

DOBF: A Deobfuscation Pre-Training Objective for Programming Languages

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Abstract

Recent advances in self-supervised learning have dramatically improved the state of the art on a wide variety of tasks. However, research in language model pre-training has mostly focused on natural languages, and it is unclear whether models like BERT and its variants provide the best pre-training when applied to other modalities, such as source code. In this paper, we introduce a new pre-training objective, DOBF, that leverages the structural aspect of programming languages and pre-trains a model to recover the original version of obfuscated source code. We show that models pre-trained with DOBF significantly outperform existing approaches on multiple downstream tasks, providing relative improvements of up to 13% in unsupervised code translation, and 24% in natural language code search. Incidentally, we found that our pre-trained model is able to de-obfuscate fully obfuscated source files, and to suggest descriptive variable names.

1. Introduction

Model pre-training with self-supervised methods such as BERT (Devlin et al., 2018), RoBERTa (Liu et al., 2019), XLM (Lample & Conneau, 2019) or XLNet (Yang et al., 2019), has become ubiquitous in Natural Language Processing (NLP), and led to significant improvements in many tasks. These approaches are based on the Masked Language Modeling (MLM) objective, which consists in randomly masking words from an input text, and training a model to recover the original input. In the original approach proposed by Devlin et al. (2018), a fraction of selected masked words is replaced by masked tokens, another is replaced by random words, and another remains unchanged. Since then, a myriad of studies have proposed to modify the MLM objective, either by masking contiguous spans of text (Song et al., 2019; Joshi et al., 2020), masking named entities

and phrases (Sun et al., 2019), sampling masked words according to their frequencies (Lample & Conneau, 2019), replacing words with plausible alternatives (Clark et al., 2020), etc. Overall, most of these pre-training objectives boil down to denoising auto-encoding tasks with different methods to add noise to the input, using arbitrary noise functions. In our case, we are interested in pre-training deep learning models for programming languages. As in natural language, pre-training was shown to be effective for source code (Feng et al., 2020; Roziere et al., 2020). However, these studies both rely on the original MLM objective proposed by Devlin et al. (2018), which was initially designed for natural languages and does not leverage the particular structure of source code. We argue that this objective is actually suboptimal in the context of programming languages, and propose a new objective based on code obfuscation.

Code obfuscation consists in modifying source code in order to make it harder for humans to understand, or smaller while keeping its behaviour unchanged. In some ancient interpreted languages, name minimization could also reduce the memory usage of the program. Today, it is used to protect intellectual property by preventing people from understanding and modifying the code, to prevent malware detection, and to compress programs (e.g. Javascript code) to reduce network payload sizes. Moreover, C compilers discard variable names, and current rule-based and neural-based decompilers generate obfuscated C code with uninformative variable names (Fu et al., 2019). Obfuscators typically apply several transformations to the code. While some operations can be reversed (e.g. dead code injection), the obfuscation of identifier names—renaming every variable, method and class with uninformative names—is irreversible and has a substantial impact on code comprehension (Gellenbeck & Cook, 1991; Takang et al., 1996; Lawrie et al., 2006).

By analyzing the overall structure of an obfuscated file, an experienced programmer can always, with time, understand the meaning of the obfuscated code. For instance, in the obfuscated example in Figure 1, one can recognize the function and guess that it implements a breadth-first search algorithm. We also expect neural networks, that excel in pattern recognition, to perform well on this task. We propose to pre-train a model to revert the obfuscation function, by training a sequence-to-sequence (seq2seq) model to convert obfuscated functions, where names of functions

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and variables have been replaced by uninformative names, back to their original forms. Suggesting proper variable and function names is a difficult task that requires to understand what the program does. In the context of source code, it is a more sensible, but also a more difficult task than MLM. Indeed, we observe (c.f. Figure 1) that predicting the content of randomly masked tokens is usually quite simple, as it often boils down to making syntax related predictions (e.g. predicting that was has been masked out is a parenthesis, a semi-column, etc.). These simple predictions actually provide little training signal to the model. In practice, MLM also masks out variable names, but if a given variable appears multiple times in a function, it will be easy for the model to simply copy its name from one of the other occurrences. Our model does not have this issue, as all occurrences of masked variables are replaced by the same `VAR_i` special tokens.

In this paper, we make the following contributions:

- We present DOBF, a new pre-training objective based on deobfuscation, and show its effectiveness on multiple programming languages.
- We show that DOBF significantly outperform MLM (e.g. BERT) on multiple tasks such as code search, code summarization or unsupervised code translation.
- We show that, by design, models pre-trained with DOBF have interesting applications and can be used to understand functions with uninformative identifier names. Besides, the model is able to successfully deobfuscate fully obfuscated source files.

In the next section, we discuss the related work. Then, we present our objective, and the downstream tasks we consider for fine-tuning. Finally, we present our results and the potential applications of our model.

2. Related work

Masked Language Modeling pre-training. Large pre-trained transformers such as BERT (Devlin et al., 2018) or RoBERTa (Liu et al., 2019) led to significant improvements in the majority of natural language processing tasks. The quality of pre-training mainly comes from the MLM objective (i.e. the cloze task), that allows the model to make predictions by leveraging left and right contexts, unlike causal language modeling (CLM) where the model predictions are only conditioned on previous words. In MLM, the model takes as input a sentence and uniformly selects 15% of its tokens. Of the selected tokens, 80% are replaced by a special symbol [MASK], 10% are left unchanged, and the remaining 10% are replaced by random tokens from the vocabulary. The MLM objective consists in recovering the

initial sentence given the corrupted one. Lample & Conneau (2019) noticed that the masked words are often easy to predict, and proposed to sample the 15% masked words according to their frequencies instead of uniformly. This way, rare words are sampled more often, making the pre-training task more difficult for the model, which results in a better learning signal and faster training. Sun et al. (2019) also noticed that recovering the tokens masked by MLM is too simple in some contexts (e.g. predicting the two tokens “Harry Potter” is much harder than predicting only “Harry” if you know the next word is “Potter”). To address this issue, they proposed to mask phrases and named entities instead of individual tokens. Joshi et al. (2020) and Song et al. (2019) made a similar observation and proposed to mask random spans of text. They showed that this simple modification improves the performance on many downstream NLP tasks.

