unique set of challenges. High-level programming languages like Java, Python, and JavaScript are syntactically rich: Variable types are preserved in these languages, while they are usually eliminated in binaries. In fact, type inferencing on binary programs still remains an open problem [8]. Moreover, modern compilers that generate machine code produce all sorts of irreversible changes [52], which diminish the power of variable name prediction techniques that are based on local data dependencies. DEBIN [19] and DIRE [30] are the pioneers in predicting variable names in stripped binary programs. DEBIN proposes a statistical model that yields poor performance and generalizability. DIRE produces much better results by employing an LSTM[23] and Gated Graph Neural Network-based model [31] that is trained on a huge...
We learn a vocabulary of code-tokens using Byte-Pair Encoding. With the help of these techniques, we propose a novel solution: Transformers [46], Masked Language Modeling [14], and BERT [14].

2 BACKGROUND AND RELATED WORK

Our solution leverages techniques in machine learning and natural language processing to refine the results of binary code decompilation. Before diving into the details of our solution, in this section, we will first present the necessary background as well as some work that is closely related to our proposed solution.

2.1 Binary Code Decompilation

Binary code decompilation is the process of converting compiled binary code to a higher-level representation, oftentimes C source code or C-like pseudocode. Compilation and binary stripping are lossy procedures where much semantic information is discarded since it is useless to CPUs. Such information, such as control flow structures, function names, function prototypes, variable types, and variable names, is very important to software reverse engineering tasks. While modern decompilers have made significant progress in recovering and inferring various types of lost information, recovering variable types in decompiled code remains challenging.

2.2 NLP and Program Analysis

Structured programs and natural languages have similar statistical properties [2, 13, 22]. This has led to the application of statistical models in program analysis and software engineering. Some of the notable applications are code completion [7, 35, 36], code synthesis [5, 18, 29, 32, 38, 54], obfuscation [33, 37], code fixing [16, 17], bug detection [40, 47], information extraction [10, 43, 51], syntax error detection [9] and correction [6], summarization [24, 25] and clone detection [49].

2.3 Statistically Predicting Variable Names

The probabilistic graphical model, Conditional Random Fields (CRF) has been useful in the prediction of syntactic names of identifiers and their semantic type information of JavaScript programs. Their system JSNICE [41] were able to correctly predict 63% of the names and 81% of the type information. Though our goal of prediction of variable names is same our approach and program domain differ considerably from theirs.

Another system AUTONYM [45] surpassed JSNICE in the prediction of variable names for Javascript codes using statistical machine translation. Jaffe et al. [26] also used statistical machine translation to generate meaningful names to the variables for the compiled source code written in C. They could achieve 16.2% accuracy in predicting meaningful names in a dataset of size 1.2TB of decompiled C code. They predicted variable names that are similar and convey the same meaning as the original names, whereas, we try to predict the original variable names from the decompiled code. In that respect, we keep a much stricter evaluation metric.

The NATURALIZE [1] framework has been quite successful (94% accuracy) in suggesting meaningful identifier names and format styles using n-gram probabilistic models. However, we use different models and training methods for the task.

With the help of machine learning techniques, researchers have made much progress in recovering variable names on decompiled binary code. However, existing techniques suffer from some major drawbacks. DEBIN uses probabilistic models like CRF [19]; Unfortunately, as shown in another paper, its accuracy and generalizability are poor, which renders DEBIN nearly useless in real-world settings [30]. DIRE leverages neural network on Abstract Syntax Trees (ASTs) extracted from collected source code [30]; While DIRE yields
a good prediction performance, the AST extraction process can be tedious and error-prone.

In this paper, we show that with advanced NLP techniques, it is possible to achieve a significantly better performance in accuracy and generalizability of variable name prediction in decompiled binary code. Moreover, our proposed solution does not require extracting ASTs from decompiled code. Instead, it directly uses raw decompiled code as input, which is simpler and more robust than DIRE.

2.4 Neural Models

The success of statistical models and progress in the development of stronger neural models led to the application of neural models for identifier name recovery. Our work is related to the following recent works in this area.