Alternative objectives. Other pre-training objectives have been proposed in addition to MLM. For instance, Devlin et al. (2018) also uses the next sentence prediction (NSP) objective, a binary classification task that consists in predicting whether two input sentences follow each other in the original corpus. The NSP objective was originally designed to improve the performance on downstream NLP tasks, but recent studies (Lample & Conneau, 2019; Liu et al., 2019) showed that training MLM on stream of sentences to leverage longer context, and removing the NSP objective improves the quality of pre-training. To improve the sample-efficiency of MLM (where only 15% of tokens are predicted), Electra (Clark et al., 2020) proposed to replace (and not mask) some tokens with plausible alternatives, and to train a network to detect the tokens that have been replaced. They showed that this new Replaced Token Detection (RTD) objective matches the performance of RoBERTa while using four times less computational resources. Dong et al. (2019) proposed a model that combines multiple pre-training tasks, including bidirectional, but also left-to-right and right-to-left language modeling objectives. Lewis et al. (2019) also proposed different pre-training objectives, to detect whether input sentences have been permuted, whether tokens have been deleted or inserted, etc.

Code Generation Pre-training. Recent studies showed that pre-training methods developed for natural language processing are also effective for programming languages. For instance, Feng et al. (2020) proposed CodeBERT, a RoBERTa-based model trained on source code using the MLM and RTD objectives. They showed that their model performs well on downstream code generation tasks and outperforms previous pre-training approaches. Kanade et al. (2020) applied MLM and the next sentence prediction objectives to pre-train models on Python code. More recently, Roziere et al. (2020) applied the unsupervised machine translation principles of Lample et al. (2018a;b) to monolingual

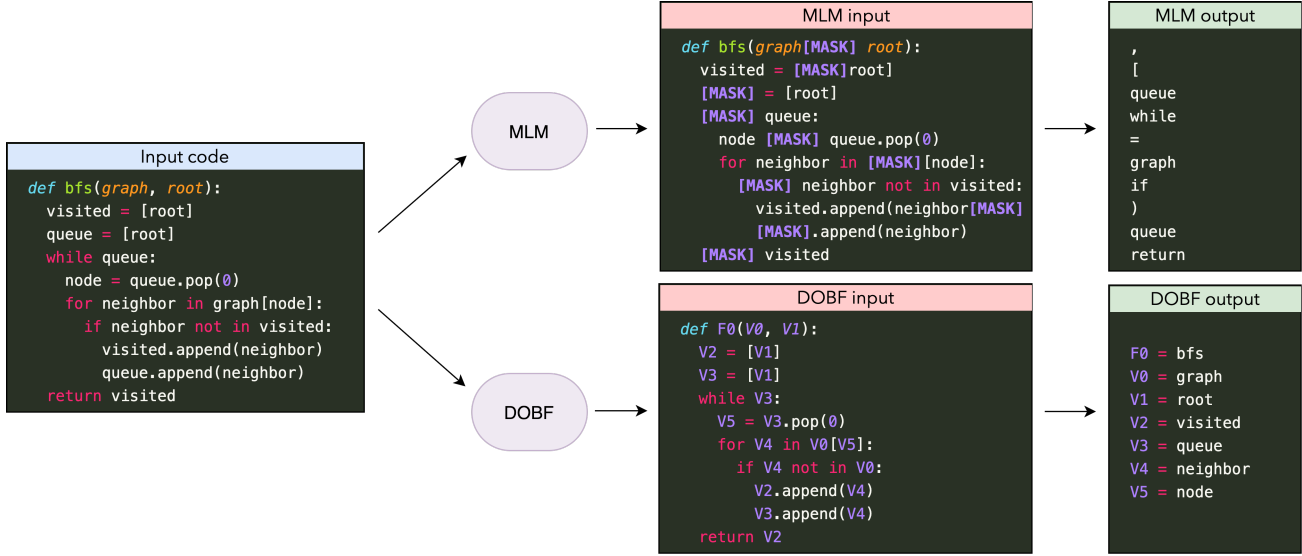


Figure 1. **Illustration of the MLM and DOBF objectives.** Given an input function, the masked language modeling (MLM) task randomly samples tokens to mask out. With source code, a large fraction of these tokens are related to the language syntax (e.g. commas, parentheses, etc.) that are trivial for the model to predict, and provide a poor training signal. Instead, we propose to obfuscate the code by masking the name of functions and variables, and to train the model to recover the original function by deobfuscating the code (DOBF). When a variable is masked out, we mask all occurrences of this variable with the same mask symbol (e.g. all occurrences of “visited” are replaced by “V0”) to prevent the model from copying names. The DOBF objective is more difficult and provides a better learning signal.

source code from GitHub. They showed that the resulting model, TransCoder, was able to translate source code between Python, Java, and C++, in a fully unsupervised way. However, the two above studies build upon pre-training strategies developed in the context of natural language processing. In this paper, we propose to use a code-specific objective to better pre-train models designed to be fine-tuned on code generation tasks: code deobfuscation.

Code deobfuscation. Empirical studies show that naming conventions and the use of informative identifier names make code more understandable, easier to maintain and lead to fewer bugs (Takang et al., 1996; Liblit et al., 2006; Butler et al., 2009). It motivated other works studying deobfuscation of identifier names and identifier name proposal using n-grams (Allamanis et al., 2014; 2015), probabilistic models (Raychev et al., 2015; Bichsel et al., 2016; Vasilescu et al., 2017; Alon et al., 2018), and recurrent neural networks (Bavishi et al., 2018; Lacomis et al., 2019). Alon et al. (2018) extract features from Abstract Syntax Tree (AST) paths and train a Conditional Random Field to predict variable and method names, and infer types for several languages. DIRE (Lacomis et al., 2019) uses a commercial decompiler to obtain C code with uninformative identifier names from binaries. They also use AST features, which go through a Graph Neural Network trained jointly with a LSTM model on the sequence of C tokens to retrieve relevant identifier names. More recently, David et al. (2020)

used a transformer together with augmented representations obtained from static analysis to infer procedure names in stripped binary files. These models are already used to understand obfuscated and compiled source code. UnuglifyJS¹, which is based on JSNICE (Raychev et al., 2015) and available online, is especially famous in the Javascript community. However, none of these studies investigated the use of deobfuscation for model pre-training.

3. Model

3.1. MLM for Programming Languages

A countless number of pre-training objectives have been introduced in the literature (Devlin et al., 2018; Clark et al., 2020; Lewis et al., 2019; Liu et al., 2019; Dong et al., 2019). Most of them rely on hyper-parameters and seemingly arbitrary decisions (Should we mask individual tokens or spans? Which fraction of them? What do we do with masked out tokens? etc.). These choices are typically based on intuition and validated empirically on natural language processing tasks. However, source code is much more structured than natural language, which makes predicting masked tokens much easier for programming languages.

The first row in Figure 1 shows an example of input / output for the MLM objective. We can see that the majority of

¹<http://www.nice2predict.org/>

tokens are composed of Python keywords or symbols related to syntax: `, [while = if) return`. These symbols are easy to recover, and a model will quickly learn to predict them with perfect accuracy. This effect is accentuated by the verbosity of the language. For instance, we would see significantly more of these tokens in Java. Retrieving the obfuscated `graph` token is also relatively simple: the model only needs to retrieve the most relevant variable in the scope. More generally, retrieving an identifier name is often easy when given its full context, including its definition and usages. Overall, we suspect that the MLM objective is too simple in programming languages and we introduce a new objective, DOBF, which encourages the model to learn a deeper understanding of code semantics.

3.2. Deobfuscation Objective

Instead of MLM, we propose a new pre-training objective, DOBF, that leverages the particular structure of programming languages. We obfuscate code snippets by replacing class, function and variable names with special tokens, and train a model to recover the original names. When an identifier is selected, all of its instances in the code are replaced by the same special token. This differs from MLM where the name of a variable can appear multiple times while being masked a single time. For instance, in Figure 1, DOBF will replace the two occurrences of `node` by the same symbol `V5`, while MLM will only mask one of these occurrences. As a result, the fraction of meaningful tokens masked by the objective is language independent: for more verbose languages (e.g. Java), the less informative syntax-related tokens will not be masked out by the DOBF objective.

Each identifier is replaced with probability $p_{obf} \in [0, 1]$. We ensure that the original input is modified: if no identifier is replaced, we draw a random one to obfuscate. When $p_{obf} = 0$, we always obfuscate exactly one random identifier in the input. When $p_{obf} = 1$, we obfuscate all the identifiers defined in the file. We ensure that the obfuscated code has the same behavior as the original. The second row in Figure 1 shows an example of obfuscated code with $p_{obf} = 1$, where we obfuscate a function `bfs` which implements a breadth-first search. The function `append` is not obfuscated as it is a standard Python function not defined in the file. The model is given the obfuscated code as input and has to restore the original name of each special token `CLASS_i`, `FUNC_i` and `VAR_i`. In other words, the model needs to output a dictionary mapping special tokens to their initial values.

Finding informative names for obfuscated identifiers requires the model to learn a deep understanding of code semantics, which is desirable for a pre-training task. MLM will mask only some of the occurrences of the identifiers and leave the other ones unchanged so that the model can

simply copy identifier names. In Figure 1, with MLM masking, the model can simply notice that a variable named `queue` is called on the fourth line. Since the variable is not defined, the model can easily guess that `queue` has to be defined on the third line, and infer the value of the corresponding `[MASK]` token. With the deobfuscation objective, the model needs to analyze code patterns and understand the semantics of the variable to infer that, since its elements are popped with `.pop(0)`, the variable `V3` implements a queue. If its elements were popped with `.pop()`, our model would name it `stack` instead of `queue` (c.f. Figure 8 in the appendix).

3.3. Implementation

Overall, the deobfuscation objective operates like a supervised machine translation objective, where a seq2seq model is trained to map an obfuscated code into a dictionary represented as a sequence of tokens. At inference time, the model is able to suggest meaningful class, function and variable names for a piece of code with an arbitrary number of obfuscated identifiers. Obfuscated classes, functions, and variables, are replaced with associated special tokens: `CLASS_0 ... CLASS_N`, `FUNC_0 ... FUNC_N` and `VAR_0 ... VAR_N`. We serialize the output dictionary as a sequence of tokens where the entries are separated by a delimiter symbol `|`.²

4. Experiments

We train DOBF with the deobfuscation objective. First, we evaluate our model on two straightforward deobfuscation applications. Then, we show its performance on multiple downstream tasks.

4.1. Deobfuscation

We evaluate our model on two applications of the deobfuscation task: when $p_{obf} = 0$ (the model has to retrieve a single identifier name), and $p_{obf} = 1$ (the model has to retrieve all the identifier names).

Deobfuscating a single identifier When $p_{obf} = 0$, only one identifier is obfuscated. In that case, the model has to propose a relevant name for a single identifier using the rest of the non-obfuscated file as context. It can be applied as a tool that suggests relevant variable names. Integrated development environments (e.g. PyCharm or IntelliJ) already perform this task, often using simple handcrafted rules.

²In the obfuscated example given in Figure 1, the model is trained to generate the sequence: `FUNC_0 bfs | VAR_0 graph | VAR_1 root | VAR_2 visited | VAR_3 queue | VAR_4 neighbor | VAR_5 node`.

Deobfuscating all identifiers Obfuscators are commonly used to make code smaller and more efficient or to protect it by making it more difficult to understand and reuse. They typically apply several transformations, one of them being to replace every identifier name with short and uninformative names (e.g. a, b, c). In our work, such a transformation corresponds to obfuscating a file with $p_{obf} = 1$. To measure our model’s ability to revert the obfuscation operation, we evaluate its accuracy when obfuscating all identifier names. Another application would be to help understand source code written with uninformative variable names.

Evaluation metric We evaluate the ability of our model to retrieve identifier names from the original non-obfuscated code. We report the accuracy, which is the percentage of recovered tokens that exactly match the ground truth. Following previous works (Allamanis et al., 2015; 2016; Alon et al., 2018; 2019), we also report the *subtoken score*, a more flexible metric which computes the precision, recall, and F1 scores for retrieving the original case-insensitive subtokens. Each token is broken into subtokens using upper-case letters for camelCase and underscores for snake_case. For instance, `decoderAttention` would be considered to be a perfect match for `decoder_attention` or `attentionDecoder.attention` would have a perfect precision but a recall of 0.5, so a F1 score of 66.7. `crossAttentionDecoder` would have a perfect recall but a precision of $\frac{2}{3}$, corresponding to a F1 score of 80.0. We compute the overall subtoken precision, recall and F1 scores averaged over each recovered token.