In a recent work, CONTEXT2NAME [4] attempted to assign meaningful names to the identifiers based on the context of minified JavaScript codes. They were able to successfully predict 47.5% of meaningful identifiers on 15,000 minified codes using recurrent neural networks. Our work differs from theirs in the sense that we use much advanced deep learning models, we predict the actual original names instead of assigning similar meaningful names and we predict variables for decompiled C code instead of minified JavaScript codes.

Few of the works attempted to predict function names from stripped binaries. Artuso et al. [3] used sequence to sequence networks in two settings (with or without pre-trained embeddings) to predict function names in a dataset created using stripped binaries compiled from 22,040 packages of Ubuntu apt repository with the precision and recall of 0.23 and 0.25 respectively. In another work, the NERO model by David et al. [12] predicted the procedure names in a dataset created from Intel 64-bit executables running on Linux, using LSTM with a precision and recall of 45.82 and 36.40 respectively. Our approach differs from both of the works in the sense that we focus on predicting the variable names instead of functions and our approach to the task.

DIRE [30] is the most recent work related to us. They were able to successfully predict the original variable names 74.3% of the time in the decompiled source code of 164,632 unique x86-64 C binaries mined from Github. They used gated graph neural networks(GGNN) [31] and bidirectional LSTM to encode the Abstract Syntax Tree (structural information) and the decompiled code(lexical information) followed by a decoder network with attention. For our work we use the same dataset published by them but our training method and inputs differ considerably.

2.5 BERT

Bidirectional Encoder Representations from Transformers is designed to pre-train deep bidirectional representations from the unlabeled text by jointly conditioning on both left and right context in all layers [14]. BERT is pre-trained in an unsupervised way on a huge collection of natural text for two tasks, first, the masked language modeling (MLM) and second, the next sentence prediction (NSP) to make the model understand the relation between tokens and sentences respectively. Since it’s release it has become ubiquitous in almost all tasks in various domains.

2.6 Vocabulary for Neural Models

All the neural models make use of a specific vocabulary set created from the training data to translate words or tokens to numeric encodings. It is created using a tokenizer on the natural language texts. The size of the vocabulary should not be too low to cover most of the words in training, validation and test data. It should not be too high either to create a massive vocabulary, which may lead to considerably large learned vector embeddings.

2.6.1 WordPiece and SentencePiece Embedding. To keep an optimal size of the vocabulary the WordPiece embedding [50] was introduced. In this embedding, each word is divided into a limited set of common sub-units(sub-words). The word-piece embedding is helpful in handling the rare words in the test samples. BERT uses WordPiece embeddings with a vocabulary of size 30,000. Unknown words are split into smaller units which are present in the vocabulary. Another type of embedding [28] can be directly trained from raw sentences without the need for pre-segmentation of text as compared to earlier approaches. It helps user to create a purely end-to-end and language-independent system.

2.6.2 Byte-Pair Encoding. Byte-Pair Encoding(BPE) [42] is a hybrid between the character and word level text representation. It can handle large vocabulary. The full word is broken down into smaller sub-unit words after performing statistical analysis on the training data. Another implementation of BPE [39] uses bytes instead of unicode characters as base sub-unit words.

3 APPROACH OVERVIEW

Our approach involves the following. We extract the decompiled raw code from the binaries. Each function is taken as an independent input instance. We create a corpus by using all such raw code to learn a vocabulary of most frequent code-tokens using the technique of Byte-Pair Encoding. We then proceed to learn representations of the code-tokens and a BERT model using the pre-training method of Masked Language Modeling. Finally, we
fine-tune the BERT model using our Constrained Masked Language Modeling technique, to predict only the variable names.

4 DATASET DESCRIPTION

In this work, we use the DIRE[30] dataset. The dataset consists of 3,195,962 decompiled x86-64 functions and their corresponding abstract syntax trees with proper annotations of the decompiled variable name and their corresponding original gold-standard names. The dataset was created by scraping open-source C codes from GitHub. The codes have been compiled keeping the debug information and then decompiled using Hex-Rays [21], a state-of-the-art industry decompiler. The decompiled variable names are the names assigned to the original variable names by the Hex-Rays. We worked on the reduced preprocessed dataset released by the authors with the same train-dev-test (80:10:10) splits. The number of train, validation and test files is 1,00,632, 12,579 and 12,579 respectively. In the dataset, there are 1,24,702, 1,24,179, and 10,11,054 functions which involve 6,74,854, 6,80,493, and 55,23,045 variables in validation, test and train files respectively.