4.2. Fine-tuning on downstream tasks

In order to evaluate DOBF as a pre-training model, we fine-tune DOBF on TransCoder and on three tasks from CodeXGLUE (Cod, 2020), a benchmark for programming languages. We only consider the Java and Python tasks with an encoder in the model architecture for which the training, validation, and test sets are publicly available.

CodeXGLUE Clone Detection This task is a binary classification problem where the model has to predict whether two code snippets are semantically equivalent. It is evaluated using the F1 score. The model is composed of a single encoder and a classification layer. An input consists in two snippets of code, which are concatenated before being fed to the model. This task is available in Java.

CodeXGLUE Code Summarization Given a code snippet, the model is trained to generate the corresponding documentation in natural language. The architecture is a sequence-to-sequence transformer model evaluated using BLEU score (Papineni et al., 2002). The dataset includes both Java and Python source code.

CodeXGLUE NL Code Search Given a code search query

in natural language the model has to retrieve the most semantically related code within a collection of code snippets. This is a ranking problem evaluated using the Mean Reciprocal Rank (MRR) metric. The model is composed of two encoders. The natural language query and the code are encoded separately, and we compute the dot product between the first hidden states of the encoders’ last layers. This task is available in Python.

TransCoder TransCoder (Roziere et al., 2020) is an unsupervised machine translation model which translates functions and methods between C++, Java, and Python. A single seq2seq model is trained for all languages. In the original work, TransCoder is pre-trained with MLM, and trained with denoising auto-encoding and back-translation. TransCoder is evaluated using the Computational Accuracy metric, which computes the percentage of correct solutions according to series of unit tests. We only consider a single model output (CA@1), with beam sizes of 1 and 10.

4.3. Experimental details

Model Architecture For DOBF, we consider a seq2seq model with attention, composed of an encoder and a decoder using a transformer architecture (Vaswani et al., 2017). We train two models with different sizes in order to provide fair comparisons to our baselines (CodeBERT and TransCoder). We train one model with 12 layers, 12 attention heads, and a hidden dimensionality of 768 and one model with 6 layers, 8 attention heads, and a hidden dimensionality of 1024.

Training dataset As in Roziere et al. (2020), we use the GitHub public dataset available on Google BigQuery and select all Python and Java files within the available projects. Following Lopes et al. (2017) and Allamanis (2019), we remove duplicate files. We also ensure that each fork belongs to the same split as its source repository. We obfuscate each file and create the corresponding dictionary of masked identifier names, resulting in a parallel (obfuscated file - dictionary) dataset of 19 GB for Python and 26 GB for Java. We show some statistics about this dataset in Table 1. We use the same tokenizers as Roziere et al. (2020). For comparison purposes, we apply either the BPE codes used by Roziere et al. (2020) or by Feng et al. (2020). In practice, we train only on files containing less than 2000 tokens, which corresponds to more than 90% and 80% of the Java and Python files respectively.

Training details We train DOBF to translate obfuscated files into lists of identifier names. During DOBF training, we alternate between batches of Java and Python composed of 3000 tokens per GPU. We optimize DOBF with the Adam optimizer (Kingma & Ba, 2014) and an inverse square-root learning rate scheduler (Vaswani et al., 2017). We implement our models in PyTorch (Paszke et al., 2019) and train them on 32 V100 GPUs. We use float16 operations to speed

Table 1. Dataset statistics.

	Java	Python
All - Size	26 GB	19 GB
All - Nb files	7.9M	3.6M
Av. nb of tokens / file	718	1245
Av. nb of identifiers / file	25.9	41.8

up training and to reduce the memory usage of our models. We try different initialization schemes: training from scratch and with a Python-Java MLM following [Roziere et al. \(2020\)](#). We train DOBF with three different obfuscation probability parameters: $p_{obf} \in \{0, 0.5, 1\}$. For each p_{obf} value, we train models with multiple initial learning rates ranging from 10^{-4} to $3 \cdot 10^{-4}$ and select the best one using the average subtoken F1 score computed on the validation dataset.

Fine-tuning details Depending on the fine-tuning tasks, we consider different model architectures: seq2seq models with encoder and decoder, architectures with two encoders or a single encoder. In all cases, we initialize the encoders of these models with the encoder of DOBF and fine-tune all parameters. For fair comparison, we rerun all baselines, and train models with the same architectures, number of GPUs, batch sizes and optimizers as in the original papers. For CodeXGLUE, we noticed that the tasks are quite sensitive to the learning rate parameter used during fine-tuning. We perform a grid search on five learning rate parameters ranging from $5 \cdot 10^{-6}$ to 10^{-4} and we select the best parameter on the validation dataset. For TransCoder, we use a learning rate of 10^{-4} as in [Roziere et al. \(2020\)](#).

5. Results

5.1. Deobfuscation

In Table 2, we evaluate the ability of our model to recover identifier names, either when only one identifier is obfuscated ($p_{obf} = 0$) or when all identifiers are obfuscated ($p_{obf} = 1$), for models trained with $p_{obf} \in \{0, 0.5, 1\}$. Even when evaluating with $p_{obf} = 0$, training with $p_{obf} = 0$ is less efficient than $p_{obf} = 0.5$ since the model is only trained to generate a single variable for each input sequence. Training with $p_{obf} = 0.5$ is a more difficult task that requires the model to learn and understand more about code semantics. Forcing the model to understand the structure of the code may be useful even when testing with $p_{obf} = 0$, as some identifier names cannot be guessed only from the names of other identifiers. When DOBF has to recover a fully obfuscated function, it obtains the best accuracy when trained with $p_{obf} = 1$. It manages to recover 45.6% of the initial identifier names. We also observe that, for every

```
def FUNC_0 (VAR_0, VAR_1):
    VAR_2 = [VAR_1]
    VAR_3 = [VAR_1]
    while VAR_3:
        VAR_4 = VAR_3.pop(0)
        for VAR_5 in VAR_0[VAR_4]:
            if (VAR_5 not in VAR_2):
                VAR_2.add(VAR_5)
                VAR_3.append(VAR_5)
    return VAR_2

def bfs(graph, start):
    visited = [start]
    queue = [start]
    while queue:
        node = queue.pop(0)
        for neighbor in graph[node]:
            if (neighbor not in visited):
                visited.add(neighbor)
                queue.append(neighbor)
    return visited
```

Figure 2. Full deobfuscation of a breadth-first-search function by DOBF. The code on top has been fully obfuscated. The code on the bottom was recovered using DOBF by replacing the function name and every variable name using the generated dictionary. DOBF is able to suggest relevant function and variable names. It makes the code much more readable and easier to understand.

configuration, pre-training DOBF with MLM improves the performance.

Figure 2 shows an example of a fully obfuscated function recovered by our model. DOBF successfully manages to understand the purpose of the function and to predict appropriate variable names. Figure 3 shows examples of function name proposal by DOBF for functions implementing matrix operations in Python. We observe that DOBF manages to identify the key tokens and to properly infer the purpose of similar but very different functions. Figures 5, 6, and 7 in the appendix show additional examples of function name proposals by DOBF in Java and Python. Figure 8 shows additional examples where we show that DOBF also leverages non-obfuscated identifier names to understand the meaning of input functions. Figures 9 and 10 in the appendix show examples of deobfuscation of fully obfuscated Python code snippets using DOBF. It is able to understand the semantics and purposes of a variety of obfuscated classes and functions, including a LSTM cell.

5.2. Downstream tasks

For fine-tuning, we considered models pre-trained with $p_{obf} = 0.5$ and $p_{obf} = 1$. Since they gave very similar results on downstream tasks, we only use models pre-trained with $p_{obf} = 0.5$ in the rest of the paper. As baselines, we consider a randomly initialized model and a model pre-trained with MLM only. For CodeXGLUE tasks, we also consider CodeBERT as a baseline. We compare results for DOBF trained from scratch and DOBF initialized with MLM (MLM+DOBF), and report results in Table 3.

Input Code	Function Name Proposals	
<pre>def FUNC_0 (m1, m2): assert m1.shape == m2.shape n, m = m1.shape res = [[0 for _ in range(m)] for _ in range(n)] for i in range(n): for j in range(m): res[i][j] = m1[i][j] + m2[i][j] return res</pre>	matrix_add	25.9%
	matrixAdd	22.5%
	matrixadd	18.8%
	matrix_sum	16.7%
	matrix_addition	16.1%
<pre>def FUNC_0 (m1, m2): assert m1.shape == m2.shape n, m = m1.shape res = [[0 for _ in range(m)] for _ in range(n)] for i in range(n): for j in range(m): res[i][j] = m1[i][j] - m2[i][j] return res</pre>	matrix_sub	26.1%
	matrix_subtract	21.5%
	matrix_subtraction	19.7%
	sub	17.6%
	sub_matrix	15.0%
<pre>def FUNC_0 (matrix): n, _ = matrix.shape for i in range(n): for j in range(i, n): matrix[i][j], matrix[j][i] = \ matrix[j][i], matrix[i][j]</pre>	transpose	36.7%
	rotate	29.5%
	rotate_matrix	17.1%
	symmetric	8.9%
	rotate_matrix_by_row	7.7%
<pre>def FUNC_0 (m1, m2): n1, m1 = m1.shape n2, m2 = m2.shape assert n2 == m1 res = [[0 for _ in range(m2)] for _ in range(n1)] for i in range(n1): for j in range(m2): res[i][j] = sum([m1[i][k] * m2[k][j] for k in range(n2)]) return res</pre>	matrix_product	28.8%
	mat_mult	23.8%
	matmul_mat	17.0%
	matprod	16.0%
	matrixProduct	14.4%

Figure 3. Additional examples of function name proposals for matrix operations in Python. DOBF is able to find the right name for each matrix operation, showing that it learned to attend to the most important parts of the code. Even when the function only differs by one token (e.g. a subtraction instead of an addition operator), DOBF successfully and confidently (c.f. scores) understands the semantics of the function and its purpose.

Table 2. Results on partial and full deobfuscation. Token accuracy and subtoken F1 score of DOBF evaluated with $p_{obf} = 0$ (i.e. name proposal, where a single token is obfuscated) and $p_{obf} = 1$ (i.e. full deobfuscation, where all tokens are obfuscated). We consider models trained with different obfuscation probabilities p_{obf} . DOBF_{0.5} performs well for both tasks, and it even performs better than DOBF₀ for Identifier Name Proposal. DOBF₀ and DOBF₁ perform poorly when evaluated on other p_{obf} parameters. Pre-training DOBF with MLM further improves the performance.

	Eval $p_{obf} = 0$		Eval $p_{obf} = 1$	
	Acc	F1	Acc	F1
DOBF ₀	56.3	68.0	0.4	0.9
DOBF _{0.5}	61.1	71.2	41.8	54.8
DOBF ₁	18.1	27.0	45.6	58.1
MLM+DOBF _{0.5}	67.6	76.3	45.7	58.0
MLM+DOBF ₁	20.0	28.3	49.7	61.1

The randomly initialized model is useful to measure the importance of pre-training on a given task. Pre-training is particularly important for the NLCS task: without pre-training, the model achieves a performance of 0.025 MMR while it goes up to 0.308 with MLM pre-training. The main differences between our MLM baseline and CodeBERT, are that 1) CodeBERT was trained on a different dataset which contains functions with their documentation, 2) it uses an additional RTD objective, and 3) is initialized from a RoBERTa model. Although code summarization and NL code search involve natural language and may benefit from CodeBERT’s dataset that contains code documentation, we obtained very similar results on this task using a simpler dataset. However, our MLM baseline did not match their performance on clone detection. We also tried to initialize our MLM model with RoBERTa, but did not observe any substantial impact on the performance on downstream tasks.

DOBF trained from scratch and DOBF pre-trained with MLM obtained state-of-the-art results on all downstream

Table 3. **Results on downstream tasks for different pre-training configurations.** Models pre-trained with MLM and DOBF significantly outperform both CodeBERT and models trained with MLM only. MLM+DOBF outperforms CodeBERT by 7% on natural language code search (NLCS), and MLM by 6% in Java \rightarrow Python computational accuracy. It also beats CodeBERT on every task except Clone Detection, on which CodeBERT scores much higher than our MLM. The tasks where MLM provides large improvements over the transformer baseline (first row, no pre-training) are also the tasks where DOBF provides the largest gains (e.g. clone detection, natural language code search, and unsupervised translation).