4.1 Vocabulary

We use Byte-Pair Encoding to learn the vocabulary. We generate a corpus by first replacing all decompiler generated variables in the raw code with original variable names and then concatenating all decompiled functions. We use the HuggingFace Tokenizers tool to learn the Byte-Pair Encoding vocabulary. We learn two sets of vocabulary for both versions is the same. Training such a huge model is the target token, \( V \), where \( V \) is the current token, \( w_c \) is the target token, \( y \) is an indicator variable which is 1 if the target is \( w_c \) and 0 otherwise and \( p \) is the probability \( w_i \) is same as \( w_c \).

5.4 Count of Token Prediction

In the task of Variable Name Recovery, during test time, we do not know the number of tokens the original variable should have. We define the Count of Token Prediction as the task to determine the count of mask tokens during test time. We solve this with the following heuristic defined in Algorithm 1. We evaluate our BERT models with both an Oracle model which gives us the number of masked tokens. In the Masked Language Modeling, we may mask sub-parts of a word. As seen in the example, a big word that is not present in the vocabulary can be captured the entire word, we perform Whole-Word Masking, in which if a word is chosen to be masked, all the tokens of the word are masked and the model is trained to predict all the original token.

5.3 Constrained Masked Language Modeling

Constrained Masked Language Modeling is a variation of Masked Language Modeling where the tokens are not masked at random. We define Constrained Masked Language Modeling as follows:

\[
\text{Let } W_0, ..., W_N \text{ be a sequence of tokens. Let } C = \{A_0, ..., A_c\} \text{ be a set of tokens which we define as the constrained set of tokens. Then in constrained masked language modeling, all tokens in } W_0, ..., W_N \text{ which belong to } C \text{ are masked. } C \text{ is a subset of } V. \text{ Here all the tokens are replaced with a masked token, unlike Masked Language Modeling. Similar to Masked Language Modeling, we train the model to predict the masked token with a cross-entropy loss:}
\]

\[
- \sum_{i=0}^{N} \sum_{c=1}^{M} y_{w_i} w_c \log(p_{w_i, w_c})
\]

\[
\text{, where } M \text{ is the size of the vocabulary, } w_i \text{ is the current token, } w_c \text{ is the target token, } y \text{ is an indicator variable which is 1 if the target is } w_c \text{ and 0 otherwise and } p \text{ is the probability } w_i \text{ is same as } w_c.
\]

5.5 Technical Details

A Transformer architecture [46] contains multiple layers, with each block using multiple self-attention heads. We train two different versions of VarBERT each differing in the number of layers \( L \), the number of self-attention heads \( A \) and the hidden dimension \( H \). The vocabulary for both versions is the same. Training such a huge
architecture requires a lot of computing and training time. We define a fixed hyper-parameter budget of two training runs over the entire dataset for each of the versions to limit our training time and compute cost. We take initial hyper-parameters from RoBERTa [34].

5.5.1 VarBERT-Base. This version has $L = 12$, $A = 12$ and $H = 768$. This leads to total parameters to be trained to be nearly 125 million. The maximum number of input tokens this version can take is 512.

5.5.2 VarBERT-Small. We hypothesize in the task of Variable Name Recovery, a smaller model in terms of depth and parameters might perform reasonably well, and hence create this version which has $L = 6$, $A = 8$ and $H = 512$. We though increase the number of input tokens the model can take to 1024 to be able to train the model with longer code sequences and be more useful for the community. The number of trainable parameters for this model is 45 million, which is 2.5 times smaller than VarBERT-Base.

5.6 Training Methodology

For the task of Variable Name Recovery, we train our models with the following methodologies.

5.6.1 Pre-Training. The need and impact of Pre-Training on auxiliary tasks before the final intended task has been demonstrated in multiple previous natural language processing and computer vision work such as in [14, 34, 44, 53]. For the task of Variable Name Recovery, we define the Masked Language Modeling task as the pre-training task. We follow the same steps as done in RoBERTa [34] to train our model and learn rich representations for our code-tokens. We train, both with and without Whole-word Masking.