	Clone Det (F1 score)	Code Sum Java (BLEU)	Code Sum Python (BLEU)	NLCS (MRR)	Python \rightarrow Java (CA@1)		Java \rightarrow Python (CA@1)	
					k=1	k=10	k=1	k=10
Transformer	88.14	16.58	16.43	0.025	37.6	38.9	31.8	42.1
CodeBERT	96.50	18.25	18.22	0.315	-	-	-	-
MLM	91.89	18.59	17.95	0.308	40.3	42.2	44.7	46.6
DOBF	96.52	18.19	17.51	0.272	38.9	45.7	44.7	46.4
MLM+DOBF	95.87	19.05	18.24	0.383	43.5	44.9	49.2	52.5

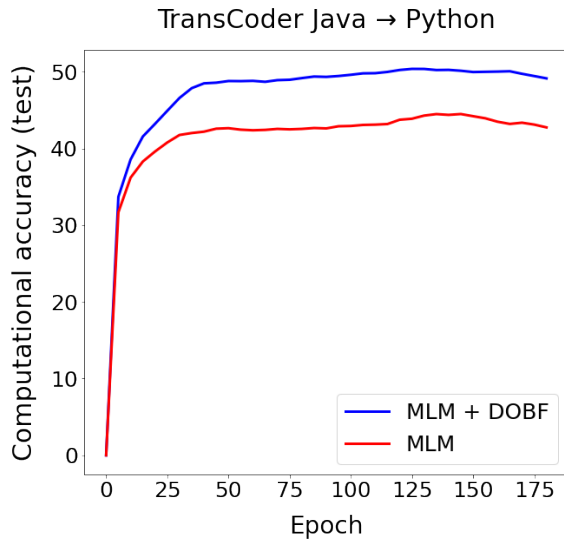


Figure 4. **TransCoder results for different pre-training schemes.** Pre-training our model with MLM+DOBF instead of MLM only, allows to quickly reach higher levels of computational accuracy when fine-tuning for Java \rightarrow Python translation. The gap between MLM+DOBF and MLM persists until convergence.

tasks, outperforming CodeBERT and MLM. The deobfuscation objective is already effective as a pre-training task: it leads to results comparable to MLM on most tasks and is much more effective on clone detection. The MLM+DOBF model outperforms MLM on all downstream tasks, the major improvement being for NL code search, which is also the task that benefited the most from MLM pretraining. For TransCoder, MLM+DOBF increases the computational accuracy of the MLM model by 2.7% when translating from Python to Java, and by 5.9% when translating from Java to Python with beam size 10. In Figure 4, we can see that com-

putational accuracy of the test set is higher for MLM+DOBF during the entire training. Also, MLM+DOBF beats CodeBERT by a wide margin on NL code search and code summarization, showing that programming language data aligned with natural language is not necessary to train an effective model on those tasks. MLM+DOBF yields higher scores than both DOBF and MLM on most tasks, showing that MLM and DOBF are complementary.

6. Conclusion

In this paper, we introduce a new deobfuscation objective and show that it can be used for three purposes: recover fully obfuscated code, suggest relevant identifier names, and pre-train transformer models for programming language related tasks. Although it does not require any parallel corpora of source code aligned to natural language, DOBF outperforms CodeBERT and MLM pre-training on multiple downstream tasks, including clone detection, code summarization, natural language code search, and unsupervised code translation. These results show that DOBF leverages the particular structure of source code to add noise to the input sequence in a particularly effective way. Other noise functions or surrogate objectives adapted to source code may improve the performance further. For instance, by training model to find the type of given variables, the signature of a method, or to repair a piece of code which has been corrupted.

Since models pretrained on source code benefit from structured noise, it would be interesting to see whether these findings can be applied to natural languages as well. Although ambiguous, natural languages also have an underlying structure. Leveraging the constituency or dependency parse trees of sentences (as opposed to abstract syntax trees in programming languages) may help designing better pre-training objectives for natural languages.

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Input Code	Proposed Function Name	
<pre> public static void FUNC_0 (String path){ try { Files.delete(path); } catch (Exception e) { System.err.println("Error deleting file " + path); } } </pre>	deleteFile	48.3%
	remove	16.9%
	DeleteFile	13.2%
	removeFile	13.1%
	deleteFileQuietly	8.4%
<pre> public static void FUNC_0 (String path){ if (!Files.exists(path)) { Files.createDirectories(path); } } </pre>	createDir	23.5%
	createDirectory	20.9%
	createDirIfNotExists	20.8%
	ensureDirectoryExists	18.5%
	createDirectoryIfNotExists	16.3%
<pre> public static List<Pair<String, Double>> FUNC_0 (List<String> list1, List<Double> list2) { return IntStream.range(0, Math.min(list1.size(), list2.size())) .mapToObj(i -> new Pair<>(list1.get(i), list2.get(i))) .collect(Collectors.toList()); } </pre>	zip	28.6%
	intersect	20.0%
	combine	17.9%
	merge	17.5%
	intersection	16.0%
<pre> public static int FUNC_0 (int n){ int a = 0, b = 1; int tmp; for (int i = 0; i < n; i++){ tmp = a + b; a = b; b = tmp; } return a; } </pre>	fib	41.5%
	fibonacci	36.6%
	fibon	9.1%
	fibonacci_series	8.8%
	fibonacci_series	4.0%
<pre> public static float FUNC_0 (List<Float> vec1, List<Float> vec2) { float size = vec1.size(); assert size == vec2.size(); float result = 0.0f; for (int i = 0; i < size; i++) { result += vec1.get(i) * vec2.get(i); } return result; } </pre>	dotProduct	40.9%
	dot	23.9%
	dot_product	16.5%
	dotproduct	10.5%
	inner	8.3%

Figure 5. Examples of name proposal in Java. DOBF is able to suggest relevant function names for a variety of Java methods and demonstrates its ability to understand the semantics of the code. In the first two examples, the first element in the beam shows that it is able to select relevant names in the context to find a function name: it uses `Files.delete` and `Files.createDirectories` to suggest the tokens `deleteFile` and `createDir`. DOBF finds relevant names for Java methods without copying any part of the other tokens. For example for the third method combining two lists as in the python `zip` function, for the fourth method which computes the n -th element of the Fibonacci series and for the last method which computes the dot product between two vectors.