5.6.2 Finetuning. We finetune our models, for the Variable Name Recovery task using the Constrained Language Modeling task.

5.6.3 Optimization. We optimize our models using BERTAdam [14, 27] with following parameters: $\beta_1 = 0.9$ and $\beta_2 = 0.999$, $\epsilon = 1e^{-6}$ and $L_2$ weight decay of 0.01. We warmup over first 10,000 steps to a peak value of $1e^{-4}$ and then linearly decay. We set our dropout to 0.1 on all layers and attention weights. Our activation function is GELU [20].

We use HuggingFace Transformers and Facebook FairSeq tools to train our models.

6 EXPERIMENTS

6.1 Experimental Setup

Our models are evaluated on the DIRE dataset. Split of the dataset given in DIRE [30] is 80:10:10. We use only the raw code generated from the decompilers and replace the decompiler generated variable names with the original variable name given by the developer. We evaluate the impact of pre-training and whole-word masking. We also evaluate the impact of constrained masked language modeling using the pre-trained only model as a baseline. We evaluate the impact of the size of the vocabulary and the size of the models.

As defined above, we train the models with a hyper-parameter budget of two, so a bigger budget might result in even better performance. The hyperparameters for pre-training and finetuning are a batch size of 1024 and the number of epochs is restricted to 40. We use 4 Nvidia Volta V-100 16GB graphics cards to train our models. Approximately, the VarBERT-Base has a training time of 72 hours and VarBERT-Small has a training time of 38 hours.
6.2 Metrics
We evaluate our models using the following metrics. *Exact Match accuracy* of predicting the correct variable name. The final goal of such a model is to provide suggestions to system reverse engineers, and our models also provide a ranking of tokens, we measure the accuracy of the correct variable at different ranks, which are 1, 3, 5 and 10. In DIRE [30] they also measure the character error rate (CER) metric, which calculates the edit distance between the original and predicted names, then normalizes the length of the original name, as defined in CER [48]. We measure this for our heuristic-driven Count of Token Prediction algorithm. We also measure the *Perplexity* of both language modeling tasks. Perplexity measures how well a probabilistic language model predicts a target token.

The binaries in the dataset use C libraries. The different splits Train, Validation and Test contain binaries that share these libraries. The functions in these libraries have the same variable names and bodies. To better understand the generalizability of our proposed models and techniques, we also report the metrics on two sets, *Body not in the train* and *Overall*. These sets are defined as meta-tags in the DIRE dataset.

6.3 Baselines
Our baseline models for the Variable Name Recovery tasks are the following.

6.3.1 *DEBIN*. It uses statistical models such as CRFs and Extremely Randomized Trees with several handcrafted features to recover variable names, along with other debugging information from stripped binaries. Few of the handcrafted features are functions used, registers used, types, flags, instructions and relationships between functions, variables, and types. This acts as a weak baseline for our proposed models.

6.3.2 *DIRE*. It uses LSTMs, Gated Graph Neural Networks and Attention Mechanism with an Encoder-Decoder architecture to generate variable names. It also uses the *raw* code as one of the inputs. In addition to the decompiled code, it uses a GNN based structural encoder to encode Abstract Syntax Trees. This acts as a strong neural baseline for our proposed models.

Both the above models, use the *raw* code to recover variable names but also use additional features. In our proposed models, we only use the *raw* code.

7 DISCUSSION AND ANALYSIS
7.1 Dataset Analysis
We start with the initial analysis of the dataset. We measure the overlap between the variables present in the Train, Validation and Test set splits with our learned vocabulary. We also measure the length of the functions. Figure 4 and Figure 5 show the respective distributions. 216 and 167 functions from the Validation and Test set were truncated due to the limitation of maximum allowed sequence length of 1024. Most of the variables in the dataset are tokenized to a wide range of [1,7]. We use these statistics to define the *MaxAllowedToken* parameter in Algorithm 1.