Input Code	Proposals for Highlighted Identifiers	
<pre>def FUNC_0 (name): return os.environ[name]</pre>	get_env	25.3%
	get_envvar	19.3%
	env	19.2%
	getenv	18.5%
	get_env_variable	17.7%
<pre>def FUNC_0 (l): return list(set(l))</pre>	unique	24.8%
	remove_duplicates	23.8%
	removeDuplicats	18.8%
	uniquify	18.7%
	unique_items	13.8%
<pre>def FUNC_0 (path): with gzip.open(path, 'rb') as f: content = f.read() return content</pre>	read_gzip_file	22.9%
	read_gzip	22.1%
	ungzip	20.8%
	gzip_content	18.2%
	gzip_read	16.0%
<pre>def FUNC_0 (n): v = [True for i in range(n + 1)] p = 2 while (p * p <= n): if (v[p] == True): for i in range(p * 2, n + 1, p): v[i] = False p += 1 v[0] = False v[1] = False return [p for p in range(n+1) if v[p]]</pre>	sieve	36.1%
	prime_sieve	18.5%
	sieve_of_eratosthenes	15.5%
	primes	15.3%
	eratosthenes	14.5%
<pre>def f(n): VAR_0 = [True for i in range(n + 1)] p = 2 while (p * p <= n): if (VAR_0[p] == True): for i in range(p * 2, n + 1, p): VAR_0[i] = False p += 1 VAR_0[0] = False VAR_0[1] = False return [p for p in range(n+1) if VAR_0[p]]</pre>	prime	30.6%
	l	20.5%
	isPrime	18.0%
	a	16.4%
	primes	14.6%

Figure 6. Examples of name proposal in Python. Our model trained with DOBF goes well beyond copying tokens from the context. For instance, in the first example, it understands that this function is used to get environment variables. In the second example, it proposes names related to what this function actually does (removing duplicates in a list) instead of the individual operations it uses (converting to set and then to list). The last two rows show proposals for two different identifiers in a function computing the list of prime numbers below n using the sieve of Eratosthenes. The proposals for the function name are all relevant, and the third one names exactly the algorithm which is used. The variable v is a list of booleans. At the end of the algorithm, $v[i]$ is true if and only if i is prime. The proposed names `prime` and `isPrime` are very relevant as they describe what the list contains. Although `l` and `a` are not very informative, they indicate that the variable is a list or an array.

Input Code	Proposed Function Name	
<pre>def FUNC_0 (v1, v2): assert len(v1) == len(v2) return [a * b for a, b in zip(v1, v2)]</pre>	multiply_lists	28.7%
	multiply_list	23.5%
	multiply	18.1%
	multiply_vectors	14.9%
	mul	14.8%
<pre>def FUNC_0 (v1, v2): assert len(v1) == len(v2) return sum([a * b for a, b in zip(v1, v2)])</pre>	dotproduct	34.8%
	dot_product	19.2%
	dotProduct	18.1%
	dot	15.6%
	multiply_by_addition	12.3%
<pre>def FUNC_0 (v1, v2): assert len(v1) == len(v2) return [a ^ b for a, b in zip(v1, v2)]</pre>	xor	62.9%
	XOR	12.8%
	vector_xor	10.8%
	xors	7.4%
	xor_lists	6.1%
<pre>def FUNC_0 (v1, v2): assert len(v1) == len(v2) return [a ** b for a, b in zip(v1, v2)]</pre>	power	29.8%
	list_power	20.9%
	lcm	19.9%
	power_list	15.1%
	powersum	14.3%
<pre>def FUNC_0 (v1, v2): assert len(v1) == len(v2) return [a + b for a, b in zip(v1, v2)]</pre>	add_lists	27.0%
	add	22.9%
	sum_lists	17.9%
	list_concat	17.7%
	list_add	14.5%
<pre>def FUNC_0 (v1, v2): assert len(v1) == len(v2) return [a - b for a, b in zip(v1, v2)]</pre>	minus	30.4%
	subtract	29.8%
	difference	14.1%
	subtract_lists	13.3%
	substract	12.4%

Figure 7. Examples of function name proposal in Python using DOBF. DOBF is able to identify the key tokens in each function, to properly infer its purpose, and to suggest appropriate names along with a confidence score. In particular, even though the first two code snippets are very similar in terms of edit distance, they implement very different functions and DOBF is able to name them appropriately.

BFS Implementation	DFS Implementation	DFS with Erroneous Variable Name
<pre>def FUNC_0 (graph, node): visited = [node] VAR_0 = [node] while VAR_0: s = VAR_0.pop(0) for neighbour in graph[s]: if neighbour not in visited: visited.add(neighbour) VAR_0.append(neighbour) return visited</pre>	<pre>def FUNC_0 (graph, node): visited = [node] VAR_0 = [node] while VAR_0: s = VAR_0.pop() for neighbour in graph[s]: if neighbour not in visited: visited.add(neighbour) VAR_0.append(neighbour) return visited</pre>	<pre>def FUNC_0 (graph, node): visited = [node] queue = [node] while queue: s = queue.pop() for neighbour in graph[s]: if neighbour not in visited: visited.append(neighbour) queue.append(neighbour) return visited</pre>
FUNC_0 bfs VAR_0 queue	FUNC_0 dfs VAR_0 stack	FUNC_0 bfs

Figure 8. Deobfuscation on graph traversal functions. These three functions perform graph traversals. The only difference between the first and the second function is that the first uses a queue to select the next element (`.pop(0)`) while the second uses a stack (`.pop()`). The first function implements a breadth-first search (bfs) in the graph and the second implements a depth-first search (dfs). DOBF is able to find the right function and variable names in each case. In the last function, we replaced the anonymized `VAR_0` variable with `queue` in the implementation of depth-first search. This erroneous information leads DOBF to believe that this function performs breadth-first search. It shows that, just like human programmers, DOBF uses the names of the other variables to understand programs and choose relevant identifier names. When working on code with misleading identifier names, it is often preferable to obfuscate several identifiers.

Obfuscated Code

```

class CLASS_0(nn.Module):

    def __init__(VAR_0, VAR_1, VAR_2, VAR_3):
        super(CLASS_0, VAR_0).__init__()
        VAR_0.VAR_1 = VAR_1
        VAR_0.VAR_2 = VAR_2
        VAR_0.VAR_4 = nn.Linear(VAR_1, (4 * VAR_2), bias=VAR_3)
        VAR_0.VAR_5 = nn.Linear(VAR_2, (4 * VAR_2), bias=VAR_3)
        VAR_0.FUNC_0()

    def FUNC_0(VAR_6):
        VAR_7 = (1.0 / math.sqrt(VAR_6.VAR_8))
        for VAR_9 in VAR_6.VAR_10():
            VAR_9.data.uniform_((- VAR_7), VAR_7)

    def FUNC_1(VAR_11, VAR_12, VAR_13):
        (VAR_14, VAR_15) = VAR_13
        VAR_14 = VAR_14.view(VAR_14.size(1), (- 1))
        VAR_15 = VAR_15.view(VAR_15.size(1), (- 1))
        VAR_12 = VAR_12.view(VAR_12.size(1), (- 1))
        VAR_16 = (VAR_11.VAR_4(VAR_12) + VAR_11.VAR_5(VAR_14))
        VAR_17 = VAR_16[:, :(3 * VAR_11.VAR_8)].sigmoid()
        VAR_18 = VAR_16[:, (3 * VAR_11.VAR_8):].tanh()
        VAR_19 = VAR_17[:, :VAR_11.VAR_8]
        VAR_20 = VAR_17[:, VAR_11.VAR_8:(2 * VAR_11.VAR_8)]
        VAR_21 = VAR_17[:, (- VAR_11.VAR_8):]
        VAR_22 = (th.mul(VAR_15, VAR_20) + th.mul(VAR_19, VAR_18))
        VAR_23 = th.mul(VAR_21, VAR_22.tanh())
        VAR_23 = VAR_23.view(1, VAR_23.size(0), (- 1))
        VAR_22 = VAR_22.view(1, VAR_22.size(0), (- 1))
        return (VAR_23, (VAR_23, VAR_22))

```

Code Deobfuscated using DOBF

```

class LSTM(nn.Module):

    def __init__(self, input_size, hidden_size, bias):
        super(LSTM, self).__init__()
        self.input_size = input_size
        self.hidden_size = hidden_size
        self.h1 = nn.Linear(input_size, (4 * hidden_size), bias=bias)
        self.h2 = nn.Linear(hidden_size, (4 * hidden_size), bias=bias)
        self.init_weights()

    def init_weights(self):
        stdv = (1.0 / math.sqrt(self.hidden_size))
        for m in self.modules():
            m.data.uniform_((- stdv), stdv)

    def forward(self, x, prev_state):
        (prev_h, prev_c) = prev_state
        prev_h = prev_h.view(prev_h.size(1), (- 1))
        prev_c = prev_c.view(prev_c.size(1), (- 1))
        x = x.view(x.size(1), (- 1))
        h = (self.h1(x) + self.h2(prev_h))
        s = h[:, :(3 * self.hidden_size)].sigmoid()
        c = h[:, (3 * self.hidden_size):].tanh()
        r = s[:, :self.hidden_size]
        g = s[:, self.hidden_size:(2 * self.hidden_size)]
        o = s[:, (- self.hidden_size):]
        c = (th.mul(prev_c, g) + th.mul(r, c))
        h = th.mul(o, c.tanh())
        h = h.view(1, h.size(0), (- 1))
        c = c.view(1, c.size(0), (- 1))
        return (h, (h, c))

```

ID	Ground Truth	DOBF
CLASS_0	LSTM	LSTM
FUNC_0	reset_parameters	init_weights
FUNC_1	forward	forward
VAR_0	self	self
VAR_1	input_size	input_size
VAR_2	hidden_size	hidden_size
VAR_3	bias	bias
VAR_4	i2h	h1
VAR_5	h2h	h2
VAR_6	self	self
VAR_7	std	stdv
VAR_8	hidden_size	hidden_size
VAR_9	w	m
VAR_10	parameters	modules
VAR_11	self	self
VAR_12	x	x
VAR_13	hidden	prev_state
VAR_14	h	prev_h
VAR_15	c	prev_c
VAR_16	preact	h
VAR_17	gates	s
VAR_18	g_t	c
VAR_19	i_t	r
VAR_20	f_t	g
VAR_21	o_t	o
VAR_22	c_t	c
VAR_23	h_t	h

Figure 9. Deobfuscation of an LSTM cell. DOBF is able to recover several of the original tokens, including the class name (LSTM) and the full signature of the `__init__` method. Even though DOBF does not always recover the original token, it generally proposes very relevant tokens which improves code readability. In particular, for some tokens the accuracy and subtoken scores would be zero but the recovered tokens are still very relevant. For instance, `reset_parameters` (FUNC_0) was renamed to `init_weights`, `std` (VAR_7) was renamed to `stdv`, and `hidden` (VAR_13) was renamed to `prev_state`. In those instances, the original and recovered tokens share no subtoken despite having very similar semantics.

Input Code	Deobfuscated Identifiers	
<pre>def FUNC_0 (VAR_0, VAR_1): return sum(map(operator.mul, VAR_0, VAR_1))</pre>	FUNC_0 VAR_0 VAR_1	dotProduct list1 list2
<pre>def FUNC_0 (VAR_0): VAR_1 = urllib2.urlopen(VAR_0) VAR_2 = VAR_1.read() return VAR_2</pre>	FUNC_0 VAR_0 VAR_1 VAR_2	get_html url response html
<pre>def FUNC_0 (VAR_0): VAR_1 = set (VAR_0) return (len (VAR_1) == len (VAR_0))</pre>	FUNC_0 VAR_0 VAR_1	all_unique iterable s
<pre>def FUNC_0 (VAR_0, VAR_1): return list (collections.deque (VAR_0, maxlen=VAR_1))</pre>	FUNC_0 VAR_0 VAR_1	tail s n
<pre>def FUNC_0 (VAR_0): return sum((VAR_1 for VAR_1 in VAR_0 if ((VAR_1 % 2) == 0)))</pre>	FUNC_0 VAR_0 VAR_1	even_sum nums n

Figure 10. **Examples of full deobfuscations of Python functions.** Even when every identifier is obfuscated, DOBF is able to propose relevant names. The proposed function name is informative and relevant in all examples since the first function computes a dot product, the second downloads a HTML page and returns its content, the third evaluates whether the input contains only unique elements, the fourth computes the tail of an iterable, and the fifth computes the sum of the even elements of an iterable.