![Figure 4: Distribution of length of gold tokenized variable names in Train, Validation and Test data. The counts are in Natural Log Scale.](image)

![Figure 5: Distribution of length of function in Train, Validation and Test data](image)

![Figure 6: Impact of training corpus size on the performance of our model. The scores are for VarBERT-Small trained with CMLM, 50K Vocab, and Heuristics.](image)

7.2 Model Analysis
Can we use just Masked Language Modeling for Variable Name Recovery? In Table 1, we compare the different modeling tasks. We observe that Constrained Masked Language Modeling
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Figure 7: Impact of training corpus size on the performance of our model. The scores are for VarBERT-Small trained with CMLM, 50K Vocab, and Heuristics based Count of Token Prediction.

Figure 8: Accuracy of VarBert-Small for different lengths of target variable names.

with Whole-word Masking performs the best. It is also observed that just Masked Language Modeling performs significantly poor. This can be explained by the random 15% of tokens which are masked, and not all the variable name tokens. Masked Language Modeling with Whole-word Masking is slightly better. Pre-training also has a significant impact, as without Pre-training model Top1 Exact Match Accuracy are in the lower 50s, with a high perplexity. This is because the task of Constrained Masked Language Modeling is insufficient to learn rich vector representations for the entire vocabulary set.

Does increasing vocabulary size help? In Table 2 we compare our models with two different sets of vocabulary learned using Byte-Pair Encoding. We observe increasing vocabulary has a significant impact. With a smaller vocabulary, we can have a smaller model that trains faster, but we lose in performance by a significant margin.

How do VarBERT-base and VarBERT-small compared to each other? Our hypothesis of a smaller model with lesser parameters being able to perform reasonably well is demonstrated across all Tables. The VarBERT-base model does perform better but given a restricted hyper-parameter budget, we observe the delta between the performances is within 2-3 % in Exact Match Accuracy. It should be noted VarBERT-small has half the number of layers compared to VarBERT-base but has double the max sequence length allowed. This makes VarBERT-small more useful as it can take input longer sequences of code.

| Metric          | Model Type | Vocab-20k | Vocab-50k |
|-----------------|------------|-----------|-----------|
| Top1 EM ↑       | Small      | 91.1      | 85.2      |
|                 | Base       | 92.6      | 87.0      |
| Perplexity ↓    | Small      | 1.054     | 1.067     |
|                 | Base       | 1.077     | 1.081     |
| CER ↓           | Small      | 11.2      | 16.4      |
|                 | Base       | 10.6      | 15.85     |

Table 3: Comparison of Count of Token Prediction algorithm on Variable Name Recovery Validation Set.

| Data Splits       | Model Type | Top1 EM ↑ | CER ↓   |
|-------------------|------------|-----------|---------|
| Overall           | Small      | 85.2      | 16.50   |
|                   | Base       | 87.0      | 15.65   |
| Body in Train     | Small      | 86.7      | 15.40   |
|                   | Base       | 89.9      | 14.34   |
| Body not in Train | Small      | 71.8      | 26.70   |
|                   | Base       | 74.7      | 24.20   |

Table 4: Comparison of the two trained models, VarBERT-Small and VarBERT-Base on the different splits of the Validation Sets. Models are trained with CMLM and Token prediction heuristics is used to predict count.
Table 5: Comparisons with Baselines Trained on 1% data. VarBERT-Small is pre-trained with MLM and finetuned with CMLM, with a vocab of 50k and Token Prediction is with heuristics. The scores are on the Validation Set.

| Method       | Top1 EM % ↑ | CER % ↓ | Body Not in Train % ↑ |
|--------------|-------------|---------|-----------------------|
| DERIN        | 2.4         | 3.3     | 30.1                  |
| DIRE         | 2.4         | 3.2     | 55.8                  |
| VarBERT-Small| 3.0         | 4.0     | 56.8                  |
| VarBERT-Base | 0.6         | 5.3     | 51.5                  |

Table 6: Comparison with the current state-of-the-art on the Test Set. Body Not In Train is also EM Accuracy.

| Method       | Top1 EM % ↑ | CER % ↓ | Body Not in Train % ↑ |
|--------------|-------------|---------|-----------------------|
| DIRE         | 74.0        | 28.3    | 35.30                 |
| VarBERT-Small| 83.10       | 17.8    | 82.47                 |
| VarBERT-Base | 86.36       | 15.4    | 84.15                 |

### How does our Heuristic Based Token Count Prediction Algorithm perform?

From Table 3 it can be seen that if we know the correct number of masked tokens, the model can predict the original variable name with very high accuracy. The heuristics-based algorithm although performs reasonably well, it has a considerable room to improve.

### How does our performance improve if we suggest users with Top K Variable Names?

Figure 7 shows our performance improves by nearly 7-9% when we suggest Top K variable names. This shows the promise of using suggestion and ranking based models for variable name recovery.

### How does our model improve with increasing train data?

Figure 6 shows the learning curve of our VarBERT-Small model trained with Constrained Masked Language Modeling and a vocabulary size of 50K. We observe an interesting curve where the overall Top1 accuracy increases more than the Body not in Train set. This indicates with more data model learns to memorize the different variable names in shared library functions.

### How does our models compare to existing baseline and state-of-the-art models?

Table 5 and Table 6 show our model performs significantly well compared to both the models across all metrics. In Table 5, we compare the baselines with models trained on 1% of the Training data corpus. We choose this approach as DEBIN requires a considerable amount of training time and does not scale to the entire dataset. We compare with DIRE by training with the entire dataset in Table 6. VarBERT-small is more robust and data-efficient compared to both DEBIN and DIRE. Our pre-trained on Masked LM and finetuned on the Constrained MLM model generalizes significantly well, which is shown on the Exact Match Accuracy in the Body not in Train set. VarBERT-small is a more accurate and generalizable technique compared to the current state-of-the-art.

### What is our performance for variables which are split into multiple tokens?

Figure 8 shows the accuracy of our model across variables that are split into multiple tokens. It is expected for the model to perform well on variables that are not split as they have rich representations learned during the pre-training task. It is interesting to note that the model performs reasonably well for variables split into two to five tokens. This shows the model has sufficient reasoning capabilities to predict such variable names.

### Where does our model go wrong?

We analyzed the different errors the model make and we classify the errors broadly into the following categories: Error in the number of mask count prediction, Partial incorrect token prediction, and Off-by-few-chars errors. Error in the number of mask count prediction occurs when a different set of mask tokens count has a higher average probability. It is observed that a smaller number of tokens have a higher average probability. We can fix this issue if we learn this task instead of a heuristic-based algorithm.

Partial incorrect token prediction happens when a part of the tokens generated is wrong. This happens when there can be several generated combinations with the same prefix token. For example, variable names like `tokenIndex` and `tokenCount`. Our model predicts `tokenIndex` when instead, the original variable is `tokenCount`. This can be corrected by a suggestion based system and it gives the user the freedom to select which variable name is more suited.

Off-by-few-chars errors occur when the model predicts tokens which only differ by a few characters. For example, `token` and `tokens`.

### What are the other sources of errors?

The DIRE dataset comprises of scraped C code from GitHub. There was no filtering and quality control implemented to ensure that the dataset represents the set of target binaries that are reverse-engineered. Moreover, these binaries were not compiled with multiple different optimization and obfuscation compiler options. There is a possibility that our models may not perform on such code with such high accuracy but may work reasonably well compared to our baselines, and current state-of-the-art. To improve on such binaries is left as future work. Our model is tightly coupled with the output of the Hex-Rays decompiler. To support other decompilers, the model may need to be re-trained with a new training corpus generated from the new set of decompilers. We leave building an adaptable and multi-decompiler supporting model as future work.

### 8 Conclusion

Improving the understandability of decompiled binary code is crucial for software reverse engineering. In this paper, we have advanced the state of the art for variable name recovery in decompiled binary code. We adapted recent advances in the field of natural language processing, such as Masked Language Modeling and Transformers, and proposed a heuristic-based Count of Token Prediction algorithm. These techniques are crucial in improving the performance of variable name recovery in decompiled binary code.

In our evaluation, we showed the impact of each module. We trained two neural network models, VarBERT-base and VarBERT-small. These neural models take raw code as input, which makes them much simpler to build and use. Our evaluation of the DIRE data set shows that our techniques advance the state-of-the-art by 12.36% on overall accuracy and improve on generalizability by 49%.
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A SUPPLEMENTAL MATERIAL